



**METHODS AND TECHNIQUES FOR HUMAN
ACTIVITY RECOGNITION USING INERTIAL
MOTION PRIMITIVES**

By

Ayman Mohamed AboElMaaty Mohamed AboElHassan

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Computer Engineering

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2017

**METHODS AND TECHNIQUES FOR HUMAN
ACTIVITY RECOGNITION USING INERTIAL
MOTION PRIMITIVES**

By

Ayman Mohamed AboElMaaty Mohamed AboElHassan

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Computer Engineering

Under the Supervision of

Assoc. Prof. Dr. **Amr Wassal**

Associate Professor
Computer Engineering
Faculty of Engineering, Cairo University

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2017

**METHODS AND TECHNIQUES FOR HUMAN
ACTIVITY RECOGNITION USING INERTIAL
MOTION PRIMITIVES**

By

Ayman Mohamed AboElMaaty Mohamed AboElHassan

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Computer Engineering

Approved by the Examining Committee:

Assoc. Prof. Dr. **Amr Wassal**,

Thesis Main Advisor

Prof. Dr. **ElSayed Hemayed**,

Internal Examiner

Prof. Dr. **Mohamed Zaki Abdelmaged**,
- Faculty of Engineering, Al-Azhar University

External Examiner

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
2017

Engineer's Name: Ayman Mohamed AboElMaaty
Mohamed AboElHassan
Date of Birth: 17/2/1992
Nationality: Egyptian
E-mail: Ayman.abo.elmaaty@eng.cu.edu.eg
Phone: +201091222727
Address: 108 El-Shaheed Ahmed Hamdy St.,
Madkoor, Faisal, Bolak Ad-Dakror,
Gizah, Egypt
Registration Date: 1 / 10 / 2014
Awarding Date: 2017
Degree: Master of Science
Department: Computer Engineering



Supervisors:
Assoc. Prof. Dr. **Amr Wassal**

Examiners:
Prof. **Mohamed Zaki Abdelmaged** (External Examiner)
- Faculty of Engineering, Al-Azhar University
Prof. **ElSayed Hemayed** (Internal Examiner)
Assoc. Prof. Dr. **Amr Wassal** (Thesis main advisor)

Title of Thesis:
Methods and Techniques for Human Activity Recognition Using Inertial
Motion Primitives

Key Words:
Learning by Demonstration; Human Activity Recognition; Online Classification;
Time-series Clustering; Hidden Markov Model

Summary:
In this thesis, we propose an inertial HAR system to recognize complex human activities using motion primitives. Inertial sensor readings are segmented into set of finite motion primitives, then recognized motion primitives are used to classify the complex activity. Complex activities are classified using 2-level hierarchical HMM classifier. We introduce a motion primitive generation algorithm that extracts most distinct time-series segments from a set of complex activities. We also apply three different features selection approaches to reduce the processing time. SBHAR and PAMAP2 public datasets are used to evaluate the system's performance, where we show that our approach achieves 93.77% and 86.84% accuracies respectively. A comparison with related researches which used the same datasets is conducted to compare our results regarding methodology, features, accuracy, time complexity and classification rate.

Acknowledgements

Firstly, I would like to thank my supervisor Dr. Amr G. Wassal for his continuous support through the course of my academic career. Our discussions have been really helpful and generated lots of creative ideas in order to achieve the research objectives.

Secondly, I want to thank Asmaa Rabie for her help and insights. Despite that we were a small research group, I couldn't have reached this level without her help. Moreover, I would like to thank my department and all its members whom have been very supportive and welcoming. They made me feel like they are my second family.

I also want to express my gratitude to my close friends: A. Ahmed, A. Nasr, Islam, M. Azab, M. Badry, M. Daif, M. Kamhawy, M. Sadek, M. Sedik, M. Shokr and Tarek whom have been always backing me up. Finally and most importantly, I want to thank my family: my father, my mother, and my brother. They have overwhelmed me with their unconditional love and support that gave me the strength and will to continue in my career.

Table of Contents

Acknowledgements	i
List of Tables	vi
List of Figures	vii
List of Symbols and Abbreviations	ix
Abstract	xi
1 Introduction	1
1.1 Learning by Demonstration	1
1.1.1 Learning by Example	1
1.1.2 Imitation	2
1.1.3 Demonstration Techniques	2
1.2 Human Activity Recognition	2
1.2.1 Human Activities	2
1.2.2 Inertial HAR	3
1.3 Motion Primitives	3
1.4 Motivation	4
1.5 Main Contribution	4
1.6 Thesis Outline	5
2 Background	6
2.1 Activity Sensing	6
2.1.1 External Sensors	6
2.1.2 Wearable Sensors	6
2.1.3 Smart-phones as Wearable Sensors	7
2.2 Machine Learning	7
2.2.1 Taxonomy of ML Approaches	7
2.2.1.1 Supervised Learning	7
2.2.1.2 Unsupervised Learning	7
2.2.1.3 Semi-Supervised Learning	8
2.2.1.4 Reinforcement Learning	8
2.2.2 ML Approaches	8
2.2.2.1 Decision Tree	8
2.2.2.2 K-Nearest Neighbors	8
2.2.2.3 Naive Bayes	8
2.2.2.4 Ensemble Learning	9
2.2.2.5 Support Vector Machine	9
2.2.2.6 Artificial Neural Network	10
2.2.2.7 Deep Neural Network	10
2.2.2.8 Deep Convolutional Neural Network	10
2.2.2.9 Recurrent Neural Network	10

2.3	Hidden Markov Model	11
2.3.1	Markov Model	11
2.3.2	Markov Chain	11
2.3.3	Hidden States	12
2.3.4	Learning	12
2.3.5	Filtering and Decoding	13
2.3.5.1	Filtering	13
2.3.5.2	Decoding	13
2.3.6	Types of HMM	13
2.3.6.1	Continuous HMM	14
2.3.6.2	Discrete HMM	14
2.3.7	HMM Extensions	14
2.3.7.1	Hierarchical HMM	14
2.3.7.2	Layered HMM	14
2.4	Performance Evaluation	14
2.4.1	Evaluation Metrics	15
2.4.1.1	Accuracy	15
2.4.1.2	Precision	15
2.4.1.3	Recall	15
2.4.1.4	F1 score	15
2.4.1.5	Multi-class Evaluation	16
2.4.2	Other System Aspects	16
2.5	Summary	16
3	Literature Survey	17
3.1	Datasets Description	17
3.1.1	Smartphone-based HAR Dataset	17
3.1.2	Physical Activity Monitoring for Aging People Dataset	17
3.2	Classification Techniques	18
3.2.1	k-NN Classifiers	19
3.2.2	AdaBoost Classifiers	19
3.2.3	SVM Classifiers	19
3.2.4	HMM Classifiers	20
3.2.5	DNN Classifiers	20
3.2.6	DCNN Classifiers	21
3.2.7	RNN Classifiers	21
3.2.8	SRC Classifiers	21
3.3	Feature Selection	22
3.3.1	Filter Approach	22
3.3.1.1	Manually Selected Features	22
3.3.1.2	Principal Component Analysis	22
3.3.1.3	Dynamic Time Warping	22
3.3.1.4	Other Approaches	23
3.3.2	Warper Approach	23
3.3.2.1	Incremental Approach	23
3.3.3	Hybrid Approach	23
3.3.3.1	RF then Incremental Approach	23

3.4	Summary	23
4	Methodology	24
4.1	Methodology Definition	24
4.2	Primitive Segmentation	24
4.2.1	Time-Series Clustering	24
4.2.2	Automatic Primitive Generation	24
4.2.3	Uniqueness Function	27
4.2.4	Parameter Configuration	27
4.3	Feature Selection	28
4.3.1	Manually Selected Features	28
4.3.2	Reducing Large Set of Features Using PCA	31
4.3.3	GA-based Feature Selection	31
4.3.3.1	Problem Representation	33
4.3.3.2	Fitness Function	33
4.3.3.3	(μ, λ) Selection	33
4.3.3.4	Crossover and Mutation Operations	33
4.4	Data Discretization	34
4.5	2-Level HMM Classifier	35
4.5.1	Online Classification	35
4.5.2	Problem Representation	36
4.5.2.1	Problem Definition	36
4.5.2.2	Motion Primitives	37
4.5.3	2-Level HMM Model	37
4.5.3.1	1st Level HMM	37
4.5.3.2	2nd Level HMM	39
4.5.3.3	Model Derivation	39
4.5.3.4	Forward-only Algorithm	40
4.5.4	Training Module	40
4.5.5	Classification Module	40
4.5.6	Complexity Analysis	43
4.6	Summary	43
5	Experimental Results	44
5.1	Experiment's Environment	44
5.2	Parameter Selection	44
5.3	Experimental Results	45
5.3.1	Experiment(1): Manually Selected Features Using Manually Se- lected Primitives	46
5.3.1.1	SBHAR Results	46
5.3.1.2	PAMAP2 Results	48
5.3.2	Experiment(2): Manually Selected Features Using APG	48
5.3.2.1	SBHAR Results	48
5.3.2.2	PAMAP2 Results	48
5.3.3	Experiment(3): Using Large Set of Features	51
5.3.4	Experiment(4): Reducing Large Set of Features Using PCA	51
5.3.5	Experiment(5): GA-based Feature Selection	53

5.3.6	Experiment(6): Train 5 activities only	54
5.4	Summary	55
6	Discussion	56
6.1	Primitive Segmentation	56
6.1.1	Time Complexity	56
6.1.2	Applicability	56
6.2	Feature Selection	56
6.2.1	Statistical Features (Mean, Gradient)	57
6.2.2	Feature Set Reduction	57
6.2.3	GA Performance	58
6.3	HAR System Performance	64
6.3.1	Accuracy Comparison	64
6.3.2	Time Complexity Comparison	64
6.4	Randomness	67
6.4.1	Discretization Randomness	67
6.4.2	APG Randomness	67
6.4.3	GA Randomness	67
6.5	Summary	67
7	Conclusion	68
7.1	Achievements	68
7.2	Future Work	69
7.2.1	Expanding Activity Set	69
7.2.2	Hybrid Sensing Approach	69
7.2.3	Motion Reconstruction	69
7.2.4	Localization	70
	References	71
	Appendix A Dataset Accelerometer Data	77

List of Tables

3.1	SBHAR Features Set	18
5.1	SBHAR Accuracies Given 6 Manual Features and Manual Primitives . . .	45
5.2	SBHAR Accuracies Given 6 Manual Features and APG Primitives	45
5.3	Number of Primitives Generated from SBHAR Dataset	45
5.6	SBHAR Accuracies Given 561 Manual Features and 30 APG Primitives with 10 PCA Components	45
5.4	SBHAR Accuracies Given 561 Manual Features and 39 APG Primitives .	46
5.5	SBHAR Accuracy Given 561 Manual Features and 30 APG Primitives . .	46
5.7	SBHAR Confusion Matrix for Experiment(1), Classification rate = 50Hz .	48
5.8	SBHAR Confusion Matrix for Experiment(2) using APG, Classification rate = 50Hz	48
5.9	PAMAP2 Confusion Matrix for Experiment(1)	50
5.10	PAMAP2 Confusion Matrix for Experiment(2)	50
5.11	SBHAR Confusion Matrix for Experiment(3) using 561 Features, Classifi- cation rate = 0.78Hz	51
5.12	SBHAR Confusion Matrix for Experiment(4) using 15 PCA, Classification rate = 0.78Hz	52
5.13	SBHAR Confusion Matrix for Experiment(4) using 30 PCA, Classification rate = 0.78Hz	53
5.14	SBHAR Confusion Matrix for Experiment(5) using GA, Classification rate = 0.78Hz	54
5.15	SBHAR Confusion Matrix for Experiment(6), Classification rate = 50Hz .	54
5.16	SBHAR Confusion Matrix for Experiment(6), Classification rate = 0.78Hz	54
5.17	SBHAR Experimental Results	55
6.1	PCA Components Variance Percentage	57
6.2	Time Complexity Legend	64
6.3	HAR System Performance Comparison	65
6.4	HAR System Time Complexity Comparison	66

List of Figures

4.1	Time-series clustering example	26
4.2	An example for segmentation of time-series sequence using a delimiter	27
4.3	Manual feature extraction procedure	29
4.4	Data processing and discretization	30
4.5	PCA-based 561 features reduction procedure	32
4.6	GMM clustering procedure	34
4.7	Online Classifier	35
4.8	Offline Classifier	36
4.9	2 Level HMM Sequence	37
4.10	1st level HMM for motion primitives	38
4.11	2nd level HMM for complex activities	38
4.12	2-level Hierarchical HMM Training	41
4.13	2-level Hierarchical HMM Classification	42
5.1	Precision and Recall of SBHAR Activities Experiment(1)	47
5.2	Precision and Recall of PAMAP2 Activities Experiment(1)	47
5.3	Precision and Recall of SBHAR Activities Experiment(2)	49
5.4	Precision and Recall of PAMAP2 Activities Experiment(2)	49
5.5	Precision and Recall of SBHAR Activities Experiment(3)	51
5.6	Precision and Recall of SBHAR Activities Experiment(4) using 15 PCA	52
5.7	Precision and Recall of SBHAR Activities Experiment(5)	53
6.1	Histogram of 1st PCA component coefficient	58
6.2	Histogram of 2nd PCA component coefficient	58
6.3	Histogram of 3rd PCA component coefficient	59
6.4	Histogram of 4th PCA component coefficient	59
6.5	Coefficient weights of each feature for 1st PCA component	60
6.6	Coefficient weights of each feature for 2nd PCA component	61
6.7	Coefficient weights of each feature for 3rd PCA component	62
6.8	Coefficient weights of each feature for 4th PCA component	63
A.1	SBHAR Accelerometer Walking Scheme	77
A.2	SBHAR Accelerometer Walking Upstairs Scheme	77
A.3	SBHAR Accelerometer Walking Downstairs Scheme	78
A.4	SBHAR Accelerometer Standing Scheme	78
A.5	SBHAR Accelerometer Sitting Scheme	79
A.6	PAMAP2 Accelerometer Laying Scheme	79
A.7	PAMAP2 Accelerometer Walking Scheme	80
A.8	PAMAP2 Accelerometer Nordic Walking Scheme	80
A.9	PAMAP2 Accelerometer Walking Upstairs Scheme	81
A.10	PAMAP2 Accelerometer Walking Downstairs Scheme	81
A.11	PAMAP2 Accelerometer Running Scheme	82
A.12	PAMAP2 Accelerometer Cycling Scheme	82
A.13	PAMAP2 Accelerometer Jumping Ropes Scheme	83

A.14 PAMAP2 Accelerometer Standing Scheme	83
A.15 PAMAP2 Accelerometer Sitting Scheme	84
A.16 PAMAP2 Accelerometer Laying Scheme	84

List of Symbols and Abbreviations

AdaBoost	Adaptive Boosting
AdaGrad	Adaptive Gradient
ANN	Artificial Neural Network
APG	Automatic Primitive Generation
B-BLSTM-RNN	binarized bidirectional Long Short-Term Memory RNN (LSTM-RNN)
CHMM	Continuous Hidden Markov Model
CQP	Constrained Quadratic Programming
DCNN	Deep Convolutional Neural Networks
DFT	Discrete Fourier Transform
DHMM	Discrete Hidden Markov Model
DNN	Deep Feed-Forward Neural Networks
DT	Decision Tree
DTW	Dynamic Time Warping
ECG	Electrocardiogram Sensor
EM	Expectation Maximization
EX-SMO	Extended Sequential Minimal Optimization
FFP	Feed-Forward Phase
FFT	Fast Fourier Transform
GA	Genetic Algorithms
GMM	Gaussian Mixture Model
GPS	Global Positioning System
HAR	Human Activity Recognition
HMM	Hidden Markov Model
IMU	Inertial-Measurement Unit
k-NN	K-Nearest Neighbors
L1-Norm	Manhattan Distance Norm

L2-Norm	Euclidean Norm
LbD	Learning by Demonstration
LbE	Learning by Example
LSTM-RNN	Long Short-Term Memory RNN
MC-LSVM	Multi-Class Linear Support Vector Machine (SVM)
ML	Machine Learning
MLP-NN	Multi-Layer Perceptron Neural Network
PAMAP2	Physical Activity Monitoring for Aging People
PCA	Principal Components Analysis
PDF	Probability Density Function
ReLU	Rectified-Linear Unit
RF	Random Forest
RMSprop	Root Mean Square Propagation
RNN	Recurrent Neural Network
SBHAR	Smartphone-based HAR
SGD	Stochastic Gradient Descent
SRC	Sparse Representation Classifier
SVD	Singular Value Decomposition
SVM	Support Vector Machine

Abstract

Learning by Demonstration (LbD) first appeared in computer engineering in 1980s. LbD gained much of interest in robotics, due to the complexity of designing and developing a robot program to perform a specific task. LbD paradigm is to create robotic framework that is capable of learning to perform a specific behavior by recording an instructors performance and repeating it. In this thesis, we propose the implementation of motion recognition, the first part of LbD paradigm. Where we build an inertial Human Activity Recognition (HAR) system to recognize complex human activities using motion primitives.

HAR goal is to recognize the activities and behaviors performed by the user given the environment and user's sensed attributes. HAR applications increased in the past decades, in order to improve the human's quality of life. However, inertial research flourished in the last few years due to the technological improvement in sensors industry. Inertial HAR approaches use IMU to capture linear and angular accelerations at certain points as chest, waist, hand and foot.

In this thesis, we investigate the capabilities of Hidden Markov Model (HMM) as a learning model to capture inertial motion sequences with high accuracy. HMM has the capability to capture time series data as in speech recognition, and has a low cost in terms of time and memory complexity. In our approach, 2-level hierarchical HMM classifier is developed to recognize the required complex activities. Inertial sensor readings are segmented into set of finite motion primitives, then recognized motion primitives are used to classify the complex activity.

We also introduce a motion primitive generation algorithm that extracts most distinct time-series segments from a set of complex activities using Pearson correlation. Where, primitive set should be unique and atomic to be differentiable from each other. Additionally, they should represent almost all atomic motions that defines the complex motion set.

We applied three different features selection approaches to reduce the processing time. SBHAR and PAMAP2 public datasets are used to evaluate the system's performance, where we show that our approach achieves 93.77% and 86.84% accuracies respectively. A comparison with related researches which used the same datasets is conducted to compare our results regarding methodology, features, accuracy, time complexity and classification rate.