Escuela Colombiana de Ingeniería Julio Garavito

Master Thesis

FATIGUE ESTIMATION FOR HIGH-INTENSITY EXERCISES IN PHYSICAL REHABILITATION

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A thesis submitted in fulfillment of the requirements for the degree of Master in Electronic Engineering

July 2020

"Research is to see what everybody
else has seen, and to think
what nobody else has thought."

Albert Szent−Gyorgyi

"Share your knowledge.
It's a way
to achieve immortality."

Dalai Lama

Acknowledgements

This thesis contributes to the development and scope of the SOCAR research project *"Robots sociales para rehabilitación cardíaca"* (grant 801-2017). I would like to acknowledge the funding institutions of this project, such as the *"Ministerio de Ciencia Tecnología e Innovación" ()* and the internal projects of the Colombian School of Engineering Julio Garavito (Bogotá, Colombia).

On the other hand, it is important to emphasize that this work would not have been possible without the support of a large group of people, relatives, and friends. Additionally, I would like to thank my thesis advisors, who have guided me through this arduous but pleasant process of becoming a researcher. To Carlos, who has taught me to see the positive side of life and always look for the best version in his students. To Marcela, who with her character has taught me to make the students' voice count, because each person has a great value. Finally, I want to express my immense gratitude and appreciation to my colleagues and friends in the laboratory. I have lived invaluable life experiences with them, and they have accompanied me during these years of work. I believe that each one of them has left a great mark in my life and I am convinced that they are the best work team. Thanks to, Sergio Sierra, Daniel Gómez, Diego Casas, Felipe Ballén, Luis Arciniegas, Miguel Sanchez, Margarita Bautista, Maria José, Nathalia Céspedes, Orión Ramos and Jonathan Casas.

Abstract

Physical exercise (PE) has become an essential tool for different rehabilitation programs. Especially, high-intensity exercises (HIEs) have demonstrated to provide better results than low and moderate-intensity exercises, in the improvement of general health conditions. Nonetheless, despite the benefits of PE, it is required to monitor patients' condition, because leading them to extreme fatigue conditions may cause physical and physiological complications. Thus, different methods, such as monitoring subject's physiological parameters and subjective scales, have been proposed for fatigue estimation. However, there is still a need for practical procedures that provide an objective estimation, especially for HIEs. Currently, novel techniques based on exercise performance features and machine learning models, have been explored, built on the idea that fatigue is reflected as a decrease in the performance. Nevertheless, the performance in each exercise is normally assessed by employing different characteristics. Therefore, considering that the sit-to-stand (STS) exercise is one of the most implemented in physical rehabilitation, this work aims to propose a computational model for estimating fatigue during this exercise. To obtain a data set that allows to develop and evaluate the proposed model, a study with 60 healthy volunteers was carried out. The model was designed for estimating three fatigue conditions: low, moderate, and high; by monitoring 32 STS kinematic features and the heart rate, with a Kinect and a Zephyr sensor. Results show that a random forest model composed of 60 sub-classifiers presented an accuracy of 82.5% and a precision of 83.3% in the classification task. Moreover, results suggest that the movement of the upper body part is the most relevant feature for fatigue estimation. However, other characteristics like the movements of the lower body or the heart rate, also contribute essential information that allows identifying the fatigue condition. Hence, this work presents an initial approach to a promising tool for physical rehabilitation and in terms of classification accuracy, this work presents remarkable results according to the literature.

Keywords: Fatigue estimation; sit-to-stand; physical exercise; physical rehabilitation; machine learning;.

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Chapter 1

Introduction

This master thesis presents the process carried out for the development and assessment of a computational model to estimate 3 fatigue levels (low, medium and high) during the sit-to-stand () exercise, which is a high-intensity exercise widely used in the physical rehabilitation. Basically, this process consists of relating the users reported fatigue level to the heart rate behavior and 32 kinematic/temporal performance features of the STS exercise, by applying machine learning techniques. These features are collected from affordable and ambulatory sensors, such as: a Kinect sensor and heart rate sensor. In order to obtain a data set, a study with 60 healthy volunteers was carried out, providing 660 STS registers related to the features previously mentioned and a fatigue level. Finally, this data set was used to develop and evaluate the proposed fatigue estimation model.

This chapter contains the objectives of the work, the main motivations and its importance in the clinical field. In addition, the work contributions and publications are presented.

1.1 Motivation

According to the World Health Organization, non-communicable diseases (also known as chronic diseases) are responsible for 71% of the global deaths (41 million approximately) each year, being cardiovascular diseases, cancer, respiratory diseases, and diabetes the most common ones [2]. There are many personal factors related to the chronic disease risks, such as unhealthy diets and a lack of physical activity, thus; these illnesses can affect any person of any group [3]. Moreover, it is predicted that the number of people with non-communicable diseases is going to increase every year, bringing many socioeconomic issues regarding the excessive cost of treatment for these patients and the amount of deaths [2].

Taking into account the socioeconomic impacts and patients well-being, different rehabilitation programs are designed and held globally, to treat each specific chronic disease, and hence, to reduce the number of deaths [4]. Although each program implements different methods for the rehabilitation of patients (specifically, because each illness affects different body functionalities), all of them are based on some basic World Health Organization recommendations [5]. Among these recommendations, one of the most important is to perform physical exercise (), because it allows to treat different disease symptoms without medication [3]. Thus, physical exercise has become a fundamental tool in several rehabilitation programs, such as cardiac, oncology, neuromuscular pulmonary, and musculoskeletal [4, 5].

However, aiming to obtain an effective and safe rehabilitation process, a personalized training program must be designed, based on the unique patient conditions (e.g. Diseases, age, injuries and medication) and the rehabilitation goals [6]. Owing to the exercise variety, it is possible to create a personalized training for each patient. Nevertheless, the exercise time and intensity, are also essential features that require to be kept in mind [4, 7]. Specifically, this has to be taken into account due to physical or physiological complications that may suffer patients at taking them to prolonged and/or extreme fatigue conditions [8].

Initially, low-intensity and moderate-intensity exercises were used in the rehabilitation therapies, essentially because they allow to manage easily the patient's fatigue condition and had shown to be sufficient for reducing chronic disease risk factors [9, 10]. Nonetheless, several studies have demonstrated that high-intensity exercises with short duration are more effective for reducing these risks [9, 11, 12]. Hence, it is highly recommended to implemented high-intensity exercises in rehabilitation therapies [4, 12].

Considering the importance of preventing patients from extreme exercise conditions, several methods to manage the fatigue have been explored, such as: monitoring physiological parameters, quantifying the exercise intensity, and asking the patient his fatigue level according to a subjective numerical scales [13]. In general, it is preferred to use objective fatigue indicators obtained directly from the patients, especially the ones related to the energy expended [4]. Therefore, it is always intended to monitor some patient's physiological parameters [4], for example, monitoring the patient's breathing rate, blood lactate level, oxygen saturation, or blood pressure [14–16].

One of the most implemented methods for low and moderate-intensity exercise consists of monitoring the heart rate () because it can be easily estimated during exercise and has shown a strong linear relationship with the exercise intensity. Nevertheless, studies have shown that the HR changes its behavior in the high-intensity exercises, thus, it is not recommended to use only this indicator [17]. In addition, many of the methods based on monitoring physiological parameters are not effective for high-intensity exercise, and/or are difficult to implement in clinical scenarios. Therefore, there is a need for new methods that allow monitoring the patient's fatigue, especially for the high-intensity exercises [18].

A novel method based on the idea that fatigue can be seen as a decrease in performance activity has been recently explored [19]. The main idea consists of monitoring one or more exercise performance features using any sensor that allows to measure directly or indirectly the corresponding characteristic (e.g. accelerometers, gyroscopes, magnetometers, pressure sensors, and force sensors). So, it is possible to determine the relationship between the fatigue condition and the performance features [20–22].

This novel technique presents a great potential for clinical scenarios, because it could provide an objective indicator of the user's fatigue condition. Moreover, in general these systems implement sensors that are easy to adapt and use in rehabilitation environments, providing a practical tool for the health staff [23, 24]. Nevertheless, owing to each activity performance is assessed with different features, this method is highly dependent on the exercise type [25], and therefore, it is required to adapt the whole system to the corresponding activity.

Due to the novelty of this fatigue estimation method, few works have explored its application in some common physical rehabilitation exercises, such as: walking [26], vertical jumps [27] and lower limb endurance [22]. In general, these works employed machine learning models to classify if the user is in fatigue or non-fatigued condition, by monitoring the exercise features with wearable sensors. The authors have reported that it is possible to design computational models with accuracies between 85% and 95%. However, they contemplate only two fatigue conditions, which according to the exercise intensity classification, three levels of intensity are normally managed in physical rehabilitation (low, moderate and high) [4]. Hence, it is preferred to implement fatigue estimation techniques that allow to determine the three states [4]. Furthermore, these models have been validated with a small healthy population. Specifically, authors in [26] recruited 17 people, which is the highest number in the reviewed articles.

These studies were carried out with healthy people and inside laboratory environments, however, they present an initial approach for a helpful clinical tool. Moreover, due to the global health emergency caused by the coronavirus disease 2019 (COVID19), the need of home clinical tool has increased lately [28]. Therefore, this type of technologies are promising for telemedicine rehabilitation applications.

Having in mind the importance of high-intensity exercises and the need of monitoring patient's fatigue condition, this work aims to develop and evaluate a fatigue estimation model for one of the most used high-intensity exercises in rehabilitation. The proposed model is based on machine learning techniques, which integrates the user's heart rate and 32 exercise performance features. Thus, a study with 60 healthy subjects was carried out, in order to obtain the corresponding data for the model development and assessment. In addition, a systematic review was performed to determine the most implemented high-intensity exercise.

Hence, the motivation of this work is regarding an initial approach for a promising tool to regulate fatigue during one high-intensity exercise, that in a future can provide a practical and objective method for monitoring the user's condition, and hence, a safer physical therapy or training.

1.2 Project Background

This thesis is developed in the context of the research project " *"Robots sociales para rehabilitación cardíaca""* () supported by the *"Ministerio de Ciencia Tecnología e Innovación"* (grant 801-2017), as well as, internal funding from the Colombian School of Engineering Julio Garavito. The project is primarily led by Prof. Dr. Carlos A. Cifuentes, Prof. Dr. Marcela C. Múnera (professors at the Department of Biomedical Engineering and head of the *Center for Biomechatronics*) and Dr. Mónica Rincon (Physiatrist leader of the cardiac rehabilitation center at the *"Fundación Cardioinfantil-Instituto de Cardiologia"*, located in Bogotá, Colombia). Besides, the research is carried out by a cooperation network comprising both national and international research groups and institutions.

The main goal of the project is to explore the use of Socially Assistive Robotics in the physical therapies of cardiac rehabilitation, by providing assistance through social interaction. In order to create an effective interaction with the user, it is required to develop a robust human-robot interface able to determinate the patient's condition. Therefore, the general interface model can be divided in two main modules: the social interaction module, which are the strategies implemented to provide the right type of assistance (e.g. motivation and feedback) based on the patient's condition; and the monitoring and control module, that consists of measuring the essential users' parameters (e.g. physiological and exercise intensity parameters) to assess their physical condition [29]. Figure 1.1 presents graphically the general diagram of the human-robot interface project, where it is possible to appreciate how the robot behavior is related to the patient's condition, during physical training. Besides, Figure 1.1 displays the specific patient's parameters used in the monitoring and control module, which correspond to cardiovascular parameters and exercise intensity parameters.

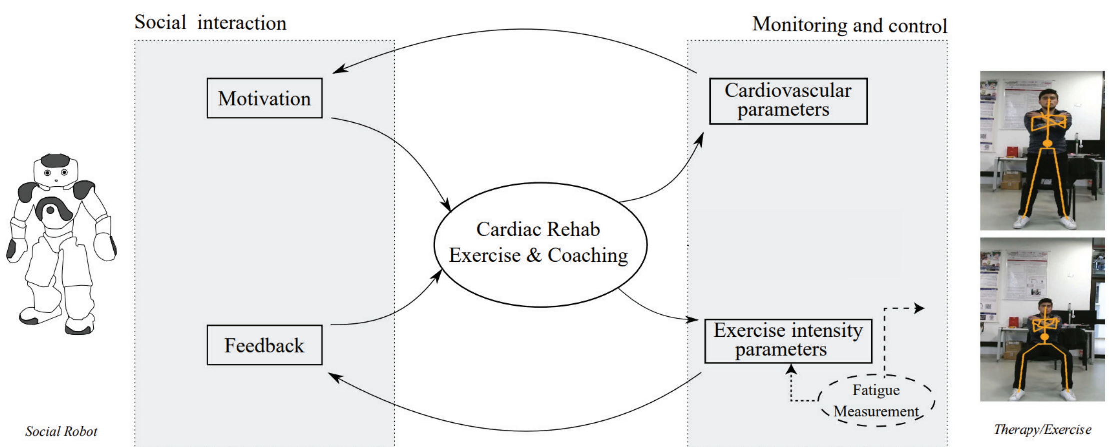

Figure 1.1: General diagram of the human-robot interface project

Taking into account the relationship between the exercise intensity and the fatigue condition, the monitoring control module contemplates a fatigue measurement tool, in order to determine the user's state. Thus, the presented thesis work is focused on proposing a tool to solve this specific task.

1.3 Objectives

Considering the background of this project, its main motivations and the different exercises, it is proposed the initial development and evaluation of a system to estimate the user's fatigue condition for one of the most implemented exercises in physical rehabilitation. Based on the findings and methodologies of previous studies, this system integrates fatigue indicators and machine learning techniques, to design a computational estimation model. Aiming to achieve the project proposal the following objectives are defined.

1.3.1 General Objective

Develop and evaluate a fatigue estimation computational model for a high-intensity exercise for physical rehabilitation, based on physiological and exercise performance parameters obtained from healthy subjects.

1.3.2 Specific Objectives

- To perform a literature systematic review to understand the context of high-intensity exercise in physical rehabilitation, regarding the type of exercises and the fatigue regulation methods implemented.
- To propose a system to estimate the user's fatigue condition through monitoring exercise performance features and physiological parameters, for a high-intensity exercise according to the systematic review.
- To develop and evaluate the proposed system, by carrying out an study with 60 healthy subjects and implementing machine learning algorithms.

1.4 Publications

The work presented in this thesis has been reported to the scientific community by means of the following publications:

1. (Conference Proceedings) **Andres A.**, Casas J., Céspedes N., Múnera M., Rincon-Roncancio M., Cuesta-Vargas M. & Cifuentes, C. A. (2019). Feasibility study: Towards Estimation of Fatigue Level in Robot-Assisted Exercise for Cardiac Rehabilitation. IEEE International Conference on Rehabilitation Robotics (ICORR) - Conference Proceedings, `https://ieeexplore.ieee.org/document/8779460`

2. (Article – under review) **Andres A.**, Cifuentes C., Oscar P., Monica R. & Múnera M. (2020). Fatigue Estimation During the Sit-to-Stand Exercise by Monitoring the User's Performance and Heart Rate. Sensors.

3. (Article – under review) Christopher K., **Andres A.**, Cifuentes C., Múnera M. & Sebastian S. (2020). Predicting Perceived Exhaustion in Rehabilitation Exercises Using Facial Action Units. IEEE Transactions on Affective Computing.

4. (Book Chapter – under review) Maria P., **Andres A.**, Cifuentes C. & Múnera M. (2020). Wearable Sensors for Monitoring Exercise and Fatigue Estimation in Rehabilitation. Internet of Medical Things: Paradigm of Wearable Devices, CRC Press.

5. (Article – under review) **Andres A.**, Sergio S., Múnera M. & Cifuentes C. (2020). Online System for Gait Parameters Estimation Using a LRF Sensor for Assistive Devices, IEEE SENSORS JOURNAL.

Chapter 2

Fatigue and Physical Exercise in Rehabilitation

Physical exercise () is understood as any activity that requires contracting muscles and more energy expenditure than a resting state [30]. Performing physical activity provides numerous benefits to people's health, such as the improvement of the cardiorespiratory system and the development of muscular groups, which are essential for daily life tasks [5]. Besides, the Word Health Organization highly recommends to prevent and treat many chronic diseases, such as cardiovascular diseases, cancer, stroke, and diabetes [3]. Therefore, several rehabilitation programs have incorporated in their therapies, in order to achieve different goals. Five examples can be seen in Table 2.1.

Table 2.1: Physical exercise objectives in rehabilitation programs

Rehabilitation program	**Physical exercise aim**
Cardiac	Improve the cardiac system capability [31–33]
Oncology	Mitigate the effects of pathological fatigue [34, 35]
Neuromuscular	Retrain the affected movement neural paths [36–38]
Pulmonary	Improve the respiratory system capability [39, 40]
Musculoskeletal	Recover joint strength after a surgery [41, 42]

2.1 Health Related Physical Skills

In general, the main aim of PE in rehabilitation is to work the health-related physical fitness () state of the patients [4], which refers to the components that are required to have a healthy life. These components are focus on preventing illness or improving functional health, instead of developing sport performance [43].

The HRPF capabilities can be divided into four individual groups, that are shown in Table 2.2 [4, 43]. First, the body composition, that contemplates the distribution of different tissues in the body (e.g. fats, water, muscle, and bone), and it is developed with diet and general exercise [43]. Second, the musculoskeletal group, which refers to the power, flexibility, resistance and strength of the muscles and joints, trained by performing endurance and stretching activities with external loads or bodyweight [12]. Third, the aerobic capability, related to the ability of the cardiac and respiratory systems to provide oxygen for creating energy, it is developed by mean of long-duration activities (between 20 to 60 minutes) with low-intensity [44]. Finally, the anaerobic capability, that is the body's capacity to create energy without using oxygen for short-duration movements with high-intensity [12]. It is worthy of mentioning that in the beginning, the anaerobic capability was not considered an essential skill for a healthy life. Nevertheless, several studies have shown that it is essential for sudden daily life movements, and now its development is included in the American Health Association manual [4, 11, 45].

2.2 Exercise Characteristics and Classification

Normally, in rehabilitation therapies, there are three exercise characteristics that are taken into account: The type of exercise, which refers to the specific activity that the patient is executing; the duration, which represents the total time the patient is going to spend

Table 2.2: Health related physical components groups

Group	Meaning	Training method
Body composition	Tissue distribution	Diet and general exercise
Musculoskeletal	Muscle strength and flexibility	Endurance and stretching exercise
Aerobic capability	Create energy using oxygen	Soft activities with long-duration
Anaerobic capability	Create energy without oxygen	Hard activities with short-duration

performing the exercise; and the intensity, that contemplates the amount of energy expended during the activity [4].

Considering the use of PE as a clinical tool, it can be seen as a drug, where the exercise characteristics are the prescription indications [4]. Despite the importance of all these characteristics, studies have shown that the intensity is the most relevant [7, 46], because it determines the energy expenditure and can be seen as the "dose" of the prescription [4]. Besides, the duration prescription is very dependent on the intensity, the more intensity, the less duration [46].

Exercise intensity can be defined as the rate of energy implemented in the corresponding activity [47]. Hence, the more energy requires an activity, the harder it is. However, due to the different body's metabolic ways to produce energy and the amount of jobs executed at the same time, quantifying the rate and amount of energy expended is a complex task [45]

One approximation technique is the metabolic equivalent (), which is a unit that represents the relation between the rate of energy expended in the physical activity and the rate of energy expended in a resting state [13]. In other words, an activity with 2 s means that it uses twice the energy than resting. Nevertheless, the energy consumption is strongly related to the specific subject's characteristics (e.g. metabolism and weight) and its measurement requires complex instrumentation [48]. Therefore, several studies have been dedicated to generalize the values of different activities, based on measurements from healthy subjects [48]. Although this technique does not provide a real-time patient's condition estimation, it allows the clinical staff to have a general idea about the activities for the training plan [49]. Moreover, the MET unit is used to classify the exercises in three groups regarding their intensity [45, 48]:

- Low-intensity exercise (): the group is composed of soft activities with a lower value of 3s, such as walking slowly on a flat surface, sitting and being stood. These exercises are commonly used for patients with extreme risk conditions.
- Moderate-intensity exercise (): the group contemplate activities between 2 and 6s. Normally, they are non-stopped activities with a long duration (between 20 to 60 minutes) that require a low effort, such as: walking on a slope and bicycling slowly.
- High-intensity exercise (): the refers to activities with a value higher than 6. Usually, they are short duration exercises (between 15 seconds to 5 minutes), that may be split in recovering and training periods [50].

It is possible to see that in general, the s and s are focused on developing the aerobic capability. In contrast, the anaerobic capability is worked through the s. Considering the importance of this capability in real-life activities (section 2.1), the s have become essential for the rehabilitation programs [51]. Moreover, studies have demonstrated that HIE is more effective to increase the maximum oxygen volume () [11, 52], which is a relevant indicator about the user's quality of life.

2.3 Types of High-Intensity Exercises

Bearing in mind the variation among exercises, several studies have been carried out to explore the use of different high-intensity activities in rehabilitation programs, such as running, cycling, climbing stairs, vertical jump, full-body endurance routines, and sit-to-stand

[9, 11, 12, 44, 52–57]. Depending on the training plan rehabilitation goals, these exercises may be non-stopped or split into training and resting intervals. Owing to the different movements and muscular groups implemented for each activity, the intensity is managed by changing specific features of exercise. Furthermore, each exercise performance can be evaluated through dynamic and/or kinematic biomechanical features and can be executed by different methods. Table 2.3 contains the intensity characteristics, the main performance features, and the execution methods of 6 common HIEs, that correspond to running, cycling, climbing stairs, vertical jump, full-body endurance routines (), and sit-to-stand ().

Exercise	**Methods**	**Intensity**	**Performance features**
Running [58]	Ground Treadmill	Inclination Speed	Cadence stride length lower limb joins angles
Cycling [59]	Bicycle ergometer	Resistance Cycling speed	Cycling rate knee angular velocity Ankle angular velocity
Climbing stairs [60]	Static stairs Stairs machine	Number of stairs Assistance of the upper-body	Average stair rate Lower limb kinematic
Vertical jump [57]	Ground	Number of repetitions resting intervals	Maximum reached height Ground forces
FBER [61]	External loads Body weight	Number of repetitions Exercise difficulty	time to complete routine Ground forces
STS [62]	Static chair	Training duration Movement displacement	STS cycle rate Lower limb kinematic

Table 2.3: High-intensity exercises in physical rehabilitation

2.4 Fatigue in Physical Rehabilitation

Despite the benefits of PE, several considerations must be kept in mind at implementing it in rehabilitation therapies. Specifically, because taking patients to inadequate exercise conditions or extreme fatigue states might lead them to suffer physical or physiological complications [8]. Hence, it is essential to monitor the patient's condition during training, especially for s [4].

Fatigue is understood as a lack of energy to keep performing an activity [63], and it is used to describe a decrease in physical performance associated with an increase in the real/perceived difficulty of a task or exercise [64]. Because of its direct relation with the energy expended, and therefore, with the exercise intensity, the measurement of fatigue has been widely implemented to regulate exercise intensity [63]. However, it is considered as a subjective experience that only the user can feel; hence, it is difficult to quantify [65]. Fatigue can be presented in different ways (e.g. mental, emotional and muscular) [66], however, physical fatigue is the most common in physical rehabilitation [67]. This type refers to a transient and recoverable reduction in the force or power production in response to contractile activity [67]. Therefore, repetitive movements with prolonged duration can lead patients to physical fatigue [68].

Considering the main aims of physical rehabilitation and its risks, monitoring the patient's fatigue during the whole process is important to provide a safe and effective rehabilitation [69]. Hence, different strategies have been developed in order to measure fatigue such as monitoring physiological parameters, implement subjective scales of fatigue perception, and analyze exercise performance [69].

2.5 Physiological Parameters

Owing to the energy consumption during physical exercise, the body needs to increment the creation and delivery of energy, by eliciting the corresponding metabolic ways and changing the behavior of the cardiorespiratory system [64]. Hence, the subject's physiological parameters, provide essential information about his/her fatigue condition [70, 71]. However, according to the type of exercise performed, these parameters may present different behaviors, making it difficult to relate directly with fatigue [72]. Furthermore, some of them may even present difficulties when monitoring in real-time or during exercise execution [72]. Due to their direct relationship with the energy expended, the most relevant parameters are the oxygen consumption (), the heart rate (), the blood lactate level () and the muscle electrical activity, measured by surface electromyography . [68, 70, 71, 73]. Table 2.4 presents the units, main advantages and disadvantages of these four parameters.

Parameter	**Unit**	**Advantages**	**Disadvantages**
[74]	$mLO_2/min/kg$	Strong linear relationship with the energy cost	Complex instrumentation and requires stabilization time
[17]	Beats per minute (BPM)	Easy to monitor during training	Indirect measurement of the energy consumption
[75]	mmol/L	Direct measurement from the user's metabolism	Difficult to measure during training and requires stabilization time
[76, 77]	mV	Direct measurement from muscles to determine physical fatigue	Affected by electrodes location and requires complex real-time processing

Table 2.4: Physiological parameters for fatigue estimation during exercise

2.6 Subjective Scales

The subjective scales of fatigue perception are ordinal numerical scales in which each number represents a level of fatigue, in such a way that the lower number represents a state of absence of fatigue, and the higher number represents a state of extreme fatigue. In extreme fatigue, the person does not feel able to carry on with the corresponding activity [78]. Although this method provide a practical and simple tool, due to its subjectivity, several studies have illustrated that the perception scales may present differences concerning other objective methods, such as physiological parameters [79].

Because of fatigue is a subjective experience and can be presented in different ways, several scales of perception have been developed, and even modified according to their application [80]. However, these can be classified in two groups: unidimensional and multidimensional scales [81].

2.6.1 Unidimensional Fatigue Scales

Unidimensional fatigue scales are the simplest because they contemplate one type of fatigue, typically, user's fatigue severity. Therefore, these scales are the most applied for fatigue managing during physical exercise therapies [82]. However, they may be composed of different items, in order to asses fatigue severity in different time or social conditions. Bearing in mind the different rehabilitation scenarios, several unidimensional scales with different fatigue levels and items, have been proposed [81]. In general, in this method a ordinal point scale is implemented to determine the level of agreement that the user feels according to a established affirmation (item) or a question. Table 2.5 presents 3 of the most common unidimensional scales according to their focused population, the item number of and the point values

Scale	Population	Item number	Point values
Brief Fatigue Inventory [83]	Patients with cancer	9	11 from 0 to 10
Fatigue Severity Scale [84]	General population	9	7 from 1 to 7
Fatigue Assessment Scale [85]	Patients with cancer, Parkinson's disease and post-stroke population	10	5 from 0 to 4

Table 2.5: Unidimensional fatigue scales according to the target population, number of items and points

2.6.2 Borg Scale

The Borg Rating of Perceived Exertion scale is a 15-point scale composed of only 1 item. It is a tool for measuring an individual's effort and exertion, breathlessness and fatigue during physical work and is highly relevant for occupational health and safety practice [1]. The scale starts with "no feeling of exertion", which rates a 6, and ends with "very, very hard", which rates a 20. The scale takes seconds to complete and can be a researcher or self-administered and used on a single occasion or multiple times [65].

During the activity, participants are asked to rate their exertion on the scale, combining all sensation, feeling of physical stress and fatigue. They are told to disregard any other factor such as leg pain or shortness of breath but to try to focus on the whole feeling of exertion. This number indicates the intensity of activity, allowing the participant to speed up or slow down movements [86].

Borg also developed the Borg CR10, which is a 11-point scale [65]. It is a general method for measuring most kinds of perceptions and experiences, including pain and also perceived exertion. Figure 2.1 illustrates the representation of the 15-point Borg rating scale and Borg

CR10.

Borg scale	Borg CR10	Representation
6	0	No exertion
7		
8	1	Very very low exertion
9		
10	2	Very low exertion
11		
12	3	Low exertion
13		
14	4	Quite moderate exertion
15	5	Somewhat moderate exertion
16	6	Moderate exertion
17	7	High exertion
18	8	Very high exertion
19	9	Very veryhigh exertion
20	10	Maximum fatigue level

Figure 2.1: Borg scale table interpretation [1]

2.6.3 Multidimensional Fatigue Scales

Multidimensional fatigue scale group differs from the unidimensional one, basically because they seek to analyze different fatigue factors and experiences, instead of only its intensity, such as duration, daily pattern, cognitive, behavioral, social, and its effect on daily activities [85]. Therefore, these types of scales are commonly composed of more items than the unidimensional ones and are more implemented for evaluating fatigue before and after the rehabilitation procedure, aiming to quantify the rehabilitation effects regarding fatigue [85]. As well as the unidimensional group, several multidimensional scales have been proposed, where in general, the idea is to use an ordinal numeric scale for determining the level of agreement that the user feels according to some established affirmations or a questions. Table 2.6 presents 3 of the most common multidimensional scales according to their fatigue factors, the number of items of each corresponding factor and the point values.

Scale	Factors	Items	Point values
Modified Fatigue Impact Scale [87]	Physical	7	
	Cognitive	7	5
	psychosocial	7	from 0 to 4
Fatigue Scale [88]	Physical	7	4
	Mental	7	from 1 to 4
Multidimensional Fatigue Inventory [88]	General	4	
	Physical	4	5
	Mental	4	from 1 to 5
	reduced activity	4	
	reduced motivation	4	

Table 2.6: Multidimensional fatigue scales regarding their Factors, items and points

2.7 Exercise Performance Features

The decrease in exercise performance has a directly proportional relationship with the increase in fatigue [72]. Therefore, novel methods for monitoring fatigue through exercise have been explored. However, as it was mentioned in section 2.3, their evaluation depends heavily on the type of exercise, which makes it difficult to propose a general method [89]. Moreover, because of its novelty exploration, to author knowledge, there is not a work that has studied this fatigue estimation technique in real rehabilitation scenarios. Hence, this technique is in an initial development stage and presents a long path to become a clinical tool. Nevertheless, it presents a great potential because it provides an objective indicator of the user's fatigue condition [26].

Although the exercise performance features can be measured by different sensors, one of the goals of this technique is to provide a practical tool for rehabilitation scenarios [90]. Therefore, this technique seeks to use sensors easy to implement, that do not affect the therapy development and exercise execution [91]. Table 2.7 contains some of the most common sensors implemented for obtaining exercise performance features. In addition, this table presents the exercise where the corresponding sensor is commonly implemented.

Sensor	Measurement	Exercises	Features
Pressure [92]	User´s exerted pressure on a surface	Running	Gait phases
Ultrasonic [93]	Displacement of an object	Running, Vertical Jump and STS	Step length, maximum height and hip displacement
Accelerometers [94]	Linear acceleration of an object	Vertical Jump and STS	Maximum acceleration and STS cycle rate
Gyroscopes [95]	Angular velocity an object	Running and Cycling	Gait phases, and cycle rate
Force platforms [96]	force and/or pressure exerted by the user's feet	Running and Vertical Jump	Lower limb dynamics and exerted ground forces
Image-based [91]	Movement of essential activity body parts	Vertical Jump and STS	Maximum height and lower limb kinematic

Table 2.7: Sensors implemented for exercise performance assessment

As an initial evaluation, current studies have shown that these previous sensors can be used to estimate some exercise features related significantly to the fatigue level [20–22]. Furthermore, other studies have gone beyond to an initial exploration, by proposing fatigue estimation models based on healthy subject metrics and machine learning techniques [22, 26, 27].

2.8 Machine Learning for Fatigue Estimation During PR

Machine learning is a branch of the artificial intelligence area, that focuses on developing algorithms for creating computational models able to "learn", in order to be able to take decisions in unknown situations based on initial data. Therefore, it is required an initial data set that allows the model to determine the possible cases that are going to face [97].

This data set is composed of two parts, the features and the targets. The features correspond to the metrics obtained from the corresponding situation, in this case, the user's exercise performance features. On the other hand, the targets represent the desired result of the model estimation, in this case, the fatigue condition. In general, machine learning techniques can find different types of patterns and relationships among features, according to the target [97]. Hence, considering the number of features that can be extracted from physical activity, machine learning algorithms are very useful [27].

The development and assessment of a computation model are normally divided into two phases, training and test [97]. In the training phase, a huge part of the data set is used to train the model (normally, between 70% and 90%), in such that way, it can process the features to find the corresponding patterns and relationships. In the testing phase, the remaining part of the data set is used to assess the trained model by comparing the estimated outputs to the targets, so that, the model is evaluated with data that were not implemented for the training [97]. In general, the model performance is evaluated by a metric called "accuracy", which is the relation between the total right estimations obtained in each testing process or true positives (TP), and the complete amount of data (N).

Studies have proposed models for estimating 2 user's fatigue conditions (non-fatigued and fatigued) in different exercises, such as vertical jump [27], lower limb endurance training [22], and walking [26]; showing an accuracy between 85% and 95%. However, there are also relevant rehabilitation exercises, where this novel method can be explored.

Chapter 3

Systematic Review of HIEs in PR

Aiming to understand the context of high-intensity exercises in physical rehabilitation, a systematic review was carried out, considering specific article inclusion criteria. Despite the huge number of articles about this topic, this review pretends to obtain a general idea about the use of different HIEs, the fatigue regulation methods, and the rehabilitation implemented areas.

3.1 Systematic Review Methodology

The review seeks to find articles that study the use of any high-intensity exercise, in a rehabilitation program, implementing any method for fatigue intensity regulation or evaluation. Therefore, the main keywords were "fatigue", "high-intensity exercise", "physical" and "rehabilitation". Nevertheless, similar words to these main keywords were also included. The Systematic Review was carried out in the "Google Scholar" database, by using the following word equation: *"(fatigue OR exhaustion OR tiredness OR lethargy) AND ((high AND intensity) OR anaerobic OR endurance) AND ((physical OR corporeal) AND (exercise OR activity OR training)) AND (rehabilitation)"*.

Moreover, there were only considered articles that fit the following inclusion criteria (IC):

- IC1: Articles written only in English.
- IC1: Articles published only in Q1 or Q2 journals.
- IC3: Articles that contemplates the usage of at least one high-intensity exercise.
- IC4: Articles about physical rehabilitation programs.
- IC5: Articles with a chronic disease study population (no healthy subjects).
- IC6: Articles that implement at least one method for fatigue or intensity regulation.

It is important to highlight that a year publish criteria was not implemented, because the use of high-intesity exercise in physical rehabilitation is currently explored. In fact, in 2012 the American Health Association recognized these activities as relevant for a good quality of life, and therefore, important for physical rehabilitation [45].

3.2 Systematic Review Results

Approximately 216.000 articles were obtained by using the specified word equation in the "Google Scholar" data base. However, after reading and analyzing the abstract of 210 articles, a total of 146 articles were taken as possible candidates. Besides, the google sorting relevance algorithm according to the research word, was used to select these initial candidates. Afterwards, each candidate was completely reviewed according to the inclusion criteria, and only 48 articles were finally selected. The discrimination result process regarding each inclusion criteria item can be seen in Table 3.1.

IC number	Number of rejected articles
IC1	0
IC2	32
IC3	19
IC4	37
IC5	3
IC6	7

Table 3.1: Systematic review inclusion criteria discrimination Results

It is possible to see in Table 3.2 the 48 selected articles, where the second column contains the rehabilitation area (as described in Table 2.1), the third column display the specific high-intensity activities studied in the corresponding population (as mentioned in section 2.3), and the third column has the specific fatigue evaluation methods implemented (from the methods seen in section 2.4).

Reference	Rehab Area	HIEs	Fatigue regulation Method
[53]	Cardiac	Ruining treadmill	Heart rate Blood pressure Borg Scale Multidimensional Fatigue Inventory
[54]	Cardiac	Sit-to-stand	Heart rate Borg Scale
[98]	Oncology	Climbing stairs	Borg Scale Multidimensional Fatigue Inventory
[99]	Musculoskeletal	Full-body routine	Fatigue Scale Heart rate
[100]	Oncology	Vertical jump Sit-to-stand	Heart rate

			Fatigue Assessment Scale
[101]	Oncology	Full-body routine Sit-to-stand	Multidimensional Fatigue Inventory Heart rate
[102]	Oncology	Full-body routines	Multidimensional Fatigue Inventory Borg Scale
[103]	Oncology	Cycling ergometer Ruining treadmill	Heart rate Borg Scale
[104]	Cardiac	Cycling ergometer	Heart rate Borg Scale
[105]	Pulmonary	Ruining treadmill	Heart rate Borg Scale
[106]	Pulmonary	Cycling ergometer	Multidimensional Fatigue Inventory Borg Scale
[107]	Neuromuscular	Cycling ergometer	Heart rate Multidimensional Fatigue Inventory Borg Scale
[108]	Cardiac	Cycling ergometer	Heart rate Borg Scale
[109]	Oncology	Cycling ergometer	Heart rate Fatigue Severity Scale
[110]	Oncology	Full-body routine	Borg Scale Modified Fatigue Impact Scale
[111]	Oncology	Ruining treadmill	Brief Fatigue Inventory Heart rate Blood lactate level
[112]	Cardiac	Cycling ergometer	Heart rate

			Borg Scale
[113]	Oncology	Cycling ergometer	Multidimensional Fatigue Inventory
[114]	Oncology	Sit-to-stand Ruining treadmill	Heart rate Borg Scale Multidimensional Fatigue Inventory
[115]	Oncology	Sit-to-stand Full-body routine	Blood lactate level Borg Scale Multidimensional Fatigue Inventory
[116]	Pulmonary	Sit-to-stand	Heart rate Borg Scale Oxygen saturation
[117]	Pulmonary	Sit-to-stand	Heart rate Borg Scale
[118]	Cardiac	Climbing stairs Sit-to-stand	Heart rate Fatigue Severity Scale
[119]	Oncology	Full-body routine	Heart rate Blood lactate level Multidimensional Fatigue Inventory Borg Scale
[11]	Cardiac	Sit-to-stand Full-body routine	Heart rate Blood pressure Borg Scale
[12]	Cardiac	Sit-to-stand Ruining treadmill	Heart rate Borg Scale
[120]	Cardiac	Ruining treadmill	Heart rate Borg Scale Multidimensional Fatigue Inventory

[121]	Oncology	Ruining treadmill Sit-to-stand	Borg Scale Modified Fatigue Impact Scale
[122]	Neuromuscular	Full-body routine Ruining treadmill	Heart rate Multidimensional Fatigue Inventory
[123]	Oncology	Sit-to-stand	Heart rate EMGs Brief Fatigue Inventory
[124]	Oncology	Full-body routine Cycling ergometer	Heart rate Multidimensional Fatigue Inventory
[125]	Pulmonary	Cycling ergometer	Heart rate Borg Scale
[126]	Pulmonary	Full-body routine	
[127]	Cardiac	Full-body routine	Heart rate Borg Scale
[128]	Oncology	Full-body routine	Heart rate Multidimensional Fatigue Inventory
[129]	Cardiac	Cycling ergometer	Heart rate Borg Scale
[55]	Cardiac	Ruining treadmill Climbing stairs	Heart rate Borg Scale
[56]	Cardiac	Climbing stairs Sit-to-stand	Heart rate Borg Scale
[130]	Other	Cycling ergometer Full-body routine	Heart rate Borg Scale EMGs Fatigue Scale

[131]	Oncology	Sit-to-stand	Heart rate Borg Scale Multidimensional Fatigue Inventory
[57]	Pulmonary	Ruining treadmill Sit-to-stand	Heart rate Borg Scale
[132]	Cardiac	Cycling ergometer Sit-to-stand	Heart rate Borg Scale
[133]	Neuromuscular	Cycling ergometer Sit-to-stand	Heart rate EMG Multidimensional Fatigue Inventory
[134]	Musculoskeletal	Sit-to-stand	Heart rate Borg Scale
[135]	Neuromuscular	Cycling ergometer	Modified Fatigue Impact Scale
[136]	Neuromuscular	Full-body routine	Heart rate Blood pressure EMGs Borg Scale
[137]	Neuromuscular	Sit-to-satnd	Borg Scale Multidimensional Fatigue Inventory
[138]	Oncology	Sit-to-stand Vertical jump	Borg Scale Fatigue Scale

Table 3.2: Systematic review table of high-intensity exercises in physical rehabilitation

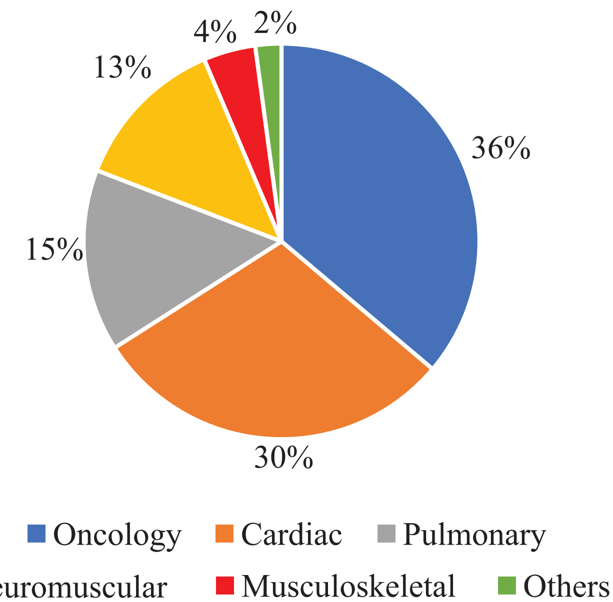

Figure 3.1: Rehabilitation area distribution for HIEs in PR

Figure 3.1 displays in a cake graph the distribution of the rehabilitation areas found in Table 3.2. It is possible to see that oncology rehabilitation is the area where the HIEs are applied the most, containing more than one-third of the reviewed articles. It is followed by the cardiac and pulmonary rehabilitation. The area "Others" refers to rehabilitation processes that were not contemplated in chapter 2, generally, they correspond to rehabilitation procedures implemented after a surgery. Hence, the musculoskeletal area contains the minimum number of articles, for the contemplated rehabilitation programs.

Figure 3.2 presents a bar graph that contains the high-intensity exercise distribution of Table 3.2. It can be seen that the sit-to-stand activity is the most implemented in rehabilitation programs, being presented in the 41.6% of the selected articles. It is followed by cycling on an ergometer (31.2%) and full body routines (31.2%). Moreover, the vertical jump activity is the less found in the reviewed articles (4.1%). It is important to mention that the sum of these percentage values, overcomes the 100%, because some articles contemplates more than one activity.

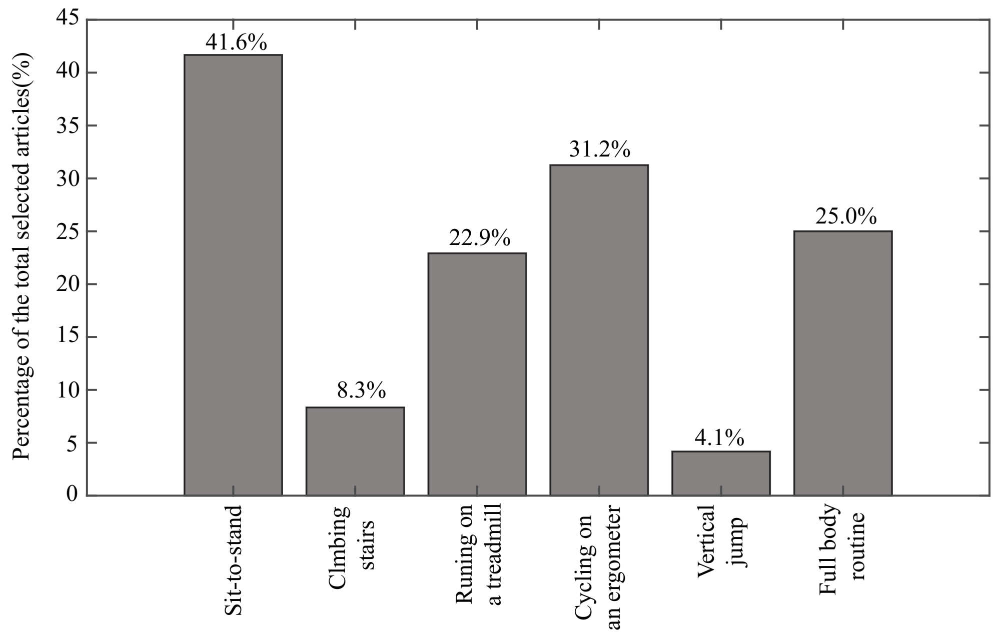

Figure 3.2: High-intensity exercise distribution in physical rehabilitation

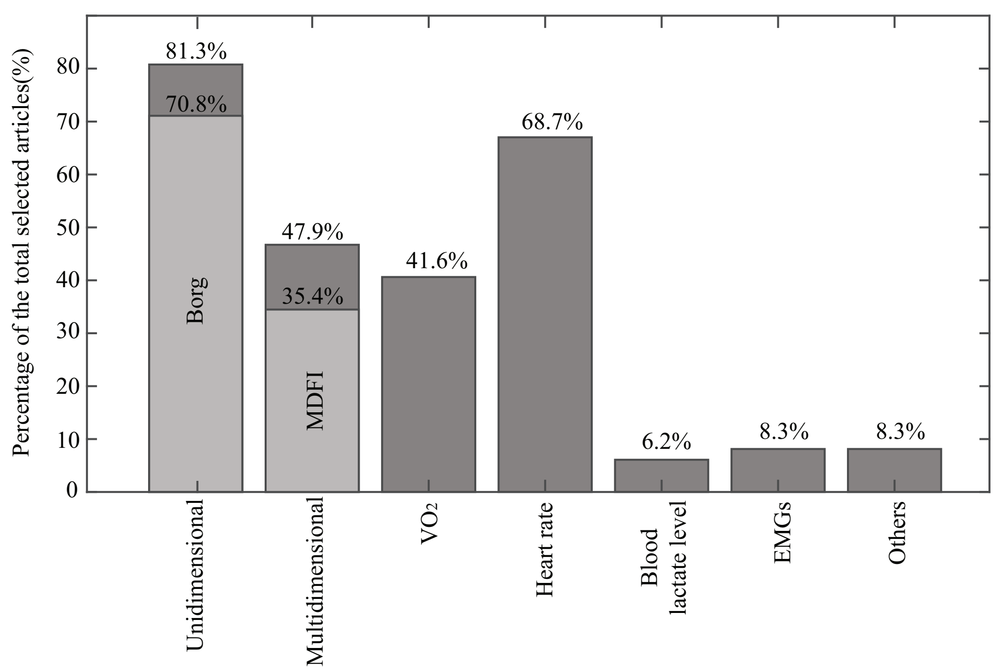

Figure 3.3: Fatigue regulation and assessment method distribution

Figure 3.3 presents a bar graph that contains the different fatigue regulation method distribution of Table 3.2. It can be seen that the unidimensional subjective scales are the most implemented in rehabilitation programs, showing a percentage value of 81.3% of the selected articles. Besides, because of the articles only implement one unidimesional method, a sub bar that represents the most used unidimensional scale is also presented, wich correspond to the Borg scale with a value of 70.8%. The second method is measuring the user's heart rate (68.7%), which is the physiological parameter used the most in the rehabilitation programs. It is followed by the multidimensional group, which presents a value of 47.9%. Furthermore, as well as the unidimensional group, it also contains a sub bar that represents the most used scales, that corresponds to the multidimensional fatigue inventory (MDFI) with a value of 35.4%. The next method are physiological parameters, where only the measurement of VO_2 shows a relevant value of 41.6%, because the other three groups have values lower than 10%. The group "Others" correspond to physiological measurements that were not taken into account in chapter 2, which are parameters difficult to measure during the exercise execution (e.g blood pressure and oxygen saturation).

3.3 Systematic Review Discussion

Due to the reaches of this work, only a part of the articles reported by the Google scholar database was considered for this review. However, rigorous inclusion criteria were defined, in order to obtain relevant articles according to the objectives of this work. Hence, it is possible to see in Table 3.2 that almost two-thirds of the candidate articles were not selected. Furthermore, it is also possible to see that the inclusion criteria items from 2 to 4 (IC2 to IC4) were the strongest filters. Considering that this elimination process is sequential and that the first item is just about the article written language, it was expected that most of the eliminated articles corresponded to these initial criteria.

It can be seen that 32 articles were not selected by the IC2, in general, because they were published in local conferences or journals without a high impact factor. On the other hand, although the keywords "high-intensity exercise" were implemented, 19 candidates were eliminated by IC3, normally because they considered exercises or routine focused on developing the aerobic capability. Despite IC4 is followed by the other 3 items, it presents the highest number of candidates eliminated. Basically, by reason of these articles are cases of study with healthy people to explore the use of HIE, these 37 articles were not selected. Hence, it may explain why the IC5 just considered 3 candidates, which are articles that consider other types of diseases. Considering the general objective of these articles, they are almost compelled to implement any method for fatigue estimation or assessment, hence, the 7 candidates eliminated by IC6 correspond to studies with a different aim to analyze the patient's fatigue regarding the use of HIE in physical rehabilitation.

Result in Figure 3.1 shows that in this preliminary review, the studies about fatigue evaluation during HIE tend to focused on Oncology rehabilitation. Taking into account that one of its main goals is to ease the effects of pathological fatigue, this result was expected. Moreover, as it was shown in section 2.6, many of the subjective fatigue scales are focused on the oncology population. Hence, in order to determine the effects of new physical intervention based on HIE, this rehabilitation area is where the subjective fatigue methods are more applied. In contrast, owing to the cardiac rehabilitation objectives and the risks of patients regarding their cardiac condition, in this area is where normally different methods are applied. Especially, methods that allow a real-time estimation, such as the Borg scale or the heart rate. A similar case is presented of the pulmonary rehabilitation. Due to these rehabilitation areas contains the 81% of the selected articles, these results suggest that in order to cover the different requirements of the rehabilitation programs, the proposed fatigue estimation system should be able to asses fatigue during the rehabilitation process and during exercise performance.

Figure 3.2 displays that the articles tend to be focused on the implementation of the sit-to-stand exercise. This may be related to the facts that the requirements of this exercise are minimum and that it is one of the most common daily life activity, which make this activity ideal for a simple and effective rehabilitation. Besides, some articles explored home physical interventions, enhancing the use of this type of exercise. Therefore, this result suggests that the proposed fatigue estimation model should focus on STS exercise.

Bearing in mind that fatigue is a subjective state that only the user can feel, it is normal to see in Figure that the subjective fatigue estimation methods are the most implemented. In addition, by reason of the importance of monitoring the patient's fatigue state, it can be seen that the Borg scale is presented in the majority of the articles, regardless it is a subgroup of the unidimensional methods. This result could be also related to its easy implementation during the rehabilitation therapies. On the other hand, the heart rate is the second method most used, and the first one comparing to the other physiological parameters. Taking into account the direct relation of this physiological parameter with the energy consumption, and that it easy to measure during training, this result was expected. Therefore, these results suggest the use of the Borg scale and the heart rate, in the development of the proposed fatigue estimation system.

This review allows understanding the context of fatigue assessment and estimation for HIE in physical rehabilitation, providing relevant information regarding the general objectives of fatigue estimation, the most used HIE exercises, and the fatigue estimation methods implemented the most. Hence, the next chapter is focused on the development and evaluation of the proposed fatigue estimation model, according to the results obtained in this chapter.

Chapter 4

Sit-to-Stand Fatigue Estimation Study

According to the results in the previous chapter, the sit-to-stand (STS) exercise is the most implemented HIE in physical rehabilitation. To the author's knowledge, only two studies have explored the use of exercise performance features, to determine the user's fatigue condition during the STS exercise. In [21], the authors determined which STS features presents a relation with fatigue, implementing a Kinect depth sensor and the Borg's scale, with twenty healthy volunteers. Results show that two temporal (stand-to stand time and sit-to-stand time) and three kinematic STS features (vertical-velocity of the spine, knee-flexo-extension velocity, and hip-flexo-extension velocity) present a significant lineal relation to the exhaustion level, however, a model to estimate fatigue is not developed. Otherwise, authors in [18] present a case of study for detecting fatigue employing EMG signals and a smartphone accelerometer, with an obese and sedentary volunteer who performed eight STS tests. Results exhibit that relative energy acceleration of the movement increase, and the number of repetitions decreases when the person is physically exhausted. Nevertheless, an estimation model is not displayed, and it is concluded that future work should use these characteristics to develop robust models [18].

Hence, considering that the implementation of a fatigue estimation computational model has not been explored completely for the STS exercise, this chapter presents the methodology, results, and discussion of a study carried out to develop and evaluate a fatigue estimation model. In general, the proposed system estimates three levels of fatigue (low-fatigue,moderate-fatigue, and high-fatigue), and is based on machine learning techniques, the user's heart rate and 32 STS performance features obtained with a Kinect sensor. Figure 4.1 illustrates the general diagram of the proposed system, where it is possible to see the STS execution, the extraction of the performance features and the user's heart rate, their integration in the fatigue estimation model, and the system output, which corresponds to the user's fatigue condition estimation.

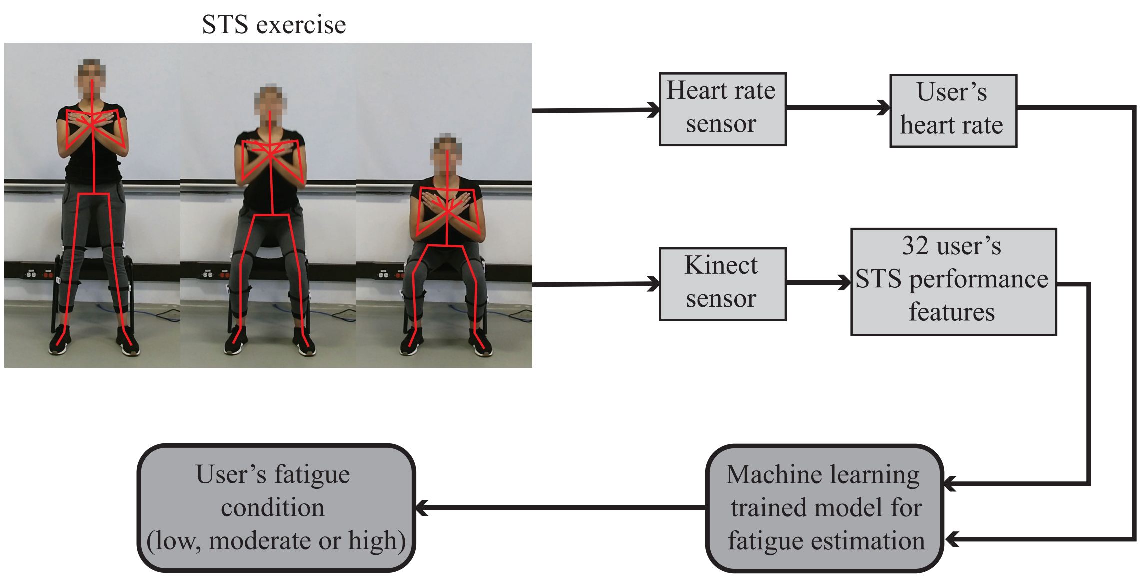

Figure 4.1: General diagram of the proposed fatigue estimation system

4.1 STS Study Methodology

This study aimed to obtain the corresponding data set that allowed to develop and evaluate a fatigue estimation model for the sit-to-stand exercise. As it was mentioned in section 2.8, it is required an initial data set in order to develop a machine learning model. This study was carried out with 60 healthy people and its protocol was accepted by the ethics committee of the "Colombian School of Engineering Julio Garavito," (Bogotá, Colombia).

4.1.1 Subjects recruitment

30 females and 30 males were recruited to perform a 2 minutes sit-to-stand test, according to the following criteria. Inclusion criteria contemplated adult healthy subjects between 18 and 30 years old, and weight between 50 and 75 Kg. Besides, volunteers must have been in a non-fatigued condition, according to the "multi-dimensional fatigue inventory" shown in Table 2.6. In contrast, subjects with physical impairments that prevent them from sitting down and standing up, cognitive impairments that do not allow them to follow instructions, conditions that put them at risk in a fatigued state and/or use prostheses or orthosis in their limbs, were excluded from the study. Finally, the volunteers signed an informed consent to clarify that they voluntarily accepted to participate in this study. The mean and standard deviation (M $\pm$ SD) of volunteers' demographic data, for the female and male groups, are shown in Table 4.1.

Table 4.1: Volunteer descriptive data (M $\pm$ SD)

Gender	**Age (years)**	**Weight (kg)**	**Height (cm)**
Female	20.8 ± 1.7	59.3 ± 5.5	164.1 ± 7.7
Male	21.9 ± 1.9	65.9 ± 6.4	172.8 ± 8.3

4.1.2 Model Tools

In order to analyze the STS kinematic, the heart rate and the fatigue level of each volunteer, a multitasking application was developed to incorporate and synchronize the following tools in a single computer process:

- Kinect V2 (Windows, USA): This sensor implements depth and RGB images to segment the human body. In this work the second version of this sensor was used with the Windows SDK, which provides 25 body points. It can measure the 3D position and orientation of each body point at a sample rate of 30Hz. Considering the analysis presented in section 2.7 this sensor presents several advantages for STS kinematic analysis, and it has been widely used to analyze the STS movement, showing great accuracy and performance [139]. The sensor was placed on a tripod at 1 meter from the floor and 4 meters from the subject, as it is suggested for a right usage [139].

- Zephyr HxM BT (Medtronic, Ireland): This sensor has been implemented in several studies for measuring heart rate. Its data was collected through a Bluetooth communication channel, with a sample rate of 1Hz. It was placed on the volunteer's chest with an elastic band. Moreover, it is implemented to measure the resting heart rate of each subject.

- Borg CR10: Bearing in mind the subjectivity of fatigue, and the several use of this tool in physical rehabilitation (as it is shown in Figure 3.3), the Borg scale was used as the target of the user's fatigue condition. Aiming to avoid as much as possible to provide different explanations of this scale, Figure 4.2 was used to explain the values meaning to each volunteer, where, it is possible to see the division of the fatigue levels (low, moderate and high). Besides, due to the multi-dimensional fatigue inventory criteria, it was considered that the initial fatigue state of the subject was 0. This scale was asked to the volunteer every 30 seconds during the STS test. Hence, if the volunteer was able to complete the 2 minutes exercise, the corresponding test register ended up with 4 Borg CR10 values.

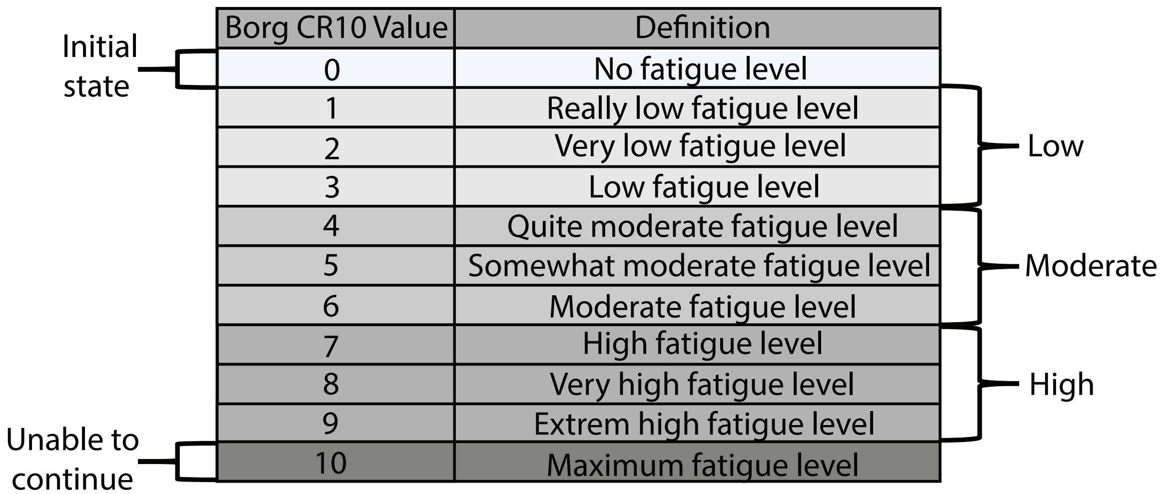

Figure 4.2: Borg CR10 table values and interpretation

4.1.3 Procedure

Initially, the maximum heart rate (MHR) of each volunteer was estimated implementing the "Tanaka equation", shown in equation 4.1. This equation uses the user age for getting an approximation of his MHR. The volunteers were informed about the use of the Borg CR10 scale and instructed to 5 minutes warm-up, composed of stretching movements and a 3 minutes treadmill walking. Afterwards, they were instrumented with the Zephyr sensor and taken to the test room, where a chair of 40cm in height and without armrests was located in front of a wall, and the Kinect V2 sensor was located 4 meters in front of the chair.

$$MHR = 206.9 - (0.67 * AGE) \tag{4.1}$$

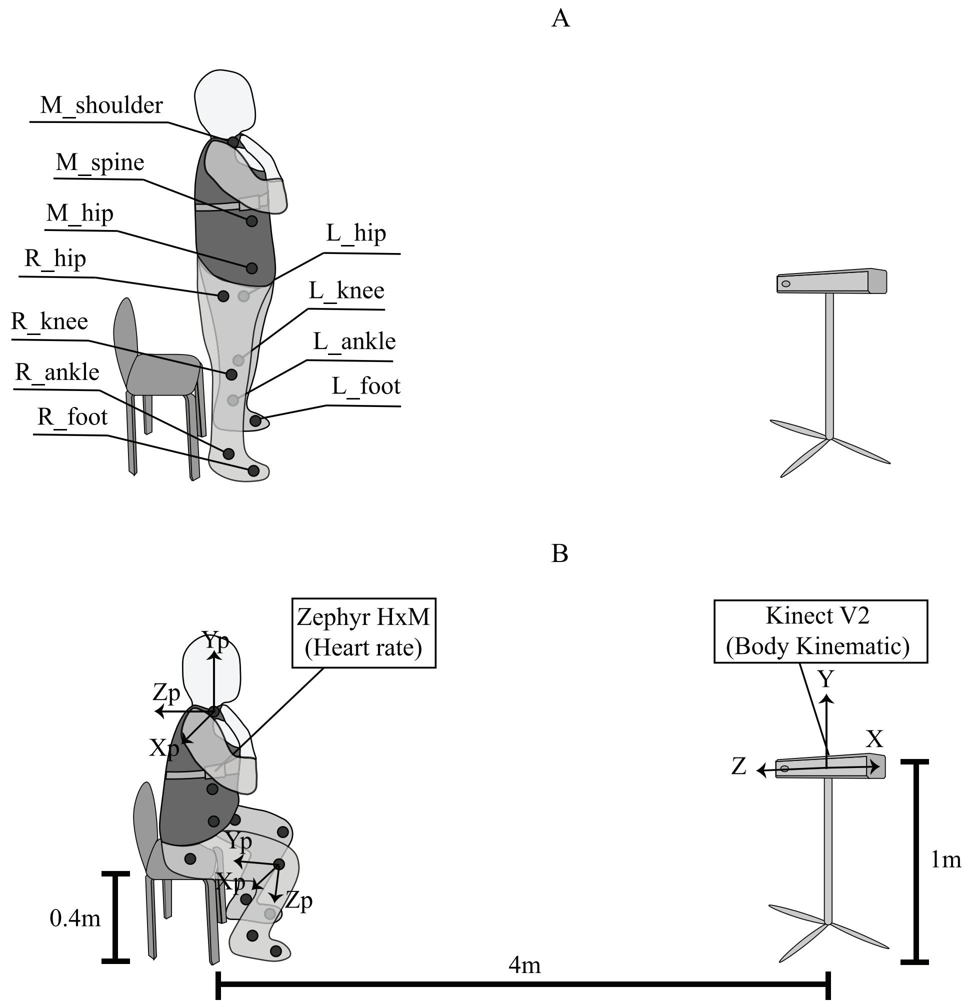

Figure 4.3: Set-up of the study and sit-to-stand representation, (A) standing position and (B) sitting position.

The test consisted of sitting down and standing up from the chair as fast as possible for 120 seconds (2 minutes), after the command "go" and starting in a standing position. The subjects were asked to be with their hands on their shoulders, to look straight forward during the whole test and not to stop executing the activity. Nevertheless, if the heart rate overcame the 90% of the MHR, or a 10 Borg value was notified, the test was immediately concluded. Finally, the volunteers were instructed to a 5 minutes cold-down. The STS exercise representation and the study set-up can be seen in Figure 4.3. Although the Kinect V2 provides 25 body markers, in Figure 4.3A only the markers used for the data processing are shown. These correspond to 3 markers located in the middle part of the upper body right (M_[name of marker]), 4 in the right leg (R_[name of marker]), and 4 in the left leg (L_[name of marker]). Figure 4.3B illustrates the sitting position, the sensor locations, the reference system of the Kinect V2 (X, Y and Z) and the orientation of some Kinect points (Xp, Yp and Zp).

4.1.4 Data processing

Considering the metrics mentioned above, Figure 4.4 presents an example of a test register. In Figure 4.4A, it is shown the movement of the M_hip marker on the Y axis (M_hip_y), where it is possible to appreciate the sit-to-stand movement as an harmonic signal, because the STS test consisted of performing a repetitive activity, which creates a repetitive behavior in the position signals, especially for the vertical movements. Figure 4.4B illustrates the heart rate register and how it increments during the test. Finally, Figure 4.4C contains the 4 Borg CR 10 values mentioned by the volunteer every 30 seconds.

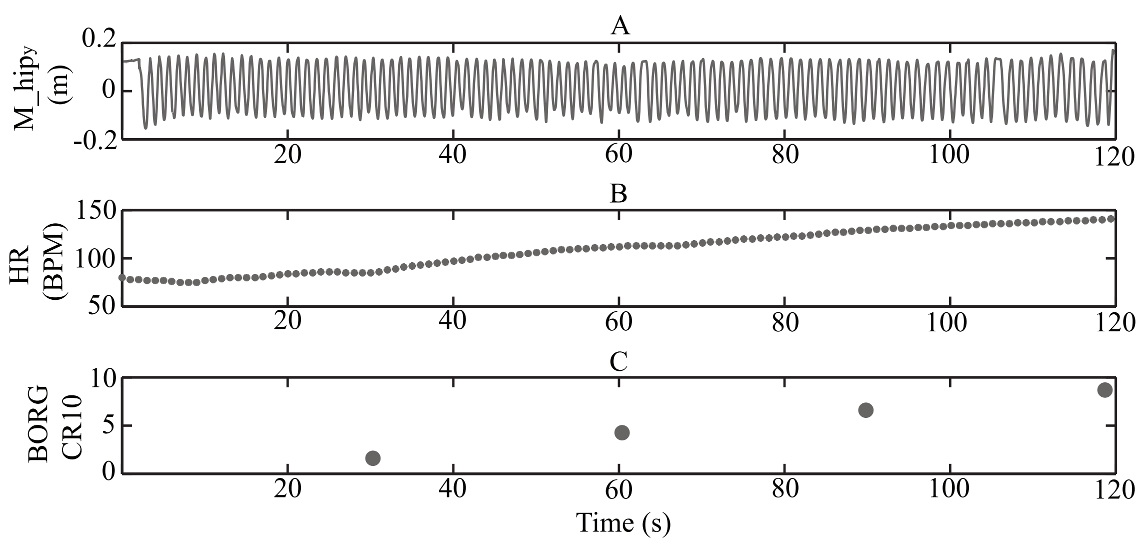

Figure 4.4: Test register example, (A) M_hip vertical signal, (B) heart rate signal and (C) Borg CR10 values.

4.1.5 Kinect STS exercise features

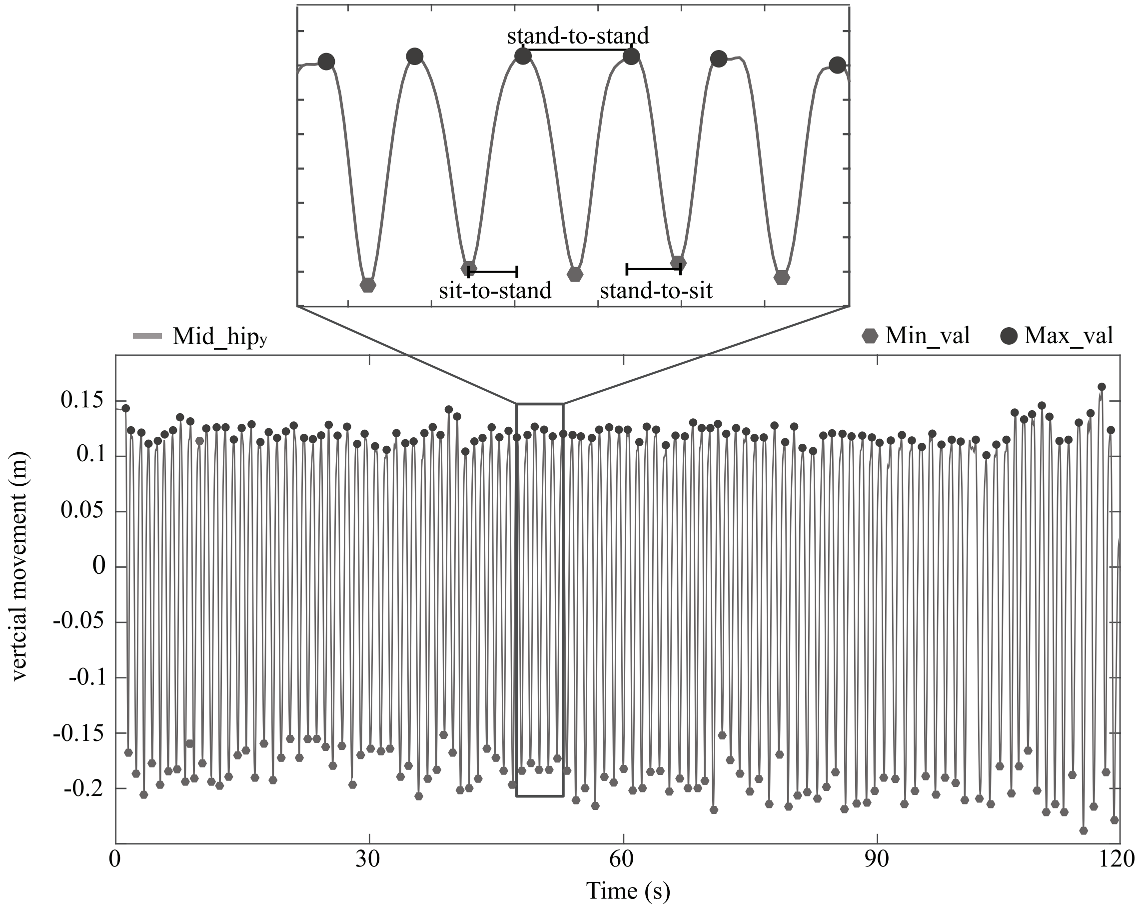

Figure 4.5: M_hip vertical movement signal, maximum, minimum and phase detection.

Taking advantage of the M_hip repetitive behavior on the Y axis, an automated procedure was implemented to detect each stand-to-stand cycle. Essentially, the process consisted of subtracting the mean value of the whole M_hip signal and detecting the minimum and maximum values of each cycle. Therefore, these maximum values were considered as the moments when the volunteer was stood, and the minimum values when he was sat. Hence, these values allow estimating the two phases of the STS activity, stand-to-sit and sit-to-stand. Figure 4.5 presents an example of M_hip signal on the Y axis (M_hip_y) of one test register, where it is possible to see the maximum values (Max_val) and minimum values (Min_val) of the corresponding signal. Furthermore, Figure 4.5 shows a zoom of one part of the signal, where a stand-to-stand cycle and its phases can be appreciated.

According to these stand-to-sit and sit-to-stand phases, the following 32 kinematic and temporal features were estimated for each stand-to-stand cycle, where "Fn" represented the feature number "n", and the symbol "*" indicates that the corresponding feature was estimated with the mean value of both sides, left and right:

- F1: Stand-to-stand time (s), estimated with the duration of the stand-to-stand cycle .
- F2: Sit-to-stand time (s), estimated with the duration of the sit-to-stand phase.
- F3: Stand-to-sit time (s), estimated with the duration of the stand-to-sit phase.
- F4: M_hip vertical range (m), measured as the difference between the maximum and minimum value of the M_hip_y signal during the stand-to-stand cycle.
- F5: M_hip depth range (m), measured as the difference between the maximum and minimum value of the M_hip_z signal during the stand-to-stand cycle .
- F6: M_hip max vertical velocity (m/s), estimated by deriving the M_hip_y signal and obtaining its maximum value during the sit-to-stand phase.
- F7: M_hip min vertical velocity (m/s), estimated by deriving the M_hip_y signal and obtaining its minimum value during the stand-to-sit phase.
- F8: M_hip max depth velocity (m/s), estimated by deriving the M_hip_z signal and obtaining its maximum value during the stand-to-sit phase.
- F9: M_hip min depth velocity (m/s), estimated by deriving the M_hip_z signal and obtaining its maximum value during the sit-to-stand phase.
- F10*: Knee flexo-extension range (^{o}). The knee flexo-extension signal was obtained by measuring angle between the vectors composed by the hip, knee and ankle Kinect 3D

points (Figure 4.3A). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase (m/s).

- F11*: Knee flexo-extension max velocity ($^o/s$), estimated by deriving the knee flexo-extension signal and obtaining its maximum value during the stand-to-sit phase.

- F12*: Knee flexo-extension min velocity ($^o/s$), estimated by deriving the knee flexo-extension signal and obtaining its minimum value during the sit-to-stand phase.

- F13*: Hip flexo-extension range (^{o}). The hip flexo-extension signal was obtained with the X axis angle of the matrix rotation between the M_hip and the knee Kinect 3D orientation (Figure 4.3B). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase.

- F14*: Hip flexo-extension max velocity ($^o/s$), estimated by deriving the hip flexo-extension signal and obtaining its maximum value during the stand-to-sit phase.

- F15*: Hip flexo-extension min velocity ($^o/s$), estimated by deriving the hip flexo-extension signal and obtaining its minimum value during the sit-to-stand phase.

- F16*: Hip abduction-adduction range (^{o}). The hip abduction-adduction signal was obtained with the Z axis angle of the matrix rotation between the M_hip and the knee Kinect 3D orientation (Figure 4.3B). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase.

- F17*: Hip abduction-adduction max velocity ($^o/s$), estimated by deriving the hip abduction-adduction signal and obtaining its maximum value during the stand-to-sit phase.

- F18*: Hip abduction-adduction min velocity ($^o/s$), estimated by deriving the hip abduction-adduction signal and obtaining its minimum value during the sit-to-stand phase.

- F19*: Ankle flexo-extension range (^{o}). The Ankle flexo-extension signal was obtained by measuring angle between the vectors composed by the knee, ankle and foot Kinect 3D points (Figure 4.3A). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase.

- F20*: Ankle flexo-extension max velocity ($^o/s$), estimated by deriving the ankle flexo-extension signal and obtaining its maximum value during the stand-to-sit phase.

- F21*: Ankle flexo-extension min velocity ($^o/s$), estimated by deriving the ankle flexo-extension signal and obtaining its minimum value during the sit-to-stand phase.

- F22: M_shoulder vertical range (m), measured as the difference between the maximum and minimum value of the $M\_shoulder_y$ signal during the stand-to-stand cycle.

- F23: M_shoulder depth range (m), measured as the difference between the maximum and minimum value of the $M\_shoulder_z$ signal during the stand-to-stand cycle.

- F24: M_shoulder max vertical velocity (m/s), estimated by deriving the $M\_shoulder_y$ signal and obtaining its maximum value during the sit-to-stand phase.

- F25: M_shoulder min vertical velocity (m/s), estimated by deriving the $M\_shoulder_y$ signal and obtaining its minimum value during the stand-to-sit phase.

- F26: M_shoulder max depth velocity (m/s), estimated by deriving the $M\_shoulder_z$ signal and obtaining its maximum value during the sit-to-stand phase.

- F27: Spine flexo-extension range (^{o}). The spine flexo-extension signal was obtained with the X axis angle of the matrix rotation between the M_shoulder and the M_hip Kinect

3D orientation (Figure 4.3B). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase.

- F28: Spine flexo-extension max velocity ($^o/s$), estimated by deriving the spine flexo-extension signal and obtaining its maximum value during the stand-to-sit phase.

- F29: Spine flexo-extension min velocity ($^o/s$), estimated by deriving the spine flexo-extension signal and obtaining its minimum value during the sit-to-stand phase.

- F30: Spine abduction-adduction range ($^o/s$). The spine abduction-adduction signal was obtained with the Z axis angle of the matrix rotation between the M_shoulder and the M_hip Kinect 3D orientation (Figure 4.3B). Hence, this feature was estimated with the difference between the maximum and minimum value of the corresponding signal during the sit-to-stand phase.

- F31: Spine abduction-adduction max velocity ($^o/s$), estimated by deriving the spine abduction-adduction signal and obtaining its maximum value during the stand-to-sit phase.

- F32: Spine abduction-adduction min velocity ($^o/s$), estimated by deriving the spine abduction-adduction signal and obtaining its minimum value during the sit-to-stand phase.

Figure 4.6 illustrates an example of some different features estimation in two consecutive stand-to-stand cycle. The dashed lines contain the stand-to-stand cycles, the superscript symbol " ' " represents the derivative operation of the corresponding signal, the dark dots presents the maximum values (Max_val) of each signal, and the gray polygons the minimum values (Min_val). Figure 4.6A presents graphically the estimation of the stand-to-stand time (F1), sit-to-stand time (F2), stand-to-sit time (F3) and M_hip vertical range (F4). Figure 4.6B shows the derivative of the M_hip_y signal (M_hip_y'), the M_hip max and min vertical velocity (F6 and F7). Figure 4.6C shows the knee flexion-extension signal (Knee fle-ext) and the estimation of the Knee flexo-extension range (F10). Finally, Figure 4.6D presents the derivative of the Knee flexo-extension signal (Knee $fle-ext'$), the Knee flexo-extension max and min velocity (F11 and F12).

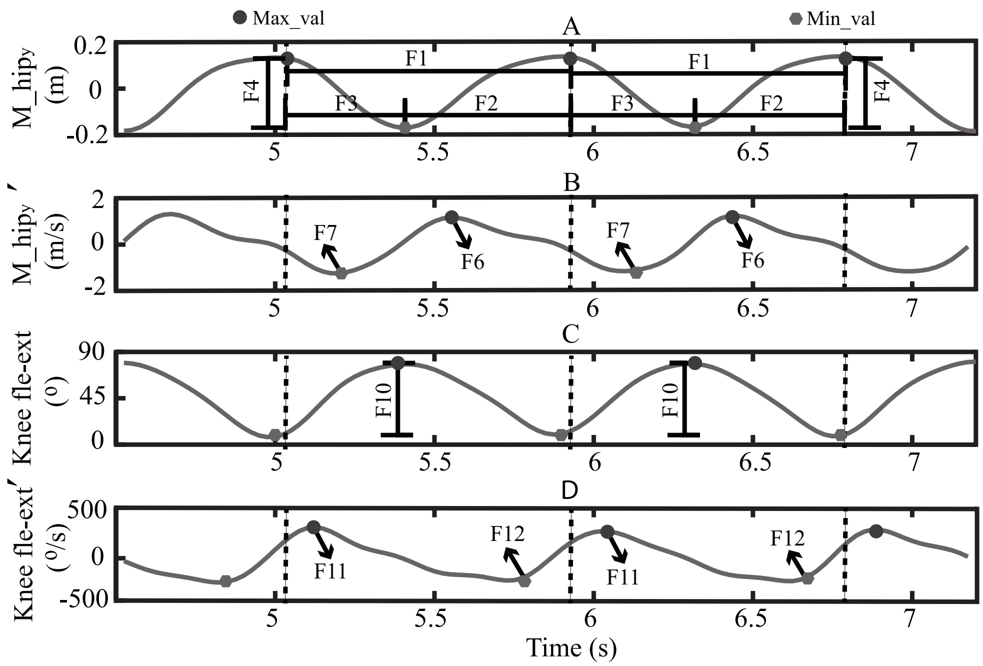

Figure 4.6: Features estimation, (A) M_hip vertical movement signal, (B) M_hip vertical velocity signal, (C) Knee flexo-extension signal and (D) Knee flexo-extension velocity signal.

4.1.6 Borg interpolation, features relation and heart rate incorporation

The 60 volunteers were able to finish the 2 minutes test, thus, at the end of the data recollection, there were 240 Borg vales, 4 for each volunteer as it is shown in Figure 4.4C. Furthermore, 8 subjects reported a 10 Borg CR10 value at the end of the test, which means that they reached the maximum fatigue level. Bearing in mind that the study aims to develop a computational model based on a data set and machine learning techniques, the idea is to get as much data as possible. Hence, in order to obtain more fatigue values, the Borg CR10 values were interpolated every 10 seconds employing linear estimation, based on the original 4 values and the assumption of the 0 Borg sate at the beginning of the test (Figure 4.2). The idea consisted of estimating the 4 straight-line equations, by using the 4 provided Borg values and then calculating the Borg value at the corresponding time. Therefore, after this process, every register contains 13 Borg values, considering the 0 as the initial one. Figure 4.7 presents an example of this procedure, where the black dots represents the original Borg values, the gray squares the interpolated Borg values, and the black lines the lineal estimation.

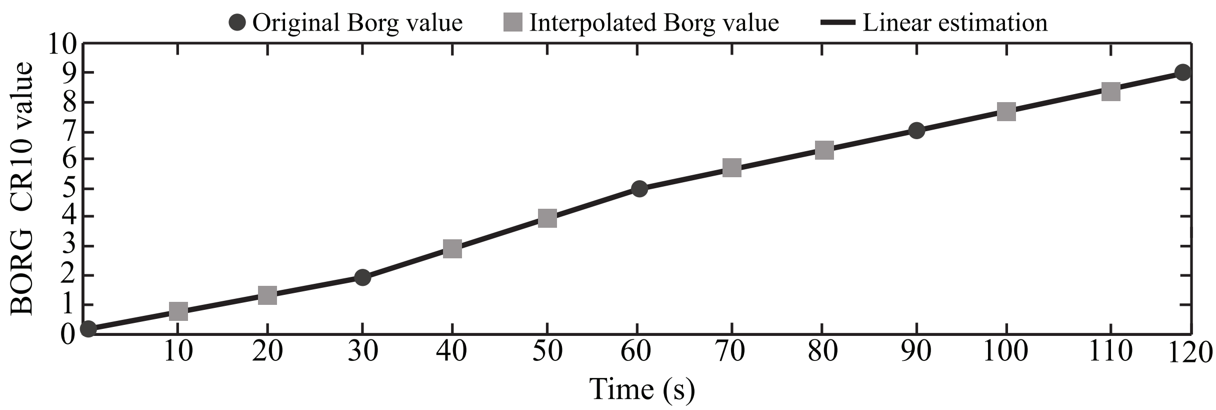

Figure 4.7: Borg value linear interpolation every 10 seconds.

On the other hand, because the performance test is strongly dependent on each subject physical capability, the number of stand-to-stand cycle executed may be different for each register, and therefore, also the amount of STS features and their values. In fact, the lowest number of cycles obtained was 71, and the highest was 127. Therefore, to relate the fatigue level to each performance feature (F1 to F32), the five closets stand-to-stand cycle to each Borg value were used to estimate an average of each STS feature. This number of cycles was obtained by analyzing the 10 registers with the least number of stand-to-stand cycle. Thus, no cycle was repeated for the Borg values, except for the last one, because in the final test part is where the lowest cycle rate is presented, which does not allow to accomplish the non-repeated cycle requirement. Figure 4.8, presents an example of these nearest cycle selection, where the dashed lines with the gray light background contain the selected sit-to-stand cycles for each Borg value. Besides, it can be seen in the white background rectangles, which cycles were not used and that the final Borg was not related to any cycle.

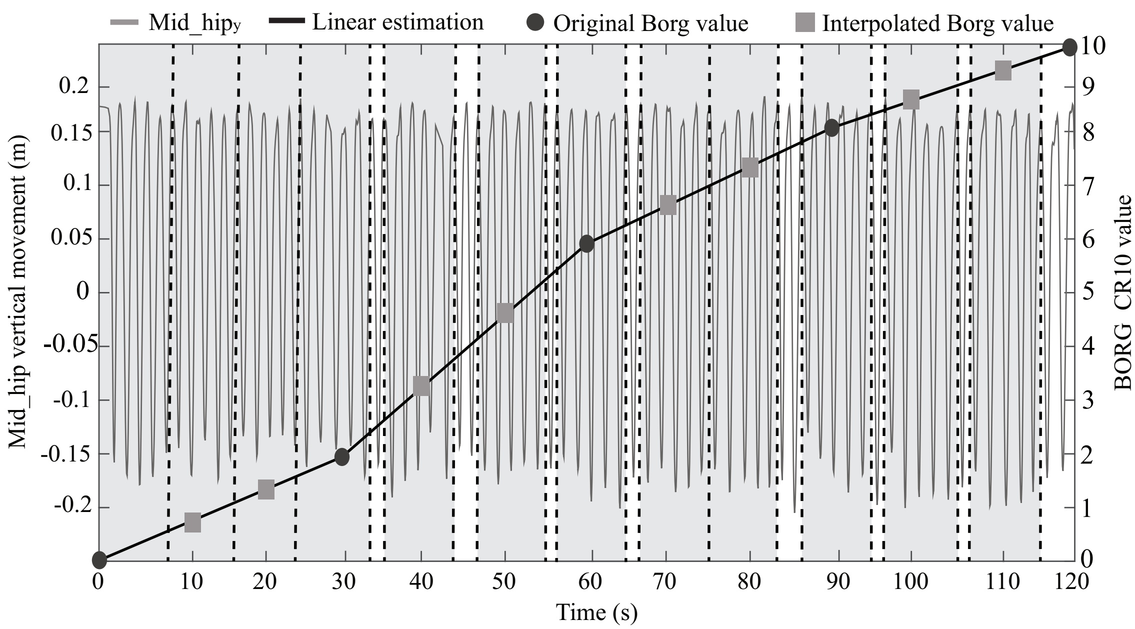

Figure 4.8: Selection of the five nearest sit-to-stand cycles to each Borg value.

Considering the importance of the heart rate for the patient's fatigue monitoring in the rehabilitation programs, this parameter was incorporated to the data set as the feature number 33 (F33), in a similar way as the other features. Due to the Zephyr sample rate is 1Hz, each test register contains 120 heart rate records. Thus, aiming to get an average value without repeating records, the mean values of the five closest heart rate measurements to each Borg value (except for the last one), were used to relate the fatigue level with this physiological parameter. Figure 4.9 presents an example of these heart rate records selection, represented by the dashed lines and the gray clear background.

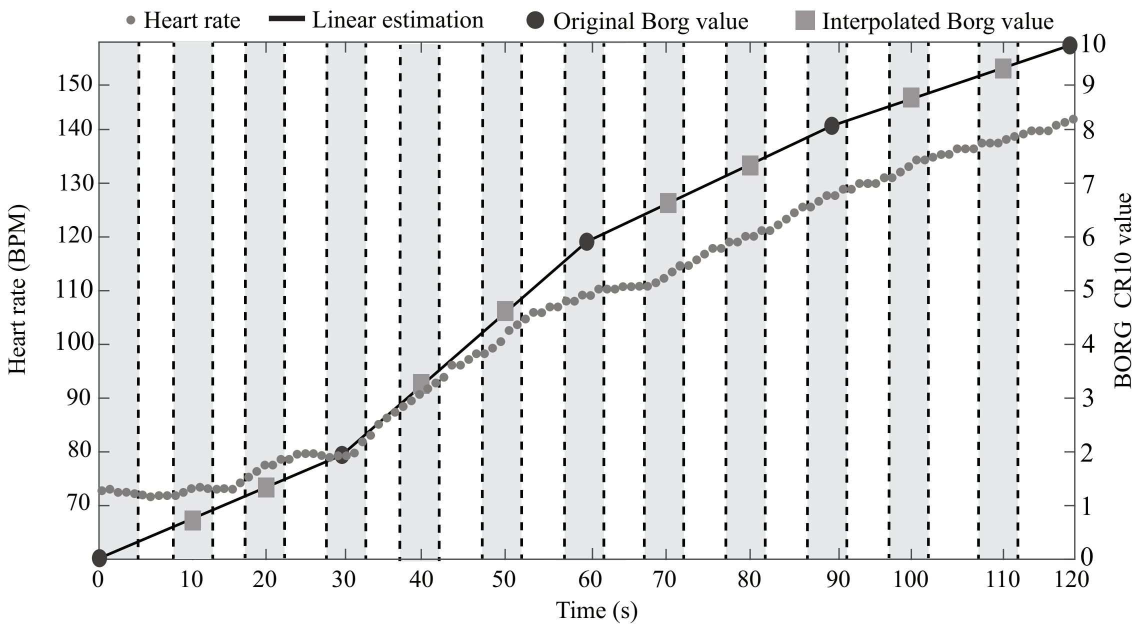

Figure 4.9: Selection of the five nearest heart rate records to each Borg Value.

Therefore, at the end of this process, the interpolated and original Borg values are related to the average of the corresponding 32 kinematic/temporal features (F1 to F32) and the average heart rate (F33).

4.1.7 Data normalization

It is important to keep in mind that with these average feature values, it is difficult to perform a direct comparison among the volunteer registers, due to the feature variability caused by the subject physical condition, which requires a normalization of the data according to each initial subject performance. Hence, considering that all the volunteers were in a 0 fatigue level at the beginning of the test and it is where the best performance should be presented, all features extracted were normalized by dividing it with the corresponding initial value. Hence, it is possible to determine how much each feature has changed regarding the beginning of the test.

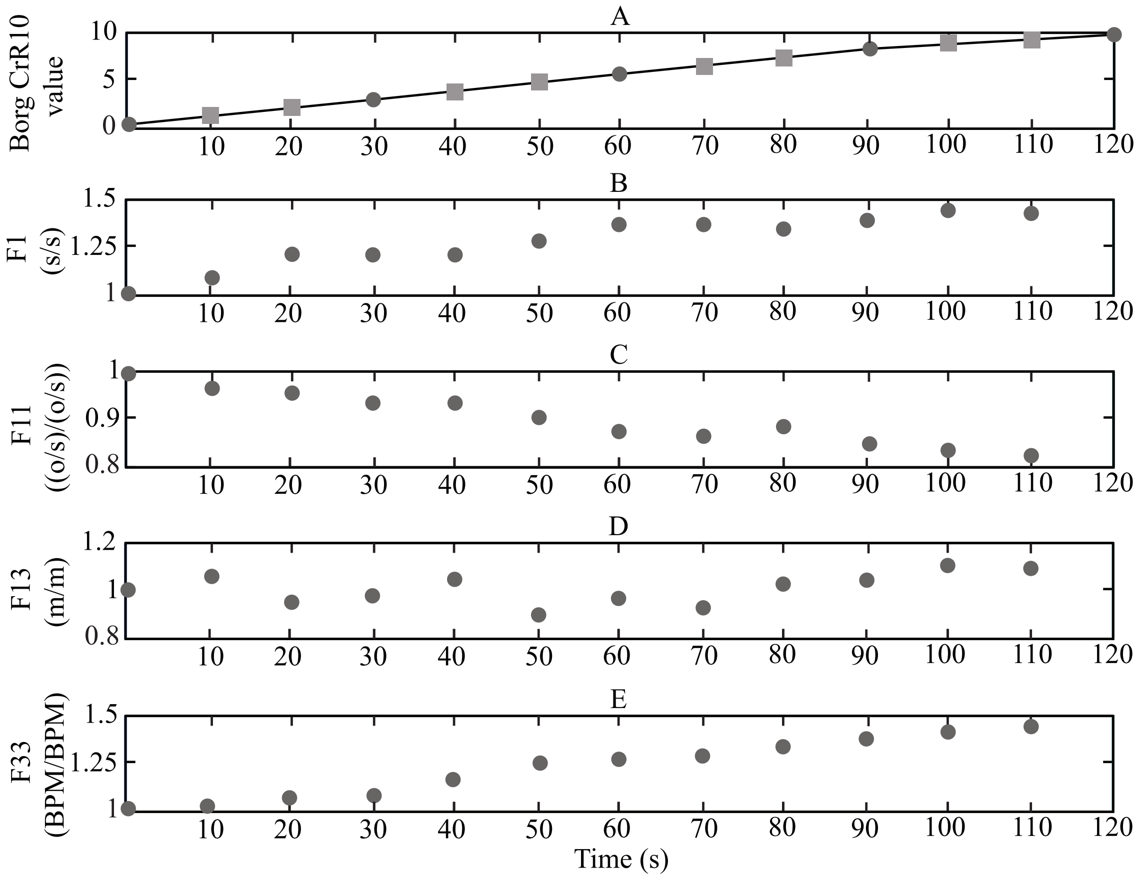

Figure 4.10: Features normalized behavior and fatigue level example of one volunteer, (A) Borg CR10 interpolated, (B) stand-to-stand time normalized, (C) Knee flexo-extension max velocity normalized, (D) Hip flexo-extension range normalized and (E) heart rate normalized.

Figure 4.10 presents an example of one volunteer for three different features normalized. Figure 4.10A shows the Borg values reported and interpolated. Figure 4.10B exhibit the behavior of the sit-to-stand time (F1) and how this feature tends to increase. Figure 4.10C display the behavior of the Knee flexo-extension max velocity (F11) and how this feature tends to decrease. Figure 4.10D shows the behavior of the Hip flexo-extension range (F13) and how this feature does not present a continues increment or decrement, however, it presents constant behaviors in some parts of the test (like at the end of the test, where this feature remains higher values than the beginning). Finally, Figure 4.10E, shows the mean normalized values of the heart rate are increasing.

4.1.8 Data set construction

Taking into account that the last Borg value was no used and that the initial one was used to normalize the features, there were 11 fatigue levels related to the STS performance features for each register. Thus, at the end of the process, a total of 660 Borg registers related to the performance features were obtained for the data set.

To determine the target for the all registers, each one was labeled with 3 fatigue states (low, moderate and high, as it is shown in Figure 4.2), according to the corresponding Borg value. In such that way, registers with a related Borg value: between 0 and 3, were considered as low fatigue (LF); between 4 and 6, as moderate fatigue (MF); and between 7 and 10, as high fatigue (HF). Thus, each register is conformed by 33 normalized features (32 STS kinematic/temporal and 1 of the heart rate) and one target. The representation of the data set can be seen in Figure 4.11, where it can be seen how the 606 registers contain their corresponding features and targets.

Features

Register	F1	F2	F3	F4	F5	⋯	F30	F31	F32	F33	Target
1	1.059	1.008	0.988	0.937	0.936	⋮	1.009	0.999	0.970	1.157	LF
2	1.084	1.050	0.955	1.104	0.991	⋮	0.975	0.982	0.940	1.184	LF
3	1.305	1.119	0.972	0.948	0.860	⋮	1.055	0.811	0.927	1.299	MF
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
658	1.115	1.086	0.984	0.947	0.937	⋮	0.933	0.948	0.951	1.137	LF
659	1.287	1.150	0.959	0.937	0.823	⋮	1.052	0.902	0.937	1.324	MF
660	1.464	1.300	0.930	1.188	0.748	⋮	0.923	0.748	0.883	1.404	HF

Figure 4.11: Data set representation composed of 660 STS registers, 33 features and the fatigue target.

Finally, to analyze in general how the features change according to the 3 fatigue categories, the mean and standard deviation were calculated for each feature regarding the fatigue condition. Therefore, it is possible to observe if the features in general present statistically different values and how they behave concerning the fatigue.

4.1.9 Fatigue estimation model development and assessment

In order to develop and evaluate a computational model for estimating the three fatigue states by mean of the 33 features, different machine learning methods were explored based on the data set obtained. In this work, a specific technique called "cross validation" was implemented for evaluating each model. This technique divides the data set in "n" equal parts, to train and assess "n" computational models of the same type, in this way, each model is trained with 'n-1' different data groups and assessed with the reminder group [97]. In the end, this technique provides a general performance metric called "accuracy", which is the relation between the total right estimations obtained in each testing process or true positives (TP), and the complete amount of data (N), as it is shown in Equation 4.2.

$$Accuracy = \frac{TP}{N} \tag{4.2}$$

Considering the size of the data set, 6 folds were selected for this validation process, hence, each fold is conformed of 110 registers. Figure 4.12 illustrates this process, where "TPn" represents the number of true positives of the corresponding "n" iteration, and "Acc" the final accuracy metric.

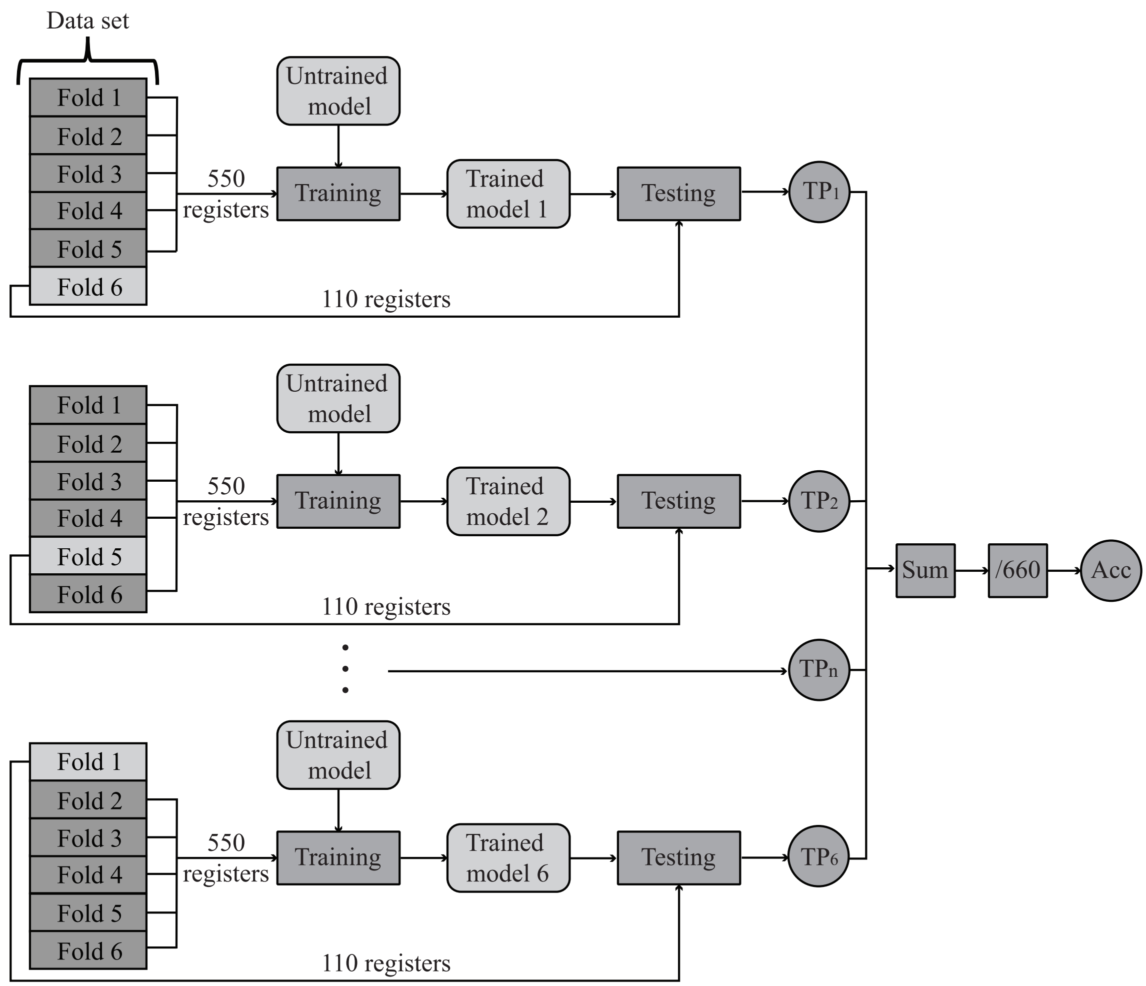

Figure 4.12: Cross validation process for the machine learning model development and assessment.

Moreover, the false negatives (FN), that represents the amount register which were estimated as other fatigue groups; and the false positives (FP), that refers to the number of registers which belong to other groups and were wrongly estimated, were calculated to obtain 3 more performance metrics known as "Precision" (Equation 4.3), "Recall" (Equation 4.4) and "F-Score" (Equation 4.5).

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4.4}$$

$$F - score = \frac{Precision * Recall}{Precision + Recall} * 2 \tag{4.5}$$

Finally, the open source python library "scikit-learn" [140] was used to execute a general quick training for different machine learning models: support vector machines, decision trees, linear discriminates, neural networks, quadratic discriminates and clustering classifiers. Afterward, according to the accuracy metric, the best 5 models were selected to be adjusted and retrained, by modifying their training parameters automatically through computational iterations.

4.2 STS Study Results

Table 4.2 shows the descriptive data of the number of stand-to-stand cycles obtained in the 60 registers, specifically, the mean, median standard deviation, maximum, and minimum cycle number. It is possible to see that on average the subjects executed 97.24 stand-to-stand cycles, which means that in general, the cycle rate was 0.803 cycles per second. Furthermore, it shows in the table that the minimum stand-to-stand cycle number gotten was 71, and the maximum was 127, obtaining a difference of 56 cycles.

Table 4.2: Descriptive data of the number of stand-to-stand cycles

Mean	**Median**	**Standard Deviation**	**Maximum**	**Minimum**
97.24	95	18.60	127	71

Table 4.3 presents the number of registers for the three fatigue states, according to the labeling

process present end in the subsection 4.1.8: low fatigue (LF), moderate fatigue (MF) and high fatigue (HF). It can be seen that the MF group contains most of the registers, followed by the LF group. Hence, the HF group has the lowest value, showing a difference of 57 registers regarding the MF group, which corresponds to 8.6% of the total data.

Table 4.3: Number of registers for each fatigue state

Fatigue state	**Number of registers**
LF	221 (33.5%)
MF	248 (37.6%)
HF	191 (28.9%)

Figure 4.13 display the mean (bars) and standard deviation (black lines) of each normalized feature, regarding the fatigue state, where the light gray bars correspond to LF, the gray bars to the MF, and the black bars to the HF. Besides, the features are split in 3 different bar graphs, hence, Figure4.13A contains features from 1 to 11, Figure4.13B from 12 to 2, and Figure4.13C from 23 to 33. It is important to highlight that these features are almost center to 1, owing to the normalization process carried out in subsection 4.1.7, which allows comparing the feature behavior among them. Therefore, it can be appreciated how some features increment or decrement their statistical values according to the fatigue condition, presenting that in general there their values have changed. Among the features, the stand-to-stand time (F1), the sit-to-stand time (F2) the and the heart rate (F33), Spine flexo-extension max velocity (F28), and M_shoulder depth range (F23), show the highest changes. Regarding the LF, MF and HF: F1 has mean values of 1.125, 1.307 and 1.477; F2 values of 1.130, 1.335 and 1.537; F33 values of 1.340, 1.497 and 1.605; F23 values of 0.904, 0.824 and 0.799; and F28 values of 0.981, 1.113 and 1.181. Finally, there are some features that do not illustrate high changes. These features correspond to the M_hip min vertical velocity (F7), M_hip max depth velocity (F8) and hip abduction-adduction max velocity (F17).

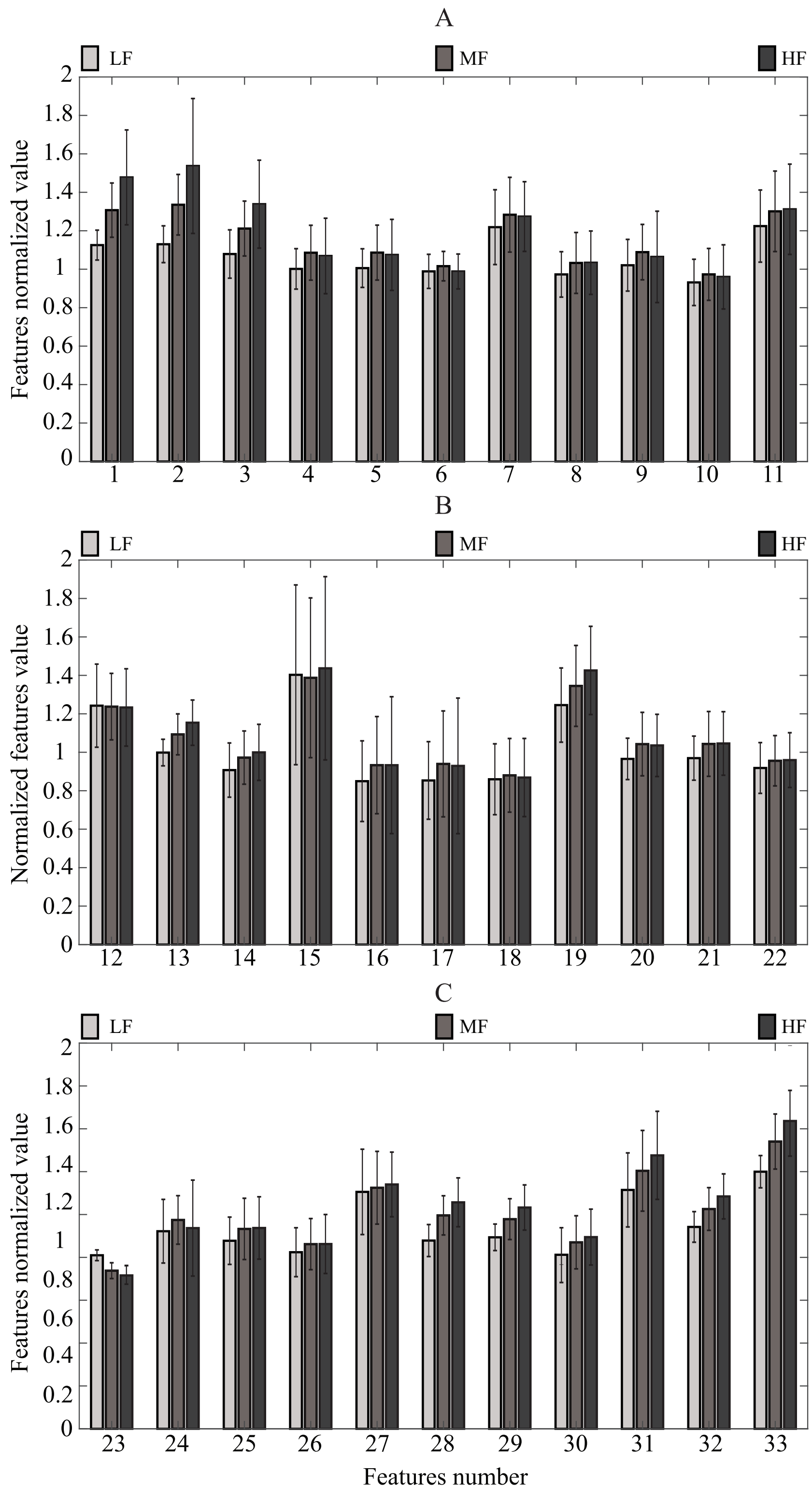

Figure 4.13: Mean and standard deviation values of each feature, according to the 3 fatigue conditions.

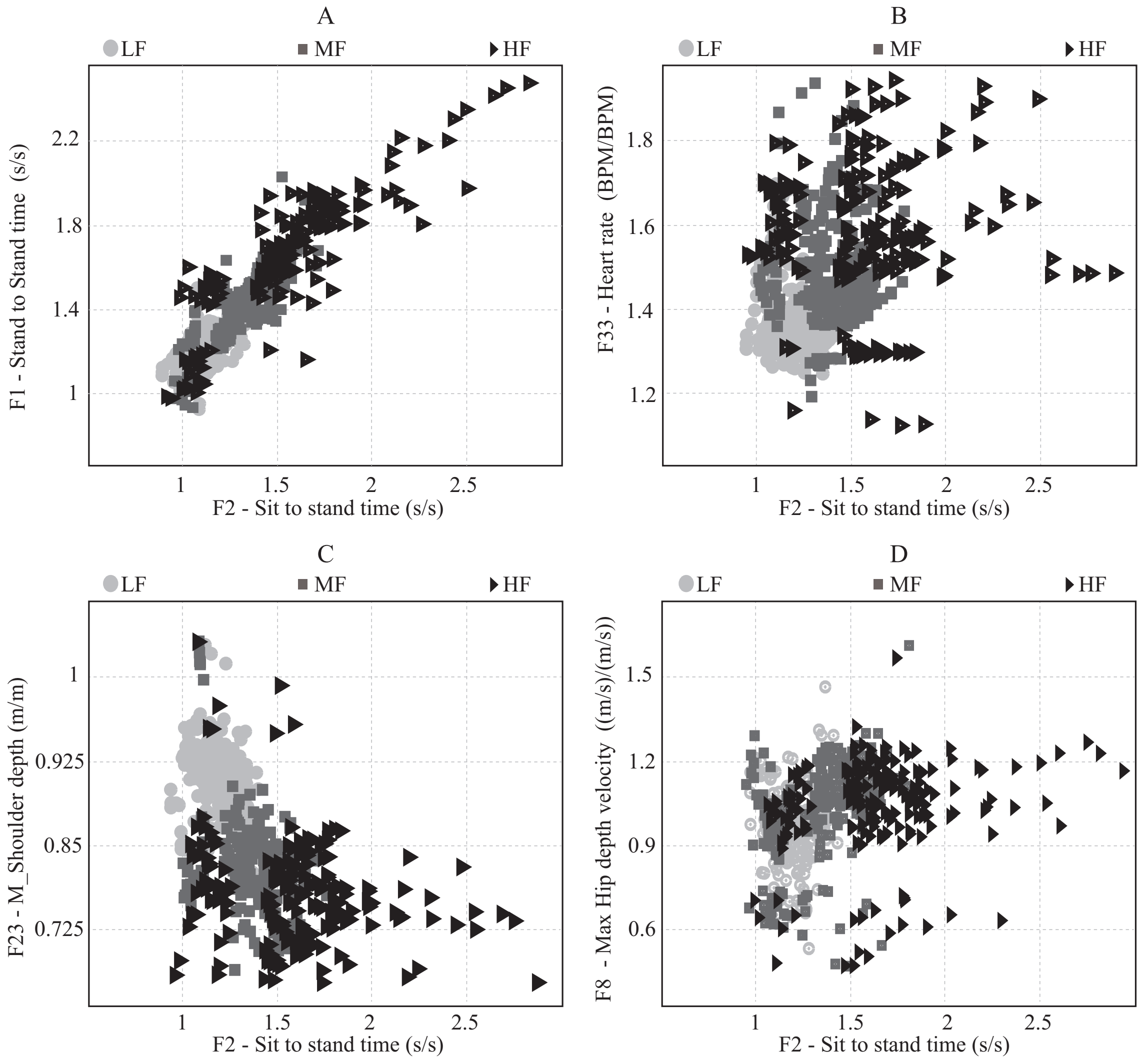

Figure 4.14: Features scatter graphs regarding the stand-to-stand time, (A) stand-to-stand time vs sit-to-stand time, (B) sit-to-stand time vs heart rate, (C) sit-to-stand time range vs M_shoulder depth range, and (D) sit-to-stand time vs M_hip max depth velocity.

Figure 4.14 presents four examples of the data distribution regarding two specific features, using the stand-to-stand time (F2) always as the horizontal axis. Therefore, the black triangles represent the high fatigue registers; the gray squares, the moderate fatigue; and the clear gray circles, the low fatigue. Specifically, Figure 4.14A shows the distribution according stand-to-stand time (F1); Figure 4.14B, according to the heart rate (F33); Figure 4.14C, according to the M_shoulder depth range (F23); and Figure 4.14D, according to the M_hip max depth velocity (F8). Essentially, these plots display some patters that can be found in the data set, where it is possible to see how some features are related (4.14A) and others not (4.14D). Considering the number of features, there are 33! scatter plot options, hence, there were shown the most relevant considering the Figure 4.13.

Nonetheless, aiming to provide a general view of how the data is distributed according to the hole features, the technique "Uniform Manifold Approximation and Projection" (UMAP) was implemented. This technique allows to reduce the number of data set features, in order to be used for visualization, and determine patters or clusters [141]. Hence, Figure 4.15 presents the obtained 2D plot, by reducing the number of features to 2. It can be seen that the LF registers tend to be apart from the MF and HF ones. However, the UMAP technique does not present a clear separation between the MF and HF registers.

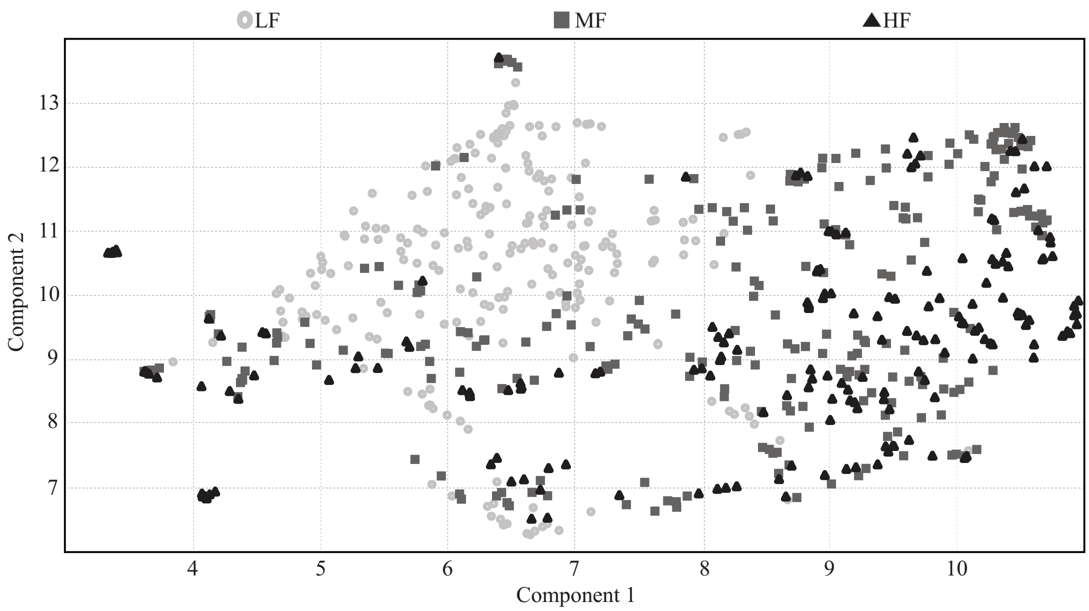

Figure 4.15: Features scatter graphs regarding the stand-to-stand time, (A) stand-to-stand time vs sit-to-stand time, (B) sit-to-stand time vs heart rate, (C) sit-to-stand time range vs M_shoulder depth range, and (D) sit-to-stand time vs M_hip max depth velocity.

Table 4.4 contains the best five models obtained after exploring in a grid search manner to the data obtained in subsection 4.1.9. The k-nearest neighbor (KNN) method using Euclidean distance classified the registers by a majority vote of its nearest elements with 27 neighbors (K=12). The logistic regression (LR) classifier implements the large-scale bound-constrained optimization as a penalty algorithm (solver=lbfgs), and a value of 1000 for its inverse of regularization strength learning parameter (C=1000). Then, the artificial neuronal network (ANN) with a stochastic gradient-based optimizer (solver=adam), and 100, 20, and 100 as hidden layer sizes (hls=(100, 20, 100). The support vector machine (SVM) with a radial basis function kernel (kernel=rbf) and a constrain value of 2 (C=2). Finally, the best model is a random forest (RF) classifier with 60 estimators (n_estimators=60), which means that the model integrates 60 decision tree models to merge their prediction. Moreover, Table 4.4 provides the mean values of the performance metrics: accuracy, recall, precision, and F-score, where the RF model presents the highest values as presented in Figure 4.4.

Table 4.4: Performance of the five best fatigue estimation models

Model	**Main parameters**	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F-score(%)**
RF	n_estimators=60	82.5%	83.2%	82.0%	81.9%
SVM	kernel=rbf, C=2	78.6%	78.5%	78.9%	78.1%
ANN	hls=(100, 20, 100)	76.0%	77.1%	74.8%	75.0%
LR	solver=lbfgs, C=1000	72.2%	73.3%	72.1%	71.5%
KNN	K=12	66.6%	75.2%	64.7%	62.1%

Taking into account that the values in Table 4.4 are the mean values obtained after the 6 test of the cross validation process (Figure 4.12), Figure 4.16 presents the box plot of each reliability metric, for the five machine learning implemented methods. Hence, each method contains four box plots, where the middle horizontal line represents the median value, the four quartiles are contained by the vertical lines and the boxes, and the black dots are atypical data. It can be seen that the RF method always presents the highest values, showing the lowest dispersion and therefore, the best consistence.

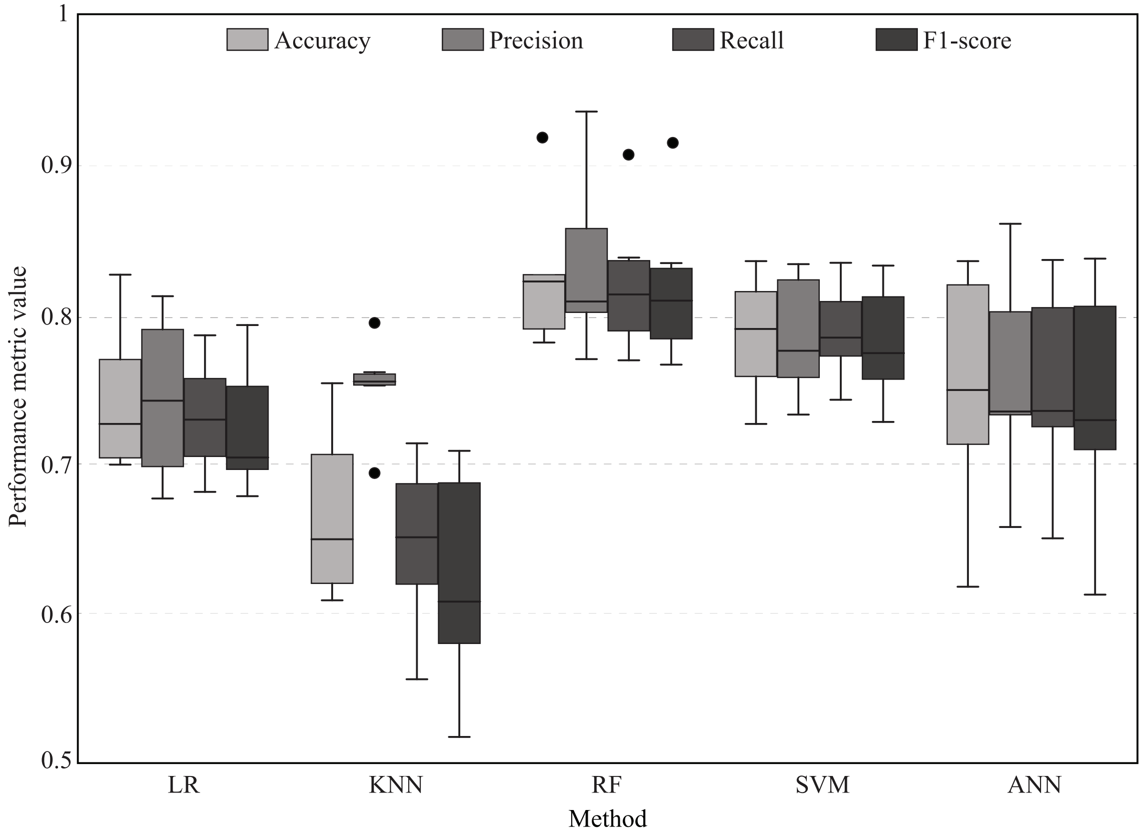

Figure 4.16: Box plot of the performance metric results for the five best machine learning methods.

Finally, considering that the best model corresponds to a random forest, its property "feature importance" was used to quantify the importance of each feature for the corresponding model. This property allows to obtain a relatively weight value to each feature, which represents a direct relation to the importance of the corresponding feature for this specific machine learning model. Figure 4.17 presents as a bar graph, the relative importance values obtained for each feature, sorted from the highest to the lowest. It is possible to see that F23 (M_shoulder depth range), F1 (stand-to-stand time) and F33 (heart rate) have the highest values.

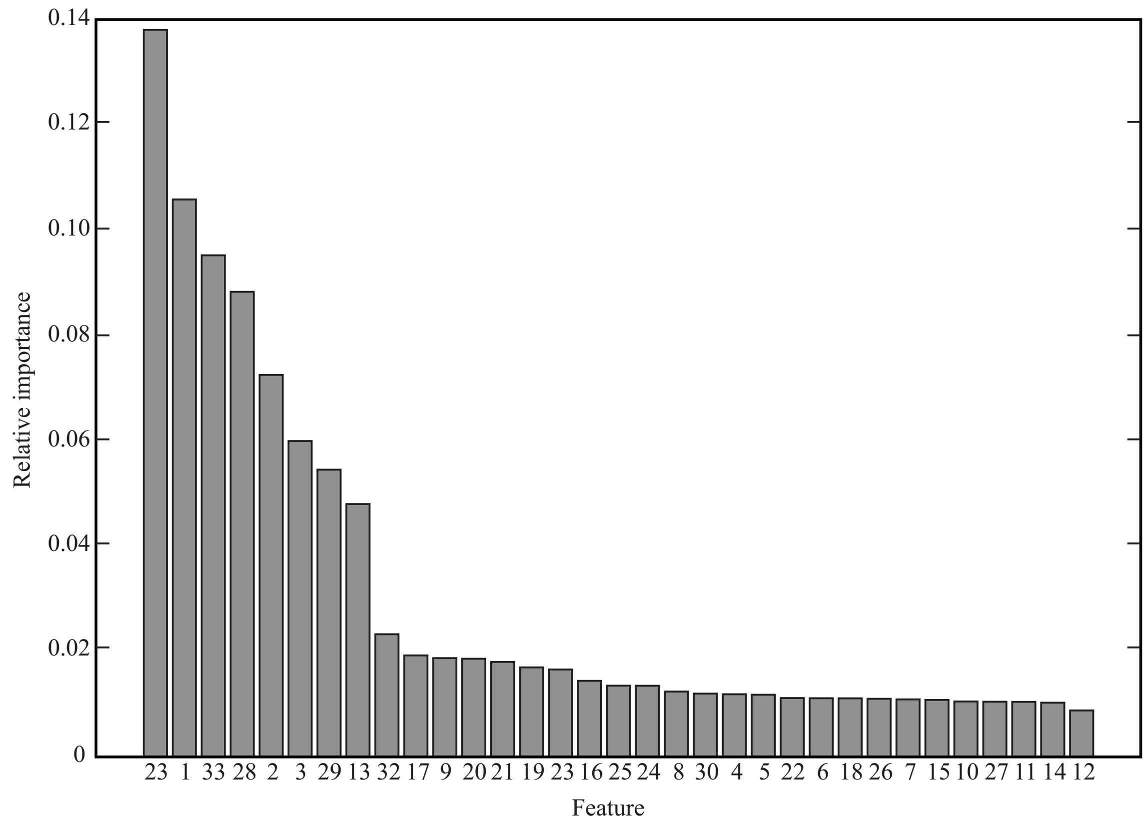

Figure 4.17: Feature relative importance for the random forest model.

4.3 STS Study Discussion

According to previous works [142] that have studied the reference number of cycles in a 1 minute STS test for healthy people, the results obtained in Table 4.6 are lower. Specifically, authors in [142] reported that subjects between 20 and 24 years have an average stand-to-stand rate of 1.183. On the other hand, results in Table 4.6 show an average rate of 0.803. This is presented because in this work the STS test ha twice longer, which makes the test harder, and hence, the general performance decrease. Moreover, these results suggest that the volunteers were being fatigued.

Despite the lowest number of cycles executed was 71, it is important to highlight that the cycle rate is not constant and tends to decrease during the test because of the induced fatigue.

This makes that at the end of the test, the number of cycles decreases. Hence, 5 cycles were used to get the average for each feature for the data set.

Although every volunteer started in a low fatigue condition, results in Table 4.3 display that most of the registers belong to the moderate fatigue (MF). In contrast, the lowest register number is presented for the high fatigue group (HF). Considering that reaching a Borg value in the HF band, requires to pass firstly for the LF and MF groups, this result was expected. However, a difference of 8.6% (57 registers) is acceptable for data analysis and training computational models [97]. Moreover, these results present that the data set registers are distributed similarly among the 3 fatigue groups and that in general, the volunteers experimented the 3 fatigue states during the test.

Bearing in mind previous studies have demonstrated that the times of the sit-to-stand phases are the most relevant exercise performance features [62], the results in Figure 4.13 are concordant to the literature. Where, an increment of approximately 20% can be seen for these types of features (F1 and F2), between the mean values of the LF and HF groups. However, despite the use of heart rate is criticized for managing the patient's fatigue condition during HIE [17], it can be seen the direct relation with fatigue level. The heart rate (F33) has a difference of 21.7%, between the LF and HF groups. Thus, the heart rate provides important information.

Nonetheless, other features present the opposite behavior. Specifically, the M_hip depth range (F5), the knee flexo-extension max velocity (F11), knee flexo-extension min velocity (F12), Hip flexo-extension min velocity (F15), M_shoulder vertical (F22) range and M_shoulder depth range (F23), present the highest decrements. Because of they are related to the phases time and the movement of the spine, it is normal that the lower limb angular velocities decrease, especially the minimum velocities that correspond to the sit-to-stand phase.

However, features that come from the upper part of the body, specifically the M_shoulder movement ranges (F22 and F23) also decrease. This phenomenon could be because the volunteers tried to change the exercise execution technique, in order to be able to keep performing the activity as fast as possible and to ease the load on the main lower limb muscles. Therefore, by moving the chest and the back to the front part, the exercise becomes easier [143], which causes the upper movement range features to decrease. Thus, although these features do not change as much as the time phases features and the heart rate, they also provide important information about the fatigue condition.

The relationship among the features themselves and the fatigue condition can be better analyzed in the 2D plots of Figure 4.14. Figure 4.14A the data distribution follows a linear straight, due to, the sit-to-stand time is part of the stand-to-stand time, hence, both features are very related. It can be seen that the HF samples are clustered around the highest values. In contrast, the LF samples tend to be grouped in the lowest values. However, this graph does not present a clear difference between the LF and MF samples. Moreover, there are also some irregular HF registers that are in the lowest values, which make it difficult to differentiate them from the other fatigue categories just with these two features, showing that with just one parameter is insufficient for a good calcification.

Figure 4.14B exhibit the data distribution regarding two features that are not related, the sit-to-stand time and heart rate. Hence, the samples are more dispersed and do not follow a clear equation. As above, the LF samples tend to be grouped in the lowest values, however, it can be seen that some LF registers reach values of about 1.6. This means that during the test, the heart rate reached values of approximately 60% higher than the repose heart rate of the corresponding volunteer, and do not overcome a value of 1.5 of the sit-to-stand time. This represents exercise conditions where the volunteers were requiring more energy for doing the exercise and did not feel fatigued, and thus, they were able to keep a similar performance. Taking into account that these heart rate values are acceptable in some rehabilitation scenarios (e.g oncology rehabilitation), this case may be optimal for physical training [4, 144]. Nevertheless, by monitoring just the heart rate, it would be difficult to distinguish this optimal training condition, from the cases where moderate or high fatigue levels are reached.

On the other hand, it is possible to see HF samples that do not overcome a 1.4 value in the heart rate and are in the highest values of the sit-to-stand time. These registers represent cases when the cardiac system was not able to adapt as fast as the exercise requires, which might happen in high-intensity exercises and very depended on the subject's cardiorespiratory capability [17], and hence, they felt exhausted and were not able to keep executing the exercise with similar performance. However, it is possible to see the opposite case, where some HF and MF samples are presented in the heart rate highest values and in the lowest values of the sit-to-stand time. This case shows conditions where the volunteers felt compelled to adapt their execution technique, to keep performing the activity quickly. Thus, it is important to monitor other exercise performance features, where these changes can be appreciated.

The execution exercise technique change and its influence in the sit-to-stand time can be appreciated in Figure 4.14C, where many HF samples are grouped in the lowest values of the M_shoulder depth range. Considering that moving the back to the front facilitates the execution of the exercise and reduce the upper body displacement on the Z-axis [143], the exercise phase times will tend to decrease, showing a better performance. However, the real situation reflects a pattern that, owing to the fatigue condition, the volunteers may modify their posture to reduce the load on the lower limbs. Therefore, the LF samples are clustered in the highest values of the M_shoulder depth range. In Figure 4.14B and Figure 4.14C, it is possible to see how the fatigue distribution changes in both axes. In contrast, Figure 4.14D presents the data distribution the M_hip max depth velocity, that does not provide visually a clear pattern. Thus, it is not possible to determinate data groups, clustered on the vertical axis, despite the feature change it values in a similar range of the sit-to-stand time.

In addition, Figure 4.15 presents that in general, the LF registries are the easier to classify, because they tend to be clustered according to the UMAP features reduction technique. It could be related to the fact that the LF state was always the initial state because it eases the errors that may have presented for the subjectivity of the Borg scale, providing a more direct relation to the initial registers. However, it is important to mention that Figure 4.15 also presents atypical registers, which may be presented because reducing the number of features does not allow to detect the hole patterns. Although Figure 4.15 does not present a clear separation between the MF and HF groups, this can be appreciated better in Figure 4.14 where the data tend to be clustered in specific ranges of the features. Specifically, it is possible to see that in the extreme values, the HF registers are normally shown.

Taking into account the different patterns that can be presented and the number of features, one of the best ways to analyze the data set, is by employing computational models able to determine these and other behaviors. It can be seen in table 4.4 and in Figure 4.16, that the machine learning model that with the lowest reliability values is the KNN, which based on distance techniques for classifying. Hence, considering the data distribution presented in the scatter plots (Figures 4.14 and 4.15), it is possible to see that this is not the recommended method for this type of data. Despite the SVM and the ANN present a better performance estimation, these models based on estimating curves for classifying do not present the best performance, because the groups are not enough separated. Hence, the RF model has the best reliability results. Considering the different cases that may be presented, this result suggests that the best method consists of merging different estimators that analyze the hole data, in order to provide a consensual result.

Despite the STS exercise is focused on the lower body part, Figure 4.17 shows that the most important feature for the RF model is the M_shoulder depth range (F23), which is extracted from the upper body part and represents the displacement of the middle shoulder Kinect marker. Considering that people try to move their upper body part to make easier the STS execution [143], it was expected that the movement of the upper part on the Z-axis was reduced. On the other hand, the second important feature corresponds to the stand-to-stand time (F1), which is the most assessed characteristic in the STS test general and it was also expected to be relevant. These results are concordant to the STS literature because authors in [18] reported that the acceleration of the chest is strongly related to the fatigue condition. Besides, authors in [21] reported that owing to the stand-to-stand time contains information about both STS phases, it is the one that presents the strongest lineal relationship according to the fatigue level.

Figure 4.17 displays that the heart rate (F33) is the third most important feature, bearing in mind the use of this parameter for fatigue regulation, it provides essential information regarding the fatigue condition. Due to the tests were carried out with healthy people, it was expected in most cases the volunteers were able to create enough energy to perform the STS activity, without increasing uncontrollably their heart rate. Hence, these results suggest that some STS performance features are more relevant for fatigue estimation than the heart rate. This provides an advantage in clinical scenarios because it is not desired to take patients to extreme physiological conditions, to determine that they are exhausted. Moreover, some features do not contribute any relevant information, because they correspond to movements on the frontal plane, like abduction-adduction movements. Hence, taking into account the STS exercise is primarily performed on the sagittal plane, it is normal that these features do no change strongly, or change randomly.

Comparing to other similar studies [18, 21], to the authors' knowledge, this work is the first that presents a model for fatigue estimation during the STS exercise execution, by monitoring kinematic/temporal features and the heart rate. Specifically in [18], the authors demonstrated that the acceleration of the chest on the vertical movement is related to the fatigue, by using an accessible and practical device, the IMU of a smartphone. However, it presents one case of study and just analyzes one kinematic feature, that may change its behavior if the subject modifies the execution technique. On the other hand, in [21] the authors carried out an analysis methodology, to determine which STS features are significantly linearly related to the fatigue level, measured with the Borg CR10 scale. However, it only presents a linear analysis and does not analyze the different patterns and behaviors that can be presented.

Similar studies that proposed fatigue estimation models during different exercises employing IMUs, such as: walking [26], vertical jumps [27], and lower limb endurance [22], have shown accuracy values between 85% and 95%. Therefore, contrasting the proposed ensemble model performance with the literature, its results are in the lowest part of the range. However, it must be considered that in these similar studies only considered two fatigue conditions, fatigued and no-fatigued. In contrast, this work contemplates three states, increasing the probability to miss the estimation, and also provides a clear separation for the LF registers, regarding the MF and HF (Figure 4.15).

Even though the proposed model is not based on IMUs, it implements a KinectV2 for obtaining the exercise features, which is an affordable sensor that has shown to be useful in clinical scenarios and allows to measure more STS features [139]. Considering the different patters that may be presented in the lower and upper body parts, this sensor present several advantages at being able to extract relevant STS features form different body parts. Furthermore, owing to the heart rate relevant information regarding the fatigue state, and its facility for being measured, this model also integrates an affordable heart rate sensor.

One limitation of this work is the tool implemented for obtaining the fatigue target of the registers. The Borg scale is a subjective measurement that can be affected by how the user interprets its values, and how it is explained. Despite, this scale was explained to each subject by using the same word and interpretation, it is a limitation that can not be ignored. Nevertheless, it is still a clinical tool widely used in rehabilitation programs. Furthermore, the purposed model compares the user's exercise condition with a database conformed of 660 different registers, providing a general estimation, and therefore, a more objective fatigue metric.

Another limitation is related to the study population, because of all the volunteers were healthy people, and the features may show different behaviors and patterns with patients, or other groups with different physical conditions. However, the normalization process makes that the model compares the user's state with his initial condition, reducing the difference features variability presented among the volunteers. Besides, the other similar studies also recruited healthy subjects [18, 21, 22, 26, 27], hence, as a first approximation for a complete clinical tool, this work presents relevant results.

Finally, owing to the global confinement caused by the COVID19, the need for clinical tools for telemedicine, has significantly increase [28]. Hence, keeping in mind the importance of fatigue monitoring in physical rehabilitation, and the practical tools that it implements, this work presents the initial development of a potential clinical tool for estimating fatigue during one of the most implemented HIE in rehabilitation programs.

Chapter 5

Conclusions and Future Works

High-intensity exercises have become an essential tool in physical rehabilitation because they have shown to be very effective at developing the patient's anaerobic capability. Because this metabolic way is required for executing sudden daily life activities, it has been considered as an important component for having a good quality of life. However, taking patients to inadequate exercise conditions or extreme fatigue states might lead them to suffer physical or physiological complications. Hence, it is required to monitor the patient's condition during training.

Bearing in mind that fatigue is a subjective experience, several studies have been carried out to propose indirect and direct methods for quantifying fatigue, such as monitoring user's physiological parameters, implementing subjective fatigue scales, and monitoring the user's exercise performance. Due to the novelty of the fatigue estimation method based on exercise performance, and the potential that it presents for physical rehabilitation, this work implements this method for developing a computational fatigue estimation model.

In order to analyze the state of the art of the implementation of high-intensity exercises in physical rehabilitation, a systematic review was performed. After a rigorous review process, a total of 48 articles were selected from 146 candidates, according to the inclusion criteria which allowed determining the exercise distribution regarding the rehabilitation area, the fatigue regulation implemented methods, and the type of activities studied. In general, most of the eliminated candidates were articles published in journals without a high impact factor or cases of study that explore the use of high-intensity exercises with healthy subjects.

The review results suggest that the implementation of high-intensity exercises, and the use of fatigue estimation and assessment methods, tend to be focused on the oncology, cardiac and pulmonary rehabilitation programs because these 3 rehabilitation areas contain the 81% of the selected articles. Oncology rehabilitation contains the most part of the selected articles (36%). This result can be related to the fact that one main goal of this rehabilitation program consists of easing the symptoms of pathological fatigue, which is a common symptom for patients that suffer cancer. Therefore, several studies have been carried out to determine the most effective physical interventions. Moreover, results present that in cardiac and pulmonary rehabilitation the use of high-intensity exercise is also relevant. However, due to the physiological conditions and risks that patients may suffer, these are the areas where real-time fatigue estimation methods are applied the most, such as heart rate, Borg scale, and oxygen consumption.

Regarding the type of high-intensity exercises, results suggest that the sit-to-stand exercise is the most high-intensity exercise implemented in physical rehabilitation, being presented in the 42.6% of the selected articles. Considering that it represents a common daily life activity and that it is easy to implement in physical therapies, this result allowed to select the exercise for the proposed fatigue estimation system. Besides, to the author's knowledge, this work presents the first approximation of a fatigue estimation model for this exercise. It is important to mention that other exercises such as cycling and full body endurance routines are relevant in the rehabilitation programs.

According to the review results the heart rate is the most used physiological parameter for fatigue regulation, showing to be in 68.7% of the selected articles. On the other hand, the Borg scale is in 70.8% of the chosen articles, which makes it the most applied subjective metric for fatigue regulation. These results led this work to develop a fatigue estimation tool based on these parameters. Besides, results showed that the multidimensional fatigue inventory is the most employed multidimensional fatigue scale. Hence taking into account that this scale is developed, for general population, it was implemented to determine the initial fatigue condition of the volunteers.

In conclusion, the systematic review results provide the corresponding information for the design of the proposed fatigue estimation model, regarding the type of exercise and the fatigue estimation metrics.

As the main contribution of this master thesis, a study was carried in order to obtain a data set of 660 sit-to-stand registers, composed of 32 kinematic/temporal exercise features and the heart rate, each one labeled with a fatigue condition (low, moderate and high) based on the Borg scale values provided by the volunteers. An analysis process was executed to determine that many of these features are related to the fatigue condition, showing different behaviors and patterns. Results suggest that the most important feature is the depth displacement of the upper body part, followed by the stand-to-stand time and the heart rate. Hence, these results suggest that the user's physiological condition, the upper body features, and the lower body features, contain relevant information regarding fatigue estimation during the STS exercise. Moreover, these results show to be concordant to the sit-to-stand literature, because previous studies have demonstrated that the upper-body movement and the sit-to-stand time have a strong relationship with the user's fatigue condition.

Taking into account that the patterns may be affected by chaining the exercise execution technique, caused by the user's fatigue, it is essential to monitor kinematic features that reflect this technique changes. In such that way, it is possible to determine the different behaviors, such as the reduction of the stand-to-stand time caused by the moment of the upper body, which makes easier the exercise execution.

An approach of a fatigue estimation model is proposed, aiming to show that these features can be implemented for estimating the three fatigue conditions with an accuracy of 82.5%, by means of accessible and practical sensors. Results suggest that the data is not enough separated to among the three fatigue groups for a perfect classification, specially between the moderate and high fatigue groups.Nevetherlss, according to similar studies, the performance classification metrics are in the acceptable range. Hence, this work presents the development of a potential tool for physical rehabilitation scenarios and telemedicine applications, which has become an important area during this global emergency caused by the COVID19.

Initially, future works should focus on adapting this proposed model to a real-time estimation tool, aiming to provide a fatigue metric that can be used during training. In order to achieve this initial future goal, the proposed model can be integrated into previously developed systems for real-time stand-to-stand cycle detection and real-time sit-to-stand permanence assessment [139], providing a fatigue estimation tool that can be used in general sit-to-stand training.

Moreover, future works should focus on the development of this tool with patients in real physical rehabilitation scenarios, especially for people with cancer or cardiac diseases, which are the areas that implement more this type of exercise. Considering the rigorous process that must be held to develop and validate a clinical tool, it is recommended that future works employ more objective fatigue, such as electromyography or oxygen consumption. Besides, it also required to study the repeatability of the proposed system, by carrying out more validation studies in different moments, and with different volunteers.

Finally, taking into account the variety of high-intensity exercise implemented in physical rehabilitation, future works should also explode this fatigue estimation methodology for other relevant high-intensity exercises, such as cycling and running, aiming to expand knowledge regarding the use of exercise performance features for fatigue estimation

Bibliography

[1] J. Scherr, B. Wolfarth, J. W. Christle, A. Pressler, S. Wagenpfeil, and M. Halle, "Associations between borg's rating of perceived exertion and physiological measures of exercise intensity," *European Journal of Applied Physiology*, vol. 113, pp. 147–155, Jan 2013.

[2] W. H. Organization *et al.*, *Global status report on noncommunicable diseases 2014*. No. WHO/NMH/NVI/15.1, World Health Organization, 2014.

[3] W. H. Organization, *Global action plan on physical activity 2018-2030: more active people for a healthier world*. World Health Organization, 2019.

[4] D. E. R. Warburton, C. W. Nicol, and S. S. D. Bredin, "Prescribing exercise as preventive therapy," *CMAJ*, vol. 174, pp. 961–974, mar 2006.

[5] B. K. Pedersen, "Physical Exercise in Chronic Diseases," in *Nutrition and Skeletal Muscle*, pp. 217–266, Elsevier, jan 2019.

[6] M. L. Pollock, G. A. Gaesser, J. D. Butcher, J. P. Després, R. K. Dishman, B. A. Franklin, and C. E. Garber, "The recommended quantity and quality of exercise for developing and maintaining cardiorespiratory and muscular fitness, and flexibility in healthy adults," *Medicine and Science in Sports and Exercise*, vol. 30, no. 6, pp. 975–991, 1998.

[7] P. Schnohr, J. L. Marott, J. S. Jensen, and G. B. Jensen, "Intensity versus duration of cycling, impact on all-cause and coronary heart disease mortality: The Copenhagen City Heart Study," *European Journal of Preventive Cardiology*, vol. 19, pp. 73–80, feb 2012.

[8] A. Manley in *Physical activity and health: A report of the surgeon general*, ch. 4, US Department of Health and human services, 1997.

[9] M. Tanasescu, M. F. Leitzmann, E. B. Rimm, W. C. Willett, M. J. Stampfer, and F. B. Hu, “Exercise type and intensity in relation to coronary heart disease in men,” *Journal of the American Medical Association*, vol. 288, pp. 1994–2000, oct 2002.

[10] I. M. Lee, H. D. Sesso, Y. Oguma, and R. S. Paffenbarger, “Relative intensity of physical activity and risk of coronary heart disease,” *Circulation*, vol. 107, pp. 1110–1116, mar 2003.

[11] D. E. Warburton, D. C. McKenzie, M. J. Haykowsky, A. Taylor, P. Shoemaker, A. P. Ignaszewski, and S. Y. Chan, “Effectiveness of high-intensity interval training for the rehabilitation of patients with coronary artery disease,” *American Journal of Cardiology*, vol. 95, pp. 1080–1084, may 2005.

[12] D. E. Warburton, N. Gledhill, and A. Quinney, “Musculoskeletal Fitness and Health,” *Canadian Journal of Applied Physiology*, vol. 26, pp. 217–237, apr 2001.

[13] B. E. Ainsworth, W. L. Haskell, A. S. Leon, D. R. Jacobs Jr, H. J. Montoye, J. F. Sallis, and R. S. Paffenbarger Jr, “Compendium of physical activities: classification of energy costs of human physical activities.,” *Medicine and science in sports and exercise*, vol. 25, no. 1, pp. 71–80, 1993.

[14] J. Qi, P. Yang, A. Waraich, Z. Deng, Y. Zhao, and Y. Yang, “Examining sensor-based physical activity recognition and monitoring for healthcare using internet of things: A systematic review,” *Journal of biomedical informatics*, vol. 87, pp. 138–153, 2018.

[15] A. I. Zeni, M. D. Hoffman, and P. S. Clifford, “Relationships among heart rate, lactate concentration, and perceived effort for different types of rhythmic exercise in women,” *Archives of Physical Medicine and Rehabilitation*, vol. 77, pp. 237–241, mar 1996.

[16] D. C. Poole, M. Burnley, A. Vanhatalo, H. B. Rossiter, and A. M. Jones, “Critical power: An important fatigue threshold in exercise physiology,” *Medicine and Science in Sports and Exercise*, vol. 48, pp. 2320–2334, nov 2016.

[17] F. A. da Cunha, P. d. T. V. Farinatti, and A. W. Midgley, “Methodological and practical application issues in exercise prescription using the heart rate reserve and oxygen uptake reserve methods,” *Journal of science and medicine in sport*, vol. 14, no. 1, pp. 46–57, 2011.

[18] C. R. Jiménez, P. Bennett, A. O. García, and A. I. Cuesta Vargas, “Fatigue detection during sit-to-stand test based on surface electromyography and acceleration: A case study,” *Sensors (Switzerland)*, vol. 19, oct 2019.

[19] T. Paillard, “Effects of general and local fatigue on postural control: A review,” vol. 36, pp. 162–176, jan 2012.

[20] C. Roldán-Jiménez, P. Bennett, and A. I. Cuesta-Vargas, "Muscular activity and fatigue in lower-limb and trunk muscles during different sit-to-stand tests," *PLoS ONE*, vol. 10, oct 2015.

[21] A. Aguirre, J. Casas, N. Cespedes, M. Munera, M. Rincon-Roncancio, A. Cuesta-Vargas, and C. A. Cifuentes, "Feasibility study: Towards Estimation of Fatigue Level in Robot-Assisted Exercise for Cardiac Rehabilitation," in *IEEE International Conference on Rehabilitation Robotics*, vol. 2019-June, pp. 911–916, IEEE Computer Society, jun 2019.

[22] F. Mokaya, R. Lucas, H. Y. Noh, and P. Zhang, "Burnout: A Wearable System for Unobtrusive Skeletal Muscle Fatigue Estimation," in *2016 15th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN 2016 - Proceedings*, Institute of Electrical and Electronics Engineers Inc., apr 2016.

[23] V. Camomilla, E. Bergamini, S. Fantozzi, and G. Vannozzi, "Trends Supporting the In-Field Use of Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review," *Sensors*, vol. 18, p. 873, mar 2018.

[24] A. Ejupi, Y. J. Gschwind, T. Valenzuela, S. R. Lord, and K. Delbaere, "A Kinect and Inertial Sensor-Based System for the Self-Assessment of Fall Risk: A Home-Based Study in Older People," *Human-Computer Interaction*, vol. 31, pp. 261–293, jul 2016.

[25] J. M. Jakicic and A. D. Otto, "Physical activity considerations for the treatment and prevention of obesity–," *The American journal of clinical nutrition*, vol. 82, no. 1, pp. 226S–229S, 2005.

[26] J. Zhang, T. E. Lockhart, and R. Soangra, "Classifying lower extremity muscle fatigue during walking using machine learning and inertial sensors," *Annals of Biomedical Engineering*, vol. 42, pp. 600–612, oct 2014.

[27] R. S. McGinnis, S. M. Cain, S. P. Davidson, R. V. Vitali, N. C. Perkins, and S. G. McLean, "Quantifying the effects of load carriage and fatigue under load on sacral kinematics during countermovement vertical jump with IMU-based method," *Sports Engineering*, vol. 19, pp. 21–34, mar 2016.

[28] J. E. Hollander and B. G. Carr, "Virtually perfect? telemedicine for covid-19," *New England Journal of Medicine*, vol. 382, no. 18, pp. 1679–1681, 2020.

[29] J. A. Casas, N. Céspedes, C. A. Cifuentes, L. F. Gutierrez, M. Rincón-Roncancio, and M. Múnera, "Expectation vs. reality: Attitudes towards a socially assistive robot in cardiac rehabilitation," *Applied Sciences*, vol. 9, no. 21, p. 4651, 2019.

[30] P. Thompson, "Exercise and Physical Activity in the Prevention and Treatment of Atherosclerotic Cardiovascular Disease: A Statement From the Council on Clinical Cardiology," *Arteriosclerosis, Thrombosis, and Vascular Biology*, vol. 23, no. 8, pp. 42e–49, 2003.

[31] L. J. Ignarro, M. L. Balestrieri, and C. Napoli, "Nutrition, physical activity, and cardiovascular disease: an update," *Cardiovascular research*, vol. 73, no. 2, pp. 326–340, 2007.

[32] K. J. Price, B. A. Gordon, S. R. Bird, and A. C. Benson, "A review of guidelines for cardiac rehabilitation exercise programmes: is there an international consensus?," *European journal of preventive cardiology*, vol. 23, no. 16, pp. 1715–1733, 2016.

[33] G. O. Dibben, H. M. Dalal, R. S. Taylor, P. Doherty, L. H. Tang, and M. Hillsdon, "Cardiac rehabilitation and physical activity: Systematic review and meta-analysis," vol. 104, pp. 1394–1402, sep 2018.

[34] M. A. Dalzell, N. Smirnow, W. Sateren, A. Sintharaphone, M. Ibrahim, L. Mastroianni, L. D. Vales Zambrano, and S. O'Brien, "Rehabilitation and exercise oncology program: Translating research into a model of care," *Current Oncology*, vol. 24, no. 3, pp. e191–e198, 2017.

[35] R. R. Spence, K. C. Heesch, and W. J. Brown, "Exercise and cancer rehabilitation: a systematic review," *Cancer treatment reviews*, vol. 36, no. 2, pp. 185–194, 2010.

[36] E. H. Cup, A. J. Pieterse, M. Jessica, M. Munneke, B. G. van Engelen, H. T. Hendricks, G. J. van der Wilt, and R. A. Oostendorp, "Exercise therapy and other types of physical therapy for patients with neuromuscular diseases: a systematic review," *Archives of physical medicine and rehabilitation*, vol. 88, no. 11, pp. 1452–1464, 2007.

[37] Y.-s. Lee and S.-w. Ahn, "The effects of kinesio taping and neuromuscular rehabilitation exercise for patients with acute whiplash-associated disorder," *The Journal of Korean Academy of Orthopedic Manual Physical Therapy*, vol. 22, no. 2, pp. 41–49, 2016.

[38] E. L. Voorn, F. Koopman, F. Nollet, and M. A. Brehm, "Aerobic exercise in adult neuromuscular rehabilitation: A survey of healthcare professionals," *Journal of Rehabilitation Medicine*, vol. 51, no. 7, pp. 518–524, 2019.

[39] Y.-s. Lee and S.-w. Ahn, "The effects of kinesio taping and neuromuscular rehabilitation exercise for patients with acute whiplash-associated disorder," *The Journal of Korean Academy of Orthopedic Manual Physical Therapy*, vol. 22, no. 2, pp. 41–49, 2016.

[40] M. A. Spruit, F. Pitta, E. McAuley, R. L. ZuWallack, and L. Nici, “Pulmonary rehabilitation and physical activity in patients with chronic obstructive pulmonary disease,” *American journal of respiratory and critical care medicine*, vol. 192, no. 8, pp. 924–933, 2015.

[41] W. R. Frontera and H. G. Knuttgen, “Exercise and musculoskeletal rehabilitation: restoring optimal form and function,” *The physician and sportsmedicine*, vol. 31, no. 12, pp. 39–45, 2003.

[42] Y. Escalante, J. M. Saavedra, A. García-Hermoso, A. J. Silva, and T. M. Barbosa, “Physical exercise and reduction of pain in adults with lower limb osteoarthritis: A systematic review,” vol. 23, pp. 175–186, jan 2010.

[43] A. C. o. S. Medicine, *ACSM’s health-related physical fitness assessment manual.* 2013.

[44] D. E. Warburton, N. Gledhill, and A. Quinney, “The effects of changes in musculoskeletal fitness on health,” *Canadian Journal of Applied Physiology*, vol. 26, no. 2, pp. 161–216, 2001.

[45] T. Guiraud, A. Nigam, V. Gremeaux, P. Meyer, M. Juneau, and L. Bosquet, “High-intensity interval training in cardiac rehabilitation,” *Sports medicine*, vol. 42, no. 7, pp. 587–605, 2012.

[46] L. B. Andersen, P. Schnohr, M. Schroll, and H. O. Hein, “All-cause mortality associated with physical activity during leisure time, work, sports, and cycling to work,” *Archives of internal medicine*, vol. 160, no. 11, pp. 1621–1628, 2000.

[47] R. Shephard, “Absolute versus relative intensity of physical activity in a dose-response context,” *Medicine and science in sports and exercise*, vol. 33, no. 6, 2001.

[48] Y. Schutz, R. L. Weinsier, and G. R. Hunter, “Assessment of free-living physical activity in humans: an overview of currently available and proposed new measures,” *Obesity research*, vol. 9, no. 6, pp. 368–379, 2001.

[49] B. E. Ainsworth, W. L. Haskell, M. C. Whitt, M. L. Irwin, A. M. Swartz, S. J. Strath, W. L. O Brien, D. R. Bassett, K. H. Schmitz, P. O. Emplaincourt, *et al.*, “Compendium of physical activities: an update of activity codes and met intensities,” Tech. Rep. 9; SUPP/1, 2000.

[50] E. L. Fox, R. L. Bartels, C. E. Billings, D. K. Mathews, R. Bason, and W. M. Webb, “Intensity and distance of interval training programs and changes in aerobic power.,” *Medicine and science in sports*, vol. 5, no. 1, pp. 18–22, 1973.

[51] A. K. Cornish, S. Broadbent, and B. S. Cheema, “Interval training for patients with coronary artery disease: a systematic review,” *European journal of applied physiology*, vol. 111, no. 4, pp. 579–589, 2011.

[52] C. M. O'Connor, D. J. Whellan, K. L. Lee, S. J. Keteyian, L. S. Cooper, S. J. Ellis, E. S. Leifer, W. E. Kraus, D. W. Kitzman, J. A. Blumenthal, D. S. Rendall, N. H. Miller, J. L. Fleg, K. A. Schulman, R. S. McKelvie, F. Zannad, and I. L. Piña, "Efficacy and safety of exercise training in patients with chronic heart failure HF-ACTION randomized controlled trial," *JAMA - Journal of the American Medical Association*, vol. 301, pp. 1439–1450, apr 2009.

[53] J. Myers, M. Prakash, V. Froelicher, D. Do, S. Partington, and J. E. Atwood, "Exercise Capacity and Mortality among Men Referred for Exercise Testing," *New England Journal of Medicine*, vol. 346, pp. 793–801, mar 2002.

[54] S. J. Keteyian, C. A. Brawner, P. D. Savage, J. K. Ehrman, J. Schairer, G. Divine, H. Aldred, K. Ophaug, and P. A. Ades, "Peak aerobic capacity predicts prognosis in patients with coronary heart disease," *American Heart Journal*, vol. 156, pp. 292–300, aug 2008.

[55] Ø. Rognmo, E. Hetland, J. Helgerud, J. Hoff, and S. A. Slørdahl, "High intensity aerobic interval exercise is superior to moderate intensity exercise for increasing aerobic capacity in patients with coronary artery disease," *European Journal of Cardiovascular Prevention and Rehabilitation*, vol. 11, pp. 216–222, jun 2004.

[56] T. T. Moholdt, B. H. Amundsen, L. A. Rustad, A. Wahba, K. T. Løvø, L. R. Gullikstad, A. Bye, E. Skogvoll, U. Wisløff, and S. A. Slørdahl, "Aerobic interval training versus continuous moderate exercise after coronary artery bypass surgery: A randomized study of cardiovascular effects and quality of life," *American Heart Journal*, vol. 158, pp. 1031–1037, dec 2009.

[57] O. J. Kemi and U. Wisløff, "High-Intensity Aerobic Exercise Training Improves the Heart in Health and Disease," *Journal of Cardiopulmonary Rehabilitation and Prevention*, vol. 30, pp. 2–11, jan 2010.

[58] S. A. Dugan and K. P. Bhat, "Biomechanics and analysis of running gait," *Physical Medicine and Rehabilitation Clinics*, vol. 16, no. 3, pp. 603–621, 2005.

[59] W. D. McLeod and T. Blackburn, "Biomechanics of knee rehabilitation with cycling," *The American journal of sports medicine*, vol. 8, no. 3, pp. 175–180, 1980.

[60] L. D. Roorda, M. E. Roebroeck, T. van Tilburg, G. J. Lankhorst, L. M. Bouter, M. M. S. Group, *et al.*, "Measuring activity limitations in climbing stairs: development of a hierarchical scale for patients with lower-extremity disorders living at home," *Archives of physical medicine and rehabilitation*, vol. 85, no. 6, pp. 967–971, 2004.

[61] R. Steiner, K. Meyer, K. Lippuner, J.-P. Schmid, H. Saner, and H. Hoppeler, "Eccentric endurance training in subjects with coronary artery disease: a novel exercise paradigm in cardiac rehabilitation?," *European journal of applied physiology*, vol. 91, no. 5-6, pp. 572–578, 2004.

[62] R. W. Bohannon, "Sit-to-stand test for measuring performance of lower extremity muscles.," *Perceptual and motor skills*, vol. 80, pp. 163–166, feb 1995.

[63] K. Fukuda, S. E. Straus, I. Hickie, M. C. Sharpe, J. G. Dobbins, and A. Komaroff, "The chronic fatigue syndrome: A comprehensive approach to its definition and study," *Annals of Internal Medicine*, vol. 121, pp. 953–959, dec 1994.

[64] A. F. Alghannam, K. Tsintzas, D. Thompson, J. Bilzon, and J. A. Betts, "Exploring mechanisms of fatigue during repeated exercise and the dose dependent effects of carbohydrate and protein ingestion: study protocol for a randomised controlled trial," *Trials*, vol. 15, no. 1, p. 95, 2014.

[65] G. Borg, "Borg's range model and scales.," *International Journal of Sport Psychology*, 2001.

[66] L. Baussard, M. Carayol, B. Porro, F. Baguet, and F. Cousson-gelie, "European Journal of Oncology Nursing Fatigue in cancer patients : Development and validation of a short form of the Multidimensional Fatigue Inventory (MFI-10)," *European Journal of Oncology Nursing*, vol. 36, no. July, pp. 62–67, 2018.

[67] J.-j. Wan, Z. Qin, P.-y. Wang, Y. Sun, and X. Liu, "Muscle fatigue: general understanding and treatment," *Experimental & Molecular Medicine*, vol. 49, pp. e384–e384, oct 2017.

[68] O. Ozalp, D. Inal-Ince, E. Calik, N. Vardar-Yagli, M. Saglam, S. Savci, H. Arikan, M. Bosnak-Guclu, and L. Coplu, "Extrapulmonary features of bronchiectasis: muscle function, exercise capacity, fatigue, and health status," *Multidisciplinary respiratory medicine*, vol. 7, no. 1, p. 3, 2012.

[69] M. P. Barnes, B. H. Dobkin, and J. Bogousslavsky, *Recovery after stroke United Kingdom.* Cambridge University Press, 2005.

[70] F. Möhler, S. Ringhof, D. Debertin, and T. Stein, "Influence of fatigue on running coordination: A ucm analysis with a geometric 2d model and a subject-specific anthropometric 3d model," *Human movement science*, vol. 66, pp. 133–141, 2019.

[71] S. R. Kang, J.-Y. Min, C. Yu, and T.-K. Kwon, "Effect of whole body vibration on lactate level recovery and heart rate recovery in rest after intense exercise," *Technology and Health Care*, vol. 25, pp. 115–123, jul 2017.

[72] J. L. Helbostad, D. L. Sturnieks, J. Menant, K. Delbaere, S. R. Lord, and M. Pijnappels, "Consequences of lower extremity and trunk muscle fatigue on balance and functional tasks in older people: A systematic literature review," *BMC Geriatrics*, vol. 10, p. 56, dec 2010.

[73] F. Yu, A. Bilberg, E. Stenager, C. Rabotti, B. Zhang, and M. Mischi, "A wireless body measurement system to study fatigue in multiple sclerosis," *Physiological Measurement*, vol. 33, pp. 2033–2048, dec 2012.

[74] T. Reybrouck, L. Mertens, S. Brusselle, M. Weymans, B. Eyskens, J. Defoor, and M. Gewillig, "Oxygen uptake versus exercise intensity: A new concept in assessing cardiovascular exercise function in patients with congenital heart disease," *Heart*, vol. 84, pp. 46–52, jul 2000.

[75] H. Ishii and Y. Nishida, "Effect of Lactate Accumulation during Exercise-induced Muscle Fatigue on the Sensorimotor Cortex," *Journal of Physical Therapy Science*, vol. 25, no. 12, pp. 1637–1642, 2013.

[76] P. A. Karthick, D. M. Ghosh, and S. Ramakrishnan, "Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms," *Computer Methods and Programs in Biomedicine*, vol. 154, pp. 45–56, feb 2018.

[77] A. Subasi and M. K. Kiymik, "Muscle fatigue detection in EMG using time-frequency methods, ICA and neural networks," *Journal of Medical Systems*, vol. 34, pp. 777–785, aug 2010.

[78] A. R. Zamunér, M. A. Moreno, T. M. Camargo, J. P. Graetz, A. C. S. Rebelo, N. Y. Tamburús, and E. A. da Silva, "Assessment of subjective perceived exertion at the anaerobic threshold with the borg cr-10 scale.," *Journal of sports science medicine*, vol. 101, pp. 130–6, 2011.

[79] A. Sehle, M. Vieten, S. Sailer, A. Mündermann, and C. Dettmers, "Objective assessment of motor fatigue in multiple sclerosis: the Fatigue index Kliniken Schmieder (FKS)," *Journal of Neurology*, vol. 261, pp. 1752–1762, sep 2014.

[80] S. Pettersson, I. Lundberg, M. Liang, J. Pouchot, and E. Welin Henriksson, "Determination of the minimal clinically important difference for seven measures of fatigue in Swedish patients with systemic lupus erythematosus," *Scandinavian Journal of Rheumatology*, vol. 44, pp. 206–210, may 2015.

[81] L. Whitehead, "The measurement of fatigue in chronic illness: a systematic review of unidimensional and multidimensional fatigue measures," *Journal of pain and symptom management*, vol. 37, no. 1, pp. 107–128, 2009.

[82] H. J. Michielsen, J. De Vries, G. L. Van Heck, F. J. Van de Vijver, and K. Sijtsma, "Examination of the dimensionality of fatigue," *European Journal of Psychological Assessment*, vol. 20, no. 1, pp. 39–48, 2004.

[83] T. R. Mendoza, X. S. Wang, C. S. Cleeland, M. Morrissey, B. A. Johnson, J. K. Wendt, and S. L. Huber, "The rapid assessment of fatigue severity in cancer patients: use of the brief fatigue inventory," *Cancer*, vol. 85, no. 5, pp. 1186–1196, 1999.

[84] L. B. Krupp, N. G. LaRocca, J. Muir-Nash, and A. D. Steinberg, "The fatigue severity scale: application to patients with multiple sclerosis and systemic lupus erythematosus," *Archives of neurology*, vol. 46, no. 10, pp. 1121–1123, 1989.

[85] H. J. Michielsen, J. De Vries, and G. L. Van Heck, "Psychometric qualities of a brief self-rated fatigue measure: The fatigue assessment scale," *Journal of psychosomatic research*, vol. 54, no. 4, pp. 345–352, 2003.

[86] N. Williams, "The Borg Rating of Perceived Exertion (RPE) scale," in *Occupational Medicine*, vol. 67, pp. 404–405, jul 2017.

[87] J. D. Fisk, A. Pontefract, P. G. Ritvo, C. J. Archibald, and T. Murray, "The impact of fatigue on patients with multiple sclerosis," *Canadian Journal of Neurological Sciences*, vol. 21, no. 1, pp. 9–14, 1994.

[88] T. Chalder, G. Berelowitz, T. Pawlikowska, L. Watts, S. Wessely, D. Wright, and E. Wallace, "Development of a fatigue scale," *Journal of psychosomatic research*, vol. 37, no. 2, pp. 147–153, 1993.

[89] H. S. Longpré, J. R. Potvin, and M. R. Maly, "Biomechanical changes at the knee after lower limb fatigue in healthy young women," *Clinical Biomechanics*, vol. 28, pp. 441–447, apr 2013.

[90] X. Qu and J. C. Yeo, "Effects of load carriage and fatigue on gait characteristics," *Journal of Biomechanics*, vol. 44, pp. 1259–1263, apr 2011.

[91] A. Muro-de-la Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications," *Sensors*, vol. 14, pp. 3362–3394, feb 2014.

[92] A. M. Howell, T. Kobayashi, H. A. Hayes, K. B. Foreman, and S. J. M. Bamberg, "Kinetic gait analysis using a low-cost insole," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 12, pp. 3284–3290, 2013.

[93] Y. Qi, C. B. Soh, E. Gunawan, K.-S. Low, and R. Thomas, "Assessment of foot trajectory for human gait phase detection using wireless ultrasonic sensor network," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 1, pp. 88–97, 2015.

[94] R. Caldas, M. Mundt, W. Potthast, F. Buarque de Lima Neto, and B. Markert, "A systematic review of gait analysis methods based on inertial sensors and adaptive algorithms," *Gait and Posture*, vol. 57, pp. 204–210, sep 2017.

[95] M. Sanchez, M. Pinto, M. Munera, and C. A. Cifuentes, "Gait Phase Detection for Lower-Limb Exoskeletons using Foot Motion Data from a Single Inertial Measurement Unit in Hemiparetic Individuals," *Sensors*, vol. 19, no. 13, p. 2988, 2019.

[96] S. R. P. C. Juri Taborri, Eduardo Palermo, "Gait Partitioning Methods: A Systematic Review," *Sensors 2016*, vol. 16, 2016.

[97] S. S. Skiena, *The data science design manual.* Springer, 2017.

[98] A. Brunelli, C. Pompili, R. Berardi, P. Mazzanti, A. Onofri, M. Salati, S. Cascinu, and A. Sabbatini, "Performance at preoperative stair-climbing test is associated with prognosis after pulmonary resection in stage i non-small cell lung cancer," *Annals of Thoracic Surgery*, vol. 93, pp. 1796–1800, jun 2012.

[99] D. Scaturro, G. Guggino, L. G. Tumminelli, F. Ciccia, and G. M. Letizia, "An intense physical rehabilitation programme determines pain relief and improves the global quality of life in patients with fibromyalgia.," *Clinical and experimental rheumatology*, vol. 37, no. 4, pp. 670–675, 2019.

[100] G. F. Bertheussen, S. Kaasa, A. Hokstad, J. A. Sandmæl, J. L. Helbostad, Ø. Salvesen, and L. M. Oldervoll, "Feasibility and changes in symptoms and functioning following inpatient cancer rehabilitation," *Acta Oncologica*, vol. 51, pp. 1070–1080, nov 2012.

[101] H. van Waart, M. M. Stuiver, W. H. van Harten, E. Geleijn, J. M. Kieffer, L. M. Buffart, M. de Maaker-Berkhof, E. Boven, J. Schrama, M. M. Geenen, *et al.*, "Effect of low-intensity physical activity and moderate-to high-intensity physical exercise during adjuvant chemotherapy on physical fitness, fatigue, and chemotherapy completion rates: results of the paces randomized clinical trial," *J Clin Oncol*, vol. 33, no. 17, pp. 1918–27, 2015.

[102] I. De Backer, G. Vreugdenhil, M. Nijziel, A. Kester, E. Van Breda, and G. Schep, "Long-term follow-up after cancer rehabilitation using high-intensity resistance training: persistent improvement of physical performance and quality of life," *British journal of cancer*, vol. 99, no. 1, pp. 30–36, 2008.

[103] K. S. Courneya, "Exercise interventions during cancer treatment: biopsychosocial outcomes," *Exercise and sport sciences reviews*, vol. 29, no. 2, pp. 60–64, 2001.

[104] T. Guiraud, M. Juneau, A. Nigam, M. Gayda, P. Meyer, S. Mekary, F. Paillard, and L. Bosquet, "Optimization of high intensity interval exercise in coronary heart disease," *European journal of applied physiology*, vol. 108, no. 4, pp. 733–740, 2010.

[105] M.-J. Hsieh, C.-C. Lan, N.-H. Chen, C.-C. Huang, Y.-K. Wu, H.-Y. Cho, and Y.-H. Tsai, "Effects of high-intensity exercise training in a pulmonary rehabilitation programme for patients with chronic obstructive pulmonary disease," *Respirology*, vol. 12, no. 3, pp. 381–388, 2007.

[106] I. Vogiatzis, S. Nanas, and C. Roussos, "Interval training as an alternative modality to continuous exercise in patients with copd," *European Respiratory Journal*, vol. 20, no. 1, pp. 12–19, 2002.

[107] R. Anna Tollbäck, R. Stefan Eriksson, R. Anna Wredenberg, and M. Göran Jenner, "Effects of high resistance training in patients with myotonic dystrophy," *Scand J Rehab Med*, vol. 31, pp. 9–16, 1999.

[108] P. Meyer, E. Normandin, M. Gayda, G. Billon, T. Guiraud, L. Bosquet, A. Fortier, M. Juneau, M. White, and A. Nigam, "High-intensity interval exercise in chronic heart failure: protocol optimization," *Journal of cardiac failure*, vol. 18, no. 2, pp. 126–133, 2012.

[109] M. Ferioli, G. Zauli, A. M. Martelli, M. Vitale, J. A. McCubrey, S. Ultimo, S. Capitani, and L. M. Neri, "Impact of physical exercise in cancer survivors during and after antineoplastic treatments," *Oncotarget*, vol. 9, no. 17, p. 14005, 2018.

[110] J. Park, D. H. Yoon, S. Yoo, S. Y. Cho, M. C. Cho, G.-Y. Han, W. Song, and H. Jeong, "Effects of progressive resistance training on post-surgery incontinence in men with prostate cancer," *Journal of clinical medicine*, vol. 7, no. 9, p. 292, 2018.

[111] A. L. Schwartz, "Fatigue mediates the effects of exercise on quality of life," *Quality of Life Research*, vol. 8, no. 6, pp. 529–538, 1999.

[112] T. Guiraud, A. Nigam, M. Juneau, P. Meyer, M. Gayda, and L. Bosquet, "Acute responses to high-intensity intermittent exercise in chd patients," *Med Sci Sports Exerc*, vol. 43, no. 2, pp. 211–7, 2011.

[113] I. C. De Backer, E. Van Breda, A. Vreugdenhil, M. R. Nijziel, A. D. Kester, and G. Schep, "High-intensity strength training improves quality of life in cancer survivors," *Acta Oncologica*, vol. 46, no. 8, pp. 1143–1151, 2007.

[114] F. Dimeo, S. Schwartz, T. Fietz, T. Wanjura, D. Böning, and E. Thiel, "Effects of endurance training on the physical performance of patients with hematological malignancies during chemotherapy," *Supportive Care in Cancer*, vol. 11, no. 10, pp. 623–628, 2003.

[115] P. H. Chang, Y. H. Lai, S. C. Shun, L. Y. Lin, M. L. Chen, Y. Yang, J. C. Tsai, G. S. Huang, and S. Y. Cheng, "Effects of a Walking Intervention on Fatigue-Related Experiences of Hospitalized Acute Myelogenous Leukemia Patients Undergoing Chemotherapy: A Randomized Controlled Trial," *Journal of Pain and Symptom Management*, vol. 35, pp. 524–534, may 2008.

[116] T. Vaidya, C. de Bisschop, M. Beaumont, H. Ouksel, V. Jean, F. Dessables, and A. Chambellan, "Is the 1-minute sit-to-stand test a good tool for the evaluation of the impact of pulmonary rehabilitation? determination of the minimal important difference in copd," *International journal of chronic obstructive pulmonary disease*, vol. 11, p. 2609, 2016.

[117] J. M. Grosbois, A. Gicquello, C. Langlois, O. Le Rouzic, F. Bart, B. Wallaert, and C. Chenivesse, "Long-term evaluation of home-based pulmonary rehabilitation in patients with copd," *International journal of chronic obstructive pulmonary disease*, vol. 10, p. 2037, 2015.

[118] Y. Zhang, L. Zhang, Y. Wang, A. Cao, C. Han, and R. Zhang, "Application of optimized cardiac rehabilitation program in exercise tolerance and quality of life of elderly patients undergoing percutaneous coronary intervention for acute myocardial infarction," *International Journal of Clinical and Experimental Medicine*, vol. 11, no. 4, pp. 4087–4093, 2018.

[119] A. Ngo-Huang, N. H. Parker, X. Wang, M. Q. Petzel, D. Fogelman, K. L. Schadler, E. Bruera, J. B. Fleming, J. E. Lee, and M. H. Katz, "Home-based exercise during preoperative therapy for pancreatic cancer," *Langenbeck's Archives of Surgery*, vol. 402, no. 8, pp. 1175–1185, 2017.

[120] D. E. Warburton, D. C. McKenzie, M. J. Haykowsky, A. Taylor, P. Shoemaker, A. P. Ignaszewski, and S. Y. Chan, "Effectiveness of high-intensity interval training for the rehabilitation of patients with coronary artery disease," *The American journal of cardiology*, vol. 95, no. 9, pp. 1080–1084, 2005.

[121] F. Cramp and J. Byron-Daniel, "Exercise for the management of cancer-related fatigue in adults," *Cochrane database of systematic reviews*, no. 11, 2012.

[122] . M. R. F. Michael, K., "Ambulatory activity intensity profiles, fitness, and fatigue in chronic stroke," *Topics in stroke rehabilitation*, vol. 14, no. 2, pp. 5–12, 2007.

[123] C. S. Kampshoff, M. J. Chinapaw, J. Brug, J. W. Twisk, G. Schep, M. R. Nijziel, W. van Mechelen, and L. M. Buffart, "Randomized controlled trial of the effects of high intensity and low-to-moderate intensity exercise on physical fitness and fatigue in cancer survivors: results of the resistance and endurance exercise after chemotherapy (react) study," *BMC medicine*, vol. 13, no. 1, p. 275, 2015.

[124] C. S. Kampshoff, L. M. Buffart, G. Schep, W. van Mechelen, J. Brug, and M. J. Chinapaw, "Design of the resistance and endurance exercise after chemotherapy (react) study: a randomized controlled trial to evaluate the effectiveness and cost-effectiveness of exercise interventions after chemotherapy on physical fitness and fatigue," *BMC cancer*, vol. 10, no. 1, p. 658, 2010.

[125] M. Emtner, M. Herala, and G. Stålenheim, "High-intensity physical training in adults with asthma: A 10-week rehabilitation program," *Chest*, vol. 109, no. 2, pp. 323–330, 1996.

[126] K. M. Thijs, A. G. De Boer, G. Vreugdenhil, A. J. Van De Wouw, S. Houterman, and G. Schep, "Rehabilitation using high-intensity physical training and long-term return-to-work in cancer survivors," *Journal of Occupational Rehabilitation*, vol. 22, pp. 220–229, jun 2012.

[127] Y. Beniamini, J. J. Rubenstein, L. D. Zaichkowsky, and M. C. Crim, "Effects of high-intensity strength training on quality-of-life parameters in cardiac rehabilitation patients," *American Journal of Cardiology*, vol. 80, pp. 841–846, oct 1997.

[128] S. Persoon, M. J. Kersten, M. J. ChinAPaw, L. M. Buffart, H. Burghout, G. Schep, J. Brug, and F. Nollet, "Design of the EXercise Intervention after Stem cell Transplantation (EXIST) study: A randomized controlled trial to evaluate the effectiveness and cost-effectiveness of an individualized high intensity physical exercise program on fitness and fatigue in patients with multiple myeloma or (non-) Hodgkin's lymphoma treated with high dose chemotherapy and autologous stem cell transplantation," *BMC Cancer*, vol. 10, dec 2010.

[129] C. Freyssin, C. Verkindt, F. Prieur, P. Benaich, S. Maunier, and P. Blanc, "Cardiac rehabilitation in chronic heart failure: Effect of an 8-week, high-intensity interval training versus continuous training," *Archives of Physical Medicine and Rehabilitation*, vol. 93, pp. 1359–1364, aug 2012.

[130] R. J. van den Berg-Emons, B. T. van Ginneken, C. F. Nooijen, H. J. Metselaar, H. W. Tilanus, G. Kazemier, and H. J. Stam, "Fatigue After Liver Transplantation: Effects of a Rehabilitation Program Including Exercise Training and Physical Activity Counseling," *Physical Therapy*, vol. 94, pp. 857–865, jun 2014.

[131] T. M. Smith, C. N. Broomhall, and A. R. Crecelius, "Physical and psychological effects of a 12-session cancer rehabilitation exercise program," *Clin J Oncol Nurs*, vol. 20, no. 6, pp. 653–9, 2016.

[132] Y. Beniamini, J. J. Rubenstein, A. D. Faigenbaum, A. H. Lichtenstein, and M. C. Crim, "High-intensity strength training of patients enrolled in an outpatient cardiac rehabilitation program," *Journal of Cardiopulmonary Rehabilitation and Prevention*, vol. 19, no. 1, pp. 8–17, 1999.

[133] L. E. Dibble, T. F. Hale, R. L. Marcus, J. Droge, J. P. Gerber, and P. C. LaStayo, "High-intensity resistance training amplifies muscle hypertrophy and functional gains in persons with parkinson's disease," *Movement Disorders*, vol. 21, pp. 1444–1452, sep 2006.

[134] J. P. Little, A. Safdar, G. P. Wilkin, M. A. Tarnopolsky, and M. J. Gibala, "A practical model of low-volume high-intensity interval training induces mitochondrial biogenesis in human skeletal muscle: Potential mechanisms," *Journal of Physiology*, vol. 588, pp. 1011–1022, mar 2010.

[135] W. J. Kop, A. Lyden, A. A. Berlin, K. Ambrose, C. Olsen, R. H. Gracely, D. A. Williams, and D. J. Clauw, "Ambulatory monitoring of physical activity and symptoms in fibromyalgia and chronic fatigue syndrome," *Arthritis and Rheumatism*, vol. 52, pp. 296–303, jan 2005.

[136] A. Weiss, T. Suzuki, J. Bean, and R. A. Fielding, "High intensity strength training improves strength and functional performance after stroke," *American Journal of Physical Medicine and Rehabilitation*, vol. 79, pp. 369–376, jul 2000.

[137] M. J. Bade and J. E. Stevens-Lapsley, "Early high-intensity rehabilitation following total knee arthroplasty improves outcomes," *journal of orthopaedic & sports physical therapy*, vol. 41, no. 12, pp. 932–941, 2011.

[138] N. Galiano-Castillo, A. Ariza-García, I. Cantarero-Villanueva, C. Fernández-Lao, L. Díaz-Rodríguez, and M. Arroyo-Morales, "Depressed mood in breast cancer survivors: associations with physical activity, cancer-related fatigue, quality of life, and fitness level," *European Journal of Oncology Nursing*, vol. 18, no. 2, pp. 206–210, 2014.

[139] M. Y. Hsiao, C. M. Li, I. S. Lu, Y. H. Lin, T. G. Wang, and D. S. Han, "An investigation of the use of the Kinect system as a measure of dynamic balance and forward reach in the elderly," *Clinical Rehabilitation*, vol. 32, no. 4, pp. 473–482, 2018.

[140] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, *et al.*, "Scikit-learn: Machine learning in python," *the Journal of machine Learning research*, vol. 12, pp. 2825–2830, 2011.

[141] L. McInnes, J. Healy, and J. Melville, "Umap: Uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*, 2018.

[142] A. Strassmann, C. Steurer-Stey, K. Dalla Lana, M. Zoller, A. J. Turk, P. Suter, and M. A. Puhan, "Population-based reference values for the 1-min sit-to-stand test," *International journal of public health*, vol. 58, no. 6, pp. 949–953, 2013.

[143] S. Parkinson, A. Campbell, W. Dankaerts, A. Burnett, and P. O'Sullivan, "Upper and lower lumbar segments move differently during sit-to-stand," *Manual therapy*, vol. 18, no. 5, pp. 390–394, 2013.

[144] A. M. Barsevick, T. Newhall, and S. Brown, "Management of cancer-related fatigue," *Clinical journal of oncology nursing*, vol. 12, no. 5 Suppl, p. 21, 2008.