Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Computer Science 19 (2013) 516 – 523
Procedia Computer Science

The 4th International Conference on Ambient Systems, Networks and Technologies (ANT 2013)

Towards a real-time error detection within a smart home by using activity recognition with a shoe-mounted accelerometer

Julien Vandewynckel[a,*], Martin Otis[b], Bruno Bouchard[a], Bob-Antoine-Jerry Ménélas[c], Abdenour Bouzouane[a]

[a]LIARA Laboratory, Universite du Quebec a Chicoutimi (UQAC), Chicoutimi G7H 2B1, Canada
[b]Applied Sciences Department, REPARTI Center, Universite du Quebec a Chicoutimi (UQAC), Chicoutimi G7H 2B1, Canada
[c]Computer et Mathematics Department, Universite du Quebec a Chicoutimi (UQAC), Chicoutimi G7H 2B1, Canada

Abstract

Taking care of the elders constitutes a major issue in the western societies. Smart homes appear to be a socially and economically viable solution. They consist in habitats augmented with sensors and actuators enabling to achieve activity recognition and to provide assistive services to a resident. Stationary aspect of sensors used in most smart homes makes the concept difficult to deploy in existing homes, and involves a high cost. In this paper, we propose an inexpensive non-vision-based system ably to recognize, in real-time, activities and errors of a resident. This proposed recognition system is based on a shoe equipped with a single sensor: a three-axis accelerometer and on a state-transition algorithmic approach using fuzzy logic. We have examined the learning data as frequency distributions, where the probability histograms have been directly interpreted as fuzzy set. We conducted experiments of the system in our smart home by simulating (multiple times) several scenarios based on a morning routine. These scenarios were based on clinical data gathered in a previous experiment with actual Alzheimer's patients. We obtained promising results showing that the proposed activity and error recognition system are highly effective.

Selection and peer-review under responsibility of Elhadi M. Shakshuki

Keyword: Healthcare systems; Mobile Computing; Wearables sensors; Ubiquitous computing

1. Introduction

The growing impact of the aging population [1] in western societies has significant consequences for healthcare systems, including medical staff shortages for home care services, and an increasing number of people suffering from dementias. As we known, silver-aged people want to stay at home as long as

*Coressponding author
Email addresse: julien.vandewynckel1@uqac.ca (Julien Vandewynckel)

1877-0509
Selection and peer-review under responsibility of Elhadi M. Shakshuki
doi:10.1016/j.procs.2013.06.069

possible, in a familiar environment where they feel safe and comfortable. These new challenges as lead to the emergence of the assistive smart home concept [2], which imposed itself as an interesting approach for exploiting the technology in an individual's living environment in order to improve his autonomy and to increase his quality of life. A smart home can be seen as an augmented environment with embedded sensors and actuators, able to keep track of the resident ongoing activities and able to assist him when required [9], in the most adequate prompting form.

In the past few years, many smart home systems have been developed trying to address such a challenge. These systems often focused on activity analysis, and rarely on error recognition, which constitutes the key issues toward the development of proactive assistance for a resident. As for example, a smart floor, embedding pressure sensors, has been deployed in the Aware Home to enhance quality of life by tracking the position of inhabitants and recognize their gait [3]. The MavHome [4], the Place Lab [5] and the Gator Tech [6] are in line with the aim of increasing comfort and productivity by anticipating activities and location of their residents based on their routines and repetitive task patterns. They all use a large amount of binary sensors such as motion sensors, electromagnetic sensors, pressure mats, and analog sensors. RFID tags, video capture, temperature sensors are often exploited for this purpose. The COACH system is dedicated for cognitive assistance and surveillance of adults with dementia attempting to complete hand washing activity by using sensors and a camera [2]. Nevertheless, most of these systems use stationary sensors, which are generally expensive, unwieldy and complex to integrate inside the house as emphasized by Helal et al [6]. Indeed, many software implementations must be developed so that the interaction between sensors and the "brain" of the house (usually a server) is possible, and many technical means should be put in place for hiding them from the residents. In contrast of these human-object interaction sensors [7], wearable sensors such as accelerometers, gyroscope, or even pressure sensors are lighter and less costly but need a microcontroller for the acquisition. They can be easily integrated in the network of smart home via wireless capabilities. They allow completing activity tracking and can enhance the information about what activity is actually done by analyzing physical movements. They can also fill the gap in design of most smart homes in the context of cognitive assistance and help to build an error recognition system necessary in this perspective.

In that sense, we propose a new approach for non-vision-based recognition with a unique sensor able to analysis pattern error. The main contribution of the paper is then a system that can accurately recognize almost six classic activities in real-time based on the gait, and able to detect those which are erroneous among pre-established series of activities, that we called an error. These errors have a consequence on the health or dangerousness of the environment. The originality of our proposal relies on a simple algorithmic approach of recognition for both normal activities and errors, and on the use of only a tri-axis accelerometer hidden in a mobile object (a shoe) that follows the occupant. This could reduce the number of sensors in the house. In a non-intrusive context, their location must be chosen carefully. Instead of a belt, or directly on the body with medical gauze [8], we have integrated the accelerometer inside a shoe because it is an everyday wear. In this way, the resident will not see nor feel it. Furthermore, this prototype has the advantage of being easily implementable in existing homes.

This paper is structured as follows. Section 2 details the important works related to our proposal, allowing positioning the contribution. Section 3 describes the proposed system, the recognition algorithm, and the shoe-mounted prototype. Section 4 exhibits an experiment conducted in a real environment to evaluate the proposed system. An analysis and a discussion are presented about the theoretical and practical performances of our algorithm. Finally, Section 5 concludes the paper with future works.

2. Related work

In ubiquitous computing, the use of wearable sensors is rather recent for activity recognition. Many approaches exist and can join the main goal of all assistance systems like those designed for smart homes.

To anticipate random execution aspect of activities and the inaccuracies of such sensors, a stage of activity learning is frequently incorporated. They can be based on probabilistic models found mainly in offline analysis, based state-space, which can be declined in real time, and based on pattern recognition that is more directed towards a real-time application.

Myong-Woo Lee et al. [9] proposed a hardware remarkably close to our project due to the application in ubiquitous environments. In this way, they studied a single tri-axial accelerometer-based on a personal life log (PLL) system capable of human activity recognition and estimation of exercise information. This recognition of state of daily activities is based validation active via linear discriminant analysis and hierarchical artificial neural networks. The statistical and spectral features used come from the accelerometer signal. Although the system operates in real-time, the use of a ten seconds length window does not allow to evaluate some issue coming from the current activity whereas short window lengths are optimal for their short duration postures/activities according to Tapia [10]. The major problem is that the accelerometer is placed on the chest which can be felt by the resident and perceived as a hindrance in the process of assistance. Currently, the analysis is not embedded and thus reduces its interest for assistance.

Liang Wang et al. [11] proposed a real-time, hierarchical model to recognize both simple gestures and more complex activities. They implemented sensors network similar to the concept used in smart homes, but on the body. First, they computed the distance between accelerometer data in a window and a template by Dynamic Time Warping. Next, they computed scores between this distance and discriminative patterns mined for each activity by including other information on objects. A certain threshold is then used to infer the activity. Their approach is optimal with a time window of one second (near meantime activity [12]). The computing time is low and is on average 10 ms. The activities inferred are mostly manual because wearable sensors are located on the forearm, and do not reflect the inhabitant's gait, therefore, not recognizing risks of falling, gait issues or foot gesture movement.

Illapha Cuba Gyllensten et al. [13] advanced an analysis of reproducibility of the accuracy of laboratory-trained classification algorithms in free-living subjects during daily life. A single accelerometer has been used for data collection during a laboratory trial. Then, they trained three models: a support vector machine, a feed-forward neural network, and a decision tree. With a window size of 6.4s and a sampling rate of 20 Hz [14], real-time activity recognition could be achieved but not for distinguishing a fast sequence of short activities. However, they are able to recognize transition activities.

As we have seen, the definition of real time makes crucial the choice of window-length depending on whether activities are unique movements or a sequence of gestures. According to Huynh [12], the necessity of a gait analysis process must be done in a window size around 1s. Therefore, an activity recognition algorithm has to take that into account while being easy implementation toward a microcontroller (low power consumption). Also, it is interesting to have a system that does not need human intervention for installation. It is why we propose, in this paper, a recognition system based on shoe-mounted accelerometer using a sequential algorithmic approach exploiting a states-transitions model with fuzzy logic classification [15]. We tried to find a representation of the training data efficiently to compensate for the required too-large dataset, often pointed to as a weakness of previous methods [16]. The nature of actions to recognize and the possibility of error recognition also directly affect the place of the accelerometer on the body. Locomotion activities are mostly pedestrian movements, where the shoe has been reflected in the closest contact with the floor.

3. The Proposed Real-Time Recognition System

The system architecture is shown in Fig 1a. A shoe-mounted accelerometer is attached on the external side of the shoe of the resident with an alligator clip. Ours is powered by a standard battery, and integrates a tri-axial accelerometer and a USB Bluetooth dongle with a PIC24 microchip microcontroller shown in Fig 1b. In this way, on the right foot we would have the x-axis parallel to the floor and directed to the front of the foot, the y-axis perpendicular to the ground and directed into the ground, and the z-axis directed towards the inside of the foot. Next, the acquired accelerometer data of the associated device is sent wirelessly to an antenna installed on the smart home server. By applying the well-known Nyquist-Shannon theorem [17], the sampling rate of human activities generally used is 50 Hz. Nevertheless, as the floor vibration is around 100 Hz, we have chosen to use 200Hz. The collected information is then processed in real-time by our activity recognition algorithm implemented on this server. High level data are therefore generated representing the name of the current activity among our six activities analyzed in this work, but not limited to: lying, ascend/descend stairs, standing, standing on tiptoes and walking through home, and afterwards written to a database. In parallel, an error recognition algorithm, also implemented on the server, takes in parameters the recognized activities and pulls the database to know the state of the various existing sensors inside the house. The errors which have occurred can be, thereafter, used by another third-party program and possibly create an assistance process.

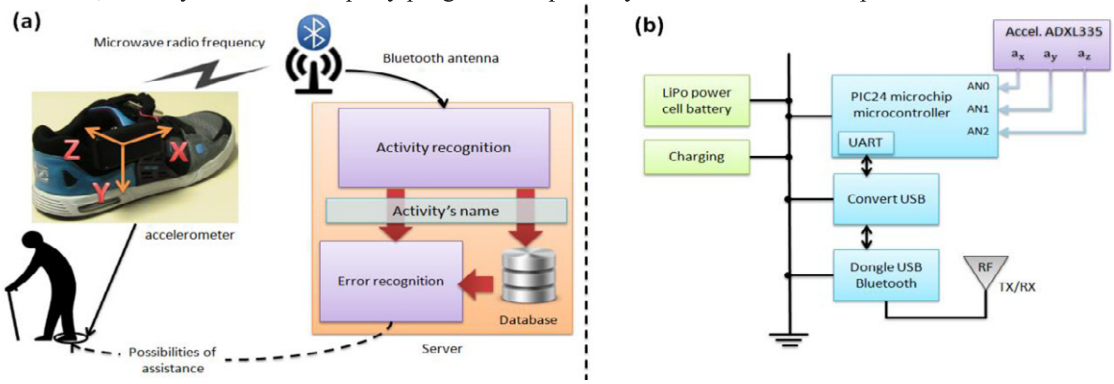

Fig. 1. (a) An overview of our recognition system; (b) circuit diagram of the embedded device

3.1. The detailed operation of activity and error recognition algorithm

Our algorithm responsible for processing the accelerometer data and achieve real-time recognition is able to detect these six following activities: “Walking through home”, “Lying”, “Standing”, “Descend Stairs”, “Ascend Stairs”, “Standing on tiptoes”. It is composed of three different threads as shown in Fig 2. The first one stores, every 5 ms, the voltage output of each incoming acceleration signal in a specific queue. The second thread is an infinite loop which waits until at least 200 elements are present in the queues corresponding to the mean duration of a gesture among our activities, and thus our window-length of one second. When this happens, it creates a copy of each axes, and computes the resultant of acceleration squared as fourth input. Then, it creates counters for activities initialized to an unknown state and treats each of our axes separately in different newly created threads named “Threads#4x”, what, in the future, would allow to increase the number of vectors passed as parameter and accept other vectors of added sensors.

In the first stage, we compute a list of height features on each axis: minimum, maximum, mean, standard deviation, percentile (50%), Kurtosis, skewness and the energy to which are added the Pearson's product-moment coefficients (measure of the correlation) between x-y axis, x-z axis, and z-y axis. In the learning phase, they had been analyzed to form frequency distribution histograms. In fact, each of those feature distributions represents a fuzzy set of one given feature on one given axis of one given activity. We had then stocked them inside an interval-tree structure where the searches can be completed in O(log n) since there is any overlap in these intervals [18]. Next, we compute the logical AND (Zadeh) between each probability (μ) associated with each feature (Fj) in Equation (1) for each activity (Ai) in our interval-trees storing our fuzzy sets from our dataset.

$$\mu_{Ai} = \mu_{F0}\ AND\ \mu_{F1} AND\ \mu_{F2} \ldots \mu_{Fn} = min\ (\ \ldots (min\ (min(\mu_{F0}, \mu_{F1}), \mu_{F2}), \ldots) \quad (1)$$

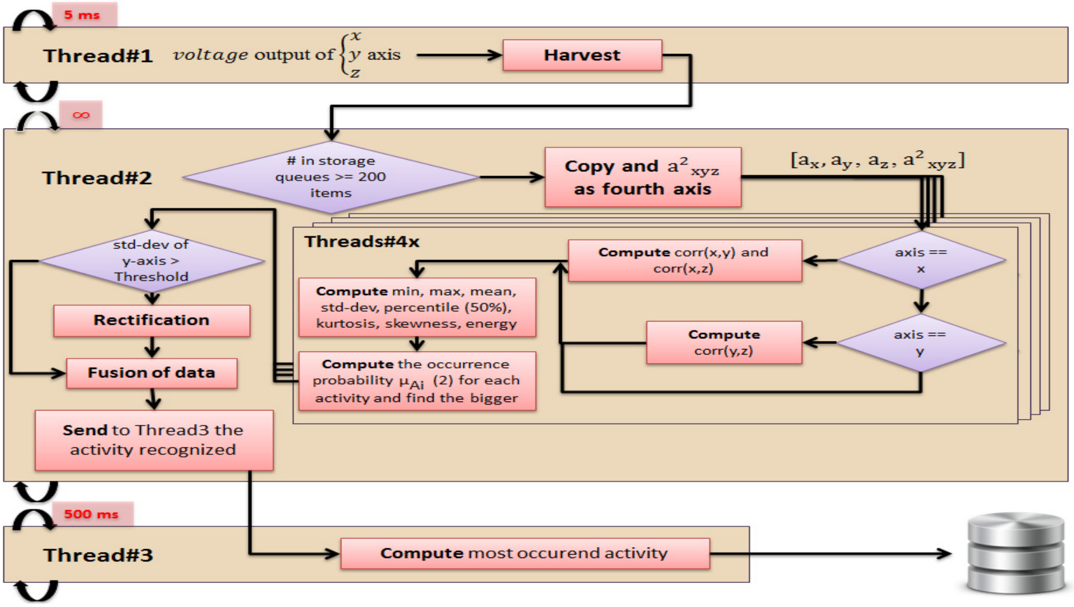

Fig. 2. Flowchart of activity recognition algorithm

However, consider a single axis does not necessarily mean that the recognized activity is the current correct activity. Consequently, the maximum value among the counters is the most probable activity because all axes have been treated. Before doing this inference, we have added a correction to help to detect the activities “be lying” and “be standing”. Although we had trained our model with these, we found that using a threshold on the standard deviation of the y-axis (this is the minimum of all standard deviations of the activities on y-axis) is more efficient thanks to the orientation of the body. It then suffices to compare the mean value of x-axis and z-axis with the mean of y-axis to conclude. The third thread receives the activities recognized, and sends to the database every 500 ms, the most frequent activity. The error recognition can be externalized of our algorithm as suggested in Fig 2. or alternatively integrated in the third previous thread. It takes as input a graph where the nodes are state of changes of the smart-home's sensors, and the transitions between these states are the activities that we can recognize. Among all the possible paths, those with errors are marked. When it recognizes one or more activities inside the graph, introduced in the initialization, belonging to a non-compliant sequence, our program sends this error to the server where a program could act accordingly e.g. with effectors.

4. Validation: Implementation and Experiment

In order to validate the proposed recognition approach, we implemented the entire system presented in Fig 1, including the shoe-mounted accelerometer, and also the algorithm presented in Fig 2. The system was then deployed and tested inside our smart home infrastructures. This real size living-lab allows us to rapidly assemble and test new prototypes. It consists of a complete apartment equipped with pressure mats, movement detectors, Radio Frequency Identification Data (RFID) tags on objects, electromagnetic contacts, temperature and light sensors, prompting systems (with auditory, pictorial, video and light prompts), ultrasound sensors, Bluetooth antenna, etc. All the systems are controlled via a server where the algorithms of artificial intelligence are deployed. Then, the server computes in real time the data gathered from the multiple sensors. For the testing phase, we exploited the Bluetooth antenna, the server, the shoe-mounted accelerometer prototype, and the daily living home environment to simulate activities. The main objective of this experiment was to evaluate the accuracy of the activity recognition process and to validate the ability of the system to recognize errors.

4.1. Experimental Protocol and Experimental Results

We wanted to elaborate an experiment close to real life conditions, taking into accounting few aspects, such as the imperfections or changes in how to perform the same movement. To do so, we created several scenarios, constituting together a morning routine. They are based on former trials that we conducted with actual Alzheimer's patients [19]. Each scenario has duration of approximately 1min30. The complete routine regroups all the actions that we are able to recognize. The scenarios are defined as follows:

- The resident is in his room on his bed (1), he gets up to stand (2), he walks (3) up to the bathroom where he stops in front of the mirror (4);
- he leaves the room by walking (5) toward the kitchen where he stops (6) to the sink to fill a glass of water, he caught in a wall cabinet (7) (8);
- once the water off, he leaves the kitchen and walks (9) out of his apartment (he should stop (10) to open the front door), he then goes out to do (11) exercise;
- once on site (12), the exercise is to climb staircases (13), turn-back walking (14), and descent (15);
- once he got his breath back, he stops (16) a few seconds at the bottom of staircases), he returns, tired to his apartment (17), he stops in front of the bed (18) and lies down (19) without even closing his door.

For the experiment, an actor simulated ten times each scenario (the complete routine), while wearing the shoe-mounted prototype. The collected data were used for the learning phase of the algorithm. We then firstly used the same data as input of the activity recognition algorithm; we evaluated the accuracies of each of six activities by varying the time of the outgoing information of our activity recognition algorithm from 40 ms to 1s by step of 40ms, as shown in Fig 3. The average, in red, has been added to observe the trend. Among the scenarios recorded, we have selected one, labeled as "pattern". By normalizing the activities of other scenarios, by using the sensors in the smart home and the signal of the accelerometer, we have computed the rate of truth for each activity and on the total duration relative to the "pattern" in blue and to a perfect pattern (without recognition errors) in red, as shown in Figure 4a.

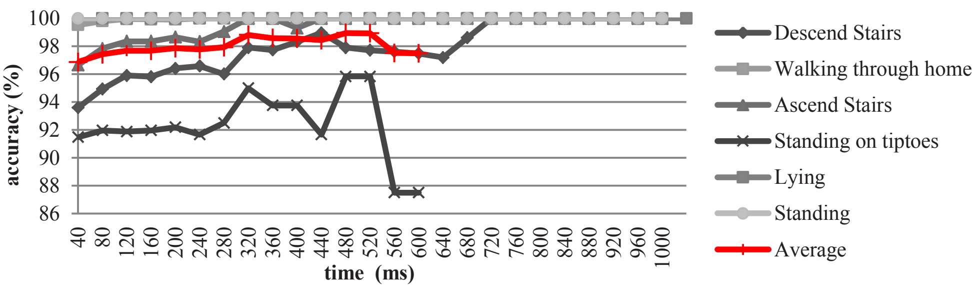

Fig. 3. Accuracy of all activities using the learning data

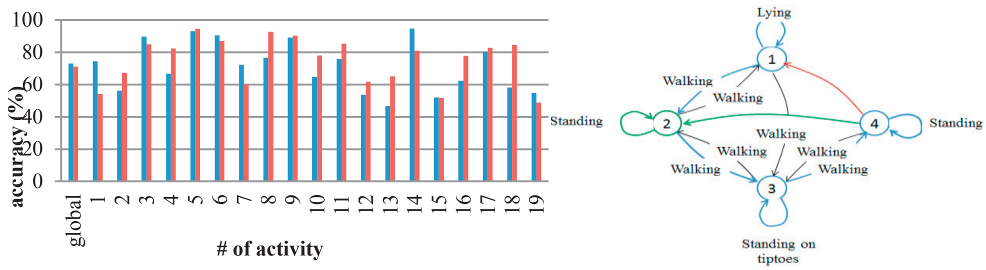

Fig. 4. (a) Practical accuracies of activities; (b) Graph state: the path traveled by the patient is in blue and green (his error);

The Fig 4b represents a given graph to the error recognition. The black arrows express the possible actions authorized for going from a node to another. The nodes designate a change of state of one sensor in the smart home, where 1 is sensory tactile mat at the foot of the bed, 2 is sensory tactile mat in front of the bathroom's mirror, 3 is an electromagnetic contact on wall cabinet in the kitchen and 4 is an electromagnetic contact on the refrigerator's door. Therefore, the red arrows are errors, which must be recognized. In this figure, we added a blue path (a sequence of activities) of the resident turning into a green path after an error. The histogram in Fig 5 indicates with a red line the beginning of the error.

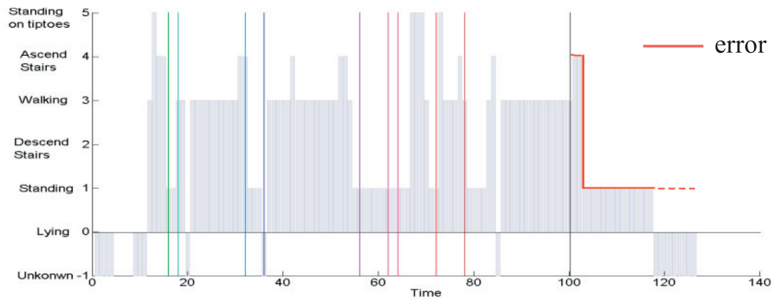

Fig. 5. Histogram of activities with the changes of states of the sensors

4.2. Analysis of the results

First, curves in Fig 3 show that the static activities and "walking through home" are all times recognized theoretically without any errors. By contrast, the accuracies of the other dynamic activities, as the average, start around 90% and increase slowly towards 100%, aside "standing on tiptoes" who is more chaotic and decreases after 520ms. This last notification is linked to the fact that this activity is very short in time (1 or 2s), and increasing the period would be flooded by other activities recognized. The maximum average of accuracies is between 98.96% and 98.92% corresponding to 40 and 520 ms, that we could call a high confidence in the recognition. Second, the practical accuracy is a bit lower than the theorical one. Indeed, we obtained rates around 73.11% and 71.11% respectively with comparison with the pattern and a perfect sequence. These percentages are very close, and it is something that reproduces on the different activities. We can conclude that a scenario recorded either by our device or home, performed by the same resident, could be used as input for our error recognition algorithm without major consequences. Looking more closely, we find that the activities with the smallest rate are the 13th and 15th (climbing and descending stairs), because these movements are variable in their executions. Thus, these percentages indicate that we must extend our learning base. Moreover, short activities as "standing on tiptoe" and our brief stop in front of the stairs (17) could mean that the size of the window is maybe too large or a correction is needed. Finally, we tested the error recognition, which worked (see Fig 5).

5. Conclusion

In this paper, we propose a new way to achieve real-time error recognition in the context of assistance in a smart home. This low-cost solution is constituted of a non-intrusive shoe-mounted sensor and on an activities/errors real-time recognition algorithm. It could be used in most architecture of smart homes or even on a mobile device to be use outside. Our implementation is straightforward; the execution is fast, and the shoe does not require the intervention of a specialist to be installed. A learning phase is necessary for training, which only require less than fifteen minutes (or training data) to be effective. We conducted a complete set of experiment of the system in our smart home living-lab by simulating (multiple times) several scenarios based on a morning routine, implying six main pedestrian events. These scenarios were based on clinical data gathered in previous experiment with actual Alzheimer's patients. We obtained promising results showing that the proposed activity and errors recognition system is highly effective. In future works, we will need to detect more pedestrian events (ex. turn left and right). We also need to test the system in multiple environments (ex. different homes) with a larger group of persons.

References

1. Economic, U.N.D.o. and S.A.P. Division, World Population Aging 2009. 2010: Bernan Assoc.
2. Mihailidis, A., et al., The COACH prompting system to assist older adults with dementia through handwashing: an efficacy study. BMC Geriatr, 2008. 8: p. 28.
3. Orr, R.J. and G.D. Abowd, The smart floor: a mechanism for natural user identification and tracking, in CHI '00 Extended Abstracts on Human Factors in Computing Systems. 2000, ACM: The Hague, The Netherlands. p. 275-276.
4. Cook, D.J., M. Youngblood, and S.K. Das, A multi-agent approach to controlling a smart environment, in Designing Smart Homes, A. Juan Carlos and D.N. Chris, Editors. 2006, Springer-Verlag. p. 165-182.
5. Intille, S.S., et al., Using a live-in laboratory for ubiquitous computing research, in Proceedings of the 4th international conference on Pervasive Computing. 2006, Springer-Verlag: Dublin, Ireland. p. 349-365.
6. Helal, S., et al., The Gator Tech Smart House: A Programmable Pervasive Space. Computer, 2005. 38(3): p. 50-60.
7. Chen, L., C.D. Nugent, and H. Wang, A Knowledge-Driven Approach to Activity Recognition in Smart Homes. IEEE Trans. on Knowl. and Data Eng., 2012. 24(6): p. 961-974.
8. Bao, L. and S.S. Intille, Activity Recognition from User-Annotated Acceleration Data Pervasive Computing. Pervasive Computing, 2004. 3001: p. 1-17.
9. Lee, M.-W., A.M. Khan, and T.-S. Kim, A single tri-axial accelerometer-based real-time personal life log system capable of human activity recognition and exercise information generation. Personal Ubiquitous Comput., 2011. 15(8): p. 887-898.
10. Munguia Tapia, E., Using Machine Learning for Real-time Activity Recognition and Estimation of Energy Expenditure. 2008, Massachusetts Institute of Technology, School of Architecture and Planning, Program in Media Arts and Sciences.
11. Wang, L., et al., A hierarchical approach to real-time activity recognition in body sensor networks. Pervasive and Mobile Computing, 2012. 8(1): p. 115-130.
12. Huynh, D.T.G., Human Activity Recognition with Wearable Sensors, in Informatik. 2008, TU Darmstadt.
13. Gyllensten, I.C. and A.G. Bonomi, Identifying types of physical activity with a single accelerometer: evaluating laboratory-trained algorithms in daily life. IEEE Trans Biomed Eng, 2011. 58(9): p. 2656-63.
14. Bonomi, A.G., et al., Detection of type, duration, and intensity of physical activity using an accelerometer. Med Sci Sports Exerc, 2009. 41(9): p. 1770-7.
15. Aggarwal, J.K. and M.S. Ryoo, Human activity analysis: A review. ACM Comput. Surv., 2011. 43(3): p. 1-43.
16. Gu, T., et al., epSICAR: An Emerging Patterns based approach to sequential, interleaved and Concurrent Activity Recognition, in Proceedings of the 2009 IEEE International Conference on Pervasive Computing and Communications. 2009, IEEE Computer Society. p. 1-9.
17. Candes, E.J. and M.B. Wakin, An Introduction To Compressive Sampling. Signal Processing Magazine, IEEE, 2008. 25(2): p. 21-30.
18. Bouchard, K., B. Bouchard, and A. Bouzouane, Guidelines to efficient smart home design for rapid AI prototyping: a case study, in Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments. 2012, ACM: Heraklion, Crete, Greece. p. 1-8.
19. Lapointe, J., et al., Smart homes for people with Alzheimer's disease: adapting prompting strategies to the patient's cognitive profile, in Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments. 2012, ACM: Heraklion, Crete, Greece. p. 1-8.