Walking movement detection using stationary stochastic methods on accelerometer data

Bachelor Thesis

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Abstract

In the area of physical activity recognition, there is a great demand for better understanding data and building useful models for data analysis. Many studies have focused on using machine learning algorithms, which provide high accuracy but are computationally expensive. However, few studies have tried to approach this problem with statistical methods.

The purpose of this study is to investigate the performance of statistical signal processing methods when applied to smartphone accelerometer data. Specifically it focuses on the distinction between walking and non-walking users, with the aim of extracting characteristics that can be useful for traffic and city planning.

Popular Science Summary

Att kunna mäta och förstå människors trafikbeteende är värdefullt eftersom det har ett direkt inflytande på stads- och mobilitetsplanering. Framväxten av smartphones med inbyggda accelerometrar de senaste åren har gjort det möjligt att samla in mobilitetsdata med lägre batteriåtgång än via GPS.

Igenkänning av fysisk aktivitet genom studier och analys av accelerometerdata har varit ett fokusområde inom bl.a. hälso- och sjukvård samt fitness. Samtidigt som sensorerna förbättrats har flera tekniker utvecklats för att identifiera fysiska aktiviteter med allt högre precision, men dessa kräver mycket beräkningskraft. Denna uppsats undersöker två statistiska signalbehandlingsmetoder för att åstadkomma aktivitetsigenkänning med hög precision mot en lägre beräkningskostnad.

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Chapter 1

Introduction

1.1 Motivation

To build a sustainable and environmentally friendly transport system requires the understanding of travelling behaviours such as how people walk, cycle and drive. A better understanding of walking and cycling is required in order to better design transportation system. Today there is a lack of detailed data about how people walk and cycle for transportation[1]. Every individual moves and walks differently at his or her own pace. The purpose of this project is to investigate signal processing and statistical methods on accelerometer for walking movement detection. Many studies have concentrated on using machine learning algorithm on physical activity detection, which provide high accuracy but are computationally costly. This problem will be approached with statistical methods in this project. The overall goal was to build a general model for activity recognition. The findings may be useful in travel survey and transportation system design.

"The traditional travel survey methods have gone through some stages." The first travel survey was an face-to-face interview in the 1950s and later on replacing with mailing survey and telephone interviews. There are some disadvantages in the traditional surveys: misreporting, non-response[2] and time-consuming. On the other hand a large-scale travel survey data have been collected using global positioning system (GPS) technology over the past decades. Still there are some constraints on GPS devices for recording travel surveys: high costs, users forget to bring the device to collect travel data and deficiency of GPS signal in certain areas[3]. With the emergence of smartphones, one can take advantage of its portability and programmable features like embedded sensors including an accelerometer, digital compass, gyroscope, GPS and camera etc. as state in a sensor survey[4].

Over the last decade a lot of studies have been done on human activity detection using smartphone-based sensors: accelerometer and GPS where the sensors record measurements of a 3-dimensional acceleration force as well as showing the location of the user. Ellis et al.[5] implemented an algorithm which combines GPS and accelerometer data using machine learning on a 150-hour dataset collecting two research assistants following specific trips to detect 5 activities using 49 features with high recognition accuracy of 91.9%[5]. However GPS navigation is a heavy drain on the battery. This is a great limitation for GPS regarding activity recognition. Even though the users can manually switch off and activate GPS whenever it is needed. It is often that the users forget to switch it on for recording so the data is incomplete like the beginning or stopping point are missing. Identification of the starting and end points of a trip is a key in movement detection[6]. With regards to battery-drain problem and missing data, acceleration sensor is a good alternative to be used for activity detection. Because the accelerometers are inexpensive, require relatively low power and are embedded in smartphones.

Accelerometer data has been widely used for medical, health, military and engineering fields for the monitoring of fall detection, heart rate and sounds, blood pressure and detection of human activities etc. In this project the data is recorded using smartphone-based accelerometer in Android and the datasets are processed in MATLAB software tool.

1.2 Objectives

The main objectives of this project are to understand accelerometer data collected by smartphones and to show that accelerometer data is beneficial for physical activity detection. As well as applying spectral analysis including autoregressive (AR) process and modified periodogram with Hanning window to extract useful features and then use statistical techniques to distinct walking and non-walking activities.

TRavelVU[7] is a travel survey project that Trivector Group is carrying out for collecting travel data using smartphone GPS. The software is capable of detecting up to 7 modes with 10 extra different modes for editing[7]. The user can modify the travelling data and the app remembers the locations where the users have been to. To be able to detect the start and stop point of a trip, the user keeps the app on all of the time. It leads to that the user has to manually turn off the app in case of battery drainage matter on the smartphone. In the near future, it will be promising that travelling projects like TRavelVU can provide an app uses accelerometer data with a wireless connection which record, analyse and detect the travelling modes with low computation. As well as recording an individual's travel behaviours.

Chapter 2

Background

2.1 Activity Recognition Approaches

A lot of work has been done regarding activity recognition using accelerometer data. With the purpose of understanding and extracting useful information that can be useful for traffic and urban planning. The sample data can be recorded in two ways: wearable sensors and smartphone-based sensors. Furthermore wearable sensors can be divided into two categories: multi-accelerometer sensors and single accelerometer sensor. The data were collected using the wearable sensors then sent to server for activity recognition.

2.1.1 Related Literature

Bao and Intille[8] carried out an activity recognition system by using 5 biaxial accelerometers worn on the 4 limb positions and right hip simultaneously to collect user's activity data. The data were collected with a sampling frequency of 76.25 Hz and data-window of 6.7 seconds. Then the recorded data were sent to a mobile computing device to perform classification using Machine Learning Algorithms: decision table, nearest neighbour and naive Bayes[8]. Despite the fact that employing more sensors benefit the accuracy rate, it requires heavy computation and power consumption.

Khan et al.[9] implemented the physical activity recognition using one single tri-axial accelerometer with sampling frequency of 20 Hz and a data-window of 3.2 seconds without overlap. They also proposed a novel hierarchical recognition scheme which is capable of recognizing 15 physical activities of daily life. However the single accelerometer sensor is a special tailored design mainly for laboratory test. The wearable sensors are not practical for real-world application.

The fact that smartphones are ubiquitous and embedded with build-in accelerometers make it an ideal device for monitoring Kwapisz et al.[10] used smartphone-based accelerometers to detect 6 activities using 43 features with high accuracy. The data were collected in a custom-build Android application WISDM (Wireless Sensor Data Mining) with sampling frequency of 20 Hz and data-window at 10 seconds with phone in pocket. It is proposed that either minimize the intelligence needed on the phone or completing the activity recognition model directly on the phones to save computational work and power consumption[10]. However the features are computed over the long data-window which reduce the chance of capturing the transition movements[10].

Many excellent activity recognition approaches have been used in the literature but some of them are too computationally expensive and heavy battery drain for smartphones. For efficient and accurate computation in movement detection better feature extractions are needed. The aim of this study is to use statistical methods and spectral analysis for the distinction between walking and non-walking.

2.1.2 Overview of procedures

There are many different methods for feature extraction from accelerometer data in the literature apart from the above mentioned studies. The main procedures are: pre-processing, feature extraction and classifying.

Pre-processing: The raw data were recorded from smartphone-based accelerometer where the sample data correspond to the gravitational and acceleration force. We applied a 5^{th} order Moving Average (MA) filter for smoothing the acceleration force[6] in the following work.

Feature Extraction: Features are the distinct characteristics and repetitive patterns of the sample signal. These are the main components for movement detection. In this thesis the focus are on the time- and frequency domain.

Classification: The purpose of this is to identifying important information from the feature components employing statistical methods.

A lot of studies have used sampling frequency of 20 Hz and as Maurer et al. pointed out in his work that the accuracy rate stabalized between 15 to 20 Hz for lower level activities like walking, running, ascending and descending stairs[11]. Here the sampling rate of 20 Hz is applied for the study of this project.

Chapter 3

Methods

3.1 Data Collection and Preprocessing

For this project, the accelerometer data were collected using the Physics Toolbox Accelerometer software which is available for both Android and iOS. The activity samples were gathered from 7 individuals with an Android based smartphone doing different activities such as walking normally, quickly or slowly; taking the train and running. For the purpose of this study, quick and slow walking trips are included for building the model. Because the intention is to discriminate walking and non-walking activities. Therefore walking slowly and quickly are considered walking in our case. There are in total 27 samples collected which are listed in Table 3.1. The individuals were asked to start the app and go out for a walk unsupervised. The phone can be placed at various places according to the individuals' habit such as in pocket, in backpack or in hand.

Table 3.1: Accelerometer sensor data sample

Index	Activity	Num. of Samples
I	Normal walking	15
II	Slow walking	3
III	Quick walking	3
IV	Run	3
V	Train trip	3

The software's sampling rate is around 220 Hz with standard deviation 7 Hz. The sample readings were saved by the individuals in a CSV file and then use MATLAB tool for activity analysis. The readings consist of 4 columns: one column vector $\mathbf{t}$ representing the relative time and the rest with each column stores acceleration in X, Y and Z direction. The readouts v_t^x, v_t^y, v_t^z can be written as,

$$\boldsymbol{v}_t = \boldsymbol{v}_t^* + \boldsymbol{\epsilon}_t, \tag{3.1}$$

where t = 1, 2,..., $\boldsymbol{v}_t = [v_t^x \; v_t^y \; v_t^z]^T$ and $\boldsymbol{\epsilon}_t \in R^3$ is a noise vector of independent, zero-mean Gaussian random variables and variance σ^2 such that $\boldsymbol{\epsilon}_t \sim \mathbb{N}(0, \sigma_\epsilon^2 \mathbb{I}^3)$[12].

First the data noise of column vectors $\{v_t^x, v_t^y, v_t^z\}$ were checked by analysing the readings when the phone sitting still on table. Observing that both X and Y-axis are close to zero because the phone is static while Z-axis measured as 1 with unit g because the acceleration and gravitational force acting on it. It is reasonable to smooth the acceleration component by applying a 5^{th} order moving average (MA) filter on the data. An example showing X, Y and Z-axis for a dog walk for 4 seconds is presented in Figure 3.1 with raw data on the top and smoothed data at the bottom.

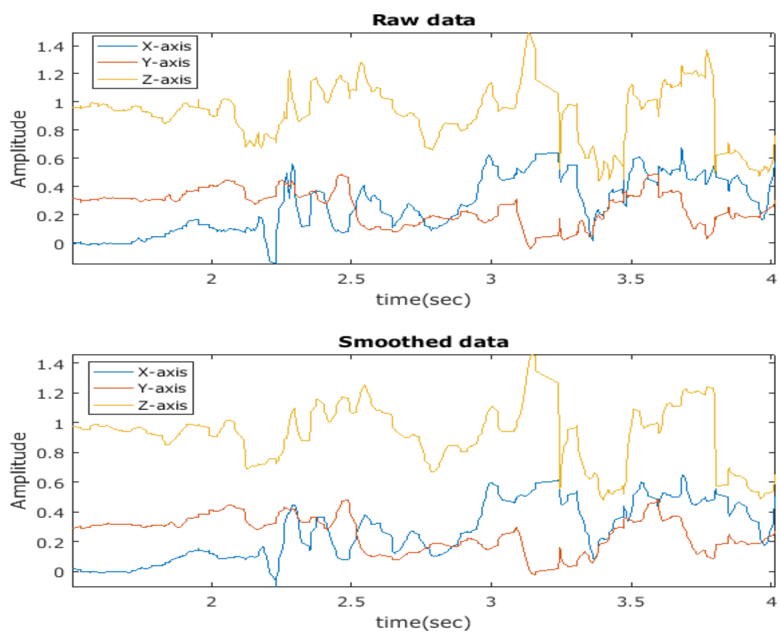

Figure 3.1: Accelerometer readouts along X, Y and Z-axis for a dog walk for 4 seconds with original data on top and smoothed data at the bottom.

In order to reduce complexity for the sensor orientation the magnitude vector of the signal sequence[8,9,10,12] is computed,

$$m_t = \| \boldsymbol{v_t} \| = \sqrt{\{(v_t^x)^2 + (v_t^y)^2 + (v_t^z)^2\}} \tag{3.2}$$

where t = 1, 2,..., N. The collected sampling rate of the time-series accelerometer data is inconsistent so the sampling rate is resampled to 20 Hz as 20 Hz is high enough to capture the repetitive moving peaks including walking, running, ascending and descending stairs. After several trials, a data-window length of 5 seconds i.e. n = 100, is the most appropriate choice in our data. This window and time interval were selected with consideration of a trade-off between the resolution and data information. It's long enough to display meaningful information from the collected data. However different sampling rates and data-window lengths can be tested out for distinction for more physical activities in the future project. After resampling the mean of the magnitude sequence was subtracted from the magnitude sequence to ensure zero mean. This step is important for the stationary process. Then the de-meaned sequence was passed through a 5^{th} order MA filter. A sample of the sequence m_t for a dog walk for a few seconds can be seen in Figure 3.2 with raw data on the top and smoothed data at the bottom. It can be seen that the filtered data is less noisy than the original data.

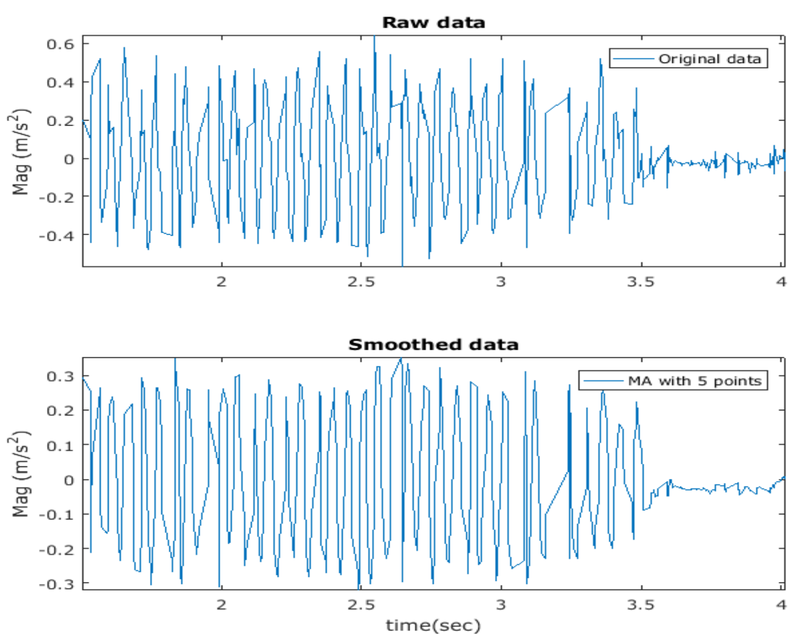

Figure 3.2: Magnitude vector m_t of acceleration data for a dog walk resampled at sampling rate of 20 Hz for a few seconds with raw signal on top and smoothed signal at the bottom.

3.2 Feature extractions

The choice of features is a significant step in classifying movement recognition. The magnitude vector is processed by statistical techniques in both time and frequency domain to explore meaningful information. Khan et al. proposed in [9] that the state recognition and activity recognition can be differentiated separately by applying a hierarchical recognition scheme. At the lower level such as static or dynamic activities they applied statistical features for recognition[9]. They implemented machine learning algorithm for detection[9] for the upper level activities such as walking, running, ascending and descending stairs. The concept of hierarchical recognition scheme is interesting and it can be applied to pursue activity distinction. In this study, the statistical techniques on the time-domain measures is applied for state recognition while the statistical techniques on the frequency-domain features is implemented for walking movement distinction. Figure 3.3 illustrates the scheme flowchart for our project.

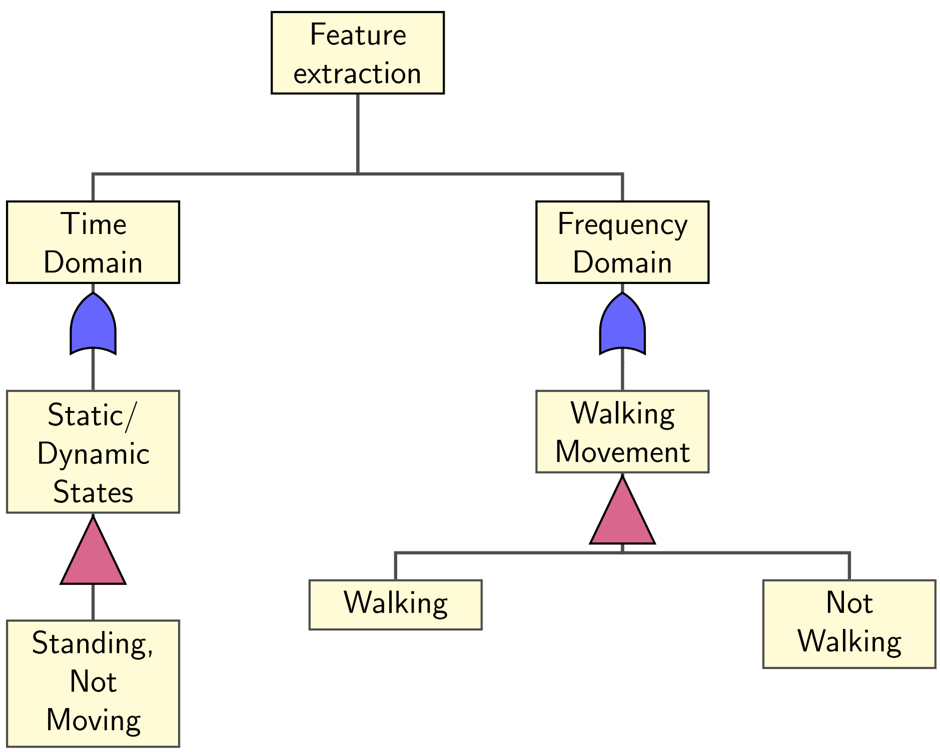

Figure 3.3: Scheme flowchart for this project

In the frequency-domain features, spectral analysis methods including AR process and modified periodogram with Hanning window method are applied for physical distinction. These two methods are widely used and known in signal processing little research has been found with respect to human activity recognition. Most of the works concentrates on other methods such as entropy, energy, Fourier Transformations, Wavelet Transformations and others. Apart from the traditional techniques, exploring different methods for extracting features may display new information of the data.

3.2.1 Time-domain Features

The time-domain features are based on the magnitude sequence m_t. A typical accelerometer signal is shown in Figure 3.4 below. It displays a dog walk in the forest for 337 seconds. Time in seconds is plotted in the x-axis and the magnitude of acceleration is in the y-axis. Apart from the amplitude of the acceleration magnitude can be seen from the plot, it is difficult to discriminate whether the individual is walking, running or taking a bus ride without any prior information.

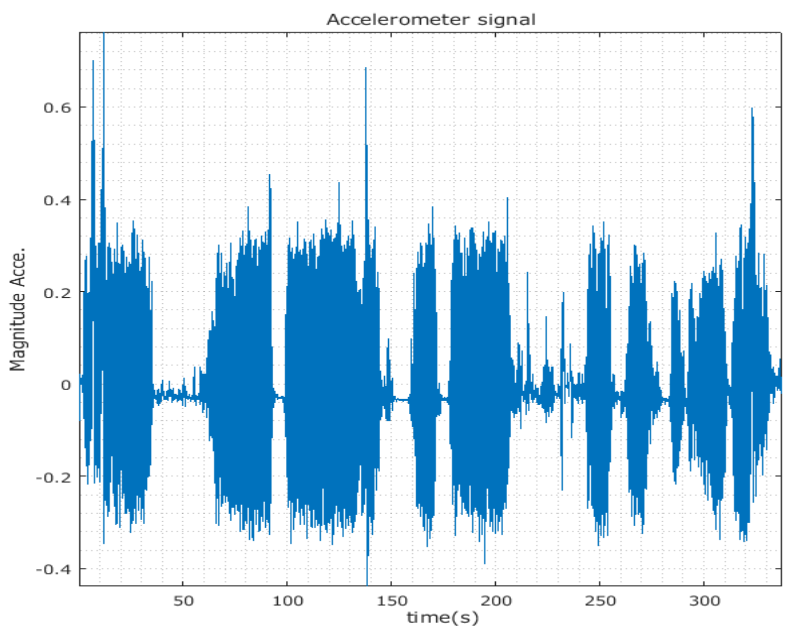

Figure 3.4: Smoothed accelerometer magnitude data for an individual's dog walk in the forest.

There are many different time-domain measures one can compute due to its efficient and direct computation. And it is straightforward to distinguish the static and dynamic activities from the descriptive time-domain features. In this study two variables have been calculated with focus for the state recognition: variance (Var) and inter-quartile range (Iqr). Variance measures the variability of the data sequence and inter-quartile range evaluates the statistical dispersion (i.e., difference between the 75^{th} and the 25^{th} percentiles). Instead of calculating the variance and inter-quartile range of the whole data sequence, the two variables are computed over a window size of 100 (i.e., a data-window of 5 seconds) with 50% overlap aiming to recognize the states: static and dynamic activities. Then taking the mean value of the sequence of the variances and inter-quartile range values give more precis measurements. The mean, minimum, maximum of the sequence as well as the correlation coefficients are also computed to get more descriptive information about the data. The correlation coefficients measures the linear relationship between two different axes.

The sequence of variances and inter-quartile ranges for a dog walk is plotted in Figure 3.5 against the original data. It differs the static and dynamic activities. The values close to zeros represent the static states while the higher values represent the dynamic activities. And the values in between are the transition activities: walk-stop and stop-walk mode. In [9] Khan et al. used the time-domain measures to identify also a transition mode besides static and dynamic. In this study the focus is on distinction between walking and non-walking so the transition status is regarded as static activity.

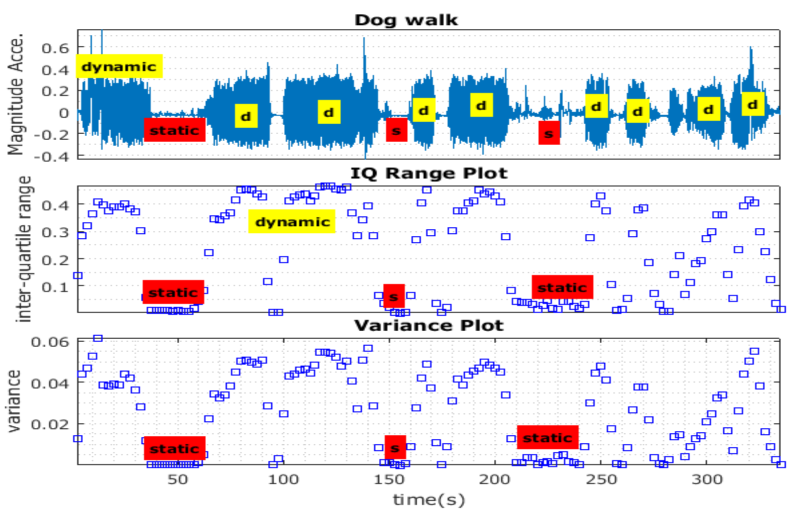

Figure 3.5: The sequence of variances and inter-quartile range values of a typical dog walk over window size of 100 with 50% overlap. The values close to zeros are marked as static while values at higher values as dynamic activities.

3.2.2 Frequency-domain Features

Transforming the data into the frequency domain can gain new information about the signal which the time-domain features fail to display. This transformation estimates the power spectral density which unveils the power density versus frequency. This insight can help identify whether the user is walking. For walking data the features of the repetitive patterns and the frequency components are important for recognition. Two main methods for spectral analysis are applied in this project: the periodogram (non-parametric) method and the AR (parametric) model for analysing the accelerometer data. The reason why the periodogram method and the AR model appropriate are: the periodogram method can be used to calculate the dominant frequencies in a time-series data to identify periodicity while AR model is a process where the future depends on the past.

3.2.2.1 Windowed Periodogram analysis

Frequency-domain analysis is based on transforming the signal into the frequency domain using the Fourier Transform. Theoretically Fourier transformation requires infinite number of samples and that the signal is stationary[13]. In reality it is rare that an infinite dataset can be obtained. The discrete Fourier transform (DFT)[13], transform a finite discrete-time magnitude sequence m_t is used here and then using Fast Fourier Transform (FFT)[13] of the DFT for efficient computation of M(f),

$$M(f) = \sum_{t=0}^{n-1} m_t e^{-i2\pi ft}, \tag{3.3}$$

where t = 0, 1, .. n-1. With the periodogram[13] defined as,

$$S_m(f) = \frac{1}{n}|M(f)|^2. \tag{3.4}$$

Since the usual periodogram has sidelobes which causes power leakage and severe bias for the spectral density estimation, a Hanning window[13] is applied on m_t,

$$S_w^{PD}(f) = \frac{1}{n}|\sum_{t=0}^{n-1} m_t w_t e^{-i2\pi ft}|^2, \tag{3.5}$$

where t = 0, 1, .. n-1 and w_t is the the normalized window function and it is defined as $w_t = \frac{h_t}{\frac{1}{n}\sum_{t=0}^{n-1} h_t^2}$ with $h_t = \frac{1}{2} - \frac{1}{2}cos(\frac{2\pi t}{n-1})$.

It can be seen from the data that the frequency is not constant over time so the data sequence is unstationary. It does not reveal how the power spectrum varies over time if FFT is taken on the whole sequence. It makes more sense to use a data-window of 5 seconds (i.e., n = 100) with 50% overlap periodogram with Hanning window on the data sequence. Then the maximum amplitude of power and dominant frequency components of each window can be extracted for analysis over time.

3.2.2.2 Short-time Autoregressive analysis

The modified periodogram estimation will be accurate if there is a large amount of data and signals are stationary. The AR(p)-process of order p is created by white noise passing through an infinite impulse response (IIR) filter[13]. The AR model uses the time history of a signal to extract useful information hidden in the signal and the model parameters are passed to analyse the signal. The output of the AR(p)-process is generated as a linear combination of p past values of the output and the present input data[13],

$$m_t = -\sum_{k=1}^{p} a_k m_{t-k} + e_t, \tag{3.6}$$

where $a_1, a_2, ..., a_p$ are the model coefficients. With p indicates the order of the model implying the number of past values can be used to predict the current value and e_t is independent Gaussian noise with mean zero and variance σ^2[13]. Furthermore the corresponding spectral density[13] is defined as,

$$S_m^{AR}(f) = \frac{\sigma^2}{|\sum_{k=0}^{p} a_k e^{-i2\pi f k}|^2}. \tag{3.7}$$

To identify the model order, the most popular time series methods: auto-correlation function (ACF) and partial auto-correlation function (PACF) are used. ACF for m_t is defined as[14],

$$\rho_m(k) = \frac{\gamma_m(k)}{\gamma_m(0)} = \frac{E[(m_t - \mu_m)(m_{t-k} - \mu_m)]}{E(m_t - \mu_m)^2}, \tag{3.8}$$

where $\gamma_m(k)$ is the auto-covariance function, $\gamma_m(0)$ the variance and μ_m is the expected value of m_t.

The PACF measures the relationship between m_t and m_{t-k} of a time series and defines the dependence of the auto-correlation $\rho_m(k)$ of the process[14]. The k^{th} partial auto-correlation coefficient, $\phi_{k,k}$, is the last (negative) AR coefficient of a k^{th} order AR model[13]. If m_t is an AR(p)-process, $\phi_{k,k}$ will be zero if $k > p$ and $\phi_{k,k} \neq 0$ if $k \leq p$[15]. Using MATLAB commands *autocorr* and *parcorr* the ACF and PACF for the time series m_t can be easily computed. The ACF plots show damped exponential or sine functions while PACF plots goes to zero after lag p[15]. After checking all the samples and model order of 2 is a good enough model for walking pattern. Figure 3.6 displays an example of ACF and PACF.

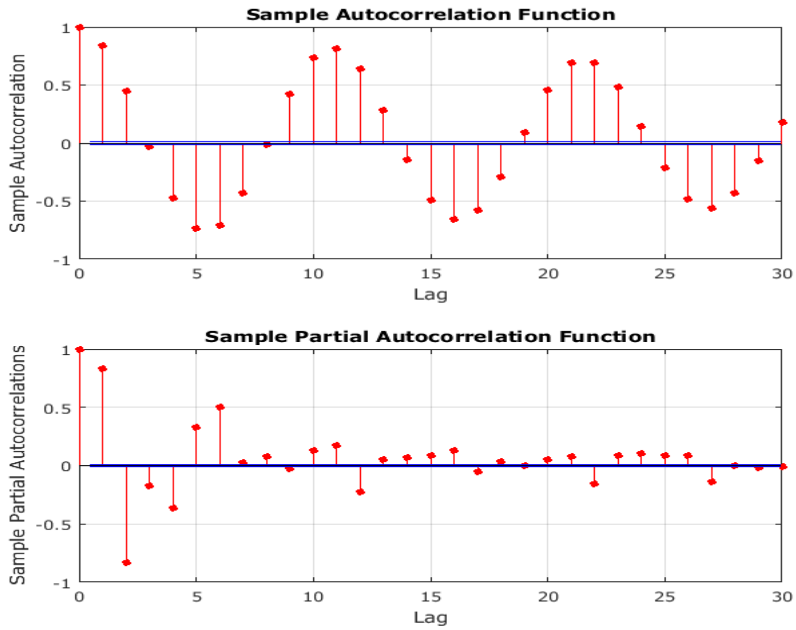

Figure 3.6: Accelerometer magnitude signal with its ACF and PACF for the data sequence.

For AR model a data-window of 5 seconds (i.e., n = 100) with 50% overlap is applied on the data sequence. This time interval is long enough for extracting useful AR-coefficients. There are different methods to compute the coefficients for example: covariance method, the Yule-Walker method and the Burg method. The linear model coefficients a_p is estimated using the covariance method. They all based on Yule-Walker and produce relatively similar results. Covariance method is chosen because there is not many orders in the model. In the next step the maximum power and frequency components are computed and extracted over each window over time. With these vector sequences it is possible that useful information can be revealed concerning the distinction between walking and non-walking.

Figure 3.7 demonstrates the plots for both the periodogram with Hanning window and the segmented AR(2)-process for a dog walk data sequence. The frequency for this walk for the periodogram and the AR(2) are similar ranging from 0.03 to 2.37 Hz. Note the increasing power variability after the user stops and begins to walk at 53 seconds, 100 seconds, 150 seconds, 200 seconds. It can be seen that AR(2)-process provide better resolution for power spectral density estimate without power leakage while the modified periodogram shows poor frequency resolution due to power leakage. However there is one drawback in AR process: it is very sensitive to noise or outliers. It cannot distinguish between spectral signal and noise 'peaks' so it will continue to find more 'peaks' as pre-specified number of 'poles'[16]. To resolve this the MATLAB command $medfilt1$, which applies a third-order median filter to take care of the outliers, is used.

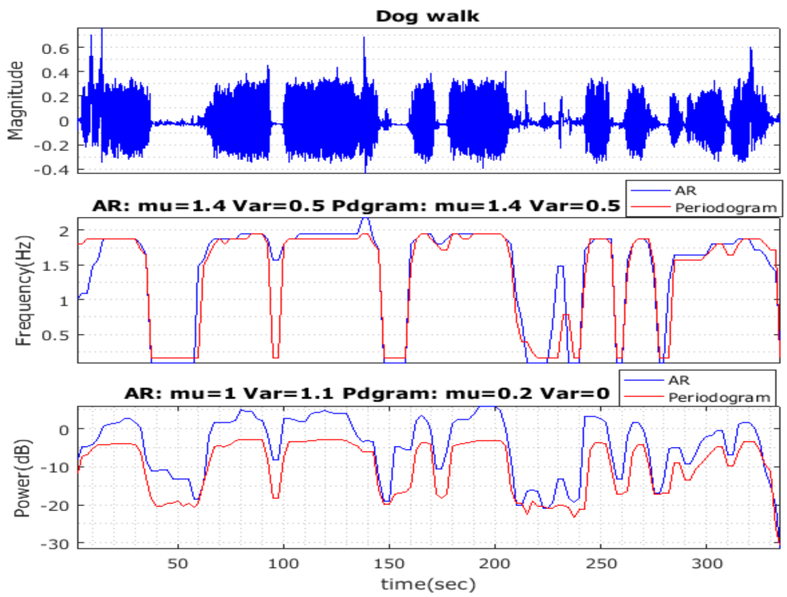

Figure 3.7: Modified periodogram and windowed AR(2) process showing the max. powers and frequency components of each window changing over time for a dog walk with smartphone in pocket.

The advantages and disadvantages of the periodogram method and the AR model are summarized in Table 3.2 below.

Table 3.2: Accelerometer sensor data sample

Category	Method	Advantage	Disadvantage
Non-parametric	Periodogram	Easy to apply	Poor resolution; power leakage
Parametric	AR-process	Better resolution; no leakage	Sensitive to outliers

Chapter 4

Results

4.1 Statistical analysis results

In this chapter the statistical analysis for 12 selected samples is concluded to build a suitable model based on the activity categories: normal, slow and quick walking. For this project slow and quick walking are considered as walking data. In the next step the model is tested on the remaining 15 datasets including 9 walking trips, 3 running trips and 3 train trips. Note that the data was resampled to the frequency of 20 Hz and the magnitude vector was used in the data. So the concern for the phone orientation and models can be omitted in this study. Because the goal of this thesis is to find out whether the two signal processing techniques: the periodogram method and the AR model can produce useful features for statistical testing.

4.1.1 Time-domain statistical analysis

The time-domain measurement results for the mean of the sequence of variances and inter-quartile range values together with the minimum, maximum and correlation coefficients are displayed in Table 4.1. The 12 selected data sample are listed in categories including normal, slow and quick walking.

Table 4.1: Statistical performance comparison among different time-domain measurements for 12 sample datasets: normal, slow and quick walking

Category	Data	Min	Max	Iqr	Var	Cor_{xy}	Cor_{xz}	Cor_{yz}
Normal walking	1	-0.40	0.43	0.31	0.03	-0.25	-0.44	0.72
	2	-0.68	0.64	0.35	0.04	0.30	-0.21	-0.49
	3	-0.51	0.90	0.33	0.04	-0.43	-0.25	-0.004
	4	-0.63	0.86	0.41	0.06	-0.08	-0.20	0.28
	5	-0.55	0.73	0.48	0.07	0.20	-0.17	0.15
	6	-0.48	0.59	0.38	0.05	-0.37	0.17	-0.33
Slow walking	1	-0.33	0.56	0.22	0.02	-0.06	0.01	0.46
	2	-0.40	0.54	0.21	0.02	0.21	-0.02	0.01
	3	-0.73	0.78	0.40	0.06	-0.34	-0.07	0.51
Quick walking	1	-0.52	0.97	0.34	0.05	0.26	0.11	0.25
	2	-0.80	1.22	0.41	0.07	0.06	-0.22	-0.06
	3	-0.56	0.65	0.42	0.06	0.34	-0.51	-0.58
Average		-0.55	0.74	0.36	0.05	-0.01	-0.15	0.08

The inter-quartile range and variance indicate the variability within a dataset. The study shows that the inter-quartile range are between 0.21 to 0.48 with an average of 0.36 while the variances are much smaller between 0.02 and 0.07 with an average of 0.05. The results are reasonable since the inter-quartile measures the dispersion based on the 75^{th} and 15^{th} percentile from the datasets removing the outliers while the variance considers every value in the datasets.

The minimum and maximum values display a descriptive picture for the walking datasets ranging from average of -0.55 to 0.74. The correlation coefficient differs depending on the phone location. For example they are negatively correlated while holding in hand, positively correlated while in pocket and the correlation varies while putting in backpack. However the coefficients are rather small. According to Waltenegus Dargie the correlation coefficient shows bigger range for car driving comparing to human movements[17]. It is believed that it can show influence if more physical activities like driving, running and jogging and others are added in the future study.

The sequence of variances and inter-quartile range values are displayed plotting against the original dog walk data. With the mean of the sequence of Iqr is 0.36 and the mean of the sequence of Var is 0.05 as treshold respectively plotted in Figure 4.1. The values close to zeros represent static movement and the values below the threshold (i.e., the transition values are also considered as static). And the values above the threshold are dynamic activities. It can be seen that if the user stopped shortly and started moving it is very difficult to identify as it can be seen in intervals like [90 100], [250 260] and [280 290] seconds in the dog walk figure below.

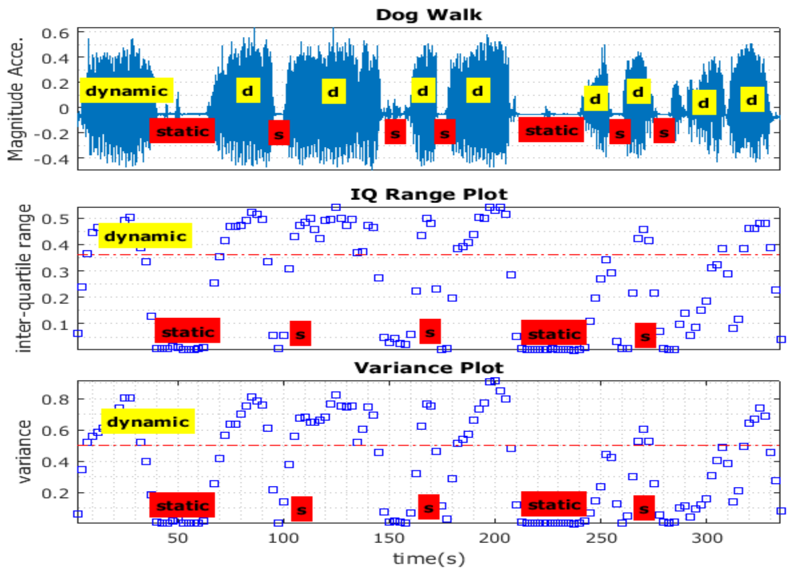

Figure 4.1: Variance and inter-quartile range with thresholds 0.05 and 0.36 respectively displaying static and dynamic activities. In the plot the variance is scaled so it is easier for comparison with the the rest plots. The values below the thresholds but above zeros values are the transition points such as stop-walk or walk-stop, and it is considered them as static in the study.

With the average of the sequence of variances and inter-quartile range values it can detect the state recognitions that identifying whether the user is static or dynamic in the same time interval against the recorded data. It seems both algorithm can detect the beginning and stop points. Our results are produced through identifying all the stopping intervals (i.e., a stop lasting more than 5 seconds). For stops less than 5 seconds it's regard it as being in motion. If the algorithm fails to identify the stops it fails to detect the state recognition for the data sequence. The same principle for detecting dynamic activities is carried out. The recognition result for state recognition is in Table 4.2.

Table 4.2: Recognition result for our remaining data sample

Method	Static	Dynamic	Start point	End point
Iqr	12	11	14	13
Var	12	12	14	14

As the results suggest that both methods are good at finding the starting, end point and static activities. Both methods fail to detect the static and dynamic activities for the train data. Variance has slightly better accuracy rate of 80% than the inter-quartile range of 73%. It is possible that variance is more robust considering all the values in the datasets while the inter-quartile range measures excludes the extreme values. Even though there are many other measurements can be computed in the time domain, they cannot reveal more information apart from the state of being static or dynamic. It is time to look into what more features can be revealed for discriminating walking with the frequency-domain measures.

4.1.2 Frequency-domain statistical analysis

AR-process and the modified periodogram provide a comprehensive map of how the frequencies and power varies over time (i.e., it can be sees the range for strong and weak frequency and power components). The minimum, maximum, mean and variance of the dominating frequencies for the selected datasets is presented in Table 4.3 below. Then the average of each measure for the frequencies of the periodgram and the AR model are calculated.

Table 4.3: Statistical performance comparison among different frequency-domain features showing the dominating frequency components over time for AR-process and periodogram for the selected 12 sample data

		AR-process frequency				Periodogram frequency			
Category	Data	Min	Max	Mu	Var	Min	Max	Mu	Var
Normal walking	1	0.08	1.95	1.83	0.06	0.16	1.95	1.85	0.09
	2	1.56	1.95	1.90	0.01	1.72	1.95	1.89	0.002
	3	0.08	1.95	1.71	0.10	0.16	2.03	1.75	0.25
	4	1.25	2.11	2.03	0.02	0.16	2.11	1.98	0.10
	5	1.80	2.34	2.14	0.10	1.88	2.19	2.11	0.004
	6	0.08	2.27	1.90	0.40	0.16	2.27	1.84	0.40
Slow walking	1	1.25	2.11	1.93	0.03	0.16	1.95	1.80	0.05
	2	0.08	2.34	1.92	0.13	0.16	2.50	1.89	0.10
	3	0.08	2.19	1.82	0.27	0.16	2.19	1.77	0.29
Quick walking	1	1.88	2.42	2.23	0.02	1.80	2.34	2.18	0.01
	2	0.63	2.34	2.04	0.03	0.16	2.34	1.96	0.16
	3	0.08	2.58	2.21	0.06	0.94	2.66	2.18	0.03
Average		0.74	2.21	1.97	0.10	0.64	2.21	1.93	0.12

For the AR-process the average minimum and maximum dominant frequencies ranging from 0.74 to 2.21 Hz and for periodogram between 0.64 to 2.21 Hz respectively for walking pattern. The average values of the variance for AR-process is smaller than the periodogram's variance with a small margin of 0.02. It can be that AR-process has good resolution and no power-leakage or the sample size is small. These frequency components are in the reasonable range for walking pattern. The statistics for the dominant powers of the magnitude signal is displayed in Table 4.4.

Table 4.4: Statistical performance comparison among different frequency-domain features representing the dominating power components over time for the selected 12 sample data

		AR-process power				Periodogram power			
Category	Data	Min	Max	Mu	Var	Min	Max	Mu	Var
Normal walking	1	0.01	3.93	1.44	0.64	0.01	0.41	0.28	0.01
	2	0.24	7.94	2.00	1.17	0.08	0.65	0.36	0.01
	3	0.10	3.07	1.22	0.66	0.08	0.81	0.36	0.03
	4	0.18	0.69	0.36	0.01	0.20	0.71	0.56	0.01
	5	0.45	3.35	1.83	0.30	0.22	1.01	0.71	0.02
	6	0.003	4.94	1.77	1.82	0.002	1.02	0.50	0.10
Slow walking	1	0.03	0.37	0.13	0.005	0.01	0.29	0.15	0.004
	2	0.01	0.93	0.28	0.04	0.01	0.35	0.16	0.01
	3	0.01	5.97	1.90	1.26	0.01	1.22	0.55	0.08
Quick walking	1	0.10	0.73	0.35	0.02	0.14	0.58	0.40	0.01
	2	0.006	1.06	0.51	0.03	0.08	0.97	0.60	0.03
	3	0.05	3.39	1.51	0.44	0.03	0.82	0.54	0.03
Average		0.10	3.03	1.11	0.53	0.07	0.74	0.43	0.03

For the AR-process the average minimum and maximum dominant powers ranging from 0.10 to 3.03 while for periodogram between 0.07 to 0.74 Hz respectively for walking pattern. The AR method has better peak resolution without power-leakage while periodogram has the power-leakage problem. It is reasonable that the average values of the mean and variance for AR-process are much higher than the modified periodogram. To be able to detect whether the user is walking the 95% confidence interval for the average values of mean and variance for both the dominant frequency and power components are computed in Table 4.5.

Table 4.5: 95% Confidence Interval for the average values of of the AR-process and periodogram's frequency and power components

Type	Average value	S.D.	95% CI for mean
AR freq.	1.97	0.316	[1.791 2.149]
Periodogram freq.	1.93	0.346	[1.734 2.126]
AR power	1.11	0.728	[0.698 1.522]
Periodogram power	0.43	0.173	[0.332 0.528]

The 95% confidence interval for the measures is then used to check the remaining datasets to evaluate whether the AR model and the periodgram method produce good performance result. The confidence bounds shows the range for walking frequencies and powers in the data sequence. The intention is to distinct walking and non-walking activities.

The activity recognition result is given in Table 4.6. In the table the number of successfully detected from the 15 remaining datasets is displayed. The performance for starting and ending point detection is not as accurate as the time-domain measures. It could be that some users turned on the App while still moving. For walking distinction AR(2)-process produces a little better result than the periodogram with Hanning window. The results from this project is considered reasonable.

Table 4.6: Result for successfully detecting walking and non-walking movements together with recognition for start and end points for the remaining 15 datasets

Method	Walking	Non-walking	Start point	End point
Periodogram	13	13	12	13
AR(2)	14	14	12	12

With the spectral analysis methods the accuracy rate can be reached to 93.33% for walking distinction. For the periodogram method it displays often more zeros or close-to zero frequencies values while the user is in motion. Through this project it indeed shows that the AR model and periodogram can extract useful features and then the extracted sequence data can be then used statistical techniques to classify the physical activities. It is certain that more physical activities added will increase the complexity hugely. The result of this small shed light on a useful link between the signal processing and statistical methods on accelerometer data for human activity recognition.

4.2 Discussion

The experiment results show that using smartphone-based accelerometer data can be adequate for identifying physical activity recognition. Static activities such as standing still and not moving are easier for recognition than the periodic activity: walking. Using hierarchical recognition scheme we first classify the state recognition and then identify if the user is walking.

Two sequences are displayed in Figure 4.2: dog walk and Figure 4.3: start-wait-run-stop trip below. The dominant frequency components for the AR model and the peridogram are showed in both plots for comparison.

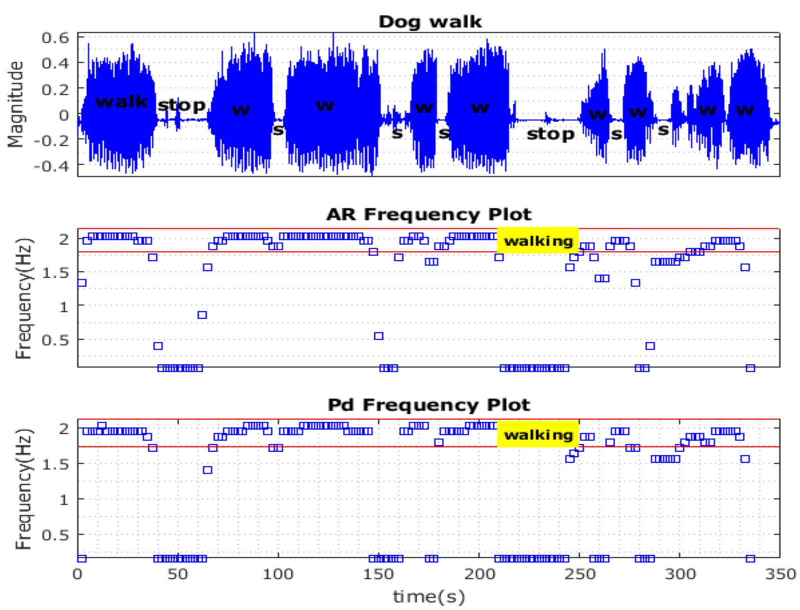

Figure 4.2: Visually analyse whether the user is walking or not with AR-process and periodogram frequency components for a dog walk. Both methods detect all the walking intervals but periodogram method show more zeros even though the user is in motion.

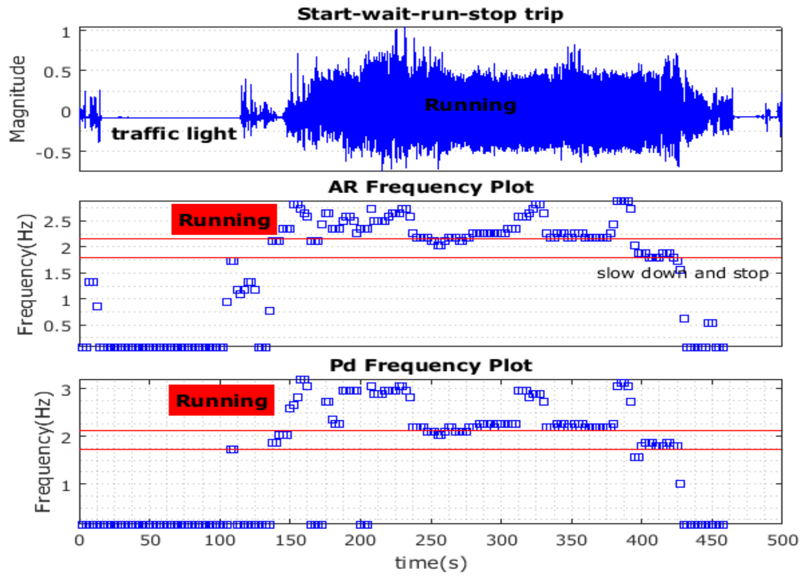

Figure 4.3: Visually analyse whether the user is walking or not with AR-process and periodogram frequency components for a running trip. Both methods are able to identifying the user is not in walking mode in this case. Our goal is to detect whether the user is walking or not.

The 95% CI for AR-process frequency components mark the walking frequency range between 1.791 and 2.149. The values outside the bounds are non-walking activities, in this case running. With the values lower the the bounds are considered as static activities. From the plot it can be seen that AR-process is better in recognition of walking while the peridogram shows more zero frequencies when the user is moving. For a short-time interval stop AR include them as moving activities. The reason for this maybe that AR-process is a model that the future steps rely on the past which leads to better precision for predicting the movement step. However the periodogram is good at identifying the peak frequencies for periodicity so for frequencies which are not dominant for example the transition state the method might not be able detect and show more zero frequencies. The achieved findings may be useful in traffic mode and physical activity detection.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

The hierarchical recognition scheme is applied for first discriminating the state recognition using time-domain measures and walking distinction using spectral analysis techniques. For human activity recognition the time-domain measurements: variance and inter-quartile range are direct to compute but difficult for interpretation apart from state recognition: static or dynamic activities. They are good measures for beginning and end point detection. The frequency-domain features: the peridogoram and AR(2) model concluded a general walking frequency pattern.

It is worthwhile to test on more feature extraction methods such as AR-process and periodogram and other signal processing methods in activity detection. The overall approach was to build a general model for walking distinction. With AR-model it gave better recognition result. The results of this analysis can be used to detect whether the user is static, walking and non-walking. The main contribution of this study is the proposal of using AR-process and periodogram method for activity recognition feature extractions using only smartphone-based accelerometer data. The findings may be useful in traffic survey and human activity detection.

5.2 Future Work

This thesis is just a start of researching signal processing and statistical methods in human activity recognition. There are still a lot of things need to be further considered in the future work for better performance. For example the following points:

- Better annotated data.

- Optimizing parameters through automatic evaluation..

- More feature: wavelet transform.

The demand for understanding the accelerometer data and building efficient and accurate model for human activity recognition can be one of the greatest challenges in the near future. The combination of signal processing methods and statistical techniques may be a promising approach in this field with respect to the power requirement.

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