University of Technology, Sydney

Faculty of Engineering and Information Technology

Proposal

Daily activities classification based on machine learning techniques

By

Zhengjie Huang

Student Number: 13029285

Project Number: A18-403

Supervisor: Dr Yi Zhang

Co-supervisor: Prof Jie Lu

External Co-supervisor: Dr Meng Shen

Introduction

The continued increase in longevity is leading to a significant rise in the old-age dependency ratio. This number is expected to double in the next 35 year, with some countries like Japan, Germany exceeding a 50% ratio (Muszynska et al. (2012)). Several sociological and economical challenges are emerging due to this trend. On the one hand, 90% of the elderly people have the desire to live as long as possible independently in their own home (Farber et al. (2011)). On the other hand, their son/daughter are usually too busy to take care of them most of the time, which suggests the huge potential of elderly health care. While the need of health care rises, the market of caregivers will be facing a shortage in the next 35 years, which calls for a kind of labor-free care for elderly badly. Ambient Assisted Living (AAL) makes it possible.

One important concept of AAL is the monitoring of activities of daily living (ADL). It is widely used in health care, summarizing activities and daily routines, on which the functional status of a person is based, and on which the ability of a person to live independently in a community is assessed. Six basic ADLs are included in the assessment including bathing/showering, dressing, feeding, functional mobility, personal hygiene and continence. Because the assessment of the ADLs of a person is not feasible in a real-life situation, automatic classification and monitoring of ADLs using sensor deployed in households is a crucial part for AAL. With the help of ADL monitoring, a lot of diseases like Alzheimer, dementia can be detected at an early age which is crucial for effective treatment (Nygard et al. (2003), Galasko et al. (1997)). **However, the health assessment is totally based on the analysis of the ADLs. The key now is how to classify users' activities accurately**.

To classify the activities accurately, there are lots of things to be considered. And that is one of the reason that existing methods are not working so well. First, data collected from sensors or bracelets are streaming data transferred to the system. But most of the existing algorithm are designed for static data. It is important or even crucial for the system to be able to analyze real-time data to give quick response. This is a challenging problem as data that completely describes an activity is not generally available in such situations and the algorithm has to rely on the partially observed data along with other contextual information to make a decision on the activity being performed. Secondly, due to limited research on this topic, available datasets are limited which severely constrains the advance of research. With limited data, technique improvement cannot be done efficiently. Thirdly, more sensor data would be helpful for achieving the highest accuracy. But that also means the intrusion of users' privacy. So, how to balance the protection of user privacy and sensor data is a significant issue. Finally, although lots of techniques have been applied to this area, they are not working pretty well even with static data, let alone streaming data. There is still a lot for those techniques to be improved.

The aim of this project is to develop an integrated system for daily activities classification. Specifically, the objectives of this project include:

A data processing model

To be able to collect data from different datasets, a data-processing model should be created. There is not a standard for data recording. So, different research institutes are using their own pattern to record data which caused the inconvenience to apply methods to different datasets. But the information to be obtained from the datasets are basically same. It will be possible to develop an algorithm to extract core information from different datasets.

A daily activity classification model

After the information is extracted from the datasets, an effective algorithm will be developed to process the data. Based on existing methods, there are several ways to do so including several machine learning algorithms like HMM, CRF, Naïve Bayes and neural networks. Further investigation will be conducted to explore possible improvements.

A visualization model

This model is develop to display the classification results. It would be better if the results can be visualized so that the strength and weakness of the algorithm can be seen clearer. And improvements therefore can be made more accordingly.

Literature review

Sensor settings

RFID tags are one of the most commonly used devices for activity classification. In a research conducted by Park et al. (2008), RFID tags are deployed on kitchen utensils like bowls, dishes and so on to detect utensil related activities such as food preparation. Without so many RFID tags, Tapia et al.(2004) introduce a system for recognizing activities in the home setting using a set of small and simple state-change sensors. They reached a highest accuracy of 89% by just utilizing a small dataset. Furthermore, Stikic et al. (2008) presents an effective and unobtrusive long term recognition of ADLs utilizing the combination of data from RFID sensors and accelerometers. And it turns out that the accuracy improved significantly by fusing those two types of sensors. Rashidi et al. (2004) introduce an automated approach to activity tracking that identifies frequent activities that naturally occur in an individual's routine. Fleury et al. (2010) introduce the Health Smart Home that includes infrared presence sensors, door contacts, temperature and hygrometry sensor, microphones, etc. They then performed a 1-h experimentation and tested the classification algorithm with real data. Vuegen et al. (2013) examines the use of low-power Wireless Acoustic Sensor Network (WASN) for the observation of clinically relevant activities of daily living from elderly. They utilize audio and ultrasound separately and achieved the highest accuracy of 85% and 61.7% each. Atallah et al. (2009) investigate the use of a light-weight ear worn activity recognition devices together with wireless ambient sensors. They also apply a two-stage Bayesian on the sensors data and claims that it bodes well for a multi-dwelling environment.

Classification models

With various kinds of datasets, lots of methods have been applied to classify activities. Nazerfard et al. (2010) describe the use of a probabilistic model: Conditional Random Fields (CRFs), which is becoming more and more widely used for its excellent performance on activity recognition. Li et al. (2007) proposes a way of using hidden Markov model (HMM) to recognize human action after dimensional reduction. Yang et al. (2008) adopted multilayer feedforward neural networks (FNNs) as activity classifiers and proposed an effective activity recognition method using acceleration data. The experiments prove that their method achieved effectiveness and satisfactory accuracy. Their experiments results are as Table 1 below.

Peer statistics

It is generally considered to be challenging to classify activities with data from just one accelerometer. But by developing an effective design procedure that consists of several steps including data pre-processing and neural classifier construction, they obtained an overall accuracy of 95%. However, the dataset is so small that hardly can this method be applied to other scenarios where sensor selection, household invariance etc. are different.

Cook introduces her approach to learning activity classification models and demonstrate their approach by using datasets collected in different environments. Her approach is setting-generalized and utilized machine learning methods. Setting-generalized approach can be applied to most of the scenarios and thus can be widely used. But the accuracy obtained by this approach is far lower than those setting-specialized models, which can be seen from Table 2.

Table 1 Confusion matrix (Yang et al. (2008))

Classified as	Walking	Running	Scrubbing	Standing	Working at a PC	Vacuuming	Brushing Teeth
Walking	313	0	2	0	0	17	0
Running	0	313	1	0	0	2	0
Scrubbing	0	0	278	0	0	0	23
Standing	0	0	0	315	0	0	0
Working at a PC	0	2	0	0	286	0	4
Vacuuming	2	0	1	0	1	296	0
Brushing teeth	0	0	33	0	0	0	288
Sitting	0	0	0	0	28	0	0
Accuracy	99.37%	99.37%	88.25%	100%	90.79%	93.97%	91.43%

Table 2 NBC, HMM and CRF recognition accuracies (Cook et al. (2012))

Dataset	NBC	HMM	CRF
Bosch 1	92.91%	92.07%	85.09%
Bosch 2	90.74%	89.61%	82.66%
Bosch 3	88.81%	90.87%	90.36%
Cairo	82.79%	82.41%	68.07%
Kyoto 1	78.38%	78.38%	97.30%
Kyoto 2	63.98%	65.79%	66.20%
Kyoto 3	77.50%	81.67%	87.33%
Kyoto 4	63.27%	60.90%	58.41%

Although scientists have put a lot of efforts into the exploration of an effective activity classification method, it turns out that those methods are either not generative enough or not accurate enough due to various constraints.

Research framework

The general research framework is shown below as Figure 1.

Literature Review will be conducted first including the methods applied to classify activities and datasets used.

Methods

Lots of machine learning models have been applied for activity classification and it almost equals to the number of types of sensor data used. Several widely used methods are naïve Bayes (NB) model, Hidden Markov Model (HMM), decision trees and Conditional Random Field (CRF) model. HMM, CRF and NB stand out because they are robust even with the existence of noise and can handle sequential data. However, there is no obvious advantage of one model over others.

Datasets

Datasets are another important part of the research. Various kinds of sensors are deployed in experiments to obtain a high accuracy. While some experiments only use nonwearable sensors like RFID sensors to detect the appearance of user which only have two states(on and off), some use wearable sensors including bracelets and smartphones to detect motion, gesture and even vital body parameters. Some experiments even combine those two types of sensor data together to do the classification. More detailed data would offer higher accuracy. But as people increasingly worry about their privacy, less privacy-invasion algorithm would be more favored.

Algorithm design

Base on the existing methods proposed for classifying activities and existing developed techniques, the improvement can be made by either proposing a new method or revise an existing method. Available datasets will be used to test the new methods to compare with existing methods.

Revise

After experiments are conducted, comparison between my method and existing methods will be helpful when revising my method.

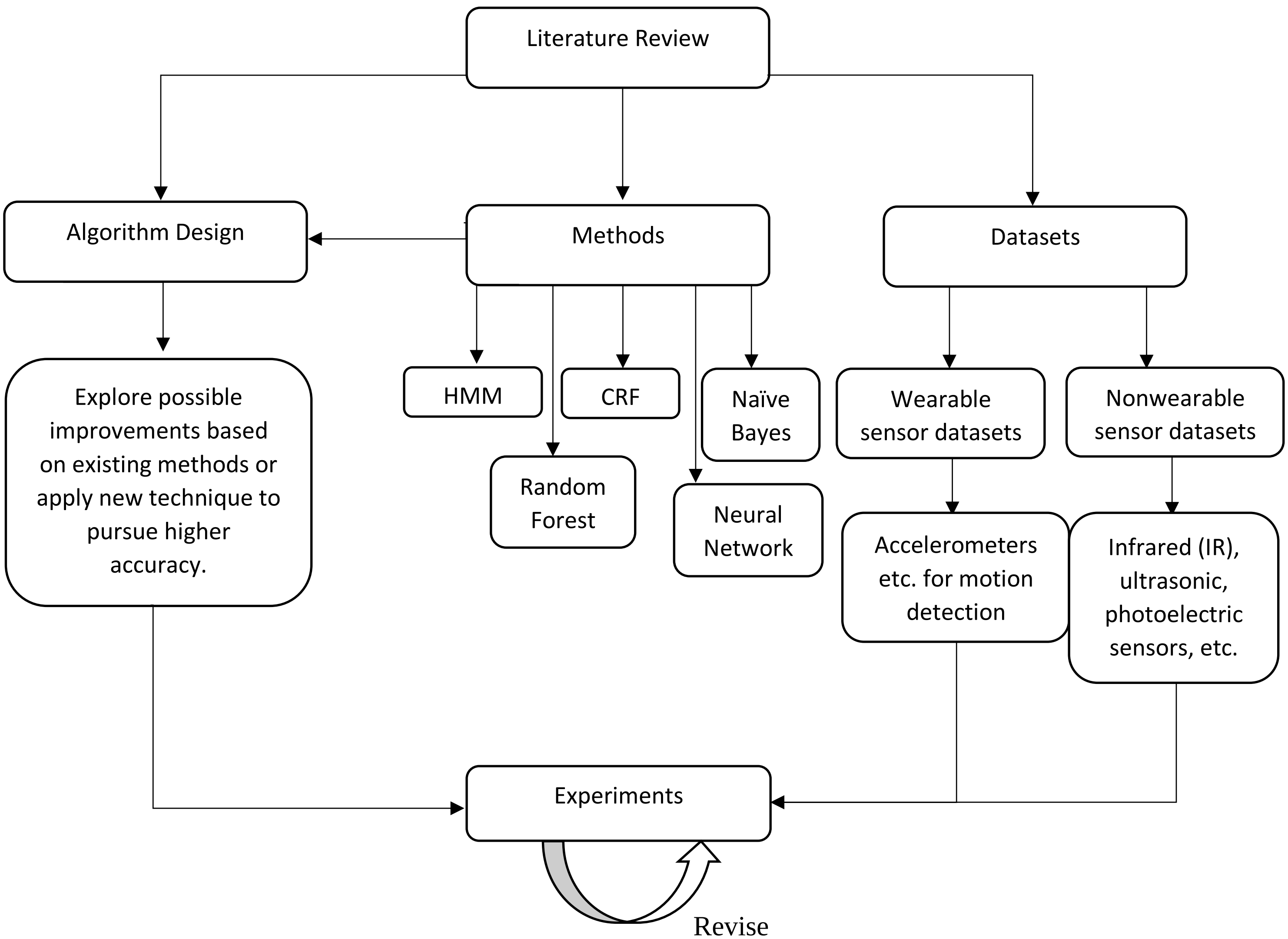

Figure 1

Schedule

Timelines

Period	Description
Week 1	Do research on the related topics.
Week 2-3	Apply existing methods on existing datasets and test the accuracy and other criteria.
Week 4	Read related papers for improvement.
Week 5-6	Get down to a new method
Week 7-8	Test the new method with existing data and analysis the accuracy of the new method.
Week 9	Keep improving the new method based on previous analysis.
Week 10	Test the improved method and compare it with other methods.
Week 11	Get down to the final report.
Week 12	Finalize the final report.

Meeting schedule

Period	Description
Week 1	Report on my reading and discuss my general idea.
Week 2-3	Report on my results and discuss about the future plan.
Week 4	Report on my reading and discuss possible solutions.
Week 5-6	Seek for academic support and talk about general direction.
Week 7-8	Report on my results and talk about possible improvements.
Week 9	Seek for academic support and report my progress.
Week 10	Report on my results and discuss about the next step.
Week 11	Seek for advice on final report.
Week 12	Submit the final report and summarize.

The schedule is indicative only and may change due to various types of reasons.

Reference

Atallah, L., Lo, B., Ali, R., King, R. and Yang, G.Z., 2009. Real-time activity classification using ambient and wearable sensors. *IEEE Transactions on Information Technology in Biomedicine*, *13*(6), pp.1031-1039.

Cook, D.J., 2012. Learning setting-generalized activity models for smart spaces. *IEEE intelligent systems*, *27*(1), pp.32-38.

Chan, M., Estève, D., Escriba, C. and Campo, E., 2008. A review of smart homes—Present state and future challenges. *Computer methods and programs in biomedicine*, *91*(1), pp.55-81.

Debes, C., Merentitis, A., Sukhanov, S., Niessen, M., Frangiadakis, N. and Bauer, A., 2016. Monitoring activities of daily living in smart homes: Understanding human behavior. *IEEE Signal Processing Magazine*, *33*(2), pp.81-94.

Fleury, A., Vacher, M. and Noury, N., 2010. SVM-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results. *IEEE transactions on information technology in biomedicine*, *14*(2), pp.274-283.

Farber, N., Shinkle, D., Lynott, J., Fox-Grage, W. and Harrell, R., 2011. Aging in place: A state survey of livability policies and practices.

Galasko, D., Bennett, D., Sano, M., Ernesto, C., Thomas, R., Grundman, M. and Ferris, S., 1997. An inventory to assess activities of daily living for clinical trials in Alzheimer's disease. *Alzheimer disease and associated disorders*.

Kim, E., Helal, S. and Cook, D., 2010. Human activity recognition and pattern discovery. *IEEE Pervasive Computing*, *9*(1).

Li, X., 2007. HMM based action recognition using oriented histograms of optical flow field. *Electronics Letters*, *43*(10), pp.560-561.

Muszyńska, M.M. and Rau, R., 2012. The old-age healthy dependency ratio in Europe. *Journal of population ageing*, *5*(3), pp.151-162.

Nazerfard, E., Das, B., Holder, L.B. and Cook, D.J., 2010, November. Conditional random fields for activity recognition in smart environments. In *Proceedings of the 1st ACM International Health Informatics Symposium* (pp. 282-286). ACM.

Nygård, L., 2003. Instrumental activities of daily living: a stepping-stone towards Alzheimer's disease diagnosis in subjects with mild cognitive impairment?. *Acta Neurologica Scandinavica*, *107*(s179), pp.42-46.

Park, S. and Kautz, H., 2008. Hierarchical recognition of activities of daily living using multi-scale, multi-perspective vision and RFID.

Rashidi, P., Cook, D.J., Holder, L.B. and Schmitter-Edgecombe, M., 2011. Discovering activities to recognize and track in a smart environment. *IEEE transactions on knowledge and data engineering*, *23*(4), pp.527-539.

Stikic, M., Huynh, T., Van Laerhoven, K. and Schiele, B., 2008, January. ADL recognition based on the combination of RFID and accelerometer sensing. In *Pervasive Computing Technologies for Healthcare, 2008. PervasiveHealth 2008. Second International Conference on* (pp. 258-263). IEEE.

Tapia, E.M., Intille, S.S. and Larson, K., 2004, April. Activity recognition in the home using simple and ubiquitous sensors. In *International conference on pervasive computing* (pp. 158-175). Springer, Berlin, Heidelberg.

Vuegen, L., Van Den Broeck, B., Karsmakers, P., Van Hamme, H. and Vanrumste, B., 2013. Automatic monitoring of activities of daily living based on real-life acoustic sensor data: a~ preliminary study. In *Proceedings of the Fourth Workshop on Speech and Language Processing for Assistive Technologies* (pp. 113-118).

Yang, J.Y., Wang, J.S. and Chen, Y.P., 2008. Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers. *Pattern recognition letters*, *29*(16), pp.2213-2220.