# Data-Driven Smart Home System for Elderly People Based on Web Technologies

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**Abstract.** The proportion of elderly people over 65 years old has rapidly increased, and social costs related to aging population problems have grown globally. The governments want to reduce these social costs through advanced technologies. The physician or medical center evaluates health conditions from the reports of elderly people. However, self-reports are often inaccurate, and sometimes reports by family or caregivers can be more accurate. To solve these problems, an evaluated objective method based on sensor data is needed. In this paper, we propose a data-driven smart home system that uses web technologies for connecting sensors and actuators. The proposed system provides a method of monitoring elderly people's daily activities using commercial sensors to register recognizable activities easily. In addition, it controls actuators in the home by using user-defined rules and shows a summary of elderly people's activities to monitor them.

**Keywords:** Elderly care · Data-driven approach · Ambient assisted living · Web technology

## 1 Introduction

Due to recent improvements in life expectancy, the proportion of older people has rapidly increased [1]. The proportion of elderly people over 65 years old is predicted to rise to 30 % in 2060 in Europe [2]. Aging population problems have emerged globally, and due to the social cost related to aging, it is difficult to support the increasing number of elderly people. Since elderly people are exposed to various risks, the governments want to reduce social costs through the monitoring of risks and diseases using advanced technologies. To determine if elderly people need the help of others or evaluate the abilities of elderly people, various methodologies are used, such as an activity of daily living (ADL) checklist. ADL is a way of determining people's routine activities [3]. Basic or physical ADL consists of self-care tasks that people tend do every day without needing assistance such as dressing, bathing, eating, ambulating, toileting, and hygiene-related tasks. Instrumental ADL (IADL) is not necessary activities for survival and supports an independent lifestyle, such as shopping, housekeeping, accounting, food preparation, using the telephone, and transportation. The physician or medical center evaluates the


N. Streitz and P. Markopoulos (Eds.): DAPI 2016, LNCS 9749, pp. 122–131, 2016.
DOI: 10.1007/978-3-319-39862-4_12

health conditions of elderly people reported through these methods. However, self-reports are often inaccurate, and sometimes reports by family or caregivers can be more accurate. To solve these problems, an evaluated objective method based on sensor data is needed.

With the advent of the Internet of Things (IoT) technologies, coined by Kevin Ashton [4], small and inexpensive IoT devices have been widely used in our daily lives, and they can help to solve common problems at a low social cost. IoT sensor devices are deployed in living spaces or on the human body and collect log data to sense human activities. To reduce the social cost, various methods have been proposed such as elderly care systems [5, 6], behavior monitoring [7, 8], and user modeling [9, 10] in smart homes. However, previous systems have supported a limited number of sensors to track the ADLs of elderly people. These sensors are designed for specific purposes, and it is not easy to purchase them in commercial markets. The number of ADLs of elderly people monitored by these sensors' data is limited because the previous systems have used reasoning based on fixed and predefined rules in the systems. To build a smart home environment for elderly people, a method of monitoring their ADLs using commercial sensors and registering recognizable ADLs easily is required. Furthermore, it is also necessary to declare control rules for actuators in the home and to provide a summary of elderly people's ADLs to monitor people.

In this paper, we propose a data-driven smart home system that uses web technologies for connecting IoT devices. The system provides a web-based user interface for monitoring elderly user to establish rules for recognizing activities and controlling actuators by selecting features from visualized log data. The proposed system monitors the behaviors of elderly people and controls IoT devices when abnormal situations are detected. While this section has introduced and provided motivation for the work, the rest of this paper is structured as follows. We present related work in Sect. 2. Section 3 describes our system design while Sect. 4 presents the current prototype implementation. Finally, we conclude with a summary and present a future work direction in Sect. 5.

## 2 Related Work

In this section, we give an overview of related projects and technologies such as data collection, activity recognition, and elderly care systems. Ambient Assisted Living (AAL) and Ambient Intelligence (AmI) are approaches that aim to provide services and systems for aging well at home. Emiliani and Stephanidis [11] discussed the anticipated opportunities and challenges of AmI for elderly people. Among previous research related to AAL and elderly care systems, Kleinberger *et al.* [12] developed and evaluated the usability and suitability of interfaces for AAL. Dohr *et al.* [13] proposed an AAL system for elderly people through the IoT using passive RFIDs or near field communication (NFC). Su and Chiang [6] introduced a personalized healthcare service named IAServ, in ubiquitous cloud computing to support a cost-efficient method of care. They used a personal profile that includes basic information and personal states for generating a personalized care plan based on predefined ontologies in the system. Costa *et al.* designed and implemented mobile and static agents for smart homes using a voice interface [14]. Dickerson *et al.* [15] proposed a flexible web and cloud-based home health care monitoring system and deployed the system in real homes. Stanford [16] and Rantz *et al.* [17] have migrated from the laboratory into the homes of real older adults in retirement communities.

To combine and configure tasks, Dey *et al.* [18] proposed a CAPpella system for the end-user configuration of a pre-deployed sensor environment, and Davidoff *et al.* [19] suggested principles of smart home control. IFTTT (If This Then That) [20] is a web-based service that connects web services. It provides a simple interface to create a trigger and an action. Tuomisto *et al.* [21] presented a Thing-centric simple rule editor for the integration of functionalities and resources. Kolkowska [22] discussed privacy principles for the design of elderly care systems in smart homes.

It is important to collect sensor data in smart homes for monitoring the activities of elderly people, summarizing the activities, and controlling devices in smart homes. Chatterjee *et al.* [23] built a wireless sensor network system within the home environment to monitor the daily routines of elderly people using environmental and wearable sensors. Lee and Dey [24] presented sensor-based observations of daily living (ODLs) for older adults and their physicians for personal sensor data. Seo *et al.* [25] proposed an activity mashup system using heterogeneous sensors and visualized personal activity logs. Ransing and Rajput [5] proposed a wireless sensor network based smart home system to help elderly people achieve safe, sound and secure living using ZigBee technology. In user modeling approaches, Casas *et al.* [9] proposed a user modeling scheme for elderly and disabled people. Raad and Yang [10] designed a user-friendly model for elderly telemedicine in a smart home.

To recognize activities, Hong *et al.* [26] proposed a recognition method for ADL inference based on human motion and object identification using accelerometers and RFID sensors. Gaddam *et al.* [8] gathered data from a limited number of simple sensors and showed the data can be used to recognize ADLs and the lifestyle of an elderly person living alone. Suryadevara *et al.* [7] presented a data-driven intelligent system that includes effective sensing and intelligent behavior detection for elderly people's ADLs in their home. Forkan *et al.* [27, 28] proposed a cloud platform that can be accessed via web service protocols and described a pattern recognition models for an AAL environment.

## 3 System Design

In this section, we introduce our system design of a data-driven system for elderly people in smart homes. To recognize ADLs according to sensing data and provide useful services through the control of actuator devices, we design the data-driven process in three steps: log aggregation, activity recognition, and device control as shown in Fig. 1. In the log aggregation stage, sensing data are stored in a logging database. Sensor data contain information about ADLs and environment contexts. The data are collected from individual sensors directly or each sensor server provider periodically using web-based RESTful APIs. The logged data from heterogeneous sensors are converted to neutral log notation to be stored in the database because the logged data have different notations.

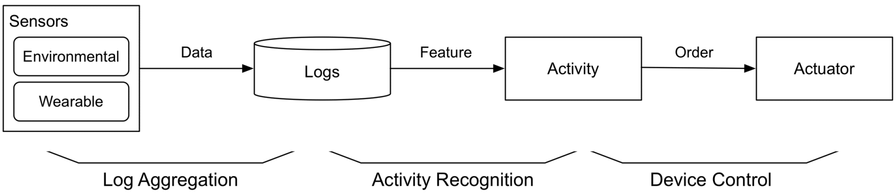


**Fig. 1.** Data-driven process overview

In the activity recognition stage, ADLs are extracted from the sensor data. The activity recognition consists of two steps: abstraction from sensor data to an activity and from subordinate activity logs to a superordinate activity. To determine the relation between sensor data and activity, a monitoring user, such as a physician, retrieves the collected log according to context queries. The monitoring user chooses filtered logged data to build a combination of features based on transitions of sensor readings for activity recognition. Similarly, the features of a superordinate activity are determined by a user's selection of filtered subordinate activity logs. In the last stage, the user established an order to control actuator devices by connecting activity recognition and actuator behaviors. The user selects a recognized activity and chooses an actuator and behaviors of the chosen actuator, which is controlled by the activity detection. When the user activities are detected, the predefined behaviors of the actuators are triggered.

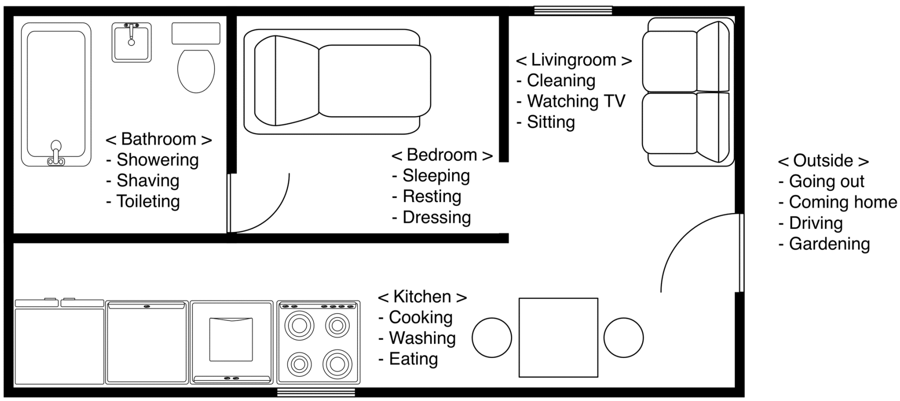


**Fig. 2.** ADL context modeling example of elderly people at home

We perform ADL context modeling to create predefined basic rules for recognizing the activities of elderly people, as shown in Fig. 2. We choose some activities related to elderly people's behaviors at smart homes from Ainsworth *et al.*'s study [29], which identified the major categories and daily physical activities. We classify the ADLs of elderly people based on places in the smart homes such as the bedroom, bathroom, and outside the home. The place information is a spatial condition for recognizing ADLs. We add temporal conditions to some rules, such as eating and sleeping. For instance, the eating activity is classified as breakfast, lunch, and dinner according to time information through the sensor data that are collected in the same place (i.e., the kitchen). Moving behavior from outside into the home is considered a "coming home" activity, and the activity depends on a change of spatial context. Likewise, we build the predefined control rules of actuator devices using recognized activities. For example, when a monitored person moves from inside to outside the home, all the lights in the home are turned off.

## 4 Prototype Implementation

We implemented a prototype system based on the design given in the previous section using web technologies. Figure 3 shows the system architecture of our system. The place manager handles a place that is a living space of a monitored user (i.e., elderly people). It also manages the deployment of devices and the indoor floor plans of the place. The rule manager deals with data-driven rules for activity recognition and device control. The user manager collects data logs from the monitored user's sensors and sends control messages to actuators. The web-based user interface supports user interaction between monitoring users and manager components in the system using the web pages on a web browser. The map server provides map tiles for determining geospatial information.

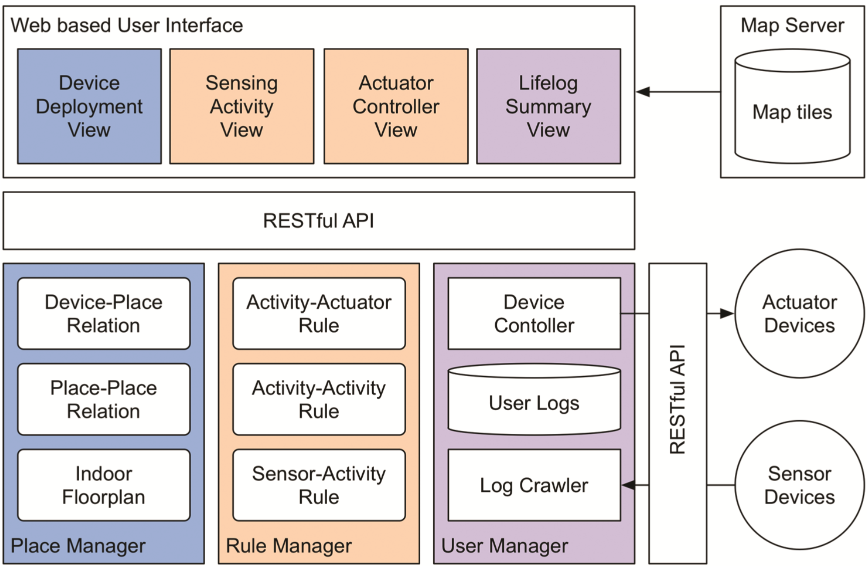


**Fig. 3.** Overview of the proposed system architecture

The proposed system supports the map-based device deployment view for arranging devices' positions. The devices' profiles are preregistered on the system. The system also provides a way of adding new device types. A monitoring user selects a pin on the map to determine a building, and the map is changed into indoor maps of the selected building. If a building or indoor floor plan does not exist on the map server, the monitoring user can add information using GeoJSON notation. To deploy a device in the indoor space, the monitoring user clicks the “add” button, chooses a device, and picks a location on the map as shown in Fig. 4. (a) of Fig. 4 shows an indoor map of the smart home and the deployment of the devices. If the user clicks the add button, a popup window is displayed to add a device to the place. The user chooses either a sensor or actuator for a device type and selects a specific commercial device profile. Lastly, the monitoring user selects the location of the deployed device and describes the device’s specific profile. The devices located in the place are listed as shown in (b) of Fig. 4. When the user clicks on device in the list, the detailed description of the selected device is displayed as shown in (c) of Fig. 4. Through this process, the monitoring user deploys sensor and actuator devices in each place of the smart homes. In a similar manner, the monitoring user chooses devices’ positions on the human body map to attach wearable devices.

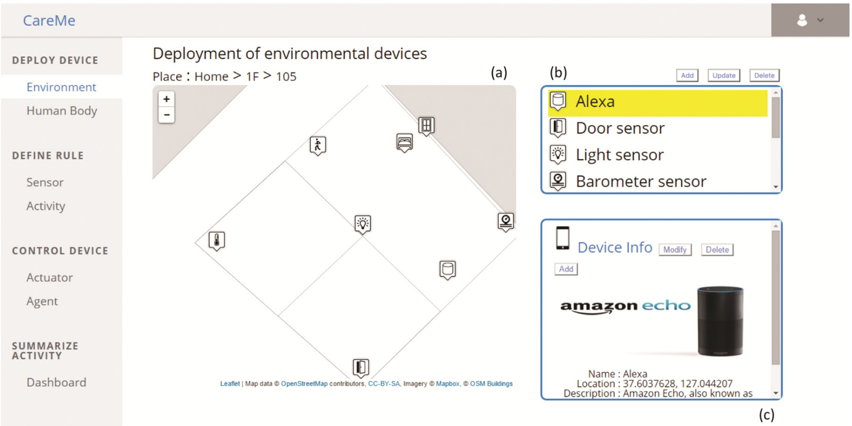


**Fig. 4.** Deployment of environmental devices

The proposed system extracts the activities of elderly people from sensor data through the sensing activity view, as shown in Fig. 5. The view has condition filters to retrieve the collected sensor data, as shown in (a) of Fig. 5. After applying the filters, the monitoring user looks at the logs of sensors in a list as shown in (b) of Fig. 5, and chooses sensor devices to determine features related to the activities of the monitored elderly people. The detailed information is depicted on the map to provide spatial context, as shown in (c) of Fig. 5, and is drawn on the graph to show changes according to temporal context, as shown in (d) of Fig. 5. When the monitoring user clicks the “add feature” button, the proposed system creates an activity recognition rule through the rule manager as shown in (e) of Fig. 5 and learns the rule for the chosen activity from the features and context. After that, when a rule is detected, the system determines what kind of activity is occurring in relation to the monitored elderly people. Determining the relation between subordinate activity logs and superordinate activity is similar.

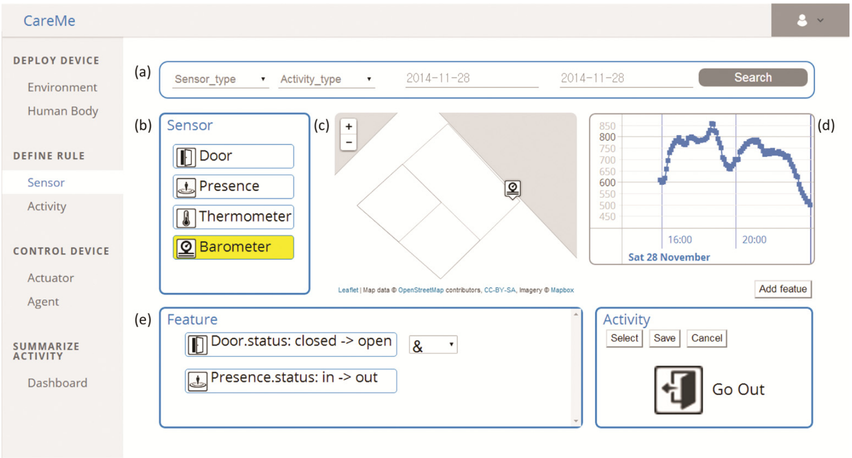


**Fig. 5.** The sensing activity view for activity recognition

The monitoring user builds the control rules using the actuator controller view, as shown in Fig. 6. At first, the user chooses a recognizable activity that will be related to a new rule, as shown in (a) of Fig. 6. (b) and (c) of Fig. 6 show the spatiotemporal context of the selected activity. The user can add or modify the time condition related to the activity. When the monitoring user clicks the "add feature" button, the system creates an actuator control rule through the rule manager, as shown in (d) of Fig. 6. The monitoring user can add control rules by performing the process repeatedly. After that, when a rule is detected, the system sends a control message to specific actuators of the rule through RESTful APIs.

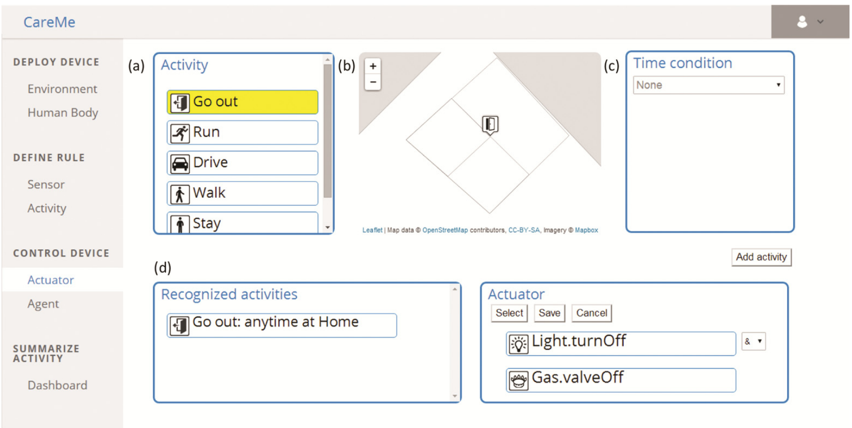


**Fig. 6.** The actuator controller view for handling actuator devices

The physician or medical center can build ADL summaries and reports of monitored people using the online dashboard as shown in Fig. 7. They input query conditions (i.e., temporal context and types of sensors or activities) to retrieve ADL logs from the database as shown in (a) of Fig. 7. The system returns the ADL logs according to the filters and shows the sensor list on the timeline as shown in (b) of Fig. 7. The monitoring user clicks on ADL log to determine whether the log is a representative activity during the time segmentation. The system depicts spatial information on the map as shown in (d) of Fig. 7 and additional information in the textbox as shown in (c) of Fig. 7. When the user double-clicks on the activity log on the timeline, the selected log is added to the summary of the ADLs, as shown in (e) of Fig. 7.

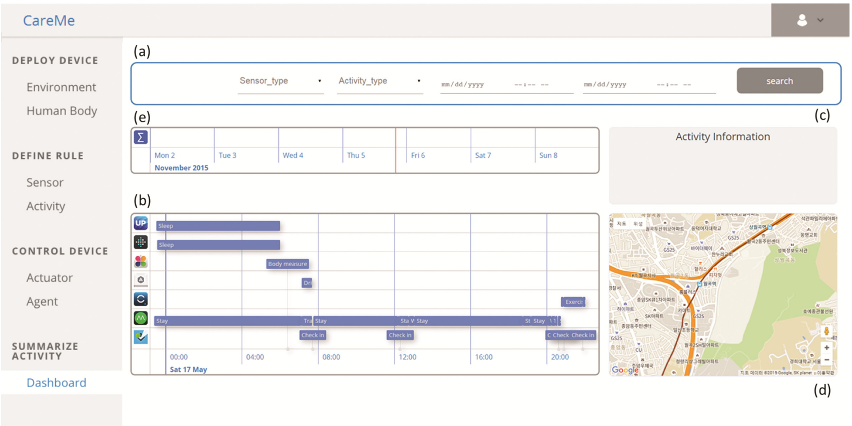


**Fig. 7.** The ADL summary view

## 5 Conclusion and Future Work

In this paper, we proposed a data-driven system for elderly people in smart homes using web technologies. The proposed system provides a method for monitoring their ADLs using commercially available sensors and registering recognizable ADLs easily. In addition, it controls actuators in the home using user-defined rules and shows a summary of elderly people's ADLs to monitor people.

We only focus on the web-based system to improve the ease of recognizing ADLs from sensor data and connecting recognized ADLs to controlling actuators. The next step of our research will consider a machine learning approach to find relationship rules between sensor logs and ADLs with the spatiotemporal context automatically based on long-term sensor logs.

**Acknowledgments.** This research was supported in part by the Korea Institute of Science and Technology (KIST) Institutional Program (Project No. 2E26450).

## References


1. United Nations (UN): World Population Aging: 1950–2050 (2002). http://www.un.org/esa/population/publications/worldageing19502050. Accessed 8 Feb 2016
2. Giannakouris, K.: Ageing characterises the demographic perspectives of the European societies. Statistics in focus 72 (2008)
3. Katz, S.: Assessing self-maintenance: activities of daily living, mobility, and instrumental activities of daily living. J. Am. Geriatr. Soc. **31**, 721–727 (1983)
4. Ashton, K.: That 'Internet of Things' thing. RFiD J. **22**, 97–114 (2009)
5. Ransing, R.S., Rajput, M.: Smart home for elderly care, based on wireless sensor network. In: International Conference on Nascent Technologies in the Engineering Field, pp. 1–5. IEEE, Navi Mumbai (2015)
6. Su, C.-J., Chiang, C.-Y.: IAServ: an intelligent home care web services platform in a cloud for aging-in-place. Int. J. Environ. Res. Public Health **10**, 6106–6130 (2013)
7. Suryadevara, N.K., Mukhopadhyay, S.C., Wang, R., Rayudu, R.K.: Forecasting the behavior of an elderly using wireless sensors data in a smart home. Eng. Appl. Artif. Intell. **26**, 2641–2652 (2013)
8. Gaddam, A., Mukhopadhyay, S.C., Gupta, G.S.: Trial and experimentation of a smart home monitoring system for elderly. In: Instrumentation and Measurement Technology Conference, pp. 1–6. IEEE, Binjiang (2011)
9. Casas, R., Marin, R.B., Robinet, A., Delgado, A.R., Yarza, A.R., McGinn, J., Picking, R., Grout, V.: User modelling in ambient intelligence for elderly and disabled people. In: Miesenberger, K., Klaus, J., Zagler, W.L., Karshmer, A.I. (eds.) ICCHP 2008. LNCS, vol. 5105, pp. 114–122. Springer, Heidelberg (2008)
10. Raad, M.W., Yang, L.T.: A ubiquitous smart home for elderly. Inf. Syst. Front. **11**, 529–536 (2009)
11. Emiliani, P.L., Stephanidis, C.: Universal access to ambient intelligence environments: opportunities and challenges for people with disabilities. IBM Syst. J. **44**, 605–619 (2005)
12. Kleinberger, T., Becker, M., Ras, E., Holzinger, A., Müller, P.: Ambient intelligence in assisted living: enable elderly people to handle future interfaces. In: Stephanidis, C. (ed.) UAHCI 2007 (Part II). LNCS, vol. 4555, pp. 103–112. Springer, Heidelberg (2007)
13. Dohr, A., Modre-Opsrian, R., Drobics, M., Hayn, D., Schreier, G.: The Internet of Things for ambient assisted living. In: International Conference on Information Technology: New Generations, pp. 804–809. IEEE, Las Vegas (2010)
14. Costa, N., Domingues, P., Fdez-Riverola, F., Pereira, A.: A mobile virtual butler to bridge the gap between users and ambient assisted living: a smart home case study. Sensors **14**, 14302–14329 (2014)
15. Dickerson, R.F., Hoque, E., Emi, I.A., Stankovic, J.A.: Empath2: a flexible web and cloud-based home health care monitoring system. In: International Conference on Pervasive Technologies Related to Assistive Environments, pp. 1–8. ACM, Corfu (2015)
16. Stanford, V.: Using pervasive computing to deliver elder care. IEEE Pervasive Comput. **1**, 10–13 (2002)
17. Rantz, M.J., Porter, R.T., Cheshier, D., Otto, D., Servey, C.H., Johnson, R.A., Aud, M., Skubic, M., Tyrer, H., He, Z., Demiris, G., Alexander, G.L., Taylor, G.: TigerPlace, a state-academic-private project to revolutionize traditional long-term care. J. House. Elderly **22**, 66–85 (2008)
18. Dey, A.K., Hamid, R., Beckmann, C., Li, I., Hsu, D.: A CAPpella: programming by demonstration of context-aware applications. In: The SIGCHI Conference on Human Factors in Computing Systems, pp. 33–40. ACM, Vienna (2004)

19. Davidoff, S., Lee, M.K., Yiu, C., Zimmerman, J., Dey, A.K.: Principles of smart home control. In: Dourish, P., Friday, A. (eds.) UbiComp 2006. LNCS, vol. 4206, pp. 19–34. Springer, Heidelberg (2006)
20. Tibbets, L., Tane, J.: IFTTT - Make Your Work Flow (2011). https://ifttt.com. Accessed 7 Feb 2016
21. Tuomisto, T., Kymalainen, T., Plomp, J., Haapasalo, A., Hakala, K.: Simple rule editor for the Internet of Things. In: International Conference on Intelligent Environments, pp. 384–387. IEEE, Shanghai (2014)
22. Kolkowska, E.: Privacy principles in design of smart homes systems in elderly care. In: Tryfonas, T., Askoxylakis, I. (eds.) HAS 2015. LNCS, vol. 9190, pp. 526–537. Springer, Heidelberg (2015)
23. Chatterjee, S., Dutta, K., Xie, H.Q., Byun, J., Pottathil, A., Moore, M.: Persuasive and pervasive sensing: a new frontier to monitor, track and assist older adults suffering from type-2 diabetes. In: Hawaii International Conference on System Sciences, pp. 2636–2645. IEEE, Wailea (2013)
24. Lee, M.L., Dey, A.K.: Sensor-based observations of daily living for aging in place. Pers. Ubiquit. Comput. **19**, 27–43 (2014)
25. Seo, D., Yoo, B., Ko, H.: Collective heterogeneous sensor mashup for enriched personal healthcare activity logging. In: International Conference on Consumer Electronics, pp. 34–35. IEEE, Las Vegas (2015)
26. Hong, Y.-J., Kim, I.-J., Ahn, S.C., Kim, H.-G.: Activity recognition using wearable sensors for elder care. In: International Conference on Future Generation Communication and Networking, Sanya, Hainan Island, China, pp. 302–305 (2008)
27. Forkan, A., Khalil, I., Tari, Z.: CoCaMAAL: a cloud-oriented context-aware middleware in ambient assisted living. Future Gener. Comput. Syst. **35**, 114–127 (2014)
28. Forkan, A.R.M., Khalil, I., Tari, Z., Foufou, S., Bouras, A.: A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. Pattern Recogn. **48**, 628–641 (2015)
29. Ainsworth, B.E., Haskell, W.L., Herrmann, S.D., Meckes, N., Bassett, D.R.J., Tudor-Locke, C., Greer, J.L., Vezina, J., Whitt-Glover, M.C., Leon, A.S.: 2011 compendium of physical activities: a second update of codes and MET values. Med. Sci. Sports Exerc. **43**, 1575–1581 (2011)