# POLITECNICO DI TORINO

**MASTER's Degree in Biomedical Engineering**

Master's Degree Thesis

# Analysis of movement patterns and quantitative parameters from inertial data to assess patients motor performances during tele-rehabilitation


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# Summary

Tele-rehabilitation is emerging as a new opportunity to deliver rehabilitation at patients' home, by extending healthcare services accessibility, ensuring continuity of care and remote monitoring. This is a consequence of COVID-19 pandemic, but it was already becoming particularly relevant for the management of a growing elder population and the higher incidence of chronic diseases. Exercise and specific rehabilitation programs are indeed known to lead to improved motor skills for various clinical conditions.

Numerous efforts are being carried out, therefore, on the development of portable devices, suitable for home use, that exploit different technologies, such as cameras or wearable inertial measurement units (IMUs). In the literature, many studies can be found facing the challenge of exploiting IMUs data to provide clinically relevant information on patients health status. IMUs are being widely used in gait analysis, for example, with the goal of assessing gait in out-of-the-lab conditions and for its continuous monitoring. Another common application is the extraction of quantitative parameters during the execution of simple movements, often taken from clinical scales, to characterize patient motor capabilities and progresses.

However, to foster adoptions of tele-rehabilitation solutions in clinical practice, there is still a need to assess patient performances and improvements from IMUs data while executing rehabilitation exercises commonly prescribed at home.

Therefore, this thesis project aims at investigating inertial data from a wide set of exercises of variable complexity, included in a rehabilitation protocol proposed by the Neurorehabilitation Clinic, Ospedali Riuniti of Ancona, and widely adopted in clinical practice. The main objective is to explore a method and find out relevant parameters to support clinicians in the evaluation of remote exercise sessions. This project has been realized in collaboration with the research company Henesis, that made available two datasets: one on healthy volunteers and a second on pathological subjects, coming from a clinical trial. The inertial data were acquired using ARC intellicare, a medical device that allows motor and respiratory tele-rehabilitation.

This thesis proposes a case study on 2 Parkinson and 2 Long COVID-19 patients: their data were processed and analyzed through a Python code, in order to find averaged movement patterns for each exercise. The patterns obtained from the patients have been compared to those from the healthy population, to look for any abnormalities or deviations. In addition, duration of exercises executions and a Dynamic Time Warping (DTW) score have been investigated to provide a complementary quantitative description. Average duration of repetitions for a subset of exercises have been computed and a DTW score, a distance metric used also in other studies, has been implemented to quantify similarity of patients' movement patterns to the obtained healthy reference. A comparison is presented between DTW scores computed on data from the first and last day of the rehabilitation program. Results show that this metric could potentially be used to analyse differences in motor performances of Parkinson and long COVID-19 patients. Future developments will include extension of the analysis to all patients and all exercises of the dataset. Correlation of results with clinical scales is then necessary to validate the proposed approach.

# Acknowledgements

I would like to thank my tutor, Dr. Alice Mantoan and my supervisor, Professor Agostini Valentina for the time and the expertise they made available to help me during this project.

*"To my Mum, Dad, Naomi and Babcia Irena"*
*who believed in me*
*giving me the strengths to persevere*

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# Chapter 1

# Introduction

Tele-rehabilitation is emerging as a new opportunity to deliver rehabilitation at patients' home, by extending healthcare services accessibility, ensuring continuity of care and remote monitoring. This is a consequence of COVID-19 pandemic, but it was already becoming particularly relevant for the management of a growing elder population and the higher incidence of chronic diseases.

It is known that patients with motor difficulties, chronic diseases or elderly people would need care and continuous assistance. In this cases, rehabilitation protocols are often prescribed to maintain or improve their health status and enable their recovery. Some of these involve performing motor exercises, which is why they need to visit rehabilitation centres. For elderly people, who suffer from complex illnesses or who live in remote locations [1], it is difficult to travel to these facilities.

Tele-rehabilitation services could be the solution in these cases [2] [3] [4] [5]. During the COVID-19 pandemic, the importance of implementing services that can assist patients from home so that they do not have to travel to hospitals and put their health at risk, became clearer [6] [7]. In addition, telemedicine [8] and tele-rehabilitation services in particular, may alleviate the costs of the healthcare system by relocating lower risk activities to the home environment.

Tele-rehabilitation enables various forms of exercise including motor rehabilitation training, speech therapy, respiratory training and many others [9]. Different types of patients could benefit from a tele-reahabilitation service, especially stroke survivors [10] [11] [12], patients with cardiovascular disease [13], chronic respiratory disease [14] [15] [16] [17] [18], subjects with speech impediments [19] [20] and patients suffering from neurological disease. Through this service, the patient can perform the exercises of the rehabilitation protocols from the comfort of his or her own home and contact the doctor in case of need. There are different types of services, some allow the patient to do the exercises under video surveillance of nurses or therapists in real time, while others allow the patient to do exercises in an unsupervised manner.

These tele-rehabilitation services do not replace standard medical procedures but complement them, enriching them and giving the patient the possibility of exercising from the comfort of home by taking away the burden of travel and encouraging patient empowerment and self-management of long-term conditions.

Numerous efforts are being carried out, therefore, on the development of portable devices, suitable for home use, that exploit different technologies, such as cameras and/or wearable inertial measurement units (IMUs) [21]. Since many tele-rehabilitation systems exploits wearable inertial sensor, a brief analysis of the state of art has been conducted.

## 1.1 State of the art of wearable inertial sensors

In the literature, many studies can be found facing the challenge of exploiting inertial sensors data to provide clinically relevant information on patients health status. Inertial sensors are a cost-effective method used to capture human movement data and since many tele-rehabilitation systems exploits them, a brief analysis of the state of art has been conducted. Wearable inertial sensor may be used for different applications; these include: recognize and sort tremor or FoG, estimation of joint kinematics and movements, real- time feedback to the patients, gait analysis.

Inertial sensors can be used in combination with machine learning algorithms to recognize and sort resting tremor and bradykinesia in patients suffering from Parkinson disease [22]. In this study, conducted by Mahadevan, they collected accelerometer data from a single wrist-worn device in order to develop a binary resting tremor classifier using a machine learning approach. Their analysis steps include context detection and symptom severity estimation in order to precisely distinguish between the two cases. To asses the resting tremor they analyzed amplitude and constancy of the inertial signal.
Another study [23] focused on quantification of tremor and bradykinesia in patients with Parkinson disease. They recorded movements of the upper limbs with gyroscope positioned on the forearms. An algorithm was proposed to detect and quantify tremor and another one to quantify bradykinesia. The estimated tremor amplitude and bradykinesia had a high correlation to the MDS-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) tremor sub scores and bradykinesia sub scores.

Referring again to Parkinson disease, a wrist mounted inertial sensor was used to detect freezing of gait (FoG) episodes [24]. A time-domain analysis was performed and entropy was assessed. They observed that during FoG episodes there is an increase in frequency movement and that mean and standard deviation of acceleration increase during or prior to the FoG event. Higher values of power were also observed during the episodes. A frequency domain analysis was performed as well on the inertial signals and a freezing index was found as a ratio between the power contained in the gait-freezing [3-8Hz] and the locomotion frequency [0.5-3Hz].

Machine learning algorithms were used in [25] to track the presence of tremor and dyskinesia in Parkinson disease patients who wore an accelerometric and surface-elecromyographic sensor. The implemented tool enables to process data acquired at home during activity of daily living. It allows to distinguish between voluntary movements and dyskinesia observing whether rapid changes occurs in acceleration. By studying power spectral densities they were able to distinguish tremor from dyskinesia.

Many studies focus also on the use of inertial sensors to estimate joint kinematics and movements. In [26] they used three sensors positioned of the dominant leg in order to develop a machine learning algorithm to estimate knee joint kinematics while the subject performed a vertical drop jump. For validation purposes of the machine learning algorithm, a stereophotogrammetric system was used.

Inertial sensors in combination with virtual reality were used in [27]. The aim of the study was to estimate wrist position during reaching exercise in people with chronic stroke. Patients had to perform movements taken from the Action Research Arm Test (ARAT) and Fugl-Meyer Assessment of Upper Extremity (FMA-UE) with inertial sensors positioned on the upper limbs. The ARAT is a test to assess upper limbs performance in stroke recovery and brain injury [28]; it was originally used to examine the recovery of patients with damage to the cortex. FMA-UE is used to assess motor functioning in patients with post-stroke hemiplegia [29]. Wrist position vector was plotted over time to determine trajectory-based metrics, such as trajectory error and reach-path-ratio. Rehabilitation outcomes of the study showed improvements in reaching ability pre and post therapy.

IMUs have been used to characterize upper extremity motion in subjects performing the ARAT test also in the study of [30]. The purpose of this work was to realize a database on the range of motion (RoM) of upper extremity joints during the execution of ARAT test movements and activities of daily living.

Many other studies, such as [21], focus on providing a biofeedback to patients performing physical therapy exercises. Subjects had a single inertial sensor positioned on one of the legs and were asked to perform exercises. A machine learning algorithm trained with time and frequency domain features was validated in a real-world setting in order to improve its accuracy.

Face-to-face feedback from therapists combined with the use of wearable sensor, can increase therapy efficiency because valuable information can help healthcare professionals in decision making. The study [31] focuses on swimming rehabilitation protocols and on providing a real-time feedback. A single 6-DoF (Degrees of Liberty) inertial sensor, attached on the lower back, provided information on stroke count, stroke style detection, stroke rate measurements, analysis of symmetry, stroke time and stroke rotation angle symmetry. Variations in swimming intensity, which can be a result of tiredness, could be detected using a machine learning algorithm, as well as asymmetry in the rotation angle magnitude related to the difference in power used during the left-hand and right-hand stroke.

IMUs are also used for rehabilitation of patients after knee replacement surgery. [32] used wearable sensors to provide exercise biofeedback for orthopaedic rehabilitation. The medical device adopted was composed of a sensor to be positioned on the shin and a tablet with an APP that counts repetitions, the machine learning system was able to give a feedback on the performance of the repetitions.

Inertial sensors can also be used for estimating 3D lower limb joint kinematics as in the study proposed by Bonnet et al. [33]. They used a single IMU located on the lower part of the tibia to collect data of subjects performing 5 rehabilitation exercises in order to monitor hip and knee joint angles. Outcomes were validated through a stereophotogrammetric system.

Bevilacqua et al. [34] proposed an algorithm that automatically analyse inertial data. The aim was to create a tool that supports at home unsupervised rehabilitation post knee surgery providing a feedback on exercise execution to the patients.

On the topic of feedback provided directly to the patient, a study [35] used three inertial sensor units positioned on the thigh, shin and on the foot of the leg being exercised. They created a tool that evaluates exercise performance as correct if the exercise is executed with correct alignment, quality of movements and speed or incorrect if there is an error in one of this features. If the exercise was incorrect, the patients would be given a severity score of the error.

IMUs are being widely used in gait analysis, for example, with the goal of assessing gait in out-of-the-lab conditions and for its continuous monitoring. One of the most common test performed on patients to asses their gait is the 6 Minutes Walking Test (6MWT) [36]. In this work in order to quantify changes during the gait, inertial sensors and data elaboration using DTW (Dynamic Time Warping) score was used.

### 1.1.1 The problem

The literature review conducted on wearable inertial sensor gives several examples of their use but to foster adoptions of tele-rehabilitation solutions in clinical practice, there is still a need to assess patient performances and improvements from IMUs data while executing many different movements, more similar to rehabilitation exercises commonly prescribed at home.

There is indeed a lack of validated studies and approaches for the estimation of metrics to characterise movement during rehabilitative exercises, and not considering only a few of them, but which are valid for many different exercises, with different complexity. In fact in literature, most of the studies propose validations on only few exercises or a specific movement [27]. Clinical rehabilitation protocols are usually composed by several exercises that target different parts of the body so it would be helpful for therapists to have tools that enabled them to asses patients performances quantitatively. Different studies [27] [23] focus on the importance of correlating data from inertial sensors to clinical evaluation scores in order to provide quantitative information to healthcare professionals while scoring patients. Most of clinical evaluation scales are based upon the skill and experience of the physician. Often, moreover, during visits to check whether improvements have occurred and update clinical scores, the patient does not perform as he or she normally would do at home because he or she feels uncomfortable. It would be a good opportunity for doctors to also exploit quantitative data acquired during unsupervised at home training to help them during the evaluation process.

### 1.1.2 Aim of the project

In order to adopt tele-rehabilitation solutions in clinical practice, there is still a need to assess patient performances from IMUs data while executing different exercises commonly prescribed at home.

Therefore, this thesis project aims at investigating data from 5 inertial sensors placed on lower and upper limbs and on the trunk to see if there may be quantitative parameters that could help therapists assessing patients performances while executing a wide set of exercises of variable complexity, included in a rehabilitation protocol proposed by the Neurorehabilitation Clinic, University Hospital “Ospedali Riuniti” of Ancona, and widely adopted in clinical practice. The main objective is to explore a method and find out relevant parameters to support clinicians in the evaluation of remote exercise session.

Some possible approaches, chosen from the literature, are explored and applied to a dataset acquired via an IMU-based medical device on Parkinson and Long COVID-19 patients who were performing different rehabilitative exercises.

# Chapter 2

# Materials & Methods

This project has been realized in collaboration with a research company based in Parma, Henesis srl, that made available two datasets of inertial data. One from healthy volunteers is the result of an company internal acquisition campaign, while the second, on pathological subjects, comes from a clinical trial (ClinicalTrials.gov Identifier: NCT05074771) led by Henesis in collaboration with the Department of Experimental and Clinical Medicine, "Politecnica delle Marche" University of Ancona and the Neurorehabilitation Clinic, University Hospital "Ospedali Riuniti di Ancona" of Ancona. In the following sections, the acquisition device will be described (Section 2.1.1) and more details on the datasets will be provided (Section 2.2). The approach developed to process and analyse the data will be then presented (Section 2.5).

## 2.1 Data acquisition

### 2.1.1 ARC intellicare

ARC intellicare (ARC), a medical device conceived and produced by Henesis, allows home motor and respiratory tele-rehabilitation [37] [38] [39]. This medical device (MD) is intended to support respiratory and motor rehabilitation of people suffering from one or more of the following conditions:

- Neurological or neuromotor disorders (post-stroke, Parkinson's Disease, Multiple Sclerosis, Long COVID-19 syndrome, chronic neuropathies);
- Loss of strength and/or muscle mass due to trauma, interventions, or situations of fragility linked to chronic, oncological or ageing-related conditions;
- Impaired respiratory function.

The use of ARC is indicated in stable clinical conditions (post-acute phase, in remission or post-surgery), to favour and guide patients in the conduct of motor and/or respiratory exercises at home, to encourage and monitor the adherence to the individual rehabilitative plan prescribed by a rehabilitation professional [38] [39].

ARC-Intellicare is indicated for:

- assisting an outpatient or inpatient rehabilitation process;
- supporting continuity of care and community care services in patients for whom a home rehabilitation process is necessary (including senior living facilities) or in isolation.

ARC, consisting of hardware components and integrated software, is classified in class I according to rule 13 of Annex VIII of the EU Regulation 2017/745. It includes 5 Inertial Measurement Units (IMU) that should be positioned on limbs and trunk, and a tablet with a dedicated Application (APP) installed used to acquire and monitor the exercises performed by the patient as shown in Figure 2.1. Figure 2.2 and Figure 2.3 details the positioning of sensors on the wrist, on the ankle and on the trunk. Figure 2.4 shows ARC tablet, the APP and the charging station with the five sensors inserted. The charging station allows sensors and tablet to be recharged when not in use. Data of accelerometers and gyroscopes are collected while patients wear the sensors and perform the prescribed exercises.—-

The device allows therapists to prescribe their own sets of exercises depending on the specific therapeutic needs, and to guide patients in their execution, while they are at home. The device, therefore, supports the therapist allowing him or her to remotely monitor the rehabilitation path and maintain contact with the user. In summary, ARC represents a support for motor and functional skills during the rehabilitation therapy, both in a clinical/professional setting and at home. Particularly, the home use of the device helps the patient to follow the prescribed therapy in compliance with the physiotherapist's instructions. ARC aims to help patients needing physical rehabilitation to perform their rehabilitative programs without the physical presence of a professional (e.g. physiotherapist, physical medicine specialist, occupational therapist).

This system has been used to collect data that constituted both healthy and patients' dataset. Healthy subjects dataset has been acquired using a customized version of the APP that allowed therapists to mark the beginning and the end of every exercise repetition. The APP showed a start and a end button through which the experimenter, while observing the subject, performed a segmentation of the inertial signals. Figure 2.5 details the APP user interface that allowed to segment repetitions simpling by clicking the start and end button on the screen. Figure 2.6 shows the interface that allowed therapists to save the sessions' registrations confirming their validity.

Patients dataset has been acquired using the standard version of the APP that allows patients to select exercises and automatically counts the number of performed repetitions thanks to a proprietary machine learning algorithm. As the subject performed the exercise, the acceleration and the angular velocity were recorded and saved into files. Every file was named including the exercise name, the day and the time in which the exercise was performed. Each file corresponds to an exercise session. The two datasets are respectively composed of 686 and 3688 files.

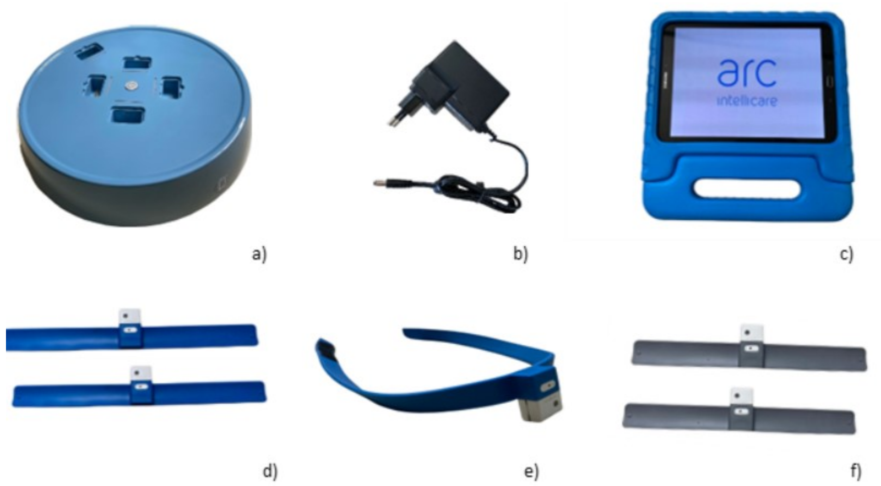


**Figure 2.1:** ARC intellicare. a) Charging station, b) Power adapter, c) Tablet inserted in case, d) Ankle supports with inertial sensors, e) Collar with inertial sensor, f) Wrist supports with inertial sensors. Reproduced with permission of Henesis Srl.

**Figure 2.2:** Sensor positioning on the wrist and on the ankle. Reproduced with permission of Henesis Srl.

**Figure 2.3:** Sensor positioning on the trunk. Reproduced with permission of Henesis Srl.

**Figure 2.4:** ARC tablet on the left and ARC sensor on the right. Reproduced with permission of Henesis Srl.

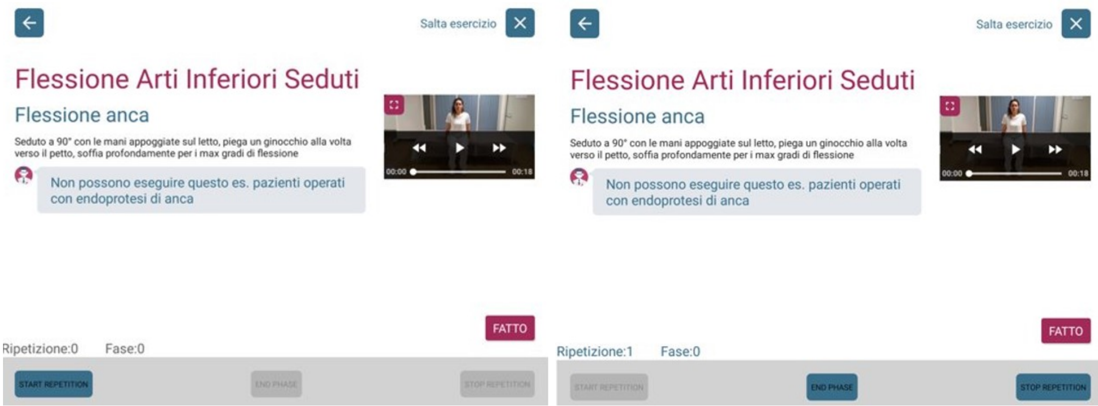


**Figure 2.5:** APP interface for healthy subjects' repetitions segmentation. Two buttons were available to the user to include in the stored data a marker in correspondence of the repetition start and stop timestamp. Reproduced with permission of Henesis Srl.

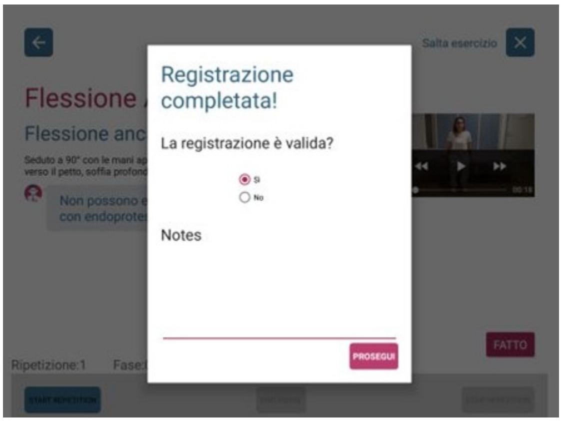


**Figure 2.6:** APP interface for healthy subjects repetition segmentation. At the end of each exercise acquisition session, the user could mark the registration as valid or invalid. Reproduced with permission of Henesis Srl.

### 2.1.2 Inertial sensor description

The inertial sensors that are used by ARC are MetaMotionR r0.4 produced by MBIENTLAB INC [40]. These rechargeable sensors contain an accelerometer, a gyroscope, a magnetometer, a temperature sensor and a barometer. For this specific application, only data from the accelerometer and gyroscope were stored and used. Data are sampled at 50Hz. Unit of measurement for acceleration is g [m/s^2] and for angular velocity is [°/s]. Neither pre-processing techniques nor filtering have been applied to the raw data. Some options of filtering have been explored at the beginning of the project but they were not used. This choice was made in order to use the same data used as input to train the machine learning algorithm implemented in the device to automatically recognize and count exercise repetitions.

Figure 2.7 shows the Cartesian axis reference system defined in the sensor [40]. Figure 2.8 shows the position of the five inertial sensors on the body, their reference systems orientation and the mapping with corresponding anatomical plans and physiological movements.

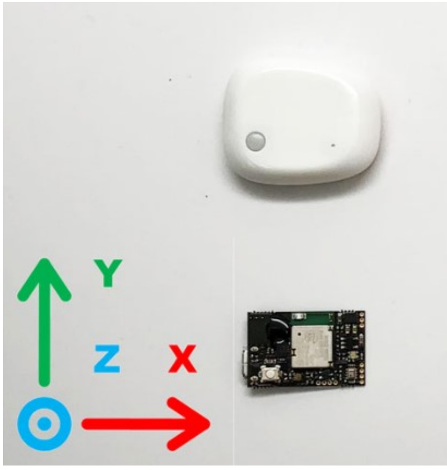


**Figure 2.7:** Cartesian axis configuration [40]

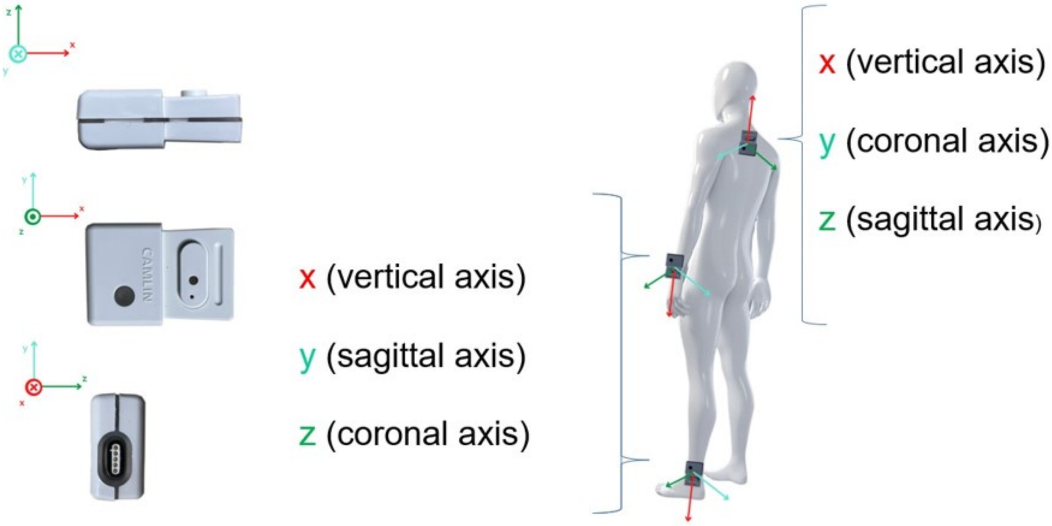


**Figure 2.8:** Sensors configuration. It shows the reference system of the sensors on the body. Reproduced with permission of Henesis Srl.

### 2.1.3 Exercise library

This medical device provides a wide library of exercises through which the therapist can create different rehabilitation protocols. Exercises can be grouped by the doctor into sets according to the patient's needs and goals.

The library, consisting of more the 60 exercises, was created by a clinical tr of the Neurorehabilitation Clinic, University Hospital "Ospedali Riuniti di Ancona" of Ancona [41]. For this project only exercises that needed inertial sensors for their execution are considered, e.g most of respiratory and stretching exercises do not need to use the wearable devices so their data are not recorded nor presented here. The clinical equip proposed this rehabilitation protocol during the COVID-19 pandemic and made it available though an online web platform [42] to support patients continuity of respiratory and motor therapy from home during the lockdown period in 2020. The protocol was also published by the Italian Society of Physical and Rehabilitative Medicine (SIMFER) [43].

All exercises are shown through a video tutorial in which a therapist demonstrates how to perform them correctly so that the patients could review them and try to avoid any mistakes in the execution. The exercises could be grouped into six categories: mobility, coordination, core stability, respiratory, static stretching, strengthening. The targeted body areas are: upper limbs, lower limbs, trunk and full body. Each exercise was scored from 1 to 5 according to its difficulty. The higher the score associated with each exercise was, the more effort required.

Furthermore, exercises can be differentiated according to their specific patterns:

- Bilateral Symmetric (BS). The exercise requires a symmetric movement of both the arms or ankles.
- Bilateral Alternated (BA). An exercise repetition is obtained when the same movement is done not at the same time, but alternating the two limbs.
- Mono-lateral Left (ML). Only left side of the body is interested.
- Mono-lateral Right (MR). Right side of the body is targeted.
- Respiratory (RE). Respiratory movements.
- Static (ST). E.g stretching exercises.

Some exercises require equipment such as a chair, a stick, an elastic band, weights, bed or a step. In order to refer to the exercises in a simple manner, a system of abbreviations has been adopted in which the first part indicates the targeted body area, the second part indicates the pattern and the last part stands for the exercise number. Ex. L.BA.001 (Targeted body area: Lower; Type of movement: Bilateral Alternated; Exercise number: 001). Table 2.1 encloses some examples of exercises included in the Ancona Neurorehabilitation Clinic's protocol.

| Pattern | Category | Name | Target Body Area | Equipment |
|---|---|---|---|---|
| BS | Mobility | Arm elevation using a stick while sitting | Upper Limbs | Stick |
| BS | Mobility | Arm elevation using a stick while standing | Upper Limbs | Stick |
| BS | Mobility | Arm pushing exercise | Upper Limb | Weights |
| BS | Mobility | Arm elevation and abduction | Upper Limbs | Chair |
| BA | Mobility | Lateral Slides | Lower Limbs | Chair |
| BA | Mobility | Hip flexion | Lower Limbs | Bed |
| BA | Balance | Single-support standing station | Lower Limbs | Chair |
| BA | Balance | Tandem with abducted limbs | Lower Limbs | - |
| BA | Mobility | Weight transfer to lower limbs | Lower Limbs | - |
| BS | Strength | Squat | Lower Limbs | Chair |
| RE | Respiratory | Open-mouth exhalation | Full body | Bed |
| ST | Stretching | Lateral torso tilt | Trunk | - |
| ML | Mobility | Extrarotation of left shoulder in decubitus with or without resistance | Upper Limbs | Bed |
| MR | Strength | Extrarotation of right shoulder in decubitus with or without resistance | Upper Limbs | Bed |
| BA | Strength | Front lunge without support | Lower Limbs | - |
| BA | Mobility | Step forward | Lower Limbs | Chair |
| BA | Mobility | Step back | Lower Limbs | Chair |
| BA | Mobility | Side step | Lower Limbs | Chair |

**Table 2.1:** Exercises Protocol examples: details of some exercises included in the rehabilitation protocol

## 2.2 Dataset description

As already introduced, ARC intellicare has been used to acquire inertial signals from healthy subjects and patients. In this project, two datasets were exploited: one from a healthy population and the second collected on Parkinson and Long COVID-19 patients during a clinical trial led at University Hospital "Ospedali Riuniti di Ancona" of Ancona (ClinicalTrials.gov Identifier: NCT05074771). In the following sections more details are provided respectively.

### 2.2.1 Healthy dataset

This dataset was collected recording healthy subjects using ARC and a customized version of the APP (Section2.1.1). They performed the prescribed exercises with a surveillance of an experimenter who digitally segmented the repetitions using a specific version of the APP that allowed him to do so. Through this APP the experimenter was able to click the start and end button at the beginning and end of each repetition thus segmenting the raw inertial signal (Figure 2.5). Using this information all the inertial signals were recorded storing labels that indicates the starting point, the ending and the change of phase in each repetition. Change of phase refers to exercises in which the patients had to use both limbs, i.e. bilateral alternated, and indicates the moment when he or she switched the limb during the execution. This dataset has been adopted as "gold standard" or "template" for each exercise to make, then, comparison with the patients' dataset. Table 2.2 reports the general information of healthy subjects whose data were acquired. Healthy subjects data has been used to train the machine learning algorithm that counts repetitions.

| | Healthy subjects<br>N = 17 |
|---|---|
| Age(years), mean (SD) | 61.9±11.0 |
| Sex | 9M, 8 F |
| Weight, mean (SD) | 71.1±9.9 |

**Table 2.2:** Description of healthy subjects data

### 2.2.2 Patients dataset

Patients' dataset has been acquired during a clinical trial conducted in 2021 in collaboration with the Università Politecnica delle Marche. ARC has been used in the clinical trial "Home REhabilitation and Monitoring of People in post-covid Condition Through ARc-inTellicare Platform (RESTART/RICOMINCIARE) (RICOMINCIARE)" (ClinicalTrials.gov Identifier: NCT05074771 [44]). This study was approved by the Ethical Committed of the Marche Region (C.E.R.M.).

The clinical trial focuses on two diseases:

- Parkinson. It is a neurodegenerative disorder of the central nervous system that affects the motor system [45] [46]. Most common symptoms are tremor, rigidity, bradykinesia/akinesia and postural instability.

- Post COVID-19 or Long COVID-19 [47] [48]. COVID-19 is an infectious disease. Motor symptoms which distinguish Long COVID-19 are: chest pain or tightness, extreme tiredness, dizziness, joint pain.

During the clinical trial, 11 Long COVID-19 and 10 Parkinson patients have been enrolled, among those who belong to the assistance services of the Neurorehabilitation Clinic ("Università Politecnica delle Marche" and "Ospedali Riuniti di Ancona"); see Table 2.3 for detailed information. They have been prescribed a motor tele-rehabilitation protocol to follow for a month.

| | Parkinson | Long COVID-19 |
|---|---|---|
| Number of patients | 10 | 11 |
| Age(years), mean (SD) | 74.7±3.6 | 57.6±12.6 |
| Sex | 7 M, 6 F | 6 M, 5 F |
| Weight, mean (SD) | 79.3±14.9 | 77.73±17.0 |

**Table 2.3:** Information about the clinical trial's participants.

The study has been conducted as follow:

- Baseline Assessment (t0). Clinical score were used to assess patients initial health status.

- Rehabilitation protocol prescription. A personal program of exercises was prescribed to each participants according to his or her conditions and clinical needs. The clinicians could specify the number of repetitions to perform for each exercise and their weekly frequency. Such program could be updated in any moment by the medical doctor, based on the patient reported outcomes and exercise performances.

- One month of unsupervised rehabilitation at home. It was monitored from remote by the therapist. During this period, patients were asked to be adherent to the rehabilitation program prescribed as much as they could. A videocall was also scheduled weekly with the clinical team. Inertial data were collected during each exercise session and stored.

- Final clinical assessment (t1). The doctor examined the patients to verify if there has been an overall improvement of their medical conditions and tracked the changes using the clinical scales listed into the study protocol.

During Baseline Assessment, the therapist assessed patients' general health condition using different clinical scale: the BFI (Brief Fatigue Inventory), EUROQoL 5D, FAC (Functional Ambulation Categories), PDSS (Panic Disorder Severity Scale), the 6MWT (6 Meter walking Test) and MSD-UPDRS (Movement Disorder Society-Unified Parkinson's Disease Rating Scale) are some examples.
The BFI [49] is a rapid assessment of fatigue severity commonly used for screening. It was originally proposed specifically for cancer patients but now it is widely used also for other pathologies [50] because it is a rapid and ready to use questionnaire with only four main questions.
EUROQoL 5D [51] [52], instead, evaluates the generic quality of life. It is composed of five questions for each of the different dimensions of mobility, usual activities, pain and discomfort, self-care and anxiety or depression.
The Functional Ambulation Categories (FAC) is a functional walking test useful to determine how much support the patient require while walking [53] [54].
The 6 Meter Walking Test [6MWT] [36] [55] was conceived in the field of cardiovascular rehabilitation. It became common in neurology to evaluate fatigue and disability in walking. The patient is asked to walk for 6 minutes along a corridor with a rigid walking surface and for a length of at least 30m. With the self-pace mode, the patient is asked to walk at the preferred speed and can make stops, resume walking and use a stick. During the examination, heart rate and saturation are monitored and the following parameters are annotated: meters travelled to the first stop, time, number of stops, the total distance covered, the perception of fatigue.
The Movement Disorder Society-Unified Parkinson's Disease Rating Scale, MDS-UPDRS, was developed to evaluate non-motor and motor experiences of daily living in patients suffering of Parkinson disease. This scale can be used in a research setting as well as in a clinical setting. [56]. It is composed by four parts:

- Part I focuses on non-motor experiences of daily living,
- Part II focuses on motor experiences of daily living,
- Part III consists on motor examination,
- Part IV focuses on motor complications.

It is specific for Parkinson patients, so it was used only to assess their status at the beginning and at the end of the clinical trial.
The Panic Disorder Severity Scale (PDSS) [57] is a self report scale useful to measure the severity of panic attacks and panic disorder symptoms [58]. It is not time consuming and it is sensitive to changes so it can be used to track symptoms over time. The scale is composed by seven questions and can be used for both adolescents and adults.

## 2.3 Data Segmentation

Data segmentation of patients signals was important to obtain the repetitions that later will be analyzed. Before this step, it was necessary to inspect and describe healthy pattern in order to have a template so that later was possible to segment only the correct patients repetitions.

### 2.3.1 Raw data: visual inspection & interpretation

The first step to understand the signals, was to analyse the dataset of healthy subjects and describe the pattern of acceleration and angular velocity for all sensors and all exercises. The work was carried out by looking for a repetitive pattern in the signals and describing it by distinguishing between right and left acceleration, right and left angular velocity, trunk acceleration and angular velocity. In order to correctly detect each pattern, every exercise was performed while the inertial signals were observed real-time. This allowed to link each movement to the corresponding anatomical plane.
The exercise patterns and the corresponding description were reported in a document and used as support for the signal segmentation, explained in the next paragraph.

### 2.3.2 Segmentation method

The second task, required to perform the processing as described in the next section, was to segment patients data that did not have any start, end and phase marks because they were collected unsupervised i.e. without the presence of an experimenter that could record the labels for each exercise repetition through the dedicated APP (Section 2.2.1).
A company internal tool, called Data Dashboard, that allows data visualization and segmentation, was used. Through this Dashboard, accelerations and angular velocity were visible and after recognizing the pattern of every singular repetitions, labels were manually positioned for each session. A session refers to when the patient selects a specific exercise and performs at least one movement. Segmenting patients data was necessary also to exploit the same data to re-train the proprietary

machine learning algorithm to improve its accuracy. Figure 2.9 shows the home page of the signal segmentation tool Dashboard. Figure 2.10 represents the tools used to draw the start, stop and phase marks on the signals. Figure 2.11 shows an example of a non segmented signal. It details the left lower limb acceleration (above in the figure) and right lower limb acceleration (below in the figure). X axis is orange, Y axis is light green and Z axis is dark green. Figure 2.12 shows the same signal but segmented with the starting label, the end point and the phase. The phase is represented by dotted lines and it is specific for bilateral alternated exercises and states the moment in which the patient switch limb. The segmentation boxes are non-consecutive as the patient was asked to stop after each repetition so that the machine learning algorithm could count the repetitions and segmentation could be easier.

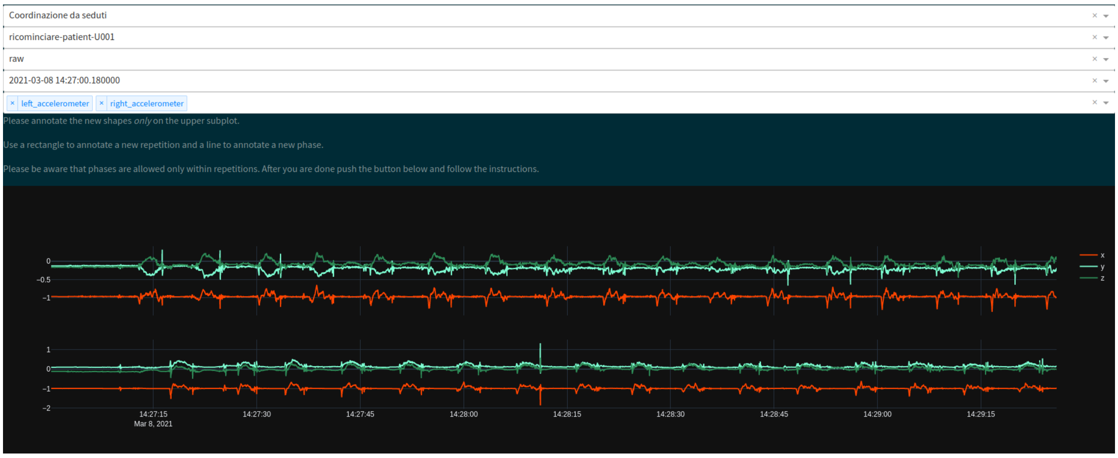


**Figure 2.9:** Data Dashboard homepage: Henesis proprietary tool for data visualization and segmentation. From the top menu it is possible to select: the exercise, the subject, the session and to review raw or already segmented data. Reproduced with permission of Henesis Srl.

All the segmentation process has been manually done for all patients, all exercises and all sessions. If same patients performed the same exercise multiple times in the same day, all the corresponding generated sessions were considered in the segmentation. This process took more than a month to be completed due to the large amount of data. Fundamental was the preliminary analysis of healthy data which led to a detailed signal description. Only correct repetitions for each exercise were segmented. All movements that did not have any similarity with the healthy pattern were not included. Healthy subjects pattern was used to discriminate and to segment patients data. This underlines the importance of the initial work done studying and describing all subjects patterns.

**Figure 2.10:** Dashboard's segmentation tools. Using the pen tool, the phase was drawn; using the box tool, it was possible to draw the start and end label. The home button allowed to return to the homepage of the Dashboard. Reproduced with permission of Henesis Srl.

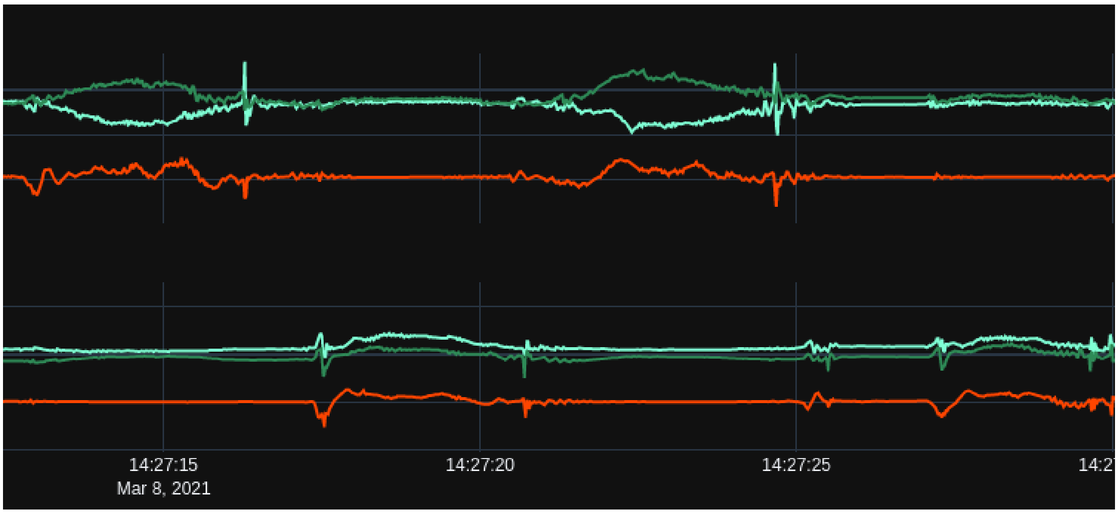


**Figure 2.11:** Example of a raw signal, not yet segmented. It details the left lower limb acceleration (above in the figure) and right lower limb acceleration (below in the figure). X axis is orange, Y axis is light green and Z axis is dark green. Reproduced with permission of Henesis Srl.

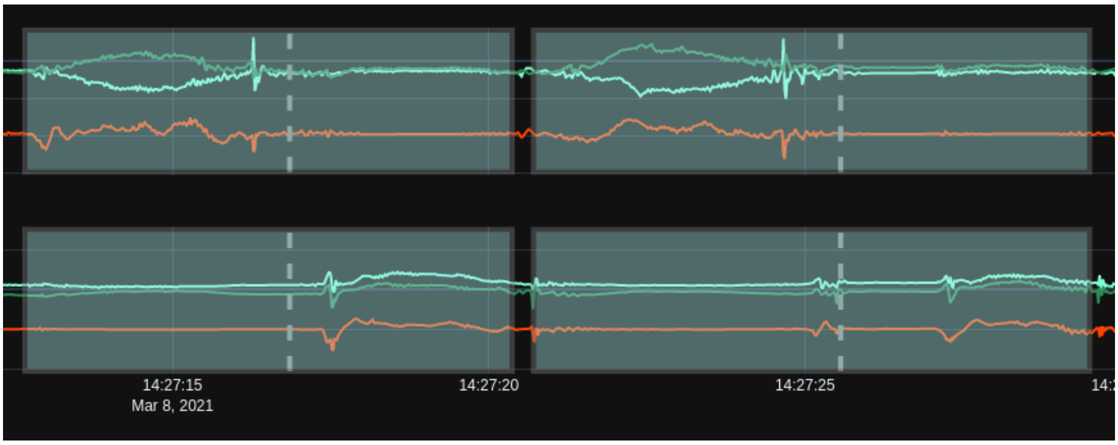


**Figure 2.12:** Example of a segmented signal. It details the left lower limb acceleration (above in the figure) and right lower limb acceleration (below in the figure). The semi-transparent box defines segmented repetition, the dotted line represents the phase. X axis is orange, Y axis is light green and Z axis is dark green. Reproduced with permission of Henesis Srl.

## 2.4 Case study definition

Since the patients dataset was large and the exercise library contains many exercises, this work focuses on 4 patients and 8 exercises. Later are proposed methods that could be applied to all exercises and patients but, specifically for this thesis project, a limited number of patients and exercises have been preliminary investigated and discussed.

A subset of exercises has been selected as well: 4 exercises targeting the lower body and 4 the upper body. As for the subjects selection, the criteria used in this case was to consider the exercises that had the higher number of sessions, so that the analysis could rely on the highest amount of available data. A session refers to when the patients select the exercise and perform at least one repetition.
The eight exercises selected are detailed in Table 2.4, Table 2.5 and Table 2.6. These tables show the exercise name, an image that represents it, a brief description and the main plane on which the movement occurs.

Among all the patients that participated to the clinical trial, a case study is here proposed on: 2 Parkinson (PK) and 2 Long COVID-19 (LC) patients. The selection has been made considering the number of sessions each patient performed during the clinical trial. The four selected patients, indeed, performed the highest number of repetitions and they were chosen so the analysis could benefit from more data. Table 2.7 details the number of segmented sessions for the four selected patients and the 8 exercises.

| Exercise ID | Exercise Name | Image | Description | Principal Movement Plane |
|---|---|---|---|---|
| L.BA.001 | Weight transfer to lower limb |  | Sitting with your knees at 90° bring the arms with elbows upwards performing a deep inhalation and exhalation. | Coronal (Z axis) |
| L.BA.007 | Hip flexion |  | Standing with arms slightly apart, bring them up with elbows outstretched upwards performing a deep inhalation and then bring them down performing a exhalation. | Sagittal (Y axis) |
| L.BA.014 | Standing upright in a one-supporting position with support |  | While standing, try to keep the balance by standing on one foot while leaning on a support. | Sagittal (Y axis) |
| L.BA.016 | Tandem with abducted limbs |  | Standing, placing the feet in front of each other with arms apart, try to keep the balance. No support needed. | Sagittal (Y axis) |

**Table 2.4:** Description of selected lower limbs exercises. Images reproduced with permission of Henesis Srl.

| Exercise ID | Exercise Name | Image | Description | Principal Movement Plane |
|---|---|---|---|---|
| U.BS.003 | Arm elevation using a stick while sitting |  | Sitting with knees at 90°, bring your arms with elbows upwards by performing a deep inhalation and then bring your hands downwards by performing a exhalation. | Sagittal (Y axis) |
| U.BS.004 | Arm elevation with a stick while standing-up |  | Standing with arms apart, bring your arms with elbows upwards performing a inhalation and then bring hands down performing a exhalation. | Sagittal (Y axis) |

**Table 2.5:** Description of selected upper limbs U.BS.003 and U.BS.004 exercises. Images reproduced with permission of Henesis Srl.

| Exercise ID | Exercise Name | Image | Description | Principal Movement Plane |
|---|---|---|---|---|
| U.BS.005 | Arm pushing exercise |  | Sitting with your legs bent at 90°, bend both elbows bringing hands holding two weights towards your shoulders and push both limbs towards the ceiling. | Coronal & Sagittal (Y,Z axis) |
| U.BS.008 | Shoulder extra-rotation with arms abducted at 45° |  | Sitting down and leaning back, bend your elbows to 90° and, with arms open to 45°, perform an external rotation of arms, then return to the starting position. | Sagittal & Coronal (Y,Z axis) |

**Table 2.6:** Description of selected upper limbs U.BS.005 and U.BS.008 exercises. Images reproduced with permission of Henesis Srl.

| | PK 1 | PK 2 | LC 1 | LC 2 |
|---|---|---|---|---|
| L.BA.001 | 1 | 1 | 4 | 5 |
| L.BA.007 | 3 | 12 | 5 | 5 |
| L.BA.014 | 1 | 6 | 5 | 4 |
| L.BA.016 | 1 | 3 | 3 | 4 |
| U.BS.004 | 9 | 2 | 4 | 6 |
| U.BS.005 | 3 | 1 | 2 | 2 |
| U.BS.003 | 4 | 4 | 11 | 8 |
| U.BS.008 | 4 | 7 | 10 | 13 |

**Table 2.7:** Number of segmented sessions for each patient for the subset of 8 exercises.

Table 2.8 shows general details about the case study patients.

| Patient | Diagnosis | Gender | Age | Height [cm] | Weight [kg] |
|---|---|---|---|---|---|
| LC 1 | Post COVID-19 | F | 29 | 172 | 64 |
| LC 2 | Post COVID-19 | M | 64 | 172 | 80 |
| PK 1 | Parkinson | F | 69 | 170 | 80 |
| PK 2 | Parkinson | F | 66 | 160 | 70 |

**Table 2.8:** Selected subjects information

Since the medical trial was composed by a baseline assessment at the beginning and by a final one, tables below details the scores. Table 2.9 details the meters covered by the 4 selected patients during the 6 Meter Walking Test. The values shown refers to the baseline assessment (t0) and to final one (t1). Table 2.10 shows the clinical scores for FAC and EUROQol5D. Table 2.11 details the clinical scores defines by the doctor for BFI. Table 2.12 and Table 2.13 show MDS-UPDRS score and the beginning and at the end of the clinical trial.

| Patient | Group | 6MWT [m] @ t0 | 6MWT [m] @t1 |
|---|---|---|---|
| PK 1 | PD | 149 | 173 |
| PK 2 | PD | 75 | 85 |
| LC 1 | COVID-19 | 140 | 208 |
| LC2 | COVID-19 | 135 | 140 |

**Table 2.9:** Comparison of meters covered to the first stop during the 6MWT. t0 indicated the baseline assessment at the beginning of the clinical trial and t1 the final clinical assessment.

| Patient | Group | FAC @t0 | FAC @t1 | EUROQol5D @ t0 | EUROQol5D @t1 |
|---|---|---|---|---|---|
| PK 1 | PD | 5 | 5 | 6 | 6 |
| PK 2 | PD | 1 | 1 | 10 | 10 |
| LC 1 | COVID-19 | 5 | 5 | 13 | 13 |
| LC2 | COVID-19 | 5 | 5 | 6 | 6 |

**Table 2.10:** Comparison of FAC and EUROQoL 5D. t0 indicated the baseline assessment at the beginning of the clinical trial and t1 the final clinical assessment.

| Patient | Group | BFI @ t0 | BFI @t1 |
|---|---|---|---|
| PK 1 | PD | 1 | 0.5 |
| PK 2 | PD | 3.5 | 2 |
| LC 1 | COVID-19 | 9.4 | 9.7 |
| LC2 | COVID-19 | 1.8 | 1.7 |

**Table 2.11:** Comparison of BFI. t0 indicated the baseline assessment at the beginning of the clinical trial and t1 the final clinical assessment.

| Patient | Group | Part I @ t0 | Part II @ t0 | Part III @ t0 | Part IV @ t0 |
|---|---|---|---|---|---|
| PK 1 | PD | 0 | 9 | 7 | 0 |
| PK 2 | PD | 1 | 15 | 21 | 4 |

**Table 2.12:** MDS-UPDRS score at the beginning of the trial. t0 indicated the baseline assessment at the beginning of the clinical trial.

| Patient | Group | Part I @t1 | Part II @t1 | Part III @t1 | Part IV @t1 |
|---|---|---|---|---|---|
| PK 1 | PD | | . | . | |
| PK 2 | PD | 1 | 15 | 21 | 4 |

**Table 2.13:** MDS-UPDRS score at the end of the trial. t1 indicated the final clinical assessment.

## 2.5 Data processing & Analysis

In this section, data processing of healthy and patients dataset are described. Description of the analysis made are reported as well. All the processing pipeline was written using Python 3.7 and Visual Studio Code. Python iterative cycles were created in order to process all the data.

### 2.5.1 Movement patterns analysis

First objective of this thesis was to analyse healthy dataset to obtain a pattern for each exercise. It was important to obtain a reference movement pattern for each exercise using healthy data in order to be able to compare the same pattern in pathological conditions. This reference pattern has been computed as the average of all repetitions made by the healthy volunteers for each single exercise separately to get a visual idea of what the signal should look like when performing a particular exercise.
All the data of a specific session were saved in a .npz file.
Each .npz file name contained: patient's code, exercise code, date and time of the

execution

Each .npz file was structured as follows:

- Acceleration of right limb, saved as ['right accelerometer']
- Acceleration of left limb, saved as ['left accelerometer']
- Acceleration of left limb, saved as ['left accelerometer']
- Angular velocity of right limb, saved as ['right gyroscope']
- Angular velocity of left limb, saved as ['left gyroscope']
- Acceleration of the trunk, saved as ['trunk accelerometer']
- Angular velocity of the trunk, saved as ['trunk gyroscope']
- Timestamps of the beginning and end of each repetitions, saved as ['timestamps']
- Timestamps of phase for BS exercise, saved as ['markers']
- Notes for each patients, saved as ['notes']

Identification of the file to be loaded for the processing was possible due to the file name containing the patient's code, the exercise code and the date and time on which the exercise was performed. If the patient performed the same exercise several times a day at different times, different files were created as the exercise execution time changed. For averaging data, the files of the same exercise performed by the same patient at different times on the same day were grouped into a single file named using the patient code, the exercise code and the date of the day of performance.

From now on, inertial data are referred to as follows:

- 'right gyroscope' as ACC_R
- 'left accelerometer' as ACC_L
- 'right gyroscope' as VEL_R
- 'left gyroscope' as VEL_L
- 'trunk accelerometer' as ACC_TRUNK
- 'trunk gyroscope' as VEL_TRUNK

### Healthy subjects movement patterns

As introduced above, in order to obtain the movement pattern for each exercise using healthy subjects data, it was important to average all their signals. Obtaining the movement pattern for each exercise is important because it gives an idea of what the pattern should look like especially for the comparison with patients that later will be proposed (Section 3.1). In order to obtain the movement pattern, all the repetitions of a subject for each exercise were collected, considering only those sessions that were labeled as valid and segmented; all the repetitions of the same exercise were resampled and then averaged to obtain the movement pattern that would then be used as a template. It is worth to notice that signals average can not be affected by wrong repetitions or errors in the data since during the preliminary step of data inspection and segmentation such repetitions were excluded.

From the implementative point of view, the key processing points are:

- Creation of lists containing all repetitions. Exercise's signals in the .npz files are continuous so to divide them into repetitions, a specific function was created. This function takes in input the signal and the timestamps in order to output a list containing all the repetitions. Timestamps are used as reference because the signal of interest is between the timestamps that represent the beginning and end of each repetition. The length, measured in samples, of each repetition was saved in a list and it is going to be used for further analysis.

- Signal resampling. All repetitions had different lengths so they have been resampled to the length of the slowest one [59]. Thanks to this operation, all repetitions were normalized to the same lengths and could be represented on the same plot.

- Signal averaging. All repetitions of the same exercise were averaged together obtaining a template for each exercise. This healthy template will be used as reference to compare the corresponding movement patterns obtained from patients. The average trend for each exercise was computed, plotted and all the data was saved in .npz file. For each exercise an average signal for x,y and z axis was computed specifically for right and left acceleration, right and left angular velocity, trunk acceleration and angular velocity. These patterns have been plotted with corresponding standard deviation. Examples are shown in Figure 2.13 for exercise U.BS.003 and also in Figure 2.14 for exercise L.BA.007. The patterns with their standard deviations along three axes (X,Y, and Z) have been plotted to better visualize the results and to check whether the averaging process created signals that were too inaccurate and dissimilar to other patterns.

- Output file creation. A specific function creates an Excel file in which minimum, maximum, mean and standard deviation of the length of all repetitions are saved.

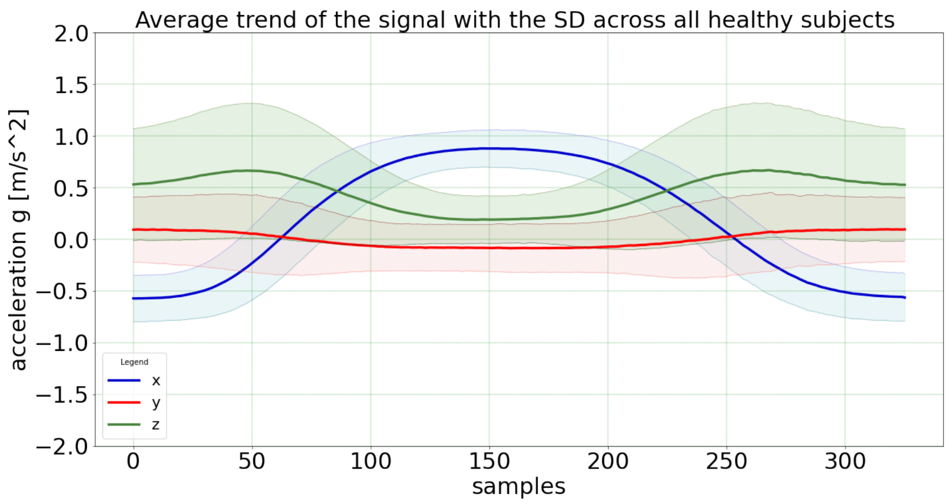


**Figure 2.13:** Acceleration: X, Y and Z axis's patterns with SD of healthy subjects for exercise U.BS.003

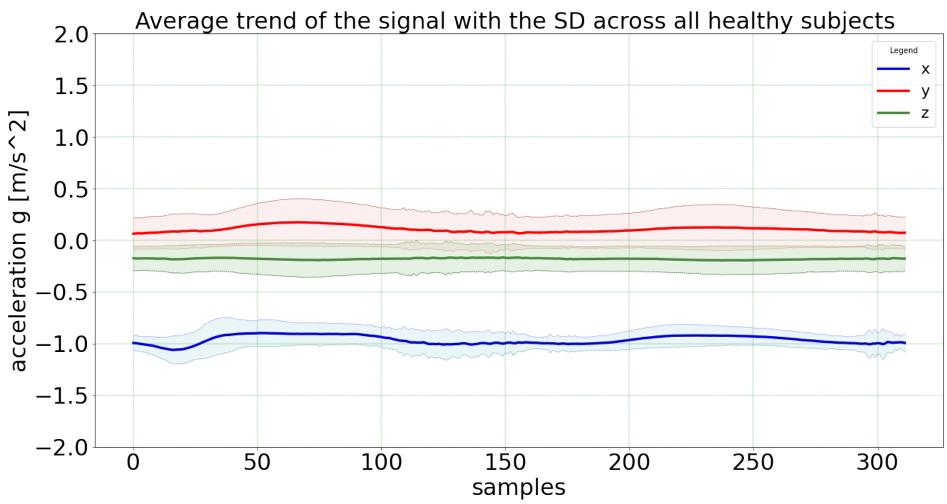


**Figure 2.14:** Acceleration: X, Y and Z axis's patterns with SD of healthy subjects for exercise L.BA.007

### Patients movement pattern

As done for healthy subjects, a second objective of this thesis was to obtain the movement pattern for each exercise and each patient to perform comparisons. The pattern was computed in order to have a template that showed how patients performed the specific exercise.
Since patients performed the exercises multiples times during different days, differently from the previous processing, it was necessary to obtain a movement pattern for each day they performed the exercises. Therefore, separately for each patient, an average of the repetitions of the same exercise performed during the same day was computed.
Figure 2.15 details average pattern of left upper limb acceleration of exercise U.BS.003 of patient PK 2 for the second day of exercise execution. Figure 2.16 shows average pattern of the acceleration of exercise L.BA.001 of patient PK 1 for the third day of exercise execution.

From the implementative point of view, it has been created a routine which is similar to the one used for healthy subjects. The main difference in the processing pipeline lies in the management of individual subjects. An averaged pattern was obtained for each day on which the patient performed the exercise during the clinical study. As for healthy subjects, plots of signal patterns along x,y and z axis with their standard deviations have been implemented also for patients.
Plots of all repetitions together were also implemented to look for any outliers via visual inspection. An example is shown in Figure 2.17. This was done as verification, to check if all outliers were correctly discarded during the segmentation phase.

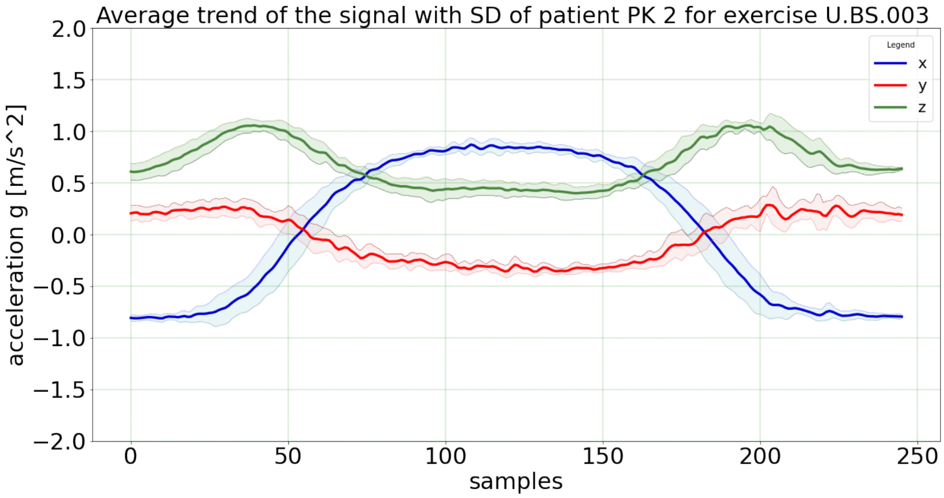


**Figure 2.15:** Patient PK 2 average pattern of left upper limb acceleration of exercise U.BS.003 the second day of rehabilitation program

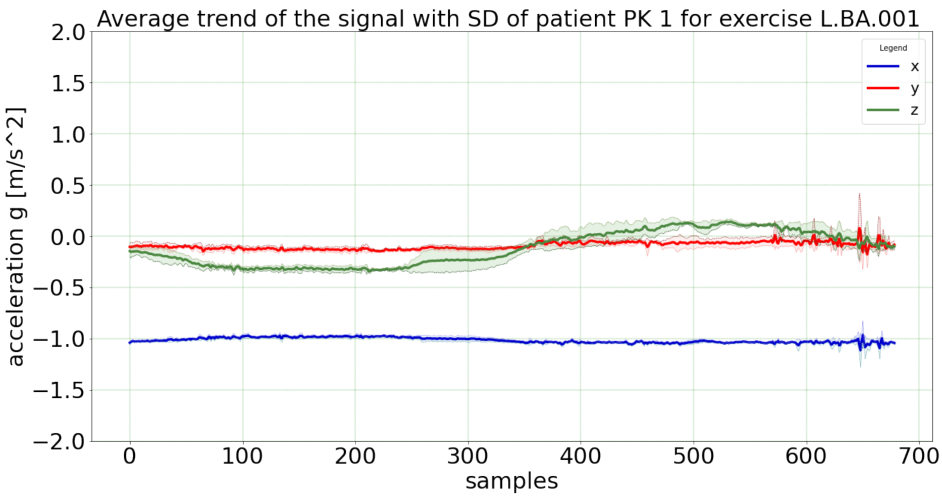


**Figure 2.16:** Patient PK 1 average pattern of acceleration of exercise L.BA.001 the third day of rehabilitation program

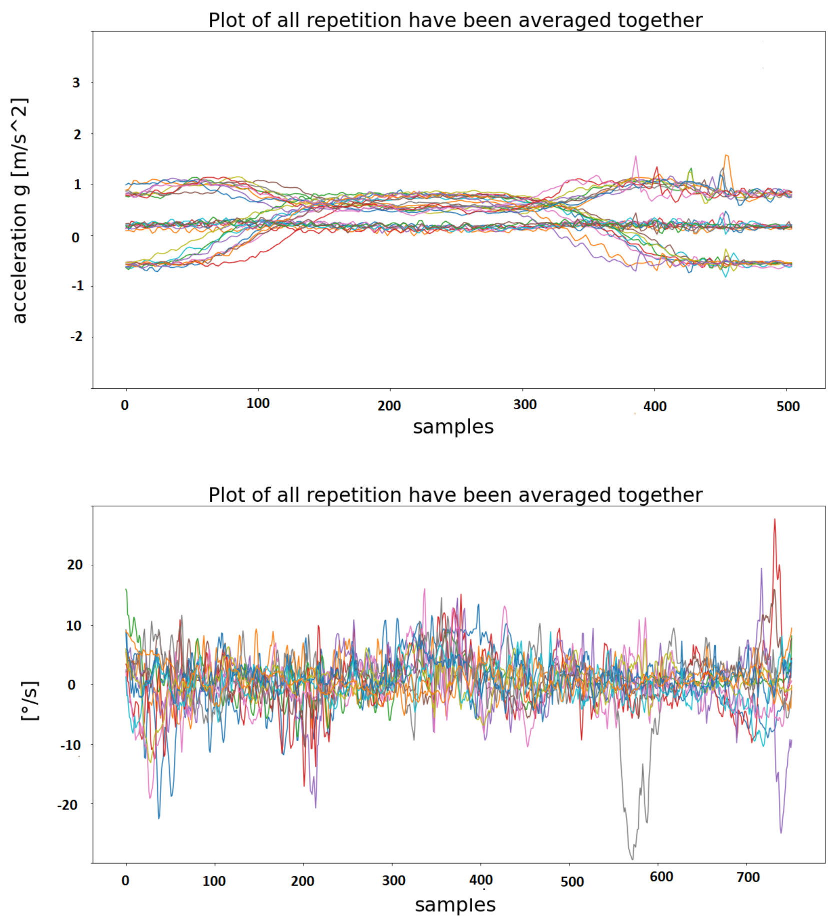


**Figure 2.17:** Example of plot of all repetitions. Plot of left upper limb acceleration for patient PK 2 (above). Plot of trunk angular velocity for patient PK 1 (below)

### 2.5.2 Duration analysis

An analysis was conducted concerning the duration of the single repetitions. The aim was to observe if any variations in the duration of the single exercise repetition execution could be detected, and in the case, if such changes could reveal or correlate with any changes in the patient motor behavior while advancing with the rehabilitation prescribed program.
Duration's maximum, minimum, average and standard deviation of all repetitions performed by a patient on the same day for a specific exercise was computed and saved into an Excel sheet. From these data, comparisons were made with same parameters obtained from the healthy subjects (Section 3.2). Obviously, the duration of repetitions was calculated before input data were resampled.

### 2.5.3 DTW: Dynamic Time Warping

In order to have a quantitative measure of patients performance during the conduct of the rehabilitation protocol and to understand how similar are patients' signals to the template, the Dynamic Time Warping (DTW) Score was computed.
DTW is an algorithm that allows to align two signals of different duration and that defines the cost of the alignment process. It is used, for examples, in many gait studies. Lee et al. [60] investigated the effectiveness of the dynamic time warping in gait research validating results obtained using a three-dimensional motion analysis system consisting of infrared cameras. DTW-based measures are were also constructed to measure progressive gait deterioration [57]. Most of DTW applications are in gait detection [61] [62] to assess patient improvement during walking test, such as the 6 Meter Walking Test [36]. The DTW score has also been used to summarize the degree of similarity between two signals following alignment and to perform gait phase detection [63].

The DTW computes which points on one of the signals corresponds to which points on the other signals and it allows to estimate the similarity among two input signals.
Supported by the promising evidences in the literature [63] [64], this project proposed the use of the DTW score to quantitatively assess patient motor performance compared to the control group at two timepoints: the first day of therapy, which was supposed to take place close to the baseline assessment, and the last day of the tele-rehabilitation treatment.
The DTW score (expressed in arbitrary units [a.u.]) was calculated between the pattern of healthy subjects, used as a template, and patients' pattern. The score was calculated twice, once using the pattern of the first day in which the patients performed the exercises, and the second time using the pattern of the last day.
The DTW algorithm (Algorithm 1) [65] is based upon the construction of the cost matrix D and has been implemented according to [66].

**Algorithm 1** Dynamic Time Warping algorithm

▷ Inputs:

x(1:N) and y(1:M). x and y are two signals that are long N and M samples respectively

▷ The cost matrix $D \in \mathrm{R} \wedge (N+1) * (M+1)$

▷ Initialisation of the cost matrix D:

- D(0,0)=0
- for i=1 to N: D(i,0) = inf
- for j=1 to M: D(0,j) = inf

▷ Recursive relation:

$$D(i,j) = d(xi, yj) + min\{(D(i-1, j-1), D(i-1, j), D(i, j-1))\} \tag{2.1}$$

▷ Output:

DTW-distance =D(N,M)

DTW algorithm is characterized by the following rules [36]:

- Every point of the first signal has to match at least one point of the second one and vice versa.
- The first point of the first signal must match with the first point of the other signal. Same procedure for the last points of both signals.
- The mapping of the points that matches must increase monotonically.

To align two input signals a cost matrix (D) is built. Cost matrix helps us figure out which points in the fist signal corresponds to which points in the second signals (Figure 2.18) and what the cost is of having those points correspond to one another. First of all, the cost matrix is initialized by filling the first column and the first row with values of infinity and by attributing the value of zero in the position D(0,0) (see Algorithm 1). Then, going through each of the row in the matrix and through each column, systematically the matrix is filled by using the Equation 2.1. Then, starting from the last column and last row, it traces back to the first column

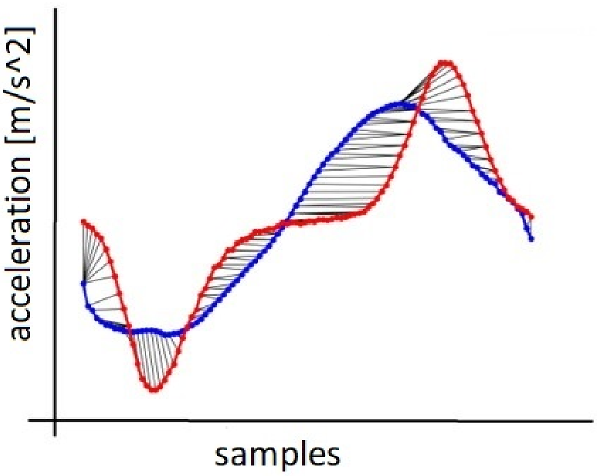


**Figure 2.18:** Example of signals alignment using DTW. Red is the patients pattern, blue is the healthy pattern. The points that correspond to each other on the two curves are joined by the black segments.

and row in the matrix and following its trace backs, it outputs the alignment path between the two signals. The path explains exactly how to align two points of the signals. The DTW score, which corresponds to the D(N,M) value in the cost matrix, expresses the overall cost of aligning the two signals. The higher the score, the higher is the cost of aligning the two signals and thus they will be more different and therefore dissimilar. If the cost is low, it means that the two signals are similar. Comparing the healthy subjects' signals with the patients' signals on the first day of exercise execution, the score is expected to be higher than the same comparison made with the patients' signals on the last day of tele-rehabilitation. It was chosen to calculate the score for each Cartesian axis separately to give the same importance to each axis and to look for potential improvements or differences in each direction.

### 2.5.4 Python pipeline code

The code used in this study was written in Python 3.7 and Visual Studio Code. All the functions and the main code were versioned using Git and a private GitHub repository of the company. In order to generate a more linear code, several functions were created to handle different parts of the project.

Below are listed the main functions used in this work, while their application is explained in subsection 2.5.1, subsection 2.5.1 and subsection 2.5.2 explain it.

The main functions implemented are:

- List-creation. Function that creates lists containing all the segmented repetitions. This was necessary because the initial files contained the whole inertial signals from all the different sensors. In order to segment the singular repetitions, lists containing them were created.

- Plots. Function that plots x, y and z axis for each signal of every sensor. Every singular axis is also plotted in a separated graph with their standard deviations bands.

- Healthy-pattern. Function specifically made for healthy subjects that: i)takes the list of repetitions of an exercise as input, ii) computes and saves the duration of the individual repetitions in a list, iii) prints out the maximum, minimum, average and standard deviation in an Excel file, iv) resamples the repetitions using the length of the longest repetition as a parameter, v) calculates the average pattern and plots, vi) saves the data in an .npz file. All 3 Cartesian axes are always computed separately for each sensor. Average patterns for each exercise are saved in a folder.

- Patient-pattern. Function that output exercise pattern for each day in which the patient performed the exercise. It is structured as the previous Healthy-pattern function, the only difference is that the pattern is output for each day of the protocol. All results are saved in a specif folder named as the type of disease (Parkinson or Long COVID-19), code of the exercise, code of the patients and the day of exercise execution.

- DTW. This function is composed of two parts: the first part, implements the dynamic time warping and the second part, computes the DTW scores, saves them in an Excel sheet and plots all the graphs.

# Chapter 3

# Results

## 3.1 Healthy vs patients movement patterns

In this section, results following the method proposed earlier are presented.

Using the average pattern obtained during the data processing, a visual comparison between healthy and patients' patterns was possible. The objective of this visual inspection was to determine whether it is possible to develop an innovative method for rehabilitation professionals to support them in assessing patients motor skills by comparing patient's movement patterns with a healthy reference. The graphs generated for the case study are numerous (more than 100). In the following some representative examples of obtained results are presented. Figure 3.1 details the right upper limb average acceleration pattern with its standard deviation of healthy subjects performing exercise U.BS.005, along the three Cartesian axes separately.

Figure 3.3 and 3.2 show raw signals related to exercise U.BS.005: the healthy template, LC 1 and LC 2 patients respectively are presented. From the visual inspection it is possible to understand that the patients performed the exercise correctly since the pattern is similar to the template. Figure 3.4 and 3.5 details patient PK 1 and PK 2 performing exercise U.BS.005 as well. It is visible that both patients had some difficulties in performing the exercise since the signal along y axis is not so similar to the template.

It is reported also, as example, the left lower limb angular velocity of exercise L.BA.001 for both groups of patients. Figure 3.6 details the left lower limb angular velocity of healthy subjects for x, y and z axes for exercise L.BA.001. Figure 3.7 and 3.8 detail the healthy template and patients LC 1 and LC 2 signals. It can be seen that patients had some difficulties in performing the exercise, the movement pattern is hardly visible but it is present. Figure 3.9 and 3.10 detail the same exercise for patients PK 1 and PK 2. In general, it is visible that the patient's movement is similar to the healthy template, but there are differences.

There is enough variability in healthy subjects as the large standard deviations bands suggests and so even if patients signals are not very similar it doesn't mean that they have necessarily execute the exercise wrong. Acceleration was chosen for exercise U.BS.005 as well as angular velocity for exercise L.BA.001 because respectively they are more descriptive of the movement.
Observing all the graphs, both groups of patients' signals are visibly more jagged and deviate from the movement pattern of healthy subjects. It is visible that the pattern is correct but the patient had some difficulties in executing the exercise.
A simple observation of the signals might be useful for the therapist to quickly see whether the patient's pattern is correct or not. The average movement pattern of healthy subjects with the standard deviation, used as template, could be helpful to check whether the patient's pattern is similar within the range presented but there is still a need for a quantification of the possible differences observed.

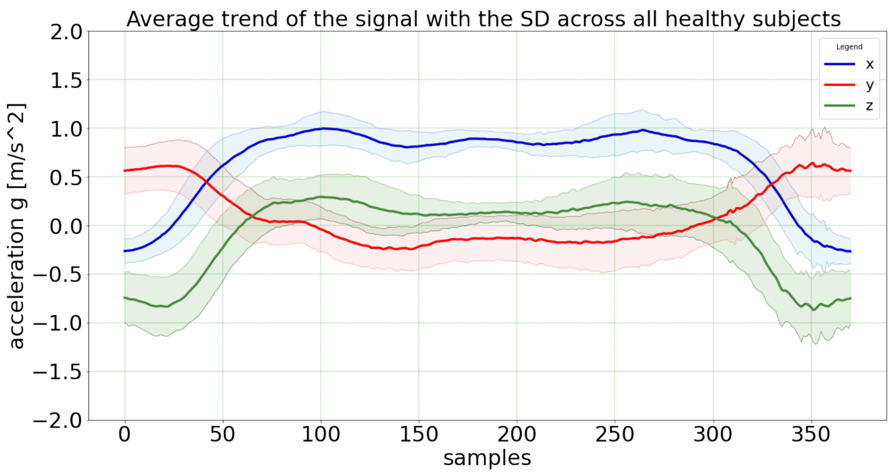


**Figure 3.1:** Exercise U.BS.005: average acceleration patterns with standard deviation from right upper limb on the 3 axes

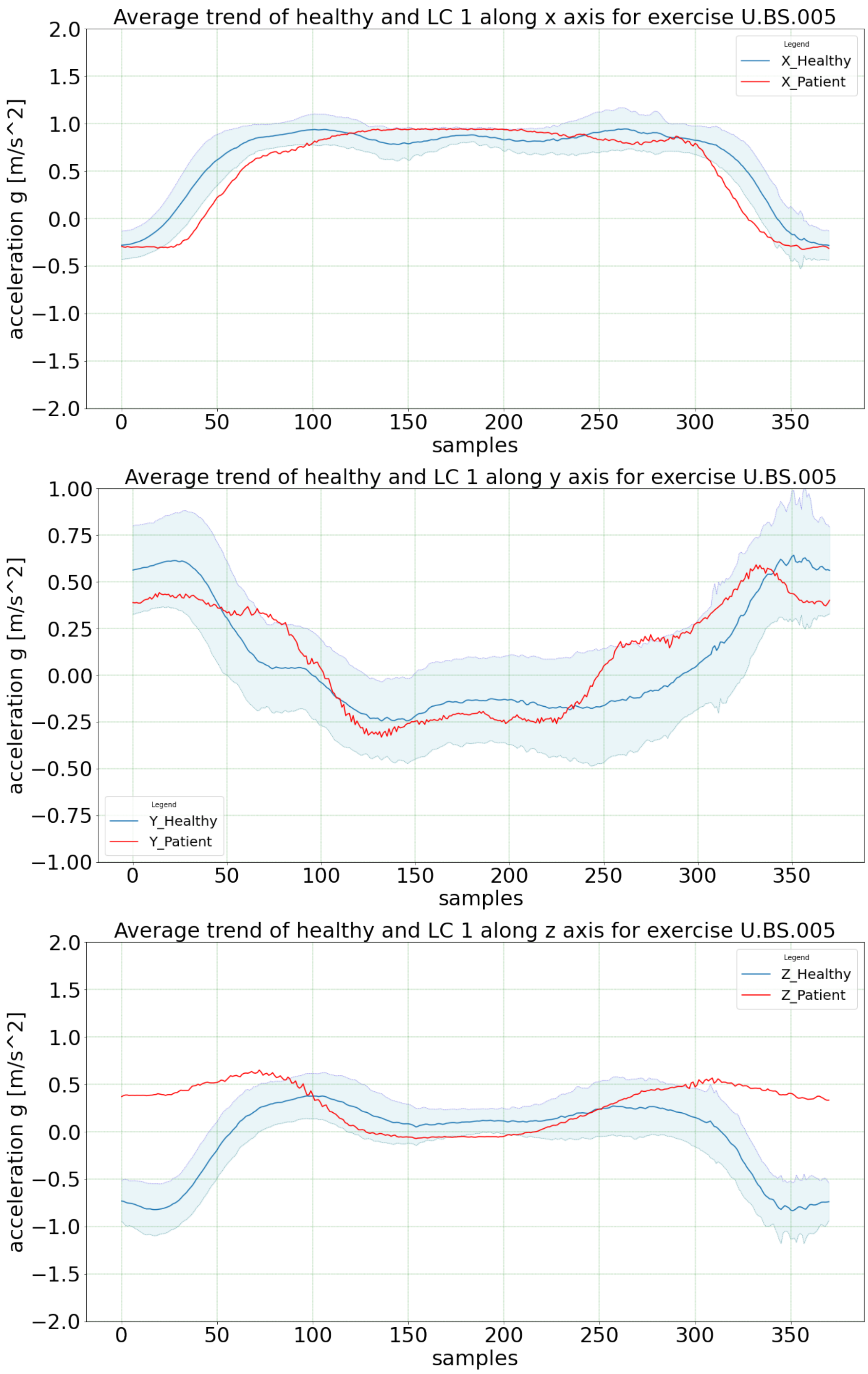


**Figure 3.2:** Visual pattern analysis. Comparison of right upper limb acceleration between healthy and LC 1 for exercise U.BS.005

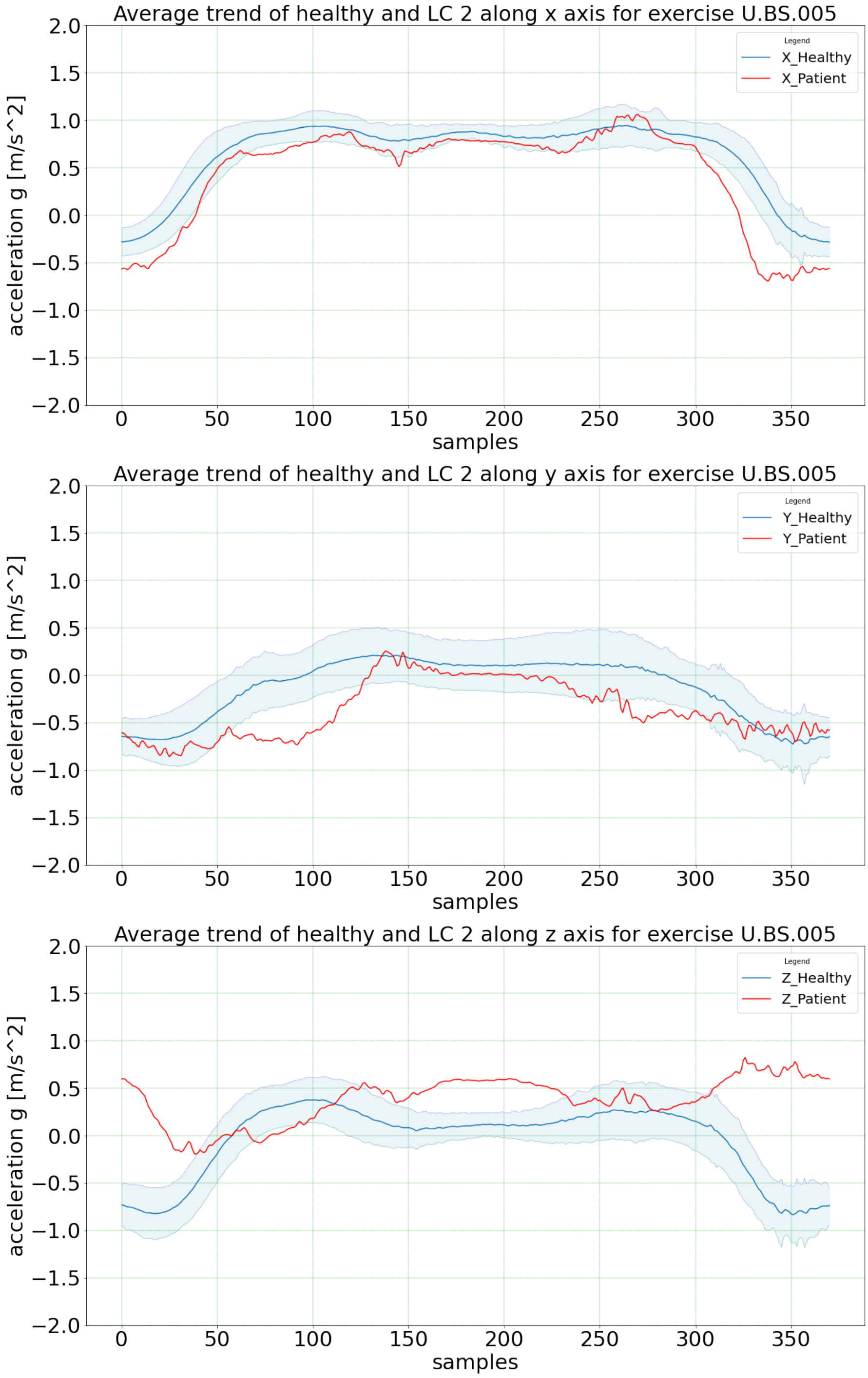


**Figure 3.3:** Visual pattern analysis. Comparison of right upper limb acceleration between healthy and LC 2 for exercise U.BS.005

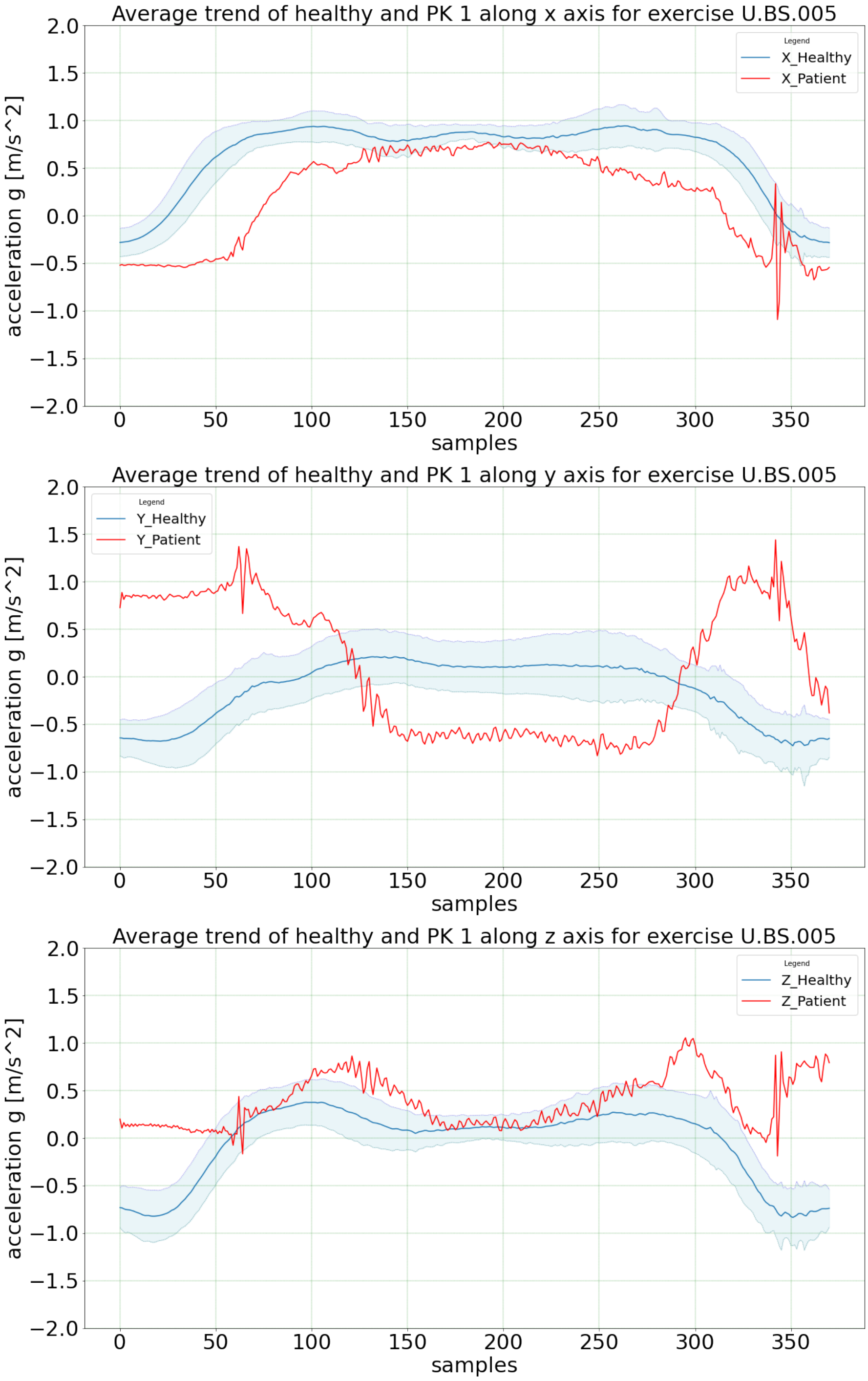


**Figure 3.4:** Visual pattern analysis. Comparison of right upper limb acceleration between healthy and PK 1 for exercise U.BS.005

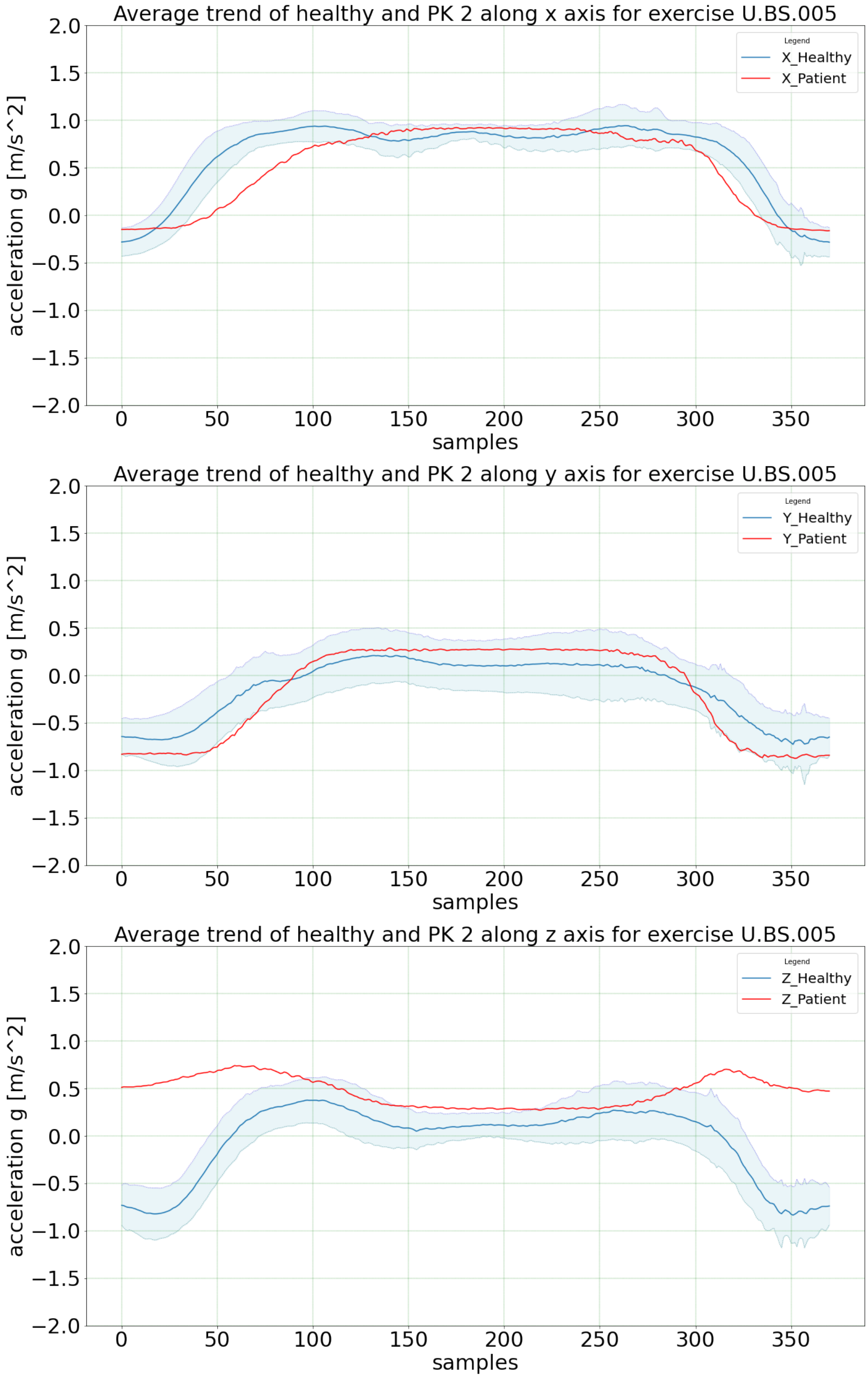


**Figure 3.5:** Visual pattern analysis. Comparison of right upper limb acceleration between healthy and PK 2 for exercise U.BS.005

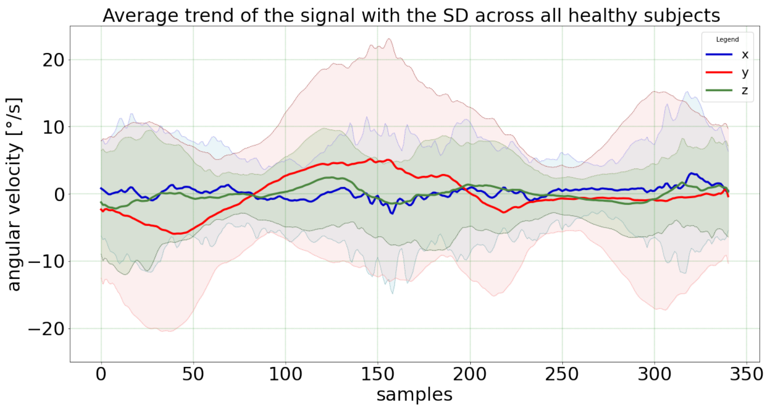


**Figure 3.6:** Exercise L.BA.001: average angular velocity patterns with standard deviation from right upper limb on the 3 axes

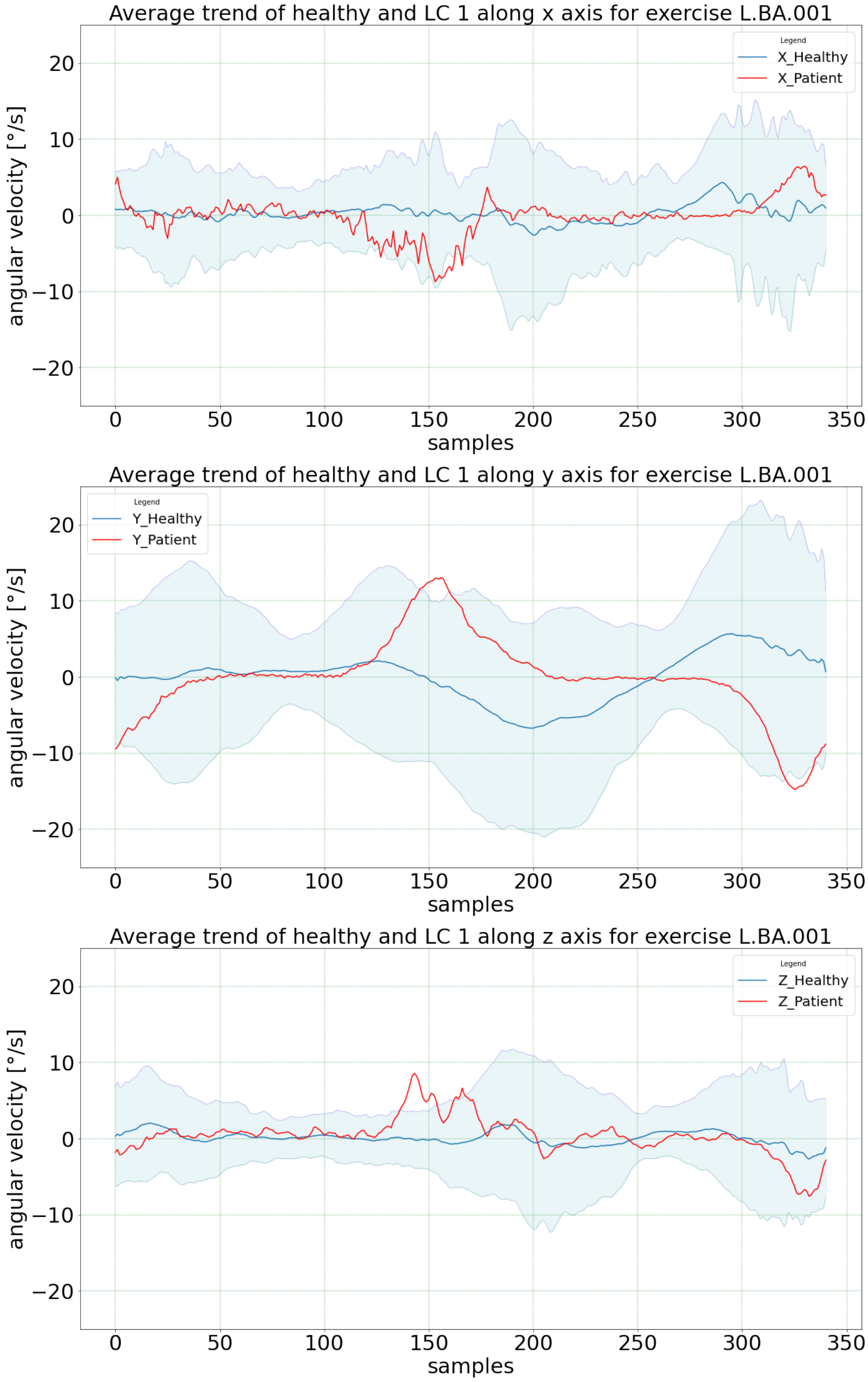


**Figure 3.7:** Visual pattern analysis. Comparison of left lower limb angular velocity between LC 1 and healthy for exercise L.BA.001

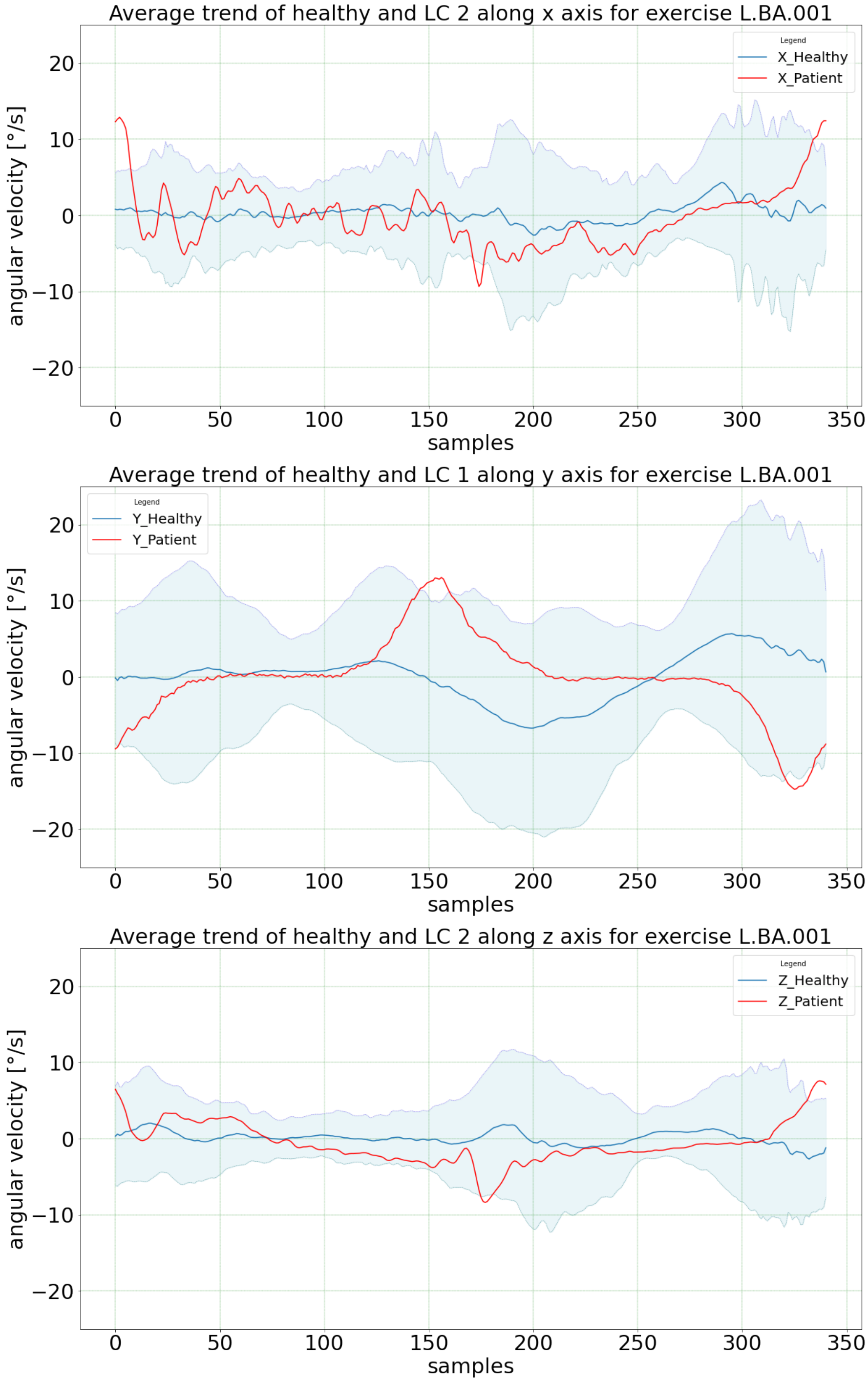


**Figure 3.8:** Visual pattern analysis. Comparison of left lower limb angular velocity between LC 2 and healthy for exercise L.BA.001

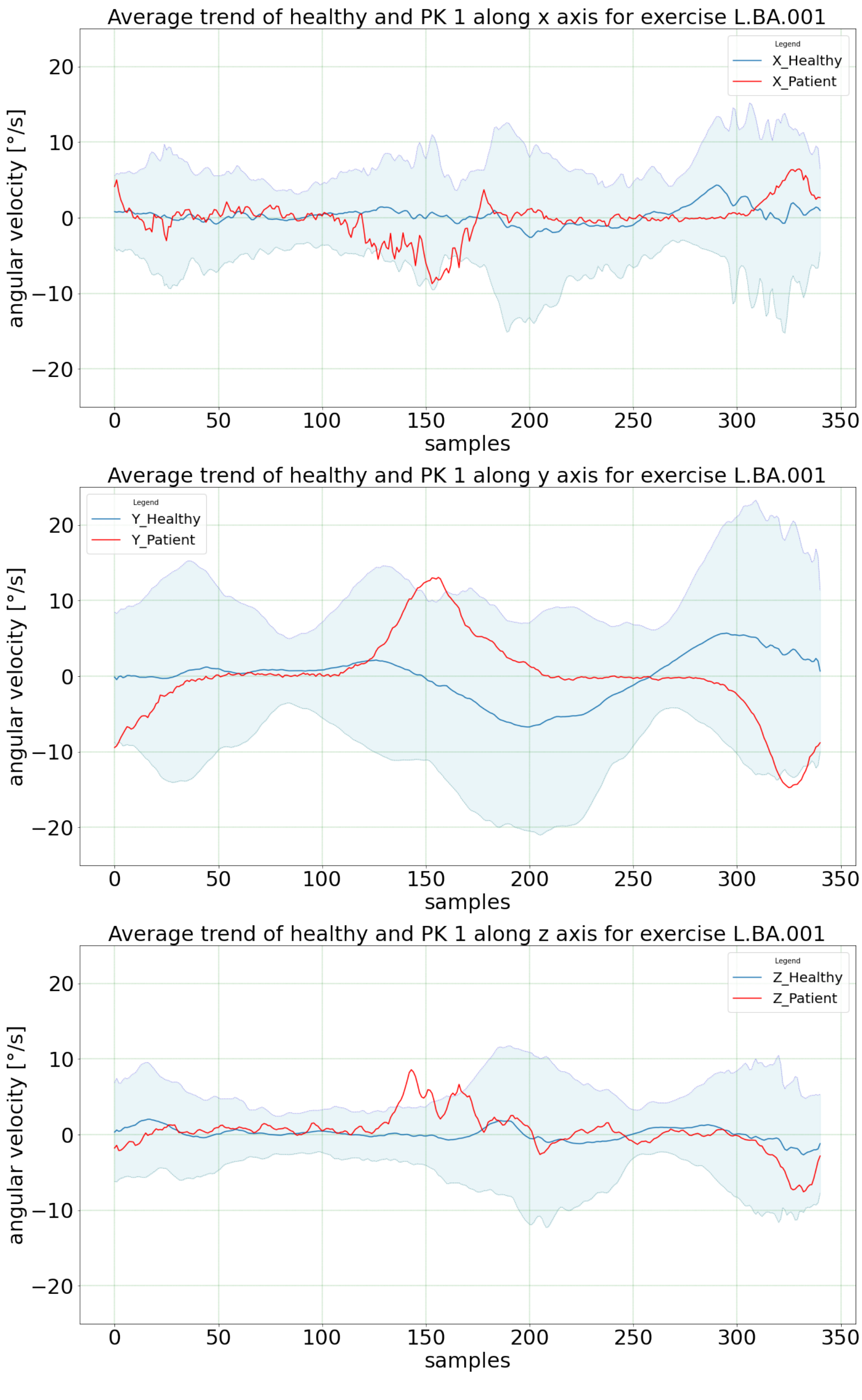


**Figure 3.9:** Visual pattern analysis. Comparison of left lower limb angular velocity between PK 1 and healthy for exercise L.BA.001

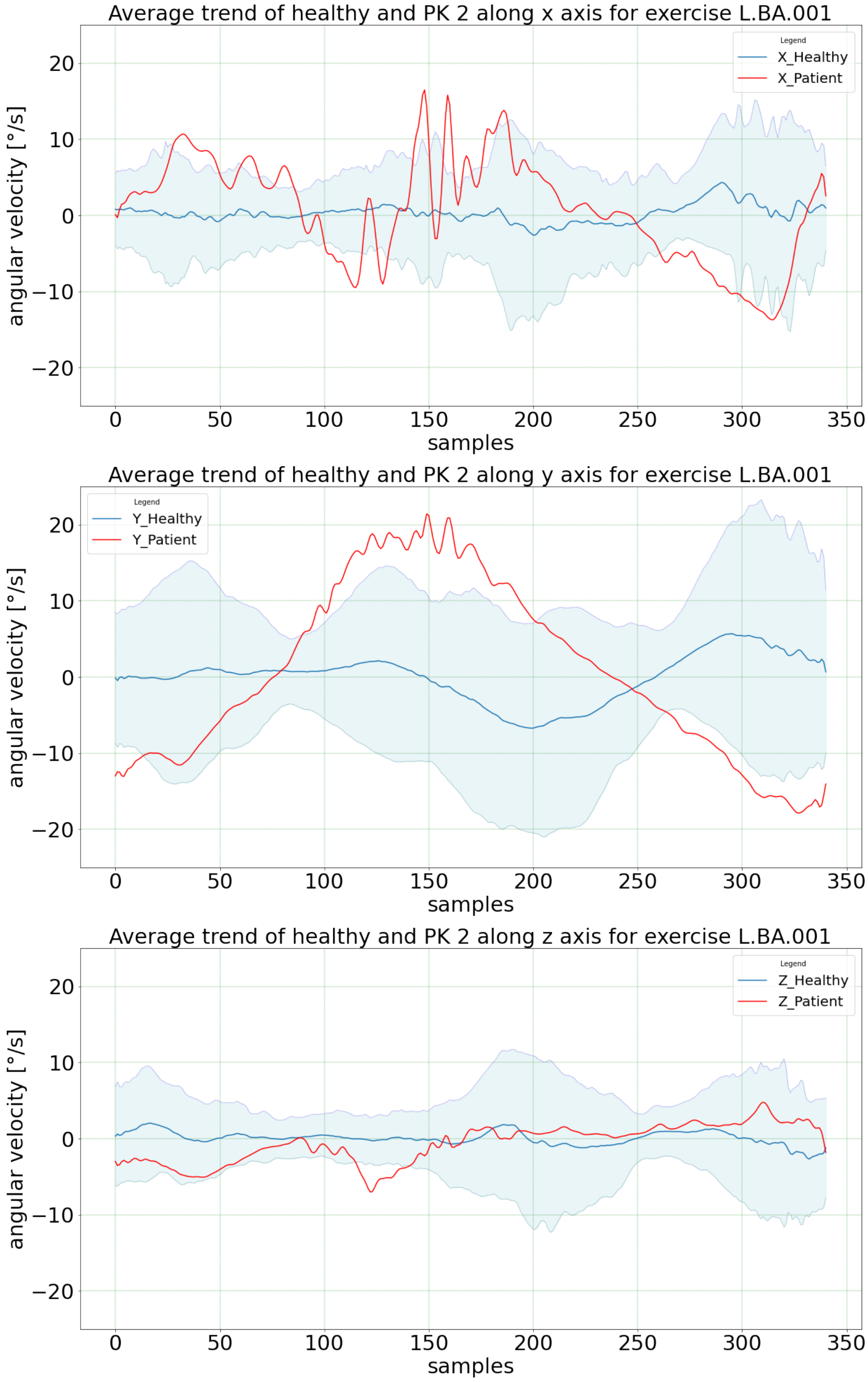


**Figure 3.10:** Visual pattern analysis. Comparison of left lower limb angular velocity between PK 2 and healthy for exercise L.BA.001

## 3.2 Exercise repetitions duration

Thanks to the data collected, a comparison between healthy duration of a repetition and patients duration was possible. Through the comparison of the mean value of the duration of the repetitions, it was possible to observe whenever there was a variation in the exercise performance.
May be interesting to observe a decrease in duration over time, as expected, because patients would have become more confident in performing the exercise but this is not always the case. It would be useful to observe if the patient is performing the exercise with an average duration that is similar to the template; average times that are shorter than the template may suggest that the patient is not performing the exercise correctly, longer duration may indicate that the he or she may have some issues during the execution. An average patient repetition duration similar to the healthy subjects' template would be a great method for therapists to assess quantitatively their patients performances. Therapist may need to observe whether patients average duration are quite similar or dissimilar in the different days. If patients are performing exercises with a certain temporal regularity or not may be a useful parameter for the healthcare professionals. Furthermore, it might be interesting to observe whether there are marked differences between the two groups of patients observed here.
Figures below detail the average duration and the standard deviation of healthy subjects repetitions, compared with the mean patients' values for each day they performed the exercise during the tele-rehabilitation protocol. Figure 3.11 details the mean duration of repetitions with its standard deviation for everyday in which Long COVID-19 patients performed exercise U.BS.008. It is visible that patient LC 1 was slower than healthy subjects in the execution meanwhile patient LC 2 took less time each day. Figure 3.12 shows Parkinson patients performing the same exercise. Both Parkinson patients have average duration that are more similar to the healthy template than Long COVID-19 patients.
Figure 3.13 details Long COVID-19 patients that executed exercise L.BA.007. In particular, patient LC 2 had an average time similar to the template but no variation over time. Figure 3.14 shows the mean values of the duration of Parkinson patients. For both of them, the values are pretty similar to the healthy template. In both patients there are not visible significative variations over time. Figure 3.15 and Figure 3.16 detail Long COVID-19 and Parkinson patients duration for exercise L.BA.016. Patient LC 2 performed the exercises more frequently than LC 1 and with a shorter average time each day. Patient PK 1 had an average duration which is less variable among the different days of execution. Figure 3.17 and Figure 3.18 show both groups of patients performing exercise U.BS.005. Among Long COVID-19 patients, LC 2 had an average time shorter than the template each day of the execution, and, on the contrary, LC 1 had longer duration every day.

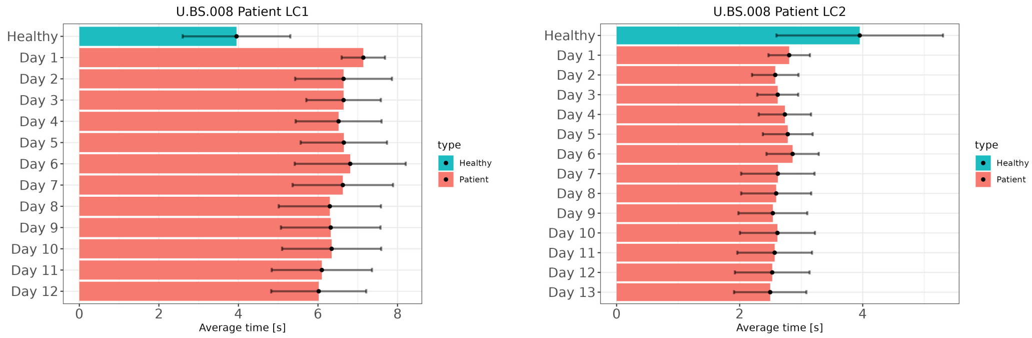


**Figure 3.11:** Exercise U.BS.008 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

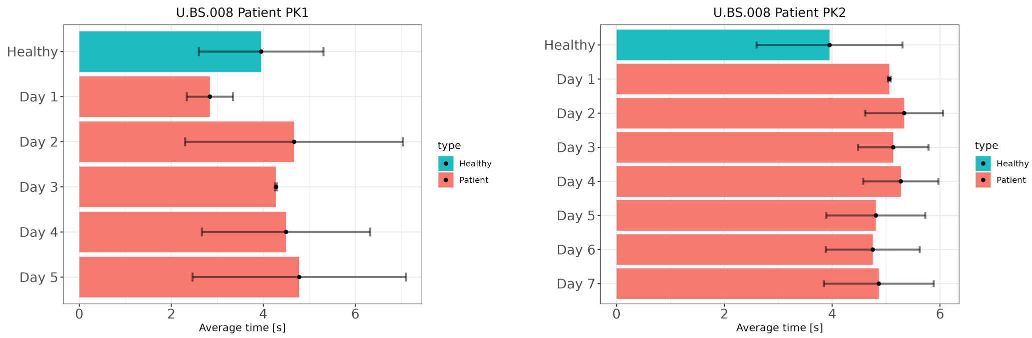


**Figure 3.12:** Exercise U.BS.008 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

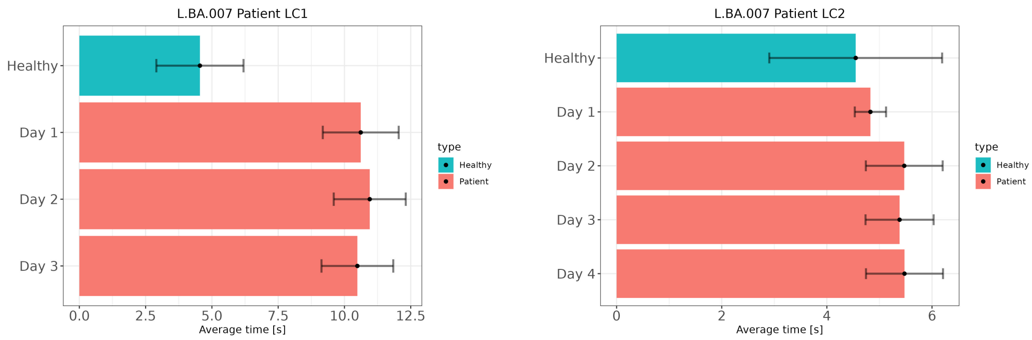


**Figure 3.13:** Exercise U.BS.L.BA.007 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

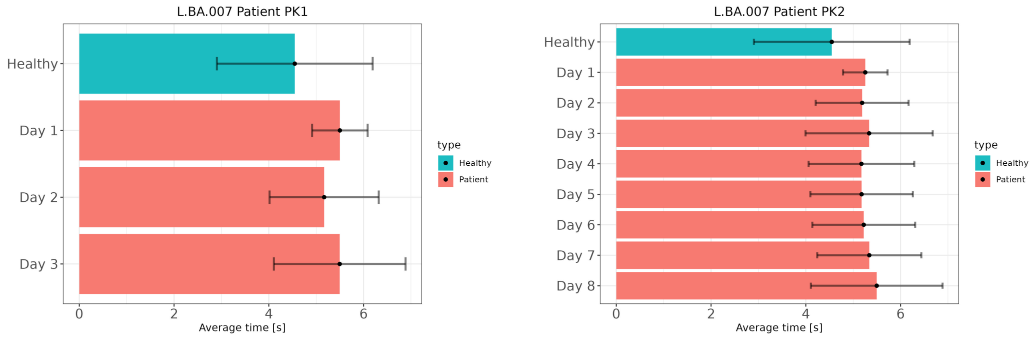


**Figure 3.14:** Exercise L.BA.007 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

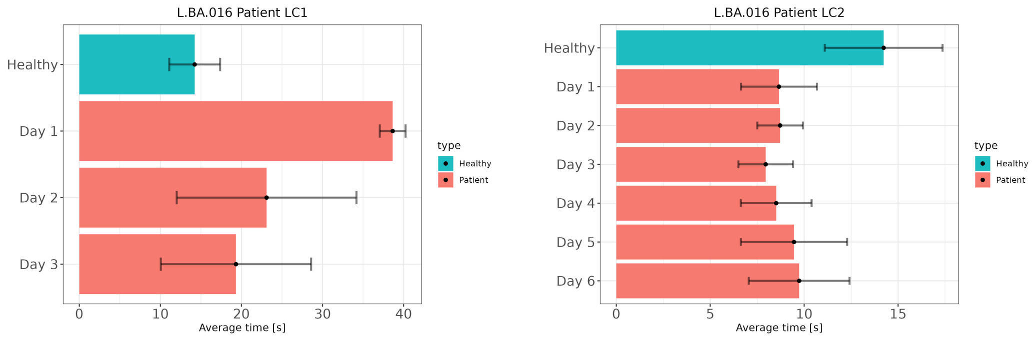


**Figure 3.15:** Exercise L.BA.016 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

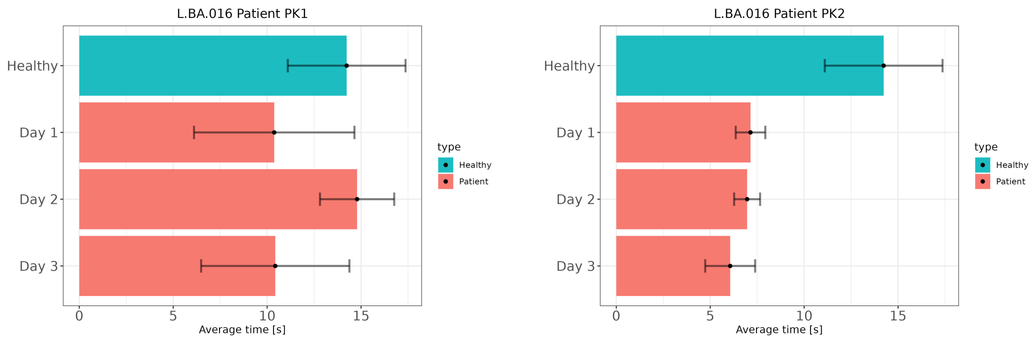


**Figure 3.16:** Exercise L.BA.016 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

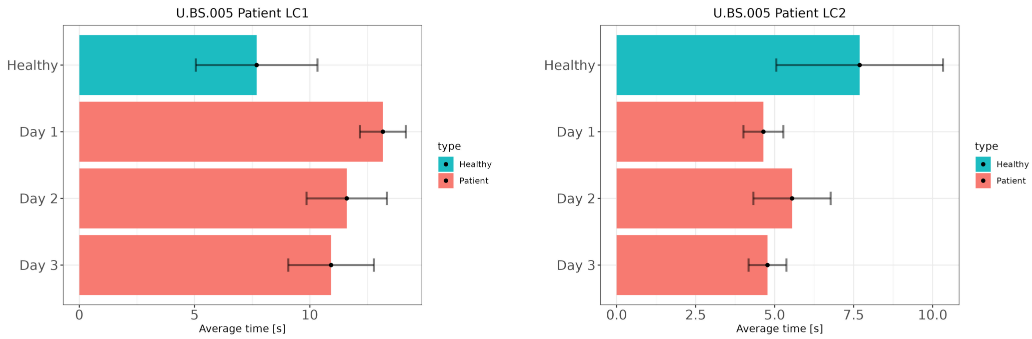


**Figure 3.17:** Exercise U.BS.005 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

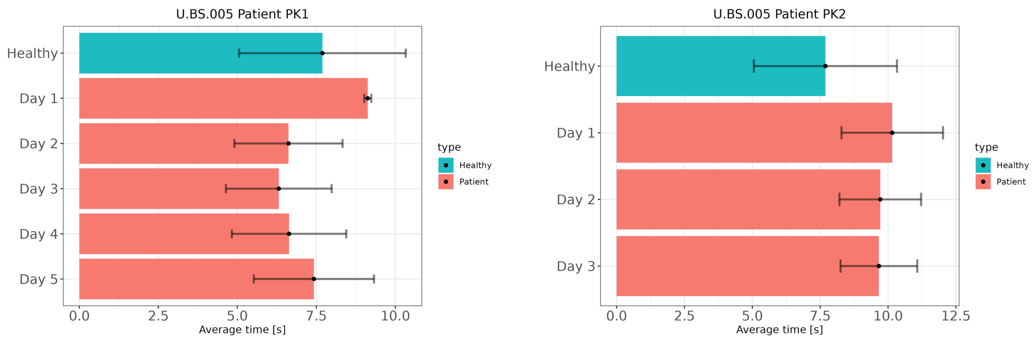


**Figure 3.18:** Exercise U.BS.005 repetitions duration over time. Average duration of a repetition in seconds [s] on the different days the patient performed the exercise compared with the average duration of healthy subjects (in red)

## 3.3 DTW score

The DTW score was calculated to quantitatively measure how similar the patients' signals were to that of the template. The DTW score was computed for all 4 patients and 8 exercises the first day and the last of the tele-rehabilitation protocol. The results of the analysis are here reported.
It was chosen to compute the score for the first and last day of the tele-rehabilitation protocol in order to check whether any differences or improvements could be detected in the performance after a month during which the patients performed the exercises at home. Theoretically, as DTW score decreases, patients are performing the exercise more similar to the template. Low values indicate that the cost of realigning the signals is low and that the signals are therefore more similar to each other, conversely, higher values indicate greater dissimilarity.

Below are reported the graphs of patients whom DTW score decreased more significantly during the rehabilitation protocol for that specific exercise.
The graphs created represent the DTW score the first and the last day patients performed a selected exercise. Scores for every sensors, separately for each axis, are reported with their own scale since their range varies. Yellow background can be found where a decrease in the DTW score is present.
The DTW score for hip flexion (L.BA.007) decreases the most for patient PK 1 (Figure 3.19). Patients LC 1 and LC 2 have a similar behavior to PK 1 so their graphs are not reported here. As for the arm pushing exercise (U.BS.005), whom main movement is along x and z axis, Figure 3.20 details patient PK 1 as well because he had the greatest variation in the DTW score.
Patient PK 2 DTW score decreases the most while performing the weight transfer to lower limbs exercise (L.BA.001), specially along the main axis (z axis) of movement (Figure 3.21). The same patient also presents the greatest variation in DTW score for exercise L.BA.014, whom main movement is along x and z axis (Figure 3.22).
As for upper limb exercises, all 4 patients performed similarly the arm elevation while sitting with stick exercise (U.BS.003). Figure 3.23 shows only the DTW score for patient PK 2 as an example.
Patient LC 1 DTW score decreased the most for tandem with abducted limbs exercise (L.BA.016), whom main movement is along x and z axis as well (Figure 3.24).
Exercise U.BS.004 main movement happens along x and z axis and Figure 3.25 details patient LC 2. The same patient's DTW score decreased for exercise U.BS.008, whom main movement is along x and z axis (Figure 3.26).
Overall, it can be observed that acceleration scores resulted lower at the end of the treatment, which means that the patterns are more similar to the healthy reference. As for angular velocity, DTW scores are way higher for all patients, this indicates that the movement patterns are dissimilar to the template. In general, the DTW

score decreased the most for patient PK 2 in lower limb exercises and patient LC 1 and LC 2 for all exercises. Meanwhile, patient PK 1 scores had more variability.

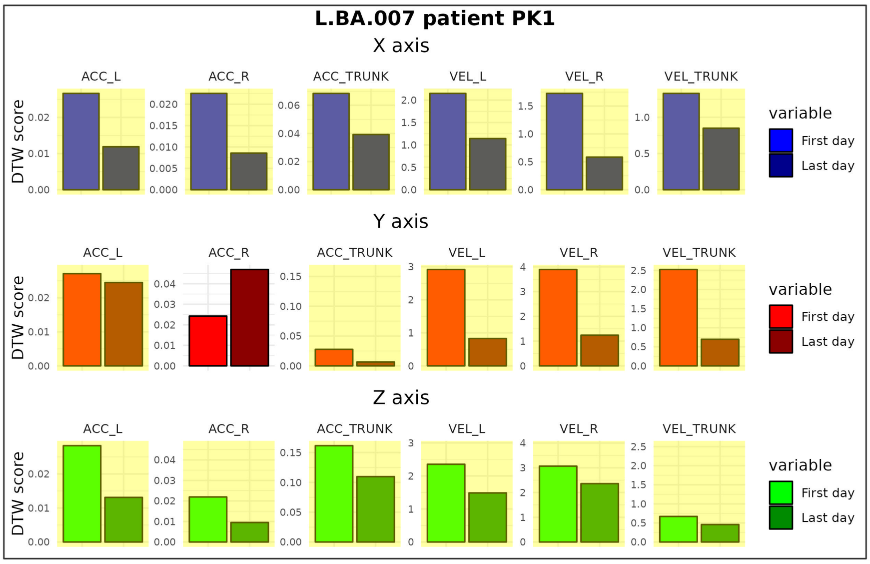


**Figure 3.19:** DTW score fist day vs. last day of the protocol for exercise L.BA.007 and patient PK 1

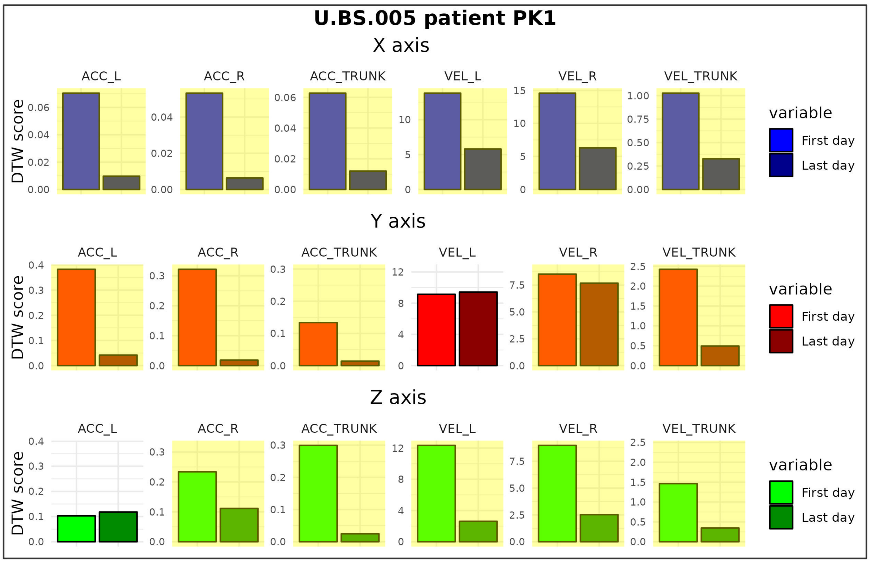


**Figure 3.20:** DTW score fist day vs. last day of the protocol for exercise U.BS.004 and patient PK 1

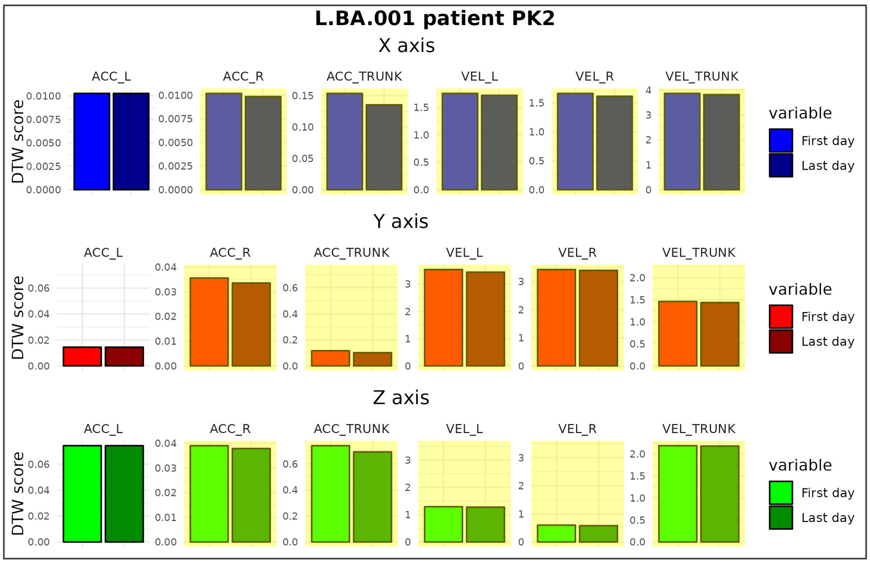


**Figure 3.21:** DTW score fist day vs. last day of the protocol for exercise L.BA.001 and patient PK 2

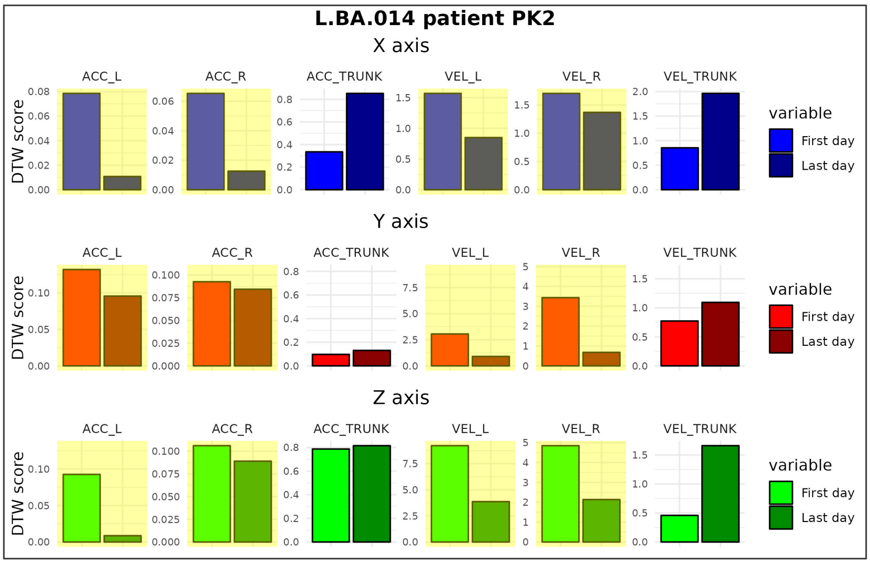


**Figure 3.22:** DTW score fist day vs. last day of the protocol for exercise L.BA.014 and patient PK 2

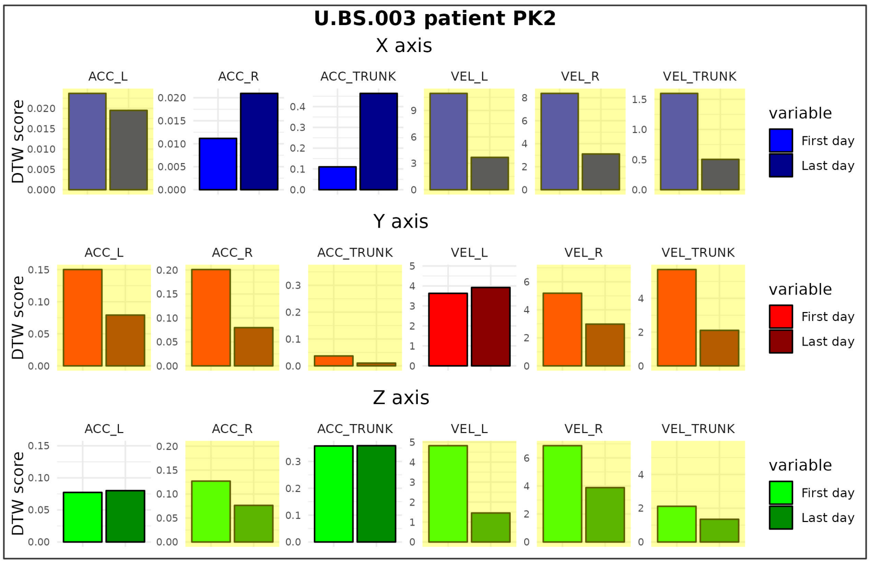


**Figure 3.23:** DTW score fist day vs. last day of the protocol for exercise U.BS.003 and patient PK 2

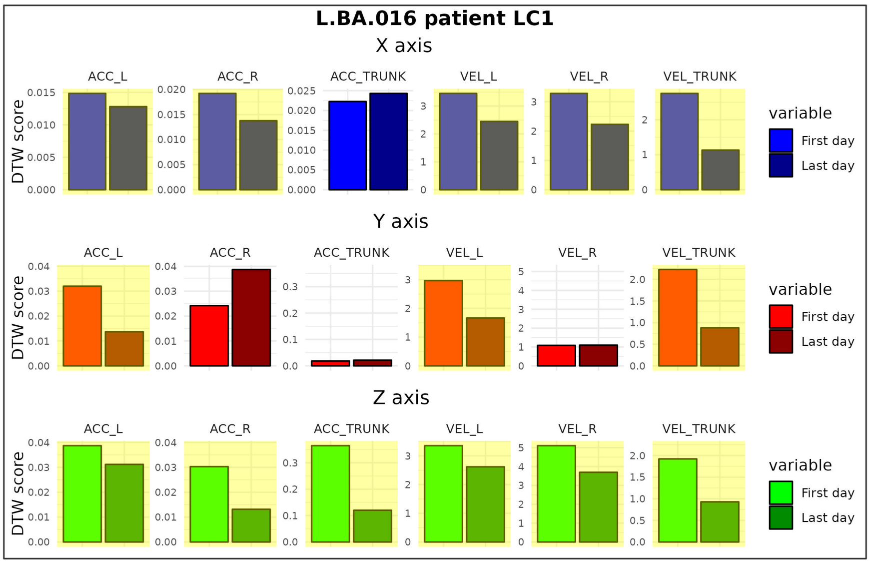


**Figure 3.24:** DTW score fist day vs. last day of the protocol for exercise L.BA.016 and patient LC 1

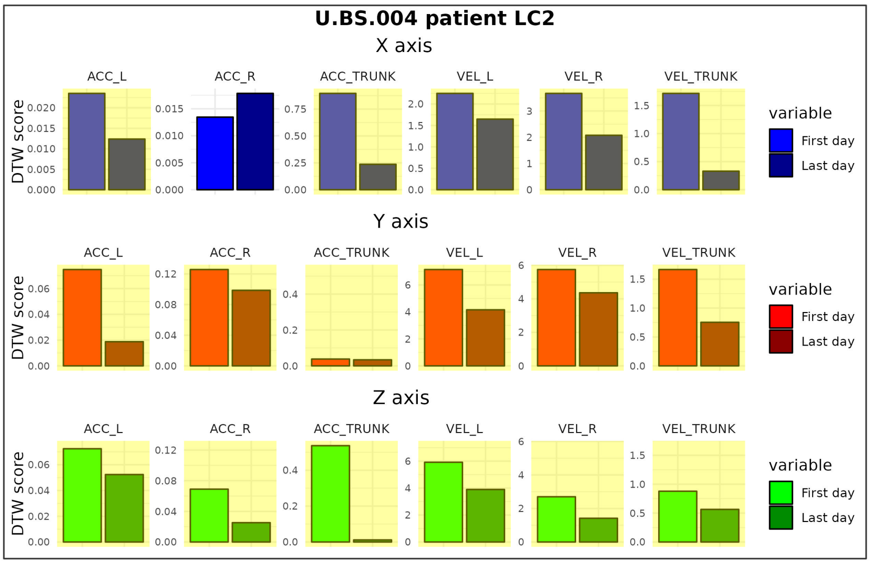


**Figure 3.25:** DTW score fist day vs. last day of the protocol for exercise U.BS.004 and patient LC 2

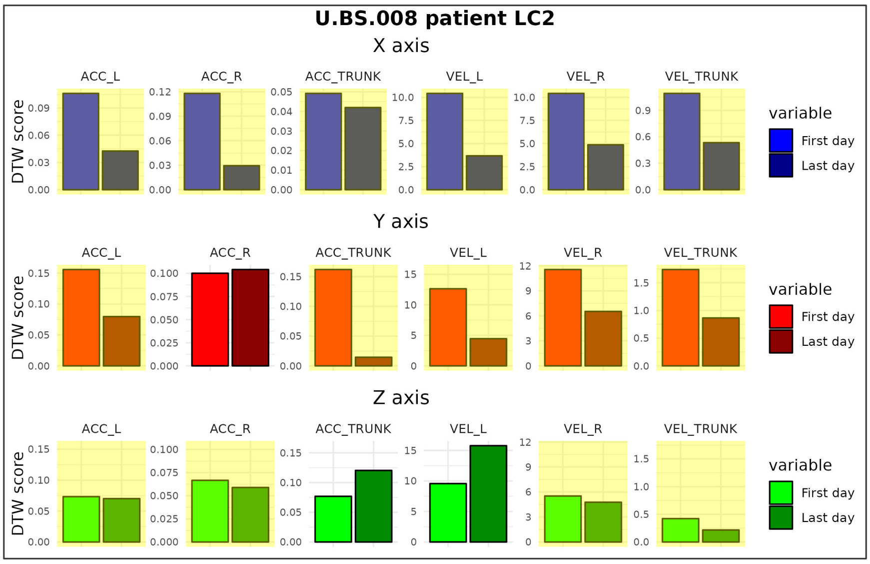


**Figure 3.26:** DTW score fist day vs. last day of the protocol for exercise U.BS.008 and patient LC 2

To compare DTW scores obtained for Parkinson and Long COVID-19 patients in the same graphs a dedicated analysis was conducted specifically for each exercise. This comparison was made with the idea to see if Long COVID-19 patients scores were closer to healthy subjects than Parkinsons, and also to understand if, from this score, it is possible to assess any differences in the progresses among LC and PK patients, as could be assumed. This analysis was not conducted to compare the 2 groups of patients because it is impossible to do due to their different pathologies. Each figure is specific for an exercise and reports the DTW score for each Cartesian axis for every subject the first and the last day of the tele-rehabilitation protocol. A segment with a downward trend indicates that the scores decreased the last day of the clinical trial.

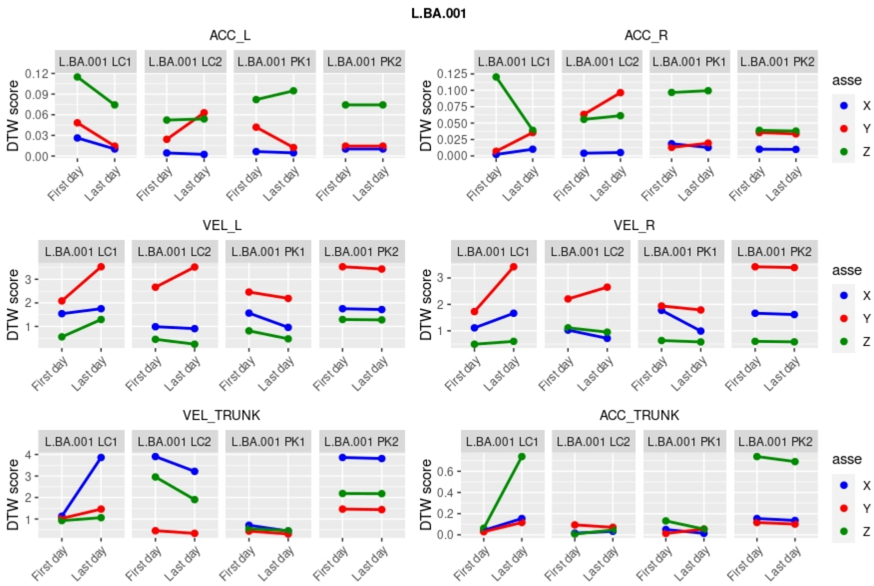


**Figure 3.27:** DTW score fist day vs. last day of the protocol for exercise L.BA.001 for all patients

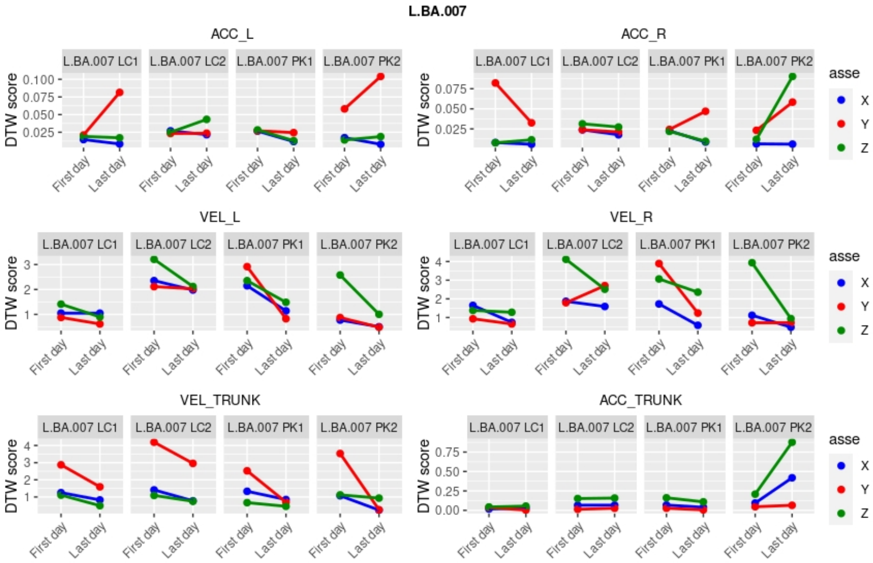


**Figure 3.28:** DTW score fist day vs. last day of the protocol for exercise L.BA.007 for all patients

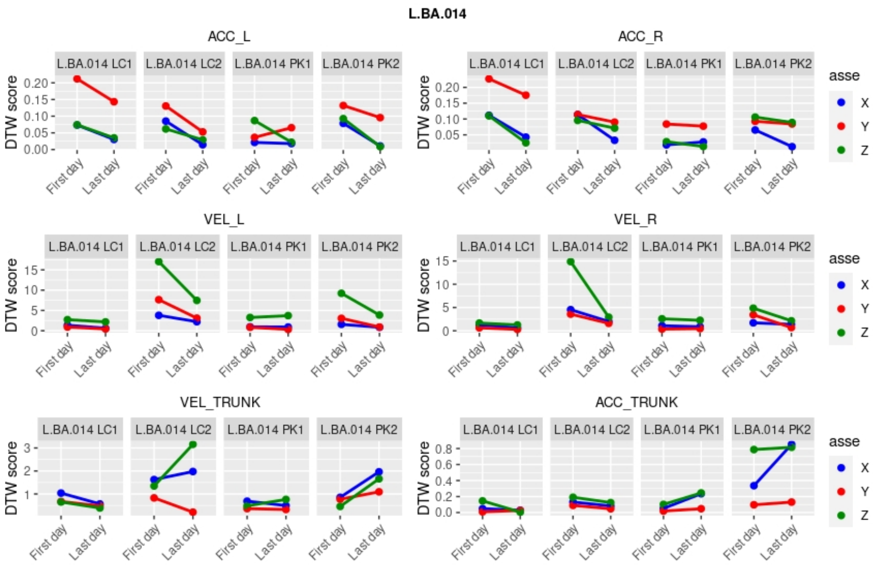


**Figure 3.29:** DTW score fist day vs. last day of the protocol for exercise L.BA.014 for all patients

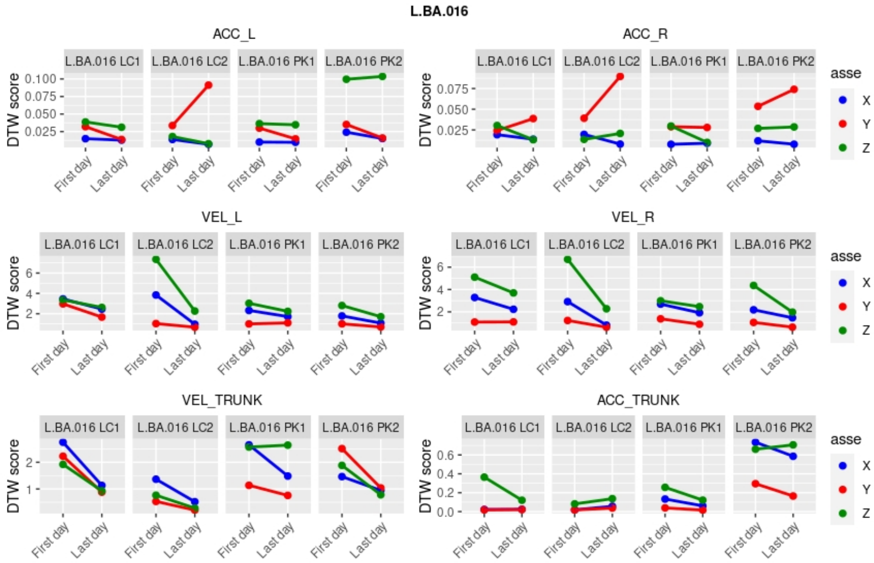


**Figure 3.30:** DTW score fist day vs. last day of the protocol for exercise L.BA.016 for all patients

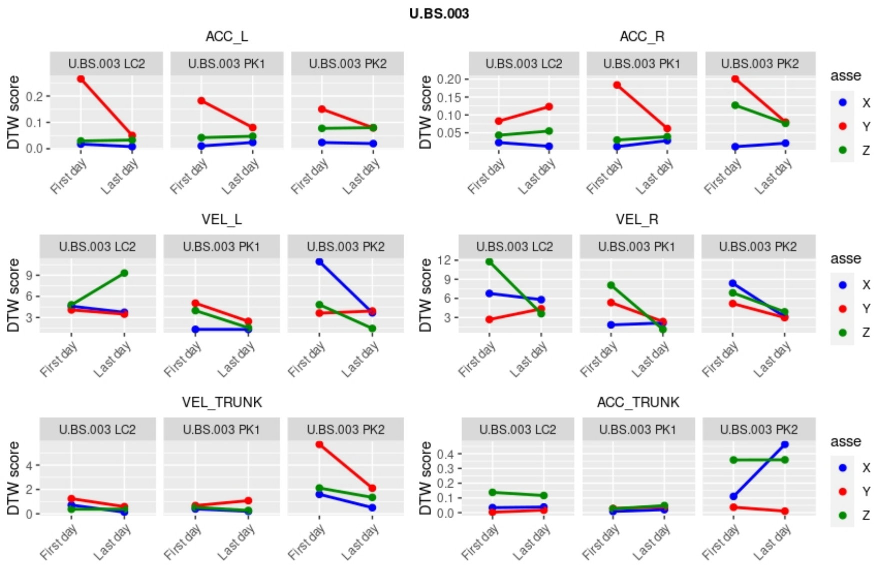


**Figure 3.31:** DTW score fist day vs. last day of the protocol for exercise U.BS.003 for all patients

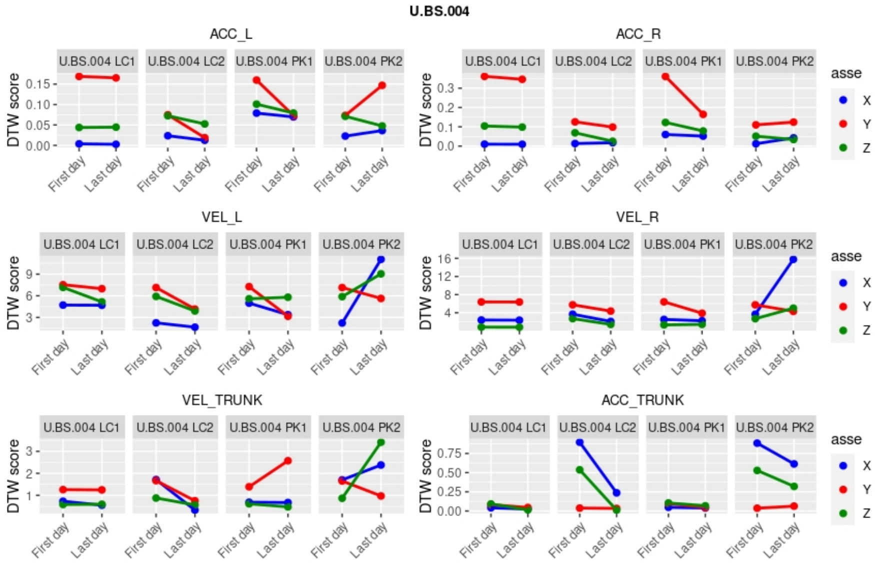


**Figure 3.32:** DTW score fist day vs. last day of the protocol for exercise U.BS.004 for all patients

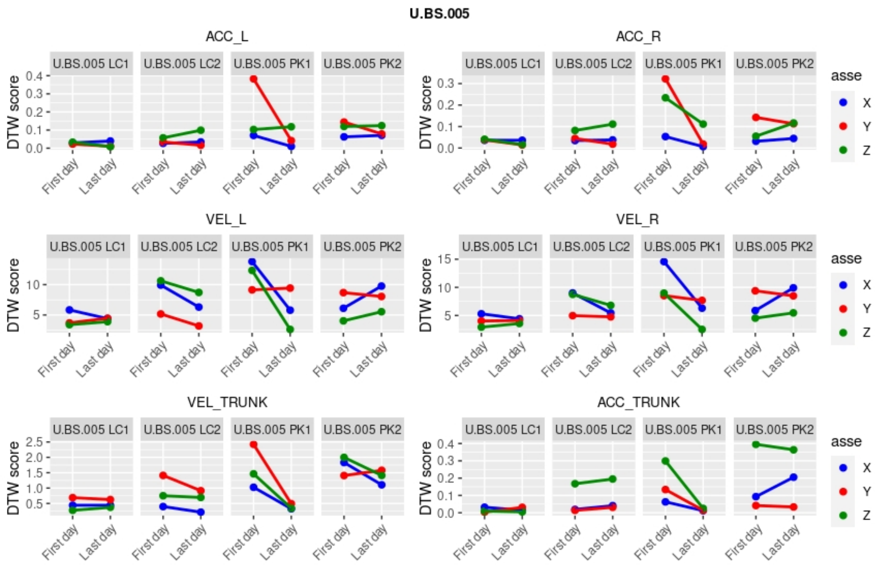


**Figure 3.33:** DTW score fist day vs. last day of the protocol for exercise U.BS.005 for all patients

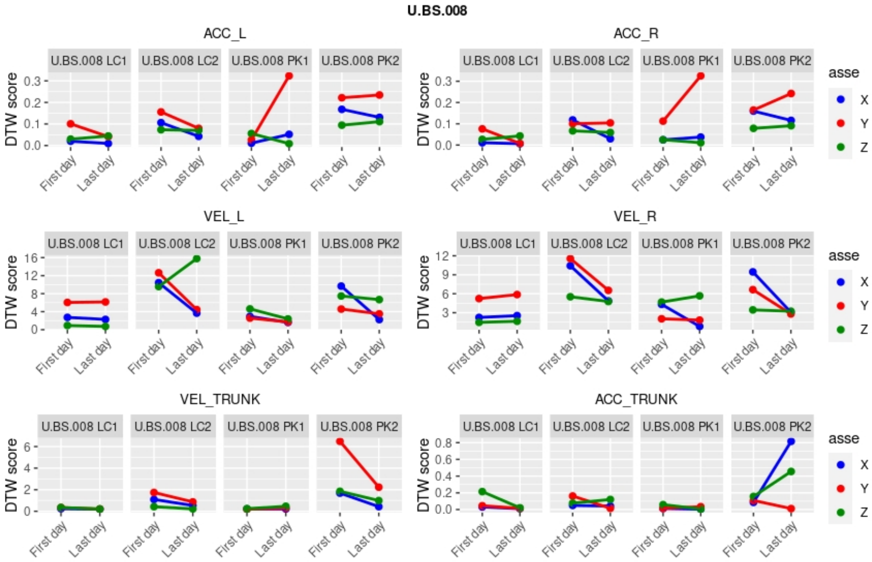


**Figure 3.34:** DTW score fist day vs. last day of the protocol for exercise U.BS.003 for all patients

# Chapter 4

# Discussion & Conclusion

## 4.1 Discussion

Analyzing the results from the visual comparison between patients movement patterns and the template, the average repetition duration and the DTW score, a summary description of each patients is possible:

- Patient Parkinson 1. It is difficult to know whether there was an improvement after the clinical trial. From the visual comparison between his patterns and the healthy subjects ones, the main movement pattern was not always recognisable. As for the duration analysis, he performed the various exercises with an average time similar to the template. The DTW score of most of the exercises is slightly higher on the last day, decreases could only be observed for exercise L.BA.001, L.BA.007 and L.BA.016.
- Patient Parkinson 2. His DTW score decreased mostly in exercises that target lower limbs. This result could be related to many variables due to his pathology. Patient's movement patterns were similar to the templates even if they were not very precise. His average repetition duration had great variability among the different exercises as well among the different days of the tele-rehabilitation protocol.
- Patient Long COVID-19 1. His movement patterns were similar to the healthy subjects templates and his average repetition duration deviate from the average time of healthy subjects in a variable manner depending on the exercise. DTW scores decreased for all exercises except for exercise L.BA.001. This suggests that he performed better each exercise and that this could be related to his better health condition.
- Patient Long COVID-19 2. His DTW scores did not improved as much as for patient LC 1. Scores are quite similar for the first and last day, they lowered

the most while performing exercise U.BS.008 and U.BS.004. His average repetitions times were variable meanwhile his movement patterns were similar to the templates.

For Parkinson patients is difficult, due to their medical condition, to see an improvement after one month because the pathology is very severe and involves many areas of the body notching up not only their mobility but also their overall well being. Long COVID-19 patients performed, overall, better each exercise and in fact most of the time, their DTW score decreased at the end of the of the trial. The aim of the score is to help the therapist to check how differently the patient is performing the exercise from how it should be done. Focusing the analysis on the DTW scores for each exercise, the following considerations are proposed:

- Exercise L.BA.007. There is a decrease in the score specifically for patient LC 2. Overall for this exercise major decreases are visible for patient LC 1 and LC 2 (Figure 3.28).

- Exercise L.BA.014. There are descreses in the DTW score as seen in Figure 3.29 for patient LC 2 and LC 1 specifically for left and right lower limb angular velocity, trunk acceleration. Among Parkinson subjects, PK 1 DTW scores are the best since they are quite stable.

- Exercise L.BA.001. Figure 3.27 shows that it is more difficult to see decreases in the scores. Both Long COVID-19 and Parkinson patients show some difficulty in performing this exercise. Weight transfer to lower limbs is a difficult balance exercise.

- Exercise L.BA.016. A decrease, as in Figure 3.30, is visible in left and right angular velocity for both group of patients.

- Exercise U.BS.003. It is not noticeable an overall decrease in the DTW score as visible in Figure 3.31. Only right upper limb angular velocity details a decrease in the score for both group of patients.

- Exercise U.BS.004. Both LC 1 and LC 2 scores are stable for most of the sensors. PK 2 shows abnormalities in all the sensors but trunk acceleration as detailed in Figure 3.32.

- Exercise U.BS.005. In this exercise, LC 1 scores are the most stable; PK 1 details a great descrese in the DTW score as Figure 3.33 shows.

- Exercise U.BS.008. LC 1 values are the most stable among all patients, PK 2 values decrease in most of the sensors beside right and trunk acceleration as Figure 3.34 details.

The tele-rehabilitation protocol lasted only one month. During this time patients had the free choice to execute or not the exercises because the training was unsupervised. At the end, therapists assesses their status to evaluate any benefits of the tele-rehabilitation treatment. Table 2.9 details the meters covered to the first stop by patients while performing the 6MWT. It is clear that all four candidates performed better at the end of the trial. Specifically, patient LC 1 has improved travelling 68m more and patient PK 1 travelling 24m more. This increase in the covered distance may be significant and may indicate that patients followed the protocol and exercised. Observing the decrease of the DTW score in lower limb exercises for patient PK 1, a longer distance covered on the test may be aligned with the fact that he performed better in lower limb exercises. Patient LC 1 scores decrease for most of the exercises so this is aligned with the clinical assessment as well. Of course, it must be taken into account that specific health conditions, pain or other ailments that the patients might have had on the day of the test are not known, and therefore might have impaired their performance. The other administered clinical scales do not show any variations (Table 2.10). The EUROQoL 5D scale asses generic quality of life so it was expected to not improve after one month due to the short period. FAC is a functional walking test that is useful to determine how much support the patient require while walking and it did not change after such a short period of time. The Brief Fatigue Inventory (BFI), as Table 2.11 shows, decreased for both Parkinson patients and also for patient LC 2. BFI is a rapid assessment of fatigue severity so its decrease may be a sign that the patients exercised but with a lower perceived exertion. Regarding the MDS-UPDRS scale, final scores were only available for patient PK 2 and comparing Table 2.12 with Table 2.13, no changes have been registered. Medical scale are very useful to assess the patient because they allow to have an overview on his or her health status, but these scales are usually not very granular, so it may be difficult to tell whether the prescribed tele-rehabilitation protocol is useful after a short period of time. Furthermore, doing these assessments requires lengthy medical examinations, so using tools or methods that help the physician to assess patients performances already during the course of the rehabilitation protocol could be useful. As medical scales are not so accurate in capturing a patient's improvement during a short amount of time, the approaches proposed here, such as visual comparison between healthy subjects movement pattern and patients' ones, duration analysis and DTW score could be useful for the therapist to check if the protocol is being carried out as it should be and to monitor patient motor behaviour.

## 4.2 Conclusion

The aim of this thesis project was to investigate inertial data from a wide set of exercises of variable complexity and widely adopted in clinical practice. The main objective was to explore a method and find out relevant parameters able to support clinicians in the evaluation of unsupervised exercises sessions.

This project has been realized in collaboration with the research company Henesis srl, that made available two datasets: a healthy one, based on 17 volunteers, and a group of 10 Parkinson and 11 Long COVID-19 enrolled at the Neurorehabilitation Clinic, "Ospedali Riuniti" of Ancona. The inertial data were acquired using ARC intellicare, a medical device that allows motor and respiratory tele-rehabilitation. A case study was conducted focusing on 2 Parkinson and 2 Long COVID-19 patients; their data were processed and analysed through a Python code, in order to find the average movement patterns for each exercise. These patterns have been compared among the healthy population and the case study patients to look for any pathological abnormalities or deviations from a healthy behavior. In addition, an exercise repetition duration and a DTW score have been investigated to provide a complementary quantitative description.

The proposed visual comparison of the patient's pattern and the healthy template may allow clinicians to make a high level check on the correctness of the movement. Signals that are similar to the template may allow the rehabilitation professionals to know whether the patients is performing correctly the exercise. Dissimilarities may be related to health problems or difficulties in understanding the movements to be performed. The comparison may be exploited as a first tool to verify patient adherence to the protocol. The capability of patients to perform exercises with expected movement patterns may represent a useful information.

Average duration of a repetition can be useful to the physician as it can be a sign of possible abnormalities. An average duration that is too short and much shorter than the average for healthy subjects may be indicative of the fact that the patient is not performing correctly the exercise, or he/she is moving too fast, depending on the exercise itself. In this case, the therapist could contact the patient to find out what the problems are and if the patient is having too much trouble doing the exercise, the therapist could intervene by modifying the rehabilitation protocol. An excessively longer duration of exercise repetition, compared to healthy average may indicate that the patient is having serious difficulties performing the exercises, and it is therefore up to the doctor to contact the subject to inquire about his or her health condition and in case of problems modify the exercises assigned.

The DTW score, used in many gait studies as a distance metric, has been implemented to assess how similar the patient's patterns are to a healthy template. A comparison between DTW scores on the first and last day of the rehabilitation protocol was performed. This could potentially represent a quantitative parameter

to describe movement patterns similarity. A decrease in the score, as also mentioned in the previous chapter, indicates that the patient is performing the exercise more similarly to the template and therefore it is more likely that his or her mobility has improved at the end of the tele-rehabilitation program. The aim of the DTW score, in fact, is to check quantitatively whether patients improved in the execution of the exercises using inertial data from the sensor.
This thesis project proposed a method that could be useful to process inertial data from wearable sensors used for tele-rehabilitation applications, to assess motor capabilities of different types of patients. It also paved the way to further analysis on larger datasets.

## 4.3 Future developments

This project considers only 8 exercises and 4 patients so future developments may focus on expanding the study to all patients and all exercises. It would be helpful also to correlate the results obtained with the clinical scales and conduct a statistical analysis on all the data computed. These 3 steps combined should lead to a possible validation of the approach proposed in this work. Validated metrics that may help the therapist quantitatively assess patients improvements while performing different rehabilitative exercises and that are correlated to clinical evaluation scales are much needed and still to explore. All the work concerning the segmentation of data, their organisation and preliminary analysis has already been done for this project so future developments may address aspects such as frequency analysis, power analysis and other scores involving inertial signals that would need the same validation process.

# Bibliography

[1] J. Harris, K. Goodman, A. Haghandish, C. Martin, and J. King. «Cardiac tele-rehabilitation programs: a study of women participation in rural settings». In: *Canadian journal of cardiology* 37.2 (2021), e6–e7. ISSN: 0828-282X (cit. on p. 1).

[2] Mercè Piqueras, Ester Marco, Maria Coll, Ferran Escalada, Alex Ballester, Carme Cinca, Roser Belmonte, and Josep M. Muniesa. «Effectiveness of an interactive virtual telerehabilitation system in patients after total knee arthroplasty: A randomized controlled trial». In: *Journal of Rehabilitation Medicine* 45 (4 2013), pp. 392–396. ISSN: 16501977. DOI: 10.2340/16501977-1119 (cit. on p. 1).

[3] Anne E. Holland et al. «Home-based rehabilitation for COPD using minimal resources: A randomised, controlled equivalence trial». In: *Thorax* 72 (1 Jan. 2017), pp. 57–65. ISSN: 14683296. DOI: 10.1136/thoraxjnl-2016-208514 (cit. on p. 1).

[4] Javier García-Alba, Susana Rubio-Valdehita, M. Julia Sánchez, Amelia I. M. García, Susanna Esteba-Castillo, and Marta Gómez-Caminero. «Cognitive training in adults with intellectual disability: pilot study applying a cognitive tele-rehabilitation program». eng. In: *International journal of developmental disabilities* (2020). ISSN: 2047-3869 (cit. on p. 1).

[5] PhD Bodil B Jørgensen MHSc, PhD Merete Gregersen MHSc, Søren Holm Pallesen, and PhD Else Marie Damsgaard MD DMSci. «Tele-Rehabilitation in Community-Dwelling Older People with Reduced Functional Capacity: A 4-Patient Case Report». eng. In: 8 (2022). ISSN: 2333-7214 (cit. on p. 1).

[6] Abayomi Salawu, Angela Green, Michael G. Crooks, Nina Brixey, Denise H. Ross, and Manoj Sivan. «A proposal for multidisciplinary tele-rehabilitation in the assessment and rehabilitation of COVID-19 survivors». In: *International journal of environmental research and public health* 17.13 (2020), pp. 1–13. ISSN: 1661-7827 (cit. on p. 1).

[7] Pamela Frigerio, Liliana Del Monte, Aurora Sotgiu, Costantino De Giacomo, and Aglaia Vignoli. «Parents' satisfaction of tele-rehabilitation for children with neurodevelopmental disabilities during the COVID-19 pandemic». In: *BMC Primary Care* 23.1 (2022), pp. 146–146. ISSN: 2731-4553 (cit. on p. 1).

[8] Ruth H Walker. «Telemedicine». In: *Neurology* 86.24 (2016), pp. 2313–2313. ISSN: 0028-3878 (cit. on p. 1).

[9] Sue Dahl-Popolizio, Heidi Carpenter, Melissa Coronado, Nicholas J. Popolizio, and Connor Swanson. «Telehealth for the provision of occupational therapy: Reflections on experiences during the COVID-19 pandemic». In: *International Journal of Telerehabilitation* 12 (2 2020), pp. 77–92. ISSN: 19452020. DOI: `10.5195/ijt.2020.6328` (cit. on p. 1).

[10] Huidi Tchero, Maturin Tabue Teguo, Annie Lannuzel, and Emmanuel Rusch. «Telerehabilitation for stroke survivors: Systematic review and meta-analysis». In: *Journal of medical Internet research* 20.10 (2018), e10867–e10867 (cit. on p. 1).

[11] A. Zedda, E. Gusai, M. Caruso, S. Bertuletti, S. Spanu, A. Pibiri, M. Monticone, A. Cereatti, and D. Pani. «A home-based tele-rehabilitation system for stroke patients exploiting magneto-inertial measurement units». eng. In: *Gait posture* 74 (2019), pp. 37–38. ISSN: 0966-6362 (cit. on p. 1).

[12] Fred S. Sarfo, Uladzislau Ulasavets, Ohene K. Opare-Sem, and Bruce Ovbiagele. «Tele-Rehabilitation after Stroke: An Updated Systematic Review of the Literature». eng. In: *Journal of stroke and cerebrovascular diseases* 27.9 (2018), pp. 2306–2318. ISSN: 1052-3057 (cit. on p. 1).

[13] Narayan Subedi, Jonathan C. Rawstorn, Lan Gao, Harriet Koorts, and Ralph Maddison. «Implementation of telerehabilitation interventions for the self-management of cardiovascular disease: Systematic review». In: *JMIR mHealth and uHealth* 8.11 (2020), e17957–e17957 (cit. on p. 1).

[14] Narelle S. Cox et al. «Telerehabilitation for chronic respiratory disease». In: *Cochrane Database of Systematic Reviews* 2021 (1 Jan. 2021). ISSN: 14651858. DOI: `10.1002/14651858.CD013040.pub2` (cit. on p. 1).

[15] Aroub Lahham, Christine F. McDonald, Rosemary Moore, Narelle S. Cox, Sarah Rawlings, Amanda Nichols, Athina Liacos, and Anne E. Holland. «The impact of home-based pulmonary rehabilitation on people with mild chronic obstructive pulmonary disease: A randomised controlled trial». In: *Clinical Respiratory Journal* 14 (4 Apr. 2020), pp. 335–344. ISSN: 1752699X. DOI: `10.1111/crj.13138` (cit. on p. 1).

[16] Jose Cerdán-De-las-heras, Fernanda Balbino, Anders Løkke, Daniel Catalán-Matamoros, Ole Hilberg, and Elisabeth Bendstrup. «Tele-rehabilitation program in idiopathic pulmonary fibrosis—A single-center randomized trial». In: *International journal of environmental research and public health* 18.19 (2021), p. 10016. ISSN: 1661-7827 (cit. on p. 1).

[17] Jose Cerdán-De-las-heras, Fernanda Balbino, Anders Løkke, Daniel Catalán-Matamoros, Ole Hilberg, and Elisabeth Bendstrup. «Effect of a new tele-rehabilitation program versus standard rehabilitation in patients with chronic obstructive pulmonary disease». eng. In: *Journal of clinical medicine* 11.1 (2022), p. 11. ISSN: 2077-0383 (cit. on p. 1).

[18] Chhaya V. Verma and Rutuja Kamble. «Tele-rehabilitation of a middle-aged female with bronchiectasis as post COVID-19 sequelae: a case report». eng. In: *International journal of research in medical sciences* 10.4 (2022), p. 964. ISSN: 2320-6071 (cit. on p. 1).

[19] Clare L. Burns, Sanjeewa Kularatna, Elizabeth C. Ward, Anne J. Hill, Joshua Byrnes, and Lizbeth M. Kenny. «Cost analysis of a speech pathology synchronous telepractice service for patients with head and neck cancer». In: *Head neck* 39.12 (2017), pp. 2470–2480 (cit. on p. 1).

[20] Agnese Capodieci, Marco Romano, Emanuela Castro, Maria Chiara Di Lieto, Silvia Bonetti, Silvia Spoglianti, and Chiara Pecini. «Executive Functions and Rapid Automatized Naming: A New Tele-Rehabilitation Approach in Children with Language and Learning Disorders». eng. In: *Children (Basel)* 9.6 (2022), p. 822. ISSN: 2227-9067 (cit. on p. 1).

[21] Rob Argent, Antonio Bevilacqua, Alison Keogh, Ailish Daly, and Brian Caulfield. «The importance of real-world validation of machine learning systems in wearable exercise biofeedback platforms: A case study». In: *Sensors* 21 (7 Apr. 2021). ISSN: 14248220. DOI: `10.3390/s21072346` (cit. on pp. 2, 3).

[22] «Development of digital biomarkers for resting tremor and bradykinesia using a wrist-worn wearable device». In: *npj Digital Medicine* 3 (1 Dec. 2020). ISSN: 23986352. DOI: `10.1038/s41746-019-0217-7` (cit. on p. 2).

[23] Arash Salarian, Heike Russmann, Christian Wider, Pierre R. Burkhard, Françios J.G. Vingerhoets, and Kamiar Aminian. «Quantification of tremor and bradykinesia in Parkinson's disease using a novel ambulatory monitoring system». In: *IEEE Transactions on Biomedical Engineering* 54 (2 Feb. 2007), pp. 313–322. ISSN: 00189294. DOI: `10.1109/TBME.2006.886670` (cit. on pp. 2, 5).

[24] Sinziana Mazilu, Ulf Blanke, Alberto Calatroni, Eran Gazit, Jeffrey M. Hausdorff, and Gerhard Tröster. «The role of wrist-mounted inertial sensors in detecting gait freeze episodes in Parkinson's disease». In: *Pervasive and Mobile Computing* 33 (Dec. 2016), pp. 1–16. ISSN: 15741192. DOI: 10.1016/j.pmcj.2015.12.007 (cit. on p. 2).

[25] Bryan T. Cole, Serge H. Roy, Carlo J. De Luca, and S. Hamid Nawab. «Dynamical learning and tracking of tremor and dyskinesia from wearable sensors». In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22 (5 Sept. 2014), pp. 982–991. ISSN: 15344320. DOI: 10.1109/TNSRE.2014.2310904 (cit. on p. 3).

[26] Serena Cerfoglio, Manuela Galli, Marco Tarabini, Filippo Bertozzi, Chiarella Sforza, and Matteo Zago. «Machine learning-based estimation of ground reaction forces and knee joint kinetics from inertial sensors while performing a vertical drop jump». In: *Sensors* 21 (22 Nov. 2021). ISSN: 14248220. DOI: 10.3390/s21227709 (cit. on p. 3).

[27] Jeffrey Z. Nie, James W. Nie, Na Teng Hung, R. James Cotton, and Marc W. Slutzky. «Portable, open-source solutions for estimating wrist position during reaching in people with stroke». In: *Scientific Reports* 11 (1 Dec. 2021). ISSN: 20452322. DOI: 10.1038/s41598-021-01805-2 (cit. on pp. 3, 5).

[28] Nuray Yozbatiran, Lucy Der-Yeghiaian, and Steven C. Cramer. «A standardized approach to performing the action research arm test». In: *Neurorehabilitation and Neural Repair* 22 (1 Jan. 2008), pp. 78–90. ISSN: 15459683. DOI: 10.1177/1545968307305353 (cit. on p. 3).

[29] AR Fugl-Meyer, L Jääskö, I Leyman, S Olsson, and S Steglind. «The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance». In: *Scandinavian journal of rehabilitation medicine* 7.1 (1975), pp. 13–31. ISSN: 0036-5505. URL: http://europepmc.org/abstract/MED/1135616 (cit. on p. 3).

[30] Hyung Seok Nam, Woo Hyung Lee, Han Gil Seo, Yoon Jae Kim, Moon Suk Bang, and Sungwan Kim. «Inertial measurement unit based upper extremity motion characterization for action research arm test and activities of daily living». In: *Sensors (Switzerland)* 19 (8 Apr. 2019). ISSN: 14248220. DOI: 10.3390/s19081782 (cit. on p. 3).

[31] Anton Kos and Anton Umek. «Wearable sensor devices for prevention and rehabilitation in healthcare: Swimming exercise with real-time therapist feedback». In: *IEEE Internet of Things Journal* 6 (2 Apr. 2019), pp. 1331–1341. ISSN: 23274662. DOI: 10.1109/JIOT.2018.2850664 (cit. on p. 3).

[32] Rob Argent, Patrick Slevin, Antonio Bevilacqua, Maurice Neligan, Ailish Daly, and Brian Caulfield. «Wearable sensor-based exercise biofeedback for orthopaedic rehabilitation: A mixed methods user evaluation of a prototype system». In: *Sensors (Switzerland)* 19 (2 Jan. 2019). ISSN: 14248220. DOI: 10.3390/s19020432 (cit. on p. 4).

[33] Vincent Bonnet, Vladimir Joukov, Dana Kulić, Philippe Fraisse, Nacim Ramdani, and Gentiane Venture. «Monitoring of Hip and Knee Joint Angles Using a Single Inertial Measurement Unit during Lower Limb Rehabilitation». In: *IEEE Sensors Journal* 16 (6 Mar. 2016), pp. 1557–1564. ISSN: 1530437X. DOI: 10.1109/JSEN.2015.2503765 (cit. on p. 4).

[34] Antonio Bevilacqua, Bingquan Huang, Rob Argent, Brian Caulfield, and Tahar Kechadi. «Automatic Classification of Knee Rehabilitation Exercises Using a Single Inertial Sensor: a Case Study». In: (Dec. 2018). DOI: 10.1109/BSN.2018.8329649. URL: http://arxiv.org/abs/1812.03880%20http://dx.doi.org/10.1109/BSN.2018.8329649 (cit. on p. 4).

[35] Oonagh M. Giggins, Kevin T. Sweeney, and Brian Caulfield. «Rehabilitation exercise assessment using inertial sensors: A cross-sectional analytical study». In: *Journal of NeuroEngineering and Rehabilitation* 11 (1 Nov. 2014). ISSN: 17430003. DOI: 10.1186/1743-0003-11-158 (cit. on p. 4).

[36] Matthew M. Engelhard, Sriram Raju Dandu, Stephen D. Patek, John C. Lach, and Myla D. Goldman. «Quantifying six-minute walk induced gait deterioration with inertial sensors in multiple sclerosis subjects». In: *Gait and Posture* 49 (Sept. 2016), pp. 340–345. ISSN: 18792219. DOI: 10.1016/j.gaitpost.2016.07.184 (cit. on pp. 4, 19, 37, 39).

[37] *ARC intellicare La riabilitazione intelligente*. https://www.arc-intellicare.com/en/home-en/. Accessed: 2022-09-01 (cit. on p. 7).

[38] L. Ascari S. Lai A. Mantoan F. Sernissi L. Moro R. Brondi G. Avveduto R. Panero E. Ponzo I. Abbiate A. Revel R. Odoni. «ARC-Intellicare, A home-based platform for an integrated rehabilitation care: the Italian case study». In: *Global clinical engineering* 2 (2019) (cit. on pp. 7, 8).

[39] Cima Rossella Mantoan A. Lai S. Moro L. Brondi R. Sernissi F. Ascari L. Hibel M. Izzo R. Casoli P. Ceravolo M.G. Capecci M. «Tele-riabilitazione motoria e respiratoria post-COVID-19 con arc-intellicare: usabilità, gradimento e risultati clinici preliminari». In: (cit. on pp. 7, 8).

[40] *MBIENTLAB Sensors*. https://mbientlab.com/. Accessed: 2022-09-01 (cit. on p. 13).

[41] *Booklet La ripresa della attività dopo COVID-19*. https://www.rehab-univpm.it/public/assets/img/home/booklet_covid.pdf. Accessed: 2022-09-08 (cit. on p. 14).

[42] *Clinica Neuroriabilitazione UNIVPM Respiratory and motor rehabilitation exercises*. `https://www.ospedaliriuniti.marche.it/portale/`. Accessed: 2022-09-08 (cit. on p. 14).

[43] *SIMFER Therapeutic Education Protocols dedicated to people recovering from post-infection from COVID-19*. `https://www.simfer.it/protocolli-di-educazione-terapeutica-dedicati-alle-persone-in-fase-di-recupero-post-infezione-da-covid-19/`. Accessed: 2022-09-08 (cit. on p. 14).

[44] *Arc intellicare clinical tial Clinical Trial*. `https://clinicaltrials.gov/ct2/show/study/NCT05074771`. Accessed: 2022-09-01 (cit. on p. 18).

[45] R. Balestrino and A. H.V. Schapira. *Parkinson disease*. Jan. 2020. DOI: `10.1111/ene.14108` (cit. on p. 18).

[46] Dennis W. Dickson. «Neuropathology of Parkinson disease». In: *Parkinsonism and Related Disorders* 46 (Jan. 2018), S30–S33. ISSN: 18735126. DOI: `10.1016/j.parkreldis.2017.07.033` (cit. on p. 18).

[47] Ana Luiza Cabrera Martimbianco, Rafael Leite Pacheco, Ângela Maria Bagattini, and Rachel Riera. «Frequency, signs and symptoms, and criteria adopted for long COVID-19: A systematic review». In: *International Journal of Clinical Practice* 75 (10 Oct. 2021). ISSN: 17421241. DOI: `10.1111/ijcp.14357` (cit. on p. 18).

[48] Harald Brüssow and Kenneth Timmis. «COVID-19: long covid and its societal consequences». In: *Environmental Microbiology* 23 (8 Aug. 2021), pp. 4077–4091. ISSN: 14622920. DOI: `10.1111/1462-2920.15634` (cit. on p. 18).

[49] Tito R. Mendoza, X.Shelley Wang, Charles S. Cleeland, Marilyn Morrissey, Beth A. Johnson, Judy K. Wendt, and Stephen L. Huber. «The rapid assessment of fatigue severity in cancer patients: Use of the brief fatigue inventory». In: *Cancer* 85.5 (1999), pp. 1186–1196. ISSN: 0008-543X (cit. on p. 19).

[50] Subrata Debnath, Rain Rueda, Shweta Bansal, Kumar Sharma, and Carlos Lorenzo. «Assessment of fatigue in hemodialysis patients: Performance of the Brief Fatigue Inventory». In: *General hospital psychiatry* 68 (2021), pp. 115–117. ISSN: 0163-8343 (cit. on p. 19).

[51] Gianluigi Balestroni and Giorgio Bertolotti. «EuroQol-5D (EQ-5D): an instrument for measuring quality of life». In: *Monaldi Archives for Chest Disease* 78.3 (Dec. 2015). DOI: `10.4081/monaldi.2012.121`. URL: `https://www.monaldi-archives.org/index.php/macd/article/view/121` (cit. on p. 19).

[52] Woo Je Lee, Kee Ho Song, Jung Hyun Noh, Yon Jong Choi, and Min Woo Jo. «Health-related quality of life using the EuroQol 5D questionnaire in Korean patients with type 2 diabetes». In: *Journal of Korean Medical Science* 27 (3 Mar. 2012), pp. 255–260. ISSN: 10118934. DOI: `10.3346/jkms.2012.27.3.255` (cit. on p. 19).

[53] *Stroke Engine Functional Ambulation Categories (FAC)*. `https://strokengine.ca/en/assessments/fac/`. Accessed: 2022-09-01 (cit. on p. 19).

[54] Ji Young Lim, Seung Heon An, and Dae Sung Park. «Walking velocity and modified rivermead mobility index as discriminatory measures for functional ambulation classification of chronic stroke patients». In: *Hong Kong Physiotherapy Journal* 39 (2 Dec. 2019), pp. 125–132. ISSN: 10137025. DOI: `10.1142/S1013702519500112` (cit. on p. 19).

[55] Gail F. Forrest, Karen Hutchinson, Douglas J. Lorenz, Jeffrey J. Buehner, Leslie R. VanHiel, Sue Ann Sisto, and D. Michele Basso. «Are the 10 meter and 6 minute walk tests redundant in patients with spinal cord injury?» In: *PLoS ONE* 9 (5 May 2014). ISSN: 19326203. DOI: `10.1371/journal.pone.0094108` (cit. on p. 19).

[56] «Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results». In: *Movement Disorders* 23 (15 Nov. 2008), pp. 2129–2170. ISSN: 08853185. DOI: `10.1002/mds.22340` (cit. on p. 19).

[57] Toshi A. Furukawa, M. Katherine Shear, David H. Barlow, Jack M. Gorman, Scott W. Woods, Roy Money, Eva Etschel, Rolf R. Engel, and Stefan Leucht. «Evidence-based guidelines for interpretation of the panic disorder severity scale». In: *Depression and Anxiety* 26 (10 Oct. 2009), pp. 922–929. ISSN: 10914269. DOI: `10.1002/da.20532` (cit. on pp. 20, 37).

[58] *Novo Psych Panic Disorder Severity Scale (PDSS)*. `https://novopsych.com.au/assessments/anxiety/panic-disorder-severity-scale-pdss`. Accessed: 2022-09-01 (cit. on p. 20).

[59] Sriram Raju Dandu, Matthew M. Engelhard, Asma Qureshi, Jiaqi Gong, John C. Lach, Maite Brandt-Pearce, and Myla D. Goldman. «Understanding the physiological significance of four inertial gait features in multiple sclerosis». In: *IEEE Journal of Biomedical and Health Informatics* 22 (1 Jan. 2018), pp. 40–46. ISSN: 21682208. DOI: `10.1109/JBHI.2017.2773629` (cit. on p. 32).

[60] Hyun Seob Lee. «Application of dynamic time warping algorithm for pattern similarity of gait». In: *Journal of Exercise Rehabilitation* 15 (4 2019), pp. 526–530. ISSN: 22881778. DOI: `10.12965/jer.1938384.192` (cit. on p. 37).

[61] Matthew M. Engelhard, Sriram Raju Dandu, John C. Lach, Myla D. Goldman, and Stephen D. Patek. «Toward detection and monitoring of gait pathology using inertial sensors under rotation, scale, and offset invariant dynamic time warping». In: 2015. DOI: `10.4108/eai.28-9-2015.2261503` (cit. on p. 37).

[62] Nikolaos V. Boulgouris, Konstantinos N. Plataniotis, and Dimitrios Hatzinakos. «Gait recognition using dynamic time warping». In: 2004, pp. 263–266. ISBN: 0780385780. DOI: `10.1109/mmsp.2004.1436543` (cit. on p. 37).

[63] Liping Huang, Jianbin Zheng, and Huacheng Hu. «A Gait Phase Detection Method in Complex Environment Based on DTW-Mean Templates». In: *IEEE Sensors Journal* 21 (13 July 2021), pp. 15114–15123. ISSN: 15581748. DOI: `10.1109/JSEN.2021.3072102` (cit. on p. 37).

[64] Rossana Muscillo, Maurizio Schmid, Silvia Conforto, and Tommaso DprimeAlessio. «Early recognition of upper limb motor tasks through accelerometers: Real-time implementation of a DTW-based algorithm». In: *Computers in Biology and Medicine* 41 (3 Mar. 2011), pp. 164–172. ISSN: 00104825. DOI: `10.1016/j.compbiomed.2011.01.007` (cit. on p. 37).

[65] Cesare Furlanello, Stefano Merler, and Giuseppe Jurman. «Combining feature selection and DTW for time-varying functional genomics». In: *IEEE Transactions on Signal Processing* 54 (6 II June 2006), pp. 2436–2443. ISSN: 1053587X. DOI: `10.1109/TSP.2006.873715` (cit. on p. 37).

[66] *DTW computation DTW implementation*. `https://github.com/kamperh/lecture_dtw_notebook/blob/main/dtw.ipynb`. Accessed: 2022-09-01 (cit. on p. 37).