Università degli Studi di Padova

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MODELLING AND IDENTIFICATION OF HEART RATE AND ENERGY EXPENDITURE DYNAMICS FOR MANUAL WHEELCHAIR USERS

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Preface

This thesis was written in the final semester of my bachelor program in Information Engineering at the University of the Studies of Padua and it is the result of a collaboration with the Norwegian University of Science and Technology (NTNU) in Trondheim.
I chose to work on this topic because I find it particularly interesting, since it makes an impact on people's real life. I like to think that I have tried to improve wheelchairs users' lifestyle, I find it rather inspiring.
I would like to thank my supervisor Damiano Varagnolo, for having introduced me to this project and invited me in Trondheim. This was a once-in-a-lifetime opportunity. I owe a special thanks also to Roya Doshmanziari and Julia Baumgart for their continuous help with the data analysis. I would like to thank the entire 'digiW' research team, you made me feel part of it even if I still have a lot to learn. You inspired me.
Finally, I would like to thank my family and my friends for their support and faith in me, even when the numbers were 'driving me crazy'. In particular, a special mention goes to Sara, who has always stood by my side (and sometimes got desperate with me).
Thank you to anyone who answered my questions.

Abstract

Manual wheelchair users often have an inactive lifestyle and hence it is easier for them to suffer from diabetes, obesity, cardiovascular problems and cancer. To prevent such inactive lifestyles, and thus indirectly help them to live a healthier life, the Norwegian University of Science and Technology (NTNU) has started working on the so-called *'digital wheelchair project'*. Its objective is developing and testing a wheelchair augmented with IT technologies that, through the help of algorithms that monitor health related parameters and opportune sensing hardware, may reliably estimate the daily energy expenditure of such wheelchair users (a feat that has always been a challenging one). This dissertation is performed in collaboration with NTNU - Norwegian University of Science and Technology - and aims at contributing to the modeling of the temporal dynamics of and correlations between heart rate and energy expenditures data. The work focuses thus on applying statistical learning and system identification concepts to reconstruct holistic (and individualized per-patient) individualized first order Ordinary Differential Equations from heart rate and energy expenditure field data. A first order model has proved to be too poor to describe such a complex system and the multitude of outliers requires a more robust approach than the simple Maximum Likelihood one, for instance one might consider to include priors. However, we have set the basis for further studies and research developments.

Sommario

Le persone in carrozzina spesso hanno uno stile di vita poco attivo e quindi è più probabile che soffrano di diabete, obesità, problemi cardiovascolari e cancro. Per prevenire tale stile di vita poco attivo e pertanto aiutarli indirettamente a vivere una vita più sana, l'Università Norvegese della Scienza e Tecnologia (NTNU) ha iniziato a lavorare al cosiddetto *'digital wheelchair project'*. Tale progetto consiste nello sviluppo e prova di una sedia a rotelle potenziata da tecnologie IT che, attraverso l'aiuto di algoritmi che monitorano parametri collegati alla salute e di opportuni sistemi di rilevamento hardware, possano stimare in modo affidabile l'energia spesa proprio dalle persone in carrozzina (una sfida che è sempre stata impegnativa e che non ha ancora soluzione). Questa tesi è stata svolta in collaborazione con NTNU - Università Norvegese della Scienza e Tecnologia - con lo scopo di contribuire alla modellazione delle dinamiche temporali del battito cardiaco e del dispendio energetico e di analizzarne una possibile correlazione. Questo lavoro si focalizza sull'applicazione delle nozioni statistiche imparate e dei concetti di identificazione di sistemi per ricostruire Equazioni Differenziali Ordinarie olistiche (e personalizzate per paziente) a partire dai dati sperimentali di battito cardiaco e spesa energetica.
Un modello del primo ordine si è rivelato troppo povero per descrivere un sistema così complesso e il vasto numero di dati da escludere richiede un approccio più robusto di uno semplice a massima verosimiglianza, per esempio si potrebbero includere delle conoscenze a priori. Ciononostante, abbiamo gettato le basi per futuri studi e sviluppi del progetto.

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Chapter 1

Introduction

In this chapter we will introduce the reader to the digital wheelchair project, exposing the ideas behind it and its goals.

1.1 The digital wheelchair project

This thesis is a result of a collaboration with the NTNU research project called 'The Digital Wheelchair'. The primary research aim of The Digital Wheelchair Project (digiW) is to conceive and validate a concept for estimating energy expenditure (EE) and physical activity (PA) in wheelchair users with different disabilities during rest and free-living activities [1]. This research will provide the basis for reaching the long-term innovation goal of the project: to develop, optimize and patent EE and PA estimation algorithms that can be incorporated into an affordable wearable device for the wheelchair user group, which individuals and future home-based health services could use to track inactivity and promote a healthy lifestyle [1]. In this thesis we will discuss about the energy expenditure data analysis.

1.1.1 Motivations of the project

In the world there are almost 65 million wheelchair users and they are three to five times more likely to not do any exercise compared with the general population. This enhances the probability to contract cardiovascular diseases, cancer, diabetes, obesity and other preventable lifestyle-related diseases. Even in Para athletes there is 12-50% increased cardio-vascular disease risk. The goal of the project is to facilitate and promote having a more active lifestyle for wheelchair users. In fact routinely doing physical activity is indeed one of the most effective tools for maintaining or increasing physical and mental health, as well as quality of life. Practically, the digiW project aims at estimating energy expenditure in wheelchair users with different disabilities during rest and free-living activities. According to the Harvard alumni study, a weekly energy expenditure of 2000–2500 kcal or a daily energy consumption of approximately 300–350 kcal, respectively, leads to the most effective decrease in the probability of suffering myocardial infarction. Hence, it is necessary to find a way to quantify the energy expenditure consumed during different types of physical activity. These parameters can easily be found for able-bodied people for almost every

[1] In this dissertation we will sometimes abbreviate 'energy expenditure' with 'EE', 'heart rate' with 'HR' and 'physical activity' with 'PA'.

conceivable physical activity, but people dependent on a wheelchair are not so lucky yet and they need their own recommendations, due to the lower daily energy expenditure [2].
The overarching aim of the project is to find algorithms that may calculate that figure, and in this way to give wheelchair users some indications to live the longest and healthiest life they could have. To be able to compute that value in a precise way without the need for expensive hardware, one would then like to use so-called *soft-sensors*, i.e., opportune observers of some state of some to-be-defined physiological model involving the quantities above (EE, HR, PA).

This thesis contributes towards the construction of such a model. This is done by investigating whether specific correlations occur amongst the parameters defining the dynamics of the single components of the just mentioned model – e.g., whether being a mid-age woman with a fast hearth rate dynamics correlates with having a fast energy expenditure dynamics or not, and if so how much.

The usefulness of detecting (and potentially analysing) such dynamics relies indeed on the fact that the stronger some correlations are, the easier the problem of reconstructing a value from another tends to be.

1.1.2 Test protocol

To obtain the contributions highlighted in the Subsection 1.1.1 this thesis makes use of data that has been collected through an opportune test protocol. In this protocol a series of participants [2] (first, a control group consisting of 20 able-bodied participants matched for age and gender, both male and female; secondly 20 real wheelchair users – 10 men and 10 women each) perform medical experiments by means of the setup shown in Figure 1.1.
The participants are tested over a range of three separate days which occur within an 8-day period, with a minimum of 24 hours between the different training, to give the body the time to recover. Participants are challenged under different physical conditions (as in Figure 1.2): rest-lying, rest-sitting and three wheeling sub-maximal phases of four minutes each (assessed through blood lactate measurements and heart rate). There is also a 5-minute warm-up and a setup-familiarization in the wheelchair between the resting and propulsion measurements on all test days. Resting time between sub-maximal stages is approximately 2-3-minutes. To rate subjective exertion after each sub-session the medical team supporting this project has been requesting to use the so-called Borg Scale (see Appendix C).
In practice, each participant executes experiments at three different inclines of the treadmill

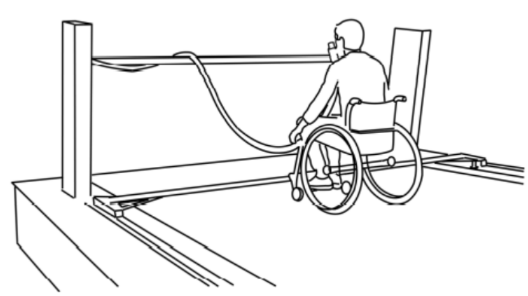


Figure 1.1: A graphical scheme representing the experimental setup used to collect the data processed in the thesis: a participant is seated on a wheelchair, the latter on top of a motorized treadmill whose inclination and speed can be controlled by the experimenters. While wheelchairing on the treadmill, the participant is instrumented with a series of medical sensors monitoring her/his physiological response.

[2] We note that this dissertation is based on the data extracted from the first group.

(either 0.5, 2.5, and 5% incline, in percentage), and each incline corresponds to different speeds. A complete showcase of the setup is given in Figure 1.3. Note that these speeds differ from men and women, but they are the same for every participant. Each incline targets a test day and their order was chosen randomly. An incremental test is conducted at the end of the 2.5% incline day, with a speed increment every minute. When the participant is unable to keep up and hits the back of the treadmill, the speed is reduced of one stage, and the incremental test continues unchanged until exhaustion or steady-state.

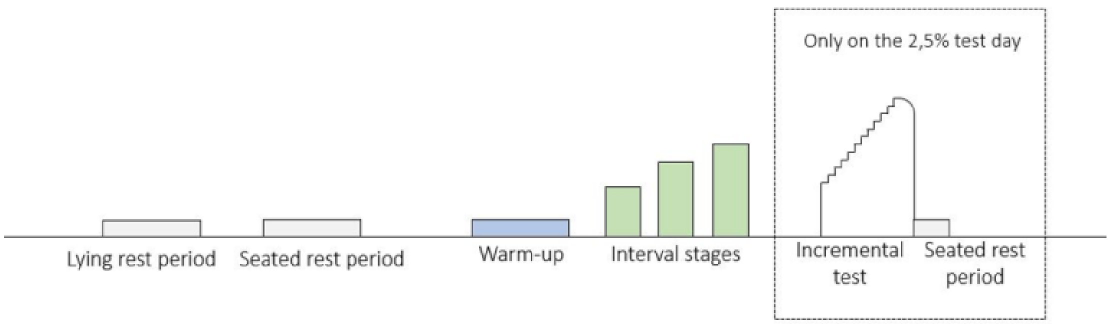


Figure 1.2: Graphical representation of the steps constituting a typical experiment.

Stages	0.5%		2.5%		5.0%	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
1	4 km/h	3 km/h	3 km/h	2 km/h	2 km/h	1 km/h
2	6 km/h	5 km/h	4 km/h	3 km/h	3 km/h	2 km/h
3	8 km/h	7 km/h	5 km/h	4 km/h	4 km/h	3 km/h
Incremental			**Start at 3 km/h**			
			1 km/h increase	0.5 km/h increase		

Figure 1.3: Table showing the combination between speed and inclines, over the different stages. As the incline increases, the speed does the opposite, whilst the latter grows during the stages on the same incline day. Note that men work with higher speed than women.

On the first test day, each participant registers their demographic variables, i.e. age, body mass, body height, gender, and disability-specific characteristics (type of disability, if they had a spinal cord injury; injury level and ASIA score), then they fill in self-reported International Physical Activity Questionnaire (IPAQ). It is used to evaluate habitual physical activity among participants [6].

Experimental setup

This subsection describes which quantities are collected each time a participant participates in an experiment.

The first types of signals that are measured are heart rate, VO_2 and VCO_2 (the latter two defined as respectively the volume of oxygen and carbon dioxide consumed per minute [3], collected by means of the following sensors:

- heart rate monitor;
- inertial measurement unit (IMU, accelerometer including gyroscope and magnetometer);
- Vyntus CPX/portable Metamax II (Metamax, n.d.);
- existing wearable devices (Fitbit and Apple) .

In addition a Qualisys motion capture system (Qualisys, n.d.) tracks the movement of the person being experimented; the information collected through this motion capture system have been used for other research purposes that are beyond the scope of this dissertation, and will thus thereafter ignored.
Starting from the signals above, EE is calculated from measured oxygen consumption (VO_2) and carbon dioxide production (VCO_2) obtained from high precision oxygen (0_2) and carbon dioxide (CO_2) analysers of the JAEGER Vyntus CPX ergospirometer. The Vyntus CPX equipped with the Sentry Suite software program and a respiratory facemask is used as the criterion device for EE comparisons. The Vyntus CPX is calibrated against a gas mixture of 15% O_2 and 5% CO_2.
Heart rate is obtained from the chest strapped Polar H10 HR sensor (Polar Electro Oy, Finland), which serves as the criterion HR device. The calculation of energy expenditure is based on the **Weir Equation**:

$$\text{Energy Expenditure} = 16.62 \cdot \left(\mathrm{VO_2} \cdot 10^{-3}\right) + 4.51 \cdot \left(\mathrm{VCO_2} \cdot 10^{-3}\right) \quad [\mathrm{kJ/min}]. \tag{1.1}$$

The Polar M400 HR monitor watch is synced to the Polar H10 sensor allowing real-time visualization of HR data, before being wirelessly uploaded to Polar Flow mobile application. Both criterion devices are directly compared to wearable devices Apple Watch series 4 (Apple, Inc., CA, USA) software version OS 7.3.3 and Fitbit Versa (2017) software version OS 5.0 (Fitbit, Inc., DE, USA). In addition to proprietary algorithms, both wearable devices combine accelerometery, gyroscopes and photoplethysmography with optical sensors to measure EE and HR. The utilized activity settings for the wearable devices are outdoor wheelchair propulsion at walking pace (Apple Watch) and general treadmill setting (Fitbit) throughout this study. Participants are fitted with the ergospirometer-attached face-mask that is secured with head straps, ensuring no leaks in the breathing circuit. Participants sit in a lightweight wheelchair which is placed on a custom motorized treadmill. The treadmill is framed with a safety bar connected to an inflated bumper at the rear. The wheelchair is connected to the construction to ensure participant safety throughout the study (See Figure 1.1) [12].

1.1.3 Scope and research objectives

This dissertation will focus on the energy expenditure and heart rate data and, starting from them, we will try to model those signals with simple first order ODE (Ordinary Differential Equation) models and secondly we will analyse and look for any kind of correlation between the two variables (in particular the time constants of the exponential laws describing them) and between the variables

[3] We chose to use the notation VO_2 and VCO_2, rather than $\dot{V}O_2$ and $\dot{V}CO_2$, keeping in mind that is expressed in volume per unit time.

and the physiological parameters (gender, body mass, IPAQ, height, age). Energy expenditure and heart rate are strictly related in able-bodied people, the latter in fact increases linearly and proportionately with exercise intensity and thus oxygen uptake [5].
The study on people with disabilities is still an open field, but it has been studied [7] that EE can be accurately predicted from HR when one knows age, sex, body mass and fitness. However, during lower intensity PA, there is a weak relationship between HR and EE. This happens mostly because of small postural changes causing alterations in stroke volume, but can also be explained by the fact that HR during low intensity PA is affected by external factors such as psychological stress, stimulants, ambient temperature, dehydration and illness [10]. The scientific hope is that predicting energy expenditure using HR data could theoretically reduce measurement errors associated with the current linear regression approaches. It may also give us the chance to avoid personalized analysis for each individual monitored.
It is an open research so we do not expect any positive correlation, but if this was the case it would be deeply meaningful to the DigiW project and it could encourage the building of a more solid model, that for sure has to be second order one. The choice of a first order one is due to the fact that one has first to investigate with the simplest model and then, if it works, try to improve it. The absence of bonds between the variables would suggest to go to another direction or to do the experiment again, maybe with a wider number of samples.

Chapter 2

Mathematical and statistical theory

This section will deal with the theoretical concepts that are useful for our research's purposes, from a mathematical point of view.

2.1 Linear model theory

System identification is a field of control theory and its aim is to build mathematical models of dynamic systems from observed input–output data. A model can be regarded to as the interface between the real world of applications and the mathematical world of control theory and model abstractions.
Estimating models is based on statistical theory and it orbits around the following concepts:

- **Model** It is a relationship (usually a mathematical formula, but it could also be a table or a graph) between observed quantities, broadly speaking it predicts some properties or behaviours of the object.

- **True description** We want our model to be as much realistic as possible. We will have to deal with a trade-off between model complexity and adherence to reality.

System identification has widespread applications and it uses different techniques that depend on the character of the models to be estimated: linear, nonlinear, hybrid, nonparametric, etc. Even if it is a very large topic, it is basically based on a small number of leading principles, e.g. one wants to build the best model in terms of complexity, information contents in the data, and effective validation [8].
The area has many facets and there are many approaches and methods and, in order to choose one of them, one has to have in mind the purpose of identification. Two are the most common ones: the first is to analyse the properties of a system (usually in biology, economy and medicine), the second is to design a controller for a particular system. In the first case it might be sufficient to have a fairly crude model of the system dynamics, while the second option might require a more accurate characterization. Before building a model there is the need of making some experiments, in order to observe the process and its answers to perturbations, which are input signals. In order to get realistic models it is often necessary to carry out the experiments during normal operation [3].

2.2 Statistical analysis

To estimate and evaluate the accuracy of a model, statistics is the most objective instrument at our disposal.

2.2.1 Least Absolute Residual Estimate

Least absolute deviation (LAD), also known as least absolute errors (LEA), least absolute value (LAV), or least absolute residual (LAR), or the L1 norm problem, is a mathematical optimization technique that attempts to find a function which closely approximates a set of data (x_i, y_i). In the simplest case, the approximation function is a "trend line" in the two-dimensional Cartesian plane. The method minimizes the sum of absolute errors (SEA), also known as "residuals", i.e. the difference between points generated by the function and corresponding points in the data. It proves to be a valid alternative to its counterpart - LSR (Least Squares Regression) method, which minimizes the sum of squared errors - when the data present many outliers. LAD is actually more robust and therefore it may be helpful in studies where outliers may be safely and effectively ignored.

Method

Let us suppose that the data set consists of n points $(x_i, y_i), i = 1, 2, .., n$ (data pairs), where x_i is an independent variable and y_i is a dependent variable whose value is found by observation. We want to find a function f such that $y_i = f(x_i)$. To attain this goal, we suppose that the function f is of a particular form containing some parameters which need to be determined. For instance, the simplest form would be a linear polynomial:

$$f(x, b) = b_0 + b_1 \cdot x \tag{2.1}$$

where b_0 and b_1 are parameters whose values are not known but which we would like to estimate. Note that the function f can be also exponential, cubic, etc. [14]. Hence, the least absolute residual method seeks to estimate the parameters that minimize the following function:

$$\min \text{SAE} = \sum_{i=1}^{n} |f(x_i) - y_i| \tag{2.2}$$

2.2.2 Correlations

Broadly speaking, correlation measures the association between variables. In correlated data, the change in the magnitude of one variable is associated with a change in the magnitude of another variable, either in the same (positive correlation) or in the opposite (negative correlation) direction. People usually think of the term correlation in the context of a linear relationship between two continuous variables and use the Pearson correlation coefficient to quantify it. Such index is typically used for jointly normally distributed data (data that follow a bivariate normal distribution). For non-normally distributed continuous data, for ordinal data, or for data with relevant outliers, a Spearman rank correlation can be used as a measure of a monotonic association.The word monotic describes scenario in which the size of one variable increases as the other variables also increases, or where the size of one variable increases as the other variable also decreases. Both correlation coefficients are scaled such that they range from –1 (negative correlation) to +1 (positive correlation), where 0 indicates the absence of linear or monotonic association, while the relationship gets stronger and ultimately approaches a straight line (Pearson correlation) or a constantly increasing or decreasing curve (Spearman correlation) as the coefficient approaches an absolute value of 1. It is always better to visualize graphically the data, as correlation fails to adequately describe non linear or non monotonic relationships, or also it can happen that different relationships between variables can result in similar correlation coefficients [11].

Spearman correlation coefficient

Spearman correlation coefficient is a particular version of the Pearson index, where the data are converted into ranks before computing the coefficient. To get the rank vector one must place the data in increasing order. The rank corresponding to a sample is the index of that sample in this ordered vector.

Example
Let $v = \begin{bmatrix} 3 & 45 & 12 & 6 & 128 \end{bmatrix}$ be the original vector,
$w = \begin{bmatrix} 3 & 6 & 12 & 45 & 128 \end{bmatrix}$ be the ordered one.
$w_{indexes} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 \end{bmatrix}$ represents the positions of the data in w.
The rank vector associated to v is $r = \begin{bmatrix} 1 & 4 & 3 & 2 & 5 \end{bmatrix}$.
One can now compute the correlation index, which is usually named ρ. Given two random variables x an y, let r and s be the respective rank vectors. Their Spearman coefficient is the following

$$\rho = \frac{cov_{rs}}{\sigma_r \cdot \sigma_s} \tag{2.3}$$

where cov_{rs} is the covariance between r and s, σ is the variance of the data.

Chapter 3

Physiological theory

This chapter introduces the reader to some biological concepts, useful for understanding of the dynamics of the experiment.

3.1 Heart rate and Energy Expenditure Delay

One could claim that most of the times the heart rate has faster dynamics than the energy expenditure: when one exercises the cardiac muscle responds faster and starts to pump more blood, instead the energy metabolism requires more steps between the demand and effective take-up by the muscles.

At the beginning of physical activity, muscles request more oxygen: hence, a stimulus goes into the brain asking to breath in and out more. Consequently, there is a flux of oxygen that goes into the lungs, then into the blood and finally into the heart, which pumps more oxygenated blood to the muscles, which can now take it up from the bloodstream and use it. Later, they shuffle deoxygenated blood back to the heart. Hence, the increase in oxygen uptake is related to the heart pump and a consequence of the faster heart rate. This relationship is described by Fick's principle:

$$\mathrm{VO}_2 = \text{Cardiac output} \cdot (\mathrm{C}_i - \mathrm{C}_o) \quad [\text{l/min}] \tag{3.1}$$

where C_i is oxygen concentration in arterial blood and C_o is oxygen concentration in venous blood and cardiac output is defined as:

$$\text{Cardiac output} = \text{Stroke volume } \cdot \text{Heart rate} \quad [\text{l/min}] \tag{3.2}$$

where stroke volume is the volume of blood pumped out of the left ventricle of the heart during each systolic cardiac contraction [4]. As a result, we would expect the energy expenditure kinetics to be slower than the heart rate kinetics [9].

Another reason behind the late raise of the energy expenditure is that our body needs time to adapt to these new stressed conditions: lungs need to keep up with the new strain, bloodstream and pressure has to adapt and mitochondria have to to adjust the respiratory chain to the new rhythm. This delay is longer for subjects with some pathological conditions or sedentary.

There is also a technical factor that contributes to this delay: the ergospirometer itself with the tube and the mixing chamber that the air needs to pass through, before gas exchange is measured, adds other delay.

Chapter 4

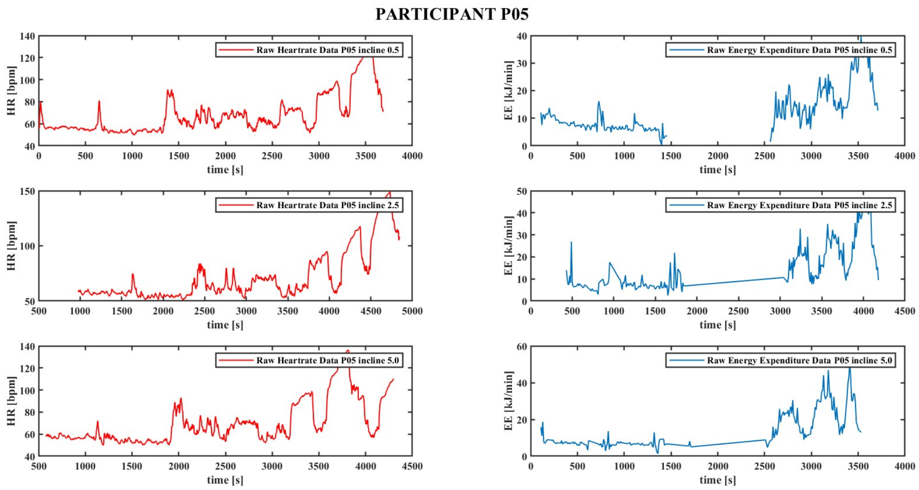
Data

This chapter will discuss the data processing strategies adopted in the data analysis flow, motivating them and presenting the most important concepts characterizing such a flow.

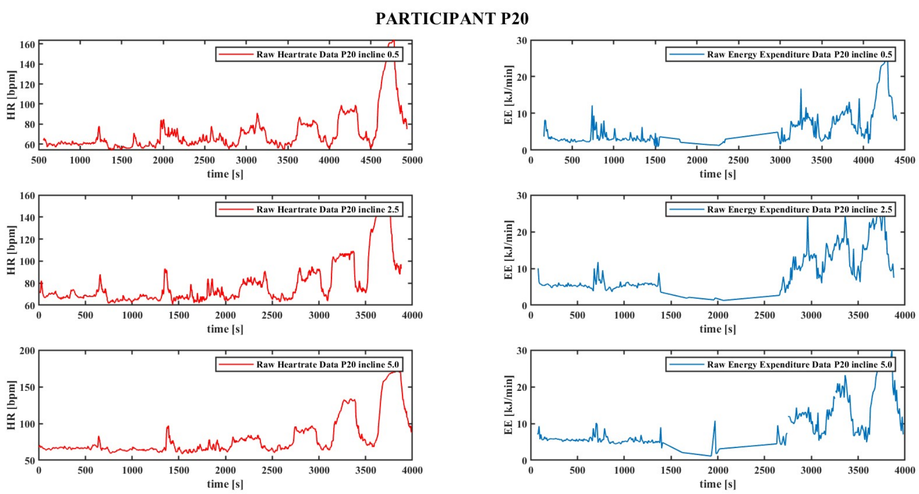
4.1 Data loading

The first phase consisted in loading the data collected by the research team during the first phase of the experiment.
I was given excel files and `.csv` files with respectively the heart rate and the energy expenditure raw data. The team had already a set of MatLab code to load them, however the resulting signal was divided into sessions, while in the first place we wanted a continuous signal to have a general view and be able later on to isolate the parts in which we are interested. In particular, we will analyse the raises and drops of the signals. To obtain a unique signal, we adapted the old code to our new needs, adding some methods and changing the existing ones. In particular, the method `LoadEnergyExpenditure.m` reads the data in a `.csv` file and takes VO_2 and VCO_2 to compute the energy expenditure using Equation 1.1. `LoadHeartRate.m` instead saves the heart rate pulses in a matrix. At the very beginning we started using the sample indexes in the x-axis instead of the time vector, but this choice was abandoned, preferring a time approach instead, which is easier and gives use the chance to compare the results and signals. In the end, one heart rate and one energy expenditure signal was obtained for each participant and for each incline of the treadmill, together with the corresponding time vector. During the experiment, it was chosen to use the sampling frequency of 1 Hz for the heart rate and 0.1 Hz for the energy expenditure, hence one will notice that the latter will be undersampled with respect to the former. This is because energy expenditure is computed from the values of VO_2 and VCO_2 (see Equation 1.1), which are collected as average data in the mixing chamber, so the air that passes through is never analyzed breath-by-breath. The code removes the NaN data (deriving from gaps in the data collection), which we do not need because they do not bring any relevant information. One could argue that we therefore lose some knowledge, but it regards only a few samples so this does not represent a problem. The code also fixes the offset due to the warm-up in the energy expenditure session, i.e. it adds the duration of the warm-up period to the start and stop times of the Vyntus sub-maximal stages. This problem does not involve the heart rate signal, since it is collected continuously, while the energy expenditure only when the participant wears the mask. By adding this warm-up offset the heart rate and energy expenditure signals should be approximately synchronised for almost all the participants (see Section 3.1 for more information).

Eventually, we obtained for each participant 6 subplots, 3 for EE and 3 for HR for the three inclines. One notices that the plots are not identical for every participant, because it depends on how the subject conducted the experiment, for example whether they managed to finish it or not and if the measuring system did not face any problem. To exemplify the results one may get with typical participants, Figure 4.1 compares the experiment results of two different participants.



(a) Participant 5



(b) Participant 20

Figure 4.1: Heart Rate and Energy Expenditure of participant 2 and 20, already cleaned

From the image above one can see the three sub-maximal stages (the three peaks at the end of the time axis), which are the sessions in which we are interested into. The first part of the signals represents instead the rest lying and rest sitting phases. Moreover, one can notice that there is a gap of 20 minutes in the energy expenditure signal, which is due to face mask removal (the signal is collected if and only if the participant wears the mask). During this gap there is the preparation of the treadmill, the subject is adorned with some markers to track motions and the warm up is performed. Moreover, we can compare participant 5 to participant 20 and for instance notice that participant 5 did not finish the incline 5.0 experiment, as sub-session 3 presents only a peak after $t = 4000\ s$ and never goes down. This is mentioned to explain that in data collection one has to take into account all of these eventualities: in our case we will not consider this subject in the analysis of the third sub-session, as it would represent an outlier.

4.2 Data cleaning

The purpose of this dissertation is to investigate the presence of correlations that may exist between raise and settling times of physiological signals during the three sub-maximal phases. Hence there are parts of the raw data that were not necessary and therefore we applied a cleaning process to them. We note that the plots exposed in Figure 4.1a and in Figure 4.1b have already been cleaned.

4.2.1 Removal of the incremental stage and unexpected peaks

As explained in Section 1.1.2, during the 2.5 incline day participants undergo an incremental test. This goes beyond our interests, so we deleted those data from the plots. To do such operation, we checked the start and stop times of the Vyntus and we loaded only the data in which we are interested in. In the code `generate_continuous_signal.m` we selected the intervals we want to consider in our analysis, for both heart rate and energy expenditure. We chose the beginning of the rest lying session as start and the sample two minutes after the end of the third stage as stop. We added this extra time to include the recovery, which will be important for the study of the drop.
By performing this cut on the signal we have also solved another issue. At the end of the experiment, in fact, some datasets presented peaks not explainable by the training session, they were due to the mask or sensor removal instead. Since they are not related to the experiment, the previously mentioned code removes them from the signal. However, there are some participants with a strange behaviour at the end, but this will be considered separately in Section 7.2.3

4.3 Input loading

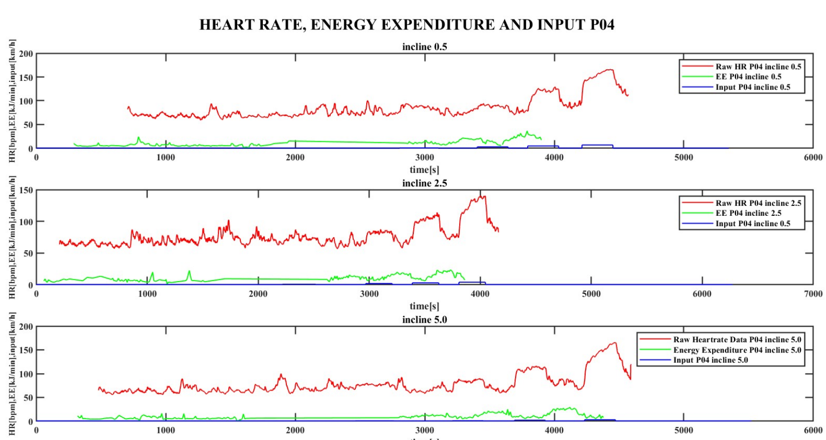


Figure 4.2: Example of plot of heart rate, energy expenditure and input signal of participant 4 at the 3 different inclines.

Eventually we had to load the input signal, which is the speed of the treadmill. It differs from men to women and from the different inclines. One can see the values in Figure 1.3. The input is

relevant only in the sub-maximal stages, when the participant is actually on the treadmill with their mask on, not in the rest lying and rest sitting or during the warm-up.
To load the signal, we created a new field (called `Input`) for each participant object to save the data and in order to load it we wrote the new method `LoadInputSignal.m`
Now we are able to plot the input signal together with the Energy Expenditure and Heart Rate. The input signal is actually a step signal with an amplitude equal to the speed of the platform. We can notice that the input and the heart rate are synchronized, while the Vyntus data are not exactly and always so, for the reasons explained in Section 3.1.

4.4 Faulty data for the continuous signal

Here we will identify those participants whose continuous data may not be reliable as far as the time axis is concerned.
As explained in Section 3.1, the energy expenditure signal is slightly delayed compared to the heart rate. This happens for most of the participants, but not for all of them, who instead show a significant offset. The reason behind this is that the researchers copy-pasted data from other files when some stages were done on a different day. The result is that the data of the resting and exercise stages are fine, though the in-between bits are not and the time axes are not aligned for this reason. One can see an example in Figure 4.3, where we notice that in incline 2.5 and 5.0 the EE signal is shifted with respect to the HR one.

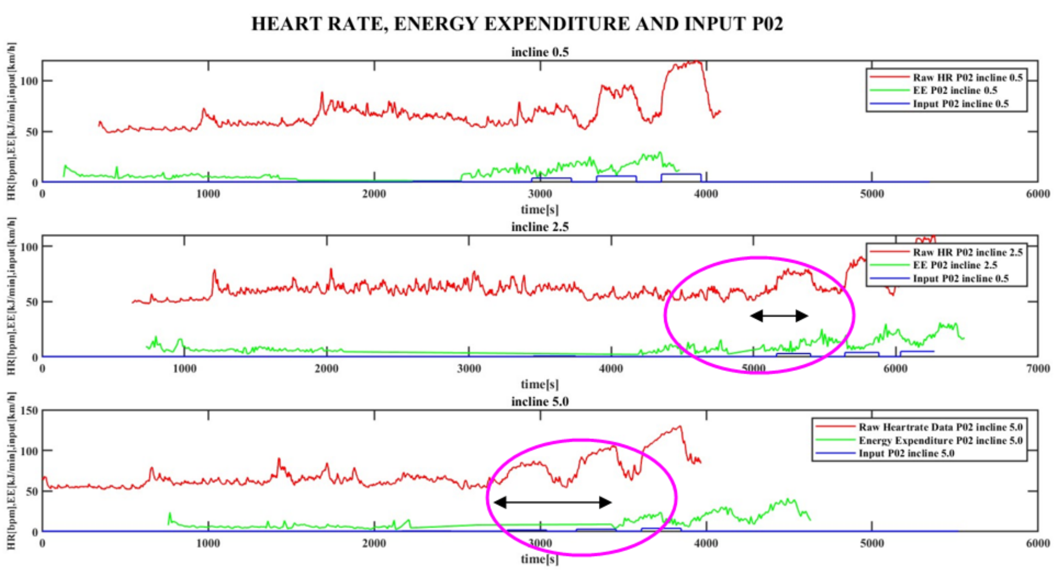


Figure 4.3: Heart Rate, Energy Expenditure and input signal of participant 2. One can notice that at incline 2.5 and 5.0 there is a consistent delay of the energy expenditure signal. The offset is marked with a black line and the phenomena is highlighted by a circle.

Here follows a list of the subjects with such characteristics

- Incline 0.5: P05, P15;
- Incline 2.5: P01, P02, P03, P09, P15;
- Incline 5.0: P01, P02, P07;

However, this concerns only the continuous signals and does not represent a problem for the our studies. Though, we included it because it is worth to explain why some subjects show such patterns.

4.5 Data splitting

The last pre-process step applied on the data was the splitting into the different sub-sessions for the further identifications of raises and drops. To do so, we adapted the code given by Dr Julia Baumgart and we obtained three files with the data of the 3 sub-sessions for every participant at each incline. Those signals comprehend also the recovery time (which here we considered to be two minutes). Note that one may notice that sometimes there are gaps in time for the Vyntus data, when the participants had the mask on for long and they took it off or when some other technical issue happened. The split signals are heterogeneous, because they depend on the response of the subject to the input. Ideally, we expect the heart rate and the energy expenditure to raise as a rect signal during the four minutes of intensive training. One can see some examples of figures in the Section 5.

Chapter 5

Data modeling

Applying the theory of Section 2.1, this chapter presents a novel model of our dataset using the LAD estimation. We are interested in the raises and drops of the sub-maximal stages, hence we loaded the split data and we manually decided the range of points over which apply the method. The starting point of the raise is the beginning of each sub-session, while the stop depends on each participant. Instead, we considered the drop starting point to be approximately the end of the sub-maximal stage, because the subject should lower their performances. However, this does not happen for all the participants, and this is caused by two main reasons. The first one is that participants saw that the end was coming, so they loosened their activity, the second one is that some of them did not manage to finish the experiment because of the fatigue. We therefore expect to have a few outliers in our data. Even if the drop took place before the end of the sub-session, our priority has been the modeling of the decrease, so we did not give much importance to the fact that the drop was anticipated with respect to the stop of the smart watch. Moreover, we claim that the number of samples over which the interpolation takes place is not always the same, because the raise or drop time is subjective. The function we used to fit the data was an exponential law of the form

$$f(x) = ae^{(bx)}, \tag{5.1}$$

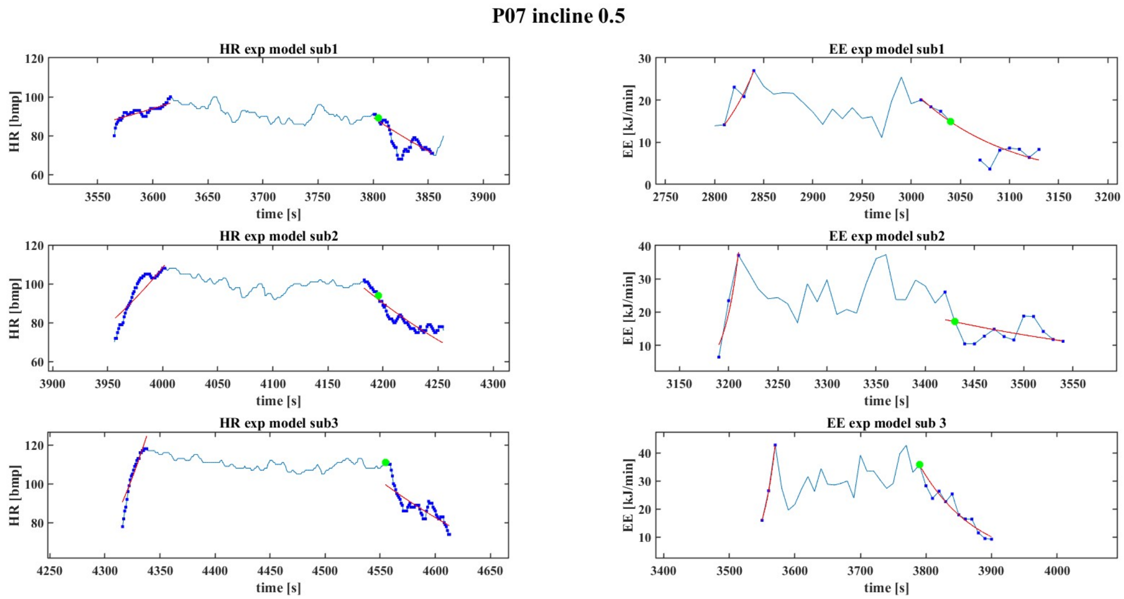
where a and b are the parameters that we aim at estimating. In particular, we are interested in $\frac{1}{b}$, which is usually known as time constant. We chose to use LAD estimation to be more robust to outliers, which are many due to the experimental collection of the data. Using the MatLab command

```
hr_drop = fit( drop_time_hr, drop_line_hr,'exp1', 'Robust', 'LAR' );
```

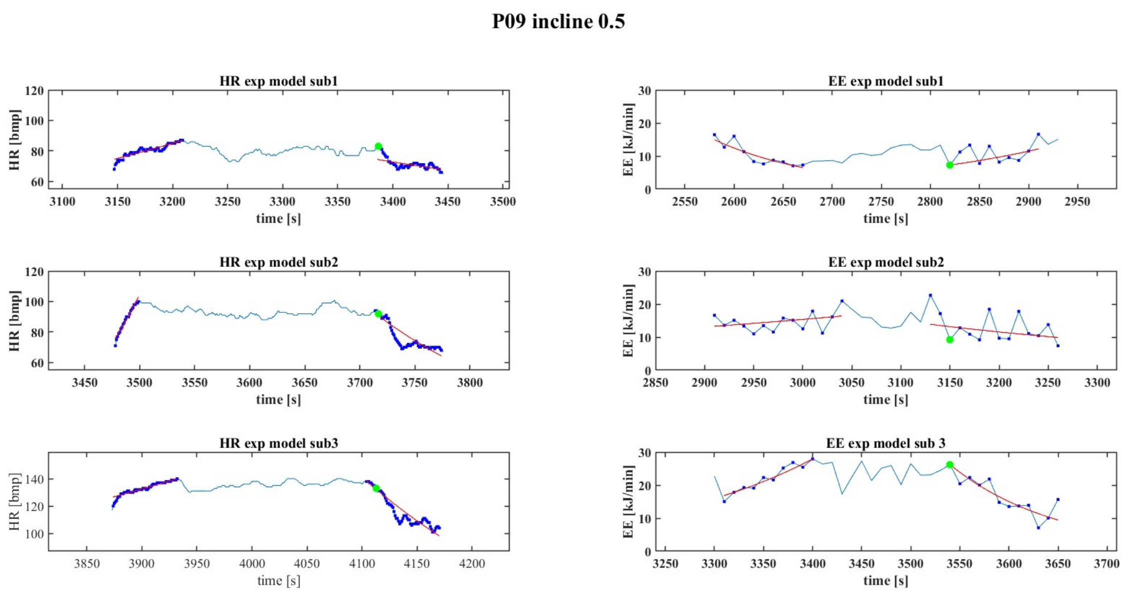
we fitted the raises and the drops to an exponential. The options `Robust` and `LAR` specify that we are using the LAD method.

The two interpolation curves are red, while the green dots represent the end of the 4 minutes of the session. As we can notice, some participants do not finish their session at the end of the time slot, for instance participant 16 does not manage to complete the third stage of the experiment. In fact, we notice in Figure 5.2a that the decrease of the heart rate takes place before the end and the Vyntus signal gets lost, probably because the subject removed the mask when they could not go on anymore. Participant 9 is for instance an outlier of sub-session 1 (see Figure 5.1b), the energy expenditure has an out of the

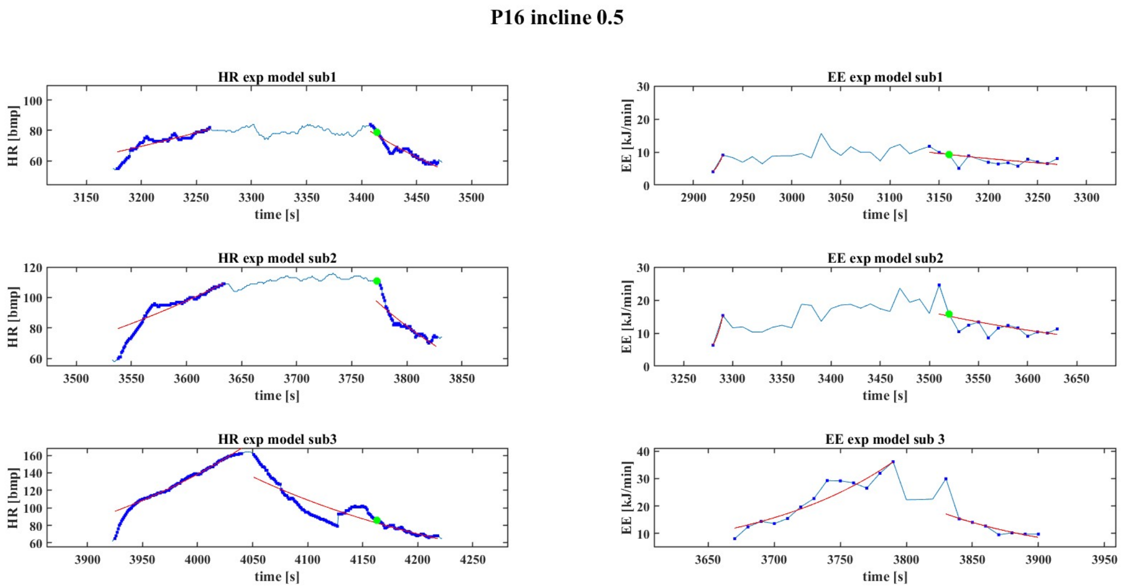
Figure 5.3: Legend relative to Figure 5.1a, 5.1b, 5.2a, 5.2b.



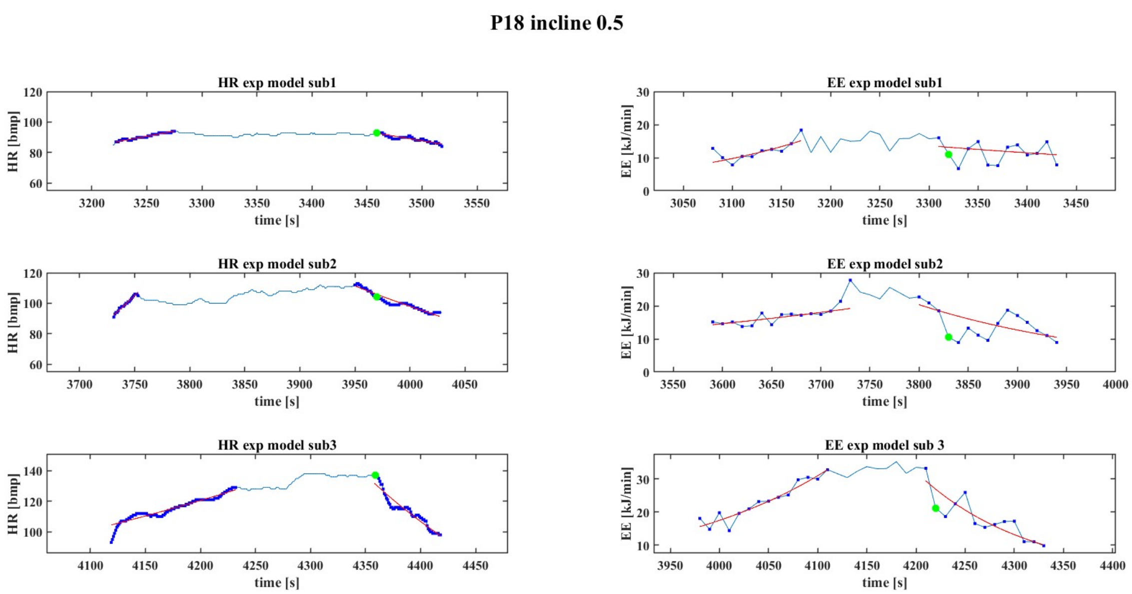
(a) Participant 7. This subject exhibits quite a steep rise.



(b) Participant 9: it is clearly an outlier in sub-session 1, since the energy expenditure presents the opposite of the expected behaviour, showing first a drop and then a raise.



(a) Participant 16. Note that this participant does not complete the third stage of the experiment.



(b) Participant 18. He/she shows a gentle growth for both signals.

ordinary behaviour. We will now try to define any common feature, thus we will compare the Figures 5.1a, 5.1b, 5.2a, 5.2b. In the broad sense we notice that the increase for the first sub-session is less steep than the others and the signal has a lower magnitude compared to the last two stages, probably because the speed is lower and hence it is easier for the subject to keep up. For instance, subject 18 presents a very gentle rise, as if he was not tired at all (see Figure 5.2b). The energy expenditure signal seems noisier than the heart rate and therefore less reliable. This may be due to the processing that oxygen and carbon dioxide undergo before being registered by the Vyntus machine.

On the whole, one sees that the energy expenditure needs more time to reach the steady state, due to the delay (see Section 3.1).

Chapter 6

Results

To analyse the presence of correlations among the parameters of the ODEs considered above we proceed by using both graphical and analytical methods.
As for the first ones, we consider plots of the scatter plots of the heart rate and energy expenditure time constants. We started with a 3D visualization in order to relate them with physiological parameters, and our goal is to find any cluster or trend in the data. We decided to study the data by sub-session, because in the same sub-session there should be the same fatigue level (based on the incline and speed). In the following plots one will be able to visualize the estimated variables on the x and y axis,and the body mass on the z-axis. Gender is signaled by the red colour for women and blue for men. The stars represent a high IPAQ level, the dots a moderate one. We obtained a subplot for each sessions and each row targets an incline, while each column a raise or drop. However, it is difficult to grab any information of correlation from the observation of the 3D plot, as one can see the graph in Figure 6.1.

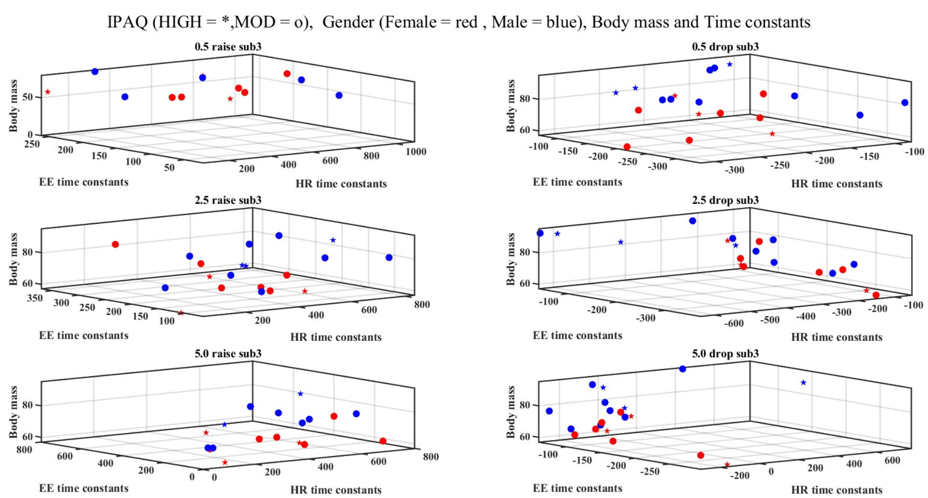
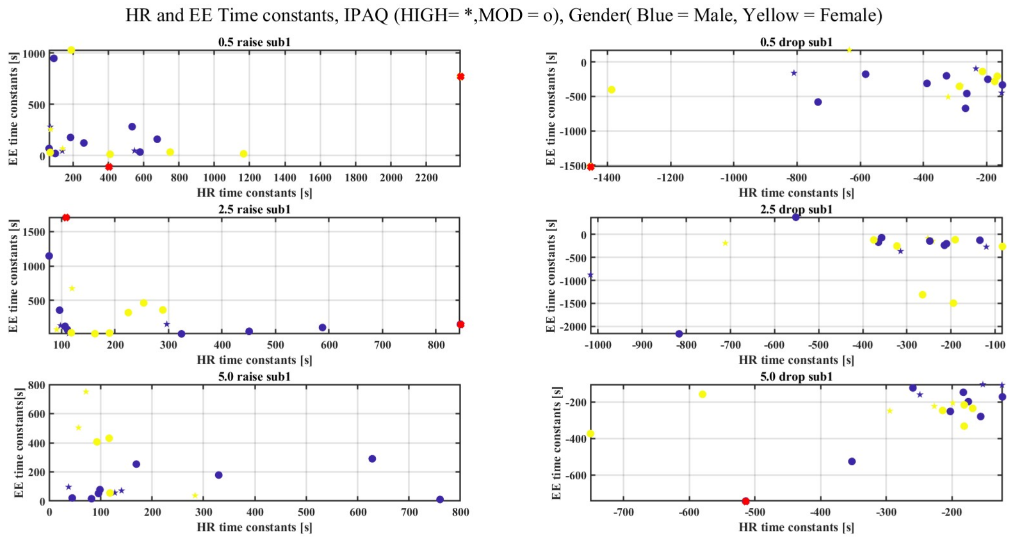
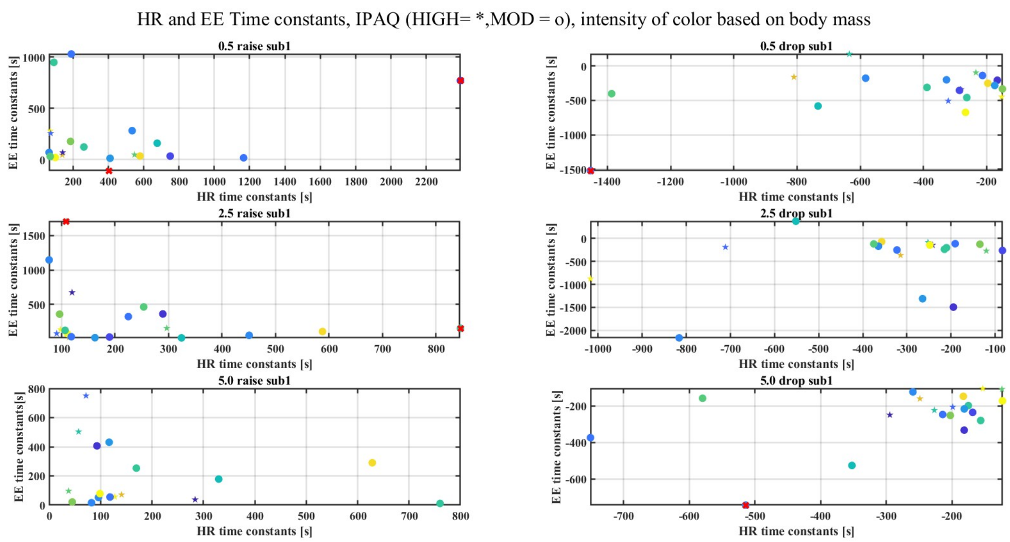


Figure 6.1: Scatter plots of the EE and HR time constants, Body mass for sub-session 3.

Hence we moved to a 2D-visualization, which may help to characterize any correlation between the estimated variables. First we visualized the 2D plots of the time constants related to the gender and IPAQ, then we substituted the gender with the body mass. To highlight the different body masses we used a color vector, which uses a range from blue yellow, where blue stands for lower body mass and yellow for higher. We kept the IPAQ parameter, because it could be useful to relate body mass with physical activity [1].



(a) HR vs EE time constants in sub-session 1, yellow represents females and blue males.



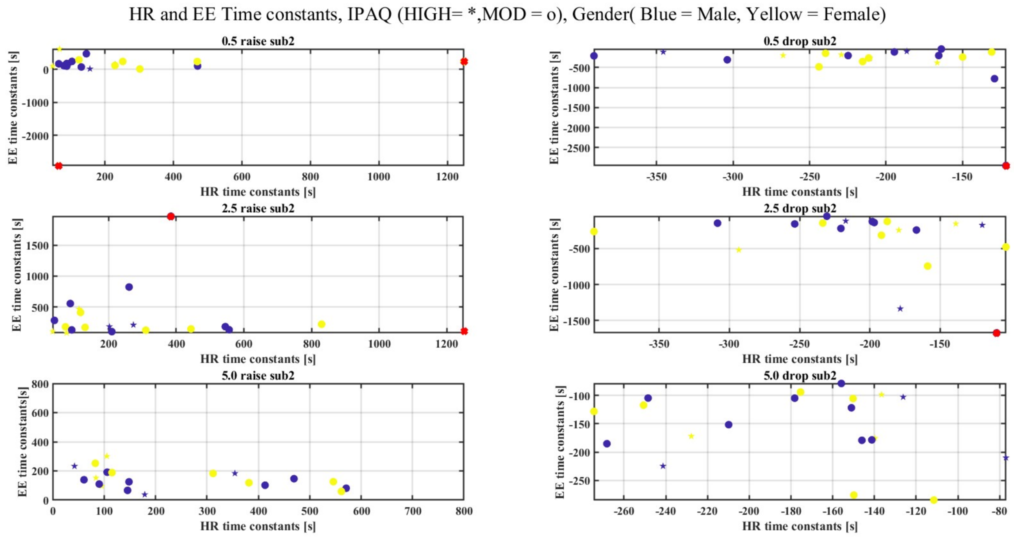
(b) HR vs EE time constants of sub-session 1, each data point has a color of intensity dependent on body mass.

Figure 6.2: Graphical representation of the relationship of the time constants, IPAQ and either gender or body mass for subsession 1. The red crosses mark the outliers.

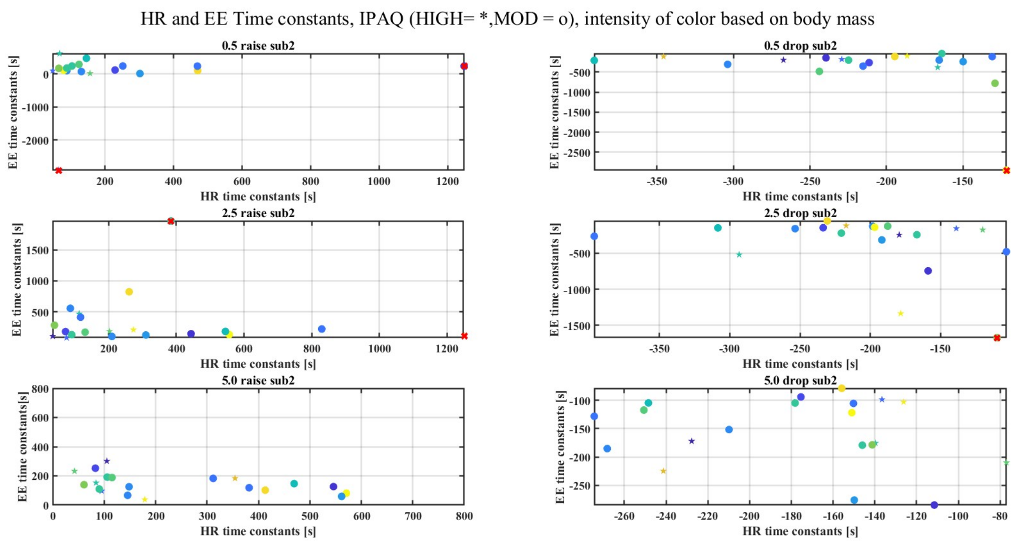
Since the scatter plots give only a qualitative analysis, to help us analyse better the data and check whether there is a monotonic relationship between the two variables, we computed Spearman correlation coefficient [2]. We chose to use this index rather than the Pearson one because the latter requires some strict conditions that our data may not satisfy, for example the normal distribution. Spearman should also be more robust to outliers.

[1] We note that the unit scale of the two axis is not the same, but this choice derives from the fact that using the same scale would have led to a poor graphical visualization.

[2] Note that we kept 4 significant figures.



(a) HR vs EE time constants in sub-session 2, yellow represents females and blue males.

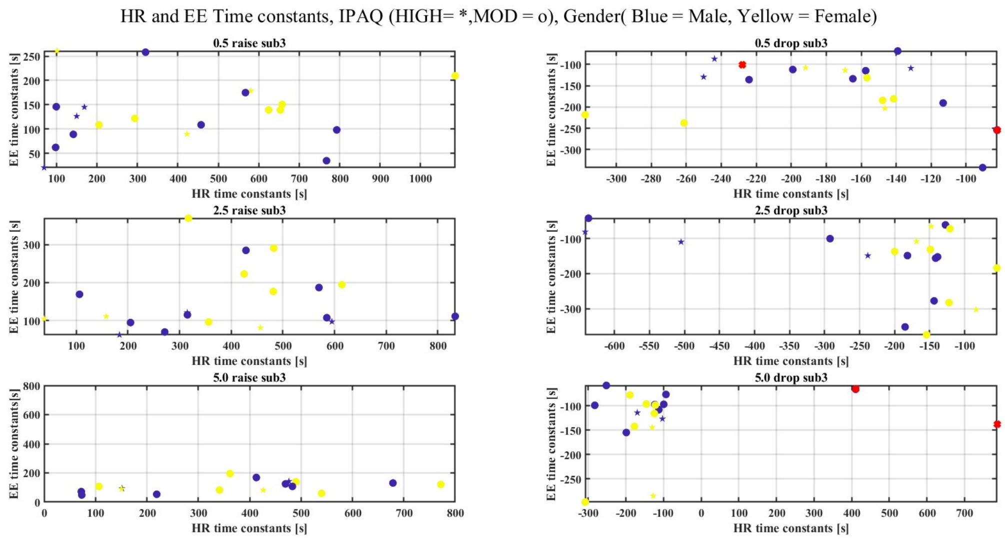


(b) HR vs EE time constants of sub-session 2, each data point has a color of intensity dependent on body mass.

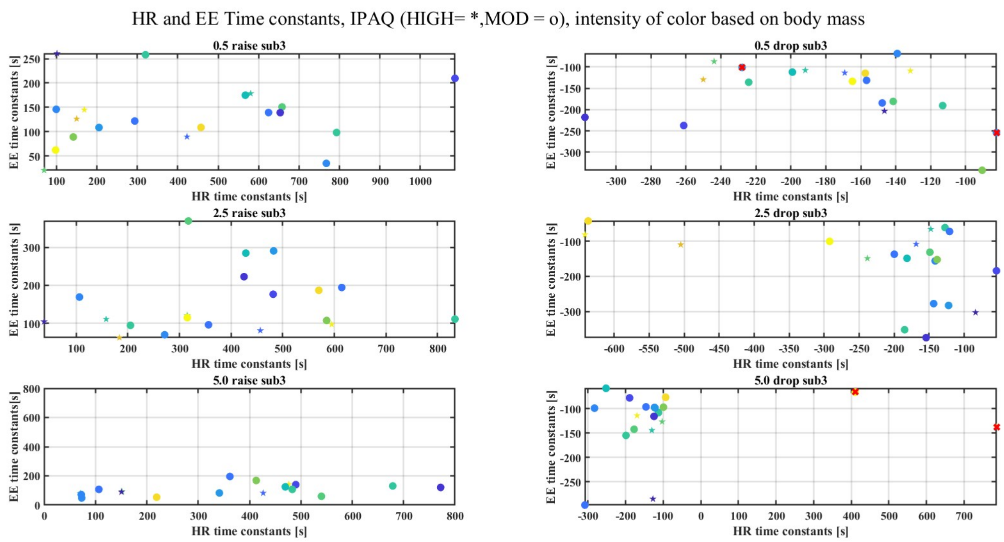
Figure 6.3: Graphical representation of the relationship of the time constants, IPAQ and either gender or body mass for sub-session 2. The red crosses mark the outliers.

sub	Incline 0.5	Incline 2.5	Incline 5.0
1	-0.1414	-0.2090	-0.06767
2	0.08421	0.01805	-0.4812
3	0.2105	0.3068	0.5865

Table 6.1: Table displaying the Spearman correlation coefficient between the time constants, computed on the **raise** data.



(a) HR vs EE time constants in sub-session 3, red represents females and blue males.



(b) HR vs EE time constants of sub-session 3, each data point has a color of intensity dependent on body mass.

Figure 6.4: Graphical representation of the relationship of the time constants, IPAQ and either gender or body mass for sub-session 3. The red crosses mark the outliers.

sub	Incline 0.5	Incline 2.5	Incline 5.0
1	0.1263	0.0090	0.4030
2	-0.1203	-0.3684	-0.1459
3	-0.2361	-0.3353	0.2331

Table 6.2: Table displaying the Spearman correlation coefficient between the time constants, computed on the **drop** data.

As further analysis, we deleted the outliers data with the method `rmoutliers` adding the option `mean`, which considers by default an outlier a value that is more than three standard deviations from the mean. Moreover we attached the condition of keeping only the positive time constants for the raises and the negative ones for the drops. Hence, we label 'outliers' those participants who either have time constants exceeding the three standard deviation range or do not finish the experiment. In the plots in Figures 6.2, 6.3, 6.4 one is able to detect these cases, identifying them with a red cross.
Here follows a list of those subjects identified as outliers:

- Sub-session 1
  - Incline 0.5: P15 (raise), P9 (raise), P13 (drop);
  - Incline 2.5: P2 (raise), P9(raise);
  - Incline 5.0: P14(drop).
- Sub-session 2
  - Incline 0.5: P15 (raise), P12 (raise), P5 (drop);
  - Incline 2.5: P10 (raise), P2 (raise), P6(drop);
  - Incline 5.0: none.
- Sub-session 3
  - Incline 0.5: P3 (drop), P16 (drop);
  - Incline 2.5: none;
  - Incline 5.0: P10 (raise and drop), P5(drop).

In the table 6.2 and 6.1 one can compare the new coefficients without outliers with the ones with outliers.

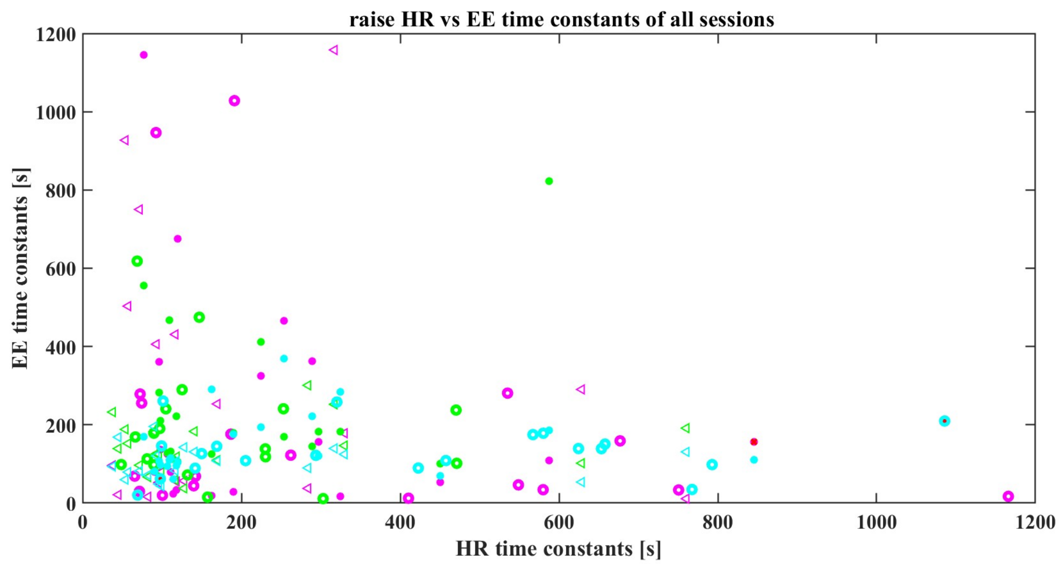
sub	Incline 0.5	Incline 2.5	Incline 5.0
1	-0.2653	-0.2074	-0.1298
2	-0.1207	0.03612	-0.4812
3	0.2105	0.3068	0.4541

Table 6.3: Spearman coefficient for the **raise** without outliers.

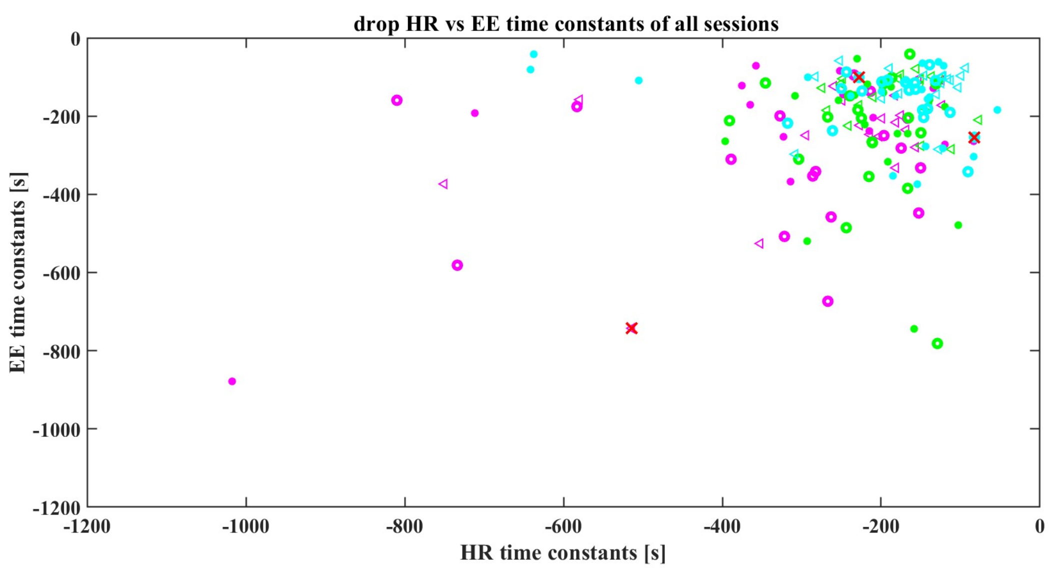
sub	Incline 0.5	Incline 2.5	Incline 5.0
1	0.08566	-0.07895	0.3333
2	0.02632	-0.2702	-0.1459
3	-0.2361	-0.3353	0.1895

Table 6.4: Spearman coefficient for the **drop** without outliers.

Eventually, we plotted the scatter plots of all the sessions and inclines together, to investigate whether there is a trend between specific inclines and sessions, hence we plotted in only one graph all the couples $(HR_{timeconstant}, EE_{timeconstant})$. Since different inclines have different speed, it could happen that one speed of a determine incline presents the same behaviour of another one because the intensity level is similar. We highlighted the outliers with the same notation adopted before, however we set the graph limits and for this reason the number of outliers observable is smaller than the actual one, because some of them exceed the boundaries.



(a) Plot overlapping the **raise** time constants of all the sessions.



(b) Plot overlapping the **drop** time constants of all the sessions.

Figure 6.5: Scatter plot of time constants of all sessions and inclines together. The red crosses symbolize the outliers.

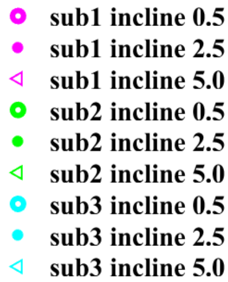


Figure 6.6: Legend relative to Figure 6.5.

Chapter 7

Discussion and analysis

In this section we will comment the graphical results obtained in the various plots shown in section 6. The focus will be mainly on understanding whether and under which circumstances there exist correlations among the various time constants that have been identified as functions of the exercises intensity.

7.1 Model performances

Exponential growths and decays represent the outputs of simple first order LTI systems, and, as mentioned before, our choice has been to start with this model structure as our first attempt for analysing the existence of the correlations we wanted to investigate. The capabilities of such a model structure in capturing the feature of the collected data is though very limited, and some improvements may likely be obtained using more complex ones. In fact, such model is too poor and does not describe well all of the data. We need a more complex one to fit them better, we should at least include one integrator. Each subject exhibited such a peculiar behaviour that a simple exponential does not portray their performance.

7.2 Estimated parameters

Using the model described by the Equation 5.1, we estimated the values for a and b. In particular we studied the time constants, which measure the time taken by the subject to go from rest to stressed conditions and viceversa. As we can see from the 3 subplots in Figures 6.2, 6.3 and 6.4, the time constants for the raises are positive numbers, while the ones for the drops are negative, with the exception of a few outliers (marked in red - the discussion about how these were identified is in Section 7.2.3). We decided to still draw such outliers in the graphs below by means of red crosses to highlight that not all of the data taken during an experiment are reliable. In the Figures 6.2, 6.3, 6.4 we notice that the energy expenditure time constants are smaller than the heart rate ones. This can be explained with the argument presented in section 3.1 about the slower kinetics of the energy expenditure, since the time constant represents the rate of increase, indeed.

7.2.1 Estimated and physiological parameters

In Figures 6.2b, 6.3b, 6.4b one can observe the relationship between the time constants, body mass and IPAQ. The first trend is that in general in the first two stages the higher the IPAQ, the smaller

the time constant: a trained person in average does not need too much time to reach the steady state. This though cannot be stated for the third session. We would indeed expect people better trained to respond and recover in average faster than the others; however this does not always happen, likely because one should take into account also potential genetic components. It would be to shallow to draw other conclusions on the relationship between body mass and time constants: there is no evident trend in the graph, the colors occupy a random position in the 2D-plane.
Instead, in Figures 6.2a, 6.3a, 6.4a, one can analyse any relationship with the gender. It seems that the plots do not show any meaningful correlation, as the various data points are mixed up in the Cartesian plane to the point that it seems difficult to identify some simple parametric probability distribution behind such a spread.
The just mentioned subplots do not show a strong correlation between the variables and the physiological parameter, however if we only consider the correlation between the heart rate and the energy expenditure there are some worth of notice results for sub-session 3. For instance, in the drop at incline 5.0 we could say that the data present a somewhat linear trend. This involves the harder work and hence this may be the one where we actually see an increase of VO_2 together with the heart rate. In the first two sub-sessions and at the lower inclines maybe the intensity of the workout is too little that the energy expenditure did not increase enough to see a correlation. This is what happens for example for able-bodied people [5].
The difficulty of stating any strong claim comes from the fact that the cross-section of the experiment was too small and various.

7.2.2 Correlation coefficients

In this section we will try to quantify what we have just said from observation only.
The coefficient found in Tables 6.3 and 6.4 show a weak correlation between the two variables, however this is not of the same nature for all inclines and stages. For instance, one may think that the correlation is positive because if we increase the heart rate also the energy should. However, as the coefficients show, this is not always true, since the data suggests a combination of positive and negative results. As a general trend, we have higher correlation at the higher intensity, for the reasons exposed in the Section 7.2.1. The removal of the outliers introduced a few light changes in the coefficients, mainly in the first two sessions - confirming the intuition exposed before - or in the last section at the highest incline, caused by those participants who did not keep up with the experiment. The steadiest and maybe therefore trustworthy stages seem to be the second one at incline 2.5 and the third one for incline 0.5 and 2.5. They may represent also the same intensity level of exercise, since the highest the incline, the lowest the speed.
In general, we could say that the easier the exercise (i.e., slow speed and small inclines) the more likely it is that the trace from the participant is identified as an outlier. Many factors could spoil the experiment, as the subject does not feel any stressed condition. Conversely, the more intense the physical activity, the more reliable the data seem to be. However, we could say that we have been unlucky, for example with the second sub-session: we could have seen some correlation, but the coefficients show the opposite; the subjects did not perform as we expected.

7.2.3 Outliers

Here we will analyze the outliers data and their nature. As we said, an outlier is either due to human (not finishing the experiment), instrumental (losing the equipment while exercising) or statistical factors (exceeding the 3 SD interval). We found that the outliers are mainly in that sessions that are executed at smaller intensities and inclines, supporting our final claim in Section 7.2.2. In the List 6 one can notice that the number of outliers decreases as we increase the exercise intensity. However, their number is not zero at the highest difficulty, because some subjects were not trained enough for this kind of physical activity. It is worth to notice that a participant who is an outlier in the raise may not be the same for the drop. This happens for example only for the tenth one, at incline 5.0, in the third sub-session. Moreover, we observed that being an outlier in a session does not imply being an outlier in another one. In fact, a subject results outlier in at most two sessions. This adds difficulty and uncertainty in our data analysis.

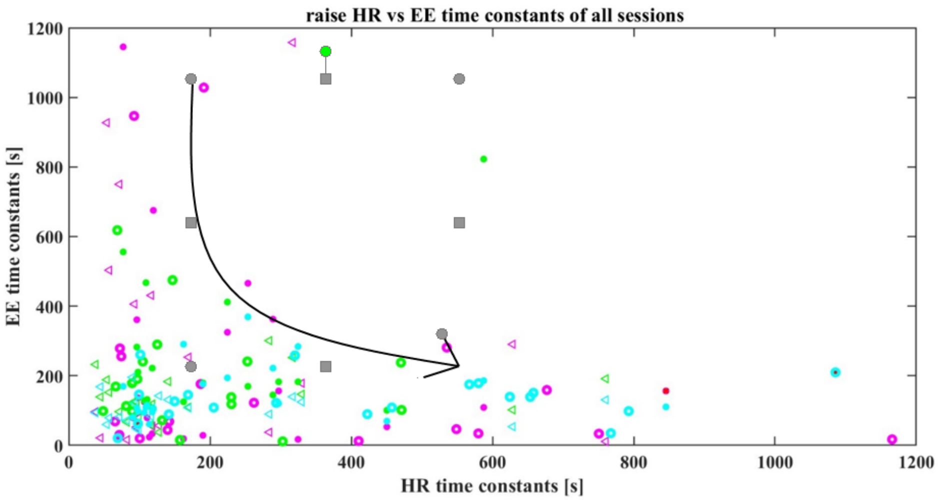
7.3 General view: comparison of all sessions

The last step of this project would be studying all the sessions and inclines together, to check whether there exists a trend as we change such parameters. Hence, we will analyse the graphs displayed in Figure 6.5. There are no consistent groups of data that lead us to any correlation between different stages. This can be explained saying that as we increase the incline, we decrease the speed and so the collected data represent the subjects in the same conditions.

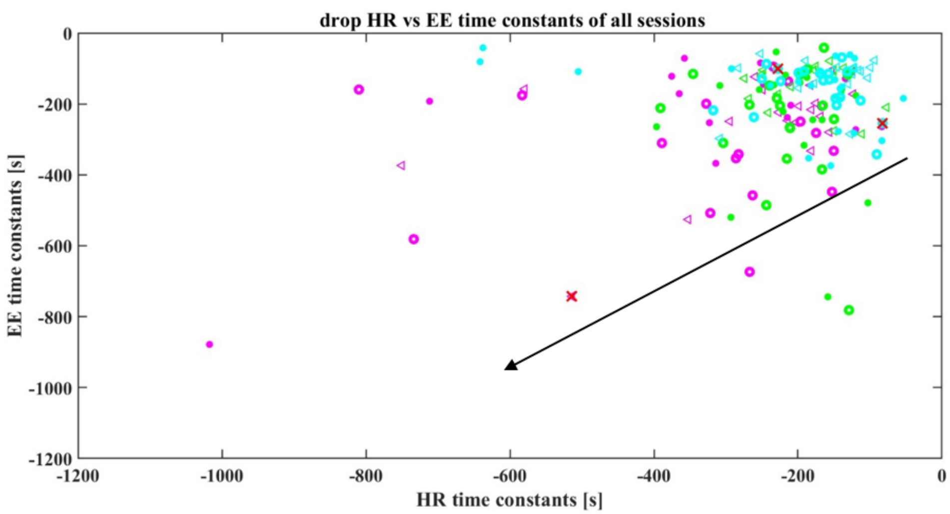
In Figure 7.1a one observes that moving from the first to the third stage the time constants rotate following the direction pointed out by the black arrow: the energy expenditure time constants decrease, while the heart rate ones increase instead. This could be explained saying that as we lower the exercise intensity, less air passes through the Vyntus mask and the ergospirometer - because the subject is not under effort and therefore does not breath deeply - and hence this causes longer delay in the energy expenditure dynamics. However, we can see from the plot that there are subjects who reach a 1200 s heart rate time constant. This is a way too high value (20 minutes to shift from resting to fatiguing), which lead us to the consideration that the model that we are using is weak: when trying to fit an exponential without any prior constraints or bounds to the signals, we get some solutions and estimates that might be noisier than they should be.

Moving to Figure 7.1b, at first sight one notices that there is a neat separation between the different colors (which represent the sub-sessions) in the graph. For instance, we notice that the samples of the third stage (light blue ones) are much closer to zero than the ones of the first one (purple ones). Moreover one can observe that not only the blue ones are smaller but they tend to create a much more dense cluster. If we follow the black arrow we can detect this behaviour. These patterns are reasonable and can be explained saying that when our body is under intense physical exercise, it is less flexible and will respond to stimuli in the most efficient way. Hence when moving from resting to fatiguing, all the subjects accomplish this transition as fast as possible, therefore the points occupy the same area. If the physical exercise is of low intensity, the subject just fools around and takes more time and this justifies why the purple data points are sparse. Constraining to the third sub-session, we notice that the triangles, hence highest intensity and incline, are the closest to zero among all the data.

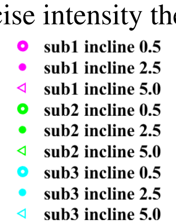
On the whole, the behaviour of the subjects at the beginning of the stages is less clear and more heterogeneous than the one at the end. As an explanation, one could mention the fact that when one starts exercising, they behave differently depending on how fit and trained the person is.



(a) Plot showing all the sessions and inclines together; the black arrow shows in which direction the time constants move as we increase the exercise intensity.



(b) Plot showing all the sessions and inclines together; the black arrow shows that as we increase the exercise intensity the time constants tend to be more dense and closer to zero.



(c) Legend relative to Figure 6.5

Figure 7.1: Plot showing all the sessions and inclines together, with black arrows highlighting the main trends.

Chapter 8

Limitations and future studies

The results of the analysis have shown that this way of modeling the data is limited. First of all, the LTI model that we are using - described by a first order ODE - is too simple to capture all the features that the data seem to exhibit. Secondly, our data proved to be too noisy (especially the energy expenditure) for a maximum likelihood approach to provide always reliable estimates. For further studies, we would suggest to extend the statistical strategy to a Bayesian one, and test more complex model structures. As for the priors to be introduced to strengthen the statistical learning approach so far, we indeed have conducted our analyses regardless of any weights we may use from physical medical knowledge that one may in the available literature. Though, this at the end was a likely important factor for the inconclusiveness of our results. E.g., injecting a prior that suggests the heart rate dynamics to statistically behave in a specific way could help us to build a more robust model and to automatically clean up the outliers.

Chapter 9

Conclusion

The aim of this project was not to find the perfect fit of all the data, but check if there is any correlation between heart rate and energy expenditure time constants and between those two and the specific parameters. The results of our study were not too discouraging; in fact, they show that there may exist some small correlation. However, we do not hazard any neat conclusion, since the number of data was not wide enough and there is a consistent number of outliers that could ruin our analysis. Moreover, the fact that in this first part the testing involves able bodied people affects the goodness of the experiment, as they are not used to ride a wheelchair. Thus, this study has to be read as a 'first draft' and first step towards the discovery of meaningful statistical laws. We thus lay the foundation and suggest directions for further studies. Researchers who will continue studying on this project will hopefully have thus in this thesis a set of suggestions about which strategy to avoid and which to try instead.

Appendix A

Experience in the lab

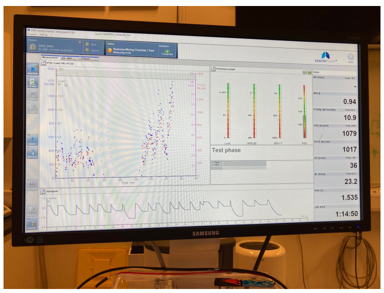
A.1 Observations

This chapter goes beyond the data analysis and modeling, and is more a sort of ”diary” of how tests are performed, and should be thus read as an insight on the life in a laboratory in a foreign country. I was given the chance to see the experiment going on in the laboratory and I took because it can result particularly useful and important to understand the data better. Asking questions to the PhD student responsible for the project (Marius) and to one of the actual participants gave me more hints on how to analyse the data, also from a human point of view.
The following is thus my experience: the experiment took place on August 22^{nd}, 24^{th}, 25^{th} in the NTNU sports centre SenTIF. It was part of the second phase of the project, so with a real wheelchair user. The participant of this experiment was born in 1963, he has been on a wheelchair for 25 years. He suffers from a spinal cord injury due to an accident. He said that whenever he can, he is happy to take part in those type of projects, because he thinks it is useful and important for the progress of science. In his opinion Norway is an advanced country in terms of wheelchair users accessibility, but things can grow further better.

(a) Figure shows the mill on which the participants are tested. One is also able to see the safety equipment at the bottom and some cameras.

(b) 032 MWU on the treadmill, picture taken during the experiment in the sub-maximal stage.

The first day of the experiment the incline (the angle of the treadmill with respect to the ground in percentage) was set to 2.5. Thus the more the incline, the more difficult is for the participant to keep up. The first day of trials takes always a little more time, because the tested person has to answer personal questions and to be measured in some basic quantities (skinfolds, circumference and weight). First the participant was weighted, then Marius took the measurements and prepared the instrumentation. The participant had an active part in the experiment because he had to tap on the smart watch to start and stop a session of data. The Vyntus machine collects data continuously as long as the participant has the mask on, while the Apple Watch or Fitbit registers only the sessions which we want to study, not the breaks in-between. After this bureaucratic part, the experiment got started with the rest-lying and rest-sitting stages. In these parts the participant was not on the treadmill yet and he was not under physical effort. The data collected by the Vyntus machine have the form displayed in Figure A.2a.



(a) Visualisation of data collection during the experiment.

(b) Participant 032 wearing all the markers, before doing the warm-up and the sub-maximal stages.

Before training on the treadmill, some sensors to track movements (for another study) were glued on the participant's skin (see Figure A.2b). The PhD assistant prepared the treadmill and checked that the cameras could detect correctly the participant (thanks to his/her markers): before the warm up the participant had to open his arms (as the Vitruvian Man) so that the canonical length needed to track the movement could be computed. After these protocol procedures, the warm-up started with the basic incline, and then the 3 sub-maximal stages with 2.5 of incline. In each session there were 30 seconds (at minute 1.30 and 3.30) during which the testers could not move, because the cameras were tracking the motion. After each session the subject was asked how tired he felt on a scale from 6 to 20 (see Borg Scale for further information in Appendix C) and Marius measured bloody lactate. The subject said that he did not feel that tired, he was glad to help. At the end there was the incremental stage, because we were in incline 2.5. During this very last step the speed of the treadmill was incremented by one every 60 seconds and the experiment continued until the participant did not keep up the pace anymore and risked to get off the treadmill.
The second day of experiment was incline 0.5. During this test the data recorded during the rest lying session presented some gaps, they were due to a too low ventilation flux. To avoid them, we asked the participant to breath deeper, but not too much otherwise we could exit the resting state. There was another issue to be solved, i.e. a marker was not reflecting, hence they had to find it and substitute to be able to track the motion. During the sub-maximal stages the participant did not feel much tired, indeed in the Borg scale his fatigue perception never overreached the threshold of 15. At the end the participant said that he did not feel stressed for the test. This can be explained saying that usually men do not struggle with the 0.5 incline, because they are more powerful. Conversely,

they are more likely to fail in the 5.0 incline than women because of their weight. The experiment ended with a friction test.
The last testing day was incline 5.0. It was supposed to be the harder for that subject because he was quite heavy. In this case he felt more effort and as a consequence his answers for the Borg scale values went beyond the threshold of 15 in sub-sessions 2 and 3. However, he completed the experiment. He has been an athlete for many years, he has played sledge hockey for the national team and this may be a reason why he managed to finish it.

A.2 Learning goals and benefits

I could not help much with the experiment because I would have needed a weeks of training, but however I did what I could: I took down the measures and I asked Marius as many details as possible. I observed the machinery and interviewed the participant to better understand the data. This period resulted particularly useful because it gave me the opportunity to get into a real laboratory and experience all the attentions and measures that one has to take when working in it. I had a bite of what it means to be a researcher: it is a never ending job, you could always try to improve your work, but one has to apply a trade-off between time and quality. Also, I felt part of the digiW team and I realised how important is to work together, share your results and discuss them.
I would suggest to stay for a longer period, in order to be an active part of the project.

Appendix B

Challenges of data collection

This section gives an insight on the challenges of collecting data. We will expose the issues emerged during the experiment and how we tried to fix them. As previously stated, a unique trend in the correlation between the time constants was not observed and this is related to the stochastic nature of the test. Instrumental and human factors interfere with the goodness of the results and sometimes they can even spoil them.

- During the rest lying session, sometimes the flux is too low and it is difficult to detect the data. If this is the case, the tester asks the participant to breath in and out deeper, but only slightly, otherwise the resting condition may be violated.
- IMU band got off the participant's arm. This brings a gap in the data collected, that in the Matlab code will be substituted with NaN entries.
- The Apple watch is started manually by each subject so it may not be perfectly synchronised with the beginning of the experiment. This cannot be controlled, but we can take it into account when studying the data.
- A marker was not reflecting: the PhD helper had to take it out and substitute it.
- This part of the experiment involved able-bodied people and thus they are not used to be on a wheelchair as the real users. Hence, the absence of a correlation may be explained also by the fact that they are not trained and they may not have enough strength in the arms as the real wheelchair users and this leads them not to conclude the experiment. For example, I have tried riding the wheelchair and I did not manage to finish it: at the higher speed and inclines I shuffled back. I would be counted as an outlier in the data.

Appendix C

Borg scale

During physical exercise, the symptom of exertion depends on the person that trains and hence it is subjective. In order to ”quantify” this stressed condition one can use the Borg scale, developed by Swedish researcher Gunnar Borg.
The Borg Rating of Perceived Exertion (RPE) scale is a tool for estimating an individual’s level of effort and exertion, breathlessness and fatigue during physical work. Hence it can be seen as a subjective measure of the work intensity undertaken across a variety of populations. It is fundamental to know the intensity of work to prevent musculoskeletal injuries and disorders, which could arising from a mismatch between the worker’s capability and the physical demands of their job. Consequently, this scale is highly relevant for occupational health and safety practice.

C.0.1 Scoring and interpretation

The scale is a very simple numerical list. Participants are usually asked to rate their exertion on the scale during the activity, combining all sensations and feelings of physical stress and fatigue, such as increased heart rate, increased respiration or breathing rate, increased sweating and muscle fatigue.
The unusual scaling, ranging not from ‘0’ to ‘20’ but from ‘6’ to ‘20’ is related to the high correlation between the scale and heart rate . Thus, a Borg RPE scale of 6 corresponds to a heart rate of 60 beats/min in a healthy adult, 8–80 beats/min and so on [13].

Rating	Descriptor
6	No exertion at all
7 8	Extremely light
9 10	Very light (easy walking slowly at a comfortable pace)
11 12	Light
13 14	Somewhat hard (quite an effort: the individual feels tired but still able to continue)
15 16	Hard (heavy)
17 18	Very hard (A healthy person can continue but must push themselves beyond their feeling of being very fatigued)
19 20	Extremely hard (extremely strenuous exercise—for most people, the hardest they have ever experienced)

Table C.1: Rating of Perceived Exertion (RPE) Scale (Borg, 1962).

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