

OPP: HOUSING & DAILY LIVING

A lifestyle monitoring system for older adults living independently using low-resolution smart meter data

B. M. Mathunjwa^a, Y. F. Chen^b, T. C. Tsai^c, Y. L. Hsu^a

Purpose There are three types of technologies commonly used in home monitoring services: (1) Wearable devices, which can be uncomfortable and intrusive to users; (2) Ambient sensors, which require extra installation; and (3) household meters, such as smart electricity and water meters. Smart household meters are becoming an essential part of the smart city infrastructure. Previous research focused on applying NIALM techniques to identify specific appliance usage using high-resolution smart meter data (one data every 10 seconds) [Delvin and Hayes, 2019]. This approach employs supervised learning, which is difficult to implement in practical situations and may cause privacy concerns. Japanese power companies have used low-resolution smart-meter data (one data every 30 minutes) to monitor the lifestyle of older adults living independently. Their approach relies entirely on power consumption data and does not map to appliance usage. In this study, we aim to develop a lifestyle monitoring system using low-resolution smart meter data (one data every 15 minutes) for older adults living independently at home. Power consumption data is mapped to appliance usage (0/1), which often relates to the elder's activities of daily living (ADL). Indices of "activity" and "regularity" of appliance usage based on comparison with the pattern of the past 28 days are calculated. **Method** As shown in Figure 1, the electricity consumption data of the previous day (96 data points) was collected. A threshold (the red line in Figure 1) was calculated by taking the average of all "valleys" in the power consumption curve. Electricity consumption data for that day is compared with the threshold, and "0" (inactive) is returned for data lower than the threshold, and "1" (active) for data higher than the threshold. The "active score" is then calculated to quantify the resident's daily activity by finding the percentage of "active" (1s) in the 96 data points of the day. Self-comparison is made between the usage data for the day and the norm data for the past 28 days (as shown in Figure 2) to understand whether there is a deviation in lifestyle from the long-term norm. Low and High norms are also calculated from the 28-day data by sorting the data in ascending order and then getting the average of each of the two halves (14 days). The regularity of the daily lifestyle is also assessed by calculating the correlation coefficient (CC) of the previous day's appliance usage data with the norm of 28 days. **Results and Discussion** The active score of the norm in Figure 2 is 38.0, with the lower norm at 10.9 and the higher norm at 65.2. The active score in Figure 1 for the previous day is 59.4 and receives a blue light on the dashboard for a normal activity level. An activity score higher than the high norm receives a green light on the dashboard for high activity levels; a yellow light on the dashboard indicates a low activity level (activity score between the norm and low norm), and a red light signals an abnormally low activity level (activity score lower than the low norm). Regularity is assessed and categorized into high regularity (green light, $CC \geq 0.7$), normal regularity (blue light, $0.5 \leq CC < 0.7$), low regularity (yellow light, $0.30 \leq CC < 0.5$), and irregular (red light, $CC < 0.3$). The CC depicted in Figure 2 registers at 0.703, suggesting a high level of regularity (green light). The lifestyle monitoring dashboard is being implemented in TaiPower's smart meter App.

References

Devlin, M.A. and Hayes, B.P., 2019. Non-intrusive load monitoring and classification of activities of daily living using residential smart meter data. *IEEE Transactions on Consumer Electronics*, 65(3), pp.339-348.

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Addresses: ^aGerontechnology Research Center, Yuan Ze University, Taoyuan 320, Taiwan; ^bTaiwan Power Research Institute, Taipei, 100046 Taiwan; ^cIndustrial Technology Research Institute, Hsinchu, 310401 Taiwan

Email: yehlianghsu@gmail.com

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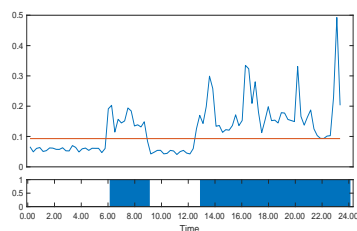


Figure 1 Power consumption data converted to household appliance usage

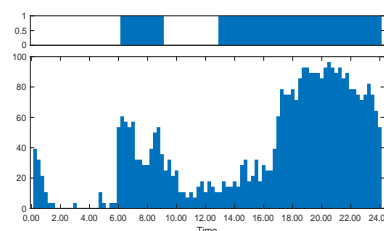


Figure 2. Compared with 28-day norm

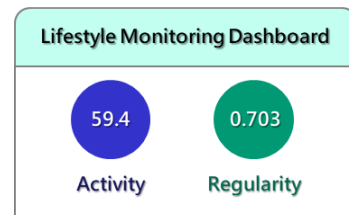


Figure 3. Dashboard showing levels of activity and regularity