



HAL
open science

Activity recognition in smart home using deep learning

Mariam El Ghazi, Noura Akinin

► **To cite this version:**

Mariam El Ghazi, Noura Akinin. Activity recognition in smart home using deep learning. Colloque sur les Objets et systèmes Connectés, Ecole Supérieure de Technologie de Casablanca (Maroc), Institut Universitaire de Technologie d'Aix-Marseille (France), Jun 2019, CASABLANCA, Morocco. hal-02296430

HAL Id: hal-02296430

<https://hal.science/hal-02296430>

Submitted on 25 Sep 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Activity recognition in smart home using deep learning

Mariam el ghazi

Information Technology and Modeling
Systems Research Unit
Abdelmalek Essaadi University
, Tetouan , Morocco
mariam.elghazi@gmail.com

Noura Aknin

Information Technology and Modeling
Systems Research Unit
Abdelmalek Essaadi University,
Tetouan , Morocco
noura.aknin@uae.ac.ma

Abstract - Modern societies are facing an important challenge of taking care of the elderly population. With the evolution of the internet of thing, health Smart home is considered as a possible solution to help to maintain their independence and monitoring elder's daily activities. It proposes to provide medicals and caregivers of the real-time status of the person at home and interfere in the emergency situation. One of the main functionalities of health monitoring systems is human activity recognition. In our work, we present a system able to recognize activities of daily living of the person in the smart home based on the deep learning approach. We propose a hybrid neural networks model based on convolutional and on a recurrent approaches using the opportunity dataset for Human Activity Recognition from Wearable Object and Ambient Sensors. We study the activity recognition workflow and the suitability of the hybrid model for different activities of daily living.

Keywords - Human activity recognition(HAR), internet of things(IoT), health smart home (HSH) , deep learning, CNN, LSTM

1. INTRODUCTION

According to UNFPA, the aging population over 60 will rise to 2 billion by 2050 [1]. This population will need daily healthcare monitoring from doctors and caregivers. This problem will have an immense impact over health institutions, the traditional method is high in cost and not efficient. As a solution, involving a health monitoring system in a smart home environment to give real-time healthcare to people who like to keep their independence, can avoid pressure on healthcare system institutions (hospitals, nursing homes....).

In this paper, we have investigated the suitability of two deep learning algorithms, namely convolutional neural networks and log short term memory , in recognizing elderly activities of daily living in the smart home, we have used the opportunity dataset. In section II, a review on sensors modality in health smart home, activity classification and the main deep learning algorithms for activity recognition . in section III, Methodology and in section IV Experiments and result.

2. LITERATURE REVIEW :

2.1 sensor modality in HSH

The smart home environment is embedded with sensors to keep track of the health status and activities of the subject, the sensor modalities used in Human Activity Recognition (HAR) are Body worn based approaches for monitoring of body physiological signals such as accelerometers, gyroscopes, and magnetometers. [5]

An object attached to objects, ambient sensors implement in the environment to deduce interaction and Hybrid combination of types often deployed in smart environment [6].

2.2 Activity classification in HSH

In the geriatric domain, the health and wellness status of individuals is measured by the so-called dependency evaluation level [2, 3]. So, in order to monitor a person at home we have to understand their main activities, as follow the classification of activities in health monitoring systems: activities of daily living (ADL): refers to the routines and basic tasks performed by subjects every day, such as eating and washing. The IADL refers to tasks required to live in a community, examples would be meal preparation and medication use. Ambulatory activities are activities that are related to the subject's motion and posture and physiological activities such as cardiac and brain activities. This type is used in real-time health parameters monitoring [4].

2.3. deep learning algorithms for Activity recognition

The General Stages of Human Activity Recognition Process That requires the following standard stages: data acquisition and preprocessing (collect raw data using a number of sensors), data segmentation (identify segments of data that contain information about the data to e classify), feature extraction and selection (finds the main characteristics of a data segment), and learning/inference. [7]

The surveyed work related to our subject [6] based on numerous works considering the three aspects: sensor modality, deep model and application. We can make several observations: Sensor deployment and preprocessing: sensor placement, suggested to use body-worn for ADL, for a more

complex activity we use ambient sensors, in this case, must collect data non-invasive way. We can deduce that there is no model which outperforms all the others in all situations. We inspect many drawbacks of the conventional HAR methods: The features are always extracted via a heuristic and hand-crafted way, which heavily relies on human experience or domain knowledge. [6], only shallow features can be learned according to human expertise [8]. Conventional Pattern Recognition approaches often require a large amount of well-labeled data to train the model, most existing models mainly focus on learning from static data. [6]

Deep learning serves to overcome the constraints of machine learning for HAR. Foremost deep learning can work with different types of networks.

Also, feature extraction and model building procedures are often executed in a simultaneous way in the deep learning models, plus the features are learned automatically rather than manually. Moreover, the deep neural network fit more for complex activity recognition tasks because it can extract high-level representation in the deep layer. [6]

2.3.1 Deep Neural Network (DNN)

DNN is developed from the artificial neural network (ANN). Traditional ANN often contains very few hidden layers (shallow) while DNN contains more (deep). With more layers, DNN is more capable of learning from large data.

2.3.2 Convolutional Neural Network (CNN):

CNN is a type of deep neural network that was developed for use with image data, e.g. such as handwriting recognition. CNN is very effective on computer vision and CNN can be applied to human activity recognition data .

2.3.3 Recurrent Neural Networks (RNN) :

RNN designed to learn from sequence data, such as sequences of observations over time.

LSTM (long short-term memory network) cells are often combined with RNN [6] LSTM is serving as the memory units, the learning speed and resource consumption are the main concerns for HAR. [9]

2.3.4 Hybrid Model:

A hybrid model is the combination of multiple deep models, like the combination of CNN and RNN in these articles [10, 11] provided good performances

Why hybrid Model?

CNN is able to capture the spatial relationship, while RNN can make use of the temporal relationship. CNN help in speeding up the training process of feature extraction [11]

By investigating the performance of DNN, CNN, and RNN through the review: RNN could make use of the time-order relationship between sensor readings, and CNN is more capable of learning deep features contained in recursive

patterns. For multi-modal signals, it is better to use CNN since the features can be integrated.

3. METHODOLOGY :

For the Problem of human activity recognition in health smart home we propose hybrid deep model based on Convolutional neural networks and long short-term memory networks, both together, are suited to learning features from raw sensor data and recognizing human activity in a smart environment.

4. Experiments and results :

In our work, we select the Opportunity Dataset suitable for the Human activity recognition problem, the data is collected from Wearable, Object, and Ambient Sensors. [12, 13]

In the experiment process we follow these stages: Analyze and preprocessed data, Separate training and test data set, create a Hybrid Deep learning model, Train and evaluate the model.

5. CONCLUSION :

In this work we explored the deep learning approaches for activity recognition, we found that deep learning reduces the dependency on human-crafted feature extraction and achieves better performance by automatically learning high-level representations of the sensor data. In our future work, we continue experimenting with the hybrid model approach for Human activity recognition in smart home and improving the result to achieve the best accuracy.

REFERENCES

- [1] United Nations Population Fund (UNFPA), 2012. Ageing in the twenty-first century: a Celebration and A Challenge. <http://www.unfpa.org/publications/ageing-twenty-first-century> [Accessed: May 2016]
- [2] Lemlouma, T., Chalouf, M.A., 2013. Smart media services through tv sets for elderly and dependent persons, Springer Lecture Notes of the Institute for Computer Sciences. Soc. Inform. Telecom. Eng. 61, 30e40.
- [3] M. King and B. Zhu, "Gaming strategies," in Path Planning to the West, vol. II, S. Tang and M. King, Eds. Xian: Jiaoda Press, 1998, pp. 158-176.
- [4] Haider Mshali, Tayeb Lemlouma, Maria Moloney, 2018 Damien Magoni, A survey on health monitoring systems for health smart homes, International Journal of Industrial Ergonomics, Volume 66, Pages 26-56, ISSN 0169-8141J.-G. Lu, "Title of paper with only the first word capitalized," J. Name Stand. Abbrev., in press.
- [5] Nweke, Henry & Wah, Teh & Ali Al-garadi, Mohammed & Alo, Uzoma. (2018). Deep Learning Algorithms for Human Activity Recognition using Mobile and Wearable Sensor Networks: State of the Art and Research Challenges. Expert Systems with Applications. 105. 10.1016/j.eswa.2018.03.056.
- [6] Wang, Jindong & Chen, Yiqiang & Hao, Shuji & Peng, Xiaohui & Lisha, Hu. (2017). Deep Learning for Sensor-based Activity Recognition: A Survey. Pattern Recognition Letters. 10.1016/j.patrec.2018.02.010.
- [7] Sakr, N.A. & Abu-Elkheir, M & Atwan, A & Soliman, H.H.. (2018). Current trends in complex human activity recognition. Journal of Theoretical and Applied Information Technology. 96. 4564-4583.
- [7] Yang, J.B., Nguyen, M.N., San, P.P., Li, X.L., Krishnaswamy, S., 2015. Deep convolutional neural networks on multichannel time series for human activity recognition, in: IJCAI, Buenos Aires, Argentina, pp. 25-31.
- [8] Inoue, M., Inoue, S., Nishida, T., 2016. Deep recurrent neural network for
- [9] mobile human activity recognition with high throughput. arXiv preprint
- [10] arXiv:1611.03607 .
- [11] Singh, M.S., Pondenkandath, V., Zhou, B., Lukowicz, P., Liwicki, M., 2017. Transforming sensor data to the image domain for deep learning-an application to footprint detection. arXiv preprint arXiv:1701.01077 .
- [12] Liu, C., Zhang, L., Liu, Z., Liu, K., Li, X., Liu, Y., 2016. Lasagna: towards
- [13] deep hierarchical understanding and searching over mobile sensing data. in: Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking, ACM, pp. 334-347.
- [14] Daniel Roggen, Alberto Calatroni, Mirco Rossi, Thomas Holleczeck, Gerhard Tröster, Paul Lukowicz, Gerald Pirkel, David Bannach, Alois Ferscha, Jakob Doppler, Clemens Holzmann, Marc Kurz, Gerald Holl, Ricardo Chavarriaga, Hesam Saghah, Hamidreza Bayati, and José del R. Millán. "Collecting complex activity data sets in highly rich networked sensor environments" In Seventh International Conference on Networked Sensing Systems (INSS'10), Kassel, Germany, 2010.
- [15] Ricardo Chavarriaga, Hesam Saghah, Alberto Calatroni, Sundarateswari Digumarti, Gerhard Tröster, José del R. Millán, Daniel Roggen. "The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition", Pattern Recognition Letters, 2013