Real time non-invasive estimation of oxygen uptake using smartphones

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2023

MASTER THESIS

Real time non-invasive estimation of oxygen uptake using smartphones

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September 11, 2023

Master's thesis work carried out at
the Department of Design Science, Faculty of Engineering, Lund University.

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Published by
Department Design Sciences
Faculty of Engineering LTH, Lund University
P.O Box 118, SE-221 00 Lund, Sweden

Subject: Ergonomics MAMM10
Division: Ergonomics and Aerosol Technology
Supervisor: Chuansi Gao, Jakob Eggeling
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Abstract

Oxygen uptake is a great indicator of cardiopulmonary health but requires specialized equipment and is time consuming to measure. There are ways to estimate oxygen uptake based on other factors such as heart rate and acceleration. The aim of this master thesis was to investigate whether models estimating oxygen uptake based on acceleration data collected from the sensors in smartphones, and steps and heart rate data from wearables could be created.

To do this ten healthy volunteers performed a cardiopulmonary exercise test (CPET) where their oxygen uptake was measured using a portable system in addition to this acceleration was measured using both an MSR 165 accelerometer and a smartphone, and their heart rate was measured using a Fitbit Edge 4. Different ways to process the raw acceleration data were used to create models linking acceleration to oxygen uptake. The models were compared to each other to investigate which model best estimated oxygen uptake.

The results show that models using the L2 norm of the acceleration, with the effect of gravity removed, performed better than models using the integral of absolute acceleration. Additionally, the models based on data collected using the smartphone outperformed the models based on data from a purpose made accelerometer. A model based on 6-axis motion data collected using the smartphone performed the best with an R^2 value of 0.98 showing great potential for estimating oxygen uptake using only a smartphone.

Keywords: Oxygen uptake, Acceleration, Smartphone, Estimation, Health

Sammanfattning

Syreupptagningsförmåga är en bra indikator av kardiopulmonär hälsa, men behöver speciell utrustning och är tidskrävande att mäta. Det finns sätt att uppskatta syreupptagningsförmåga baserat på andra faktorer så som puls och acceleration. Målet med denna masteruppsats var att undersöka om modeller som uppskattar syreupptag baserat på accelerationsdata insamlad från sensorer i smartphones, samt steg- och hjärtfrekvensdata från en bärbar enhet, kunde skapas.

För att göra detta utförde tio friska försökspersoner ett kardiopulmonärt ansträngningstest (CPET) där deras syreupptag mättes med hjälp av ett portabelt system. Dessutom mättes acceleration med både en MSR 165 accelerometer och en smartphone, och deras hjärtfrekvens mättes med hjälp av en Fitbit Edge 4. Olika sätt att behandla rå accelerationsdata användes för att skapa modeller som kopplade acceleration till syreupptag. Dessa modeller jämfördes med varandra och med modeller skapade med hjärtfrekvens- och stegdata från en Fitbit.

Resultaten visar att modeller som använder L2-normen för acceleration, med gravitation borttagen, presterade bättre än modeller som använde integralen av absolut acceleration. Dessutom överträffade modellerna baserade på data insamlad med smartphones de modeller som baserades på data från MSR 165 accelerometern. En modell baserad på 6-axlig rörelsedata, insamlad med smartphones presterade bäst med en $\boldsymbol{R}^2$-värde på 0,98 och visade stor potential för att uppskatta syreupptag med endast en smartphone.

Nyckelord: Syreupptagningsförmåga, Acceleration, Smartphones, Uppskattning, Hälsa

Acknowledgements

First, I would like to thank my supervisors Chuansi Gao and Jakob Eggeling for all their help and guidance during this project.
Thank you also to all of you who participated in the study, without you there would be no thesis.
To my family and friends, thank you for all your support through the years and for the late night discussions about everything and nothing.
Finally, to Johanna, thank you for your love and support through the years.

Contents

Chapter 1
Introduction

1.1 Background

Maximum oxygen uptake ($\dot{V}O_{2max}$), first described by Hill et al. in 1921 [1] is considered a great indicator of cardiopulmonary health. The applications are numerous, both in the medical field and for recreational and professional athletes. Additionally, instantaneous oxygen uptake ($\dot{V}O_2$) has shown potential as an indicator for post-operative health [2] and could be used to estimate metabolic rate [3] in real time. However, the standard method of measuring oxygen uptake ($\dot{V}O_2$) is both time consuming and costly as it requires special equipment. Models exist that estimate $\dot{V}O_2$ based on maximum heart rate, and more recently models based on acceleration measured by accelerometers placed on different parts of the body have been developed [4]. These methods can be invasive with regards to the placement of the accelerometer and as it requires special extra equipment in the form of said accelerometers they are limited in who can perform studies. Modern smartphones and smart wearables contain accelerometers and can track heart rate and step data, thus they could in theory be used to record the same data as accelerometers used in other studies and estimate $\dot{V}O_2$ that way. This would provide greater access to $\dot{V}O_2$ data, both for individuals and for population studies and could enable applications to be developed that can give information on $\dot{V}O_2$ and related health aspects such as metabolic rate and energy expenditure. It is not clear, however, if the acceleration measured in the phone just by having it placed in the pockets of a persons pants is good enough to create this model and this is something that needs to be investigated. Furthermore, new models using 6-axis motion data including both the linear acceleration and the angular velocity of an accelerometer and gyroscope have been developed [5]. Smartphones can also log 6-axis motion data and this can potentially give even better models.

1.2 Aim & Method

The aim of this thesis is to see if a model can be created that estimates $\dot{V}O_2$ uptake in real time based on the sensors in a smartphone placed in the pocket of a person's pants. This would then be compared with the model based on an accelerometer placed on the lower back, as well as a wrist worn fitness tracker. This would eliminate the need for special accelerometers and would be less invasive than having to tape said accelerometer to the skin on the body. If the model based on the phone data can be shown to be as good or nearly as good as the model using a purpose made accelerometer without the need for calibration or fixing it in place in the pocket, then it would lower the barrier of use significantly when estimating $\dot{V}O_2$. This would enable more people to get access to information about their $\dot{V}O_2$ which in turn would give them better information about their health, exercise and/or work intensity, and metabolic rate. This could help them exercise more efficiently and could give health care providers better information about their patient's health.
This will be done by performing a $\dot{V}O_2$ test until $\dot{V}O_{2max}$ is reached, while collecting data from both a commercial accelerometer, a smartphone and a Fitbit and performing a linear regression on the data to create a linear model. Different ways to process the raw acceleration data will be tested to find out which model gives the best estimation of real oxygen uptake and hence physical activity level and metabolic rate (energy expenditure).

1.3 Research questions

The overall aim of this thesis was also summarized as two research questions, these were:

- Develop a model to estimate oxygen uptake and physical activity based on data collected using smart wearables.
- Which device/variable can better estimate oxygen uptake?

1.4 Global sustainable development goals

In 2015 the United Nations set new Global Sustainable development goals to be fully implemented in 2030 [6]. This thesis should contribute to goal 3: "Ensure healthy lives and promote well-being for all at all ages" by providing greater access to health data on both a personal and global scale. It might also contributes to goal 10: "Reduce inequality within and among countries" by reducing the need for complex and expensive equipment when studying oxygen uptake, something that richer countries will have greater access to [6].

1.5 Structure

This thesis will begin by going over previous research that is the basis for the methods chosen for the project. Next the methodology used in the study is presented, followed by the results of said study. Finally the results will be discussed and related to the previous research.

Chapter 2

Previous research

This chapter will present previous research on oxygen uptake, its uses and ways to estimate it, and acceleration processing methods. Hopefully this will provide the reader with enough information to understand the reasoning behind why certain methods were used in the study.

2.1 Oxygen uptake

Oxygen uptake is a measure of the amount of oxygen the body can take up and utilize. This increases with increased work load up to a point, after which plateaus, this is called the maximum oxygen uptake ($\dot{V}O_{2max}$). $\dot{V}O_{2max}$ is unique for each individual and depends on factors such as age, gender, lung function and fitness level [7]. According to the American College of Sports Medicine's Guidelines for Exercise Testing and Prescription [8] the average $\dot{V}O_{2max}$ for males aged 20-29 is 43.9 ml/kg/min and for males aged 40-49 it is 40.4 ml/kg/min, showing that the average maximum oxygen uptake decreases with age.

The current gold standard for measuring oxygen uptake is through indirect calorimetry by doing a maximum exertion test while directly measuring the oxygen uptake using a gas exchanger [8–10]. The most commonly used method is the Bruce treadmill test developed by Bruce in 1971 [11] where test subjects run on a treadmill at increasing speed and inclination for 3-minute periods until exhaustion [8,12]. When performing tests where $\dot{V}O_2$ for different activity levels is studied a steady state level needs to be reached which requires performing at said activity level for at least three to four minutes [8,13–16].

A standard incremental exercise test, like the Bruce protocol, gives very accurate values for $\dot{V}O_{2max}$ if done correctly but requires the test subject to wear a mask over the mouth and nose while being connected to the system which can be uncomfortable and requires specialized equipment. Therefore, tests such as these can be expensive and time consuming [17] and thus ways of estimating $\dot{V}O_{2max}$ from sub maximum tests have been developed which can be accurate at estimating the $\dot{V}O_{2max}$ to an extent [18].

2.2 $\dot{V}O_2$ and health

Maximum oxygen uptake has been linked to cardiovascular health with a higher $\dot{V}O_{2max}$ indicating a better physical fitness. This is important as cardiovascular disease is one of the leading causes of death worldwide [19–21]. Chiaranda et al. [22] studied $\dot{V}O_2$ and cardiorespiratory fitness based on models using the FRIEND registry and sub-max testing and found that increased fitness as measured by the percentage improvement in FRIEND score led to decreased hospital readmission. One of the limitations of their study was the use of a sub-max test to measure fitness and thus a way to better estimate $\dot{V}O_{2max}$ is needed, for example using acceleration [22].

In addition to $\dot{V}O_{2max}$, Rose et al. [2] showed how instantaneous $\dot{V}O_2$ could be of interest in post operative care to evaluate patient recovery. Their study showed that there is an increased need for oxygen in the immediate post operative period. However, in this kind of situation it might not always be possible to perform a full cardiopulmonary exercise test (CPET) and this is one possible area where a model estimating $\dot{V}O_2$ and not just $\dot{V}O_{2max}$ could be useful. If the patient's own phone could be used to do this estimation doctors would have access to much more information about their patients which could lead to more individualized care that could improve survival odds in the patients. This is further corroborated by the study done by Negus et al. [23] in which they showed that it can be important to include heart rate and instantaneous $\dot{V}O_2$ when coming up with a recovery plan for orthopaedic patients. As we can see there is a need for methods that can track $\dot{V}O_2$ in real time and not only estimate $\dot{V}O_{2max}$.

2.3 Metabolic rate

Oxygen uptake is also useful in determining metabolic rate which measures the energy required for different muscular loads and thus can give a value for activity level. Metabolic rate is not very affected by temperature, but a high metabolic rate can worsen the effects of heat stress since large amounts of heat is generated in the body [3]. It is therefore important to keep track of, especially in hot conditions [3]. Estimating metabolic rate through $\dot{V}O_2$ could be used to keep up to date on the risks of heat stress in real time. With climate change becoming an increasing problem, heat stress is becoming a greater issue as well which can impact all parts of life [24].

In addition to oxygen uptake, there are other ways of determining metabolic rate, as outlined in the ISO 8996 standard [3], of which the analytical methods involving accelerometry [25–28] and heart rate [27] are especially interesting [3]. By estimating $\dot{V}O_2$ using models then metabolic rate and energy expenditure, can also be estimated [28] which could be useful when exercising to know how much energy or fat you have burned. Sirichana et al. [28] further showed that energy expenditure can be reliably estimated using accelerometry based on Metabolic Equivalents (METs) where $\dot{V}O_2$ is converted into METs by assuming that 1 MET = 3.5 ml/kg/min $\dot{V}O_2$. Their model was especially accurate for lower activities below 6 METS.

One issue with using $\dot{V}O_2$ to estimate metabolic rate is that, as No et al. [29] showed, $\dot{V}O_2$ is higher at submaximal exercise for higher temperatures. In contrast $\dot{V}O_{2max}$ decreases in hot conditions [29, 30] and thus models developed at room temperature might not be accurate in hotter environments, if they are based on $\dot{V}O_2$ and $\dot{V}O_{2max}$. Potentially a compensation factor relating to the decrease in $\dot{V}O_{2max}$ in hot conditions, similar to the one described for heart rate in the ISO 8996 standard [3], could be used, but this needs to be studied. Using accelerometry to estimate metabolic rate directly could be used instead, but it would need to be generated based on data other than $\dot{V}O_2$, such as doubly labelled water [3]. It also needs to be studied how the acceleration changes depending on temperature. If it is not temperature dependent, it would be a better way to estimate metabolic rate compared to other methods. Using accelerometry to estimate metabolic rate also depends on the type of activity as stated in the ISO8996 [3] standard. Falcone et al. [31] further corroborate this. They showed that different tasks needed individual models to be accurate when estimating metabolic rates based on accelerometry.

2.4 $\dot{V}O_2$ estimation

Smartphones and smart wearables have become more and more common with 98% of the population in Sweden reporting using a mobile phone for private use [32] and models aimed at estimating $\dot{V}O_2$ using the sensors in both phones and wearables have started to be developed. Oftentimes these models focus on using heart rate as the basis for the model [33] but there is also potential for using the acceleration sensors found in smartphones or smart watches [34].
Recent studies have shown that acceleration data from accelerometers worn on the body could be used to estimate $\dot{V}O_2$ and $\dot{V}O_{2max}$ as well which could lead to even more accurate models [5, 35–37]. These methods normally use commercial accelerometers that are taped to the tibia [35], lower back [5, 36] or to the wrists or ankles [34, 35]. Additionally, Brinkløv et al. [4] showed that a smartphone placed in the pockets of the test subject's pants could predict $\dot{V}O_{2max}$ using their InterWalk app with an R^2 value of 0.6 in patients with type 2 diabetes. However, their test protocol did not include higher activity intensities, so it is unclear how well the smartphone collection method works when the subjects run at higher intensity. They also found that placing the smartphone in a lower position, such as the pants pockets, was better than in an upper position, such as on the torso or arm. If the methods developed for accelerometers fixed to the body could be applied to data collected from smartphones or wearables, then it would give the general public greater access to $\dot{V}O_2$ estimates and decrease the equipment needed for tests. This could be of interest in studying the general health of a larger population than could be studied by doing a normal $\dot{V}O_{2max}$ test since everyone with a smartphone could theoretically be included in such a study. Heart rate has also been widely used to predict $\dot{V}O_2$ and $\dot{V}O_{2max}$ [38] and by combining heart rate measurements and acceleration there is the potential for even better models [36, 39–41]. An issue with this is that the estimation by heart rate alone can be affected by environmental conditions such as temperature and thus it needs to be corrected if used for predictions in hot environments. Heart rate is further affected by age and physical fitness which also needs to be considered when creating models based on heart rate [3, 29].

2.4.1 Acceleration processing for $\dot{V}O_2$ estimation

When using accelerometers to estimate oxygen uptake the raw acceleration data needs to be processed. Different techniques for doing this exists, for example vector magnitude or the L2

norm [5, 31, 42, 43] and the Integral of absolute acceleration [25, 36, 44].
Cook et al. [36] outline one of these methods for processing the acceleration data collected from an accelerometer and creating a model for estimating instantaneous $\dot{V}O_2$. Their method revolves around taking the Integral of absolute acceleration (IAA) for 30 second periods and plotting this for corresponding 10 second periods of $\dot{V}O_2$ uptake. They calculated IAA using the following formula:

$$IAA = \int_{t=0}^{30s} a_x dt + \int_{t=0}^{30s} a_y dt + \int_{t=0}^{30s} a_z dt \tag{2.1}$$

$\dot{V}O_2$ was then calculated by performing a linear regression on the measured $\dot{V}O_2$ and the calculated IAA giving:

$$\dot{V}O_2 = k \cdot IAA + c \tag{2.2}$$

They especially found that including heart rate in the model improved performance and could become a new gold standard for instantaneous $\dot{V}O_2$ estimation.
However, in this study [36], the authors created their own wearable device using an accelerometer and ECG. It should be possible, as they mention, to use their model on other devices, such as smartphones [36]. As previously stated, using the accelerometer in a smartphone instead would be more interesting. However it is unclear whether the movement of the phone when placed in a pocket is enough, which would be interesting to study.

Another method that can be used is the one proposed by Miyatake et al. [5] where the L2 norm, sometimes called the Vector Magnitude (VM) in other articles [31, 42, 43], of the acceleration is taken. In their study, both 3-axis acceleration data and 6-axis motion data was analysed. According to their research treating each axis of the 6-axis motion data separately gave improved results rather than combining all 6-axes to one value. Since smartphones can also track 6-axis motion data it would be interesting to study if this could also be used in a similar way. From Miyatake et al. [5] the following equation for calculating the L2 norm of the acceleration is found

$$A_i^2 = \sqrt{|a_{x,i} - \bar{a}_x|^2 + |a_{y,i} - \bar{a}_y|^2 + |a_{z,i} - \bar{a}_z|^2} \tag{2.3}$$

Where $a_{x,i}$ $a_{y,i}$ $a_{z,i}$ are the ith samples for acceleration over a 10 second interval for the x, y and z directions respectively. The component of gravity is removed by subtracting the average acceleration over the 10 second interval. Another way to remove the gravity component is to use a high pass filter [31, 43].
Next the average of all i samples of L2 norms over the 10 second interval is taken.

$$I_2 = \frac{1}{N} \sum_{i=1}^{N} A_i^2 \tag{2.4}$$

This value is then used to predict $\dot{V}O_2$ as

$$\dot{V}O_2 2 = k \cdot I_2 + c \tag{2.5}$$

The values for k and c are then found using linear regression on the collected data.

For the 6-axis method I_2 is calculated independently for each axis of acceleration and these are then used for the linear regression giving a formula for $\dot{V}O_2$ [5]

$$\dot{V}O_2 = w_1 \cdot I_{ax} + w_2 \cdot I_{ay} + w_3 \cdot I_{ay} + w_4 \cdot I_{gx} + w_5 \cdot I_{gy} + w_6 \cdot I_{gz} + c \tag{2.6}$$

Chapter 3
Method

In this chapter the equipment and methods used in the study will be described. This includes the $\dot{V}O_2$ measurement and data logging as well as the data processing.

3.1 Participants

Ten healthy male volunteers were recruited as test participants. The participants were primarily recruited from friends, fellow students and family. They were not chosen based on fitness level, gender or age. All the participants had prior experience with running but not generally on treadmills. In total 13 people were recruited but three were unable to participate in the end due to illness. No monetary rewards were able to be offered to entice people to participate, instead each participant was able to find out their $\dot{V}O_{2max}$ as a form of reward. One hour was set aside for each test and this was communicated to each participant.

There were some exclusion criteria for the study. First, the participant could not have a history of cardiovascular and/or respiratory disease. In addition to this they could not have a history of musculoskeletal disorders, or recent lower limb or trunk surgery. They were also discouraged to participate if they had a cold or a fever. All subjects self-reported that they had no health problems or prior lower limb surgery that would exclude them from the study. Furthermore, all subjects signed informed consent forms to participate in the study. All subjects were asked to refrain from exercising on the day of their test, and from drinking coffee at least two hours before their test so as to not affect resting heart rate. Table 3.1 shows the participant characteristics of the study.

3.2 Equipment and setup

Participants were fitted with a polar H7 heart rate monitor (Polar Electro Oy, Kempele, Finland) over the chest which was connected to a Metamax 3B $\dot{V}O_2$ measuring system (COR-

Table 3.1: Participant data. Mean values for all participants ± standard deviation.

Gender:	Male
n:	10
Age (years)	27.6 ± 5.3
Height (cm)	181.7 ± 6.0
Weight (kg)	77.3 ± 8.2
$\dot{V}O_{2max}$ (ml/kg/min)	51.9 ± 5.6

TEX Biophysik GmbH, Leipzig/Germany) which measured oxygen uptake breath-by-breath. In addition, a wearable device, Fitbit Edge 4 (Fitbit LLC, San Francisco, USA), was placed on the left wrist to measure heart rate and steps per minute. After this an MSR 165 accelerometer (MSR Electronics GmbH) was fixed with tape to the lower back of each participant, sampling the acceleration at a rate of 100Hz for the duration of the test. Lastly, a Oneplus 6 smartphone (OnePlus Technology (Shenzhen) Co., Ltd.) was placed in the left pocket of the participants while walking and running, with the app MATLAB Mobile (Mathworks, Natick, MA, US) logging acceleration and angular velocity at a rate of 100Hz during the test. A screenshot of the app can be seen in figure 3.3 showing the acceleration as selected. Figure 3.4 shows the sampling parameters selected in the app. Acceleration from the phone was logged for all ten participants but angular velocity was only logged for seven participants. All analysis performed using angular velocity was thus based on seven participants rather than all ten. The Fitbit was forgotten for one participant, so this participant was excluded for the analysis performed on data from the Fitbit, and the polar H7 heart rate monitor would not connect to the system for one participant so this was excluded for the models including that data. A list of all the equipment used to log data can be seen in Table 3.2, including information about sampling rate and how many participants each piece of equipment was used on.

Table 3.2: List of equipment used in the study, the measurement they logged and how many of the participants they were used on.

Equipment	Measurement	Sampling rate	Number of participants
Metamax 3B	$\dot{V}O_2$	Breath-by-breath	10
Oneplus 6 smartphone	Acceleration	100Hz	10
	Angular velocity	100Hz	7
MSR 165 accelerometer	Acceleration	100Hz	10
Polar H7	Heart rate	Breath-by-breath	9
Fitbit Edge 4	Heart rate	0.2Hz	9
	Steps	0.016Hz	9

3.3 Procedure

Prior to each test the test participant's age, height and weight were recorded. Age and height were self-reported and the weight was measured using a high precision digital scale. Before the whole study the Metamax 3B system was calibrated in terms of volume and flow for

Figure 3.1: The kind of MSR 165 accelerometer used in the test. (https://www.msr.ch/en/product/datalogger-vibration-shock-acceleration-msr165/)

Figure 3.2: Photo of the Fitbit Edge 4 used in the test.

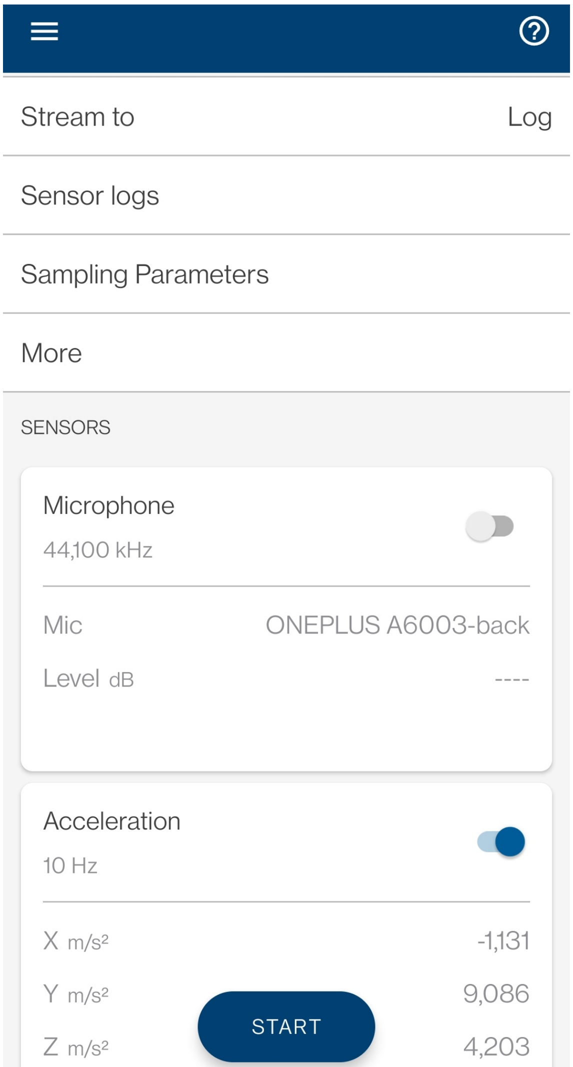


Figure 3.3: Screenshot of the MATLAB mobile app showing that the acceleration sensor is selected and tracking the acceleration

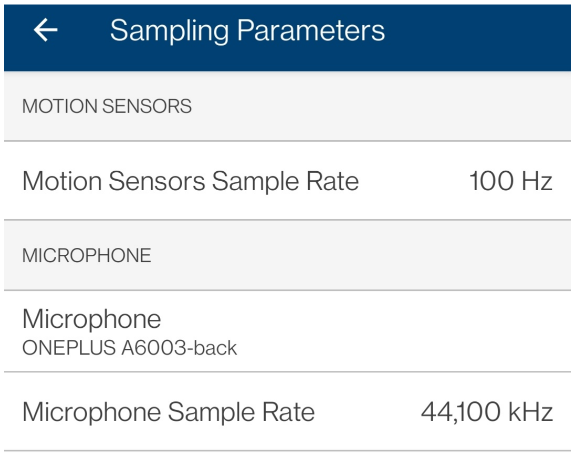


Figure 3.4: Screenshot of MATLAB mobile app showing the selected sampling parameter of 100Hz for the Motion Sensors Sample Rate

each test. New O2 and CO2 sensors were calibrated with standard gas (with O2 and CO2 concentration similar to exhaled air) before the study. Prior to each individual test ambient air calibration was performed according to the system manual, this provided a reference value for the oxygen level in the ambient air that is breathed in. The participants then performed an incremental exercise test, similar to the Bruce protocol [12, 45], on a treadmill. Meanwhile data from different sensors was synchronized and collected, like the tests done by Miyatake et al [5] and Halder et al. [13]. Other test protocols exist, such as the athlete-led protocol developed by Hamlin et al. [46] but since the Bruce protocol is widely used [11] it was decided that a modified version of this worked best for the study. In a standard Bruce protocol test the speed and inclination are increased in three minute intervals [12, 45]. For this study, the protocol was modified slightly by not increasing the inclination from the start, and by increasing the time at each interval to four minutes. This ensured that steady state for $\dot{V}O_2$ and heart rate had been reached at each interval. To reach steady state takes at least three minutes [16] and by increasing the time to four minutes it was deemed more certain that this stage had been reached. The protocol details can be seen in Table 3.3. All participants started with five minutes of sitting rest followed by four minutes of walking, jogging and running at five, eight and ten km/h respectively. After this, each participant carried on at increased speed and inclination until he felt he could no longer continue at which point the test was finished. Before each test each participant was asked about their running experience and the speed after the ten km/h section was decided based on this and was therefore different for each participant. All participants carried on at a speed of eleven or twelve km/h for at least two minutes, after which the inclination was increased in 3 grade increments for two minutes at each inclination. This was continued until the test subject was no longer able to continue at which point exhaustion was considered to have been reached. $\dot{V}O_{2max}$ was defined as the maximum $\dot{V}O_2$ registered during the test. The exact protocols for each participant can be seen in Appendix A. The start of data collection for each measuring device was synced so that collection was started at roughly the same time. As mentioned $\dot{V}O_2$ was measured breath-by-breath and since the polar H7 heart rate monitor was connected to the same Metamax

Table 3.3: Base test protocol used in the study. After all these stages were performed speed was increased by one to two km/h depending on participant. When each participant felt they had reached the maximum speed they were comfortable running at, inclination was increased in increments of grade 3. These stages were done in two to three minute intervals, depending on participant, until exhaustion.

Duration (minutes)	Speed (km/h)	Treadmill inclination (grade)
5	0 (sit and rest)	0
4	5	0
4	8	0
4	10	0

3B system, the heart rate was also logged breath-by-breath. The logging from the MSR 165 and smartphone were both started manually, and the Fitbit gathers data continuously while worn. Therefore, the start and end times were noted so that the Fitbit data could be extracted after the test using time stamps.

3.4 Data analysis

The Metamax 3B measures the $\dot{V}O_2$ and Heart rate breath by breath, thus the sampling rate is not uniform throughout the test. Therefore, the data was smoothed by taking the average over thirty seconds giving data points in thirty second intervals. This smoothing was performed in the data collection software Metasoft (CORTEX Biophysik GmbH, Leipzig/Germany) directly rather than in MATLAB.

A script written by Github user rz0012 [47] in Python to download the intraday heart rate and steps/minute data for a specific time period from the Fitbit, was used to access this data. This is possible if the same Fitbit account is used to collect the data, as the Fitbit API can be used to access your own data freely. The following is stated on Fitbits developer website "A Fitbit developer's personal Intraday data is automatically available through the "Personal" application type. You do not need to submit a request." [48]

3.5 Acceleration data processing

Two methods were used to process the acceleration data. One was the method described by Cook et al. [36] shown in equation 2.1 and 2.2 calculating the integral of absolute acceleration (IAA) over a 30 second period. The other method was the L2 norm method used by Miyatake et al. [5] described in the literature review and shown in equations 2.3-2.5. For the 6-axis motion data the method described by Miyatake et al. [5] shown in equation 2.6 was used. Similar to the IAA method the L2 norm was calculated for a 30 second time period. After the acceleration data was processed the value for the final 30 seconds of each activity level in the test protocol was plotted against the corresponding value, for the final 30 seconds of each activity level, for the $\dot{V}O_2$. Additionally, each participant's $\dot{V}O_{2max}$ and corresponding acceleration for that point was included in the data set. This was not used as a separate

Figure 3.5: Test set up. Subject running on treadmill wearing mask connected to Metamax 3B

variable, but as a data point in the whole set. Since the test protocol for each participant was different after the first four stages, only the $\dot{V}O_{2max}$ was included from the final section.

3.6 Linear Models

Linear regression [49] was performed in MATLAB in order to create a model to describe the relationship between acceleration and $\dot{V}O_2$. The model that was created was a simple linear model with a slope and intercept.

$$\dot{V}O_2 = m \cdot acc + b \tag{3.1}$$

Four different models were created using the acceleration data from the MSR 165 and from the phone. For both collection methods, the acceleration data was process in two different ways (IAA or L2 norm). In the equation above acc. represents either the IAA or L2 norm and b is the y-intercept.

$$\dot{V}O_{2_{MSR_{IAA}}} = a \cdot IAA_{MSR} + b \tag{3.2}$$

$$\dot{V}O_{2_{MSR_{L2}}} = a \cdot L2_{MSR} + b \tag{3.3}$$

$$\dot{V}O_{2_{Phone_{IAA}}} = a \cdot IAA_{Phone} + b \tag{3.4}$$

$$\dot{V}O_{2_{Phone_{L2}}} = a \cdot L2_{Phone} + b \tag{3.5}$$

Four additional models were created by performing multiple linear regression with the acceleration and heart rate as predictor variables. This gave four models:

$$\dot{V}O2_{MSR_{IAA+HR}} = a \cdot IAA_{MSR} + b \cdot HR + c \tag{3.6}$$

$$\dot{V}O2_{MSR_{L2+HR}} = a \cdot L2_{MSR} + b \cdot HR + c \tag{3.7}$$

$$\dot{V}O2_{Phone_{IAA+HR}} = a \cdot IAA_{Phone} + b \cdot HR + c \tag{3.8}$$

$$\dot{V}O2_{Phone_{L2+HR}} = a \cdot L2_{Phone} + b \cdot HR + c \tag{3.9}$$

In the models, a and b are model constants and c is the y-intercept.

In addition to these models linear regression was performed on $\dot{V}O_2$ and heart rate, measured using the Polar H7 and Fitbit, on its own. A model based on $\dot{V}O_2$ and steps/minute measured using the Fitbit was also created. Finally a model combining steps/minute and heart rate was created.

$$\dot{V}O2_{PolarH7_{HR}} = a \cdot HR_{PolarH7} + c \tag{3.10}$$

$$\dot{V}O2_{Fitbit_{HR}} = a \cdot HR_{Fitbit} + c \tag{3.11}$$

$$\dot{V}O2_{Fitbit_{Steps}} = a \cdot Steps_{Fitbit} + c \tag{3.12}$$

$$\dot{V}O2_{Fitbit_{Steps+HR}} = a \cdot Steps_{Fitbit} + b \cdot HR_{Fitbit} + c \tag{3.13}$$

For the 6-axis data set one model was created, a multiple linear regression was performed in MATLAB with six predictor variables as described by Miyatake et al. [5]. No model was created combining all 6 axes, as the performance was lower than that with them assessed independently as shown by Miyatake et al. [5]. All models were based on the final 30 seconds of each activity level that was common between all test subjects. In addition to these the $\dot{V}O_{2max}$ value was added for each subject and the corresponding 30 second period preceding the time this was reached for the acceleration data.

3.7 Leave one out validation

Since the data set consisted of data from only ten subjects, leave one out cross correlation [4, 50] was used on the data. This meant that for each method a model was created based on nine test subjects and this was then used to estimate the $\dot{V}O_2$ for the tenth subject. This was then repeated ten times creating ten models that were used to estimate ten different subjects. Then, for each model, the Mean Absolute Error of $\dot{V}O_2$ was calculated for each test subject and its model by calculating the absolute error for selected data points when comparing the estimated $\dot{V}O_2$ from the models to the actual measured $\dot{V}O_2$ and then taking the mean of this [35].

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|VO2_{estimated} - VO2_{measured}| \tag{3.14}$$

Chapter 4
Results

This chapter will present the results of the tests that were performed and the models that were created based on the collected data.

4.1 Oxygen uptake and acceleration

The measured $\dot{V}O_2$ with 30 second smoothing, as well as the L2 norm of the acceleration and the IAA of the acceleration, for one test subject are shown in figures 4.1 and 4.2. The scale for $\dot{V}O_2$ is shown on the left and for acceleration to the right. Vertical lines indicate the breakpoints for the different stages of the test as shown in Table 3.3, beginning with the rest period. For all the participants the actual start time of the 5 km/h part was slightly delayed by roughly 15 seconds due to them moving to the treadmill and starting running. This is not indicated in the graphs since the time region of interest is the final 30 seconds of each stage, when steady state has been reached. The points for the acceleration is the processed acceleration of the preceding 30 seconds.

4.2 Linear models

The subfigures in figure 4.3 show the results of linear regression performed on $\dot{V}O_2$ and acceleration data. Specifically, figures 4.3a and 4.3c shows the results of the linear regression performed on the MSR 165 data and figures 4.3b and 4.3d show the linear regression performed on data from the smartphone. These models are shown in equations 4.1 to 4.4.

Four additional models were created combining either the IAA or L2 norm with the heart rate, measured using the polar H7 heart rate monitor, and then performing multivariable regression with these as predictor variables as described in section 3.5, equations 3.6 - 3.9. The combined acceleration and heart rate models are shown in equations 4.6 to 4.9.

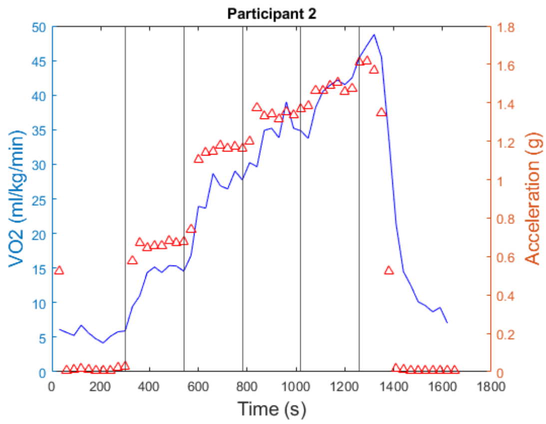


Figure 4.1: $\dot{V}O_2$ and the L2 norm of acceleration over the duration of the test for one participant. The blue line shows the $\dot{V}O_2$ with 30 second smoothing and the triangles show the L2 norm of the acceleration, measured from the smartphone and calculated using MATLAB. Scale for $\dot{V}O_2$ to the left and acceleration to the right. The vertical lines represent the breakpoints for the different parts of the test protocol.

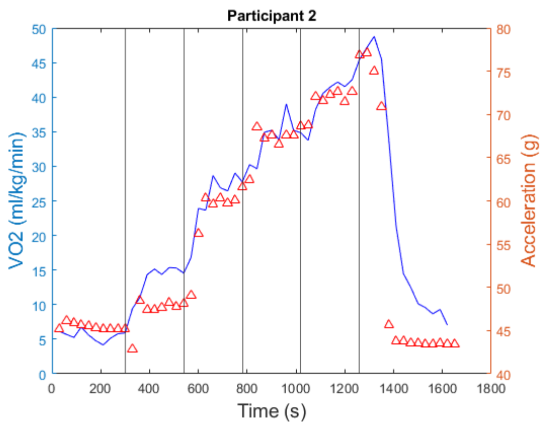
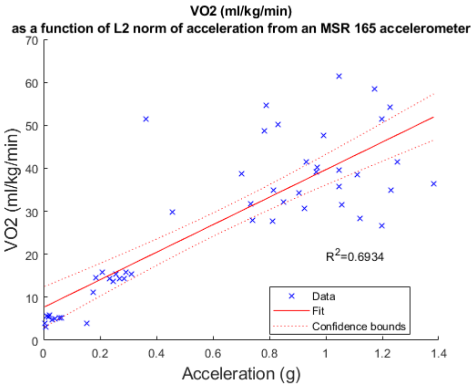
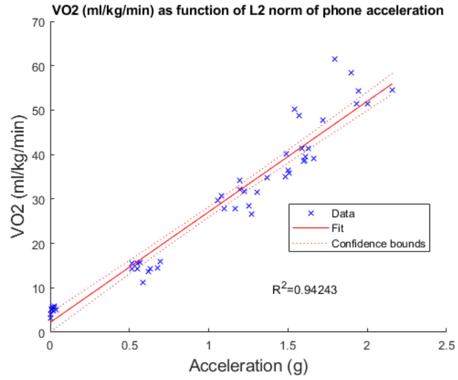


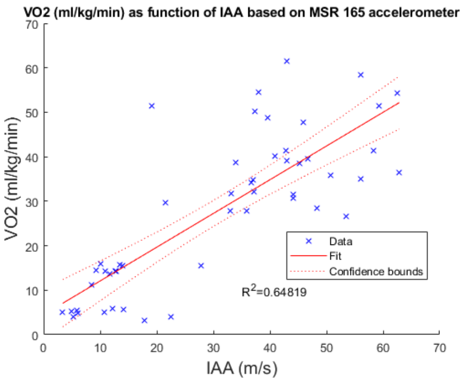
Figure 4.2: $\dot{V}O_2$ and the IAA for the duration of the test for one participant. The blue line shows the $\dot{V}O_2$ with 30 second smoothing and the triangles show the IAA of the acceleration, measured from the smartphone and calculated using MATLAB. Scale for $\dot{V}O_2$ to the left and acceleration to the right. The vertical lines represent the breakpoints for the different parts of the test protocol.



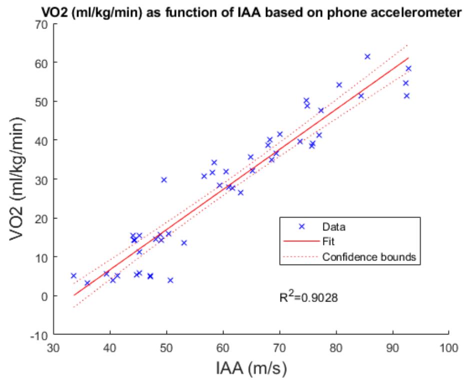
(a) L2 MSR 165.



(b) L2 phone.

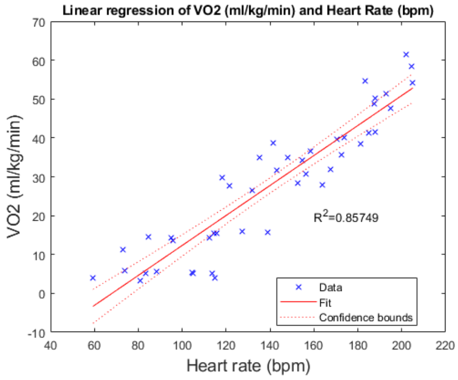


(c) IAA MSR 165.

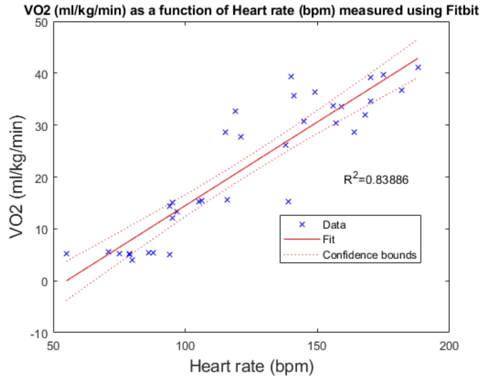


(d) IAA Phone.

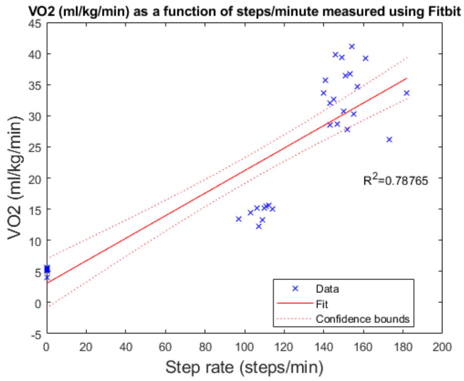
Figure 4.3: Linear regression plots of $\dot{V}O_2$ and the integral of absolute acceleration or L2 norm, calculated on acceleration data collected with either MSR 165 accelerometer (a and c) or MATLAB Mobile running on a Oneplus 6 smartphone (b and d). With line of best fit and 95% confidence bounds.



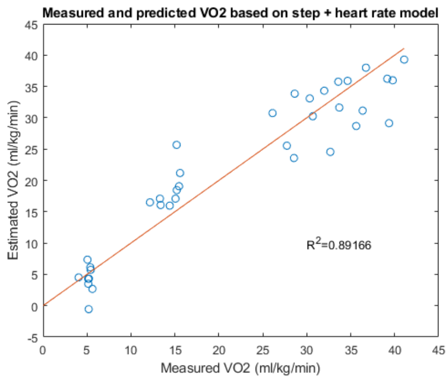
(a) Polar H7 HR



(b) Fitbit HR



(c) Fitbit Steps/min



(d) Steps & HR

Figure 4.4: Results of the linear regression performed on $\dot{V}O_2$, heart rate and steps/min. $\dot{V}O_2$ measured using Metamax 3B, heart rate measured using Polar H7 heart rate monitor or Fitbit Edge 4 and steps/min measured using Fitbit Edge 4. The first two figures show models based on only heart rate, figure three shows model based on steps and final figure shows results of multiple linear regression based on steps and heart rate.

$$\dot{V}O_{2_{L2(MSR)}} = 32.0339 \cdot L2_{MSR} + 7.6431 \tag{4.1}$$

$$\dot{V}O_{2_{L2(Phone)}} = 24.9047 \cdot L2_{Phone} + 2.2028 \tag{4.2}$$

$$\dot{V}O_{2_{IAA(MSR)}} = 0.7583 \cdot IAA_{MSR} + 4.4980 \tag{4.3}$$

$$\dot{V}O_{2_{IAA(Phone)}} = 1.0312 \cdot IAA_{Phone} - 34.6236 \tag{4.4}$$

$$\begin{aligned}\dot{V}O_{2_{6-axis}} = {} & 17.2488 \cdot I_{ax} + 24.3149 \cdot I_{ay} + 11.3253 \cdot I_{az} \\ & -3.3050 \cdot I_{gx} - 1.5313 \cdot I_{gy} + 0.4606 \cdot I_{gz} + 4.4929\end{aligned} \tag{4.5}$$

$$\dot{V}O_{2_{L2HR(MSR)}} = 11.5130 \cdot L2_{MSR} + 0.2813 \cdot HR - 19.0565 \tag{4.6}$$

$$\dot{V}O_{2_{L2HR(Phone)}} = 18.0016 \cdot L2_{Phone} + 0.1283 \cdot HR - 8.6515 \tag{4.7}$$

$$\dot{V}O_{2_{IAAHR(MSR)}} = 0.2463 \cdot IAA_{MSR} + 0.2983 \cdot HR - 21.7885 \tag{4.8}$$

$$\dot{V}O_{2_{IAAHR(Phone)}} = 0.6669 \cdot IAA_{Phone} + 0.1558 \cdot HR - 34.2266 \tag{4.9}$$

Four models were created using linear regression based on heart rate and steps, measured using a Polar H7 heart rate monitor and Fitbit Edge 4. These can be seen in figure 4.4a-4.4d. The first two models show the linear regression performed on $\dot{V}O_2$ and heart rate with figure 4.4a showing the Polar H7 model and figure 4.4b showing the Fitbit HR data. Figure 4.4c shows the linear regression results of the steps/min data from the Fitbit. Finally, figure 4.4d shows the estimated $\dot{V}O_2$ from the combined steps and heart rate model created using multiple linear regression plotted against the measured $\dot{V}O_2$. The corresponding models are shown in equations 4.10 - 4.13.

$$\dot{V}O_{2_{PolarH7HR}} = 0.3856 \cdot HR_{PolarH7} - 26.2272 \tag{4.10}$$

$$\dot{V}O_{2_{FitbitHR}} = 0.3224 \cdot HR_{Fitbit} - 17.7302 \tag{4.11}$$

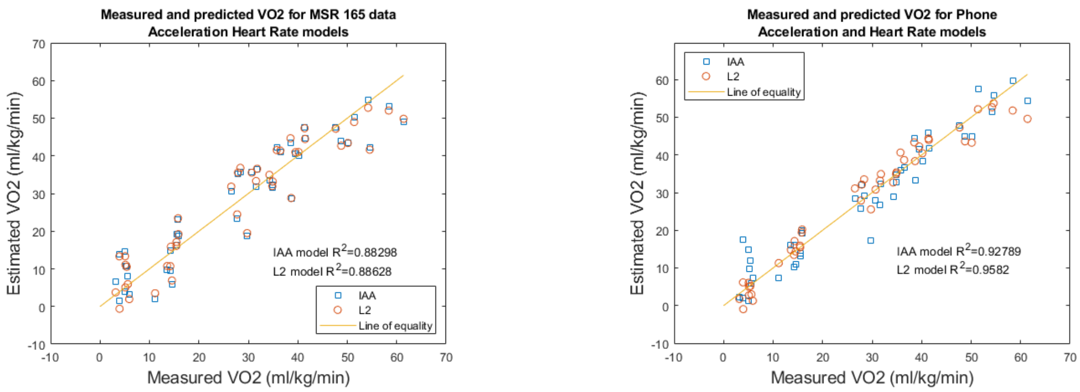
$$\dot{V}O_{2_{FitbitSteps}} = 0.1811 \cdot Steps_{Fitbit} + 3.0763 \tag{4.12}$$

$$\dot{V}O_{2_{FitbitSteps+HR}} = 0.0837 \cdot Steps_{Fitbit} + 0.2027 \cdot HR_{Fitbit} - 11.7084 \tag{4.13}$$

The R^2 values for the models given in eq. 4.1 to 4.13 are shown in table 4.1. All models are significant with p<0.001. The phone models all have R^2 values greater than 0.9 and the models that include heart rate have greater R^2 values than the models that do not include it.

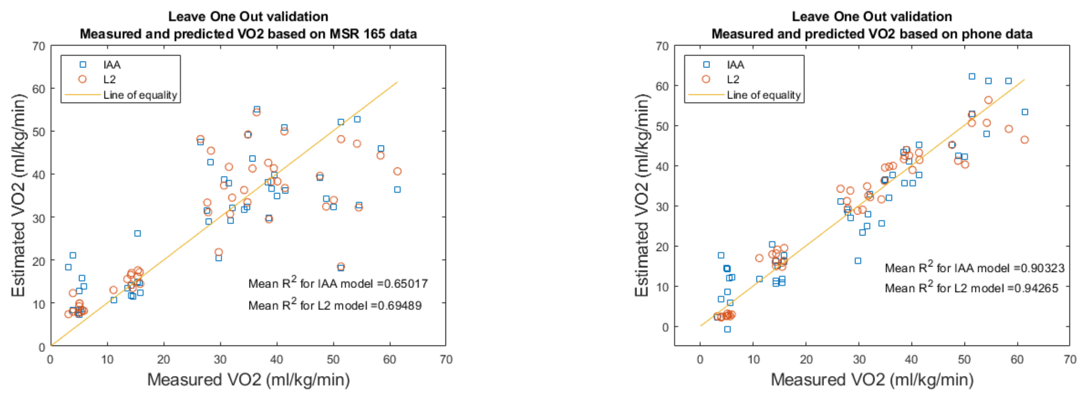
In figure 4.5 the models created in equations 4.6 - 4.9 were used to predict $\dot{V}O_2$ based on the acceleration data. The predicted values were plotted against the measured $\dot{V}O_2$ for the corresponding acceleration and the resulting plots are shown in figures 4.5a and 4.5b where the line of equality where the predicted value is equal to the measured value is shown. The squares show the results of the IAA models and the circles show the L2 norm models.

The results of the leave one out analysis is shown in figure 4.6 as the predicted $\dot{V}O_2$ from the models plotted against the corresponding measured $\dot{V}O_2$. All models created in the leave one out analysis are combined in one plot together with the average R^2 value for all models. The squares represent the IAA acceleration processing method and the circles represent the L2 method. Leave one out validation was also performed on the 6-axis motion model. The



(a) MSR 165 **(b)** Phone

Figure 4.5: Measured $\dot{V}O_2$ on x-axis and predicted $\dot{V}O_2$ based on acceleration and heart rate models on y-axis. Squares represent the IAA method of acceleration processing and circles the L2 norm method. The line is the line of equality where the predicted value is equal to the measured value.



(a) MSR 165 **(b)** Phone

Figure 4.6: Measured $\dot{V}O_2$ on x-axis and predicted $\dot{V}O_2$ based on leave one out validation performed on all the data. Squares represent the IAA method of acceleration processing and circles the L2 norm method. The line is the line of equality where the predicted value is equal to the measured value.

Table 4.1: R^2 values for the different linear models created using linear regression. The MSR subscript indicates a model based on data collected using the MSR 165 accelerometer, and the Phone subscript indicates that the model was based on data collected using the smartphone. Heart rate for the combined acceleration and heart rate models was logged using the polar H7 heart rate monitor connected to the Metamax 3b.

Model	R^2	Eq.
$L2_{MSR}$	0.6934 (p<0.001)	4.1
$L2_{Phone}$	0.9424 (p<0.001)	4.2
IAA_{MSR}	0.6482 (p<0.001)	4.3
IAA_{Phone}	0.9028 (p<0.001)	4.4
$L2 + HR_{MSR}$	0.8863 (p<0.001)	4.6
$L2 + HR_{Phone}$	0.9582 (p<0.001)	4.7
$IAA + HR_{MSR}$	0.8830 (p<0.001	4.8
$IAA + HR_{Phone}$	0.9279 (p<0.001)	4.9
$HR_{PolarH7}$	0.8575 (p<0.001)	4.10
HR_{Fitbit}	0.8389 (p<0.001)	4.11
$Steps_{Fitbit}$	0.7877 (p<0.001)	4.12
$Steps + HR_{Fitbit}$	0.8917 (p<0.001)	4.13

predicted $\dot{V}O_2$ from all models are plotted against the measured $\dot{V}O_2$ in figure 4.7.

The mean R^2 values, calculated using leave one out validation, for the IAA and L2 models based on both MSR 165 and phone data, and the 6-axis model are shown in table 4.2. The mean R^2 is greatest for the 6-axis model, and the phone models are greater than the MSR 165 models. Including the heart rate in the models increases the R^2 value for all models with the increase being largest for the MSR models. All models have a mean p<0.001 meaning they are significant.

Additionally, the mean absolute error and root mean square error was calculated for the models using leave one out validation, the results of which are shown in table 4.3. The MAE and RMSE are lower for the phone models and the 6-axis model where the L2 acceleration processing has a lower MAE and RMSE than the IAA method.

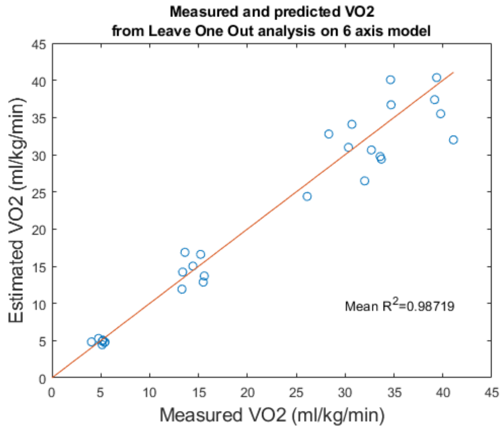


Figure 4.7: Measured $\dot{V}O_2$ on x-axis and predicted $\dot{V}O_2$ based on leave one out validation performed on the 6-axis motion model. The line of equality is shown, indicating when the predicted $\dot{V}O_2$ is equal to the measured.

Table 4.2: Mean R^2 calculated using leave one out validation for the models described in equations 4.1 - 4.9 and the 6-axis model. The heart rate for the models was logged using a polar H7 heart rate monitor connected to the Metamax 3B system.

Model	Mean R^2
$L2_{MSR}$	0.6949 (p<0.001)
$L2_{Phone}$	0.9427 (p<0.001)
IAA_{MSR}	0.6502 (p<0.001)
IAA_{Phone}	0.9032 (p<0.001)
$6-axis$	0.9872 (p<0.001)
$L2+HR_{MSR}$	0.8819 (p<0.001)
$L2+HR_{Phone}$	0.9516 (p<0.001)
$IAA+HR_{MSR}$	0.8801 (p<0.001)
$IAA+HR_{Phone}$	0.9295 (p<0.001)

Table 4.3: Mean absolute error (MAE) of $\dot{V}O_2$, and Root Mean Square Error (RMSE) of $\dot{V}O_2$ for the models described in equations 4.1 - 4.9 and for the 6-axis model.

Model	MAE (ml/kg/min)	RMSE (ml/kg/min)
$L2_{MSR}$	6.9	9.9
$L2_{Phone}$	3.2	4.2
IAA_{MSR}	7.5	10.6
IAA_{Phone}	4.4	5.5
$6-axis$	2.3	3.1
$L2+HR_{MSR}$	5.4	6.4
$L2+HR_{Phone}$	3.0	3.9
$IAA+HR_{MSR}$	5.5	6.5
$IAA+HR_{Phone}$	4.0	5.0

Chapter 5
Discussion

This chapter will first go over some general thoughts about the project as a whole. Then, there will be some discussion on the results and it will link the results to the theory presented in the chapter on previous research. Finally some future research possibilites and uses will be discussed.

5.1 General thoughts

Designing and carrying out a study involving human participants from scratch was a challenging but rewarding experience. Several factors made the project take longer than initially planned and with hindsight the initial end date was probably optimistic. For example, at the start, when the research questions were posed and solidified, it was not even certain that acceleration data from the phone could be accessed, not to mention the fact that no participants had yet been recruited.

The acceleration problem proved to be no problem at all, MATLAB had the answer with their mobile app. Recruiting test participants, was also not as difficult as one might expect. Friends, family, friends of friends and fellow classmates were asked if they wished to participate and the response was surprisingly enthusiastic. Most felt that the project sounded interesting, and since a lot of them were runners themselves they wished to find out their $\dot{V}O_{2max}$. Finding time for all the tests and actually carrying them out was a different matter. The approach chosen for the planning of test dates and times was to do it on an individual basis, talking to each participant and finding a time that suited them. Unfortunately, this meant that there was a lack of overview of the whole test and when each participant was available. In a future test a more sensible approach would be to send out a form where each participant can fill in the times they are available, and then plan from that. Further problems arose when participants wrote on the day of the test that they were ill. Obviously they could not participate if they were ill, so when possible their tests were rescheduled. This meant that the tests took many weeks to finish and some participants could not reschedule and could not participate in the end. It should be mentioned, however, that the wish before the study was to have at least ten participants and this was achieved, which was a huge plus, and is not something to take lightly. Finding participants for studies is hard, especially when you cannot offer a concrete reward.

There is a risk that the fact that the participants were mostly people who regularly exercise, and who were interested in finding out their $\dot{V}O_{2max}$ influenced the results by being a group with above average fitness. This is indicated by the fact that the average $\dot{V}O_{2max}$ for the participants was 51.9 ml/kg/min as seen in Table 3.1 which is above the average of 43.9 ml/kg/min for the age group [8]. This was purely unintentional as there was no focus on this in the selection process. Rather the selection was one of convenience and anyone who could and wanted to participate was welcome.

When designing the $\dot{V}O_2$ test, a version of the Bruce protocol [12] was chosen since it is the most common test protocol used [11]. Since the test is mainly used to measure $\dot{V}O_{2max}$ [11,12] it was modified to put more emphasis on the intermediary phases and not push to exhaustion as quickly as possible. By emphasising these phases steady state was reached for the different activity levels since four, rather than three minutes [16], at each increment was chosen as the time. The inclination was not increased until after the ten km/h section since it is not certain how the inclination affects the acceleration data. Investigating that is something that should be done in a future test. This had the end effect that each test took longer than is perhaps ideal when measuring the maximum uptake [16] but it felt like a decent compromise.

5.2 Estimation Models

Based on the results of the tests there seems to be a good linear relationship between oxygen uptake, $\dot{V}O_2$, and acceleration, both when measured with an accelerometer placed on the lower back, and when a smartphone placed in the front pockets of a person's pants was used. The linear relationship for both collection methods is similar to the results from Cook et al. [36] and it would therefore seem that the results are reliable. The R^2 values for the models created using the MSR 165 data were significantly lower compared to the results by Cook et al. [36] and Miyatake et al. [5], which the methodology was based on. One possible explanation could be that the accelerometer was placed differently on the back or that the placement on different test participants was slightly different. This could influence the results and explain why the results disagree with those from the other studies. When studying this type of activity using the smartphone these problems do not exist as the phone is simply placed in the pants pocket of the test participant which is another benefit to being able to use the smartphone for data collection. However, for other kinds of activity, such as lifting heavy things using the hands and lower back then the accelerometer on the lower back might be better suited.

The results show that the R^2 values for the models created using the smartphone data were higher than those created using the MSR 165 data. This suggests that simply using a smartphone without calibration and by only placing it in the pocket of your pants and gathering data this way could be used to estimate oxygen uptake. From figure 4.3, we can see that for lower acceleration levels, the MSR 165 models are performing quite well but for higher accelerations the data becomes more spread out and does not follow the linear model as well. In contrast, for the models created using phone data there is a much more linear grouping of the data even for higher intensities. This is true for both the IAA and L2 norm methods of acceleration processing. The indication here is that using the phone gives a better response to higher running speed than an accelerometer placed on the lower back. One potential reason for this is that the legs move a lot more than the trunk when running and this movement is less dependent on the individual and more on the actual running speed. Since only running on a treadmill was studied it is possible that the same is not true for running in the field instead as in that case it is more difficult to run at a specific speed. Further testing is therefore needed to validate the models beyond running on a treadmill.

As can be seen in table 4.3 the mean absolute error (MAE) was lowest for the model created based on the phone data and using the L2 norm method, with the L2 method being significantly better than the IAA model for the phone. For the MSR 165 data both the IAA and L2 models performed similarly, with the L2 method being slightly better. Therefore, when using the phone to collect data the L2 norm method should be used as it has a significantly lower MAE meaning the estimated $\dot{V}O_2$ will be closer to the actual $\dot{V}O_2$. When using a normal accelerometer fixed to the lower back, the L2 norm model is still better but not significantly so and there might be other things to take into consideration such as computation time or performance at different exercise levels. From figures 4.6 we can in fact see that for the rest period the L2 norm predictions are much better grouped near the line of equality. The next grouping represents the 5 km/h walking speed and here both models group well near the line with the L2 norm model for the phone overestimating the $\dot{V}O_2$ slightly and the IAA underestimating it. For the MSR data both models perform similarly for this activity level. At the higher activity level, the data is more spread out showing that, especially for the MSR 165, the models perform better at lower activity levels. The predicted $\dot{V}O_2$ from the L2 model on the phone overestimates the $\dot{V}O_2$ slightly but is overall grouped linearly together better than the IAA model.

When including heart rate in the models the ones based on the MSR 165 improve significantly with R^2 values increasing by 0.2 for both IAA and L2 norm as we can see in table 4.1. The models based on the phone also improve but not as much. The performance is especially improved at higher activity levels when the $\dot{V}O_2$ is higher as can be seen when comparing figure 4.5 to figure 4.6. Based on these results we can say that if an accelerometer that is placed on the lower back is used then heart rate should also be measured and used to get accurate estimates of $\dot{V}O_2$. When using the phone on the other hand the performance improvement is not as large and it should be enough to simply use the phone. As previously mentioned it should also be taken into consideration what task is performed when deciding which data collection method should be used and whether heart rate should be included or not.

In figure 4.4 the different regression models created based on heart rate alone and with steps/min from the Fitbit are shown. There is no large difference between the models based on the heart rate from the Polar H7 heart rate monitor and from the Fitbit. This indicates that the Fitbit can be used to measure the heart rate and estimate $\dot{V}O_2$ based on this, just as it can be done using the Polar H7. However, for the rest and 5km/h activity levels the heart rate is quite spread out even though the $\dot{V}O_2$ at these levels is roughly the same. It thus seems as though the resting and low activity heart rate is more individual than the $\dot{V}O_2$ at these levels and that using these models to estimate $\dot{V}O_2$ will not be accurate. This is in contrast to the models based on acceleration where the estimated $\dot{V}O_2$ for lower activity levels are quite good, especially for the L2 and 6-axis models.

For the model based on steps/min, however, we can see in figure 4.4c that there is a grouping of date well outside the confidence bounds, corresponding to the steps/min for 5km/h. Thus, even though the R^2 value is 0.78, which sounds good, the model will probably severly underestimate the $\dot{V}O_2$ for lower activity levels such as walking. This problem is eliminated in the model that combines steps and heart rate, shown in figure 4.4d, here we can see that the predicted $\dot{V}O_2$ from the model is slightly overestimated for the 5 km/h level and then more evenly spread around the line of equality for the higher activity levels. Therefore we can say that using only step data from a Fitbit is not accurate enough but combining it with heart rate also measured from the Fitbit improves the performance.

The main issue with heart rate based models is that heart rate for different activity levels can change depending on environmental temperature. [3, 29] The maximum heart rate reached will be lower in hotter environments as will the $\dot{V}O_{2max}$, but for lower activity levels the heart rate and $\dot{V}O_2$ is lower, as shown by No et al. [29] Since this study was performed in room temperature nothing can be said about the performance of the models in a hot or cold environment. It does provide a good benchmark for future testing, however, since thermal stressors probably increase the individual response making it harder to say things about a population. One of the benefits of using acceleration based models could be that they might be less temperature dependent but further research needs to be done to assess this. It is possible that a temperature dependency term needs to be added to the regression model to ensure that it performs well in higher or lower temperatures since the $\dot{V}O_2$ is also affected by temperature [29].

When comparing the 6-axis model to the triaxial models the R^2 value of 0.98 for the multivariable 6-axis model is higher than all the other models, including the ones that combine heart rate and acceleration. In figure 4.7 we can see that the data points are grouped very well along the line of equality meaning the estimated $\dot{V}O_2$ is very close to the measured $\dot{V}O_2$ with no consistent under- or over estimation of $\dot{V}O_2$. In table 4.3 wa can also see that the 6-axis method had the lowest MAE and RMSE of all the models. This indicates that using the accelerometer and gyroscope found in a smartphone, to gather 6-axis data, is a good way to estimate $\dot{V}O_2$ uptake. Thoguh, it is not certain that all phones have this possibility. The MATLAB mobile app that was used to log the acceleration and motion data on the phone is free and available on Android phones. However, a MATLAB account is needed for this which is not free unless you are a student. The use of MATLAB mobile does show that the phone has sensors for both triaxial acceleration and angular velocity so one could fairly easily develop an app that logs that data, eliminating the need for MATLAB mobile. The results shown are in line with those found by Miyatake et al. [5] and a model using 6-axis motion data with all accelerations used separately in the model seems to be the best option. It should be mentioned that this model was created based on only seven participants as this data was not collected for the first three participants. Thus, it is possible that the results would be different with more participant data.

5.3 Acceleration analysis methods

When analysing the acceleration data, two different methods were used. From figures 4.1 and 4.2 we can see that the acceleration follows the $\dot{V}O_2$ quite well but there are some key differences for the two methods. For the IAA we can see that when the test person was stationary, sitting down, at the start of the test the IAA is nonzero but stable at different levels depending on the test subject. This could be good as the $\dot{V}O_2$ is also not zero during resting, but the acceleration processing should represent the level of activity which for this stage was basically zero for all participants. For the L2 norm method however the norm is zero when the test subject is not moving which better represents their actual activity level. This shows that the L2 norm method successfully removes the gravity component as otherwise it would show 1G when no other movement is present. Instead of this method for eliminating the gravity component, a high pass filter could be used, as done by Falcone et al. [31], however as the method used worked well this seems unnecessary.

One thing that can be seen is that the IAA and L2 norm models differ mainly at the resting level and perhaps if this was excluded from the model the results would be different. Including the rest level does give a good intercept for the model however and should therefore probably be included.

5.4 Test set up

Creating a test that could both work for measuring instantaneous $\dot{V}O_2$ as well as getting a value for $\dot{V}O_{2max}$ was tricky. For $\dot{V}O_{2max}$ you generally want to increase the activity level quickly to exhaustion [8,11], whereas to measure the $\dot{V}O_2$ at different activity levels you want a steady state value which is reached after more than three minutes in general [13–16]. This means that the test set up used for this study worked well for the $\dot{V}O_2$ at different levels but might not give a completely accurate value for $\dot{V}O_{2max}$.

Another issue was the fact that the test terminated immediately after $\dot{V}O_{2max}$ was reached and thus $\dot{V}O_2$ and the other measurements were not performed at rest after the running. This is especially problematic when creating the model using the L2 norm method for acceleration. When using this method, the values at rest are zero, as can be seen in figure 1 in the results. However, the $\dot{V}O_2$ at rest before and immediately after the exertion is not necessarily the same which can be seen in figure 1. The acceleration immediately drops to zero when the test is terminated and the subject rests but the $\dot{V}O_2$ takes some time to reach its base level. Thus, when the values at rest before the test are used in the model creation a very stable intercept is found. If the values at rest after the test were to be included this intercept would not be as well defined. It can therefore be discussed if the rest values should be included when creating the model or not.

The MATLAB mobile application was used to log the acceleration data on the phone. This worked well and the data was saved as .m files that could be downloaded and used easily. One issue that was encountered was that the timestamp data that was saved was incorrect and did not correspond to the 100Hz sample rate that was used. At first the timestamp data was assumed to be correct but after studying the data and comparing it to the $\dot{V}O_2$ results it was discovered that the 100Hz sample rate was in fact used. Therefore the acceleration data was plotted not against the timestamps logged but to the time after the start which was set to zero. This meant that there were 100 samples per second which is what was used in the data processing.

When carrying out the test it was somewhat difficult to start logging all data at the same time as there were several different measuring tools that needed to be started at the same time. This meant that two researchers had to start measurements, and the test subjects were asked to start the logging on the phone and then put the phone in their pocket. However, even if all the logging was not started at the exact same time it should not be a problem. This is because the $\dot{V}O_2$ data is smoothed over a 30 second interval in the first place, and the acceleration data is processed over 30 second intervals, this means that even if there was a difference in start time of one or two seconds it should not matter as each second is not individually processed.

5.5 Limitations of the study

The study was carried out on only healthy male test subjects and therefore the models created can only really be used on data from men to estimate their $\dot{V}O_2$. Since the study only had ten participants this is perhaps a good thing since there is a difference in $\dot{V}O_{2max}$ based on gender and by having both genders in the study the results for each gender would be less certain. Further studies with a larger study group and a greater mix of genders are needed to validate the models for use by women as well. Furthermore, only healthy participants were included and if one wants to use the model to estimate $\dot{V}O_2$ for patients in post operative care, for example, then testing on patients in post operative care would have to be carried out. This is difficult as you do not want to have unhealthy people perform $\dot{V}O_{2max}$ tests. Perhaps a test where $\dot{V}O_2$ is measured at exercise intensity while logging acceleration data and basing a model on this could be carried out on these patients to create a model based on them. Here there are other issues such as different types of surgery etc. that would need to be considered, but this is for a future study and beyond the scope of this one.

5.6 Potential Uses

The results show that there is a potential for creating phone applications that can estimate oxygen uptake based on the acceleration measured from the phone's accelerometer, which could simplify test protocols significantly, and conduct large scale population studies. There could even be the possibility of using the test subjects, or a researcher's, own phone when performing a test, rather than purchasing potentially expensive accelerometers that then have to be placed on the subject's skin. However, as the test was performed using one specific model of phone, further tests need to be done to test different phones as there could be differences in how good the accelerometers are.

The potential for phone apps extends further than the research sphere. Smart wearables are getting more and more popular, and people want to know more about their health. As it stands now, $\dot{V}O_2$ max tests can be expensive. A quick Google search showed tests costing upwards of 2400 SEK [51] in Sweden at a facility focused on providing health and fitness testing, and thus an app that calculates it for you which needs nothing more than your phone would enable more people to get a better understanding of their health. It should be said, however, that such an app would work best when used in combination with a test set up in the same way as the test in this study as the model has not been compared to data collected in the field. This is a potential future research area that could be interesting.

Using the estimated $\dot{V}O_2$ to estimate the metabolic rate in real time also has great potential when it comes to aiding with exercise and preventing issues such as heat stress. By combining metabolic rate estimates, for example through $\dot{V}O_2$ estimated using accelerometry as described in this thesis, with information about ambient air temperature and information about an individual then warnings could be issued when the individual is at higher risk of heat stress. Models combining these will need to be created and validated but that is for a future project.

5.7 Ethics

Whenever health data is gathered the ethics of its use needs to be discussed. If, for example, an application was to be created it is important to consider who has access to the data that is collected using it. For an app aimed at providing information to aid in planning an exercise regime the collected data should only be able to be accessed by the user of the app and not for data collection on a larger scale. In this use case it should also be clear that the $\dot{V}O_2$ estimate is not to be used as an indication of health. This type of information is already available from fitness trackers and thus there should be rules in place for how the data is used already.

If the data is used in a medical setting by a physician, perhaps to track oxygen uptake in patients recovering from different illnesses, then it needs to follow laws and regulations regarding medical information about patients. The data should also only be analysed by a medical professional and any smartphone application that is created should not make any judgements or give advice. There is otherwise a risk that people might be more, or less, inclined to seek help depending on what information they are given. It would be disastrous for an application to give a clean bill of health by only interpreting the oxygen uptake and not taking other health factors into account.

Since maximum oxygen uptake is a great indicator of cardiopulmonary health, there could be an interest to keep track of data from a large population to see the overall health of said population. For example, public health agencies in countries around the world might want to use an application to get an idea of the health of their country. Collecting this type of data by measuring oxygen uptake directly would be very time consuming and expensive so using a smartphone app to estimate it could be of interest. In this case there are serious ethical considerations with regards to who would have access to this data and everyone whose data is collected would need to consent to its collection.

Furthermore, it is one thing for government public health agencies to access health data, but say that insurance companies would have access to it. In that case they could base insurance rate on perceived health and since we are only talking about estimations they might not even be correct.

Clearly there needs to be rules in place for the use of collected data, and it needs to be clear that the information shown is only estimates and that for any serious health checks actual measurements would need to be done.

Chapter 6
Conclusions

Estimating $\dot{V}O_2$ in real time using a linear model based on 6-axis motion data collected using a smartphone gave the best results compared to tri-axial data collected both using a commercial accelerometer and a smartphone. Including a heart rate term improved performance in all models with the greatest improvement seen in the models acquired using the MSR 165 accelerometer and only slight improvement in mean absolute error for the phone models. The 6-axis model did not include heart rate but still had the lowest mean absolute error.

Such a model could be implemented in a smartphone app that could give a real time estimate of a person's $\dot{V}O_2$ when performing different activities. This could in turn be used both by athletes and recreational runners to keep track of performance, and by medical professionals that wish to monitor their patients' health. It could also provide data on general population health as $\dot{V}O_2$ is linked to cardiovascular health. The impact of this on a global scale is that more research can be done easily, better health care can be provided, and general health and fitness can be improved. It would also provide the possibility for more people to have access to their $\dot{V}O_2$ information as they would no longer need to pay for expensive $\dot{V}O_2$ tests.

Further research needs to be done to validate the findings, especially by expanding the study to include women, different activities and to have a larger sample size in order to eliminate possible population biases. It would also be interesting to see the effects of temperature and humidity and if these factors should be included in the models.

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Appendices

Appendix A
Individual test protocols

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
10 km/h + 3 incline	2 minutes
10 km/h + 6 incline	15 seconds

Table A.1: Subject 1

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
12 km/h	2 minutes
12 km/h + 3 incline	2 minutes

Table A.2: Subject 2

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
11 km/h	4 minutes
11 km/h + 3 incline	2 minutes
11 km/h + 6 incline	2 minutes
11 km/h + 9 incline	30 seconds

Table A.3: Subject 3

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
11 km/h	3 minutes
11 km/h + 3 incline	2 minutes
11 km/h + 6 incline	27 seconds

Table A.4: Subject 4

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
10 km/h + 3 incline	3 minutes
10 km/h + 6 incline	2 minutes

Table A.5: Subject 5

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
12 km/h	4 minutes
12 km/h + 3 incline	2 minutes
12 km/h + 6 incline	1 minute

Table A.6: Subject 6

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
11 km/h	3 minutes
11 km/h + 3 incline	2 minutes
11 km/h + 6 incline	30 seconds

Table A.7: Subject 7

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
12 km/h	3 minutes
12 km/h + 3 incline	2 minutes
12 km/h + 6 incline	1 min. 41 seconds

Table A.8: Subject 8

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
11 km/h	4 minutes
11 km/h + 3 incline	2 minutes
11 km/h + 6 incline	1 minute

Table A.9: Subject 9

Activity Level	Completed time
Sitting Rest (0km/h)	4 minutes
5 km/h	4 minutes
8 km/h	4 minutes
10 km/h	4 minutes
10 km/h + 3 incline	2 minutes
10 km/h + 6 incline	22 seconds

Table A.10: Subject 10

Appendix B
Full size figures

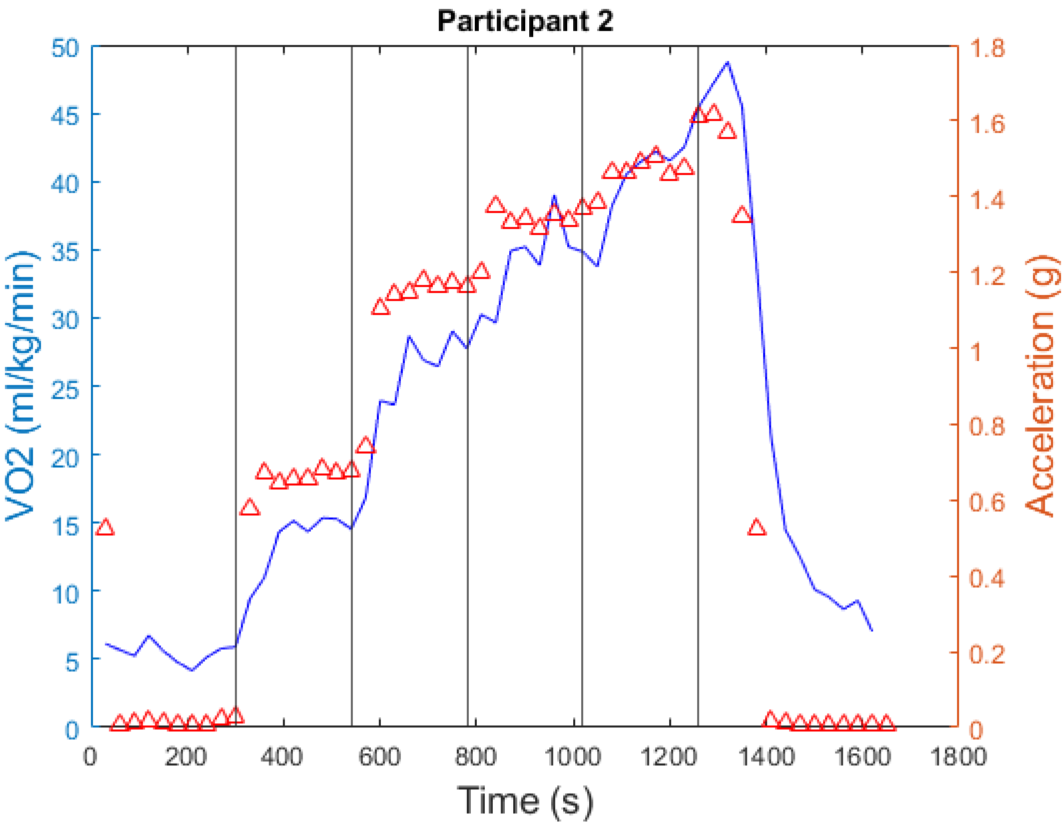

Figure B.1: Figure 4.1 full size.

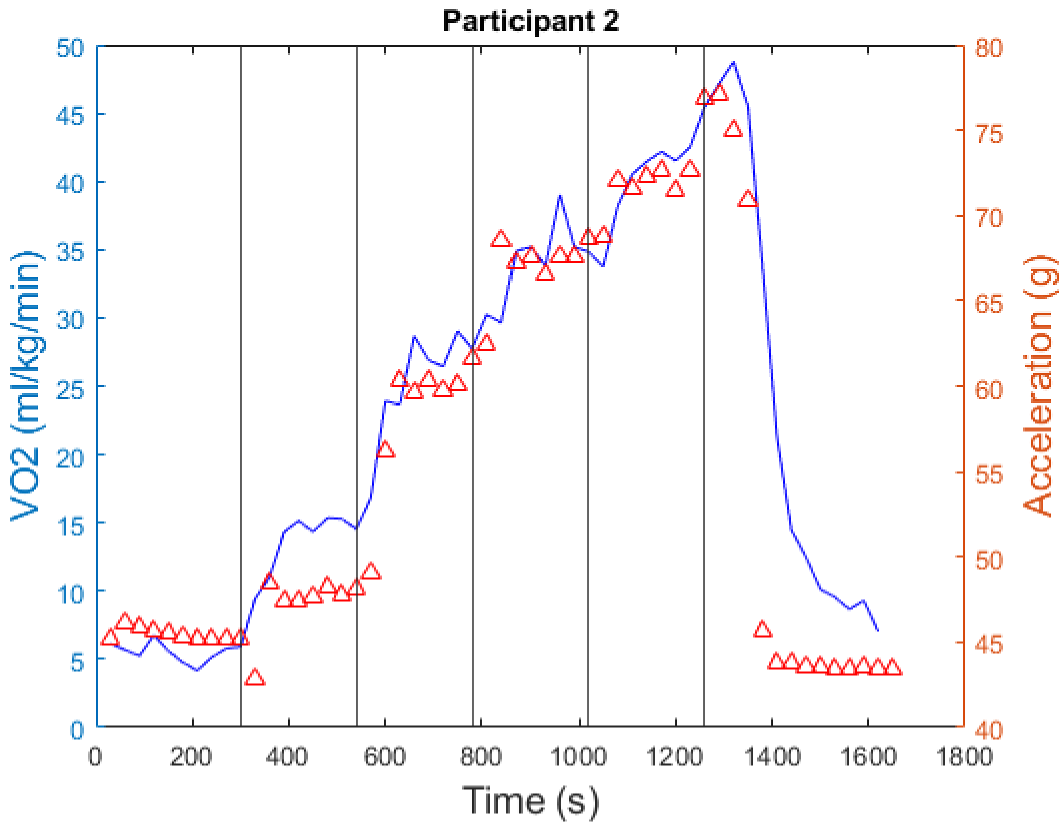

Figure B.2: Figure 4.2 full size.

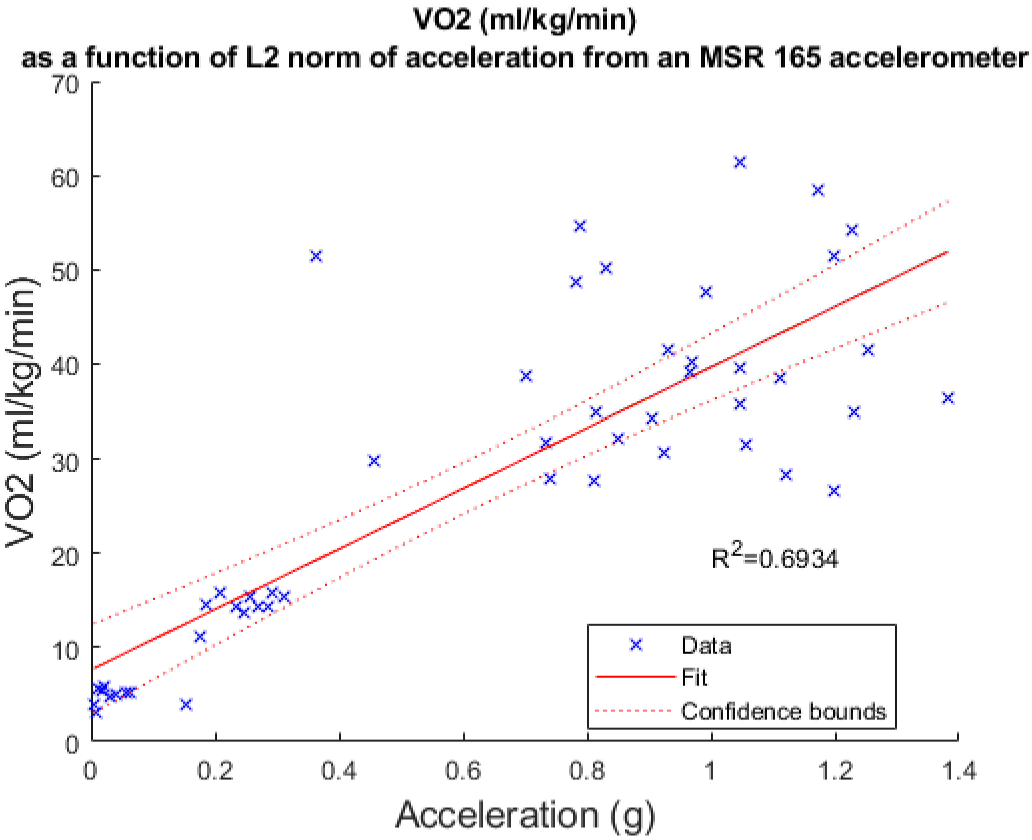

Figure B.3: Figure 4.3a full size.

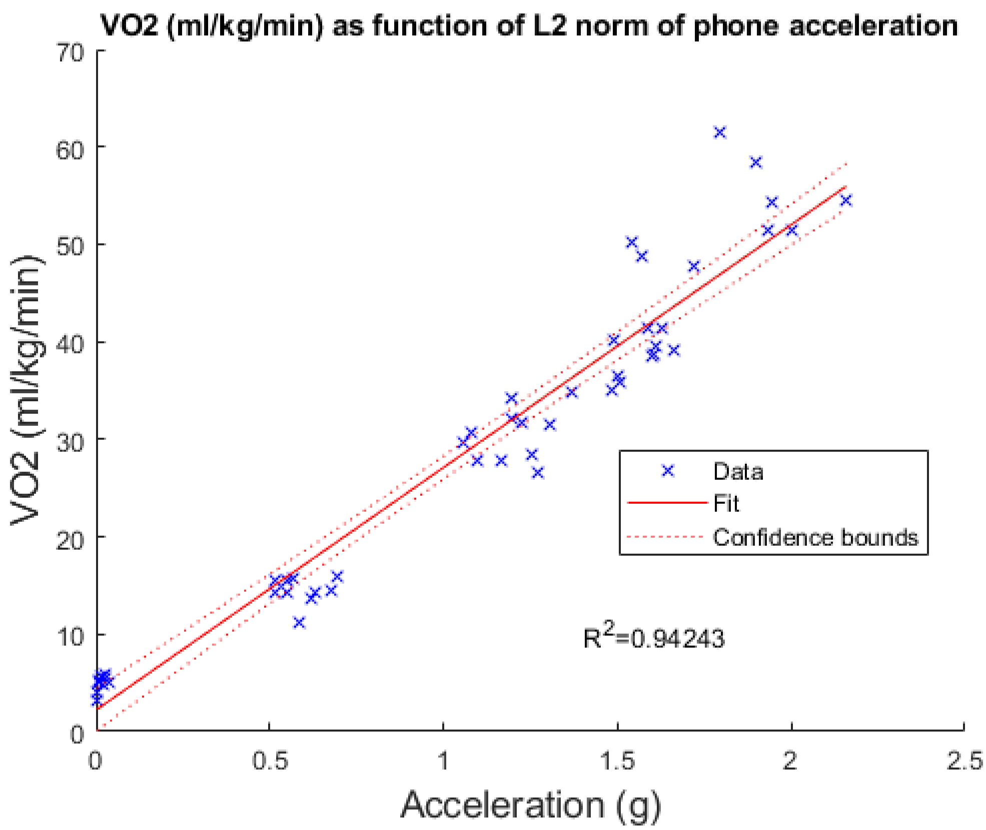

Figure B.4: Figure 4.3b full size.

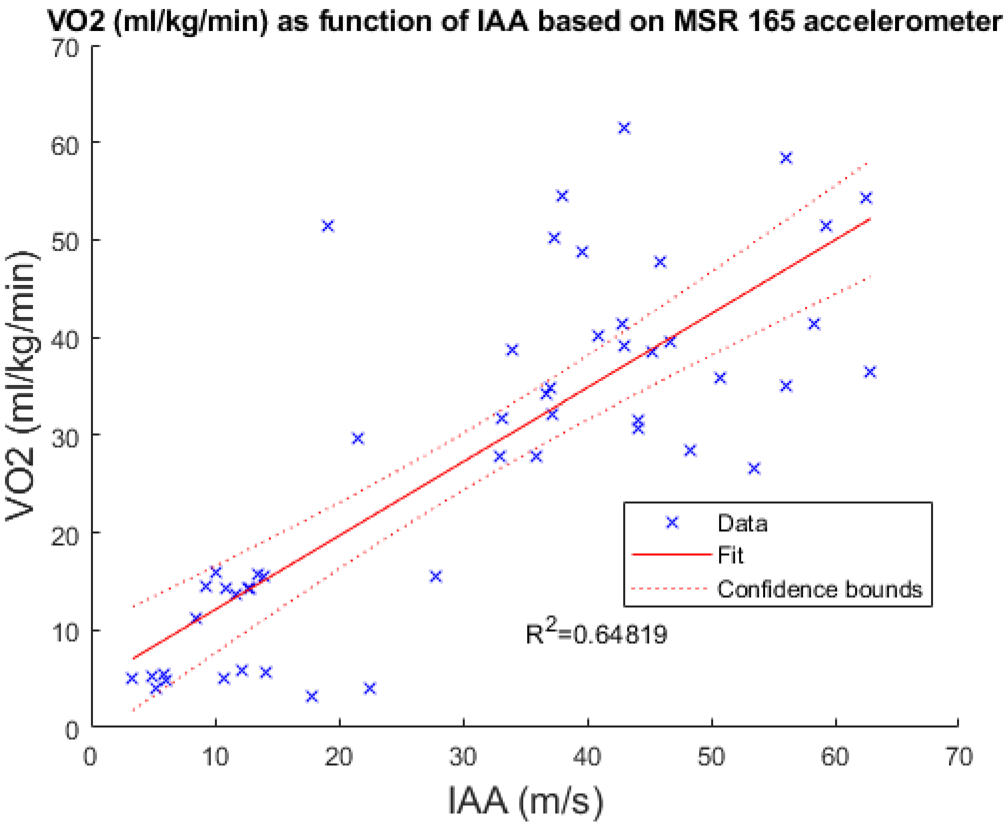

Figure B.5: Figure 4.3c full size.

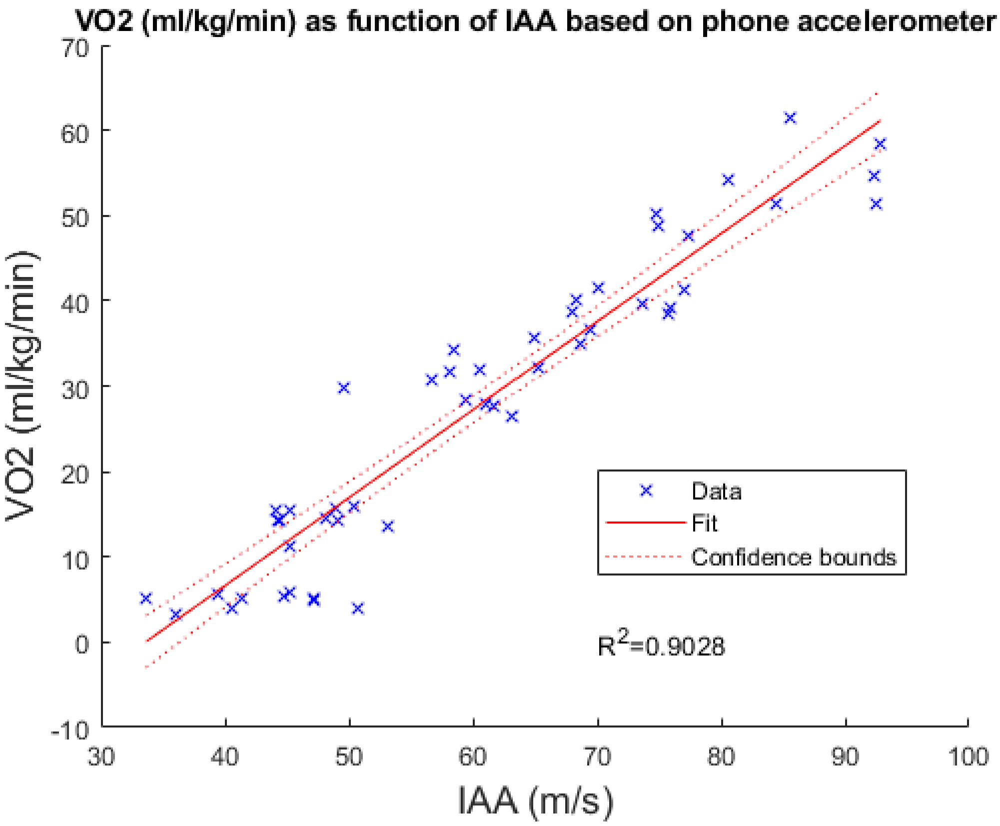

Figure B.6: Figure 4.3d full size.

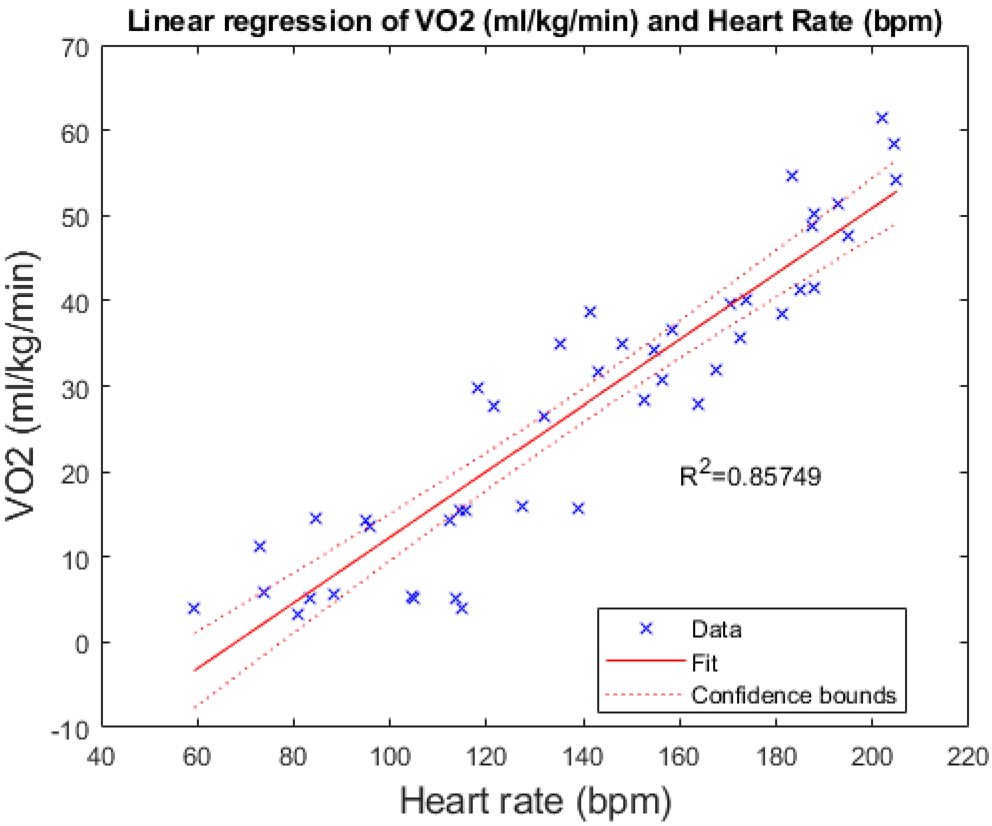

Figure B.7: Figure 4.4a full size.

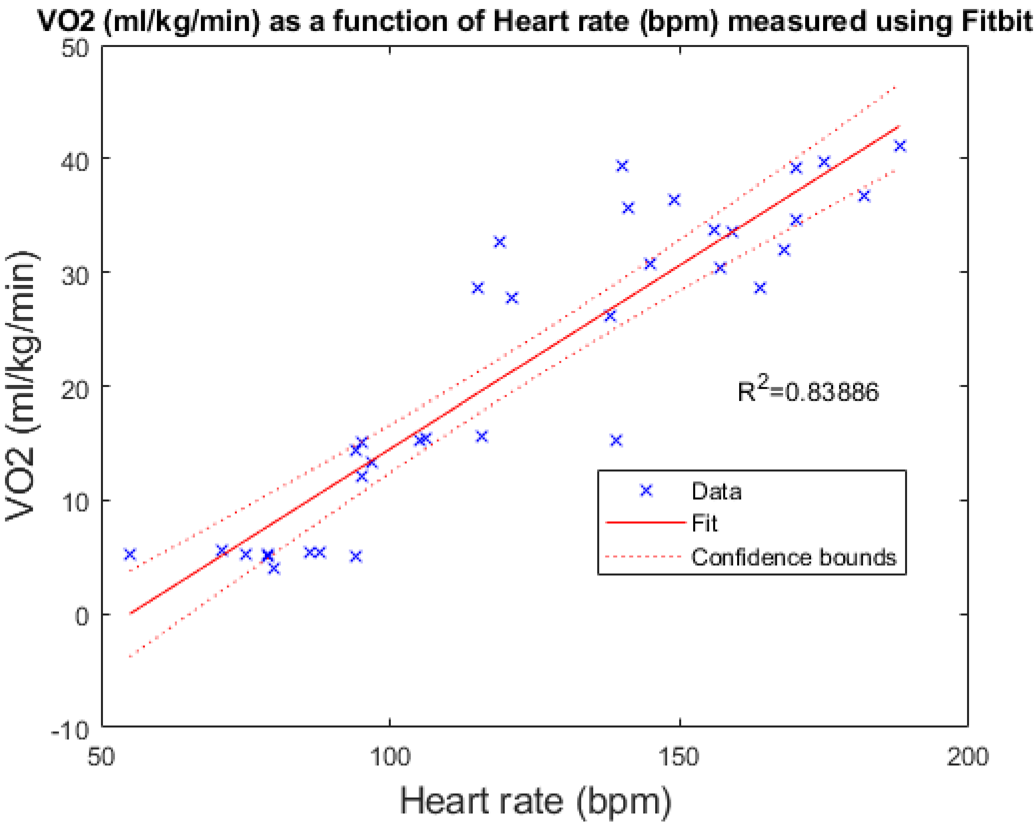

Figure B.8: Figure 4.4b full size.

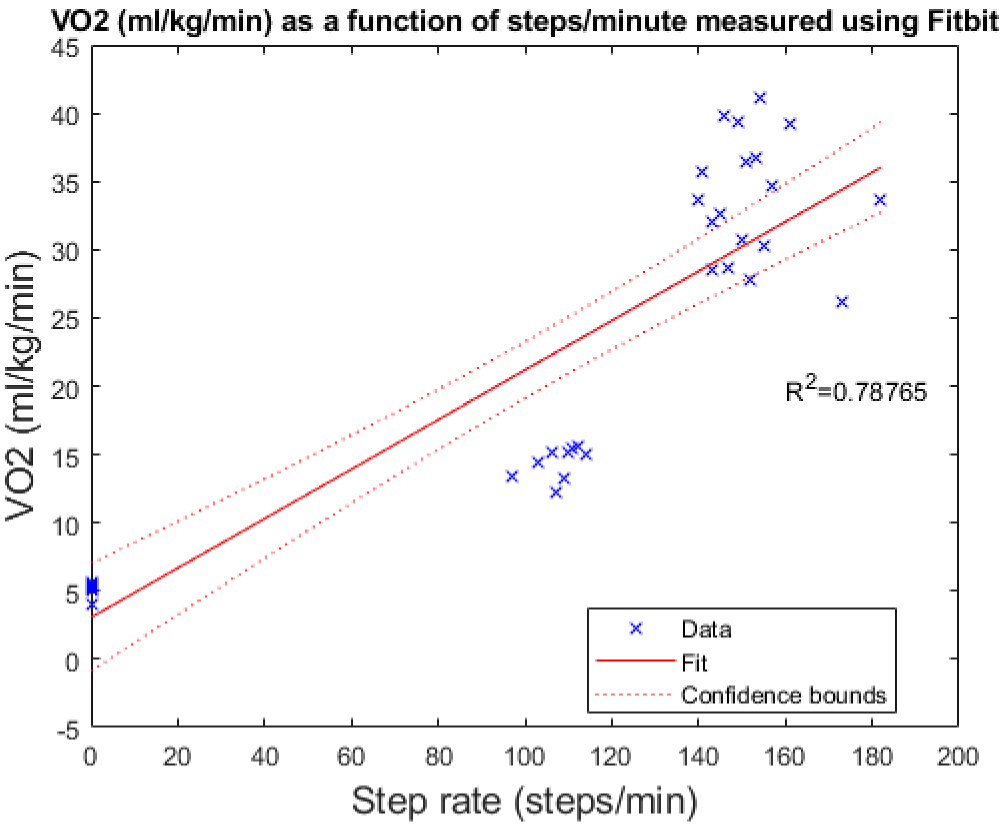

Figure B.9: Figure 4.4c full size.

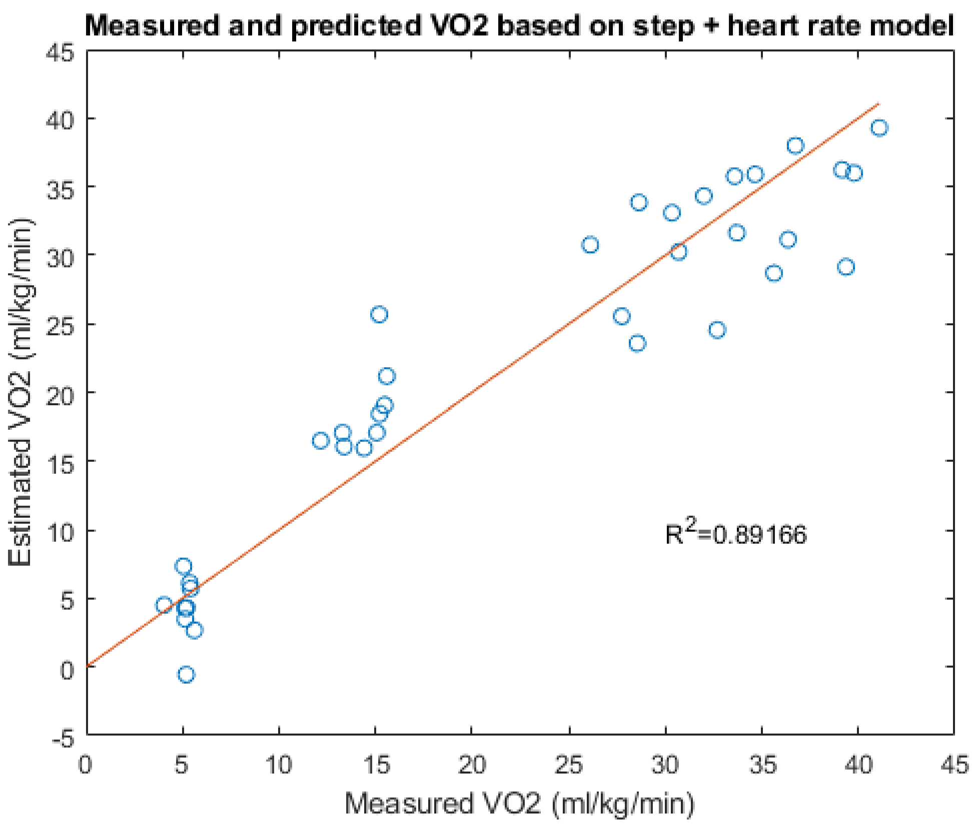

Figure B.10: Figure 4.4d full size.

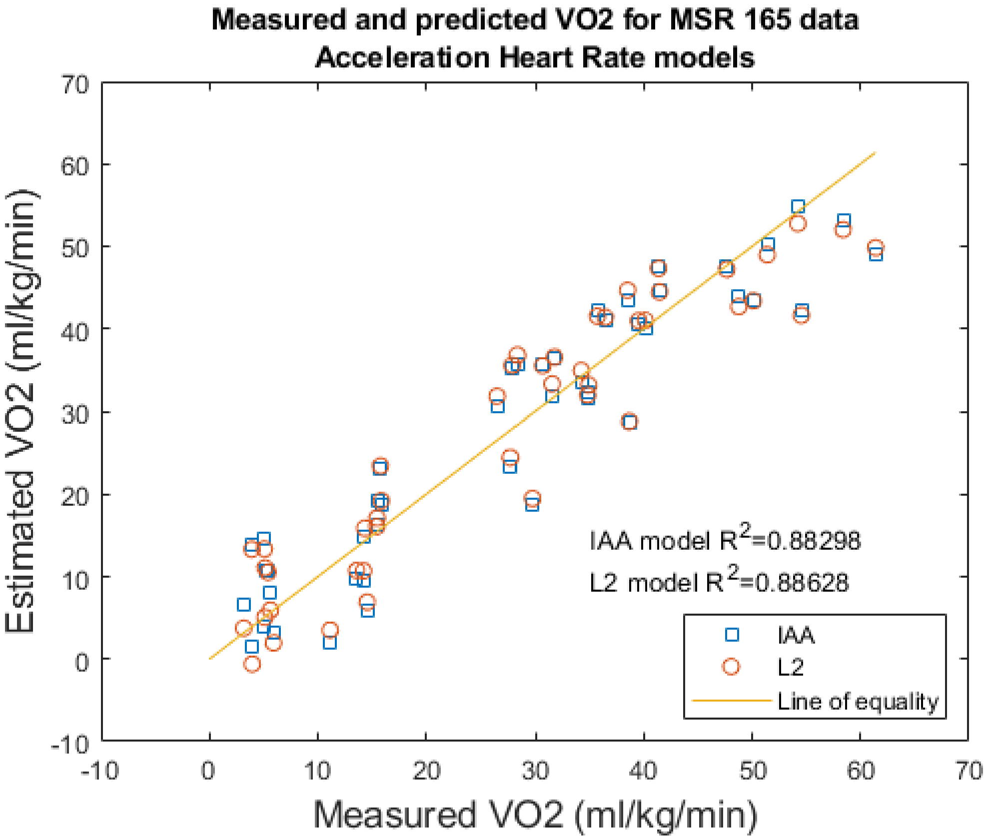

Figure B.11: Figure 4.5a full size.

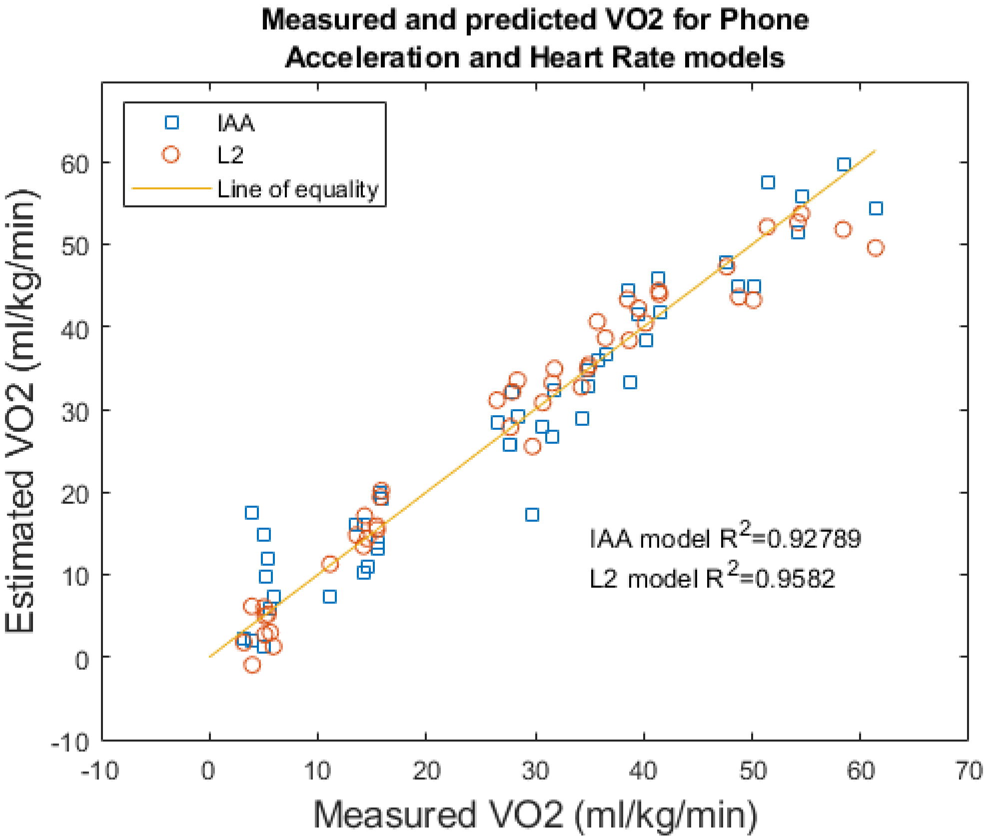

Figure B.12: Figure 4.5b full size.

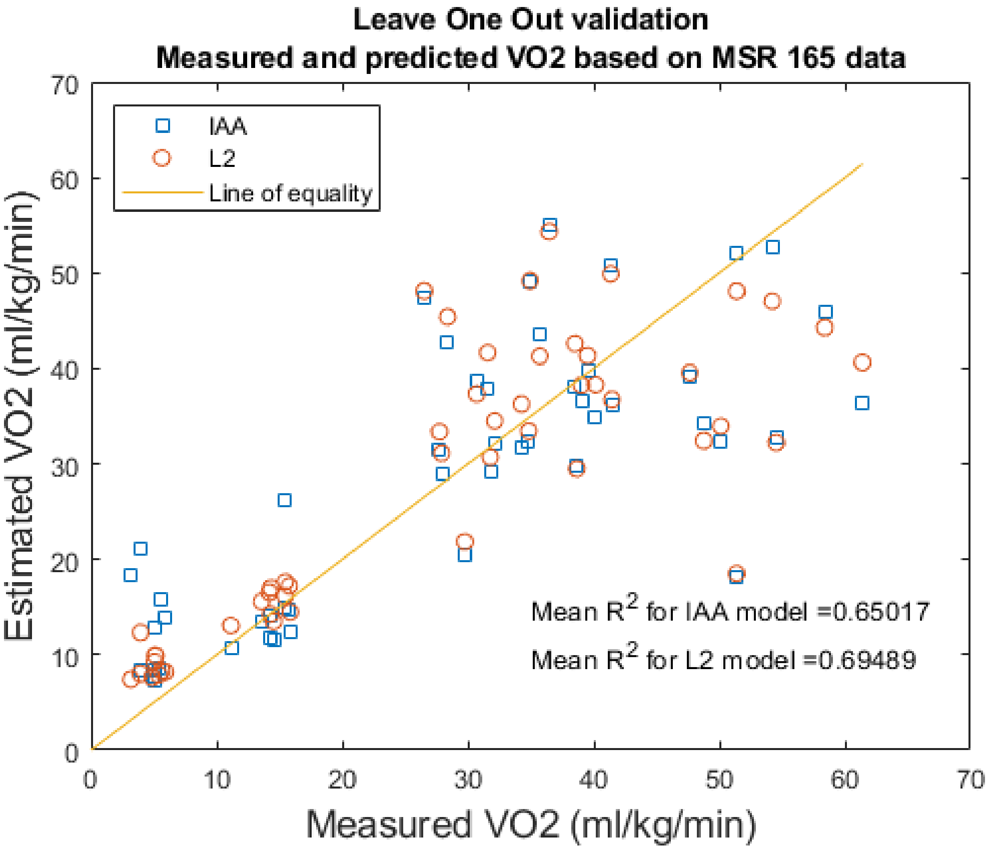

Figure B.13: Figure 4.6a full size.

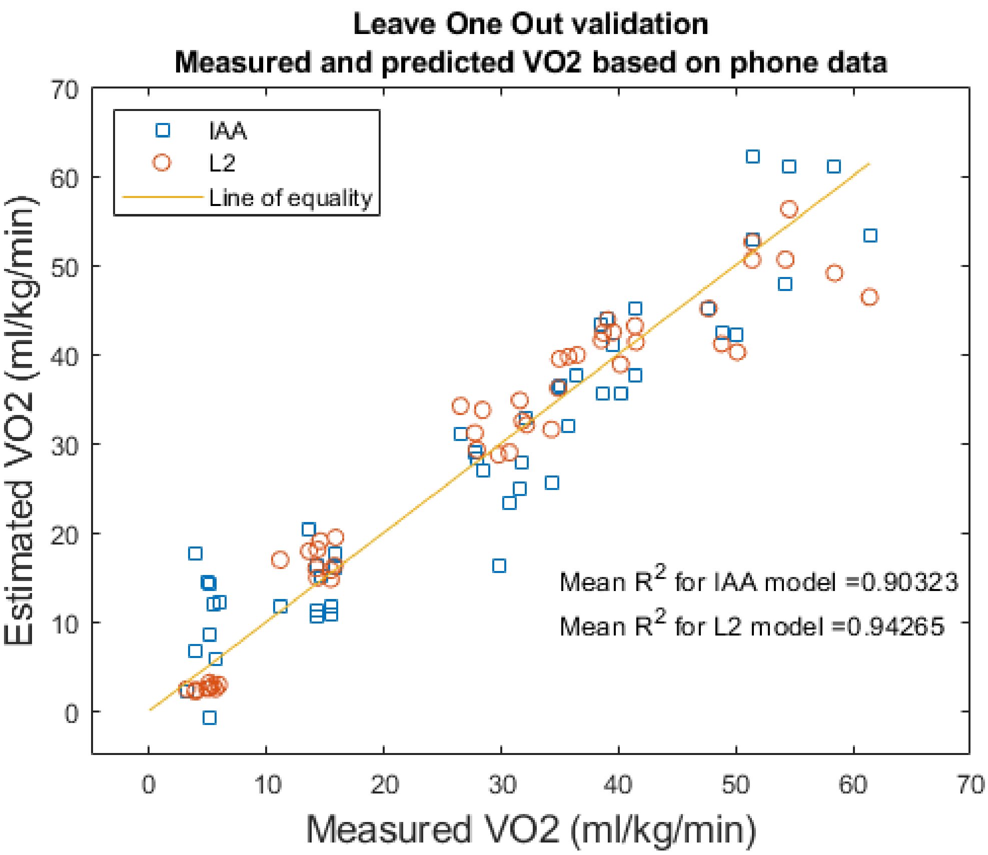

Figure B.14: Figure 4.6b full size.

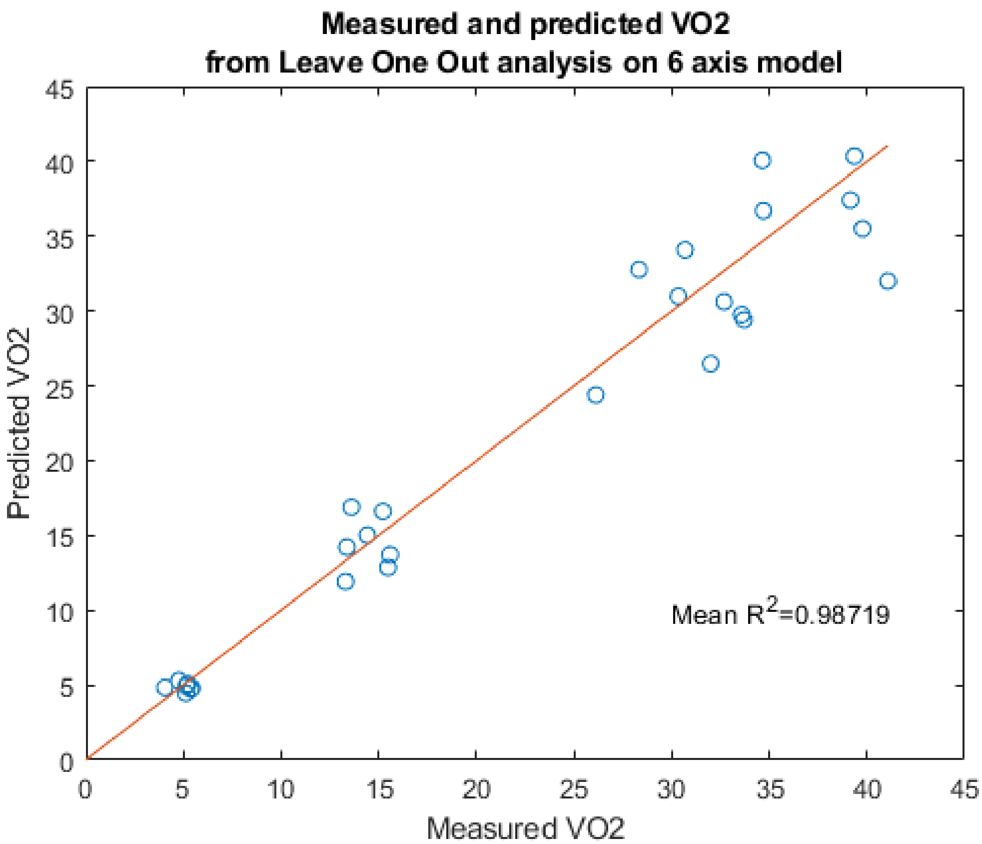

Figure B.15: Figure 4.7 full size.

Appendix C

Matlab code

C.1 Leave One Out

```
%---------------------------------Leave one out cross
   validation
   --------------------------------------------%
function [measuredVO2,predictedVO2,avgCorrCoff, R2, p] =
   LeaveOneOut(phoneI_model,phoneI_forModel,VO2_model,
   VO2_forModel,amountOfTestSubjects)
% Create model using n-1 test subjects where n is the
   total amount of
% subjects.
% Test model on the subject that was left out. Do this by
    taking the
% I values for the indexes used and the VO2 for the
   corresponding time
% using its index. Insert the I value into the model as
   the x value and
% extract the VO2 as the y value for that x value.
%
subjects = amountOfTestSubjects;
for i = 1:subjects

AccelTrainingSets(:,i) = setdiff(phoneI_model,
   phoneI_forModel(i,:),'stable');
AccelTestSets(:,i) = phoneI_forModel(i,:);
VO2TrainingSets(:,i) = setdiff(VO2_model,VO2_forModel(i
   ,:),'stable');
```

```
VO2TestSets(:,i) = VO2_forModel(i,:);

leaveOneOutModel{i} = fitlm(AccelTrainingSets(:,i),
   VO2TrainingSets(:,i));

predictedVO2_corrCoff(:,i)= leaveOneOutModel{i}.
   Coefficients{1,1} + leaveOneOutModel{i}.Coefficients
   {2,1} .*AccelTestSets(:,i);



R2(i) = leaveOneOutModel{i}.Rsquared.Ordinary;
p(i) = leaveOneOutModel{i}.ModelFitVsNullModel.Pvalue;
end
avgCorrCoff =mean(R2);
predictedVO2 = reshape(predictedVO2_corrCoff,numel(
   predictedVO2_corrCoff),1);
measuredVO2 = reshape(VO2TestSets,numel(VO2TestSets),1);

end
```

C.2 L2 Norm

```
    %
       ----------------------------------------------------------------
       Calculation of L2 norm
       ----------------------------------------------------------------

% Code by Arvid Lund based on procedure by Miyatake et al
   . 2016


x = accelerationX;       % Logged X-axis acceleration
y = accelerationY;       % Logged Y-axis acceleration
z= accelerationZ;        % Logged Z-axis acceleration
t = accelerationTime;           % Time from recorded data,
    should start at 0 and then have values for each
   registered acceleration. It might need to be
   normalized to  start at 0 by
                                % subtracting t(0) from
                                   every value. Will
                                   depend on sample rate

sampleRate = 100; % Set the sample rate to the one used
   in the experiment
```

```
interval = 10; % 10 second interval studied as in
   Miyatake et al.
samples = interval * sampleRate; % Number of samples for
   the given time interval that is studied based on
   sample rate
p = 1; % Index for the final output I
A = zeros; % A is the L2 norm of the acceleration data as
    given by Miyatake et al. eq. 1

for n = 1:samples: length(t)-samples % Loop over the
   whole data set in 10 second intervals.
    for w = 0:samples-1 % Internal loop to calculate A
       for the 10 second interval that is studied.
A(w+1) = sqrt(abs(x(n+w) - mean(x(n:n+samples))).^2 ...
    +abs(y(n+w) - mean(y(n:n+samples))).^2 ...
    +abs(z(n+w) - mean(z(n:n+samples))).^2);


    end
I(p) = mean(A); % I is the mean of the L2 norm over the
   10 second interval.
A = zeros; % Zero A to calculate for a new 10  second
   interval in next loop
time2(p) = t(n); % Set the time to match the start of the
    10 second interval
p=p+1; % Increase index for I
end
```

C.3 6-axis

```
function [Iax, Iay, Iaz, Igx, Igy, Igz] = sixAxis(
   filename,sampleTime)
load(filename)

xVel = AngularVelocity.X;
yVel = AngularVelocity.Y;
zVel = AngularVelocity.Z;
x = Acceleration.X ./9.82;
y = Acceleration.Y  ./9.82;
z = Acceleration.Z ./9.82;
timestamp = Acceleration.Timestamp;
t = zeros(size(timestamp));

for n = 1 : length(timestamp)
```

```
  t(n) = seconds(timestamp(n) - timestamp(1))+(n-1)
      *0.001;
end
Fs = 1/t(2);
samples = round(Fs*sampleTime);
p = 1;
A = zeros;
for n = 1:samples: length(t)-samples
    for w = 0:samples-1
Ax(w+1) = sqrt((x(n+w) - mean(x(n:n+samples))).^2);
Ay(w+1) = sqrt((y(n+w)-mean(y(n:n+samples))).^2);
Az(w+1) = sqrt((z(n+w)-mean(z(n:n+samples))).^2);

Gx(w+1) = sqrt((xVel(n+w)-mean(xVel(n:n+samples))).^2);
Gy(w+1) = sqrt((yVel(n+w)-mean(yVel(n:n+samples))).^2);
Gz(w+1) = sqrt((zVel(n+w)-mean(zVel(n:n+samples))).^2);

    end
Iax(p) = mean(Ax);
Iay(p) = mean(Ay);
Iaz(p) = mean(Az);
Igx(p) = mean(Gx);
Igy(p) = mean(Gy);
Igz(p) = mean(Gz);
Ax = zeros;
Ay =zeros;
Az=zeros;
Gx=zeros;
Gy=zeros;
Gz=zeros;
time2(p) = t(n);
p=p+1;
end

end
```

C.4 IAA

```
    function [normedAccel, IAA,meanAccel,I, t, time,time2
       ] = TestScript(filename,sampleTime)
load(filename)

x = Acceleration.X ./9.82;
y = Acceleration.Y  ./9.82;
z = Acceleration.Z ./9.82;
```

```
timestamp = Acceleration.Timestamp;

% meanX = movmean(x,[200 0]);
% meanY = movmean(y,[200 0]);
% meanZ = movmean(z,[200 0]);


t = zeros(size(timestamp));

for n = 1 : length(timestamp)
  t(n) = seconds(timestamp(n) - timestamp(1))+(n-1)
     *0.001;
end
Fs = 1/0.01;
samples = round(Fs*sampleTime);
k(1)= 1;
for i = 1:length(timestamp)/samples

IAA(i) = trapz(t(k(i):(k(i)+(samples-1))),abs(x(k(i):(k(i
   )+(samples-1)))))+trapz(t(k(i):(k(i)+(samples-1))),abs
   (y(k(i):(k(i)+(samples-1)))))+trapz(t(k(i):(k(i)+(
   samples-1))),abs(z(k(i):(k(i)+(samples-1)))));
 k(i+1) = k(i)+samples;
 time(i) = t(k(i));
end
end
```