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Analysis of household power consumption data for social safety net services

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Abstract

Much interest in lonely death and activity of daily living (ADL) monitoring services through analysis from household power consumption data is increasing. For this, anomaly detection and power disaggregation are needed, respectively. However, the existing technologies suffer from inaccuracy problem, so they are not widely used. In this study, activity perception-based anomaly detection and appliance activation profile-based disaggregation methods are newly presented to improve accuracy. According to the experimental results, the proposed methods showed better performance than the existing methods.

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Keywords: Lonely death; Activity of daily living; Activity perception; Anomaly detection; Appliance activation profile; Power disaggregation

1. Introduction

As household power consumption data is gradually opened, differentiated services through analyzing the data have been developed. Two social safety net services [1,2] are explored as the examples in this study.

The first service is lonely death monitoring. It detects anomalous patterns from power consumption and sends an alarm of the risk of lonely death to the person in charge. For this purpose, Internet of Things (IoT) device-based approach as in [3–5] can be used, but there is difficulty in operating the device and privacy issues from the user's viewpoint [6]. In addition, there is the problem that a large introduction cost is required from the service provider's viewpoint. On the other hand, many methods as in [7–10] for inferring a problematic situation through the difference between the observed value and the predicted result by time series analysis have been studied. It is possible to implement the service by analyzing data measured in 15- or 30-min units from the existing meter. However, the analysis model must be built for each individual household.

The second service is activity of daily living (ADL) monitoring. It checks whether certain types of residential appliances were used during normal life. There are the IoT device-based method, also known as intrusive load

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monitoring (ILM), which monitors operation through an attached smart plug to the target appliance, and the disaggregation method, also known as non-intrusive load monitoring (NILM) [11], which infers an activation of the specific type of appliance from total power consumption data. Research on various data pre-processing schemes [12–14] and algorithms using statistics [15,16], deep neural networks [17–19], and ensemble trees [20,21] for disaggregation analysis has been conducted. To develop the disaggregation model, 1–60 s interval data must be provided [22]. Before the electricity utility company's existing meters are to be replaced with smart meters that support high-frequency sampling, data can be obtained through consumer's products such as home energy monitors [23,24]. Developing a disaggregation model for each individual house is too expensive, so it needs to be built as a single, pre-trained, common model.

Table 1 explains the two analysis services to be explored, along with the enabling technologies and requirements.

Table 1. Household power consumption data analysis services.

Service	Lonely death monitoring	ADL monitoring
Analysis	Anomaly detection	Disaggregation
Model	For each household	As a common pre-trained
Data requirement	15- or 30-min sampled	1–60 s sampled
Metering device	Existing meter	Home energy monitor

The problem is that the accuracy performance of existing anomaly detection and disaggregation techniques used to implement the above services is not sufficient. Therefore, this study focuses on the following contributions.

- We propose a new anomaly detection method through activity perception that can be applied directly without model training. This method showed better performance compared to the previous study.
- We introduce an improved disaggregation method through result processing by appliance activation profile. This method improved disaggregation accuracy to performance above the commercial service level.
- Finally, as a use case, we present a method of implementing a social safety net service using the proposed anomaly detection and disaggregation techniques.

2. Anomaly detection

2.1. Activity perception-based analysis method

The total power consumption (C_T) measured in a household can be defined as the sum of the consumption by appliances (C_A) that people activate and the consumption by the base load (C_B). The base load refers to a load generated by constant electricity consumption source, such as a refrigerator, without human intervention.

$$C_T = C_A + C_B \tag{1}$$

The above equation can be rewritten as $C_A = CT$ - C_B. Because C_T is measured and provided as input data for a service, if C_B can be obtained, C_A can be recognized. In the previous study in [25], the method of extracting the base load by utilizing communication data was used. In this study, the following practical method is proposed.

First, the median of power consumption between 0 and 6 o'clock, which is a period when most residents are sleeping and there is little possibility of using residential appliances, is estimated as the base load. The method was proved to be effective for inferring the base load. It also has the advantage of not requiring model training.

Second, the case where the difference between C_T and C_B is greater than a certain bound is found and regarded as activity. The activity means an activation by human. Conditions for determining an activity are as follows.

- The difference (C_A) must be outside the 1 sigma standard deviation interval (68.3%).
- At the same time, the difference (C_A) must be at least 25 W, which is the power consumption for watching television for 15 min.

Fig. 1 describes the activity perception method. The method regards an anomaly when there is no found activity.

2.2. Experimental results

None of the public datasets provides household power consumption data with label data for the status of residents. Therefore, a proprietary dataset, which was measured in single-person household caring service provided for 100

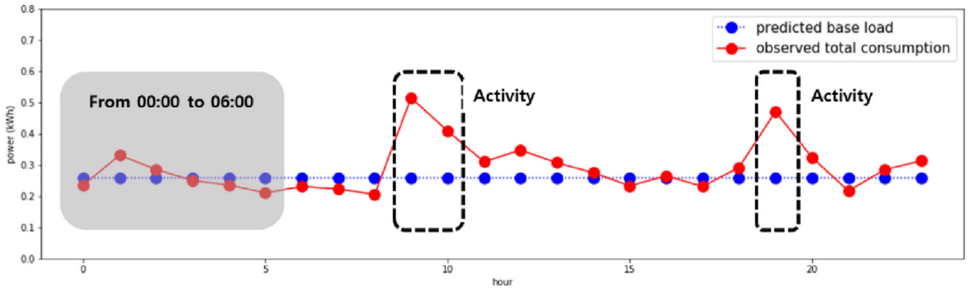

Fig. 1. Activity perception from household power consumption.

households by a Korea's local government in 2020, was used for the experiments. There was no lonely death in the service for one month from June 16 to July 15, 2020.

We implemented autoencoder-based anomaly detection using the open-source of [26] as an existing method, and compared the performance with the proposed activity perception method. The recall, among classification performance metrics, was used to verify whether actual positive cases are predicted as normal.

$$recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

As shown in Table 2, the activity perception method shows 8% better performance than the existing method. This improvement means that the amount of work to check the safety by phone or visit has been reduced.

Table 2. Performance comparison between the existing method.

Metric	Existing method	Activity perception
Recall	0.90	0.97

3. Disaggregation

3.1. Appliance activation profile-based analysis method

Disaggregation is the analysis that infers individual appliance power consumption (C_A) from total power consumption (C_T). Therefore, training and prediction are performed as follows.

- train(C_T, C_A)
- $C_A{}' \approx$ predict(C_T)

To develop a disaggregation model, performance evaluation is necessary to find a suitable machine learning algorithm. According to the previous study of [17], the deep neural network-based algorithms, recurrent neural network (RNN), gated recurrent unit (GRU), window GRU (WGRU), denoising autoencoder (DAE), and sequence-to-point (S2P), performed better than the statistical-based algorithm such as hidden Markov model (HMM). In the recent studies as in [20,21], tree ensemble-based random forest (RF) and gradient boosting machine (GBM) showed good performance, so it is necessary to consider those algorithms as candidates. The open-source project of [27] was used to implement all the disaggregation models with different algorithms.

To evaluate the performance, model training time (T) is measured and mean absolute error (MAE) is calculated between the prediction result (x) and the actual data (y). In addition, computing efficiency (CE) is obtained by T and MAE. The optimal algorithm must show the smallest value of CE. These metrics are defined as follows.

$$MAE = \frac{\sum |y_i - x_i|}{n} \tag{3}$$

$$CE = \sum (MAE \times T) \tag{4}$$

The next step is to apply a feature extraction scheme. This study uses the following 28 features as specified on the right side of Fig. 2.

- 10 consecutive data of total power consumption (including 9 past data)
- 10 Fourier transformed data
- 8 statistical data, maximum, minimum, difference between maximum and minimum, mean, standard deviation, 25% quartile, 50% quartile, and 75% quartile

Next, the disaggregation result must be converted into the classification performance value that is not an error, such as MAE. For this, a peak exceeding a specific threshold (100 W) is extracted as an activation period, and the prediction for the corresponding period is cross-checked. If the ground truth data is 50% or more in the activation period, the prediction is regarded as successful.

The disaggregation performance issue is caused by the power consumption by the unknown appliances shown on the left side of Fig. 2. The consumption is also trained and makes noise in the results. To minimize the effect, this study introduces an appliance activation profile-based result processing. Activation characteristics on the target appliance, such as width, height, and running time, are separately profiled during model training, and used to filter erroneous prediction results.

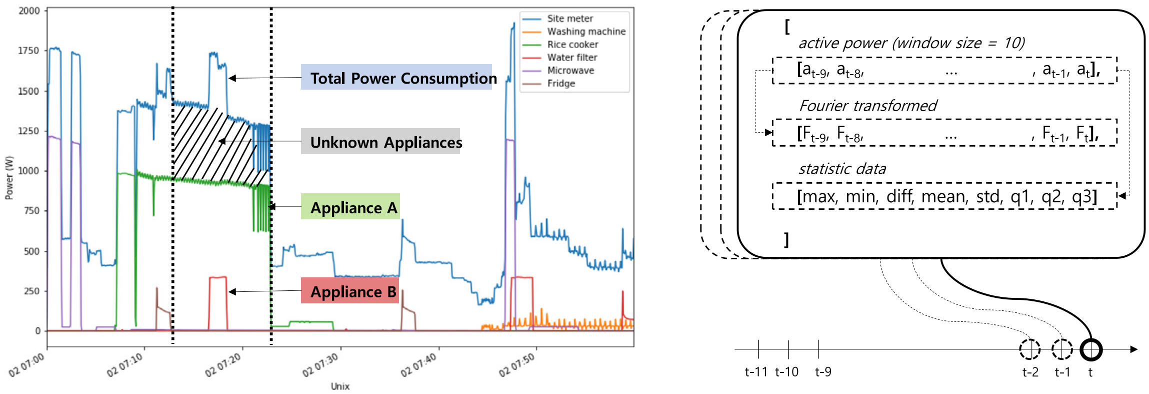

Fig. 2. Overview of disaggregation analysis and the adopted data pre-processing scheme.

3.2. Experimental results

UK-DALE [28] dataset was used to evaluate performance. It provides the total and appliance power consumption data measured in 5 houses at 6-second interval for 912 days. According to the results in Table 3, it can be concluded that RF algorithm is optimal for disaggregation model implementation.

Table 3. Disaggregation performance on algorithms.

Appliance	Metric	RNN	GRU	WGRU	DAE	S2P	RF	GBM
Television	MAE	14.62	17.96	11.95	11.17	13.38	14.79	14.79
	Time (s)	346.03	179.39	3 761.98	13.88	909.85	13.40	84.16
Boiler	MAE	32.26	36.44	45.09	43.16	33.69	34.98	35.15
	Time (s)	349.67	244.62	3 718.58	12.76	773.86	11.99	85.06
Freezer	MAE	36.02	36.02	30.56	30.26	30.75	30.18	30.36
	Time (s)	351.46	245.77	3 716.41	12.52	774.49	13.56	83.28
Washing machine	MAE	17.40	22.99	19.14	21.52	22.00	18.94	19.58
	Time (s)	352.64	246.03	3 715.67	12.68	784.78	13.59	90.11
–	CE	35 133.78	26 646.40	397 316.58	1357.38	79 329.73	1284.20	8527.60

Dataset: UK-DALE, House ID: 4, Train: 1/1/2013–3/31/2013, Test: 4/1/2013–4/30/2013.

Table 4 shows the performance of the disaggregation model to which the RF algorithm, feature extraction, and result processing are all applied. When the classification performance of 0.7 or higher, which is the level of the commercial service in [29], is set as the target level, the results, except for recall, are unsatisfactory.

Table 4. Disaggregation performance on appliances.

Appliance	Recall	Precision	Accuracy	F1 score
Washing machine	0.75	0.33	0.59	0.46

Dataset: UK-DALE, House ID: 4, Train: 3/1/2013–3/31/2013, Test: 4/1/2013–4/10/2013.

Fig. 3 shows the architecture and example operation by the disaggregation model that filters noise from predicted results using the appliance activation profile.

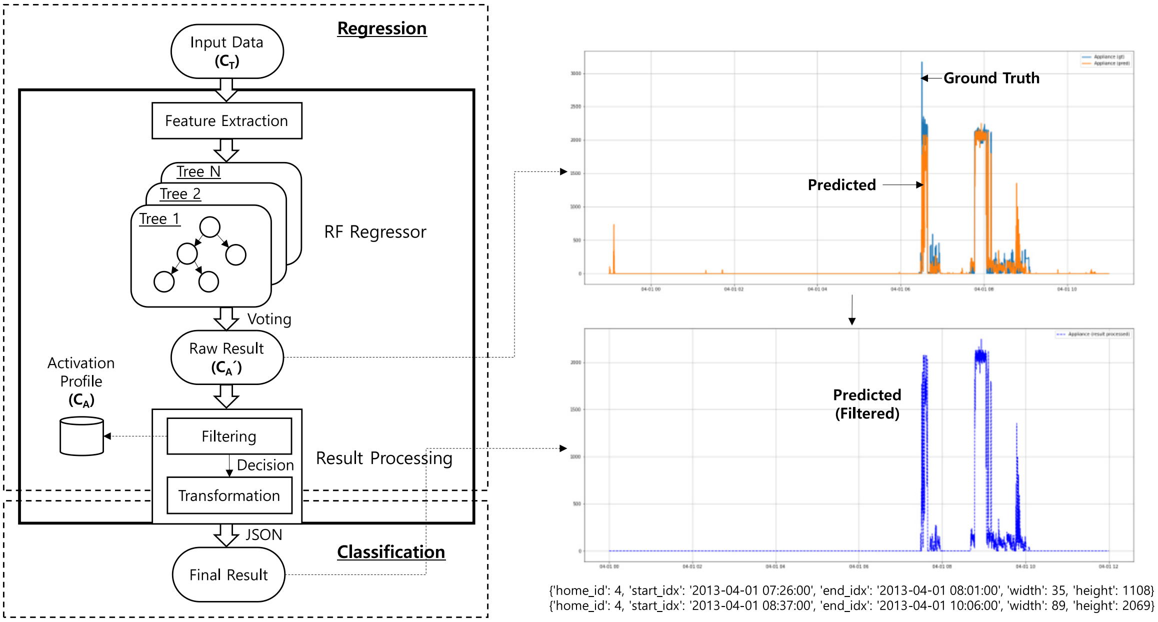

Fig. 3. Model architecture and disaggregation example.

Table 5 shows the results of applying the result processing by the appliance activation profile. It can be seen that the performance was improved, and the target performance was achieved with 17%, 136%, 41%, and 78% improvement in recall, precision, accuracy, and F1 score, respectively.

Table 5. Disaggregation performance with result processing by appliance activation profile.

Appliance	Recall	Precision	Accuracy	F1 score
Washing machine	0.88	0.78	0.83	0.82

Dataset: UK-DALE, House ID: 4, Train: 3/1/2013–3/31/2013, Test: 4/1/2013–4/10/2013.

4. Conclusion

Lonely death monitoring by anomaly detection and ADL monitoring by disaggregation can be provided as one connected service. Although no lonely death is found, the service continues to examine whether the person is leading a normal life by examining the target appliance activation as a vital sign indicating whether a normal life is maintained (see Table 6).

Since the number of households managed by one caring agent is large in social safety net services, without such an intelligent service, all households have to be checked every day or caring of them is provided in turns. Anomaly detection and disaggregation technologies automatically find problematic events and support selective and intensive caring, thereby reducing the work of care agents and increasing the effectiveness of the entire service.

Table 6. Example of connected service operation.

Lonely death monitoring	ADL monitoring	Final result
NOK	Skipped	Alarm (Critical)
OK	NOK	Alarm (Warning)
OK	OK	OK

The proposed activity perception-based anomaly detection and appliance activation profile-based disaggregation have been proven to show higher accuracy than the methods of previous studies. Therefore, it is possible to implement more reliable social safety net services such as lonely death and ADL monitoring through the technologies.

The proposed activity perception-based anomaly detection has the advantage of being a practical method that can be directly applied without model training. However, in case of disaggregation, high sampling frequency data by smart meter that is not being widely deployed is required. Thus, currently, there is a limit in that it is possible to provide services only through products such as home energy monitors.

Since there are few appliances that can be disaggregated, it is also important to select a relevant target appliance. According to our observation, an appliance with a distinct power consumption pattern that can be easily distinguished by appliance activation profile is suitable for disaggregation.

In addition, as it is difficult to develop the disaggregation model in units of individual households, it is essential to develop the disaggregation as a pre-trained model. However, there is no dataset that can provide enough data for more than 30 households for training.

Therefore, it is necessary to develop more advanced analysis technology to overcome the above-mentioned issues. That is the direction of future research.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sanghyun Park reports financial support was provided by Institute of Information & communications Technology Planning & Evaluation (IITP).

Data availability

The authors do not have permission to share data

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References

[1] C. Nordahl, M. Persson, H. Grahn, Detection of residents' abnormal behaviour by analysing energy consumption of individual households, in: IEEE international conference on data mining workshops, 2017.

[2] K. Ishizu, T. Mizumoto, H. Yamaguchi, T. Higashino, Home activity pattern estimation using aggregated electricity consumption data, Sens Mater 33 (1) (2021) 69–88.

[3] M. Al-khafajiy, T. Baker, C. Chalmers, et al., Remote health monitoring of elderly through wearable sensors, Multimedia Tools Appl 78 (4) (2019).

[4] D. Dias, J. Cunha, Wearable health devices? Vital sign monitoring, systems and technologies, Sensors 18 (2018).

[5] A. Grewal, M. Kaur, J. Park, A unified framework for behaviour monitoring and abnormality detection for smart home, Wirel Commun Mob Comput 6 (2019).

[6] S. Woo, Benefits and challenges of long term self-tracking to prevent lonely deaths and detect signs of life, in: ACM SIG CHI, 2018.

[7] M. Hori, T. Harada, R. Taniguchi, Anomaly detection for an elderly person watching system using multiple power consumption models, in: International conference on pattern recognition applications and methods, 2017, pp. 669–675.

[8] B. Gao, X. Liu, Z. Zhu, A bottom-up model for household load profile based on the consumption behavior of residents, Energies 11 (2018).
[9] L. Feng, S. Xu, L. Zhang, et al., Anomaly detection for electricity consumption in cloud computing: Framework, methods, applications, and challenges, EURASIP J Wireless Commun Networking 194 (2020).
[10] C. Chahla, H. Snoussi, L. Merghem, et al., A novel approach for anomaly detection in power consumption data, in: International conference on pattern recognition applications and methods, 2019, pp. 483–490.
[11] G. Hart, Nonintrusive appliance load monitoring, Vol. 80, IEEE, 1992, pp. 1870–1891.
[12] A. Rehman, T. Lie, B. Valles, et al., Comparative evaluation of machine learning models and input feature space for non-intrusive load monitoring, Mod Power Syst Clean Energy 9 (5) (2021) 1161–1171.
[13] M. Hinterstocker, P. Schott, S. Roon, Disaggregation of household load profiles, in: International energy industry conference, 2017.
[14] G. Angelis, C. Timplalexis, S. Krinidis, et al., NILM applications: Literature review of learning approaches, recent developments and challenges, Energy Build 261 (2022) 111951.
[15] S. Tomkins, J. Pujara, L. Getoor, Disambiguating energy disaggregation: a collective probabilistic approach, in: International joint conference on artificial intelligence, IJCAI, 2017, pp. 2857–2863.
[16] X. Huang, B. Yin, Z. Wei, et al., An online non-intrusive load monitoring method based on hidden Markov model, J Phys 1176 (4) (2019) 042036.
[17] J. Kelly, W. Knottenbelt, Neural NILM: Deep neural networks applied to energy disaggregation, in: ACM international conference on embedded systems for energy-efficient built environments, 2015, pp. 55–64.
[18] R. Teixeira, M. Antunes, D. Gomes, Using deep learning and knowledge transfer to disaggregate energy consumption, in: International conference on wavelet analysis and pattern recognition, 2021.
[19] H. Shastri, N. Batra, Neural network approaches and dataset parser for NILM toolkit, in: ACM international conference on systems for energy efficient buildings, cities, and transportation, 2021, pp. 172–175.
[20] C. Marino, E. Masquil, F. Marchesoni, et al., NILM: Multivariate DNN performance analysis with high frequency features, in: IEEE PES innovative smart grid technologies conference, 2021.
[21] C. Timplalexis, G. Angelis, S. Krinidis, et al., Low frequency residential nonintrusive load monitoring based on a hybrid feature extraction tree learning approach, Energy Sources 44 (2022) 493–514.
[22] K. Armel, A. Gupta, G. Shrimali, et al., Is disaggregation the holy grail of energy efficiency? The case of electricity, Energy Policy 52 (2013) 213–234.
[23] Sense. https://sense.com.
[24] Smappee. https://www.smappee.com.
[25] G. Kim, S. Park, Activity detection from electricity consumption and communication usage data for monitoring lonely deaths, Sensors 21 (9) (2021).
[26] Timeseries Anomaly Detection using an Autoencoder. https://keras.io/examples/timeseries/timeseries_anomaly_detection.
[27] Neural Disaggregator. https://github.com/OdysseasKr/neural-disaggregator.
[28] J. Kelly, W. Knottenbelt, The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes, Sci Data 2 (2015).
[29] Smappee. https://www.smappee.com/blog/smappee-appliance-recognition.