



Faculty of Engineering

## **Lower Limb Gait Activity Recognition**

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**MECHANICAL ENGINEERING**

By

**Mohammed Mahmoud Hamdy**

B.Sc. Mechanical Engineering

Ain Shams University

Supervisors:

**Prof. Farid Abdel Aziz Tolbah**

**Prof. Magdy Mohammed Abdelhameed**

**Dr. Mohammed Ibrahim Awad**

### **Statement**

This thesis is submitted in the requirement for master degree in Mechanical Engineering to Ain Shams University.

The author carried out the work included in this thesis, and no part of this thesis has been submitted for a degree or qualification at any other university.

Signature

Mohammed Mahmoud Hamdy

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## Abstract

Lower limb activity recognition, recently, has shown large demand in health care and rehabilitation fields. Wearable activity recognition system has the ability to monitor patients' activities, especially those need to be followed up such as people suffering from traumatic brain injuries. Furthermore, home-based self rehabilitation can be provided for disabled people using assistive systems where activity recognition plays an essential role.

However, sensor data acquisition and preprocessing, data segmentation, feature extraction and selection, training and classification are considered as the research challenges that face any lower limb recognition system. Although the sensor data acquisition step affects the prediction performance, only few studies dealt with the sensors positioning challenge. In this research work, the author targets to determine the lower limb segments with the highest contribution to the activity recognition process.

The 3-D kinematics and orientation profile of the lower limb segments are acquired using a sensor network of four Inertial Measurement Units (IMU) spread over the lower limb segments of one leg. Time (statistical) and time-frequency (wavelet components) features are extracted from the segments motion profile (kinematics and orientation). Those features are used in the proposed algorithm for sensor localization, which depends on determining the sensors of the most discriminative features selected by a filter type feature selector. Most of the discriminative features are found to be extracted from the sensors fixed on the thigh segment followed by the foot sensors.

The results are validated by using random forest classifier for lower limb activity recognition. The validation process supported the results that the thigh kinematics and orientation data are sufficient to recognize the lower limb activities. The overall recognition accuracy using thigh sensor only is 95.7%, while 97% if both thigh and foot sensors are used, in other words the accuracy decreased by 2.3% and 1%, respectively, compared to the accuracy using the four IMU sensors. To overcome the reduction in the accuracy rate several amendments to the extracted features and classification techniques are suggested.

## Keywords

Motion Capturing system, IMU sensor network, Mutual Information Features selector, Random forest, Multi-layer classifier

## Summary

The number and location of the Inertial Measurement Units (IMU) used in the motion capturing system for the lower limb activity recognition plays a vital role in the recognition performance and the computational time. Searching for the lower limb segments that contains the most discriminable information about the different activities (walking, stair ascending, stairs descending, ramp ascending, ramp descending) helps in increasing the sampling frequency and reducing the time needed for signal conditioning and processing due to the reduction in the gathered data by eliminating the redundant and non relevant signals before proceeding to the feature stage. Consequently, removing the non-relevant data reduces the over fitting problem that may affect the classifiers, while training, which is a main reason for accuracy reduction. However, this shows the importance of localizing the IMU sensors. Finally, at the end of the thesis, Physical features are suggested to improve the recognition system accuracy, in addition to, presenting multi layer classifier technique.

Chapter 1 introduces the thesis objectives and layout, which could be concluded in optimizing the IMU sensor network for motion capturing by eliminating the sensors that captures non-relevant or redundant data without affecting the activity recognition process. This objective has been successfully achieved in the following six chapters.

Chapter 2 presents an overview of the lower limb activity recognition stages and the previous research efforts done within each stage in order to improve the prediction accuracy for the activities, by emphasizing on the motion capture techniques used for these systems and specially the design of the systems depending on inertial sensors.

Chapter 3 illustrates the implementation details of the full set of the IMU sensor network (motion capture system), that will be modified in the following chapter, reaching to the most important sensors and locations in this system.

Chapter 4 shows the procedure followed in this work in order to elect the best sensor location for lower limb activity recognition systems.

Chapter 5 presents the recognition system that validates the election hypothesis resulted from the procedure shown in the previous chapter. Furthermore, this chapter

discusses the modification that could be done on the same recognition system in order to recover the decrement in the recognition accuracy due to the reduction in the number of the sensors in the IMU sensor network.

Chapter 6 is the results and discussion chapter, which shows the output of the chapter 4 procedure that results the best sensor's location hypothesis. Moreover, it illustrates the effect of using the hypothesis on the validation recognition system presented in chapter 5.

Based on this work, some recommendations and future research have been introduced in chapter 7.

# Table of content

Acknowledgement .....	III
Abstract .....	IV
Summary .....	VI
Table of content .....	VIII
List of Figures .....	XI
List of Tables .....	XV
Chapter 1      Introduction .....	1
1.1 Motivation.....	1
1.2 Objectives.....	2
1.3 Thesis Overview.....	2
Chapter 2      Background .....	4
2.1 Normal Human gait Activities' biomechanics.....	4
2.2 Activity Recognition Systems.....	11
2.2.1 Motion Capture Systems and Data Acquisition....	13
2.2.2 Feature extraction, selection and classification....	14
2.2.3 Gap of Knowledge.....	16
Chapter 3      IMU Sensor Network (Experimental Setup).....	17
3.1 Inertial Measurement Unit Instruments... ..	17
3.2 Gyroscope....	19
3.3 Network's Hardware and Outputs... ..	20

3.3.1 IMU & FSR Sensory Network.....	21
3.3.2 Sensor data.....	22
3.3.3 On-body Calibration.....	25
3.3.4 Orientation Estimation using Kalman Filter.....	25
3.3.5 Lower Limbs Inclination and Joints Angle Estimation.....	26
3.4 Gait Segmentation.....	27
3.5 Motion Profile.....	28
3.6 Data Acquiring.....	28
3.7 Data Evaluation.....	30
Chapter 4 Sensor Election (Methodology) .....	32
4.1 Introduction.....	32
4.2 Feature Extraction.....	32
4.2.1 Time Features.....	33
4.2.2 Frequency Features (Fourier Transform).....	33
4.2.3 Time-frequency Features (Discrete Wavelet Components).....	34
4.3 Feature Evaluation and Selection.....	35
4.3.1 Evaluation Methods.....	35
4.3.2 Selection Methods.....	40
4.4 Election Hypothesis System.....	43
Chapter 5 Hypothesis Validation.....	44
5.1 Introduction.....	44
5.2 Classifier.....	44

5.2.1	Support Vector Machine (SVM)...	45
5.2.2	Artificial Neural Network (ANN)...	46
5.2.3	Decision Tree (DT).....	48
5.2.4	Random Forest (Boot Strapping).....	51
5.2.5	Classifiers comparison and selection.....	53
5.3	Feature selector (Hybrid mutual information and genetic algorithm ).....	54
5.4	Prediction accuracy improvement techniques.....	56
Chapter 6	Results .....	63
6.1	Introduction.. .....	63
6.2	Experiment protocol.....	63
6.3	Lower limb sides' contribution on activity recognition... ..	65
6.4	Sensor election process (Election Hypothesis).. .....	67
6.5	Contribution of segments to the recognition system.....	70
6.6	Lower limb activity recognition system components efficiency.. ..	72
6.7	The impact of the proposed techniques on the recognition system.....	74
Chapter 7	Conclusion and Future Work .....	78
7.1	Conclusion.....	78
7.2	Future Work... ..	79
References	.....	80
Appendix A	.....	85
Appendix B	.....	87

# List of Figures

Figure 1-1 Thesis layout .....	2
Figure 2-1 walking gait cycle (Anon., 2004) .....	4
Figure 2-2 Ascending stairs gait cycle (stance phase), Modified from (Andriacchi et al., 1980) .....	7
Figure 2-3 Ascending stairs gait cycle (swing phase), Modified from (Andriacchi et al., 1980) .....	7
Figure 2-4 Ascending and descending stairs gait cycle comparison (Inman et al., 1981) .....	9
Figure 2-5 (a) angular velocities and foot angle through a full gait cycle for different gait activities (Svensson & Holmberg, 2010) .....	10
Figure 2-6 Different COM positions at the moment of heel strike for different activities (a) Ascending stairs, (b) Walking, (c) Descending stairs. ....	11
Figure 2-7 Activity recognition stages .....	12
Figure 3-1 The human vestibular system (Loudon, 2008) .....	17
Figure 3-2 Accelerometer sensor model (Bulling et al., 2014) .....	18
Figure 3-3 (Bulling et al., 2014) .....	19
Figure 3-4 Gyroscope working principle .....	20
Figure 3-5 Motion capture system overview. ....	21
Figure 3-6 IMU sensors location. (a) Elevation view (b) Side view (c) Real photo of the proposed capturing system. ....	21
Figure 3-7 Fourier transform (frequency components) of the data signals. (a) Thigh, (b) Shank, (c) Foot and (d) Pelvis kinematics and orientation signals in the frequency domain .....	24

Figure 3-8 signal segmentation, (a) Normal Walking, (b) Stair Ascending, (c) Stair Descending, (d) Ramp Ascending, (e) Ramp Descending .....	28
Figure 3-9 Lower limb kinematic signals for one full gait cycle (a) Thigh Angular velocity, (b) Shank Angular velocity, (c) Foot Angular velocity, (d) Thigh linear acceleration, (e) Shank linear acceleration, (f) Foot linear acceleration along longitudinal axis, (g) Waist angular velocity around z-direction. ....	30
Figure 3-10 Lower limb segments' inclination .....	31
Figure 3-11 Standard deviation of (a) Hip, (b) Knee and (c) Ankle angles. Amount of error between David Winter's angles and (d) Hip (e) Knee and (f) Ankle angles. ....	31
Figure 4-1 Wavelet coefficients calculation .....	35
Figure 4-2 Genetic algorithm feature selector steps .....	37
Figure 4-3 One point cross over.....	38
Figure 4-4 Mutation operator.....	38
Figure 4-5 Sensor election procedure .....	42
Figure 5-1 Neural network model layout.....	47
Figure 5-2 Decision tree structure.....	48
Figure 5-3 Decision tree basic notations.....	49
Figure 5-4 Information gain for discrete, non-parametric distributions (A. et al., 2011) .....	50
Figure 5-5 Example weak learners (A. et al., 2011) .....	51
Figure 5-6 split and leaf nodes.....	51
Figure 5-7 Ensemble model. (a) The posterior of four different trees. (b) averaging all trees posteriors. (c) production of all tree posteriors. (A. et al., 2011) .....	53
Figure 5-8 Hybrid Mutual Information and Genetic Algorithm feature selector (HMIGA) steps .....	55

Figure 5-9 (a) Thigh angle at heel strike. (b) Thigh angle at toe off for different activities. ....	57
Figure 5-10 Shank angle slope at steady state for different activities (a) Ramp ascending, (b) Stair ascending .....	57
Figure 5-11 Foot inclination angle at stance phase for (a) Descending ramp, (b) Walking, (c) Ascending ramp activities.....	58
Figure 5-12 Features distribution for all activities.....	59
Figure 5-13 Double layer classifier layout.....	60
Figure 5-14 Feature distribution for walking and ramp descending activities using the Inter quartile range of the Thigh inclination signal and the RMS of the Thigh angular velocity in the Y-direction .....	61
Figure 5-15 Features distribution for stairs and ramp descending activities using the average derivative range of the Thigh inclination signal and the sixth wavelet component of the ankle angle .....	61
Figure 6-1 Data displaying window.....	64
Figure 6-2 Features selected by mRMR .....	68
Figure 6-3 Prediction error rate using all sensors against Thigh sensor .....	70
Figure 6-4 Prediction error rate using shank sensor, foot sensor or pelvis sensor.....	71
Figure 6-6 Prediction error rate using bi-sensors (2) .....	71
Figure 6-5 Prediction error rate using bi-sensors (1) .....	71
Figure 6-7 Prediction error rate using Frequency coefficient features against wavelet component features .....	72
Figure 6-8 Prediction error rate using segments' angle signals against joints' angle signals .....	73

Figure 6-9 Prediction error rate using either HMIGA, genetic algorithm or mRMR feature selector.....	74
Figure 6-10 Prediction error rate using SVM, Neural Network and Random Forest Classifier. ....	74
Figure 6-11 Prediction error rate using physical features .....	75
Figure 0-1 .....	85

## List of Tables

Table 2-1 .....	15
Table 4-1 Time features .....	43
Table 6-1 Participants' data.....	63
Table 6-2 Captured signals .....	64
Table 6-3 Features extracted.....	65
Table 6-4 T-test results .....	67
Table 6-5 Selected features types .....	68
Table 6-6 Selected features details .....	68
Table 6-7 Activity recognition performance before and after applying double layer classifier (a) single layer confusion matrix, (b) double layer classifier confusion matrix .....	75
Table 6-8 class prediction examples using multi layer classifier. ....	76