DCNN-based elderly activity recognition using binary sensors

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***Abstract*— In the past few decades, the number of elderly people who prefer to live independently is significantly increasing among the elderly people due to the issues of privacy invasion and elderly care cost. Device-free non-privacy invasive activity recognition is preferred for long-term monitoring. Thus, we propose a deep learning classification method for elderly activities using binary sensors (PIR sensor and door sensor). In particular, we present a Deep Convolutional Neural Network (DCNN) classification approach for detecting four basic activity classes which represent the basic human activities in a home monitoring environment, namely: Bed_to_Toilet, Eating, Meal_Preparation, and Relax. A real-world long-term annotated dataset is employed for evaluation of the activity recognition classifier. Dataset was offered by Center for Advanced Studies in Adaptive Systems (CASAS) project, and was collected by monitoring a cognitively normal elderly resident by binary sensors for 21 months First, we converted the annotated binary sensor data into a binary activity images for corresponding activities. Then, activity images are used for training and testing the DCNN classifier. Finally, classifiers are evaluated with 10-fold cross validation method. Experimental results showed the best DCNN classifier gives 99.36% of accuracy. Our next step is to improve this classifier for detection of intertwined complex activities of elderly and to implement it on a real life long-term elderly monitoring system.**

Index Terms*— *non-privacy invasive, device-free, deep learning, assistive technology, travel pattern, smart house, elder care

I. INTRODUCTION

In the past few decades, one of the biggest worldwide trend among the elderly people is a single life-style [1]–[7] and the number of single-resident homes [6] are increasing worldwide as well. The global elderly population (over 60 years old) is estimated to be 1.2 billion by 2025 [8].

Thus, elderly household daily life activity monitoring will be crucial factor to keep elderly for maintaining their independent lifestyle by early detection of any abnormal activities. In general, there are three types of monitoring systems by using: (1) stationary sensors such as cameras [9]–[12]; (2) wearable devices or wearable devices with stationary sensors [13]–[27]; (3) anonymous binary sensors [8], [28]–[31] such a[32]s passive infrared (PIR) sensors, magnetic switches, piezo sensors, passive RFID tags, etc. However, camera based systems are the least preferred due to its privacy invasiveness. Wearable device based systems are less invasive but not practical in a long-term monitoring application due to its natural flaws such as wearable device can be lost easily, short battery life, constant maintenance, and uncomfortableness to wear [33]. Finally, anonymous binary sensors based systems are most preferable solution for long-term monitoring application because they are device-free and non-privacy invasive.

Main objective of this study is to propose a device-free non-privacy invasive Deep Convolutional Neural Network (DCNN) classifier for elderly activity recognition using an annotated open dataset collected by wireless binary sensors. The open dataset is provided by Center for Advanced Studies in Adaptive Systems (CASAS) project, Washington State University [34]. First, we converted the annotated data into a binary activity images for corresponding activities. Then, activity images are used for training and testing the proposed DCNN classifier. To find the best classifier, we compared the performances of several DCNN classifiers with different architectures and parameters. Finally, classifiers are evaluated with 10-fold cross validation method. Experimental results showed the best DCNN classifier gives 99.36% of accuracy. We summarize our contributions in this study as follows:

- We propose a novel device-free non-privacy invasive activity recognition classification method for the elderly people living alone;

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- For the first time, we converted a sequence of PIR sensor logs into an activity image for the deep machine learning purpose;
- To our best of knowledge, we implemented DCNN classifier, which has the highest performance for activity recognition among the systems with binary sensors.

The rest of this paper is organized as follows. Section II defines the proposed methods in detail. In section III, the performance evaluation on annotated open dataset is demonstrated. The limitation and advantages of our systems are discussed in section IV. Finally, in section V, the paper is concluded.

II. METHODS

Fig. 1 (a) illustrates a framework of the dataset preparation for the elderly daily activity classifiers. In dataset preparation, firstly, 4342 activities are segmented as .csv files from the annotated raw data which are collected via device-free non-privacy invasive binary sensors. There were 157, 247, 1298, and 2640 activities for, respectively, Bed_to_Toilet, Eating, Meal_Preparation, and Relax. Then the .csv files were converted into 300×150 binary activity images as shown in Fig. 3. Fig. 1 (b) illustrates the training process of the machine learning models with labels and extracted features of the training set as inputs. Fig. 1 (c) represents the evaluation part of the models where the extracted features of the test set are inputted to the trained classifier, and then the model yields the predicted labels for the corresponding features.

A. Smart Home Environment

Aruba testbed, shown in Fig. 2 (a), is one of the testbeds of CASAS project which is chosen for this study. CASAS is a large-scale long-term project that studies about daily life events of residents in the smart home using wireless binary sensors. The ethical approval is granted from their institutional review board for real-life experiments with real people. Fig. 2 (a) illustrates a layout of Aruba testbed which has a kitchen, a dining area, a living room, an office, two bedrooms, two bathrooms, a pantry, a garage, and a backyard.

The testbed is equipped with 31 wireless motion sensors, four door sensors, and four temperature sensors. However, only motion sensors and door sensors are relevant in this study; thus the other sensors are not illustrated in Fig. 2 (a).

B. Resident

A single voluntary elderly woman lived in the testbed, and she regularly receives her children and grandchildren during the experimental period. There is no information about the resident's exact age, cognitive state, daily activity level, etc. available in the dataset, thus we consider her as a healthy person.

C. Binary Sensors

All binary sensors have a battery and a ZigBee wireless module; and they are installed on the ceilings of the testbed. Any detected motion or no motion is an event, and events are logged chronologically in the server after received via wireless sensor network. Event logs consist of four parts which are date, time, sensor type, and status (Fig. 2 (b)). In Fig. 2 (a), M0XX are PIR motion sensors, represented by red and grey circles that was installed on the ceiling. PIR motion sensors send "ON" signal when they sense any motion, then send "OFF" signal briefly after the motion is stopped. Information of the grey sensors are neglected, because they have wide field of view that overlaps with the field of view of surrounding other PIR sensors. Supposedly, locations of the binary sensors were strategically chosen so that resident's common activities can be detected.

D. Dataset and Technical Specification

In the raw dataset, 5228655 events were recorded in 625 days during 2010-2012. Fig. 2 (b) shows typical samples from the raw dataset. From the smaples, we can realize that the resident walked from the bed to the bathroom.

We employed a desktop computer which has i7-7700 CPU at 3.6 GHz speed and NVIDIA GeForce GTX 1080 graphic

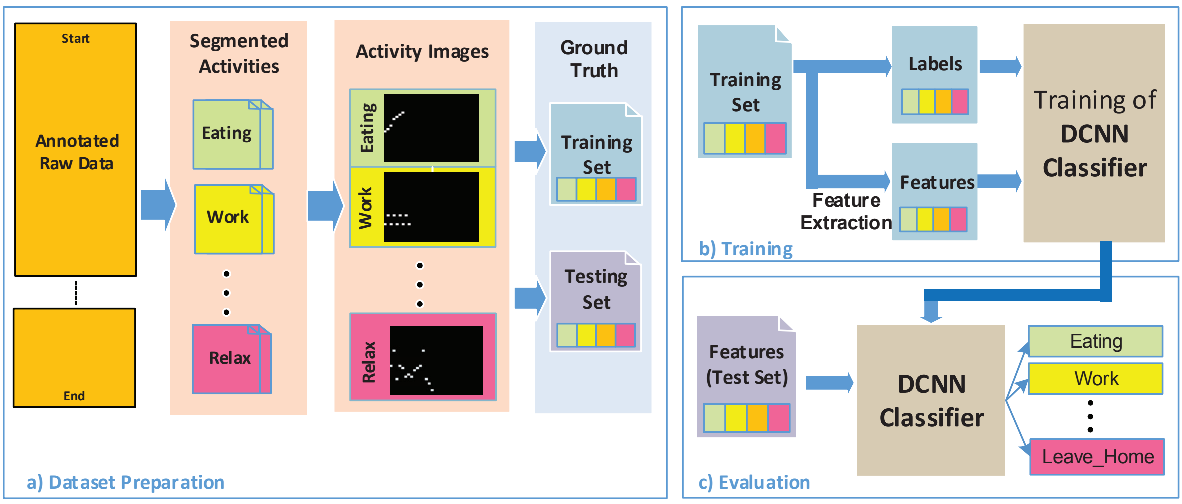

Fig. 1. Framework of the dataset preparation for the machine learning travel pattern classifiers.

card. GTX 1080 has a graphical processor unit (GPU) which enhances the calculation speed of the DCNN classifier.

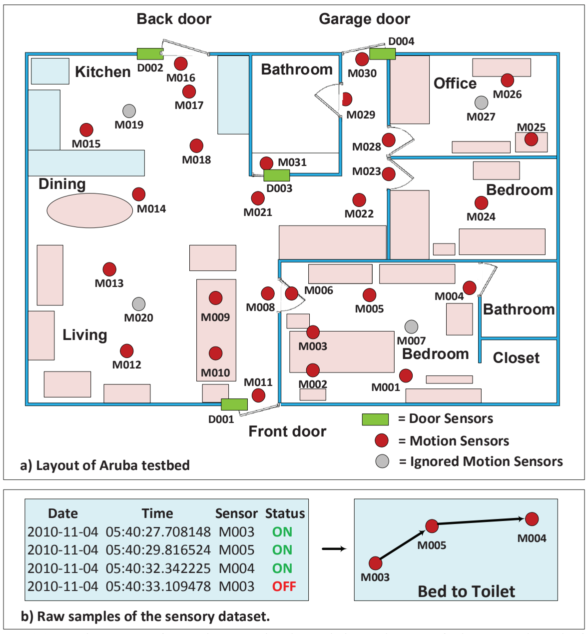

Fig. 2. (a) A layout of Aruba testbed and locations of the passive infrared motion sensors and door sensors; (b) Raw samples from the dataset and their representation.

E. *Activity Image*

We propose a novel *activity image* converted from the logs of binary sensors as shown in Fig. 3. The activity image has 300×150 resolution which represents 300 events in the x-axis and sensors in the y-axis. The activity image has a black background and white pixels will be drawn on the activity image corresponding to each "ON" and "OPEN" signal from, respectively, PIR sensors and door sensors. Fig. 4 illustrates sample activity images for each activity.

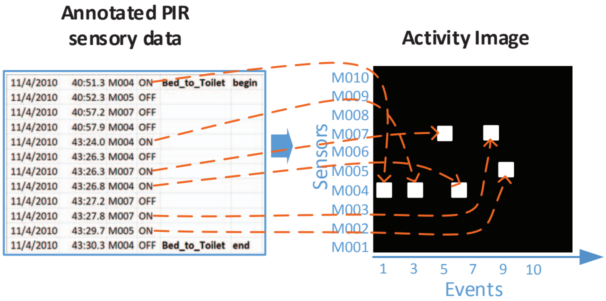

Fig. 3. Conversion of an activity image from binary sensor data.

F. *DCNN Architecture*

Fig. 5 summarizes the architecture of our proposed DCNN classifier. The model architecture has two convolutional layers and two fully connected layers. Each convolutional layer is

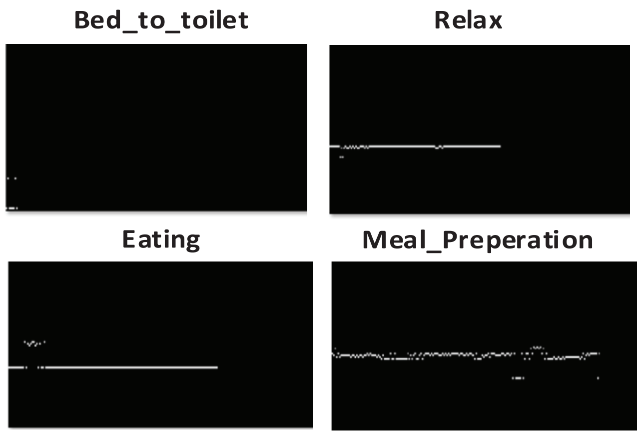

Fig. 4. Sample activity images for each activity.

followed by subsampling (max-pooling) layer. Convolutional layers have multiple feature filters of size 3×3, and max-pooling layers have a pooling window of size 2×2. Zero padding is used for the convolutional operation, thus the sizes of the episode image and the feature maps can be the same.

In the max-pooling layers, outputs are two times smaller than the inputs since the pooling window is 2×2.

Finally, all neurons of the third fully connected layer are connected to four outputs i.e. Bed_to_Toilet, Eating, Meal_Preparation, and Relax.

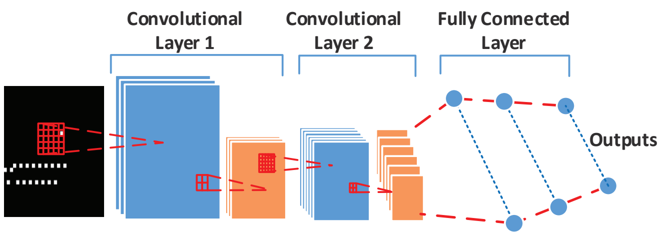

Fig. 5. Conversion of an activity image from binary sensor data.

Mathematical expression of feature maps that generated by 2D convolution at each convolutional layer is as follows:

$$y_j = \frac{1}{1+\exp(b_j + \sum_i k_{ij} * x_i)} \quad (1)$$

where $*$ denotes the convolutional operator, k_{ij} is the convolutional filter on the i-th input map x_i to generate the j-th output feature map y_j, b_j is a bias. Max-pooling creates position invariance over larger local regions and sub-samples the input map. Max-pooling enables the faster convergence rate by choosing superior invariant features which improves generalization performance. The output map y_i is achieved by finding maximum values over the non-overlapping pooling regions of the input map x_i with a square filter m × m:

TABLE I.
WEIGHTED AVERAGE AND STANDARD DEVIATION OF 10-FOLD CROSS-VALIDATION RESULTS FOR DCNN CLASSIFIER*

DCNN classifier 16C3×3−S2×2−32C3×3−S2×2	**Bed_to_ Toilet**	**Eating**	**Meal_ Prep.**	**Relax**	**precision**	**recall**	**specificity**	**f1_score**	**accuracy**	**error**	**latency [ms]**
Bed_to_Toilet	**15.7**	0	0	0	1.0	1.0	1.0	1.0	100.00	0.00	<10
Eating	0	**23.5**	1.5	0.5	0.963	0.922	0.999	0.935	99.71	0.29	<10
Meal_Preparation	0	0.8	**495.4**	3.8	0.984	0.991	0.985	0.987	98.78	1.22	<10
Relax	0	0.2	6.6	**493.2**	0.991	0.986	0.992	0.989	98.93	1.07	<10
Mean					**0.985**	**0.975**	**0.994**	**0.978**	**99.36**	**0.64**	
Standard Dev.					**0.014**	**0.031**	**0.006**	**0.025**	**0.513**	**0.513**	

*"C" and "S" denote convolutional layer and subsampling (maxpooling) layer, respectively. The DCNN architecture is described as "{the number of output maps}C{map size}-S{pooling size}.

$$a_j = \max_{i \in R_j} a_i \quad (2)$$

where a_j denotes the pixel value of the output map that is found within the pooling region R_j of the input map, and a_i is an activation in a set $\{a_1, \dots, a_{|R_j|}\}$.

G. Performance Validation

In this study, 10-fold cross-validation technique is employed to validate the performance of the trained classifiers. The classifier accuracy is calculated as the average of all 10 results from 10 different. Moreover, the results are obtained by seven validation metrics: precision, recall (sensitivity), specificity, F_1-score [35], accuracy, error, and latency.

In addition, we evaluate the computational cost of the classifiers, which is the time period that spent for classifying an episode.

III. EXPERIMENTAL RESULTS

Table 1 represents the results of 10-fold cross-validation. For each classifier, weighted average (mean) and standard deviation of seven measures, which are averaged performances of four activities, are calculated. From the table, classifier detects Bed_to_Toilet activity with 100% accuracy, and the rest of the activities with over 98.78%. The mean weighted accuracy of the classifiers is 99.36%, and standard deviation of the accuracies over different type of activities is 0.513. Represented architecture had the highest accuracy among our simulated DCNN classifiers, however the other classifiers with 16C5×5−S2×2−32C5×5−S2×2−64C5×5−S2×2 and 16C3×3−S2×2−32C3×3−S2×2 architecture's mean weighted accuracies were, 98.76% and 98.93 %, respectively.

IV. CONCLUSIONS AND FUTURE WORKS

This paper has proposed a novel DCNN classifier for device-free non-privacy invasive activity detection of elderly people living alone in the smart houses. Open dataset that collected by binary sensors [34] for two years in Aruba testbed is employed for the 10-fold cross-validation of the proposed DCNN classifier.

With our best of knowledge, this is the first work proposing an activity image converted from binary sensory (PIR sensor and switch sensors) data for DCNN classifier.

As the experimental results suggest, DCNN classifier detects all activities with accuracy over 98.78%, while the average accuracy is 99.36%. Thus, we think the proposed classifier can be a useful tool for detecting activities.

Our next step is to implement the method on a real-life long-term experiments with real people. In addition, we will improve the classifier for intertwined complex activities.

REFERENCES

[1] N. S. Lawand, P. J. French, J. Van Driel, J. J. Briaire, and J. H. M. Frijns, Sensing Technology: Current Status and Future Trends II, vol. 12. Springer, 2014.

[2] S. C. Mukhopadhyay, Next Generation Sensors and Systems, vol. 16. Springer, 2015.

[3] S. Häfner, J. Baumert, R. T. Emeny, M. E. Lacruz, M. Bidlingmaier, M. Reincke, H. Kuenzel, R. Holle, R. Rupprecht, and K. H. Ladwig, "To live alone and to be depressed, an alarming combination for the renin–angiotensin–aldosterone-system (RAAS)," Psychoneuroendocrinology, vol. 37, no. 2, pp. 230–237, Feb. 2012.

[4] K. Kinsella, J. Beard, and R. Suzman, "Can populations age better, not just live longer?," Gener. - J. Am. Soc. Aging, vol. 37, no. 1, pp. 19–27, 2013.

[5] K. Raworth, State of the World 2013, vol. 461. 2013.

[6] U. S. C. Euromonitor International, "Living Alone Statistics," 2015. [Online]. Available: http://www.statisticbrain.com/living-alone-statistics/.

[7] T. H. Tan, M. Gochoo, F. R. Jean, S. C. Huang, and S. Y. Kuo, "Front-Door Event Classification Algorithm for Elderly People Living Alone in Smart House Using Wireless Binary Sensors," IEEE Access, vol. 5, pp. 10734–10743, 2017.

[8] A. Akl, B. Taati, and A. Mihailidis, "Autonomous unobtrusive detection of mild cognitive impairment in older adults," IEEE Trans. Biomed. Eng., vol. 62, no. 5, pp. 1383–1394, 2015.

[9] D. Chen, A. J. Bharucha, and H. D. Wactlar, "Intelligent video monitoring to improve safety of older persons," in Proc. 29th Int. Conf. IEEE Eng. in Med. and Biol. Soc., 2007, pp. 3814–3817.

[10] C. Di Huang, C. Y. Wang, and J. C. Wang, "Human Action Recognition System for Elderly and Children Care Using Three Stream ConvNet," in Proc. of 2015 International Conference on Orange Technologies, ICOT 2015, 2016, no. 4, pp. 5–9.

[11] S. N. Gowda, "Human Activity Recognition Using Combinatorial Deep Belief Networks," in Proc. of IEEE Conf. on Computer Vision and Pattern Recognition Workshops (CVPRW), 2017, pp. 1589–1594.

[12] M. Papakostas, T. Giannakopoulos, F. Makedon, and V. Karkaletsis,

"Short-Term Recognition of Human Activities Using Convolutional Neural Networks," in Proc. of 12th Int. Conf. on Signal Image Technology and Internet-Based Systems (SITIS 2016), 2017, pp. 302–307.
[13] S. Abbate, M. Avvenuti, and J. Light, "MIMS: A minimally invasive monitoring sensor platform," IEEE Sens. J., vol. 12, no. 3, pp. 677–684, 2012.
[14] N. K. Vuong, S. Chan, C. T. Lau, S. Y. W. Chan, P. L. K. Yap, and A. S. H. Chen, "Preliminary results of using inertial sensors to detect dementia-related wandering patterns," in Proc. 37th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., 2015, pp. 3703–3706.
[15] A. Kumar, C. T. Lau, S. Chan, M. Ma, and W. D. Kearns, "A Unified Grid-based Wandering Pattern Detection Algorithm," in Proc. 38th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., 2016, pp. 5401–5404.
[16] K.-J. Kim, M. M. Hassan, S. Na, and E.-N. Huh, "Dementia Wandering Detection and Activity Recognition Algorithm Using Tri-Axial Accelerometer Sensors," in Proc. of the 4th Int. Conf. on Ubiquitous Information Technologies & Applications, 2009, pp. 1–5.
[17] K. Makimoto, M. Yamakawa, N. Ashida, Y. Kang, and K.-R. Shin, "Japan-Korea joint project on monitoring people with dementia," in Proc. 11th World Congress on the Internet and Med., 2006, pp. 1–5.
[18] W. D. Kearns, D. Algase, D. H. Moore, and S. Ahmed, "Ultra wideband radio: A novel method for measuring wandering in persons with dementia," Gerontechnology, vol. 7, no. 1, pp. 48–57, 2008.
[19] C. Price, "Monitoring people with dementia -- controlling or liberating?," Qual. Ageing, vol. 8, no. 3, pp. 41–44, Apr. 2007.
[20] J. Cohen-Mansfield, P. Werner, W. J. Culpepper, M. Wolfson, and E. Bickel, "Assessment of Ambulatory Behavior in Nursing Home Residents Who Pace or Wander: A Comparison of Four Commercially Available Devices," Dement. Geriatr. Cogn. Disord., vol. 8, no. 6, pp. 359–365, Oct. 1997.
[21] D. De Venuto, V. F. Annese, and G. Mezzina, "Remote Neuro-Cognitive Impairment Sensing based on P300 Spatio-Temporal Monitoring," IEEE Sens. J., vol. 16, no. 99, pp. 8348–8356, 2016.
[22] K. Ohnishi, A. Kanehira, A. Kanezaki, and T. Harada, "Recognizing Activities of Daily Living with a Wrist-Mounted Camera," in Proc. of 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 3103–3111.
[23] T. Zebin, P. J. Scully, and K. B. Ozanyan, "Human Activity Recognition with Inertial Sensors Using a Deep Learning Approach," in Proc. of IEEE Sensors 2016, 2016, no. 1, pp. 1–3.
[24] M. Panwar, S. R. Dyuthi, K. C. Prakash, D. Biswas, A. Acharyya, K. Maharatna, A. Gautam, and G. R. Naik, "CNN Based Approach for Activity Recognition Using a Wrist- Worn Accelerometer," in Proc. of 39th Ann. Int. Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC), 2017, pp. 2438–2441.
[25] J. Li, R. Wu, J. Zhao, and Y. Ma, "Convolutional Neural NetWorks (CNN) for Indoor Human Activity Recognition Using Ubisense System," in Proc. of 29th Chinese Control And Decision Conference (CCDC), 2017, pp. 2068–2072.
[26] S.-M. Lee, S. M. Yoon, and H. Cho, "Human Activity Recognition From Accelerometer Data Using Convolutional Neural Network," in Proc. of IEEE Int. Conf. on Big Data and Smart Computing (BigComp), 2017, pp. 131–134.
[27] S. Ha, J.-M. Yun, and S. Choi, "Multi-modal Convolutional Neural Networks for Activity Recognition," in Proc. of IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC), 2015, pp. 3017–3022.
[28] H. H. Dodge, N. C. Mattek, D. Austin, T. L. Hayes, and J. A. Kaye, "In-home walking speeds and variability trajectories associated with mild cognitive impairment," Neurology, vol. 78, no. 24, pp. 1946–1952, 2012.
[29] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Automated Cognitive Health Assessment Using Smart Home Monitoring of Complex Tasks," IEEE Trans. Syst. Man, Cybern. Syst., vol. 43, no. 6, pp. 1302–1313, Nov. 2013.
[30] B. Das, D. J. Cook, N. C. Krishnan, and M. Schmitter-Edgecombe, "One-Class Classification-Based Real-Time Activity Error Detection in Smart Homes," IEEE J. Sel. Top. Signal Process., vol. 10, no. 5, pp. 914–923, 2016.
[31] J. Petersen, D. Austin, N. Mattek, and J. Kaye, "Time out-of-home and cognitive, physical, and emotional wellbeing of older adults: A longitudinal mixed effects model," PLoS One, vol. 10, no. 10, pp. 1–16, 2015.
[32] Y. Chen and Y. Xue, "A Deep Learning Approach to Human Activity Recognition Based on Single Accelerometer," in Proc. of 2015 IEEE International Conference on Systems, Man, and Cybernetics, 2015, pp. 1488–1492.
[33] "Wearables have a dirty little secret: 50% of users lose interest - TechRepublic." [Online]. Available: http://www.techrepublic.com /article/wearables-have-a-dirty-little-secret-most-people-lose-interest/. [Accessed: 16-Dec-2016].
[34] D. J. Cook, "Learning Setting-Generalized Activity Models for Smart Spaces," IEEE Intell. Syst., vol. 27, no. 1, pp. 32–38, 2012.
[35] N. K. Vuong, S. Chan, and C. T. Lau, "Automated detection of wandering patterns in people with dementia," Gerontechnology, vol. 12, no. 3, pp. 127–147, 2014.