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IMPROVING MULTI-RESIDENT ACTIVITY RECOGNITION IN SMART HOME USING MULTI LABEL CLASSIFICATION WITH ADAPTIVE PROFILING

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By

RAIHANI MOHAMED

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

September 2018

DEDICATION

To my beloved family.

To my Momma.

To the Partner in this life and hereafter.

To our kids, Dani Iffat, Nur Farahiya Aliah & Faqeih Aqharie.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

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Chairman : Thinagaran Perumal, PhD
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"Smart Home" services offer to improve living conditions and levels of independence for the elderly that require support with both physical and cognitive functions via Activities of Daily Living (ADL). Due to human ethics and privacy concern, ambient-based sensor technologies are preferred and deployed in the environment. Nevertheless, as human activities gradually becoming complex and thus complicate the inferences of activities especially involving multi-resident within the same home premises that deploy solely ambient-based sensor technology.

Existing works and solutions focused on separate models for recognizing the residents, activities and interactions. On top of that, data association and algorithm modification inherit drawbacks on recognizing the residents and interactions of multi-resident complex activities. When the data are induced with the lower quality model, the performance is also truncated. Furthermore, there is tendency that multi label classifications used instead of traditional single label classification technique. Consequently, this could cater the simple and complex activity recognition of multi-resident in a separate model. Moreover, with the incremental numbers of resident living together in the same smart home environment, the class-overlapping sensor event sequence could occur and might share the same features for sub-sequences that correspond to each individual activity. At the same time, the sensor events are always uncertain and intricate in nature led to conflict occurs at its interaction layer.

In accordance to the mentioned problem, Label Combination (LC) of multi label classification is introduced because of its ability to transform the multi label problem into 2^L multi-class problem and exploit the correlation between the class labels. On top of that, the label correlation can be solved with the Random Forest (RF) as a base classifier due to its capability to produce the most probable class from its majority-voting task as output. Nevertheless, the learning complexity of classification is increased due to the increment number of residences and activities are also intricate. Therefore, Adaptive Profiling (AP) for multi-resident involving context information includes temporal and spatial information is proposed to address the class-overlapping using Expectation-Maximization (EM) clustering. The clusters parameter is adaptively generated from the active labelset from the real-world data. The multi label relation method using Two-Stage Label Construction (TSLC) is presented, resolve the conflicts in complex activity of multi-resident is also outlined in this research.

Two publicly available datasets; WSU's CASAS and ARAS Dataset are selected and experimented to evaluate the proposed framework. About 26 pairs of volunteer performing 15 scripted activities collected over four months' time with almost 17,500 instances from CASAS. In addition, three days of house A from ARAS dataset is also selected to evaluate its effectiveness. LC-RF is tested with other base classifiers such as k-NN, SVM and HMM. However, LC-RF showed the most promising results among others. Furthermore, its performance is also benchmarked with previous work that used single label classification. Consequently, the obtained results demonstrate the improvement of 2.4% increment in Hamming score as compare with the highest results from the previous work. Experimental results have significantly promised an improvement level in multi-resident simple and complex activity recognition simultaneously, capable to cater the problems mentioned specifically when the number of resident increase and reside together in the same smart home environment.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MENINGKATKAN PENGECAMAN AKTIVITI PELBAGAI PENDUDUK DALAM RUMAH PINTAR MENGGUNAKAN KLASIFIKASI PELBAGAI LABEL DENGAN PROFIL SUAI

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Perkhidmatan yang ditawarkan oleh "Rumah Pintar" adalah untuk memperbaiki keadaan hidup dan tahap berdikari bagi warga tua yang memerlukan sokongan dengan fungsi fizikal dan kognitif melalui Aktiviti Kehidupan Harian (ADL). Disebabkan oleh etika kemanusiaan dan keprihatinan privasi, teknologi sensor berasaskan ambien lebih disukai dan digunakan dalam persekitaran. Walau bagaimanapun, aktiviti manusia secara beransur-ansur menjadi kompleks dan ini menyukarkan pengecaman aktiviti terutama melibatkan pelbagai penduduk di dalam premis rumah yang sama yang menggunakan teknologi sensor berasaskan ambien sahaja.

Kerja dan penyelesaian yang sedia ada memberi tumpuan kepada model berasingan bagi mengecam penduduk, aktiviti dan jenis interaksi. Di samping itu, persatuan data dan pengubahsuaian algoritma juga menghadapi masalah dalam pengecaman penduduk dan interaksi dalam aktiviti kompleks pelbagai penduduk. Apabila data diinduksi dengan model berkualiti rendah, prestasi juga menurun. Selain itu, ada kecenderungan klasifikasi pelbagai label yang digunakan dan bukannya teknik tradisional, klasifikasi label tunggal. Oleh itu, ini dapat mengatasi masalah pengecaman aktiviti mudah dan kompleks pelbagai penduduk dalam model yang berasingan. Lebih-lebih lagi, dengan peningkatan jumlah penduduk yang tinggal bersama dalam persekitaran rumah pintar yang sama, peristiwa sensor kelas turutan yang bertindih boleh berlaku dan mungkin berkongsi ciri yang sama untuk sub-turutan yang sesuai dengan setiap aktiviti individu. Pada masa yang sama, kejadian sensor selalu tidak menentu dan rumit menyebabkan konflik terjadi pada lapisan interaksi.

Selaras dengan masalah yang disebutkan, klasifikasi Gabungan Label (LC) bagi pelbagai label diperkenalkan kerana keupayaannya mengubah masalah perbagai label ke dalam masalah 2^L pelbagai kelas dan mengeksploitasi korelasi di antara kelas label. Di samping itu, korelasi label boleh diselesaikan dengan *Random Forest* (RF) sebagai pengelas asas kerana kemampuannya untuk menghasilkan kelas yang paling mungkin dari tugas majoriti-undiannya sebagai keluaran. Walau bagaimanapun, kerumitan pembelajaran pengelasan meningkat disebabkan oleh peningkatan jumlah penduduk dan aktiviti yang rumit. Oleh itu, Profil Suai (AP) untuk pelbagai penduduk yang melibatkan maklumat konteks termasuklah maklumat temporal dan ruang yang dicadangkan untuk menangani kelas yang bertindih menggunakan teknik pengawalan gugusan-Permintaan Pengoptimuman (EM). Pembolehubah pengawal gugusan yang sesuai dihasilkan secara serentak dari set label yang aktif dari data sebenar. Kaedah hubungan pelbagai label menggunakan Pembinaan Label Dua Peringkat (TSLC) dicadangkan untuk menyelesaikan masalah konflik dalam aktiviti kompleks oleh pelbagai penduduk yang juga termasuk dalam kajian ini.

Dua set data yang tersedia secara umum; CASAS, WSU dan ARAS Set Data dipilih dan dilaksanakan untuk menilai rangka kerja yang dicadangkan. Sejumlah 26 pasang sukarelawan melakukan 15 aktiviti skrip yang dikumpulkan dalam masa empat bulan dengan hampir 17,500 contoh dari CASAS. Di samping itu, tiga hari contoh rumah A daripada set data ARAS juga dipilih untuk menilai keberkesanannya. LC-RF diuji dengan pengelas asas yang lain seperti k-NN, SVM dan HMM. Walaubagaimanpun, LC-RF menunjukkan hasil yang paling menjanjikan berbanding dengan yang lain. Selain itu, prestasinya juga diukur dengan kerja sebelumnya yang menggunakan klasifikasi label tunggal. Kesimpulannya, hasil yang diperoleh menunjukkan peningkatan kenaikan 2.4% dalam skor *Hamming* berbanding dengan hasil kerja yang sebelumnya. Keputusan eksperimen telah menjanjikan peningkatan tahap pengecaman aktiviti mudah dan kompleks pelbagai penduduk pada masa yang sama, mampu menyelesaikan masalah yang tersebut secara khusus apabila bilangan penduduk yang tinggal bersama bertambah ramai dalam persekitaran rumah pintar yang sama.

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May ALLAH bless all of us by plentitude of blessings. Ameen.

I certify that a Thesis Examination Committee has met on 6 September 2018 to conduct the final examination of Raihani bt Mohamed on her thesis entitled "Improving Multi-Resident Activity Recognition in Smart Home Using Multi Label Classification with Adaptive Profiling " in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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I hereby confirm that:

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LIST OF ABBREVIATIONS

ADL	Activities of Daily Living
AAL	Ambient Assisted Living
AALO	Approach Learning Overlapping Activities
AP	Adaptive Profiling
ADLMR	Activities Daily Living of Multi-Resident
AmI	Ambient Intelligence
ARAS	Activity Recognition with Ambient Sensing
BR	Binary Relevance
CART	Classification and Regression Tree
CASAS	Center For Advanced Studies in Adaptive Systems
CC	Classifier Chains
CHMM	Coupled Hidden Markov Model
CRF	Conditional Random Field
DBN	Dynamic Bayesian Network
DBSCAN	Density Based Clustering
EM	Expectation-Maximization
FHMM	Factorial Hidden Markov Model
FSR	Force Sensitive Resistors
GMM	Gaussian Mixture Model
HAR	Human Activity Recognition
HMM	Hidden Markov Model
ICHMM	Interaction-Feature Enhanced Chmm
ICT	Information and Communication Technologies
KNN	k-Nearest Neighbors
LC	Label Combination
LC-RF	Label Combination-Random Forest
PHMM	Parallel Hidden Markov Model
RF	Random Forest
SCHMM	Structure-Switchable CHMM
SVM	Support Vector Machine

TSLC	Two-Step Label Construction
WSU	Washington State University

CHAPTER 1

INTRODUCTION

1.1 Motivation

Smart home established with aims of improving the quality, comfort and efficiency in human life (Cook & Youngblood, 2004; Debes et al., 2016). It is well equipped with sensor-based technologies including types of wearable, video camera and ambient-based sensors (Ding et al., 2011). Applications and services associated with smart home that are benefitting from the technology include surveillance and safety, energy management, healthcare and Activities of Daily Living (ADL) monitoring system. Hence, activity recognition is the key study to infer Human Activity Recognition (HAR).

The mix and combine sensor technology are well accepted for this purpose. However, due to privacy concern and non-obtrusive way, ambient-based sensors are more preferred, especially for a smart home user with limited capability and elderly to support independent living and ageing in place. Ambient-based sensor is a bespoke sensor such as motion, door and pressure sensor installed and configured in the environment (Cicirelli et al., 2016). It models the uncertainty at a lower-layer sensor that has the ability of managing the reliability of the systems in term of inference human activity.

Currently, smart home is customized to track and recognize the individual resident in the environment (Cook, 2012; Wen & Zhong, 2015). However, with increased population that stays together at home, much of the resident activities are becoming diverse and complex (Crandall & Cook, 2009). Common Ambient Assisted Living (AAL) and ADL detection systems are restrained for single-resident. About 28% of older American citizens live in single-resident smart home. However, at about 57% of elderly adult live with their spouse (Administration on Aging, Administration for Community Living, & U.S. Department of Health and Human Services, 2014). This indicates that high request is demanded for smart home systems that consider the multi-resident standards. In addition, smart homes in Malaysia also shows better acceptance in household penetration at 2.4% in 2018 and forecasted to hit 10.9% by year 2020 (Statista Market Forecast, 2016).

The ADL taxonomy has been proposed by Katz (1983) and Lawton & Brody (1969). The ADL index tool in healthcare is utilized to assess cognitive and physical capabilities of an elderly adult. The ADL is defined as routine activities that people normally do in everyday basis without assistance from others such as feeding themselves, bathing, dressing, grooming and work by the medical community. ADL is used in smart home as an umbrella term encompassing self-care and domestic activities or tasks (Urwyler et al., 2015). Daily assessment measures are essential for physicians to evaluate the health stage of the elderly adult to optimize medication and personal care.

In multi-resident activity recognition paradigms, ADL such as bathing, dressing as well as grooming can be addressed as simple activity and often can be inferred by sensor data directly. However interaction of activities such as cooperative and parallel also occur due to each activity consist of temporally and coherently related to the events, require more structured models (Liu et al., 2016). The interaction types such as parallel and cooperative occurred due to human are socially interacted each other thus, it can be categorised as complex activity. It is found that most of the human activities are hierarchically structured and thus it is necessary to improve model performance of activity recognition (Zacks & Tversky, 2001). Other than that, the model should be able to track and identify the activity performers in the smart home. Smart home that equipped and installed with the only ambient-based sensor technology has difficulty to track and recognize the identity of the resident. Hence, this type of technology is rather popular and well accepted among the elderly adults who are resisting to bring the sensor together at their body. Therefore, the model with the ability to track and recognize the activity and its performers are necessary when the smart home premises only uses the ambient-based sensor technology.

A smart home should be capable of granting efficient information about the environment. The activity model should account for temporal and spatial structures of complex activities and should convey the hierarchical of activity relations. Hence, the sensor events itself is overlapping since the dataset contains is a combination of individual, parallel and cooperative type activities (Cook et al., 2010; Ni et al., 2015). Thus, this may cause inadequate accuracy of the model. In this context, the activity model should consider the temporal and spatial structures for complex activities from the interaction of the multi-resident. It happened as a result from conflict detection from the sensor signals from its lower-layer structures (Liu et al., 2015).

In regard to the complexity of the problem domain, the model is required to handle the events uncertainties due to intricate events by the sensor. In this research, a framework using multi label classification of Label Combination-Random Forest (LC-RF) is proposed to cater the increment number in multi-resident and diversities of activities. The class-overlapping and conflicts in interaction are needed to address in order to solve the uncertainties and ambiguity of the sensor layers. The framework is able to automatically detect and resolve the abovementioned problems in order to attain overall satisfaction in AAL and ADL detection systems for multi-resident in smart home environment.

1.2 Problem Statement

Generally, sensor-based activity recognition in smart home environment is divided into various sensor layers such as sensor, contact and activity layers. McKeever et al. (2010) address these layers as inference knowledge to infer human activity using evidence theory. Hence, inferring human activities become a challenge when involving more than one resident living in the same smart home environment. The combination of the simple activity derived the notion of complex activity. Despite of individual activity, the parallel and cooperative activity also may exist due to social interaction of the multi-resident (Kim et al., 2010; Mohamed et al., 2017). Consequently, the sensor contact layer and simple activity layer addressed as low-level layer, while the high-level layer are considered as complex activity (Saguna et al., 2013).

In addition, many approaches from the previous researches attempt to recognize the simple, individual activities in this environment. Particularly, the approaches are based on issues they want to tackle in separate way such as separate model for each resident (Singla et al., 2010), manual data association (Hsu et al., 2010; Wilson & Atkeson, 2005) and algorithm modification (Benmansour et al., 2017; Chiang et al., 2010; Lu & Chiang, 2014; Tran et al., 2010, 2018). Each of the methods mentioned has their own drawbacks. There are always incremental number of residents that staying together within the same space. At the same time, there is a need to recognize who is the performer of the particular activity from the installed and embedded ambient-based sensors within the home premises. Nevertheless, it still does not cater the sensor relations at its lower-layer that have relations with higher-layer.

During activity recognition, class-overlapping also occurs when the features of the instances are very similar for two or more classes, hence making it difficult to distinguish between these classes (Ni et al., 2015). This condition happened due to sensor events sequence share the same features for sub-sequences that correspond to each individual activity in multi-resident paradigm. Therefore, when dealing with binary and discrete (0, 1) state-change ambient-based sensor, some methods are not always appropriate, worst case it affects the model performance. Hence, there are some issues regarding the social interaction among the multi-resident that has been unfulfilled in the sensor lower-layer of the smart home. Increasing number of elderly population that stay together with other family members at home, diversity and complexity in their activities resulted uncertainties and ambiguity from sensor events to infer their activities as well as resident identification at the higher-layer. Thus, this condition resulted the conflict occurrence in interaction of complex activity in multi-resident paradigm. Moreover, the approaches mentioned are for learning sensor event relations that often lack of capability to handle uncertainties. Hence, some researchers ignore the potential interactions in the ADL in order to simplify the problems and some consider the individual and cooperative interaction same as parallel interaction (Benmansour et al., 2017; Chen & Tong, 2014; Lu & Chiang, 2014; Tran et al., 2018). This is due to the ambient-based sensor are unobtrusive, ambiguous and noisy in nature. Thus, the tendency of conflict in interaction is always possible.

Besides, due to the increasing numbers of resident living together in the smart home environment, the existing works using traditional multi-class single label classification is no longer incapable to cater the mentioned problem. Hence, the multi label classification technique is deemed fit to incorporate with the challenges in smart home environment. Therefore, with growth of multi-resident in the same smart home, numbers of difficulties have aroused which are summarized as follow:

1. Inefficient performance of existing works due to suffer from the inflexibility of expressing intricate of the sensor events relations to detect activity and track the performers.

2. Class-overlapping in datasets from the real-world setting causing ambiguity in prediction, as several classes may be associated with several different classes with similar probabilities.

3. Conflict at interaction layer in multi-resident complex activity due to increments number of resident living in the same smart home.

1.3 Research Objectives

The main purpose of this research is to improve the accuracy of activity recognition for multi-resident in smart home environment. In order to achieve this objective, other sub-objectives are proposed as follows:

1. To propose Adaptive Profiling (AP) of multi-resident consist of context information of spatial to cater the class-overlapping problem from the real-world setting datasets in the pre-processing stage.

2. To propose a Label Combination (LC) of multi label classification technique with Random Forest (RF) as base classifier to improve the accuracy to cater activity recognition of more than one resident.

3. To propose a multi label relation algorithm with Two-Stage Label Combination (TSLC) method to detect and resolve the conflict occurrence in interaction of complex activity of multi-resident.

1.4 Research Scope

This works limited to:

1. Environmental-based sensor also called ambient-based sensor embedded in the smart home environment provided but not limited to motion, pressure, items, cupboard and door with binary states (ON/OFF, OPEN/CLOSED, PRESENT/ABSENT), discrete-event sensors.

2. The multi-resident involved consisting of two residents due to current public dataset available with not more than two residents only.

3. The two publicly available dataset; CASAS and ARAS datasets are selected due to these dataset contain interaction activity including cooperative and parallel activity that are considered as complex activity.

4. The multi-resident datasets are consisting the various types of activities of daily living (ADL) such as bathing, dressing, grooming at the same time must have the overlap activity such as pay bills, play checkers, move furniture etc. based on the ADL performed by the multi-resident. However, there are not much types obtainable but are limited from the mentioned available public datasets only.

1.5 Research Contributions

This research is carried out to recognize activity of multi-resident in smart home using ambient-based sensor technology that are installed and embedded in the environment. The main contribution of this study is to improve the activity recognition of multi-resident at the same time the social interaction is also detected by using context information based on the multi-resident profiling. Thus, the contributions listed as follows:

1. The correlation between activity and interaction layer of the ambient-based sensor layer are explored to differentiate between simple and complex activity of multi-resident.

2. The context layer of the ambient-based sensor layer is investigated to identify possible context information including the temporal and spatial information that is related with the multi-resident profiling.

3. The generated feature from spatial region table in smart home is proposed based on sensor signal triggered that installed within the smart home environment.

4. The profiling for multi-resident consists of context information of temporal and spatial information is proposed for the smart home domain. It contains desirable features augmentation such as adaptively previous activity information with possible number clusters based on active labelsets.

5. The probability-based spatial region scanned is introduced to detect different regions of certain activity performed within the environment.

6. Temporal information is presented to enhance pattern of individual resident profiling based on sequence pattern from the routine activity of multi-resident.

7. The multi label classification technique using Label Combination with Random Forest (LC-RF) method is introduced to accommodate with the increment number of residents living together in the same environment due to its robustness and simplicity. The accuracy level has been compared with other different base classifiers including k-NN, SVM and HMM.

8. The label augmentation is proposed using Two-Step Label Construction (TSLC) method to resolve the conflict at the interaction layer based on the current activity of the multi-resident.

1.6 Organization of the Thesis

The thesis is organized and structured into six chapters.

Chapter 1 gives brief introduction on the background of activity recognition from various perspectives. The current trend and challenges in activity recognition from numerous viewpoints have also been discussed. Limitation of present work, research objectives, scopes and contribution of this research are explained in this chapter.

Chapter 2 provides the background knowledge of sensor-based activity recognition in smart home environment, simple and complex activity and machine learning techniques including traditional single label multi-class and multi label classification technique in smart home. Moreover, related studies and mechanism for context information and conflict resolution approaches were reviewed.

Chapter 3 presents the first part of methodology applied in this research. It specifies the research design, introduces the multi label learning framework, justification and explanation of the methods of the research. Identifying the selected performance metrics and evaluation of the proposed framework are elaborated in this chapter.

Furthermore, the proposed methods in the framework are narrated in this thesis. In Chapter 4, the proposed method is discussed to tackle the class-overlapping problem, conflict resolution and multi label classification technique that have been proposed in this research. The Adaptive Profiling (AP) and Two-Stage Label Construction (TSLC) methods are proposed to cater the class-overlapping and label dependency problems that coexist from the real-world datasets. Label Combination with Random Forest (LC-RF) also narrated in this chapter.

Chapter 5 is dedicated for experimental setup and results for the proposed framework. Furthermore, the results from the experimentation will be presented for evaluating the proposed methods of the framework in different directions. In this chapter, the proposed framework also will be compared with previous works.

The last chapter, Chapter 6 covers the conclusions of the entire research to ascertain that the problem highlighted is solved and is aligned with the objective stated. The recommendation based on the work for upcoming research is also presented.

REFERENCES

Abidine, M. B., & Fergani, B. (2015). News schemes for activity recognition systems using PCA-WSVM, ICA-WSVM, and LDA-WSVM. *Information (Switzerland)*, *6*(3), 505–521. http://doi.org/10.3390/info6030505

Achilleos, A. P., Kapitsaki, G. M., & Papadopoulos, G. A. (2012). A framework for dynamic validation of context-aware applications. *Proceedings - 15th IEEE International Conference on Computational Science and Engineering, CSE 2012 and 10th IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, EUC 2012*, (i), 532–539. http://doi.org/10.1109/ICCSE.2012.79

Administration on Aging, Administration for Community Living, & U.S. Department of Health and Human Services. (2014). *A Profile of Older Americans: 2014*. Retrieved from https://www.acl.gov/sites/default/files/Aging and Disability in America/2014-Profile.pdf

Albanna, B. H., Moawad, I. F., Moussa, S. M., Sakr, M. A., Ibrahim, F. M., Moussa, S. M., & Mahmoud, A. S. (2009). Semantic Trajectories: A Survey from Modeling to Application. *Information Fusion and Geographic Information Systems*, 59–76. http://doi.org/10.1007/978-3-642-00304-2

Alemdar, H., Durmaz Incel, O., Ertan, H., & Ersoy, C. (2013). ARAS Human Activity Datasets in Multiple Homes with Multiple Residents. In *Proceedings of the ICTs for improving Patients Rehabilitation Research Techniques* (pp. 1–4). http://doi.org/10.4108/icst.pervasivehealth.2013.252120

Alemdar, H., & Ersoy, C. (2017). Multi-resident activity tracking and recognition in smart environments. *Journal of Ambient Intelligence and Humanized Computing*, *8*(4), 513–529. http://doi.org/10.1007/s12652-016-0440-x

Alhamoud, A., Muradi, V., Böhnstedt, D., & Steinmetz, R. (2016). Activity Recognition in Multi-User Environments Using Techniques of Multi-label Classification. In *Proceedings of the 6th International Conference on the Internet of Things - IoT'16* (pp. 15–23). http://doi.org/10.1145/2991561.2991563

Altman, N. S. (1992). An Introduction to Kernel and Nearest-Neighbour Nonparametric Regression. *The American Statistician*, *46*(3), 175–185. http://doi.org/10.1198/016214507000000932

Anjum, A., & Ilyas, M. U. (2013). Activity recognition using smartphone sensors. *2013 IEEE 10th Consumer Communications and Networking Conference, CCNC 2013*, 914–919. http://doi.org/10.1109/CCNC.2013.6488584

Antos, S. A., Albert, M. V., & Kording, K. P. (2014). Hand, belt, pocket or bag: Practical activity tracking with mobile phones. *Journal of Neuroscience Methods*, *231*, 22–30. http://doi.org/10.1016/j.jneumeth.2013.09.015

Arif, M., Bilal, M., Kattan, A., & Ahamed, S. I. (2014). Better Physical Activity

Classification using Smartphone Acceleration Sensor. *Journal of Medical Systems*, *38*(9), 95. http://doi.org/10.1007/s10916-014-0095-0

Balta-Ozkan, N., Davidson, R., Bicket, M., & Whitmarsh, L. (2013). The development of smart homes market in the UK. *Energy*, *60*, 361–372. http://doi.org/10.1016/j.energy.2013.08.004

Benmansour, A., Bouchachia, A., & Feham, M. (2015). Multioccupant Activity Recognition in Pervasive Smart Home Environments. *ACM Computing Surveys*, *48*(3), 1–36. http://doi.org/10.1145/2835372

Benmansour, A., Bouchachia, A., & Feham, M. (2017). Modeling interaction in multi-resident activities. *Neurocomputing*, *230*(May 2016), 133–142. http://doi.org/10.1016/j.neucom.2016.05.110

Blockeel, H., Leander, S., Struyf, J., Dzeroski, S., & Clare, A. (2006). Decision Trees for Hierarchical Multilabel Classification: A Case Study in Functional Genomics. *Knowledge Discovery in Databases:PKDD 2006, 10th European Conference on Principles and Practice of Knowledge Discovery in Databases*, *4213*, 18–29. http://doi.org/10.1007/11871637_7

Bourobou, S. T. M., & Yoo, Y. (2015). User activity recognition in smart homes using pattern clustering applied to temporal ANN algorithm. *Sensors (Switzerland)*, *15*(5), 11953–11971. http://doi.org/10.3390/s150511953

Boutell, M. R., Luo, J., Shen, X., & Brown, C. M. (2004). Learning multi-label scene classification. *Pattern Recognition*, *37*(9), 1757–1771. http://doi.org/10.1016/j.patcog.2004.03.009

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. http://doi.org/10.1023/A:1010933404324

Brinker, K., Furnkranz, J., & Hullermeier, E. (2006). A unified model for multilabel classification and ranking. *Frontiers in Artificial Intelligence And*, 1–5. Retrieved from http://scholar.google.com/scholar?q=intitle:%22A+Unified+Model+for+Multilabel+Classification+and+Ranking%22#0

Carvalho, A. C. P. L. F. De, & Freitas, A. A. (2009). A Tutorial on Multi-label Classification Techniques, *5*, 177–195.

Chang, C.-C., & Lin, C.-J. (2013). LIBSVM : A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *2*, 1–39. http://doi.org/10.1145/1961189.1961199

Charte, F., Rivera, A. J., del Jesus, M. J., & Herrera, F. (2015). Addressing imbalance in multilabel classification: Measures and random resampling algorithms. *Neurocomputing*, *163*, 1–14. http://doi.org/10.1016/j.neucom.2014.08.091

Chen, L., Hoey, J., Nugent, C. D., Cook, D. J., & Yu, Z. (2012). Sensor-based activity recognition. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, *42*(6), 790–808. http://doi.org/10.1109/TSMCC.2012.2198883

Chen, L., & Khalil, I. (2011). Activity Recognition: Approaches, Practices and Trends. *Activity Recognition in Pervasive Intelligent Environments*, *4*, 1–31. http://doi.org/10.2991/978-94-91216-05-3_1

Chen, & Tong, Y. (2014). A two-stage method for solving multi-resident activity recognition in smart environments. *Entropy*, *16*(4), 2184–2203. http://doi.org/10.3390/e16042184

Chiang, Y. T., Hsu, K. C., Lu, C. H., Fu, L. C., & Hsu, J. Y. J. (2010). Interaction models for multiple-resident activity recognition in a smart home. In *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010 - Conference Proceedings* (pp. 3753–3758). http://doi.org/10.1109/IROS.2010.5650340

Cicirelli, F., Fortino, G., Giordano, A., Guerrieri, A., Spezzano, G., & Vinci, A. (2016). On the Design of Smart Homes: A Framework for Activity Recognition in Home Environment. *Journal of Medical Systems*, *40*(9), 200. http://doi.org/10.1007/s10916-016-0549-7

Cook, D. J. (2012). Learning setting-generalized activity models for smart spaces. *IEEE Intelligent Systems*, *27*(1), 32–38. http://doi.org/10.1109/MIS.2010.112

Cook, D. J., Crandall, A. S., Thomas, B. L., & Krishnan, N. C. (2013). CASAS: A smart home in a box. *Computer*, *46*(7), 62–69. http://doi.org/10.1109/MC.2012.328

Cook, D. J., Crandall, A., Singla, G., & Thomas, B. (2010). Detection of Social Interaction in Smart Spaces. *Cybern Syst.*, *41*(2), 90–104. http://doi.org/10.1080/01969720903584183.Detection

Cook, D. J., & Youngblood, M. (2004). Smart Homes. *Encyclopedia of Human-Computer Interaction*. Retrieved from http://www.eecs.wsu.edu/~cook/pubs/ehci04.pdf

Crandall, A. S., & Cook, D. J. (2009). Coping with multiple residents in a smart environment. *Journal of Ambient Intelligence and Smart Environments*, *1*(4), 323–334. http://doi.org/10.3233/AIS-2009-0041

Das, B., Chen, C., Seelye, A. M., & Cook, D. J. (2011). An automated prompting system for smart environments. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6719 LNCS*, 9–16. http://doi.org/10.1007/978-3-642-21535-3_2

Debes, C., Merentitis, A., Sukhanov, S., Niessen, M., Frangiadakis, N., & Bauer, A. (2016). Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior. *IEEE Signal Processing Magazine*, *33*(2), 81–94. http://doi.org/10.1109/MSP.2015.2503881

Dembczynski, K., Waegeman, W., Cheng, W., & Hüllermeier, E. (2012). *On label* *dependence and loss minimization in multi-label classification*. *Machine Learning* (Vol. 88). http://doi.org/10.1007/s10994-012-5285-8

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society Series B Methodological*, *39*(1), 1–38. http://doi.org/http://dx.doi.org/10.2307/2984875

Denisova, A., & Sergeyev, V. (2017). Using Hierarchical Histogram Representation for the EM Clustering Algorithm Enhancement. *Image and Signal Processing and Analysis (ISPA), 2017 10th International Symposium*, (Ispa), 41–46. http://doi.org/10.1109/ISPA.2017.8073566

Dey, A. K., & Abowd, G. D. (1999). Towards a Better Understanding of Context and Context-Awareness. *Computing Systems*, *40*(3), 304–307. http://doi.org/10.1007/3-540-48157-5_29

Dey, A. K., Abowd, G. D., & Salber, D. (2001). A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications. *Human-Computer Interaction*, *16*(2), 97–166. http://doi.org/10.1207/S15327051HCI16234_02

Ding, D., Cooper, R. a., Pasquina, P. F., & Fici-Pasquina, L. (2011). Sensor technology for smart homes. *Maturitas*, *69*(2), 131–136. http://doi.org/10.1016/j.maturitas.2011.03.016

E. Baum, L., & Petrie, T. (1966). Statistical inference for probabilistic functions of finite state Markov chains. *The Annals of Mathematical Statistics*, *37*(6), 1554–1563. Retrieved from https://projecteuclid.org/DPubS/Repository/1.0/Disseminate?handle=euclid.aoms/1177699147&view=body&content-type=pdf_1

Eiben, A. E., Michalewicz, Z., Schoenauer, M., & Smith, J. E. (1999). Parameter control in evolutionary algorithms. *Studies in Computational Intelligence*, *54*(2), 19–46. http://doi.org/10.1007/978-3-540-69432-8_2

Elisseeff, A., & Weston, J. (2001). A Kernel Method for Multi-labelled Classification. In *Proceedings of the 14th International Conference on Neural Information Processing Systems: Natural and Synthetic* (pp. 681–687). Cambridge, MA, USA: MIT Press. Retrieved from http://dl.acm.org/citation.cfm?id=2980539.2980628

Emi, I. A., & Stankovic, J. A. (2015). SARRIMA: Smart ADL Recognizer and Resident Identifier in Multi-resident Accommodations. *Proceedings of the Conference on Wireless Health*, 4:1--4:8. http://doi.org/10.1145/2811780.2811916

Fahad, L. G., Ali, A., & Rajarajan, M. (2013). Long term analysis of daily activities in a smart home. *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, (April), 419–424. Retrieved from https://www.elen.ucl.ac.be/Proceedings/esann/esannpdf/es2013-71.pdf

Fahad, L. G., Tahir, S. F., & Rajarajan, M. (2014). Activity Recognition in Smart Homes

Using Clustering Based Classification. *2014 22nd International Conference on Pattern Recognition*, 1348–1353. http://doi.org/10.1109/ICPR.2014.241

Fang, Z., & Zhang, Z. (2012). Simultaneously combining multi-view multi-label learning with maximum margin classification. In *Proceedings - IEEE International Conference on Data Mining, ICDM* (pp. 864–869). http://doi.org/10.1109/ICDM.2012.88

Feng, Z., Mo, L., & Li, M. (2015). A Random Forest-based ensemble method for activity recognition. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (Vol. 2015–Novem, pp. 5074–5077). IEEE. http://doi.org/10.1109/EMBC.2015.7319532

Fisher, R. (2000). Sources of Conflict and Methods of Conflict Resolution. *International Peace and Conflict Resolution School of International Service The American University*, (1965), 1–6. Retrieved from http://www.ulstergaa.ie/wp-content/uploads/coaching/team-management-2012/unit-3/sources-of-conflict-and-methods-of-resolution.pdf [accessed: June 5, 2012]

Fleury, A., Vacher, M., & 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), 274–283. http://doi.org/10.1109/TITB.2009.2037317

Fotiadou, E., & Nikolaidis, N. (2014). Activity-based methods for person recognition in motion capture sequences. *Pattern Recognition Letters*, *49*, 48–54. http://doi.org/10.1016/j.patrec.2014.06.005

Gayathri, K. S., Easwarakumar, K. S., & Elias, S. (2017). Probabilistic ontology based activity recognition in smart homes using Markov Logic Network. *Knowledge-Based Systems*, *121*, 173–184. http://doi.org/10.1016/j.knosys.2017.01.025

Gillani Fahad, L., Khan, A., & Rajarajan, M. (2015). Activity recognition in smart homes with self verification of assignments. *Neurocomputing*, *149*(PC), 1286–1298. http://doi.org/10.1016/j.neucom.2014.08.069

Guiry, J. J., van de Ven, P., Nelson, J., Warmerdam, L., & Riper, H. (2014). Activity recognition with smartphone support. *Medical Engineering and Physics*, *36*, 670–675. http://doi.org/10.1016/j.medengphy.2014.02.009

Ham, C., Dixon, A., & Brooke, B. (2012). Transforming the Delivery of Health and Social Care: The case for fundamental change, 1–52. http://doi.org/10.3399/bjgp13X668104

Hoque, E., & Stankovic, J. (2012). AALO: Activity recognition in smart homes using Active Learning in the presence of Overlapped activities. In *Proceedings of the 6th International Conference on Pervasive Computing Technologies for Healthcare* (pp. 139–146). http://doi.org/10.4108/icst.pervasivehealth.2012.248600

Hsu, K. C., Chiang, Y. T., Lin, G. Y., Lu, C. H., Hsu, J. Y. J., & Fu, L. C. (2010). Strategies for inference mechanism of conditional random fields for multiple-resident activity recognition in a smart home. *Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6096 LNAI*(PART 1), 417–426. http://doi.org/10.1007/978-3-642-13022-9_42

Jakkula, V. R., & Cook, D. J. (2008). Anomaly detection using temporal data mining in a smart home environment. *Methods of Information in Medicine*, *47*(1), 70–75. http://doi.org/10.3414/ME9103

Jakkula, V. R., Crandall, A. S., & Cook, D. J. (2007). Knowledge discovery in entity based smart environment resident data using temporal relation based data mining. *Proceedings - IEEE International Conference on Data Mining, ICDM*, 625–630. http://doi.org/10.1109/ICDMW.2007.107

Jakkula, V. R., Crandall, A. S., & Cook, D. J. (2009). Enhancing anomaly detection using temporal pattern discovery. *Advanced Intelligent Environments*, 175–194. http://doi.org/10.1007/978-0-387-76485-6_8

Jurek, A., Nugent, C., Bi, Y., & Wu, S. (2014). Clustering-based ensemble learning for activity recognition in smart homes. *Sensors (Basel, Switzerland)*, *14*(7), 12285–12304. http://doi.org/10.3390/s140712285

Kalaiselvi, P. (2018). MOART : Multiple Occupants Activity Recognition and Tracking in Smart Home. *International Journal of Advanced Computer and Communication Engineering*, *7*(3), 21–25. http://doi.org/10.17148/IJARCCE.2018.734

Kaneko, T., Shimosaka, M., Odashima, S., Fukui, R., & Sato, T. (2014). A fully connected model for consistent collective activity recognition in videos. *Pattern Recognition Letters*, *43*(1), 109–118. http://doi.org/10.1016/j.patrec.2014.02.002

Kasteren, T. Van, Noulas, A., Englebienne, G., & Kröse, B. (2008). Accurate activity recognition in a home setting. In *Proceedings of the 10th international conference on Ubiquitous computing - UbiComp '08* (p. 1). http://doi.org/10.1145/1409635.1409637

Katz, S. (1983). Assessing self-maintenance: Activities of daily living, mobility, and instrumental activities of daily living. *Journal of the American Geriatrics Society*, *31*(12), 721–727. http://doi.org/10.1111/j.1532-5415.1983.tb03391.x

Khan, Z. a., & Sohn, W. (2011). Abnormal human activity recognition system based on R-transform and kernel discriminant technique for elderly home care. *IEEE Transactions on Consumer Electronics*, *57*(4), 1843–1850. http://doi.org/10.1109/TCE.2011.6131162

Khattak, A. M., Khan, W. A., Pervez, Z., Iqbal, F., & Lee, S. (2016). Towards a self adaptive system for social wellness. *Sensors (Switzerland)*, *16*(4). http://doi.org/10.3390/s16040531

Kim, E., & Helal, S. (2011). Revisiting Human Activity Frameworks. *Sensor Systems and Software*, (5), 219–234. http://doi.org/10.1007/978-3-642-23583-2

Kim, E., Helal, S., & Cook, D. J. (2010). Human Activity Recognition and Pattern

Discovery. *Pervasive Computing, IEEE*, *9*(1), 48–53. http://doi.org/10.1109/MPRV.2010.7

Kim, S. C., Jeong, Y. S., & Park, S. O. (2013). RFID-based indoor location tracking to ensure the safety of the elderly in smart home environments. *Personal & Ubiquitous Computing*, *17*(8), 1699–1707. http://doi.org/10.1007/s00779-012-0604-4

Kim, S., & Wilbur, W. J. (2011). An EM clustering algorithm which produces a dual representation. *Proceedings - 10th International Conference on Machine Learning and Applications, ICMLA 2011*, *2*, 90–95. http://doi.org/10.1109/ICMLA.2011.29

Krishnan, N. C., & Cook, D. J. (2014). Activity recognition on streaming sensor data. *Pervasive and Mobile Computing*, *10*(PART B), 138–154. http://doi.org/10.1016/j.pmcj.2012.07.003

Kumar, R., Qamar, I., Virdi, J. S., & Krishnan, N. C. (2015). Multi-label Learning for Activity Recognition. *2015 International Conference on Intelligent Environments*, 152–155. http://doi.org/10.1109/IE.2015.32

Kuutti, K. (1995). Activity theory as a potential framework for human-computer interaction research, 17–44. Retrieved from http://dl.acm.org/citation.cfm?id=223826.223828

Laput, G., Zhang, Y., & Harrison, C. (2017). Synthetic Sensors: Towards General-Purpose Sensing. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*, 3986–3999. http://doi.org/10.1145/3025453.3025773

Lau, S. L., & David, K. (2010). Movement recognition using the accelerometer in smartphones. *2010 Future Network & Mobile Summit*, 1–9. http://doi.org/http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5722356

Lawton, M. P., & Brody, E. M. (1969). Assessment of older people: self-maintaining and instrumental activities of daily living. *Gerontologist.*, *9*(3), 179–186. http://doi.org/10.1093/geront/9.3_Part_1.179

Lee, J., & Kim, D. (2013). Feature selection for multi-label classification using multivariate mutual information. *Pattern Recognition Letters*, *34*(3), 349–357. http://doi.org/10.1016/j.patrec.2012.10.005

Li, R., Liu, W., Lin, Y., Zhao, H., & Zhang, C. (2017). An Ensemble Multilabel Classification for Disease Risk Prediction, *2017*. http://doi.org/10.1155/2017/8051673

Liaw, a, & Wiener, M. (2002). Classification and Regression by randomForest. *R News*, *2*(December), 18–22. http://doi.org/10.1177/154405910408300516

Lillywhite, K., Lee, D. J., Tippetts, B., & Archibald, J. (2013). A feature construction method for general object recognition. *Pattern Recognition*, *46*(12), 3300–3314. http://doi.org/10.1016/j.patcog.2013.06.002

Liu, L., Peng, Y., Wang, S., Liu, M., & Huang, Z. (2016). Complex activity recognition using time series pattern dictionary learned from ubiquitous sensors. *Information Sciences*, *340–341*, 41–57. http://doi.org/10.1016/j.ins.2016.01.020

Liu, Y., Nie, L., Han, L., Zhang, L., & Rosenblum, D. S. (2015). Action2Activity: Recognizing complex activities from sensor data. In *IJCAI International Joint Conference on Artificial Intelligence* (Vol. 2015–Janua, pp. 1617–1623).

Liu, Y., Ouyang, D., Liu, Y., & Chen, R. (2017). A novel approach based on time cluster for activity recognition of daily living in smart homes. *Symmetry*, *9*(10). http://doi.org/10.3390/sym9100212

Loh, W.-Y. (2011). Classification and regression trees. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *1*(1), 14–23. http://doi.org/10.1002/widm.8

Loza Mencía, E. (2010). An Evaluation of Multilabel Classification for the Automatic Annotation of Texts. In *Proceedings of the LWA 2010: Lernen, Wissen, Adaptivit{ä}t, Workshop on Knowledge Discovery, Data Mining and Machine Learning (KDML 2010)* (pp. 121–123). Retrieved from http://www.kde.cs.uni-kassel.de/conf/lwa10/papers/kdml11.pdf

Lu, C., & Fu, L. (2009). Robust location-aware activity recognition using wireless sensor network in an attentive home. *IEEE Transactions on Automation Science and Engineering*, 598–609. http://doi.org/10.1109/TASE.2009.2021981

Lu, C. H., & Chiang, Y. T. (2014). Interaction-feature enhanced multiuser model learning for a home environment using ambient sensors. *International Journal of Intelligent Systems*, *29*(11), 1015–1046. http://doi.org/10.1002/int.21674

Luor, T., Lu, H. P., Yu, H., & Lu, Y. (2015). Exploring the critical quality attributes and models of smart homes. *Maturitas*, *82*(4), 377–386. http://doi.org/10.1016/j.maturitas.2015.07.025

Madjarov, G., Kocev, D., Gjorgjevikj, D., & Dzeroski, S. (2012). An extensive experimental comparison of methods for multi-label learning. *Pattern Recognition*, *45*(9), 3084–3104. http://doi.org/10.1016/j.patcog.2012.03.004

Magill, E., & Blum, J. (2016). Exploring conflicts in rule-based sensor networks. *Pervasive and Mobile Computing*, *27*, 133–154. http://doi.org/10.1016/j.pmcj.2015.08.005

Mannini, A., Intille, S. S., Rosenberger, M., Sabatini, A. M., & Haskell, W. (2013). Activity recognition using a single accelerometer placed at the wrist or ankle. *Med Sci Sports Exerc.*, *45*(11), 2193–2203. http://doi.org/10.1249/MSS.0b013e31829736d6.Activity

McKeever, S., Ye, J., Coyle, L., Bleakley, C., & Dobson, S. (2010). Activity recognition using temporal evidence theory. *Journal of Ambient Intelligence and Smart Environments*, *2*(3), 253–269. http://doi.org/10.3233/AIS-2010-0071

Mehr, H. D., Polat, H., & Cetin, A. (2016a). Resident activity recognition in smart homes by using artificial neural networks. *2016 4th International Istanbul Smart Grid Congress and Fair (ICSG)*, 1–5. http://doi.org/10.1109/SGCF.2016.7492428

Mehr, H. D., Polat, H., & Cetin, A. (2016b). Resident activity recognition in smart homes by using artificial neural networks. *2016 4th International Istanbul Smart Grid Congress and Fair (ICSG)*, 1–5. http://doi.org/10.1109/SGCF.2016.7492428

Mennitt, D., Sherrill, K., & Fristrup, K. (2014). A geospatial model of ambient sound pressure levels in the contiguous United States. *The Journal of the Acoustical Society of America*, *135*(5), 2746–2764. http://doi.org/10.1121/1.4870481

Mohamed, R., Perumal, T., Sulaiman, M. N., & Mustapha, N. (2017). Multi Resident Complex Activity Recognition in Smart Home : A Literature Review. *International Journal of Smart Home*, *Vol. 11*(No. 6 (2017)), 21–32. Retrieved from http://www.sersc.org/journals/IJSH/vol11_no6_2017.php

Natarajan, K., Li, J., & Koronios, A. (2010). Data mining techniques for data cleaning. *Engineering Asset Lifecycle Management*, (September), 796–804. http://doi.org/10.1007/978-0-85729-320-6_91

Ni, Q., Hernando, A. B. G., & de la Cruz, I. P. (2015). *The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development*. *Sensors (Switzerland)* (Vol. 15). http://doi.org/10.3390/s150511312

Niu, W., & Kay, J. (2008). Location conflict resolution with an ontology. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 5013 LNCS, pp. 162–179). http://doi.org/10.1007/978-3-540-79576-6_10

Okeyo, G., Chen, L., Wang, H., & Sterritt, R. (2014). Dynamic sensor data segmentation for real-time knowledge-driven activity recognition. *Pervasive and Mobile Computing*, *10*(PART B), 155–172. http://doi.org/10.1016/j.pmcj.2012.11.004

Pal, S. K., & Mitra, P. (2002). Multispectral image segmentation using the rough-set-initialized EM algorithm. *IEEE Transactions on Geoscience and Remote Sensing*, *40*(11), 2495–2501. http://doi.org/10.1109/TGRS.2002.803716

Paré, G., Jaana, M., & Sicotte, C. (2007). Systematic Review of Home Telemonitoring for Chronic Diseases: The Evidence Base. *Journal of the American Medical Informatics Association*, *14*(3), 269–277. http://doi.org/10.1197/jamia.M2270

Portet, F., Vacher, M., Golanski, C., Roux, C., & Meillon, B. (2013). Design and evaluation of a smart home voice interface for the elderly: Acceptability and objection aspects. *Personal and Ubiquitous Computing*, *17*(1), 127–144. http://doi.org/10.1007/s00779-011-0470-5

Prossegger, M., & Bouchachia, A. (2014). Multi-resident Activity Recognition Using Incremental Decision Trees. *Adaptive and Intelligent Systems*, 182–191.

http://doi.org/10.1007/978-3-319-11298-5_19

Qian, H., Mao, Y., Xiang, W., & Wang, Z. (2010). Recognition of human activities using SVM multi-class classifier. *Pattern Recognition Letters*, *31*(2), 100–111. http://doi.org/10.1016/j.patrec.2009.09.019

Ranganathan, A., Al-Muhtadi, J., & Campbell, R. H. (2004). Reasoning about uncertain contexts in pervasive computing environments. *IEEE Pervasive Computing*, *3*(2), 62–70. http://doi.org/10.1109/MPRV.2004.1316821

Rashidi, P., Cook, D. J., Holder, L. B., & Schmitter-Edgecombe, M. (2011). Discovering Activities to Recognize and Track in a Smart Environment. *IEEE Transactions on Knowledge and Data Engineering*, *23*(4), 527–539. http://doi.org/10.1109/TKDE.2010.148

Read, J. (2008). A Pruned Problem Transformation Method for Multi-label Classification. *New Zealand Computer Science Research Student Conference, NZCSRSC 2008 - Proceedings*, (April), 143–150. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-84880106608&partnerID=40&md5=ccdd19f7d0f111a2fdda8df7af0a8075

Read, J., & Hollmen, J. (2014). A Deep Interpretation of Classifier Chains. In *ADVANCES IN INTELLIGENT DATA ANALYSIS XIII* (Vol. 8819, pp. 251–262).

Read, J., Pfahringer, B., & Holmes, G. (2008). Multi-label classification using ensembles of pruned sets. *Proceedings - IEEE International Conference on Data Mining, ICDM*, 995–1000. http://doi.org/10.1109/ICDM.2008.74

Read, J., Pfahringer, B., Holmes, G., & Frank, E. (2011). Classifier chains for Multi-label Classification. *Machine Learning*, *85*(3), 333–359. http://doi.org/10.1007/s10994-011-5256-5

Resendes, S., Carreira, P., & Santos, A. C. (2013). Conflict detection and resolution in home and building automation systems: a literature review. *Journal of Ambient Intelligence and Humanized Computing*, 1–17. http://doi.org/10.1007/s12652-013-0184-9

Roy, N., Misra, A., & Cook, D. J. (2016). Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments. *Journal of Ambient Intelligence and Humanized Computing*, *70*(12), 773–779. http://doi.org/10.1097/OGX.0000000000000256.Prenatal

Russell, J. S., Ye, M., Anderson, B. D. O., Hmam, H., & Sarunic, P. (2017). Cooperative Localisation of a GPS-Denied UAV in 3-Dimensional Space Using Direction of Arrival Measurements. *IFAC-PapersOnLine*, *50*(1), 8019–8024. http://doi.org/10.1016/j.ifacol.2017.08.1226

Ruyter, B. de, & Pelgrim, E. (2007). Ambient assisted-living research in carelab. *Interactions*, *14*(4), 30. http://doi.org/10.1145/1273961.1273981

Saguna, S., Zaslavsky, A., & Chakraborty, D. (2011). Complex activity recognition using context driven activity theory in home environments. *Smart Spaces and Next Generation Wired/Wireless Networking*, 38–50. Retrieved from https://www.diva-portal.org/smash/get/diva2:1004072/FULLTEXT01.pdf

Saguna, S., Zaslavsky, A., & Chakraborty, D. (2013). Complex activity recognition using context-driven activity theory and activity signatures. *ACM Transactions on Computer-Human Interaction*, *20*(6), 1–34. http://doi.org/10.1145/2490832

Satyanarayanan, M. (2001). Pervasive computing: Vision and challenges. *IEEE Personal Communications*, *8*(4), 10–17. http://doi.org/10.1109/98.943998

Schapire, R. E., & Singer, Y. (2000). BoosTexter: A Boosting-based System for Text Categorization. *Machine Learning*, *39*, 135–168. http://doi.org/10.1023/A:1007649029923

Sebbak, F., Chibani, A., Amirat, Y., Mokhtari, A., & Benhammadi, F. (2013). An evidential fusion approach for activity recognition in ambient intelligence environments. *Robotics and Autonomous Systems*, *61*(11), 1235–1245. http://doi.org/10.1016/j.robot.2013.05.010

Shahi, A., Woodford, B. J., & Deng, J. D. (2015). Event Classification Using Adaptive Cluster-Based Ensemble Learning of Streaming Sensor Data. *Springer International Publishing Switzerland*, *9457*, 505–516. http://doi.org/10.1007/978-3-319-26350-2

Silva, L. C. De. (2009). Multi-sensor based human activity detection for smart homes. *Proceedings of the 3rd International Universal Communication Symposium on - IUCS '09*, (9), 223. http://doi.org/10.1145/1667780.1667827

Singla, G., Cook, D. J., & Schmitter-Edgecombe, M. (2010). Recognizing independent and joint activities among multiple residents in smart environments. *Journal of Ambient Intelligence and Humanized Computing*, *1*(1), 57–63. http://doi.org/10.1007/s12652-009-0007-1

Skocir, P., Krivic, P., Tomeljak, M., Kusek, M., & Jezic, G. (2016). Activity Detection in Smart Home Environment. *Procedia Computer Science*, *96*, 672–681. http://doi.org/10.1016/j.procs.2016.08.249

Sorower, M. S. (2010). A literature survey on algorithms for multi-label learning. In *Oregon State University, Corvallis* (pp. 1–25). Retrieved from http://people.oregonstate.edu/~sorowerm/pdf/Qual-Multilabel-Shahed-CompleteVersion.pdf

Spolaôr, N., Monard, M. C., Tsoumakas, G., & Lee, H. (2014). Label construction for multi-label feature selection. *Proceedings - 2014 Brazilian Conference on Intelligent Systems, BRACIS 2014*, 247–252. http://doi.org/10.1109/BRACIS.2014.52

Spolaôr, N., Monard, M. C., Tsoumakas, G., & Lee, H. D. (2016). A systematic review of multi-label feature selection and a new method based on label construction. *Neurocomputing*, *180*, 3–15. http://doi.org/10.1016/j.neucom.2015.07.118

Spyromitros, E., Tsoumakas, G., & Vlahavas, I. (2008). An Empirical Study of Lazy Multilabel Classification Algorithms. *The 5th Hellenic Conference on Artificial Intelligence (SETN 2008)*, 401–406. http://doi.org/10.1007/978-3-540-87881-0_40

Statista Market Forecast. (2016). Smart Home - Malaysia | Statista Market Forecast. Retrieved June 1, 2018, from https://www.statista.com/outlook/279/122/smart-home/malaysia#

Struyf, J., Džeroski, S., Blockeel, H., & Clare, A. (2005). Hierarchical multi-classification with predictive clustering trees in functional genomics. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 3808 LNCS, pp. 272–283). http://doi.org/10.1007/11595014_27

Su, X., Tong, H., & Ji, P. (2014). Activity recognition with smartphone sensors. *Tsinghua Science and Technology*, *19*(3), 235–249. http://doi.org/10.1109/TST.2014.6838194

Suryadevara, N. K., Mukhopadhyay, S. C., Wang, R., & Rayudu, R. K. (2013). Forecasting the behavior of an elderly using wireless sensors data in a smart home. *Engineering Applications of Artificial Intelligence*, *26*(10), 2641–2652. http://doi.org/10.1016/j.engappai.2013.08.004

Tai, F., & Lin, H. T. (2010). Multi-label classification with principle label space transformation. In *International Workshop on Learning from Multi-Label Data* (p. 45). Retrieved from http://ntur.lib.ntu.edu.tw/retrieve/188514/18.pdf%0Ahttp://ntur.lib.ntu.edu.tw/retrieve/188514/18.pdf%0Ahttp://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.170.1860&rep=rep1&type=pdf#page=46

Trabelsi, W., Azzouz, R., Bechikh, S., & Said, L. Ben. (2016). Leveraging Evolutionary Algorithms for Dynamic Multi-Objective Optimization Scheduling of Multi-tenant Smart Home Appliances, 3533–3540.

Tran, S. N., Zhang, Q., & Karunanithi, M. (2010). Mixed-Dependency Models for Multi-resident Activity Recognition in Smart-Homes. *ACM Transactions on the Web*, *9*(39), 39.1-39.16. http://doi.org/https://doi.org/0000001. 0000001

Tran, S. N., Zhang, Q., & Karunanithi, M. (2018). On Multi-resident Activity Recognition in Ambient Smart-Homes. *Computer Vision and Pattern Recognition*, *2018*. Retrieved from http://arxiv.org/abs/1806.06611

Tsoumakas, G., & Katakis, I. (2007). Multi-Label Classification: An Overview. In *Database Technologies* (Vol. 3, pp. 309–319). IGI Global. http://doi.org/10.4018/978-1-60566-058-5.ch021

Tsoumakas, G., Katakis, I., & Vlahavas, I. (2009). Mining Multi-label Data. In *Data Mining and Knowledge Discovery Handbook* (pp. 667--685). Boston, MA: Springer US. http://doi.org/10.1007/978-0-387-09823-4_34

Tsoumakas, G., Katakis, I., & Vlahavas, I. (2011). Random k-labelsets for multilabel classification. *IEEE Transactions on Knowledge and Data Engineering*, *23*(7), 1079–1089. http://doi.org/10.1109/TKDE.2010.164

Tsoumakas, G., & Vlahavas, I. (2007). Random k-labelsets: An Ensemble Method for Multilabel Classification. *European Conference on Machine Learning*, 406–417. http://doi.org/10.1007/978-3-540-74958-5_38

Tunca, C., Alemdar, H., Ertan, H., Incel, O. D., & Ersoy, C. (2014). Multimodal wireless sensor network-based ambient assisted living in real homes with multiple residents. *Sensors (Switzerland)*, *14*(6), 9692–9719. http://doi.org/10.3390/s140609692

United Nations: Department of Social and Economic Affairs. (2013). World Population Prospects: The 2012 Revision. *Population Division 2013*. Retrieved from http://esa.un.org/unpd/wpp/Excel-Data/population.htm

Urwyler, P., Rampa, L., Stucki, R., Büchler, M., Müri, R., Mosimann, U. P., & Nef, T. (2015). Recognition of activities of daily living in healthy subjects using two ad-hoc classifiers. *BioMedical Engineering Online*, *14*(1), 1–15. http://doi.org/10.1186/s12938-015-0050-4

van Hoof, J., Kort, H. S. M., Rutten, P. G. S., & Duijnstee, M. S. H. (2011). Ageing-in-place with the use of ambient intelligence technology: Perspectives of older users. *International Journal of Medical Informatics*, *80*(5), 310–331. http://doi.org/10.1016/j.ijmedinf.2011.02.010

Wan, J., O'Grady, M. J., & O'Hare, G. M. P. (2014). Dynamic sensor event segmentation for real-time activity recognition in a smart home context. *Personal and Ubiquitous Computing*, *19*(2), 287–301. http://doi.org/10.1007/s00779-014-0824-x

Wang, L., Gu, T., Tao, X., Chen, H., & Lu, J. (2011a). Multi-User Activity Recognition in a Smart Home. *Activity Recognition in Pervasive Intelligent Environments*, *4*, 59–81. http://doi.org/10.2991/978-94-91216-05-3_3

Wang, L., Gu, T., Tao, X., Chen, H., & Lu, J. (2011b). Recognizing multi-user activities using wearable sensors in a smart home. *Pervasive and Mobile Computing*, *7*(3), 287–298. http://doi.org/10.1016/j.pmcj.2010.11.008

Wang, L., Gu, T., Tao, X., & Lu, J. (2009). Sensor-based human activity recognition in a multi-user scenario. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 5859 LNCS, pp. 78–87). http://doi.org/10.1007/978-3-642-05408-2_10

Wang, W. M., & Ting, S. L. (2011). Development of a computational simulation model for conflict management in team building. *International Journal of Engineering Business Management*, *3*(2), 9–15.

Wilson, D., & Atkeson, C. (2005). Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors. *Proceedings of the Third International Conference on Pervasie Computing, (PERVASIVE2005)*, *3468*, 62–79. http://doi.org/10.1007/11428572_5

Yang, Y. (1999). An Evaluation of Statistical Approaches to Text Categorization. *Information Retrieval*, *1*(1), 69–90. http://doi.org/10.1023/A:1009982220290

Ye, J., Clear, A. K., Coyle, L., & Dobson, S. (2010). On using temporal features to create more accurate human-activity classifiers. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 6206 LNAI, pp. 273–282). http://doi.org/10.1007/978-3-642-17080-5_29

Zacks, J. M., & Tversky, B. (2001). Event structure in perception and conception. *Psychological Bulletin*, *127*(1), 3–21. http://doi.org/10.1037/0033-2909.127.1.3

Zainudin, M. N. S., Mohamed, R., Sulaiman, M. N., Perumal, T., Mustapha, N., & Ahmad Nazri, A. S. (2017). Multi-label Classification Using Label Combination to Recognize Human Activity Based on Various Sensor Positions. In *ICOCI Kuala Lumpur. Universiti Utara Malaysia* (pp. 669–674). Retrieved from http://icoci.cms.net.my/PROCEEDINGS/2017/Pdf_Version_Chap15e/PID63-669-674e.pdf

Zainudin, M. N. S., Mustapha, N., Perumal, T., & Mohamed, R. (2017). RECOGNIZING COMPLEX HUMAN ACTIVITIES USING HYBRID FEATURE SELECTIONS BASED ON AN ACCELEROMETER SENSOR. *International Journal of Technology*, *8*(5), 968–978. http://doi.org/https://doi.org/10.14716/ijtech.v8i5.7217

Zainudin, M. N. S., Sulaiman, M. N., Mustapha, N., & Perumal, T. (2016). Activity recognition based on accelerometer sensor using combinational classifiers. In *ICOS 2015 - 2015 IEEE Conference on Open Systems* (pp. 68–73). http://doi.org/10.1109/ICOS.2015.7377280

Zainudin, M. N. S., Sulaiman, M. N., Mustapha, N., Perumal, T., & Ahmad Nazri, A. S. (2018). Hybrid Relief-f Differential Evolution Feature Selection for Accelerometer Actions. *Advanced Science Letters*, *24*(2), 1168–1171. http://doi.org/10.1166/asl.2018.10709

Zainudin, M. N. S., Sulaiman, M. N., Mustapha, N., Perumal, T., Ahmad Nazri, A. S., Mohamed, R., & Abd Manaf, S. (2017). Feature Selection Optimization using Hybrid Relief-f with Self-adaptive Differential Evolution. *International Journal of Intelligent Engineering and Systems*, *10*(3), 21–29. http://doi.org/10.22266/ijies2017.0430.03

Zhang, M.-L., & Zhang, K. (2010). Multi-label learning by exploiting label dependency. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '10* (p. 999). http://doi.org/10.1145/1835804.1835930

Zhang, M. L., & Zhou, Z. H. (2006). Multilabel Neural Networks with Applications to Functional Genomics and Text Categorization. *IEEE Transactions on Knowledge and Data Engineering*, *18*(10), 1338–1351. http://doi.org/10.1109/TKDE.2006.162

Zhang, M. L., & Zhou, Z. H. (2007). ML-KNN: A lazy learning approach to multi-label learning. *Pattern Recognition*, *40*(7), 2038–2048.

http://doi.org/10.1016/j.patcog.2006.12.019

Zhang, M. L., & Zhou, Z. H. (2014). A review on multi-label learning algorithms. *IEEE Transactions on Knowledge and Data Engineering*, *26*(8), 1819–1837. http://doi.org/10.1109/TKDE.2013.39

Zhang, S., Wei, Z., Nie, J., Huang, L., Wang, S., & Li, Z. (2017). A Review on Human Activity Recognition Using Vision-Based Method. *Journal of Healthcare Engineering*, *2017*, 3090343. http://doi.org/10.1155/2017/3090343

Zhao, R., Zhao, Y., Deng, R., & Li, F. (2017). Hierarchical random forest for senior action recognition in videos. In *International Conference on Wavelet Analysis and Pattern Recognition* (Vol. 1, pp. 171–176). http://doi.org/10.1109/ICWAPR.2017.8076684

Ziaeefard, M., & Bergevin, R. (2015). Semantic human activity recognition: A literature review. *Pattern Recognition*, *48*(8), 2329–2345. http://doi.org/10.1016/j.patcog.2015.03.006