TASK ORIENTED FEATURE EXTRACTION FOR COMPLEX HUMAN ACTIVITY RECOGNITION

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

Razak Faculty of Technology and Informatics
Universiti Teknologi Malaysia

JANUARY 2022

DEDICATION

This thesis is dedicated to my beloved mother, father, wife, son, and brothers.

ACKNOWLEDGEMENT

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Assoc. Prof. Dr. Suriayati Chuprat, for the encouragement, guidance, critics, advice, motivation and friendship. Without her continuous support and interest, this thesis would not have been the same as presented here.

My fellow postgraduate students should also be recognized for their support. My sincere appreciation also extends to all my colleagues and others who provided assistances at various occasions. Their views and tips are indeed useful. Unfortunately, it is not possible to list all of them here in such a limited space. I am grateful to all my family members.

ABSTRACT

Human Activities Recognition (HAR) using mobile phone devices provides valuable contextaware information about the type of activities individuals perform within a time interval. HAR leverages sensory data available on today's sensor-rich, cheap, and portable mobile phones. It enables mobile phones to provide personalized support for many healthcare and well-being applications. It also has significant contributions to robotic, homeland security and smart environments. However, current recognition systems based on mobile phone sensors have observable issues in recognizing composite activities that occur concurrently or interleave i.e., complex activities, limiting their use in real-world applications. In those activities, the existence and variations of each activity as well as the order and length may vary. In this research, the issues of low recognition accuracy and high computing cost of complex human activities using mobile phone sensors are addressed. The composition and variations of human activity are examined as factors that impact the complexity of activity recognition. This research proposes to increase the quality of extracted features to increase the recognition accuracy with less resource consumption. It proposes extracting the wrist velocity as a feature for recognizing the performing arm's complex activity. The wrist velocity feature is task oriented. Using the task-oriented wrist velocity feature will help to reduce recognition errors and therefore increase recognition accuracy. For this purpose, an extraction method for the wrist velocity feature is developed. In addition, the developed method is applied to recognize complex human activities using the Complex Activity Recognizer through Wrist velocity system (CARWV). Firstly, the extraction method begins by integrating the accelerometer and gyroscope data of the smartphone, which is placed on the upper arm and forearm. The integrated data is used to calculate the rotational angles of the upper arm and forearm. Then, the calculated rotational angles and lengths of the upper arm and forearm are used to calculate the position and the velocity of the wrist while performing the activity. Secondly, in the proposed recognition system (CARWV), the complex activity is broken into tasks that are represented by basic arm movements. The wrist velocity while performing the basic arm movements is extracted. The decision tree classifier is used to recognize the basic arm movements through the extracted feature. Then, the existing and order of recognized basic arm movements in the complex activity are used as features for recognizing the complex activity by measuring the similarity using the distance metric. The experiments demonstrate the validity of the task-oriented property of the extracted feature. The experiments also show increased recognition accuracy when using the proposed system up to 86% over performance for the state-of-the-art works, with 13 sec execution time and 31264 kb allocated memory in a notebook computer with Core i7 processor and 8GM memory. This study can facilitate future research in other fields where performance and limited resources are critical quality factors such as robotics and Wireless Sensor Networks (WSN).

ABSTRAK

Pengenalpastian aktiviti manusia (HAR) menggunakan peranti telefon mudah alih menyediakan maklumat konteks yang berharga tentang jenis aktiviti yang dilakukan oleh individu dalam sesuatu selang masa. HAR memanfaatkan data sensori yang terdapat pada telefon bimbit pada hari ini yang dipenuhi dengan sensor, murah dan mudah alih . Ia membolehkan telefon mudah alih memberi sokongan peribadi untuk pelbagai aplikasi penjagaan kesihatan dan kesejahteraan. Ia juga memberi sumbangan penting kepada bidang robotik, keselamatan tanah air serta persekitaran pintar. Walau bagaimanapun, sistem pengenalpastian semasa yang menggunakan sensor telefon bimbit mempunyai masalah dalam mengenal pasti aktiviti komposit yang berlaku secara serentak atau selang masa, iaitu aktiviti kompleks, , menghadkan penggunaannya dalam aplikasi dunia sebenar. Dalam aktiviti tersebut, kewujudan dan sampel setiap aktiviti serta susunan dan jangka masa aktiviti tersebut mungkin berbeza-beza Dalam kajian ini, isu ketepatan pengenalpastian yang rendah dan kos pengkomputeran yang tinggi untuk aktiviti manusia yang kompleks menggunakan sensor telefon bimbit ditangani. Komposisi dan variasi aktiviti manusia dikaji sebagai faktor yang memberi kesan kepada kerumitan pengenalpastian aktiviti. Kajian ini bercadang untuk meningkatkan kualiti ciri yang diekstrak supaya dapat meningkatkan ketepatan pengenalpastian dengan penggunaan sumber yang rendah. Ia mencadangkan untuk mengekstrak halaju pergelangan tangan sebagai ciri untuk mengenal pasti aktiviti kompleks lengan. Ciri halaju pergelangan tangan adalah berorientasikan tugasan. Dengan menggunakan ciri halaju pergelangan tangan berorientasikan tugasan akan membantu mengurangkan. kesilapan pengenalpastian dan oleh itu meningkatkan ketepatan pengenalpastian. Untuk tujuan ini, kaedah pengekstrakan untuk ciri halaju pergelangan tangan dibangunkan. Selain itu, kaedah yang dibangunkan digunakan bagi mengenal pasti aktiviti kompleks manusia menggunakan Pengenalpastian aktiviti kompleks melalui Sistem HalaJu Tangan (CARWV). Pertama , kaedah pengekstrakan bermula dengan mengintegrasi data pecutan dan giroskop telefon pintar yang diletakkan pada bahagian lengan atas dan lengan bawah. Data yang diintegrasi digunakan untuk mengira sudut putaran lengan atas dan lengan bawah. Kemudian, sudut putaran yang dikira dan pajang lengan atas dan lengan bawah digunakan untuk mengira posisi dan halaju pergelangan lengan semasa melakukan aktiviti. Kedua, dalam sistema pengenalpastian yang dicadangkan (CARWV), aktiviti kompleks dibahagikan kepada tugasan mengikut pergerakan asas lengan. Halaju pergelangan tangan semasa melakukan pergerakan asas lengan diekstrak. Pengkelasan pokok keputusan digunakan untuk mengenali pergerakan asas lengan melalui ciri yang diekstrak. Kemudian, urutan pergerakan asas lengan yang sedia ada dan mengikut susunan dalam aktiviti kompleks t digunakan sebagai ciri untuk mengenal pasti aktiviti kompleks dengan mengukur persamaannya menggunakan metrik jarak. Ujikaji menunjukkan kesahihan ciri berorientasikan tugasan bagi ciri yang diekstrak . Ujikaji juga menunjukkan peningkatan ketepatan pengenalpastian apabila menggunakan sistem yang dicadangkan sehingga 86% berbanding prestasi untuk kaedah-kaedah terkini, dengan masa pelaksanaan 13 saat dan memori yang diperuntukkan 31264 kb menggunakan komputer notebook dengan pemproses Core i7 dan memori 8GM. Kajian ini boleh membantu kajian lain di masa hadapan dalam bidang lain di mana prestasi dan sumber yang terhad merupakan faktor kualiti yang kritikal seperti robotik dan rangkaian sensor tanpa wayar (WSN)

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ADLs	-	Activities of Daily Living
CARWV	-	Complex Activity Recognizer through Wrist Velocity
HAR	-	Human Activity Recognition
IOT	-	Internet of Things
ISB	-	International Society of Biomechanics
RUA	-	Right Upper Arm
UTM	-	Universiti Teknologi Malaysia
WSN	-	Wireless Sensor Networks
SACAAR	-	Situation And Context-Aware Activity Recognition
SC2	-	Shapelet-based Classification technique for Complex activity recognition
PEMAR	-	Pervasive Middleware for Activity Recognition

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CHAPTER 1

INTRODUCTION

1.1 Overview

A paradigm shift is occurring in the field of computing technology as computing devices become progressively smaller and more powerful, from previously utilizing the desktop PC to relying on a more distributed and embedded form of computing referred to as ubiquitous computing (Weiser, 1991). Ubiquitous computing deals with the integration of technology in everyday objects with the aim of providing people with technological means that can help ease their everyday life.

One of the most important topics in ubiquitous computing is context (Abowd et al., 1999; Cruz, 2019). The use of context is important in interactive applications particularly when the user's context is changing rapidly such as the rapid change in smartphone devices. Context is any information that can be used to characterize the situation of an entity. There are four primary context types for characterizing the situation of a particular entity i.e. location, identity, time, and activity.

Activity plays an important role in context awareness, since it is considered as one of the four most important context types while the other three types (location, identity and time) can be acquired quite precisely by now. Human activities recognition (HAR) can provide valuable context-aware information about the type of activities/routines individuals perform within a time interval (Ortiz, 2015). Activity context-aware information can be acquired using different sensors such as video captures, ambient, wearable sensors, and sensors of mobile devices.

Current smartphones have rich sensors (Abdallah et al., 2015) such as the accelerometer and gyroscope. These smartphone sensors are more advantageous than other sensors such as wearing sensors, ambient sensors, and camera (Reyes Ortiz & Jorge Luis, 2015). They are embedded within the smartphones so that users do not feel burdensome when carrying them throughout the entire day. The sensors are also inexpensive which significantly helps to reduce the cost of setup and energy consumption compared to ambient sensors. In addition, they are portable and provide some degree of privacy compared to a fixed camera. Thus, these privileges provide opportunities for potential use in several applications as a human activity recognition device.

Activity recognition using smartphone devices focuses on inferring the current user's activities by leveraging on the sensory data available on today's sensor-rich, cheap, and portable smartphones (Abdallah et al., 2015). Being able to recognize the state of the user enables the smartphones to provide the corresponding services based on what the user is doing. For example, assuming that the phone detects that the user is about to leave the room and its weather application indicates that it will rain later, a reminder will pop up with a message reminder of "Bring an umbrella. There is a high probability of rain" (Abdallah et al., 2015).

Current works on HAR using smartphones mainly focus on simple single locomotion activities such as walking, running, biking, jogging, static (stationary), walking upstairs and walking downstairs. In real-world situations, human activities are often performed in complex manners. These include a single actor that performs interleaved and concurrent activities as well as multiple actors that perform a cooperative activity (Chen et al., 2012).

Recognizing complex activities enables the smartphone to provide personalized support for various real world healthcare and well-being applications (Liu et al., 2015) such as human-machine interaction (e.g. robot), as well as those in security and military domains whereby performance and limited energy are critical quality factors.

More recently, several studies have been conducted investigating the recognition of complex activities using smartphones. However, the reported recognition accuracy of previous works with reference to computing cost is unsatisfactory in relation to complex activities using smartphone sensors (Yang, et al., 2019; Yang, et al., 2018; Ramasamy et al., 2018). Firstly, these works have low accuracy in recognizing complex activities. Secondly, works which obtained higher results than the recognition accuracy often suffer from high computing cost. The relationship between recognition accuracy and computing cost issues in recognizing complex human activities could be explained as follows.

Firstly, recognition accuracy of human activities is assessed by measuring two classes of error the recognition method can make: false positives and false negatives. A false positive means that the method wrongly considered two different activities as same activity (also called inter-activity similarity error), while a false negative means the method failed to match two same activities (also called intra-activity variability error). Complex human activities have challenges which cause the occurrence of such errors of recognition, particularly intra-activity variability error. For example, a complex activity comprises more than one activity that might be performed in changing order such as in interleave or parallel manner (composition property). However, the activities should be in particular structures and sequences to be recognized by current recognition methods (Liu et al., 2016).

Also, several factors can affect the performance of activity, such as physical body differences or environmental state in which the activity is performed. Hence, the same activity may be performed differently by different subjects (variation property). In addition, the current features, which are used to recognize complex human activities, provide general information about the target activity which may not be suitable for describing all activities uniquely and for differentiating between the variations of activities (Preece et al., 2009). Furthermore, the number of proposed features is huge and extracting them could be extremely difficult for a microprocessor (Rosati et al., 2018). This is partly due to the broad range of human activities as well as the rich variation in how a given activity can be performed (Chen et al., 2020). Those challenges might confuse the recognition method which is trained in particular patterns and order. Thereby, the recognition methods may consider the variations of activity as new and different activities thus leading to recognition errors (Younes et al., 2018).

Secondly, the aforementioned challenges of recognizing complex human activities could be addressed by training the recognition model using a larger amount of data that captures as much of the variability as possible. However, processing such a substantial amount of reliable data would entail higher overhead due to the recognition method, so it is computationally expensive. On the other hand, increasing the operations of the recognition method to improve its ability to differentiate between similar activities is also computationally expensive, especially with mobile devices which have limited resources (Kim et al., 2009; Alzahrani & Kammoun, 2016; Minnen et al., 2006; Minnen et al., 2006; McGeoch, 2012).

Another promising system is by increasing the recognition accuracy by increasing the quality of extracted feature that differentiates the activities. This increases the robustness of the recognition method by learning the recognition model using features that are common to activity variations and of which represent the activity uniquely with less resource consumption. Following the later system, this study proposes the extraction of the wrist velocity feature to address the issues of low accuracy in recognizing complex activities and high computing cost.

1.2 Problem Statement

The use of smartphones for the recognition of human activities enables the provision of personalized support for many healthcare and well-being applications as well as provides significant contributions to the robotic, security and military domains. However, the current recognition systems of concurrent and interleave (i.e. complex) human activities used in smartphones have observable issues that limit their usage in real world applications. In this research, three of these issues are addressed. The main issue is related to the performance of recognition systems and the other two influences in this performance.

The main issue is in the overall performance of the recognition systems. The issue is on how to get high accuracy while keeping the resource consumption low. The proposed system should have high accuracy in recognizing the various durations and sequences of composite activities. In addition, it should have light computation for smartphone usage. Several benchmark works had attained relatively high accuracies, but had demonstrated major resources consumption. For example, the SC2 (Liu et al., 2016) and SACAAR (Saguna et al., 2013) methods demonstrated relatively high recognition accuracies. However, the SC2 (Liu et al., 2016) takes a long time to evaluate a large amount of candidate shapelets to find the discriminative shapelet required and consumes the smartphone battery. Meanwhile, the SACAAR (Saguna et al., 2013) uses HMM classifier which entails heavy computing for complex activity recognition.

The other issue is choosing the right features to describe human activities. The great majority of HAR applications use time-domain and frequency-domain features. However, those features are affected by the variations of activities (Preece et al., 2009). The recognition methods may consider the variations of activity as new and different activities thus leading to recognition errors. Furthermore, the number of proposed features is huge and extracting them could be extremely difficult for a microprocessor (Rosati et al., 2018). In addition to the current statistical features such as time or frequency domain features, several benchmark works had used other techniques to describe human activities. For example, the SC2 method (Liu et al., 2016) uses the time series shapelet to describe the activities. Meanwhile, the PEMAR method (Vaka et al., 2015) splits the complex activities into smaller clusters which represent the simple activities. Both shapelets and clusters are also effected by the subject performance style of activity.

Furthermore, there is the issue of choosing the right features to describe how human activities are combined to form the related complex activity. The complex activity comprises more than one activity that might be performed in changing order such as in interleave or parallel manner. Some of the recognition methods classify the complex activity as a whole unit. It considers simple and complex activities as equal classification labels. Hence, it uses the same classification methods to recognize both

(Garcia-Ceja & Brena, 2013; Dernbach et al., 2012). But complex activities have several and varied actions that reduce recognition accuracy when they are classified directly as one activity (Peng et al., 2016). On the other hand, other recognition methods deal with a complex activity as a combination of simple activities (Liu et al., 2016; Vaka et al., 2015; Saguna et al., 2013). They delineate a complex activity as a predefined and fixed set of simple activities which in turn are predefined by human knowledge. For example, the SACAAR (Saguna et al., 2013) uses Context-Driven Activity Theory (CDAT) to define the complex activities (CA). For each complex, it defines tube attributes such as simple A and context C attributes, their weights (Waca), and situation (S). Meanwhile, the SC2 method (Liu et al., 2016) uses the predefined rules based on common knowledge to describe how simple activities form the complex activity. Both predefined tube and rules depend on the domain knowledge. However, the dependence on expert opinions to define simple and complex activities produces discrepancies and leads to the loss of fine-grained components in complex activities.

Thus, a lightweight recognition system to get high recognition accuracy for various durations and sequences of composite human activities is desired to use them in real world applications. The related current works which studied the recognition of complex human activities and reviewed the features and classification methods used are discussed in Chapter 3 (e.g., Saguna et al., 2013; Liu et al., 2016; Vaka et al., 2015). Also in other domains, there are works which used the trajectory velocity as a feature for recognizing human activity and for other applications (e.g., Vatankhah et al., 2016; Xu & Ding, 2017; Svinin et al., 2019).

1.3 Research Questions

To address the issues as stated in the previous section, the following research questions were formulated:

(a) What are the current methods used to recognize the complex activities with smartphone sensors?

(b) What is a possible method to increase the recognition accuracy of complex human activities with smartphone sensors?

(c) What is a possible method to minimize usages of smartphone resources during complex activity recognition?

(d) How do we evaluate the proposed method?

1.4 Research Objectives

This research proposes to increase the quality of the extracted feature so as to increase recognition accuracy with less resource consumption. It proposes extracting the wrist velocity feature which contains the task oriented property. The goal of this research is to develop an extraction method for wrist velocity feature. Then, the extracted feature is applied with other techniques to recognize complex human activities in order to improve recognition accuracy and reduce resource consumption. Thus, the research objectives that guide this study are:

(a) To identify the current methods used for recognizing complex human activities using smartphone sensors.

(b) To develop an extracting method for the task oriented wrist velocity feature.

(c) To propose a recognition system for complex human activities by using the extracted wrist velocity feature.

(d) To evaluate the proposed system in terms of recognition accuracy and resource consumption.

1.5 Contributions

In this study, to address the issues of low recognition accuracy and high resource consumption in recognizing complex human activities using smartphone sensors, the following contributions can be achieved from the results obtained:

(a) Developing an extracting method for task oriented wrist velocity feature from integrated smartphone sensors. This task oriented feature was inspired by the principles and rules that control body movements from a neurophysiological perspective. Those rules are used by the Central Nervous System (CNS) to coordinate different body parts. The extracted feature is strongly affected by the perfomed activity, hence reducing false positive errors. On the other hand, it is less affected by the same activity when perfomed by different subjects, hence reducing false negative errors. Reducing those errors helps to increase recognition accuracy. Extracting the wrist velocity feature is fundamental to this research. The result of experiments showed that wrist velocity feature is sufficient to differentiate between the activities. For example, both the Coffee time and Sandwich time activities share similar arm movements when reaching for items (e.g., the bread, cheese, tea, or cupboard) and moving the hand near the mouth to sip coffee or eat sandwich. But from the results of experiments using wrist velocity, there is no confusion between them.

(b) Proposing a recognition system for complex human activities by applying the extracted task oriented feature with other techniques. The system is called Complex Activity Recognizer through Wrist Velocity (CARWV) system. To the best of our knowledge, for the first time the CARWV synthesized different techniques targeted to reduce the composition and variation of complex human activities. The CARWV contributes further to our understanding regarding the effect of reducing these two factors i.e. the composition and variation of complex human activities in addressing the issues of low recognition accuracy and high resource consumption. The CARWV yields superior results in improving recognition accuracy with less resource consumption which addresses the main issue in this research. The system consists of three layers namely the sensory layer, low level activity recognition layer, and high level activity recognition layer. It was built by the MATLAB software. To reduce the composition of the activities and increase recognition accuracy, our system breaks up the complex activity into tasks which are represented by basic arm movements. Wrist velocity feature is extracted from basic arm movements to address the second issue of suggesting the right feature to describe simple activities while reducing the effect of variation. Then, the extracted feature is used to recognize the basic arm movements by decision dree classifier. After that, the exist (histogram) and order (transition matrix) of recognized basic arm movements are used as features to recognize the related complex activity by measuring the similarity using distance metric. Using the histogram and transition matrix to recognize the complex activities allows us to identify the different ways and variations that those basic movements are combined to produce the complex activity which addresses the third issue in this research.

(c) A dataset was collected to evaluate the CARWV system against other state-of-the-art activity recognition systemes. We collected data from 20 subjects performing three complex human activities. Additionally, we evaluated the dataset to recognize the complex human activities with another public dataset i.e. the opportunity dataset. In these two datasets, we conducted a series of experiments that were simulated on a personal computer with an Intel i7-7700K CPU and 8GM RAM capacity.

(d) Establishing the superiority of the evaluation results of the CARWV in addressing the issues of low recognition accuracy and high resource consumption of complex human activities recognition. The proposed method (CARWV) was practically implemented and evaluated with other benchmarks. It obtained a recognition accuracy of 86% with a 13-second execution time and 31264 kb memory allocation. The results indicate the superiority of the CARWV in recognizing complex human activities with low computing cost compared to other state-of-the-art works.

1.6 Scope of the Study

In order to achieve the study objectives, the scope of the reseach was itemized as follows:

(a) The accelerometer and gyroscope of smartphones were used for activity sensing. The activity sensing could either be vision or ambient sensors as used in other works.

(b) While most of the works in human activity recognition had focused on recognizing simple human activities such as running, walking, and jumping, this research addressed the recognition of complex human activities. It investigated the recognition of single user complex physical human activities in two datasets i.e. our own dataset and the Opportunity public dataset and their related set of basic arm movements. Our own dataset contains subjects that perform three complex activities i.e. preparing breakfast, preparing tea, and preparing a sandwich. Meanwhile, the Opportunity dataset involves four complex activities i.e. early morning moving, coffee time, sandwich time, and cleanup.

(c) The complexity of human activity has different dimensions. The research examined two dimensions i.e. the composition and variations of human activity. These two factors could confuse the recognition methods which were trained in specific patterns and order and thereby leading to recognition error and reduction of recognition accuracy performance of the recognition systems.

(d) Different factors influence the performance of the recognition systems of complex human activities which are collected using smartphone sensors. This research proposes to increase the quality of extracted features in order to improve the performance.

(e) The formulated method was evaluated by recognition accuracy, F1 measure, execution time, and allocation memory criteria. Other performance measurements were also used for different purposes.

1.7 Significance of the Study

The outcomes of this research would greatly contribute to the application of human activity recognition. The significance of this research are:

(a) Recognition of complex activities using smartphones sensors which provides continuous health and medical data about the user's real life activities so as to give a better picture of his fitness levels and diagnosis of diseases that need longer periods of examination. This will improve the medical emergency response for people who suffer from critical conditions such as Parkinson's Disorder.

(b) Improvement of the performance recognition of complex activities that leads to the exploration of extensive studies in human-robot interaction, human computer interfaces, and smart homes. For example, inferring the robot to human activities will help the robot to coordinate the actions of search and rescue operations with the human rescue team. In addition, recognition of real life activities helps to improve the user's experience by customizing the device or place's behavior depending on user status i.e. when he is outdoors, at the workplace, or at home.

(c) Figuring out a lightweight method for recognizing human activities will help other devices that have limited energy resource such as wireless sensor networks (WSN) which have important military and security applications. Military-based applications could monitor soldier mobility in real-time for health status updates and training scenarios. Military sensing can include crawling, kneeling, or situation assessments, which can be critical for military missions. Security fields may use real-time mobility tracking for personnel on foot and detect enemy intrusion.

1.8 Thesis Organization

This thesis is organized in six chapters as follows. The first chapter introduces the problem area and the research objectives that guide the study. In the second chapter, comprehensive reviews of literature on the system of recognizing complex human activities, comparison with other approches related to the proposed system for recognizing complex human activities as well as the limitations of the respective systemes are presented. In the third chapter, the operational framework that maps the objectives and the outcomes of the study are discussed. In addition, the methodological system concerning research data, research procedure and data analysis procedure are described and justified. In Chapter 4, the architecture of the proposed CARWV system is thoroughly explained along with discussions on the ways CARWV is used to recognize basic movements and complex activities and its key techniques and limitations. Chapter 5 addresses the results of the study which include discussions on the evaluation process of the CARWV system. These include explanations on the experiments conducted to evaluate the capability of the CARWV system in recognizing complex human activities using smartphone sensors, experiments that compare the performance (i.e. recognition accuracy and F1 measure) and computational cost (i.e. total execution time and allocation memory) of our system with three state-of-the-art works. In addition, explanations on experiments conducted to test the effects of sensor modularity and window sizes in the recognition of complex activities using the CARWV are also presented in the chapter. Finally, Chapter 6 highlights the contributions of this study and concludes the study.

1.9 Chapter Summary

This chapter focused on the identification and statement of problems as well specifications of the research scope. The objectives and the signficance of the research were also presented. The next chapter focuses on the review of literature that relates to studies on HAR and complex activity recognition using smartphone sensors.

REFERENCES

Abdallah, Z. S., Gaber, M. M., Srinivasan, B., & Krishnaswamy, S. (2015) 'Adaptive mobile activity recognition system with evolving data streams', *Neurocomputing*, 150, 304-317.

Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., & Steggles, P. (1999) Towards a better understanding of context and context-awareness. *International symposium on handheld and ubiquitous computing*. September. Berlin, Heidelberg: Springer. 304-307.

Admiraal, M. A., Kusters, M. J., & Gielen, S. C. (2004) 'Modeling kinematics and dynamics of human arm movements', *Motor Control*, 8(3), 312-338.

Aggarwal, J. K., & Ryoo, M. S. (2011). Human activity analysis: A review. ACM Computing Surveys (CSUR), 43(3), 1-43.

Akhavian, R., & Behzadan, A. H. (2018) 'Coupling human activity recognition and wearable sensors for data-driven construction simulation', *Journal of Information Technology in Construction (Itcon)*, 23(1), 1-15.

Bao, L., & Intille, S. S. (2004) Activity recognition from user-annotated acceleration data. *International Conference on Pervasive Computing*. April. Berlin, Heidelberg: Springer. 1-17

Benmansour, A., Bouchachia, A., & Feham, M. (2015) Human activity recognition in pervasive single resident smart homes: State of art. *Programming and Systems (ISPS), 2015 12th International Symposium*. April: IEEE. 1-9.

Bertomeu-Motos, A., Lledó, L., Díez, J., Catalan, J., Ezquerro, S., Badesa, F., & Garcia-Aracil, N. (2015) 'Estimation of human arm joints using two wireless sensors in robotic rehabilitation tasks', *Sensors*, 15(12), 30571-30583.

Bharti, P., De, D., Chellappan, S., & Das, S. K. (2018) 'HuMAn: complex activity recognition with multi-modal multi-positional body sensing', *IEEE Transactions on Mobile Computing*, 18(4), 857-870.

Blachon, D., Coşkun, D., & Portet, F. (2014) On-Line Context Aware Physical Activity Recognition from the Accelerometer and Audio Sensors of Smartphones. *European Conference on Ambient Intelligence*. November. Springer International Publishing. 205-220.

Bravo, J., Alamán, X., & Riesgo, T. (2006) 'Ubiquitous computing and ambient intelligence: New challenges for computing', *Journal of Universal Computer Science*.

Bugdol, M. D., Mitas, A. W., Grzegorzek, M., Meyer, R., & Wilhelm, C. (2016) Human Activity Recognition Using Smartphone Sensors. *Information Technologies in Medicine*. Springer International Publishing. 41-47.

Bulling, A., Blanke, U., & Schiele, B. (2014) 'A tutorial on human activity recognition using body-worn inertial sensors', *ACM Computing Surveys (CSUR)*, 46(3), 33.

Cha, S. H. (2007). Comprehensive survey on distance/similarity measures between probability density functions. City, 1(2), 1.

Chavarriaga, R., Sagha, H., Calatroni, A., Digumarti, S. T., Tröster, G., Millán, J. D. R., & Roggen, D. (2013) 'The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition', *Pattern Recognition Letters*, 34(15), 2033-2042.

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.

Concone, F., Re, G. L., & Morana, M. (2019) 'A Fog-Based Application for Human Activity Recognition Using Personal Smart Devices', *ACM Transactions on Internet Technology (TOIT)*, 19(2), 20.

Cruz, S. B. (2019). Mobile sensing towards context awareness. Tech. Rep. Accessed: Jan. 10, 2019.[Online]. Available: https://web.fe.up.pt/~dee10014/documents/individual_topics.pdf

Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. (2012) Simple and complex activity recognition through smart phones. *Intelligent Environments (IE), 2012 8th International Conference*. June. IEEE. 214-221.

Dhillon, J. K., & Kushwaha, A. K. S. (2017,) A recent survey for human activity recognition based on deep learning system. *2017 fourth international conference on image information processing (ICIIP)*. December. IEEE. 1-6.

Fang, C., Ding, X., Zhou, C., & Tsagarakis, N. (2019) 'A2ML: A general human-inspired motion language for anthropomorphic arms based on movement primitives', *Robotics and Autonomous Systems*, 111, 145-161.

Filios, G., Nikoletseas, S., Pavlopoulou, C., Rapti, M., & Ziegler, S. (2015) Hierarchical algorithm for daily activity recognition via smartphone sensors. *Internet of Things (WF-IoT), 2015 IEEE 2nd World Forum*. December. IEEE. 381-386.

Gagniuc, P. A. (2017) *Markov chains: from theory to implementation and experimentation*. John Wiley & Sons.

Garcia-Ceja, E., & Brena, R. (2013) 'Long-term activity recognition from accelerometer data', *Procedia Technology*, 7, 248-256.

Garcia-Ceja, E., Brena, R. F., Carrasco-Jimenez, J. C., & Garrido, L. (2014) 'Long-term activity recognition from wristwatch accelerometer data', *Sensors*, 14(12), 22500-22524.

Głowiński, S., Krzyżyński, T., Pecolt, S., & Maciejewski, I. (2015) 'Design of motion trajectory of an arm exoskeleton', *Archive of Applied Mechanics*, 85(1), 75-87.

Hasan, S. M. S., Masnad, M., Khan, M. M., Mahmud, H., & Hasan, M. K. 'Human Activity Recognition using Smartphone Sensors with Context Filtering'.

Incel, O. D., Kose, M., & Ersoy, C. (2013) 'A review and taxonomy of activity recognition on mobile phones', *BioNanoScience*, 3(2), 145-171.

Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. IEEE Transactions on pattern analysis and machine intelligence, 22(1), 4-37.

Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009) 'Systematic literature reviews in software engineering–a systematic literature review', *Information and software technology*, 51(1), 7-15.

Knudson, D. (2007). Fundamentals of biomechanics. Springer Science & Business Media.

Krishnan, R., Björsell, N., Gutierrez-Farewik, E. M., & Smith, C. (2019) 'A survey of human shoulder functional kinematic representations', *Medical & biological engineering & computing*, 57(2), 339-367.

Lee, Y. S., & Cho, S. B. (2011) Activity recognition using hierarchical hidden markov models on a smartphone with 3D accelerometer. *International Conference on Hybrid Artificial Intelligence Systems*. May. Berlin, Heidelberg: Springer. 460-467.

Lester, J., Choudhury, T., & Borriello, G. (2006) A practical system to recognizing physical activities. *International conference on pervasive computing*. May. Berlin, Heidelberg: Springer. 1-16.

Li, C., & Yung, N. H. (2016) 'Arm Poses Modeling for Pedestrians with Motion Prior', *Journal of Signal Processing Systems*, 84(2), 237-249.

Liu, K., Xiong, C. H., He, L., Chen, W. B., & Huang, X. L. (2018) 'Postural synergy based design of exoskeleton robot replicating human arm reaching movements', *Robotics and Autonomous Systems*, 99, 84-96.

Liu, L., Peng, Y., Liu, M., & Huang, Z. (2015) 'Sensor-based human activity recognition system with a multilayered model using time series shapelets', *Knowledge-Based Systems*, 90, 138-152.

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, 41-57.

Lockhart, J. W., Pulickal, T., & Weiss, G. M. (2012) Applications of mobile activity recognition. *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. September. ACM. 1054-1058.

Lukowicz, P., Pirkl, G., Bannach, D., Wagner, F., Calatroni, A., Förster, K., ... & Doppler, J. (2010) Recording a complex, multi modal activity data set for context recognition. *Architecture of Computing Systems (ARCS), 2010 23rd International Conference*. February. VDE. 1-6.

Mannini, A., & Sabatini, A. M. (2010) ‘Machine learning methods for classifying human physical activity from on-body accelerometers’, *Sensors*, 10(2), 1154-1175.

Mantyjarvi, J., Himberg, J., & Seppanen, T. (2001, October). Recognizing human motion with multiple acceleration sensors. In 2001 ieee international conference on systems, man and cybernetics. e-systems and e-man for cybernetics in cyberspace (cat. no. 01ch37236) (Vol. 2, pp. 747-752). IEEE.

Messing, R., Pal, C., & Kautz, H. (2009, September). Activity recognition using the velocity histories of tracked keypoints. In 2009 IEEE 12th international conference on computer vision (pp. 104-111). IEEE.

Minnen, D., Westeyn, T., Starner, T., Ward, J., & Lukowicz, P. (2006) ‘Performance metrics and evaluation issues for continuous activity recognition’, *Performance Metrics for Intelligent Systems*, 4.

Mobark, M., Chuprat, S., Sarkan, H., Mahrin, M. N. R., Azmi, N. F. M., & Yahya, Y. (2018) ‘Recognition Of Complex Human Activity Using Mobile Phones: A Systematic Literature Review’, *Journal of Theoretical & Applied Information Technology*, 96(12).

Modayil, J., Bai, T., & Kautz, H. (2008, September). Improving the recognition of interleaved activities. In Proceedings of the 10th international conference on Ubiquitous computing (pp. 40-43).

Natasha, S. (2019, Jan 13). Importance of Distance Metrics in Machine Learning Modelling. Retrieved December 16, 2019, from < https://towardsdatascience.com/importance-of-distance-metrics-in-machine-learning-modelling-e51395ffe60d >

Nweke, H. F., Teh, Y. W., Al-Garadi, M. A., & Alo, U. R. (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, 233-261.

Nyan, M. N., Tay, F. E. H., Seah, K. H. W., & Sitoh, Y. Y. (2006). Classification of gait patterns in the time–frequency domain. Journal of biomechanics, 39(14), 2647-2656.

Ordóñez, F., & Roggen, D. (2016) ‘Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition’, *Sensors*, 16(1), 115.

Ortiz, J. L. R. (2015) *Smartphone-based human activity recognition*. Springer.

Pearson, K. (1895) ‘X. Contributions to the mathematical theory of evolution.—II. Skew variation in homogeneous material’, *Philosophical Transactions of the Royal Society of London.(A.)*, (186), 343-414

Peng, L., Chen, L., Wu, X., Guo, H., & Chen, G. (2016) ‘Hierarchical complex activity representation and recognition using topic model and classifier level fusion’, *IEEE Transactions on Biomedical Engineering*, 64(6), 1369-1379.

Prekop, P., & Burnett, M. (2003) ‘Activities, context and ubiquitous computing’, *Computer communications*, 26(11), 1168-1176.

Quinlan, J. R. (1986). Induction of decision trees. Machine learning, 1(1), 81-106.

Ramasamy Ramamurthy, S., & Roy, N. (2018) ‘Recent trends in machine learning for human activity recognition—A survey’, *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(4), e1254.

Reddy, S., Mun, M., Burke, J., Estrin, D., Hansen, M., & Srivastava, M. (2010) ‘Using mobile phones to determine transportation modes’, *ACM Transactions on Sensor Networks (TOSN)*, 6(2), 13.

Rishabh, J. (2017, Mar 21). Decision Tree. It begins here. Retrieved December 16, 2019, from <https://medium.com/@rishabhjain_22692/decision-trees-it-begins-here-93ff54ef134>

Rosati, S., Balestra, G., & Knaflitz, M. (2018) ‘Comparison of Different Sets of Features for Human Activity Recognition by Wearable Sensors’, *Sensors*, 18(12), 4189.

Roy, N., Misra, A., & Cook, D. (2016) ‘Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments’, *Journal of ambient intelligence and humanized computing*, 7(1), 1-19.

Saguna, S., Zaslavsky, A., & Chakraborty, D. (2013) ‘Complex activity recognition using context-driven activity theory and activity signatures’, *ACM Transactions on Computer-Human Interaction (TOCHI)*, 20(6), 32.

Sahyudi, B. N., Khairunizam, W., Majid, M. S. H., Vijayam, S., Mustafa, W. A., Zunaidi, I., & Desa, H. (2018) Investigation of upper limb movement for VR based post stroke rehabilitation device. *2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA)*. March. IEEE. 52-56.

San-Segundo, R., Blunck, H., Moreno-Pimentel, J., Stisen, A., & Gil-Martín, M. (2018). Robust Human Activity Recognition using smartwatches and smartphones. Engineering Applications of Artificial Intelligence, 72, 190-202.

Sargano, A., Angelov, P., & Habib, Z. (2017) ‘A comprehensive review on handcrafted and learning-based action representation systemes for human activity recognition’, *Applied sciences*, 7(1), 110.

Schütz, C., & Schack, T. (2013). Motor primitives of pointing movements in a three-dimensional workspace. Experimental brain research, 227(3), 355-365.

Sefik, I. S. (2018, August 27). A Step by Step CART Decision Tree Example. Retrieved December 16, 2019, from <https://sefiks.com/2018/08/27/a-step-by-step-cart-decision-tree-example/>

Sekine, M., Tamura, T., Akay, M., Togawa, T., & Fukui, Y. (2000). Analysis of acceleration signals using wavelet transform. Methods of information in medicine, 39(02), 183-185.

Shoaib, M., Bosch, S., Incel, O. D., Scholten, H., & Havinga, P. J. (2015) 'A survey of online activity recognition using mobile phones', *Sensors*, 15(1), 2059-2085.

Su, X., Tong, H., & Ji, P. (2014) 'Activity recognition with smartphone sensors', *Tsinghua Science and Technology*, 19(3), 235-249.

Suarez, I., Jahn, A., Anderson, C., & David, K. (2015) Improved activity recognition by using enriched acceleration data. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. September. ACM. 1011-1015.

Sukor, A. S. A., Zakaria, A., Rahim, N. A., Kamarudin, L. M., Setchi, R., & Nishizaki, H. (2019). A hybrid system of knowledge-driven and data-driven reasoning for activity recognition in smart homes. Journal of Intelligent & Fuzzy Systems, 36(5), 4177-4188.

Suto, J., & Oniga, S. (2018) 'Efficiency investigation of artificial neural networks in human activity recognition', *Journal of Ambient Intelligence and Humanized Computing*, 9(4), 1049-1060.

Svinin, M., Goncharenko, I., Kryssanov, V., & Magid, E. (2019) 'Motion planning strategies in human control of non-rigid objects with internal degrees of freedom', *Human movement science*, 63, 209-230.

Taniai, Y., & Nishii, J. (2015) 'Optimality of upper-arm reaching trajectories based on the expected value of the metabolic energy cost', *Neural Computation*, 27(8), 1721-1737.

Theodoridis, S. (2020). Machine learning: a Bayesian and optimization perspective. Academic press.

Ustev, Y. E., Durmaz Incel, O., & Ersoy, C. (2013) User, device and orientation independent human activity recognition on mobile phones: Challenges and a proposal. *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*. September. ACM. 1427-1436.

Vaka, P., Shen, F., Chandrashekar, M., & Lee, Y. (2015) PEMAR: A pervasive middleware for activity recognition with smart phones. *Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference*. March .IEEE. 409-414.

Vatankhah, R., Broushaki, M., & Alasty, A. (2016) 'Adaptive optimal multi-critic based neuro-fuzzy control of MIMO human musculoskeletal arm model', *Neurocomputing*, 173, 1529-1537.

Wan, J., O'grady, M. J., & O'hare, G. M. (2015) 'Dynamic sensor event segmentation for real-time activity recognition in a smart home context', *Personal and Ubiquitous Computing*, 19(2), 287-301.

Wang, Z., & Chen, Y. (2017) 'Recognizing human concurrent activities using wearable sensors: a statistical modeling system based on parallel HMM', *Sensor Review*, 37(3), 330-337.

Webb, A. R. (2003) *Statistical pattern recognition*. John Wiley & Sons.

Weiser, M. (1991) 'The Computer for the Twenty-First Century Scientific American', *September Elsevier Ltd*.

Wilde, A. G. (2010) 'An overview of human activity detection technologies for pervasive systems', *Department of Informatics University of Fribourg, Switzerland, 212*.

Wu, W., Dasgupta, S., Ramirez, E. E., Peterson, C., & Norman, G. J. (2012) 'Classification accuracies of physical activities using smartphone motion sensors', *Journal of medical Internet research*, 14(5), e130.

Xu, H., & Ding, X. (2017) 'Human-Like Motion Planning for a 4-DOF Anthropomorphic Arm Based on Arm's Inherent Characteristics', *International Journal of Humanoid Robotics*, 14(04), 1750005.

Yang, Y., Hou, C., Lang, Y., Guan, D., Huang, D., & Xu, J. (2019) 'Open-set human activity recognition based on micro-Doppler signatures', *Pattern Recognition*, 85, 60-69.

Yang, Z., Raymond, O. I., Zhang, C., Wan, Y., & Long, J. (2018) 'DFTerNet: Towards 2-bit Dynamic Fusion Networks for Accurate Human Activity Recognition', *IEEE Access*, 6, 56750-56764.

Ye, L., & Keogh, E. (2009) Time series shapelets: a new primitive for data mining. *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*. June. ACM. 947-956.

Yuan, G., Wang, Z., Meng, F., Yan, Q., & Xia, S. (2019). An overview of human activity recognition based on smartphone. Sensor Review.

Yurur, O., Liu, C. H., & Moreno, W. (2014) 'A survey of context-aware middleware designs for human activity recognition', *IEEE Communications Magazine*, 52(6), 24-31.

Zainudin, M. S., Sulaiman, M. N., 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.

Zhan, Y., & Kuroda, T. (2014) 'Wearable sensor-based human activity recognition from environmental background sounds', *Journal of Ambient Intelligence and Humanized Computing*, 5(1), 77-89.

APPENDIX A

LIST OF PUBLICATIONS

From the material in this thesis there are, at the time of submission, papers which have been published, or submitted for publication as following:

Papers Published

Mobark, M., Chuprat, S., Sarkan, H., Mahrin, M. N. R., Azmi, N. F. M., & Yahya, Y. (2018) 'Recognition of complex human activity using smartphones: a systematic literature review', *Journal of Theoretical & Applied Information Technology*, 96(12).

Mobark, M., Chuprat, S., & Mantoro, T. (2017) Improving the accuracy of complex activities recognition using accelerometer-embedded smartphone classifiers. *2017 Second International Conference on Informatics and Computing (ICIC).* November. IEEE. 1-5.

Mobark, M., Chuprat, S., Mantoro, T., & Azizan, A. (2017) 'Utilization of Smartphone Sensors for Complex Human Activity Recognition', *Advanced Science Letters,* 23(6), 5466-5471.