University of Genova

PhD in Science and Technology for Electronic and Telecommunication Engineering

Signal Processing Techniques for Data Analysis in Telerehabilitation: Intelligent Remote Rehabilitation Monitoring Enhancement

by

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Thesis submitted for the degree of *Doctor of Philosophy* (36° cycle)

2020-2023

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Abstract

In recent years, ICT and IOT devices have been employed to monitor and assist with patients' rehabilitation, as well as to analyze their conditions and create and update individualized care plans. Additionally, they promote continuity of care by allowing a patient to continue receiving supervision from a multidisciplinary team even after being released from the hospital. Virtual reality and exergames are further ICT-enabled technologies that have shown strong potential in the treatment of cognitive and motor impairments.

The implementation of the ReMoVES telerehabilitation platform in different situations is the focus of the current thesis. In order to extract the key features and examine the statistical significance between the patient and healthy groups, the main contribution of the research activity is to offer a method for evaluating a subject's rehabilitation efforts while giving special attention to the pre-processing of the multidimensional signals obtained during rehabilitation sessions.

In addition, there will be a proposal, description, and application of a systematic protocol for signal processing and data analysis for specific clinical scenarios.

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Chapter 1

Introduction

Thanks to the impressive development of the last few decades in Information and Communication Technologies (ICT), including Electronics, Telecommunications, and Signal Processing, the Internet of Medical Things (IoMT) is starting to represent a preferred solution with the goal of supporting rehabilitation in a continuous and safe way, guaranteeing both social distancing and the reduction of travel to the rehabilitation site. Connected devices are used for assessing patients' conditions, monitoring and supporting rehabilitation, so that a personalized plan of care can be defined and kept updated. This also fosters continuity of care, enabling a patient to be supervised by a multidisciplinary team even after dehospitalization. Furthermore, the collection of data and information on patient activity during the prescribed exercise is a required feature to allow the therapist to understand the patient's behavior, and eventually correct wrong attitudes such as compensation movements.

In such a framework, the present thesis concerns the application of the ReMoVES (Remote Monitoring Validation Engineering System) telerehabilitation platform on different scenarios. ReMoVES was developed by the Department of Naval, Electrical, Electronics and Telecommunications Engineering (DITEN) of Università degli Studi di Genova, and as IoMT system provides a set of services to support motor and cognitive maintenance and recovery through exergames and digital versions of standard rehabilitation tests, carried out via Microsoft Kinect, Leap Motion, and touchscreen. The primary contribution of the research activity is to provide an approach to assess a subject's rehabilitation efforts while paying particular consideration to the pre-processing of the multidimensional signals acquired during telerehabilitation sessions. On a technical level, the different methodologies found in the literature were examined, and an explicit procedure was defined for their application to specific clinical contexts. This work paves the way for a clinical in-hospital and in-home strategy to monitor patients, helping the clinical staff in the management and treatment of various pathologies and in the study of new protocols and personalized treatment plans.

The aims of the present work are:

- the employment of the telerehabilitation system ReMoVES for the intelligent remote monitoring of patients;
- the application of data analysis and signal processing techniques for performance evaluation during rehabilitation activities;
- the extraction of the main features and the study of statistical significance;
- the creation of specific treatment protocols based on ReMoVES.

In Chapter 2, the State of the Art revision in discussed. In particular, the technologies and approaches applied in the telerehabilitation context are disclosed, along with the different pathologies in which ReMoVES has been applied. Chapter 3 introduces the ReMoVES platform, describing its hardware and software architectures and the exergames present. Then, Chapter 4 introduces the data and signal processing methods used in the various scenarios investigated. Results are discussed in Chapter 5 and to conclude, Chapter 6 offers some concluding remarks and discussions on the work's future development.

Chapter 2

State of the Art

The ongoing digital transformation in our society has significant impact on several technological aspects, such that the term Fourth Industrial Revolution has been used for a few years. As another revolution [1], Internet of Things (IoT) solutions are becoming increasingly relevant, and their use is consistently growing in several application domains. Regarding healthcare, the IoT market size was valued at USD 252.1 billion in 2022 [2], and is expected to reach USD 861.3 billion by 2030, expanding at a compound annual growth rate (CAGR) of 16.8% from 2023 to 2030 [3]. All this is due to growing investments in digital technology implementation at healthcare institutions that address the need for the care of a growing geriatric population [4] coupled with the rising prevalence of chronic conditions [5].

In addition, the outbreak of Covid-19 has had strong impact on the health system, which had to adapt itself to various needs such as guaranteeing access to care for patients in forced quarantine or in solitary confinement, and meeting the needs for social distancing and reduction in access to healthcare facilities. Medical IoT solutions are an essential tool for responding to patient care needs under safe conditions. Hence, applications such as telemedicine, remote patient monitoring, and interactive medicine have a precise and crucial position in the fight against the coronavirus, such that several nations officially recommended their use [6, 7]. The key benefit of the IoT in the medical domain is connected technology. Devices are used for assessing patients' conditions, and monitoring and supporting rehabilitation, so that a personalized plan of care can be defined and kept updated. This also fosters continuity of care, enabling a patient to be supervised by a multidisciplinary team even after dehospitalization. The most ubiquitous of such devices are wearable or robotic devices, for instance, smart bands for data collection related to some physical activity [8] or other wearables for motion analysis, which can be devoted to specific body-part rehabilitation (e.g., shoulders [9] and knees [10]).

Even though a deep interest in such devices is manifested in the healthcare context, wearables, robotic devices, and devices based on smartphone interaction are not very suitable for the elderly population or for dehospitalized and disabled patients. Indeed, to fully exploit the potential of an IoT solution, patients should be able to deal with it autonomously; however, the presence of wearable devices or controllers means that some external support may be needed for such activities.

Even though acceptability towards such solutions is continuously increasing, it is still rare that such technologies are guaranteed and covered by national health services. For instance, only recently the Conferenza Stato Regioni approved the new National Indications for the provision of telemedicine and telerehabilitation services [11, 12] in Italy. In particular, these documents provide the indications to be adopted at a national level for the provision of certain telemedicine and telerehabilitation services by healthcare professions. Furthermore, for the latter, the areas of applications and the advantages that it can offer are also provided, i.e., guaranteeing continuity of the rehabilitation process; improve the rehabilitation intervention, adapting it to the patient's needs and preferences; increase the efficiency of home rehabilitation services; encourage self-monitoring and health education activities. Lastly, among the ICT-enabled technologies approved by the guidelines, there are also virtual reality and serious games.

2.1 Exergames in the field of rehabilitation

The term exergame refers to videogames that impart physical exercise/support rehabilitation practice (in the context of their clinical application) in which the repetitive and task-oriented components of rehabilitation activities are reformulated in terms of videogame tasks. In recent times, exergames have gained great popularity and demonstrated scientific reliability, thus going beyond their original goal of mere entertainment. The exergames can also be considered as a Virtual Reality (VR) tool, which can be a safe instrument to access activities otherwise not accessible to people with cognitive and motor disabilities in everyday life contexts. Furthermore, gamification [13] determines a motivating and engaging environment in order to contrast boredom and fatigue in patients, and thus fostering the continuity of care.

Even though the role of traditional therapy and clinicians is irreplaceable, exergames have demonstrated their utility for both cognitive and motor rehabilitation, as they exert beneficial effects on attention, visuo-spatial function, executive control, strategic planning, and processing speed [14, 15]. By developing game-based rehabilitation tools that are tailored to the therapy goals of different patient categories, it is possible to provide the clinician with more meaningful performance data [16]. Several studies reported the efficacy in maintenance and improvement balance and mobility function in the elderly population [17, 18] and in post-stroke rehabilitation [19–21]. Some solutions providing exergames for entertainment have been utilized for rehabilitative purposes, also in the context of Multiple Sclerosis patients [22, 23] or for Parkinson disease [24], and with particular emphasis on physical activity [25, 26].

Since 2011, a fundamental role has been assumed by the Microsoft Kinect device [27–29]: it is based on an inexpensive depth sensing camera technology that provides marker-less motion sensing on a conventional PC and allows the spatial tracking of a human body. Microsoft Kinect is a satisfactory tool for rehabilitation due to its low cost and adequate accuracy [30, 31]. Studies have focused in more detail on post-stroke recovery [32, 33], Parkinson assessment [24, 34] or orthopedic rehabilitation [35]. The exergames based on Microsoft Kinect have a significant field of application in assistive technologies for the elderly, such as for fall risk reduction [36], to improve physical performances, and reverse the deterioration process in frail and pre-frail elder people. Despite the deep research interest in this field, publications that provide the raw data acquired during the execution of exergames were not found. The substantial lack of available data limits the development of assistive computing technologies based on exergames, affecting both the technical aspect and the scientific innovation of the results. In particular, the possibility to compare body tracking methodology with data transfer solution, and data-log format is hampered from the data. Furthermore, in recent years, the use of big data processing algorithms is precluded by the impossibility of accessing the data collected in numerous studies proposed by other researchers.

2.2 Signal processing for motion evaluation

In experimental analyzes of a given phenomenon, measurement tools are generally used to obtain interpretable information through appropriate evaluation and manipulations [37]. Signal processing consists of a set of methodologies and procedures used to extract from the analog signal all the information necessary for the physical interpretation of the problem studied. It starts with the acquisition of the signal, passes through the analysis and manipulation of it to extract the information of interest, and to conclude with the interpretation of the data obtained. This allows to describe in a synthetic and meaningful way the quantities in question, to determine their possible temporal variation, to correlate the various quantities with each other in order to find any causal or non-causal relationships, to investigate internal parameters and reduce any errors present in the measurement data. Finally, a signal is a means of transmitting information regarding the past, present and future states of a variable [38].

Considering a biomedical phenomenon in particular, it is inevitable to collide with the complexity of the organism's systems, which often interact with internal subsystems. With the processing of biomedical signals, doctors have a strong ally in improving the monitoring of human pathological states. The development of new biomedical equipment gives the field of biomedical signals analysis a continuous and constant evolution [39, 40]. Initially, the focus was on noise reduction by means of filtering techniques applied to biomedical instrumentation such as electrocardiography (ECG), magnetic resonance imaging (MRI), electromyography (EMG), and ultrasound [41–44]. Subsequently, technological advancement has not only affected "traditional" biomedical instrumentation but has led to the creation of new sensors and devices such as Leap Motion, Microsoft Kinect or Nintendo Wii, and new methods of administering care treatment, rehabilitation, and monitoring (such as the use of exergames) adapted to medical experience. Based on the various studies conducted over time, it can be seen how the combination of the use of signal processing and biomedical-rehabilitation engineering is always ready to produce technologically more sophisticated techniques, algorithms and methods [45].

In the field of telerehabilitation systems, the literature provides different proposals: systems with wearable solutions [46], the use of virtual reality [47], the exclusive creation of exergames [48] or double avatars [49], but few of them apply signal processing techniques before extracting the information they need. There are also studies that have included the analysis of signals for the evaluation of certain rehabilitative parameters, such as the speed of the movements of the upper limbs using the Kinect sensor [50], the angles of the upper limbs [51, 52], or the kinematics of the human movement [53]. In general, existing telerehabilitation systems do not pay attention to the acquired signals and there is a lack of preprocessing methods. Another problem encountered by most of the works reside in the use of global indicators that measure statistical information over long time intervals, which are not significant from the point of view of the analysis as the temporal chain of the elementary actions are not observed independently but are mediated all together.

2.3 Field of application

This section will describe the various fields of application covered during the experimentation phases with ReMoVES. The different pathologies will be divided into macro areas and the rehabilitation techniques involved will also be illustrated, both traditionally and with digital tools.

First it is important to define the terminology that will be used later. In the healthcare context, a *symptom* is the expression of an anomalous state, i.e., the consequence of a phenomenon that manifests itself in a body. The presence of one or more symptoms does not serve as definitive confirmation that a person's health is compromised and therefore is a sign of a disease.

The term *disorder* indicates an alteration of the normal state of health due or not to a disease. This concept simply serves to describe the signs of the abnormal and altered state of health in which a person is.

A *disease* is an abnormal condition of a living organism, caused by organic or functional physical alterations, which compromise its health. In addition to one or more symptoms, a disease must also have recognizable changes in the body and/or a known biological cause.

Lastly, the term *syndrome* designates a precise set of symptoms and signs arising simultaneously, which constitutes a well-defined clinical picture. A given syndrome can be caused by different pathologies, precisely because different pathologies can determine a set of overlapping symptoms and signs.

2.3.1 Neurological diseases

Multiple Sclerosis

Multiple Sclerosis (MS) is a common neurological disease that affects the central nervous system (CNS) [54] and provokes the impairment of several functions including motor skills [55], balance [56], cognition [57], and activities of daily living (ADLs). Cognitive impairment (CI) affects up to 70% of the MS population and refers to domain-specific deficits rather than uniform global cognitive decline [58]. The patient with MS (pwMS) may encounter difficulties in information processing speed, sustained and selective attention, learning and episodic memory, with impaired executive functions in the more advanced progressive stages [58], as well as visuospatial problems [59], which negatively affect social, occupational activities, and the quality of life in general. As it is well known, therapy for MS can be divided into two categories: disease modifying therapies (DMT) and symptomatic or supportive therapies. In principle, DMTs might improve cognition as their agents are primarily designed to arrest the disease and prevent relapses, but the actual benefit on improving cognition is still matter of debate [60]. On the other hand, the goal of cognitive and behavioral rehabilitation strategies is to enhance patients' ability as related to executive functional tasks. Although the focus on this topic is a relatively recent phenomenon, the growth of research studies addressing the need for effective cognitive rehabilitation programs has been substantial over the past decade, as is well documented in the literature [61–72]. In this context, for instance, in recent years the Italian National MS Society (Associazione Italiana Sclerosi Multipla-AISM) has recommended remedial interventions and accommodations to manage cognitive impairment and improve everyday functioning in both adult and pediatric MS populations [73]. In general, signs of cognitive involvement are present already in early stages of the disease process [64], even though severe cognitive impairment is more likely in persons with secondary progressive MS. Indeed, approximately half of persons with MS report having either minimal or mild cognitive difficulties within the first year of diagnosis [74], with greater complaints over the first decade. Furthermore, although uncommon, some persons with MS present cognitive impairment as their primary symptom. In addition, sometimes cognitive issues may be present pre-clinically [74]. As a matter of fact, these impairments yield to major consequences for everyday life. Indeed, CI is the leading cause of occupational disability and of difficulties in ADLs for such patients [75].

To manage such impairments, some recommendations include more comprehensive assessment for anyone who tests positive for cognitive impairment on cognitive screening or demonstrates substantial cognitive decline, as well as neuropsychological evaluation for any unexplained change in academic performance or behavioral functioning in school-aged children with MS. Evidence suggests that cognitive rehabilitation has a long-term impact well beyond the treatment period and might enhance cognition in the face of future brain changes. Such sustained effects have been documented in the literature on aging, in which cognitive rehabilitation not only improved everyday life activities, but also resulted in a 29% reduction in dementia risk 10 years after treatment [76]. People with MS also belong to the so-called "fragile" populations subjects who are at higher risk in relation to pandemic emergencies.

Rehabilitation therapy is considered an interdisciplinary approach in which different professionals carry out a rehabilitation intervention aimed at the individual patient, called the Individual Rehabilitation Project (PRI), in order to improve their physical, psychological, and social functions and maintain their autonomy. The exploitation of novel technologies, such as virtual reality and exergame, is suggested as a supplement to the rehabilitation therapy of MS patients [23, 77]. The importance of using technology in the treatment of MS has long been acknowledged, so that several solutions addressing diagnosis, monitoring, and rehabilitation can be found in the literature [78, 79]. Several studies have shown that patients better perceive their goals and physical and mental well-being, thanks to the improved feedback that technology provides, thus leading to a better practice and to an enhanced engagement in the therapy [80]. In addition, technology support also favors intense and repetitive training that yields effective results in functional recovery for pwMS [77,81]. Of note, the IoMT technologies can support patients in taking control of their own MS disease and collaborate more effectively with the clinical staff [82]. Despite the large interest towards assistive technology in MS, solutions are still not as widespread as they may be, because of some barriers for patients in terms of usability and feasibility, and also because of the high costs of some devices [83]. Indeed, pwMS can experience difficulties in dealing with technological devices, as well as poor skills in using it [84]. In addition, technological solutions made up of wearable devices or controllers may require external support from caregivers, limiting the independent use. Furthermore, the high cost of solutions hinders the possibility of a large home-based usage.

Stroke

Prior the spread of the Covid-19 pandemic, stroke was usually referred to as the 21st Century epidemic by the medical community. Stroke is indeed the second leading cause of death worldwide, and also the second most common cause of disability-adjusted life years (DALYs) [85]. Many people experiencing a stroke are left permanently disabled, placing a burden on family and society. It is then clear that stroke is an important sanitary emergency and, therefore, also the need for rehabilitation has become a very crucial issue. In such a context, cerebellar stroke accounts for approximately 2% to 3% of all strokes. Acute cerebellar stoke manifests itself with axial or limb ataxia, nystagmus, vertigo, action tremor and dysarthria. The cerebellum works as a motor feedback control system: it compares the motor command elaborated in premotor areas with sensory-motor inputs, and then produces an error signal. A cerebellar damage can impair its ability to sufficiently integrate sensory input in order to monitor and correct movements. By practicing some activity while tracking patients' movements, their conditions can be assessed taking into consideration whether a strategy is being adopted or not.

To this end, a combination of an ICT support and classical rehabilitation is the starting point in order to foster patients' rehabilitation and enhance their engagement, also with activities delivered in the form of exergames. For instance, studies [86, 87] propose a stroke rehabilitation program to develop a system to support the ambulatory rehabilitation therapy based on motor learning principles and theories in rehabilitation. In addition, aerobic exercise was proved to have a crucial role in post-stroke therapies, in order to enhance brain function [88]. Eventually, immediate feedback turns out to be highly important, as it determines an instantaneous motor control to adjust the movement, thus promoting motor learning and neural plasticity [89]. There are lots of solutions which focus on upper-limbs exergames rehabilitation, such as [90–94].

Ataxia

Cerebellar ataxias are a large, heterogeneous group of movement disorders affecting neurons in the cerebellum and its associated pathways as the neural connections with vestibular nuclei, brainstem areas and the contralateral motor cortex [95]. It is therefore possible to observe abnormalities in movement characterized by increased variability and poor accuracy. These disorders result in unsteady gait, increases in postural sway, abnormal eye movements, uncoordinated limb movements, difficulties in speech. Nowadays these cerebellar dysfunctions are at the center of medical research interest, in particular, the efficacy of rehabilitation strategies is greatly debated. Ataxia causes a general in-coordination of movement, in particular in dynamic ataxia there is a lack of control of distal segments of the body. For instance, equilibrium and walk are largely involved in studies as [96–98]. The study in [99] reported that cerebellar damage might cause an inertial mismatch between an internal representation of body dynamics and the actual body dynamics. According to these results, there are hypometric and hypermetric patients which respectively underestimate or overestimate their limb's inertia. This work also showed that altering the apparent inertia of the limb to correct the mismatch via robot could improve simple single-joint elbow movements for both types of patients. It follows that for single-joint movements, hypometric patients should theoretically improve with the addition of mass to the limb because it would reduce the discrepancy between the internal model and the actual limb dynamics. The research in [100] has already shown interest to this peculiar strategy. They found some immediate benefits of weighting on single-jointed elbow movements, but no benefits on multi-jointed reaching movements.

Cerebral palsy

Cerebral Palsy (CP) affects a large group of neurological disorders caused by a permanent, non-progressive lesion of the developing brain that occurs before, during, or after birth [101]. The presence of central nervous system damage variably affects both global motor function and overall development of the child. The consequences of brain injury primarily affect posture (the relationship between the different parts of the body) and movement (the movement in space and time of one or more parts of the body). These disturbances can be associated with sensory problems (particularly visual), intellectual, communicative (difficulty in articulating speech or more general language difficulties), swallowing and emotional problems with difficulty relating to others. Even if the brain lesion that causes CP is not reversible, its consequences are variable and can change during growth. The potential for recovery is sensitive to rapid and targeted interventions. The causes can be pre-natal, peri-natal or post-natal, of various nature: infectious, traumatic, hypoxic, or genetic. Children learn coping strategies as they grow, and treatment often results in significant improvements in affected functional areas. Even if the intervention cannot be directed at the cause of the disorder i.e., the brain injury, it is possible to work on the symptoms and their impact on the child's life, as well as on the prevention of muscle contractures and bone deformities. Interventions in children with CP can be very different based on age, type of neurological damage, present problems, available development potential, modifiability of functions, characteristics of the child's living environment and his/her family. Due to the different influence of these factors, the rehabilitation process can vary greatly from child to child. Treatment generally consists of neuromotor rehabilitation of communication, cognitive and sensory skills. The rehabilitation process is long and complex, and can be made discontinuous by various problems, due to factors external to the patient and the family unit or health reasons. The treatment of CP includes intervention in various areas, including rehabilitation-physiotherapy, psychomotor, speech therapy, psycho-pedagogical and possibly psychological. Rehabilitative treatment, in particular, is essential to be introduced from the first months of life, in order to exploit the neuroplasticity of the synaptic circuits of the Central Nervous System [102]. It aims to recover a lost or reduced competence, activate one that has not appeared and attenuate functional regression. The therapies consist of treatments that require numerous sessions with different specialists. The forced and prolonged interruption of therapy has a negative impact on the development of young patients, risking not only stopping learning, but also causing the loss of goals already achieved. Technological innovation has made it possible to solve these problems with the introduction of telemedicine techniques based on serious games or exergames. Telerehabilitation, intended to complement traditional practices without replacing them, is a tool that allows to enhance and give continuity to the treatment, offering the possibility of continuing it at home [103]. Although it is a technology widely studied in the case of adults and the elderly, there are few studies and applications for children. Most of the exergames-based rehabilitation systems found in the literature make use of sensors and wearable tracking devices, which make their use at home difficult and are often inaccessible due to costs. As a result, alternative solutions involving the use of low-cost optical tracking devices are becoming increasingly widespread, such as MoveHero [104], Playstation Move [105] and Nintendo Wii [106].

2.3.2 Neuropsychological syndrome

Unilateral Spatial Neglect

Unilateral Spatial Neglect (USN) is a neuropsychological condition following a damage to one hemisphere of the brain [107]. It can be induced by neurodegenerative diseases [108, 109], trauma [110], neoplasia [111], and it is very frequent after stroke events with rates between 50% and 82% of patients [112, 113]. Although it can be a consequence of both right and left hemispheric lesions, USN is much more frequent after a right hemispheric injury and affects about 50% of patients in the acute post-stroke phase [114]. Failing to respond to stimuli usually located on the side contralateral to the brain lesion significantly affects the quality of life of patients suffering from such a disease. For instance, colliding into objects around, ignoring food on one side of the plate, and attending to only one side of the body are some everyday signs of USN [115]. Furthermore, the presence of USN has been strongly associated with an increased risk for injury and with poor functional outcomes. The effects of USN extend beyond the basic skills for self-care (bathing, dressing, walking, etc.) to instrumental activities of daily living (IADL) that are crucial for successful reintegration into community life. Patients suffering from USN show slow functional progress during rehabilitation and need long hospitalization times, and are less likely to be able to live independently, with deterioration of the quality of life.

Several tests have been designed for the diagnosis and assessment of USN [116, 117]. Among them, one can mention *barrage tests*, where patients are asked to cross out stimuli on a paper [118]; *reading tests*, aimed at discerning the errors in reading both words and whole sentences [119]; *bisection tests*, where patients are required to split a segment into two congruent parts [120]; and *drawing tests*, where the goal is to copy a figure, or to draw it from memory [121]. Furthermore, these tests can be used to prevent USN disability after that clinical staff has determined the presence of brain injury. In this way, the impact of USN in the patient's life may decrease considerably. All of these tests are paper-pencil based, hence their evaluation often results in a time consuming endeavor by the clinical staff. However, their administration is pretty simple and could also be designed on a digital format. That enables automatic collection and summarization of data, thus also fostering the remote practice, for instance at patient's home and without the supervision by clinical experts. It can be deduced that in the digital version a larger amount of information can be obtained as compared with the paper and pencil version, so that a fairly complete clinical picture can be seen from a single test, instead of making patients carry out several different tests. Other studies to evaluate the cancellation tests have been carried out in the literature and they confirm this inference. For instance, [122] quantify the spatial organization, reconstructing target-marking pathways. Moreover, authors of [123] determine if the use of computer recording of standardized test identifies abnormalities in the process and in the outcome of the tasks. The results of the preliminary study [124] showed good sensitivity, specificity and usability of digital tests, suggesting that they can be a promising tool for USN assessment, both in clinical and research settings.

In addition to assessment tests, several rehabilitation strategies for USN (TENS, optokinetic stimulation, somatosensory electrostimulation, mirror therapy) have been reported [125]. Their efficacy, however, is still a matter of debate. A meta-analysis by Pollock et al. [126] states that there is only a limited number of high quality studies suggesting the efficacy of USN interventions in improving functional outcomes and reducing disability. Azouvi et al. [127], in a review, concluded that there still is only a low level of evidence for the different rehabilitation methods and emphasized the need for longer validation trials using innovative techniques such as non-invasive brain stimulation (NIBS). NIBS techniques have recently emerged in restorative neurology due to their hypothetical advantage in enhancing the efficacy of traditional therapeutic intervention. In this view, the re-discovery of the application of a direct-current flow of low intensity $(1-2\mu A)$ has raised much interest. This technique is known as transcranial direct-current stimulation (tDCS). It acts by a tonic modulation of the resting membrane potential of the cortical neurons, which occurs in an opposite direction, depending on the polarity (anodal vs cathodal) of the electrodes, placed on the chosen areas. It is commonly stated that cathodal stimulation (C-tDCS) decreases cortical excitability due to neural hyperpolarization, while anodal stimulation (A-tDCS) reaches the opposite effect by a subthreshold depolarization [128]. The use of tDCS has been shown to be a promising approach in order to improve post-stroke neglect. A-tDCS and bilateral tDCS appears to be more effective than C-tDCS [129]. A cognitive therapy is usually associated to the tDCS approach, which consists of performing tasks with the aim of improving the patient's capability of investigating the ignored hemispace.

2.3.3 Frailty syndrome

Frailty syndrome involves a slow decline in the functions of organs and systems causing a state of increased vulnerability with negative results on functional and cognitive performance. In the elderly corresponds to a broad clinical issue that concerns the physical, cognitive, and social aspects of the patient, particularly for people over the age of 75 [130, 131]. The study by Fried et al. [132] defined a phenotype and thereby some characteristic traits of frailty in the elderly. Specifically, frailty is considered if at least 3 of the following symptoms are present: unintentional weight loss, fatigue, reduction in muscle strength, slower walking speed, and decreased physical activity. In cases where fewer than 3 of the symptoms are detected, one can speak of pre-frailty. Frailty, therefore, differs from disability because it is characterized by a decline in several physiological aspects. Thus, in this sense, disability manifests itself more as a consequence of frailty itself.

In recent years the global health system has had to adapt to the increase in the average age of the world population [133, 134]. Indeed, due to age and related cognitive impairments, weakness is a major limiting factor related to daily life activities. For instance, the reduction in torque generation is reported at the level of the elbow, shoulder, fingers, and thumb, which worsens due to prolonged physical inactivity. Furthermore, simple activities, such as standing up, may be affected, causing falling risk and insecure gait. In addition to cases of psychiatric and neurological diseases, cognitive abilities inevitably decline in a healthy elderly population, thus leading to severe social and economic impact. In this context, strength training associated with task-oriented training can intensify rehabilitation and reinforcement [135]. The study of Erickson et al. [136] suggested that physical exercise can produce cognitive improvements (associated with an increase in hippocampal volume) in accordance to [137] about increased levels of brain-derived neurotrophic factor (BDNF) in response to exercise. By design, exergames are appropriate for this aim as they require the patient to produce physical movements in order to complete a task-oriented exercise in response to visual cues [138]. They are simultaneously able to improve patient engagement and train multiple cognitive processes [139].

Frail elderly individuals are among end users who most need and would benefit from easy-to-use IoT solutions. Such technologies can provide a set of services to monitor elderly healthcare and behavior, and to reduce the risk of injuries. For instance, Tao et al. studied fall prediction based on human biomechanical equilibrium by analyzing data acquired by a Microsoft Kinect sensor installed in elderly individuals' homes [140]. The interest toward the well-being of the elderly is well-documented in the literature from environmental [141] and independent-living [142] perspectives. As health issues and frailty symptoms start arising, it is crucial to take action in effective ways. Traditionally, a great portion of physical therapy, rehabilitation, and assessment is based on a clinician's observations and judgment. Sensor and computing technologies that can be used for motion capture, performance assessment, and range of movement measurements have drastically advanced in the past few years. In such a context, many works focus on the early detection of frailty to help caregivers and patients, and address such a problem from several points of view. For instance, the authors of [143] evaluated the acceptability of solutions for detecting signs of frailty on the basis of techniques and clinical practice described in the literature. Their conclusion was that minimal clinic interruption, low requirements for resources, and added benefit (e.g., stratify risk, enhanced understanding of frailty) yield to higher acceptability. The study in [144] highlighted the importance of frailty detection in a home-based context aimed at supporting the independent living of elderly individuals at home. In [145], a platform for favoring personalized interventions to frail elderly persons was introduced. It deploys dashboards for doctors and patients, giving them control of the system and data visualization, respectively. Along with the spread of solutions targeting healthy and active aging, the need for aligning and combining the informative content obtained by different platforms arises. On the basis of [146], the information-uniformity issue was tackled in the fundamental study by Madueira et al. [147]. Indeed, the proposed My-AHA software is able to integrate multiple healthy and active aging platforms, thus providing a solution to be used in conjunction with other technologies.

2.3.4 Balance disorders

Balance is one of the most important physical skills for humans, as it is necessary for postural control, and therefore affects the ability to perform countless activities, ranging from the most basic to the most difficult [148]. The equation is simple, the greater the balance, the greater the postural control and therefore less falls, risk of injury and greater autonomy in the activities of daily life. Despite this naive rationale as to why balance is crucial, a myriad of factors contribute to maintaining sufficient balance in people. Although some of them may be due to external causes, many are related to people's health conditions. In recent literature there are several works that study balance and its relationship to other diseases, with particular emphasis on the role of technology in promoting rehabilitation and the maintenance of abilities. Stroke is a classic case of an event that compromises balance, for example for those patients who manifest hemiparesis which then results in less postural control [149]. It is worth mentioning that more than half people surviving a stroke experience motor deficits due to reduced balance [150]. Another disease that typically impairs balance is Parkinson's. Here the patients show slowness of movement, muscle stiffness and postural instability [151], symptoms destined to worsen due to the progressive nature of the disease. As a result, patients experience loss of balance, leading to frequent falls and to low independence on activities of daily living [152, 153]. In general, several clinical conditions affecting balance are strictly linked to the age, thus frail elders result in a population which typically presents balance impairment. It is noteworthy that falls are the leading cause of fatal and non-fatal injuries among seniors [154].

The study of balance impairment is therefore arousing great interest also from a technological point of view, since innovative services could be designed and delivered for the benefit of patients, therapists and caregivers [155–160]. Robotic devices and wearable solutions are widely recognized as effective rehabilitation tools [161–164]. But, at the same time, even lighter non-wearable technologies related to sensors, signal processing and telecommunications begin to become available to implement tools to support the rehabilitation process. Specific services can be provided with the possibility of remotely acquiring a large amount of patient information useful for the evaluation and planning of the individual activity. In such a framework, the use of exergame is emerging as an interesting new approach to treat balance disorders by stimulating patients. In fact, exergames are conceived as physical activities delivered in the form of videogames, and therefore have the ultimate goal of improving patient involvement during postural control training. Among the numerous contributions in this context, the most widespread technology for the study of balance consists in the use of gaming platforms combined with sensors or controllers for user interaction and data collection. In addition to stabilometric platforms and robotic systems [165], the most used devices are Nintendo

Wii balance board [166], and Microsoft Kinect [140, 167]. Balance exercises are involved in studies for a broad spectrum of conditions including Parkinson [168], stroke outcomes [149] and frail elders [169].

2.3.5 Healthy subjects

The control group, generally made up of healthy individuals with characteristics (i.e., age and gender) similar to those of the pathological subjects, is important in order to construct a sample that can be used to compare the functional capacities of the pathological individuals. The goal is to allow doctors and physiotherapists to draw conclusions relating to the degree of disability caused by the pathology and to modify the exercises and activities administered in relation to the individual patient while the treatment plan is being carried out. By comparing the therapy sessions performed by each individual patient it is also possible to establish whether this was conducted according to the indications provided and whether it had a significant effect.

Numerous studies have been performed on the Range of Motion (ROM) and the quality of movement performed by healthy subjects, in order to create a behavioral model that can be compared with patients suffering from various disorders and diseases. Carey et al. [170] examined the effects of age, gender, and hand dominance on the precise control of voluntary movement of the metacarpophalangeal joint of the index finger. Based on the research results, it was concluded that for healthy subjects aged between 20 and 79 who perform a joint motion tracking test: (1) younger subjects demonstrate greater accuracy than older subjects, (2) men demonstrate greater accuracy than women and (3) subjects' non-dominant hand performance shows greater accuracy than their dominant hand performance in the flexion phase. Data from these healthy subjects provide a basis for comparison of patient data, which may be useful for early recognition and monitoring of accuracy problems in motion control. Carpinella et al. [171] provided a multi-finger characterization of the spatial-temporal aspects of hand movement, through mathematical modeling of multi-joint finger movement in healthy subjects and stroke patients. The quantitative method proposed in the study proved to be a valid tool to accurately characterize the opening/closing movements of the hands in healthy subjects and people with hemiparesis due to stroke, moreover it was useful to quantify the hemiparetic motor deficits of the hand and to discriminate the motor performance of stroke patients from that of the control group. In addition to the analysis of the movement of the hand and fingers of healthy subjects, studies relating to the movement of the lower limbs have also been carried out in the literature. For example, an ankle training system was tested using a balance board with a group of healthy subjects, in order to determine a series of parameters that could be used as reference values during the rehabilitation and training sessions carried out by the patients [172]. Furthermore, in the study [173] a real-time and adaptive computational method to evaluate human gait events using repeated measures of gait patterns of healthy people was presented and validated. Finally, Oosterwijk et al. [174] studied the ROM required to perform activities of daily living. The information found can be used to interpret the impediments at the individual level and to establish the rehabilitation objectives in terms of functionality and prevention.

Chapter 3

The ReMoVES platform

The Remote Monitoring Validation Engineering System (ReMoVES) is a flexible platform developed by the Numip laboratory of the Department of Electrical, Electronics, and Telecommunication Engineering and Naval Architecture (DITEN) of Università degli Studi di Genova [175]. ReMoVES is an IoT system and an integrative solution to traditional rehabilitation, aimed at encouraging continuity of care and patient involvement through the use of specific task-oriented exercises proposed in the form of a videogame. It is possible to carry out screening and remote monitoring of patients, to facilitate the dehospitalization and convalescence phases and to promote a healthy and active life for the elderly. ReMoVES Patient Client performs calibration on the individual user in order to provide "tailored" results and allows the therapist to monitor tests and activities through a Therapist Client that can be consulted from different technologies (PCs, phones, tablets) to prepare personalized treatment plans.

The Chapter 5 will illustrate the various results obtained with ReMoVES in different fields, including: cognitive rehabilitation for patients with Multiple Sclerosis [176] or affected by Unilateral Spatial Neglect [177, 178]; improved balance for frail elderly patients [179]; and post stroke rehabilitation [180, 181].

Currently ReMoVES is used by three centers, San Martino hospital, La Colletta hospital, and Fiumara ASL3 clinic.

3.1 Existing solutions and differences

The area of medical rehabilitation is now significantly impacted by digital innovation and an increasing numbers of facilities are considering it a fundamental part of their therapeutic and commercial offerings. Systems in the telerehabilitation sector have increased in recent years thanks to a greater demand from health facilities for alternative methods to follow patients especially in the post-acute period. Many hospitals and healthcare facilities do not have a sufficient number of beds to meet the needs of the high number of patients who are affected by pathologies with consequent motor or cognitive deficits every year and who require long rehabilitation programmes. In order to have access to treatment, patients are therefore forced to bear very high costs, feeling obliged to abandon the therapy and losing a large part of the progress acquired during the hospitalization period. This lack of assistance in the post-acute phase could be filled precisely with the introduction of telerehabilitation systems, guaranteeing continuity of care within a familiar context such as one's own home. The home environment, in fact, is an additional component that helps patients in their recovery, able to increase the level of satisfaction of the patient and that of his family. There are many projects at the research stage, especially in Europe, but the systems currently on the market are not many and they all have shortcomings, especially in terms of costs and autonomous usability by the end user. At present, the choice of facilities as regards the use of innovative and technological systems for rehabilitation falls on commercial systems usually used for recreational games (for example Nintendo Wii [182]) or on solutions that use specially designed devices (for example Tyro-Motion products [183]). The former do not provide useful outputs for movement analysis for rehabilitation purposes, while the latter, being configured as sophisticated electromedical equipment, are offered in a high price range. In this scenario, some rehabilitation facilities are looking for alternative solutions designed with rehabilitation purposes but with low cost. Unlike other systems, ReMoVES allows an analysis of physiological data and game/rehabilitation data coming from the system, which is adaptable to different therapies and users. The measurements of the performance of the rehabilitation activities are processed to provide the therapist with clear and concise indications a posteriori in order to facilitate the diagnosis and interpretation of the evolution of the therapy.

In general, existing systems do not pay attention to the lack of stationarity and homogeneity of the acquired signal, resulting in erroneous or insignificant statistical analysis results. To cope with this drawback, adaptive signal segmentation was introduced in ReMoVES, at each game session in order to separate the complex pattern of the patient's execution task into primitive elements. The studies in the literature have sections dedicated to the analysis of the results obtained with their systems, even commercial, i.e., Jintronix and Mira, but there is lack of the pre-processing phase of the raw signal [48, 184] . In addition, ReMoVES is programmed to acquire the positions of all the patient's joints while they carry out their rehabilitation program. The performance characteristics such as angles, range of motion, and trajectories will then be identified in order not only to assess the correctness of the movement suggested by the activity in question, but also to analyze any compensations and strategies. Due to the large individual variability between patients and their impairments, and given the relatively small sample of users, a supervised approach or generalized model is not practical in this case. Compared to other systems based on machine learning techniques [185], a wide use of unsupervised adaptive analysis methods is used here to derive useful information from the acquired signals. To conclude, despite the deep interest in such a topic, each solution is focused towards particular needs, developed independently from the others, and this makes it difficult to compare them. Furthermore, publications that provide raw data acquired during the execution of exergames were not found. The limited development of assistive computing technologies based on exergames is hindered by the high variability and poor similarity of these solutions, as previously noted in [147], as well as by the significant lack of data available. This has an impact on both the scientific innovation and the technical aspect of the results. In particular, the possibility of comparing body-tracking methodologies (e.g., articulations to track; frequency), data-transfer solutions (e.g., client–server architecture or local storage only), and data-log formats (e.g., JSON or CSV) is hindered. Furthermore, the impossibility of accessing collected data in many studies proposed by other researchers in recent years precludes the use of big-data processing algorithms.

3.2 ReMoVES architecture

Several IoT architectures for telemedicine systems and e-health were proposed in the literature [186–188] but the most compliant with ReMoVES is the one composed of four layers, as shown in Figure 3.1. These levels ensure the archiving, processing, monitoring, and the proper evaluation of patients' rehabilitation performance. The four levels are described in depth below, with references to the technologies and tools employed.

Figure 3.2 displays the hardware architecture of ReMoVES. The Patient Client is composed of a local PC unit to which the sensors are connected on the basis of the therapist's recovery plan, thereby, exergames are assigned to the patient. An Internet connection is not mandatory for the user identification phase and to locally start the exergames, but it is necessary for data synchronization with the server. The central unit is composed of the ReMoVES server, which performs the data synchronization with the local units, and stores and processes data in the MySQL database. Therapists can access from any device the web application supplied by WEB server functions.

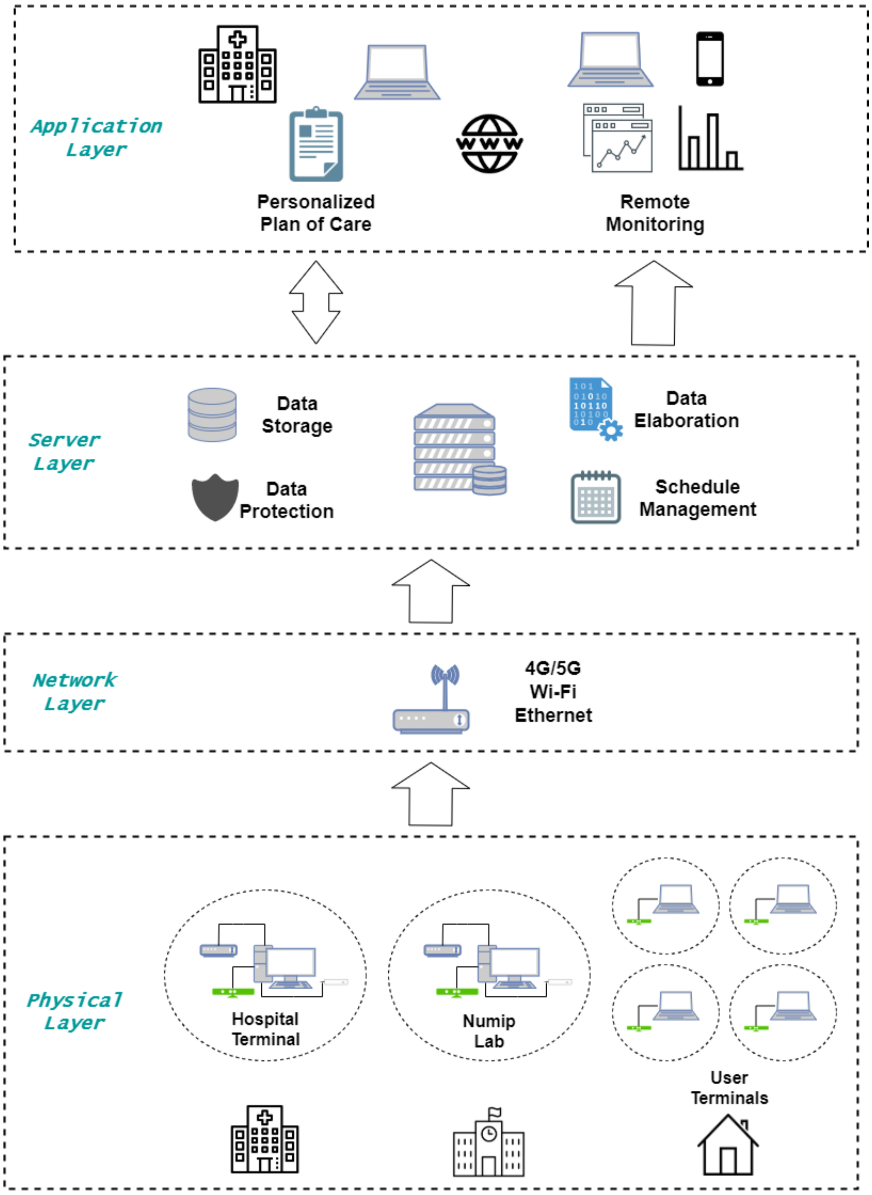


Figure 3.1: IoT architecture of ReMoVES system.

3.2.1 Physical Layer

The bottom layer is the sensor or physical layer and consists of the Patient Client. It deals with the management of so-called "things" (i.e., sensors connected to the system). ReMoVES employs off-the-shelf and commercial devices, such as Microsoft Kinect V2, Leap Motion, and a touchscreen. These sensors are installed and connected to a computer, and through simple body gestures or touches (in

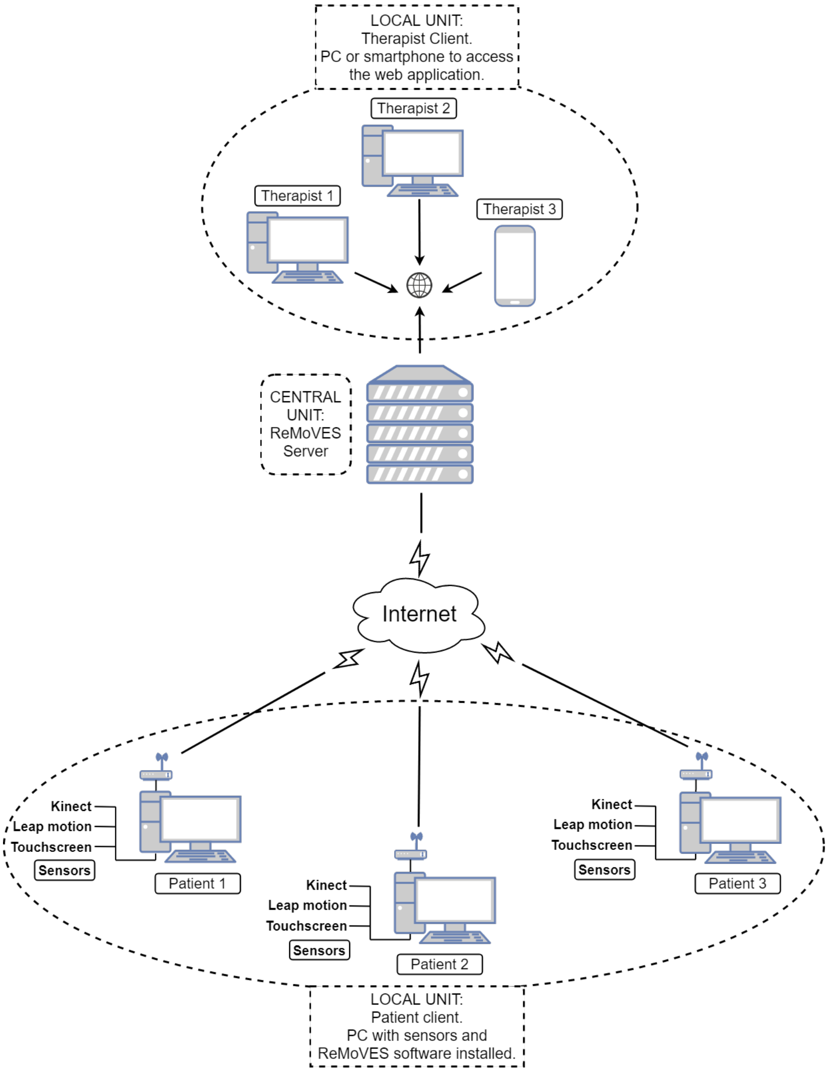


Figure 3.2: Hardware architecture of ReMoVES.

the case of touchscreen), the patient interacts with the game shown on the screen. After the patient finishes the game session, raw information is generated from tracked data and sent to the upper levels. A brief description of the included sensors in the platform is provided.

Microsoft Kinect

The Microsoft Kinect V2 is a motion sensing markerless input device based on a high-resolution RGB camera and an infrared time-of-flight camera for depth analysis. A depth sensing camera automatically detects the presence of any nearby object and measures its distance to it. One of the most popular and commonly used depth technologies is the time-of-flight; this term refers to the time taken by light to travel a given distance. Time-of-flight cameras work based on this principle where the distance to an object is estimated using the time taken by the light emitted to come back to the sensor after reflecting off the object's surface. A time-of-flight camera, like Microsoft Kinect, can ensure patient anonymity in remote monitoring setups as their movements can be detected by acquiring depth data only and not RGB camera data, thus ensuring their privacy.

The Microsoft Kinect offers a wide field of view (70x60 degrees) and recognition up to 4.5 m from the device [189]. Several studies have demonstrated that through the Microsoft Kinect V2 spatio-temporal parameters can be validly obtained [190, 191] and can be also a satisfactory tool for rehabilitation due to its low cost and adequate spatial accuracy (with an order of magnitude of centimeters) [192]. The set-up of the interface between the Microsoft Kinect V2 and the Unity3D engine is effortless because the manufacturer provides a Software Development Kit (SDK) and a Unity add-on, which gives developers access to body joint positions and orientations that can be used directly in rehabilitation game development. In ReMoVES the data and signals from the tracked user's body are recorded at a frequency of 10 Hz.

The Kinect sensor acquires 25 joints in 3D space (x, y, z) typically at a sampling rate of 30 Hz:

$$j \in N \quad and \quad j \in \{1, ..., 25\} \tag{3.1}$$

The coordinate system of the Kinect is composed by x that is the mediolateral (ML) axis, positive to the left of the sensor and then positive to the right of the user; y is the vertical (VT) axis, positive upward; and z is the anterior-posterior axis, positive direction from front to back of the user. The signal acquired from the $j - th$ joint is:

$$\{\vec{v}_j(kT_s)\} = \begin{bmatrix} \{x_j(kT_s)\} \\ \{y_j(kT_s)\} \\ \{z_j(kT_s)\} \end{bmatrix} \quad where \quad f_s = 30[Hz] \quad and \quad T_s = 0.0\overline{3}[s] \tag{3.2}$$

Leap Motion

The Leap Motion controller is a small USB peripheral and low-cost device for hand movements tracking. The device consists of two cameras, which generate 2D frames, and three infrared LEDs. Leap Motion takes 2D frames and converts them into 3D positional data. Its area of interaction is limited to a hemisphere with a radius 0.60 m around the device, with a theoretical accuracy of 0.01 mm according to the manufacturer (or 0.7 mm under real conditions) [193].

Touchscreen

A touchscreen is required for interacting with the subset of exergames for cognitive assessment. The monitor is positioned on the table with an angle to the plane of a few degrees.

Exergame

The system currently includes 15 different activities, which encourage the patient to carry out functional exercises autonomously along with the traditional motion rehabilitation. The interface was designed using the Unity platform, which is a popular graphic engine used for the development of games and virtual reality applications. The language used to write ReMoVES exergames is C#. The interface configuration between Microsoft Kinect and Leap Motion and the Unity engine is straightforward as the manufacturers provide the Software Development Kit (SDK) and an add-on for Unity. Developers can easily access the positions and the orientations of body joints for direct use in the virtual environment of the game scenes. In the ReMoVES project, all the 2D and 3D graphical resources have been downloaded from different online sources with a Creative Commons license. The creation of these activities involved different processes, technologies, and specialists. It is necessary to pay particular attention to the specifications provided by physiotherapists and physiatrists, who share their skills to define the requirements and parameters of the game. The present exergames are considered to be assessment and rehabilitation activities, delivering task-oriented training by requiring the patients to fulfill consecutive and repetitive movement tasks or cognitive function practicing. They foster mild-intensity activity, and allows for the preservation or reacquisition of functional skills that are involved in real-life activities.

A more detailed explanation on the individual exergames proposed by the system will be illustrated in Section 3.4.

3.2.2 Network Layer

The network layer represents the link between physical and server layers. To obtain a resilient functionality facing eventual connection disruption, data log-files containing the data tracked by the sensors, are temporarily stored in the local unit in JavaScript Object Notation (JSON), and the actual transmission is executed when connection is available via Ethernet or Wi-Fi. Data communication is in secure mode based on hypertext transfer protocol secure (HTTPS), the communication protocol is encrypted using transport layer security (TLS), and certificates are issued by the Let's Encrypt authority.

3.2.3 Server Layer

The server layer can manage content-independent dataflow to be compliant with software reuse logic. Server software consists of a traditional Linux-Apache-MySQL-PHP (LAMP) stack, and provides data storage solutions, data processing methods, and a web application for clinicians to view information through dedicated graphic interfaces. Only three types of application programming interfaces (APIs) for the management of client/server data synchronization are used. The MySQL relational database contains a structured collection of JSON files, each of them describing an array of temporal events. In each element of the array, there are key-value pairs that provide data. Some keys are common to all exergames, in addition, other keys are provided depending on the game. Figure 3.3 shows the software architecture and the server side operations.

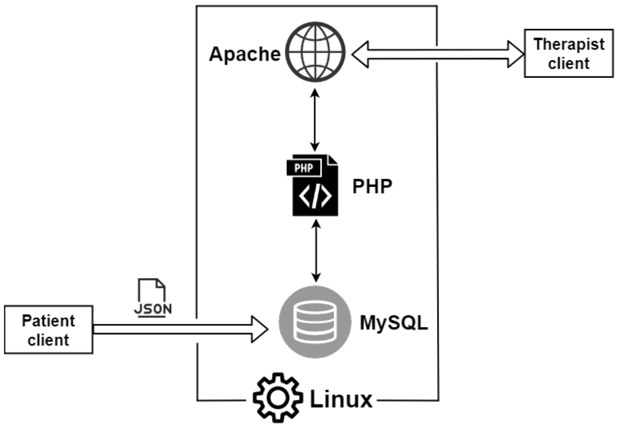


Figure 3.3: Software architecture of ReMoVES.

3.2.4 Application Layer

The application layer includes the Therapist Client, who provides the medical staff with all the necessary information on the patients being followed, displaying their performance in graphical mode and verifying their current treatment plan. The layout dynamically adapts to the size and type of device; this allows for connection even from a smartphone in the case that the therapist does not have an available computer. More details will be discussed in Section 3.5.

3.3 The STORMS project

The "Solution Toward Occupational Rehabilitation in Multiple Sclerosis" (STORMS) project is an example of an IoT work in progress and study protocol devoted to remote hospital and home monitoring of patients with multiple sclerosis. STORMS is one of the two winners of the "2020 Digital Innovation in Multiple Sclerosis" award, sponsored by Merck [194], whose goal is to promote adaptation and coexistence with the disease through new digital technologies. With the aim of improving the patient's quality of life and increasing the opportunities for contact with the multidimensional medical team, STORMS is based on ReMoVES system. Based on such a past experience, new stakeholder roles have been defined in close coordination between medical and technical developers to address the new MS use case target and update related goals and actions. Based on the clinical needs of MS patients and the particular types of cognitive impairment they are affected by, six new activities delivered in form of exergames have been developed to address the following functional abilities:

- **Working memory**: describes the processes involved in the control, regulation and active maintenance of information relevant to the task at the service of complex cognition.
- **Inhibition control**: it is an executive function that allows a person to control the impulses and behavioral responses to stimuli in order to choose the most appropriate behavior consistent with achieving the objectives.
- **Selective attention**: it is the act of focusing on a single object in the environment for a specific period of time.
- **Task switching and cognitive shifting**: they are two executive functions that involve the ability to respectively, unconsciously or consciously shift the attention between one task and another.
- **Multitasking**: it is the ability to focus on multiple tasks or activities at once.
- **Sustained attention**: it is the ability to focus on an action or stimulation for an extended period of time.
- **Top-down attention task**: this type of attention refers to the ability to focus on specific features, objects or regions in space that are relevant to a goal, filtering out irrelevant stimuli.

The new activities will be explained later in Section 3.4.1.

3.4 Exergames

The system currently includes six different exergames for the Kinect sensor, five exergames for the Leap Motion sensor, and four activity for the touchscreen, respectively show in Figure 3.4. An initial calibration phase and real-time adjustment adapt the game to the mobility of the user. Each game is made up of simple 2D elements to prevent the patient from being distracted by irrelevant background elements. The entire performance is recorded and at the end of the each game session, the parameters useful for investigating the player's activty are collected in a JSON file and provided for the analysis. Also motion data can be reconstructed, as the joints positions are recorded by the Kinect and the Leap Motion sensors. The JSON file is composed of an array that collects temporal events. Each element of the array expresses data in key-value form. Some keys such as Time, Score and Kinect/Leap (i.e., the position of the joints detected by the sensor) are common to most exergames, while other parameters depend on the type of exercise or test. All the exergames for Kinect and Leap sensors, except the Sit-to-Stand activity, have a total game time of 90 seconds.

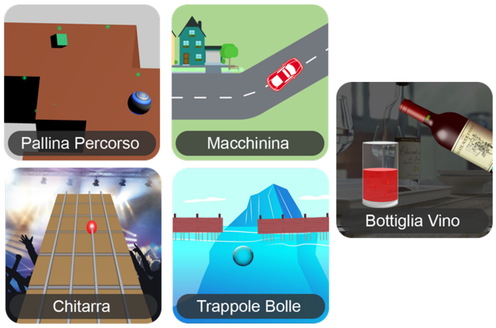
Equilibrium Paint (Sit to Stand)

This game is an interactive version of the standard Sit-to-Stand (STS) exercise proposed in the Berg Balance Scale battery [195]. The user repeatedly stands up and sits down within 30 seconds. The scene shows a horizontal wooden beam on which paint cans are placed. The inclination of the beam directly depends on the angle of the user's shoulders, traced by Microsoft Kinect. When the patient does not symmetrically stand up, the paint cans fall down, causing a score penalty in the game. STS is a well-known assessment test of which the importance in estimating lower-limb strength is widely recognized [196]. Many studies discussed its effectiveness as an indicator of leg weakness and related falling risk in elderly and disabled people [197]. In addition to assessment, STS is a task-oriented and strength-reinforcing exercise [198].

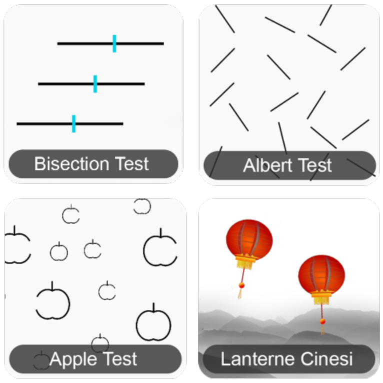
Owl Nest (Gufi Nido)

Three colorful owls randomly appear in certain positions in the screen, and the goal is to grab them with the flexion-extension of the arm (reaching task) and bring them into a nest placed in the middle of the screen. When the user brings an owl into the nest, another owl appears at a different point and the in-game score increases.

(a) *Microsoft Kinect exergames.*



(b) *Leap Motion exergames.*



(c) *Touchscreen tests.*

Figure 3.4: Thumbnails of exergames in the current ReMoVES catalogue.

Shelf Cans (Lattine Bibite)

In this exergame, the player is required to store items on a wall unit with the arm motion. In detail, the game activity is to move a colored can of soda towards the corresponding shelf. The up-right, up-left,and bottom-left corners are for orange, green, and red tin cans, respectively. Therefore, Shelf Cans contributes to improve the attentive capacities of patients, who must respect the rule of matching the color between the can of soda and the shelf correctly. The penalty for making a mistake is the reduction of the score accompanied by a disappointing sound. This game is aimed at stimulating hand-eye coordination of voluntary arm movements, reaction time, inhibition and selective attention, and processing speed.

Hot Air (Mongolfiera)

The game is set in a hilly landscape where a hot-air balloon flies and advances automatically. The player can control the lateral displacement of the balloon by performing a load shifting exercise between the lower limbs. The aim of the game is to guide the balloon towards the blue rings that appear along the way. The progressive position of the rings is pseudo-random so that there is a continuous shift. This game is for postural balance and correction reactions, shifting, and attention.

Push Box (Spingi Scatola)

The purpose of this exercise is to push a box into a hole a few meters in front of the box. To reach this goal the patient must stretch forward with their arms parallel to the ground. This exergame takes inspiration from a phase of the Berg Balance Test.

Flappy Cloud (Nuvoletta)

The leg abduction-adduction movement reflects the position of a cloud object in the game screen, the patient makes it move forward without hitting some obstacles. This is a functional exercise for the strengthening of the lower limbs.

Endless Zig (Pallina Percorso)

In this activity, the patient drives a marble along a zigzag path appearing on the screen. Going out of the boundaries causes score loss. Similarly, some bonus gems appear on the path to increase the score. The patient controls the marble movement with radial–ulnar deviation of the hand.

City Car (Macchinina)

The user controls a car along a randomly-generated road. The user should steer in the presence of curves and crossroads with the movement of flexion–extension of the wrist. Penalties are introduced when the car goes off-track.

Finger Tap (Chitarra)

The scene of the game represents a neck of a four-string guitar. In a sequential mode, some coloured marbles fall off the strings. The colour sequence is green, yellow, red and blue. To stop the falling marbles, the patient must "plucks" the right string, opposing the right finger to the thumb, at the correct timing. The more precise is the stop, the more the score increases. If the patient misses some marbles or touches the wrong finger, the score decreases.

Floating Trap (Trappole Bolle)

The patient is led to open the hand and make a fist alternatively. This exercise requires a good level of concentration; indeed, the user moves a floating raft on the left or on the right according to the finger flexion–extension in order to avoid some objects in the scene.

Wine Bottle (Bottiglia Vino)

This exercise mimics a real-world scenario, pouring liquids from a bottle. With the pronation–supination movement of the hand, the patient should control the rotation of a bottle of wine appearing on the screen. They must fill a glass over and over again to collect as many points as possible.

Bisection Test

The Bisection test is an assessment tool that is part of the Behavioral Inattention Test (BIT) battery [199]. The patient must place a pencil mark at the center of a series of horizontal lines. The resulting score is lower as the pencil mark is far from the center of the line. The digital version of this test allows customization of the color, width, height, position, and rotation of the lines in order to provide several variants of the standard one and in-depth analysis.

Albert Test

Another activity from the BIT battery tests is the Albert test. In this test, patients must use a pencil to cross out forty 2.5 cm lines which are positioned in pseudo-random orientations on a piece of paper. The actual disposition of these lines is standardized, allowing for a systematic analysis of subjects' performance on the left, on the right, and in the middle of the page. More specifically, in the Albert's test, the paper is divided in seven sections by column, which are hereinafter numbered from left to right. Scoring is based on the number and location of lines left uncrossed, in particular USN is indicated when these lines are on the same side of the page as the patient motor deficit is located. The maximum score for this test is 36 (the four segments of the central column are not counted). The cut-off is 34. The digital version of Albert's test is carried out in the same way as the paper one, but through the use of a touchscreen and two minutes to complete the test. The digital version of the Albert's test can provide more granular information about the patient's exploration capability.

Apple Test

This activity is the digital version of the Italian standardization of the Apples Cancellation Test [200]. It is an instrument useful to evaluate both egocentric and allocentric forms of neglect. Apple test is a cancellation task in which outline drawings of 150 apples are shown scattered over a sheet. Several apples are presented in an upright position. One-third of the apples are full (targets), and two-thirds are open on either the left or on the right side (distracting elements). In the digital version, each participant was asked to touch on the screen all the full apples and to ignore all the ones with holes.

Lantern (Lanterne Cinesi)

In this exergame, Chinese lanterns appear from the lower side of the screen and rise towards the upper part of the screen. The player must act as quickly as possible and touch them using on the screen. This activity is for the assessment of mental alertness and awareness. Moreover, it can have applications for the neglect assessment by comparing the performances relative to the targets shown on the right or left of the screen.

3.4.1 Exergames for STORMS project

The new cognitive games introduced in the STORMS project aim to treat some of the most common symptoms of multiple sclerosis such as coordination disorders, balance problems, and dizziness (Hot Air); vision disturbances which may also include impaired color vision (Owl's Nest), cognitive disorders that incorporate problems with memory and learning, difficulties in maintaining concentration, difficulties in attention, in computational problems; and inability to perform operations of a certain complexity and in problems to correctly perceive the environment (Supermarket, Numbers, Shelf Cans, and Business by Car). It is possible to obtain indirect measurements of symptoms such as numbness of the body and/or extremities or spasticity which can complicate movement when games are performed with pelvic or limb movement. In some exergames, the patient is encouraged to reach consecutive on-screen targets with the arm motion (reaching task). The more targets are taken, the higher the in-game score. Such games aim at improving hand–eye coordination, and spatial awareness. In addition, some other exergames promote the trunk balance used to guide an object along a path. In the Owl Nest, Supermarket, Numbers, and Business By Car exercises there are different levels, from easy to extremely difficult, while Shelf Cans and Hot Air activities have a single level and can be used by patients to familiarize themselves with the system. This is in order to define the treatment plan based on the patients' disability, aimed

Figure 3.5: Thumbnails of STORMS exergames.

at selecting the most appropriate game and level to start and continue therapy. In all the exergames, except Business By Car, the total game time is 90 seconds. Business By Car has a longer duration (600 seconds) to ensure that the patient can reach the end of the game even if he sometimes makes a mistake along the path.

Owl Nest (Gufi Nido)

This exergame, already present in the standard version of ReMoVES, has been expanded with 3 new difficulty levels (the first level is the base game explained in the previous Section).
Second level: some eagles appear on the screen as distracting elements. No more than five owls and three eagles can appear simultaneously. The time between the appearance of two consecutive eagles randomly ranges from 0 to 5 s. After 10 s the eagle disappears. Catching an eagle makes the game score decrease.
Third level: the player is required to catch only the pink owls and do it as quickly as possible, since after 15 s the owls will disappear. Every time an owl disappears, another reappears in a different location until a maximum of seven owls are simultaneously on the game scene. The score decreases either when grabbing a blue owl or when a pink owl disappears.
Fourth level: it is a combination of all the goals of the previous levels. No more than four owls and three eagles appear simultaneously. The user must bring the pink owls into the nest and avoid both eagles and blue owls. Eagles disappear after ten seconds, while owls disappear after 8 seconds.

Numbers (Numeri)

The patient has to pop some numbered (from 0 to 99) balloons according to temporary instructions. Four instructions alternate according to the level difficulty:

- pop the balloons in ascending order;
- pop the balloons in descending order;
- pop the balloons with even numbers;
- pop the balloons with odd numbers.

The number of balloons varies depending on the difficulty level; they also have different colors and sizes to make the game more dynamic and visually appealing. If the user takes a wrong balloon, a red mark appears at the bottom of the screen, otherwise a green one does. In both cases, all the balloons still on the screen will be destroyed and a new round will begin with new balloons. The aim of this exergame is to improve the attention, the task and cognitive switching, the processing speed, and the hand–eye coordination.
First level: four balloons appear on screen. They must be popped in either ascending or descending order.
Second level: it is as the first level, except that the patient is also required to pop either the even or the odd balloons and there are five balloons in the game scene. Two visuo-verbal stimuli are added. When the text relating to the assignment "take the odd numbers" shows, a red bird will appear for a few seconds flying from one side of the scene to the other. Conversely, a plane will appear on the screen for a few seconds when the text relating to the task "take the even numbers" appears.
Third level: six balloons are simultaneously displayed. Once more, all the tasks can be performed, but this time the patient must remember the stimuli association previously described, because in the cases of "take the odd numbers" and "take the even numbers" no writing appears on the screen.
Fourth level: it is structured like the third level, but also the writings "pop in ascending/descending order" will disappear after a couple of seconds.
Fifth level: the player has to quickly pop as many correct balloons as possible before they disappear. In fact, all the four balloons will fly off and disappear from the screen. Only the tasks about the odd and the even numbers with their relative visuo-stimuli, will be displayed.

Supermarket (Supermercato)

This exergame is set into a supermarket where the player is instructed to buy some objects. A list of items to pick up is displayed at the game start. The user has

a time between 8 and 25 s to memorize this list, depending on the level. When the game starts the patient has to take the correct objects by moving the arm. An audio feedback is provided, with either a positive or negative sound occurring in case of correct or incorrect action, respectively. In the first, third, and fourth levels, once the list has been completed and the patient collected all the objects, they reappear on the screen in changed position. The user can collect the stored objects again. The aim of this game is to train memory (verbal, non-verbal, and visual), inhibition and selective attention, and hand–eye coordination.
First level: a temporary list of three food names must be memorized in eight seconds. Then, the player has to collect the relative objects, moving them from the two lateral shelves into the shopping bag (placed in the middle of the screen). Some non-food distractors appear on the shelves. The semantic property (food or non-food) of the objects is the crucial correctness factor of the activity. The game score decreases if wrong objects are put into the bag. A visual feedback is also provided (initially yellow health bar turns red when mistakes are made).
Second level: the player has to memorize four ordered objects in ten seconds. These objects must be collected among other distracting items sliding on the conveyor belt. The game score decreases if the wrong object is taken or if the order is not followed.
Third level: the player must memorize and follow four sequenced instructions in twenty seconds. Each instruction refers to a different semantic characteristic (shape, color, or material) of the objects to be collected. Collected items will not reappear.
Fourth level: it is like the third level, but it differs for the higher number of the objects in the scene and the number of instructions (five instead of four, to remember in 25 s). In addition, the objects will reappear on the screen once collected.

Business By Car (Commissioni Auto)

In this activity, the patient drives a car along a randomly generated road. In particular, the car turns either left or right as the player moves the trunk laterally to the left or to the right, respectively. The increase of the car speed is progressive, until the player goes out of the carriageway, which causes a penalty in the score and returns the speed to the initial condition. In this last case the car will be repositioned on the path. At the beginning of the game, a list of places to visit appears on the screen. The patient will have to memorize this list in a time that varies between ten and twenty seconds, based on the selected level. Afterwards, the game will start and the patient will have to drive the car along the path and select the correct street at the crossroads to pass by the required places. Once the errands are finished, a series of multiple choice questions will appear on the

screen, relating to the list and places or about details present in the game scenes or in the buildings visited. To answer the questions the patient has to raise his arm and guide the hand that appears on the screen towards the answer button. In detail, the three levels will be described which differ according to the number of places to remember and the difficulty of the final questions. The aim is to train visual memory, attention, postural balance, and correction reactions.
First level: in the easiest level, the patient must remember only four places to visit. The buildings to see are simply written on the list, with no further writings, to make the goal clear. At a crossroads, the navigator at the bottom-right will indicate the correct route to take. If the patient happens to take the wrong path, a message will appear, reminding him/her of the correct place to visit and to pay more attention to the next crossroads. In the question scene, there will be two questions relating only to the stuff to do, e.g., "Was the first building to visit the Supermarket?"
Second level: in this level the patient must remember five places. This time a real list of errands to be carried out will appear at the beginning of the game (e.g., "Do the grocery shopping at the Supermarket."). It can help the patient in providing context and remembering where he/she needs to go. The navigator does not indicate the correct path to take and only a warning message will appear on screen if the player goes on the wrong direction. The final questions are three, two of them about the list and the last one relating to a detail of a visited building (i.e., "What color was the Supermarket awning?").
Third level: in the last level, the player must keep in mind six places. No warning message will appear if the wrong way is taken. In the final scene, the patient should answer to four questions, one related to the initial list and three concerning details seen in the visited buildings.

Hot Air (Mongolfiera) and Shelf Cans (Lattine Bibite)

As anticipated, these two games are also present in the standard version of ReMoVES and are used to illustrate the movements to be performed and to familiarize with the system. The movement of Hot Air activity has been modified as requested by the clinical staff, now providing only a lateral movement of the trunk without loading the weight on one leg.

3.5 Therapist Client

The Therapist Client is a web interface that allows user-friendly interaction with the features offered by ReMoVES. The back-end is written in PHP and the front-end uses the Bootstrap 4 framework and jQuery. Since Bootstrap 4 allows the layout to dynamically adjust to the size and kind of device, the portal is "responsive" and ensures the appropriate level of accessibility. This feature also permits connections from mobile devices. Through data processing, the most important characteristics are extracted and represented with graphs and figures. Therefore, this data is better understandable and immediately available to medical personnel, helping them to obtain a more accurate interpretation.

The Therapist Client management method has been structured according to the following basic principles:

- Data aggregation: where multiple data sources are combined (game events with motion data from Microsoft Kinect or Leap Motion sensors).
- Data selection: where the most relevant data for the analysis is restored from the database.
- Data transformation: where data is transformed and consolidated into an appropriate format for processing.
- Data processing: the essential process in which intelligent methods are applied to extract information of interest.
- Graphic presentation: in which visualization and representation techniques are used to present the extracted information to the specialist.

The first three phases represent different forms of data manipulation that have the objective of preparing them for the data processing. The last phase uses the results obtained from the processing phase to propose different points of view that make the information direct, clear and easy to read and understand. By processing the data and extracting the patient's performance indicators, it is possible to provide the doctor with aggregate information of a single session, an entire therapy, a single patient or multiple patients (dashboard); the doctor therefore has the possibility of comparing these parameters. By applying this method, therapists can easily access daily or periodic information about patients without having to process data or read long reports. Furthermore, this approach does not exclude doctors from viewing individual patient data of interest.

The possible functions of the Therapist Client, still being updated, are the following:

1. Dashboard: inside the dashboard the doctor can monitor all the patients he is following. For example, with a first visualization he can check which patients have carried out the prescribed activity and give a first overview. Next, the specialist in detail can monitor a report of the actual activity of individual patients. A possible "alert" can be added to indicate whether or not the patient has complied with the prescription ordered by the doctor.

2. Prescription of the individual treatment plan: in this section, the therapist has the possibility to create the treatment plan prescription, by planning the type of activity, how many times a day or a week, what levels and in what period (Figure 3.6).

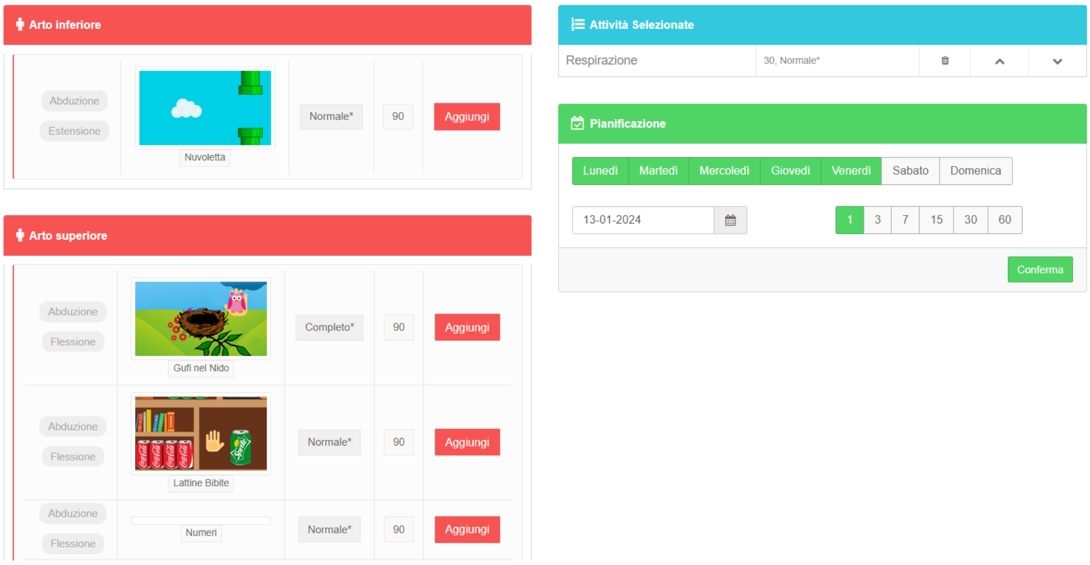


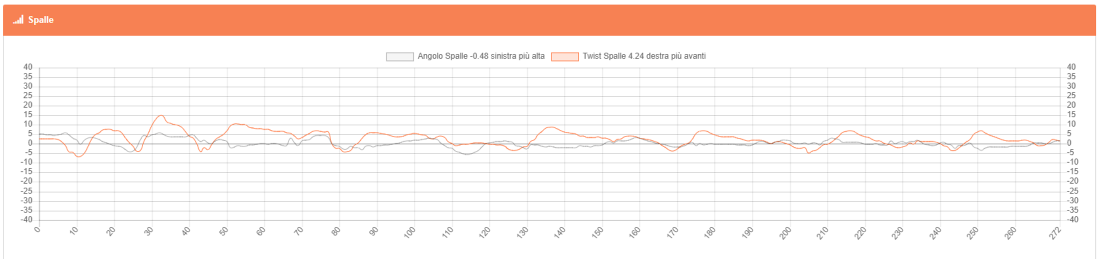
Figure 3.6: Treatment plan selection page within the Therapist Client.

3. Visualization of possible activities and pathologies: it will be possible to search for patients through two filters, that of the type of activity and the type of pathology, to have a faster search for patients of interest and to facilitate comparisons.

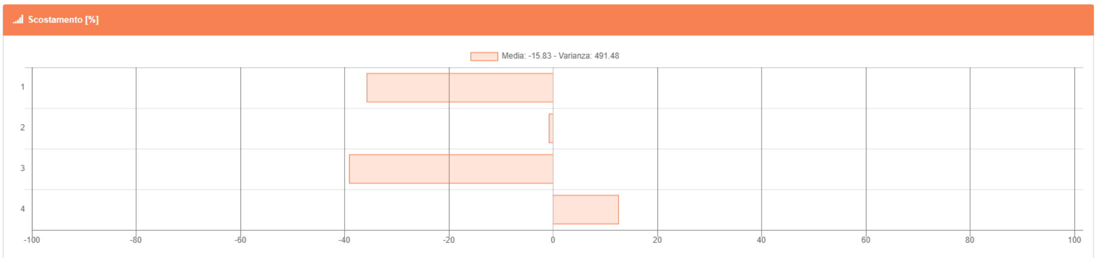
4. Viewing facilities and patients being treated: in the therapist client there will also be a division dedicated to the management of users divided according to the place where they carry out the telerehabilitation activity.

5. Personalized patient section: there may be a section relating to the patient profile in which some non-sensitive personal data such as age, pathology, place of hospitalization and start of treatment will be entered. Through this page it will be possible to access the prescription of the personalized treatment plan and to view all the gaming sessions that the patient has played.

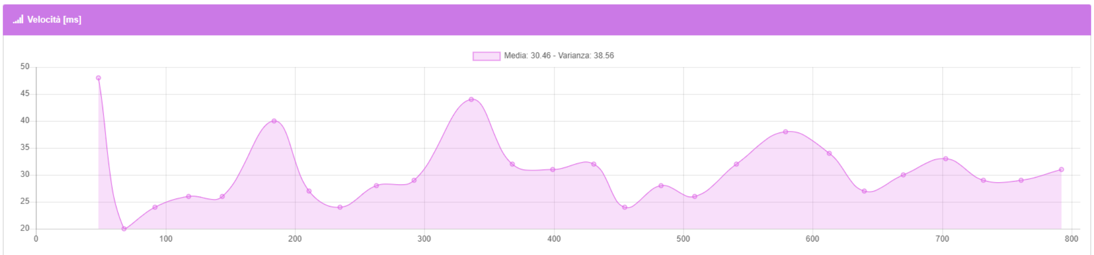
6. Automatic analysis of significant parameters: the significant parameters that the multidimensional team will want to view automatically will be agreed



(a) Shoulder rotation and lateral angles (Equilibrium Paint).



(b) Percentage of deviation (Bisection Test).



(c) Velocity (Owl Nest).

Figure 3.7: Automatic analysis of some parameters displayed in the Therapist Client.

upon and the system will be updated accordingly. The Figure 3.7 shows some display examples.

Chapter 4

Signal processing for human movement analysis

The problem of human movement tracking is addressed here in relation to the possibility of acquiring and estimating the position of body points from sensors of various types.

A stochastic (or random) process is a correspondence that associates a temporal function to each possible result of an experiment. Each repetition of the experiment (i.e., a trial) gives rise to one of the process realizations.

Given a 3D space defined by the axes (x, y, z), a generic point j belonging to the human body can ideally be traced during movement and described by the 3-component vector random signal $\{\vec{v}_{Bj}(t)\}$ defined as:

$$\{\vec{v}_{Bj}(t)\} = \begin{bmatrix} \{x_{Bj}(t)\} \\ \{y_{Bj}(t)\} \\ \{z_{Bj}(t)\} \end{bmatrix} \tag{4.1}$$

This is a three-dimensional random process that carries information on the actual instantaneous position of the generic $j - th$ body point. When referencing the position to an external marker attached to the body surface, the signal carries the actual position of the corresponding point in space. On the contrary, when it comes from a skeletal representation of the movement of the human body, j points corresponding to the main human joints are reconstructed.

Starting from these basic signals, other useful signals can be obtained in the kinematic analysis of the person's movements. For example, displacements and trajectories in 3D space, on a plane, or along an axis, as well as speed, acceleration, etc. can be instantly measured. Distances, speed and acceleration of each point or set of points can be studied in the same way. From the 3D coordinates any angle can be measured as well. A temporal feature signal $\psi(t)$ can be then measured and studied.

Assuming that the subject is in a given state Γ, some characteristics of interest can be observed. Accordingly, a resting state R_β is defined, along with a specific motion state, M_α, to indicate specific resting positions or certain motions during which the features can be extracted. In the former case one can speak of *Instant Features*, i.e., $\psi(t)|R_\beta$, in the latter case one deal with *Dynamic Features*, $\psi(t)|M_\alpha$.

The prerequisite for a random process to be stationary concerns its statistical behavior; the analysis of the statistical properties of any order is meaningful only if this property is verified. In such a complex pattern as in the signal depicting human movement, stationarity holds only if the signal is conditioned to a specific rest or dynamic state.

For the subsequent definition of signals and noise models it is therefore necessary to define some working conditions, which are also fundamental in the subsequent signal processing and analysis phases.

The three components of signal $\{\vec{v}_{Bj}(t)\}$ are independent, their mean power, under stationarity hypothesis, being $S^2_{ij}(t)$ where i is the spatial index $i \in \{x, y, z\}$ of the $j-th$ joint. For instance, in the vertical axis, the mean power of joint j conditioned to a generic state Γ is:

$$S^2_{yj}(t)|\Gamma = E\{y^2_{Bj}(t)|\Gamma\} \tag{4.2}$$

Stationarity is a precondition to verify the ergodicity property that allows to use temporal mean operator in the place of statistical expected values.

Markerless sensors are able to produce, through an analytical reconstruction process, 3D signals for a series of points of the human body not necessarily belonging to the external surface, very often referring to a skeletal representation.

Noise Models

The major signal noise sources in real applications refer to the classical additive and multiplicative noises, as described in Equation 4.3 for the x-coordinate of the $j-th$ point, taken as an example:

$$\{x_j(t)\} = \{(x_{Bj}(t) + n_{xj}(t))\} \cdot \{m_{xj}(t)\} \tag{4.3}$$

where $x_j(t)$ is the acquired signal, $n_{xj}(t)$ is the independent additive noise and $m_{xj}(t)$ is the independent multiplicative noise used generally to describe impulsive non linearities.

Additive Noise

The multidimensional additive noise $\{n_{ij}(t)\}$ is a zero-mean 3-component vector signal for each joint j:

$$\vec{n}_j(t) = \begin{bmatrix} \{n_{xj}(t)\} \\ \{n_{yj}(t)\} \\ \{n_{zj}(t)\} \end{bmatrix} = \{n_{ij}(t)\} \tag{4.4}$$

Additive noise is generally independent on the signal and in many applications is supposed to be independent, identically distributed (IID), meaning that the covariance matrix, defined by:

$$\Sigma_n = \{\vec{n}_j(t) \cdot \vec{n}_k(t)^T\} = E\{n_{ij}(t) \cdot n_{lk}(t)\} \quad \forall i, j, l, k \tag{4.5}$$

is diagonal with:

$$\sigma^2_{n_{ij}} = constant \quad \forall i, j \tag{4.6}$$

Impulsive Noise

One of the most used models for impulsive noise is the Poisson-Gaussian model. A random sequence of Dirac pulses based on a Poisson point process, $\{b(t)\}$ is given, that is amplitude modulated with the independent Gaussian random process $\{a(t)\}$. This is given as input to a linear time-invariant filter whose pulse response is a rectangle pulse of fixed length T:

$$h(t) = \Pi\left(\frac{t}{T}\right) \tag{4.7}$$

The output is then:

$$\{w(t)\} = \left\{\sum_{m=-\infty}^{+\infty} a \cdot h(t - t_m)\right\} = \left\{\sum_{m=-\infty}^{+\infty} a \cdot \Pi\left(t - \frac{t_m}{T}\right)\right\} \tag{4.8}$$

with randomly placed rectangle pulses, amplitude modulated, occurring at random time instants t_m with a rate governed by the Poisson density λ.

4.0.1 Kinect signal noise models

Occlusion by the body or joint, incorrect posture, scenarios in which the skeletal joint position is outside the sensor's field of view, or the distance of a human body from the sensor are some of the factors that may compromise the accuracy of the Kinect. In these kinds of situations, the skeletal joint is incorrectly inferred, which results in an atypical tracking and changing of the skeletal joint's position. Moreover, the acquisition computer's runtime computational and memory capacity greatly influences the variable frame rate at which Kinect data is obtained. Combining a portable and low-cost sensor with suitable signal processing techniques could yield systems with acceptable performance in most medical and rehabilitation applications [31, 53].

The Kinect signal is the digitized version of the signal described at 4.3. The additive and multiplicative noises of the Kinect have been analyzed empirically and the following conclusions can be drawn, also based on the SoA works [201].

Additive noise in the Kinect Sensor

Additive noise is independent of the signal, with independent components that are not identically distributed. Then, the covariance matrix is diagonal, but its elements are not necessarily equal as in the case of IID noise. In fact, $\forall$ joints j, k and $\forall$ axis i, l it holds:. They are:

$$\sigma^2_{n_{ij}} \neq \sigma^2_{n_{lk}} \tag{4.9}$$

Following the definitions, $\sigma^2_{n_{ij}}$ has the meaning of variance and mean power at one time.

Impulsive noise in the Kinect Sensor

Based on a statistical analysis of the Kinect signal, as it is also reported in the literature, a loss of the signal at the sensor is experienced which randomly happens at some independent instant times, that can be modeled as a multiplicative noise. A good statistical model is based on an unmodulated Poisson process. The $\{b(t)\}$ process of Poisson distributed ideal Dirac pulses is now provided directly as input to a filter whose response is a rectangular pulse of random length d. Given the impulse response $h(t) = \prod\left(\frac{t}{d}\right)$, the randomness refers to the duration of the pulse rather than its amplitude (of fixed unit value). It follows that:

$$\{w(t)\} = \left\{\sum_{m=-\infty}^{+\infty} \prod\left(\frac{t - t_m}{d}\right)\right\} \tag{4.10}$$

Finally, the loss of signals occurring at the generic axis i of the joint j is the multiplicative model:

$$\{m_{ij}(t)\} = \{1 - w(t)\} \tag{4.11}$$

In conclusion it is clear that, by construction, this noise turns to be a binary stationary process with the following probability density function (pdf):

$$f_m(M) = P_0 \cdot \delta(M) + P_1 \cdot \delta(M - 1) \tag{4.12}$$

where

$$P_0 = P\{m(t) = 0\} = P\{w(t) = 1\} \tag{4.13}$$

4.1 Signal filtering

To deal with the noise problem that affects the Microsoft Kinect, the proposed procedure is here described. First, the zero runs of the signal were automatically located, then the missing samples are filled by a spline interpolation. The type of noise that primarily affects the signal is impulsive. Hence a non-linear filtering operation is required. However, the classic median filter does not work properly in the current situation, due to the large peak density. As a result, adaptive filtering, consisting of a combination of outlier detection with median value substitution, is designed to guide the de-noising operation based on the statistical properties of the signal. In particular, once the outliers are detected, they are replaced by the median value in a window of dimension fifteen, in order to remove the noise while preserving the original signal as much as possible. After impulsive noise removal the error becomes:

$$\epsilon^2_{yjF} = P_1 \cdot \sigma^2_{n_{yj}} \tag{4.14}$$

The expected improvement is reflected on the error reduction factor:

$$\frac{\epsilon^2_{yjF}}{\epsilon^2_{yj}} = \frac{P_1}{1 + P_0 \cdot (SNR - 1)} \tag{4.15}$$

where SNR is the signal-to-noise ratio defined as:

$$SNR = \frac{S^2_{yj}}{\sigma^2_{n_{yj}}} \tag{4.16}$$

One can notice that the error decreased more consistently in the case of large SNR and large P_0 values.

After eliminating non-linearities, a final low-pass filtering is performed to make the signal smoother.

4.1.1 Interpolation

The interpolation is a method for identifying new points on the Cartesian plane starting from a discrete set of data points.

Given a sequence of N distinct real numbers x_k and for each of these is given a second number y_k. A function f capable of describing a relationship between the set of x_k and the set of y_k is identified in such a way that:

$$f(x_k) = y_k \quad \text{for} \quad k = 1, ..., N \tag{4.17}$$

A pair (x_k,y_k) is called data point and f is called interpolating function for the data points. Interpolation methods differ in terms of accuracy, cost, number of data points needed, and smoothness of the resulting interpolating function.

For sake of conclusion, the spline interpolation, that were used during the analysis of the Kinect signals, will be described below.

Spline interpolation

A spline $f_m \colon [a,b] \to \mathbb{R}$ is a piecewise polynomial function of degree m, such that

$$f_m \in C^{m-1}([a,b]) \tag{4.18}$$

whose $m-1$ derivative is differentiable. In particular, given the pairs (x_k,y_k), with $x_k < x_{k+1}(k = 1, ..., N)$ the spline is said to interpolate if

$$f_m(x_k) = y_k \quad \text{for} \quad k = 1, ..., N \tag{4.19}$$

With $m = 3$ the so-called cubic splines f_3 are obtained, i.e., functions which in every interval $[x_i, x_{i+1}]$ (for $i = 1, ..., N-1$) are polynomials of degree $m = 3$ and globally functions of class $C^2([a,b])$. In each interval $[x_i, x_{i+1}]$ the function takes the form:

$$f_3(x) = a_k x^3 + b_k x^2 + c_k x + d_k \quad \text{for} \quad x \in [x_i, x_{i+1}] \tag{4.20}$$

Spline interpolation is often preferred over polynomial interpolation because the interpolation error can be made small even when using low-degree polynomials for the spline. Furthermore, spline interpolation is easier to evaluate than the high degree polynomials required by polynomial interpolation and does not suffer from Runge's phenomenon, since it is less susceptible to heavy oscillation between data points.

In the present work, zero runs of the signal were automatically identified and a traditional spline interpolation was applied to fill in the missing samples. The results obtained appear to be reliable and accurate, as shown in the Figure 4.1. A possible future improvement could be to use probabilistic interpolation, as described by the authors of [202].

4.1.2 Chebyshev outlier detection method

Impulsive behaviors were observed in the three dimensions of signals, possibly due to the temporary loss of Kinect joint tracking. Since large or high-frequency calibration errors can significantly alter the movement of signals and lead to errors in the measurement of clinical indicators, filtering techniques had to be applied prior to their calculation. The way to deal with outliers was to remove values

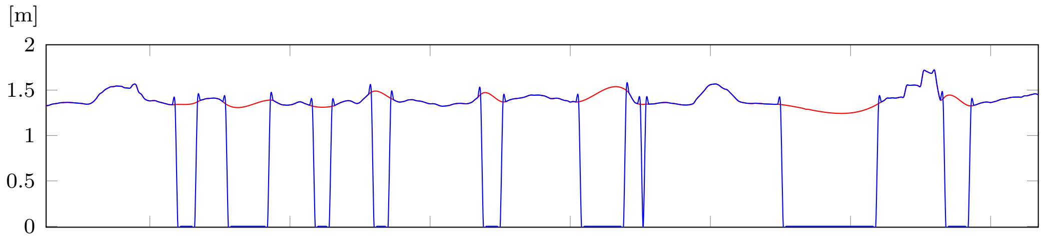


Figure 4.1: In blue the original signal, in red the interpolation.

whose distance from the mean of the signal was greater than λ times its standard deviation.

Since the signal statistical model is not perfectly known, the more conservative Chebyshev inequality approach [203, 204] is applied to obtain the lower bound value:

$$P(|x - \mu| \leq \lambda\sigma) \geq 1 - \frac{1}{\lambda^2} \tag{4.21}$$

with x being the random variable associated to a generic signal sample, described by μ and σ^2, which are respectively the estimation of its mean and variance. If $1 - 1/\lambda^2 = 0.89$, outlier values are the ones differing more than $\lambda = 3$ times the standard deviation from the mean value. The Chebyshev inequality can also gives the upper bound of the probability expressed as:

$$P(|x - \mu| \geq \lambda\sigma) \leq \frac{1}{\lambda^2} \tag{4.22}$$

The Chebyshev outlier detection method was inspired by work in the literature [205]. The lower and upper outlier detection values (ODVs) will be calculated and when data values exceed these thresholds, they will be treated as outliers. To determine which values are outliers, the following steps are performed:

1. The expected probability p of seeing outlier is decided.

2. The probability p value is used to find λ using Equation 4.22:

$$\lambda = \frac{1}{\sqrt{p}} \tag{4.23}$$

3. The upper and lower ODVs are calculated using the following equations:

$$ODV_u = \mu + \lambda * \sigma \tag{4.24}$$

$$ODV_l = \mu - \lambda * \sigma \tag{4.25}$$

All data larger than ODV_u or smaller than ODV_l are considered outlier.

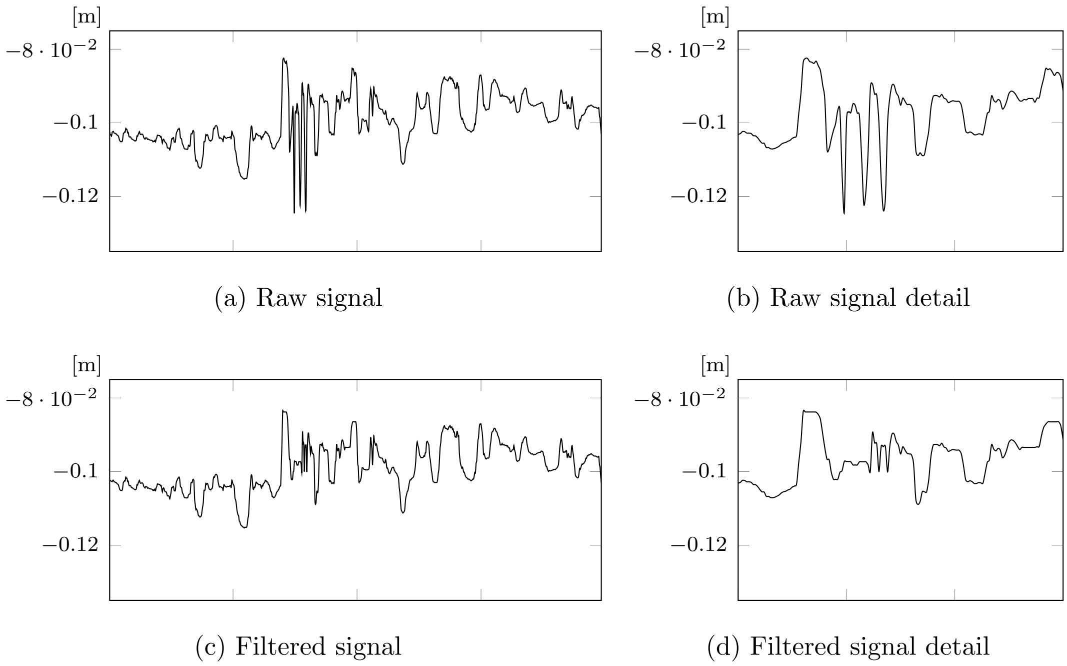


Figure 4.2: Signal filtering action through the Chebyshev method - full signal and frame detail.

4. The outlier values are replaced by the median value in a window of dimension fifteen.

An example of outlier detection operation is provided in Figure 4.2.

4.1.3 Butterworth filter

Once the outliers are detected and substituted, the low-pass Butterworth filter is applied. The signals acquired by the sensor appear to be stationary with respect to the mean, and devoid of useful information at high frequencies. The Butterworth filter [206] has the purpose of keeping the frequency response in the passband as flat as possible. On a Bode plot, the frequency response slopes off linearly towards negative infinity (Figure 4.3 [207]). The attenuation of a first order filter is equal to 20 dB/decade; of second order filter is 40 dB/decade and so on, with a steeper slope as the order increases. The frequency response of an n-order filter can be defined as:

$$|(T(j\omega)| = \frac{1}{\sqrt{1+\omega^{2n}}} \tag{4.26}$$

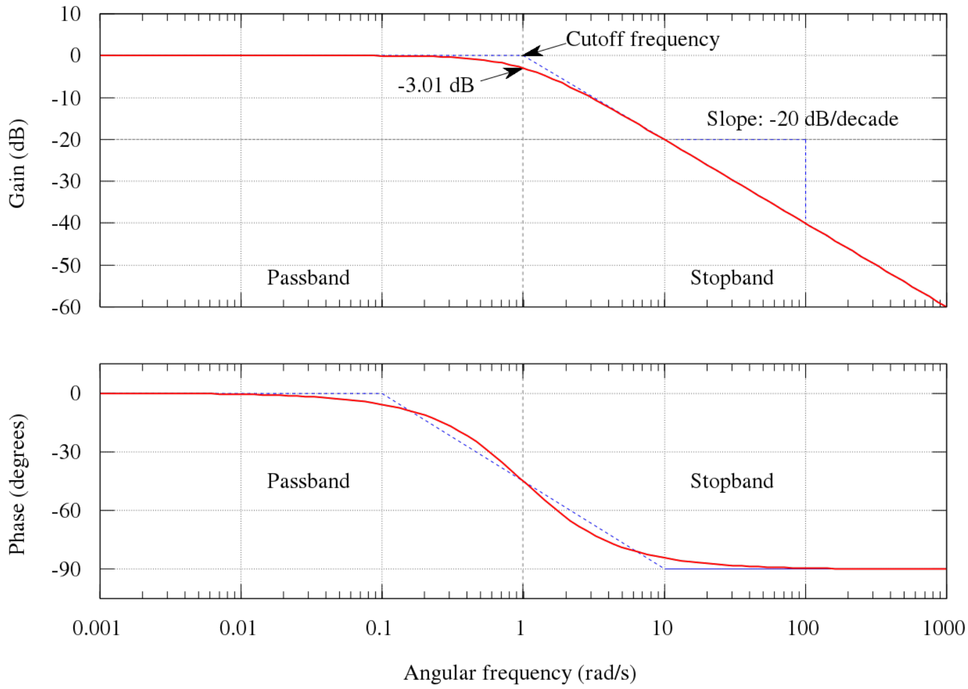


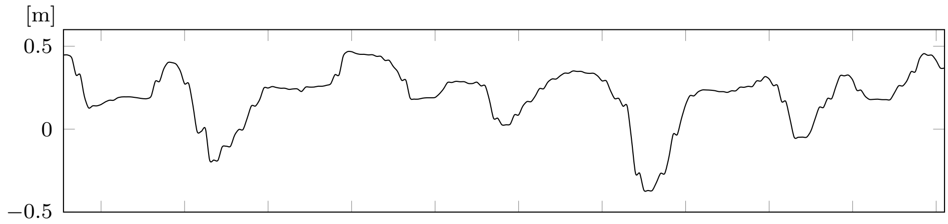
Figure 4.3: The frequency response of a first-order low-pass Butterworth filter.

where n is the order of the filter, ω is the ratio between the frequency of the signal and the cut-off frequency.

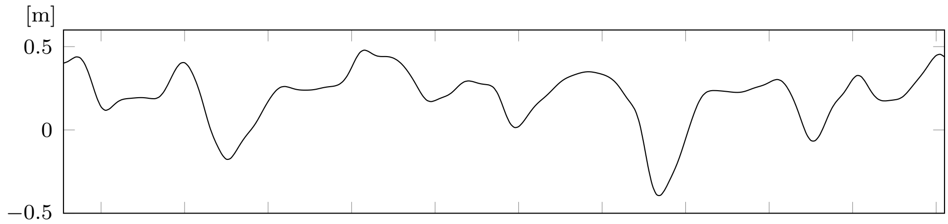
For signal regularization, after few tests a 2^{nd} order Butterworth filter with cut-off frequency of 2 Hz was implemented. An example of such filtering operation is provided in Figure 4.4.

4.2 Motion segmentation

A segmentation step is necessary in order to analyze reliable characteristics from the data. It is applied to extract individual repetitions from a continuous motion sequence of an exercise, and it depends on the exergame, namely it is driven by the movement pattern required by the game task. Decomposing the signal formed by complex movements into portions of elementary movements is of fundamental importance for the study of the patient's behavioral pattern and for the evaluation of rehabilitative physical exercise. In fact, these complex movements are stimulated with task-oriented exercises, but for the extraction of the main features (e.g., speed of execution, range of motion, trajectory performed, etc.) it is necessary to study the primitive movement in order to obtain a more precise and accurate analysis.



(a) Portion of the raw signal.



(b) Portion of the filtered signal.

Figure 4.4: Signal filtering action with the low-pass Butterworth filter.

The studied approaches are of 2 types: (1) approaches that use other signals to identify the start and end of movement, and (2) approaches that determine the segments based on the zero crossing method.

In the first case the Shelf Cans activity is considered which requires the execution of three specific movements, which are a set of basic flexion-extension and adduction-abduction movements of the upper limb. The movements M_α, M_β, and M_γ are defined to indicate respectively the movements to bring the red, orange and green can on the respective shelves. The multilevel signal *CanColor* retrived from the game session, consists of 4 levels that change based on the can taken (i.e., 0 - no can, 1 - green can, 2 - orange can, 3 - red can). Such signal allows to divide and consider separately the three trajectories made by the patient. The segmentation begins the instant the patient takes a can and ends when he places it on a shelf. An example of such segmentation is provided in Figure 5.17.

The second approach was used in the Sit-to-Stand exercise to discern the ascending and descending phases by determining the segments through zero crossings of the velocity of the Center of Mass (CoM). For a better robustness the CoM is introduced as a virtual joint given by the middle point between the right and the left hips (joints 17 and 19 in Figure 4.5, respectively), and spine middle joint (joint 7):

$$COM = (\bar{x}, \bar{y}, \bar{z}) = \left(\frac{x_{17} + x_{19} + x_7}{3}, \frac{y_{17} + y_{19} + y_7}{3}, \frac{z_{17} + z_{19} + z_7}{3} \right) \tag{4.27}$$

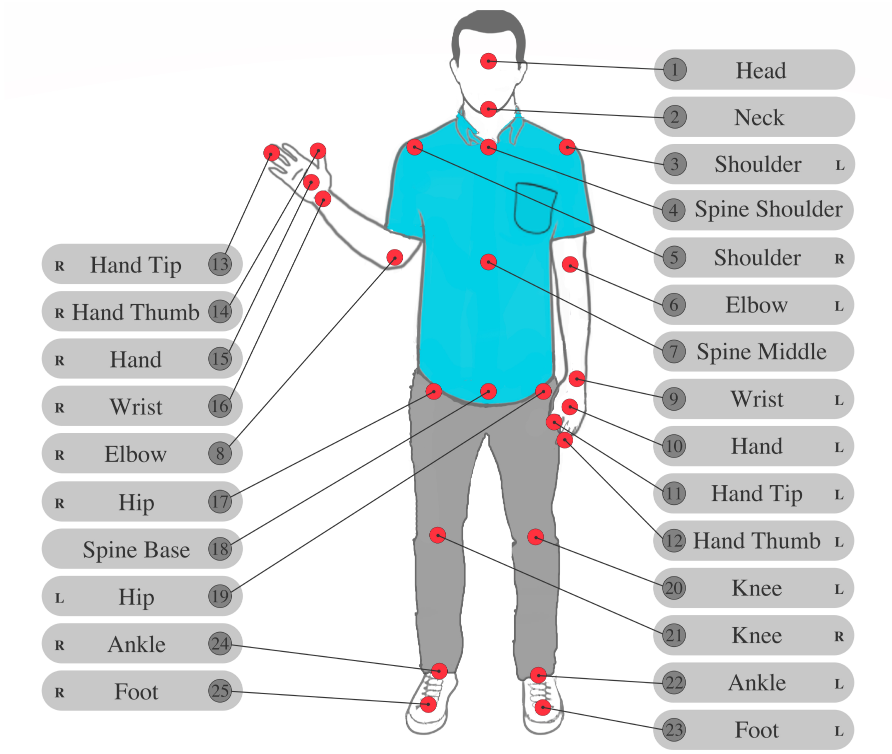


Figure 4.5: Joints tracked by Microsoft Kinect sensor.

The identification of the activation times corresponding to reaching the standing and sitting positions is then based on the vertical speed of the CoM. When the person is standing or sitting the vertical speed is approximately zero, when the person is standing up the speed increases; on the contrary when the person sits down the speed is negative. The local maxima and minima are then identified as the zero-crossings of CoM speed as shown in Figure 4.6. All the available signals can subsequently be automatically split into Up Phase and Down Phase so that features can be computed separately with respect to these basic movements.

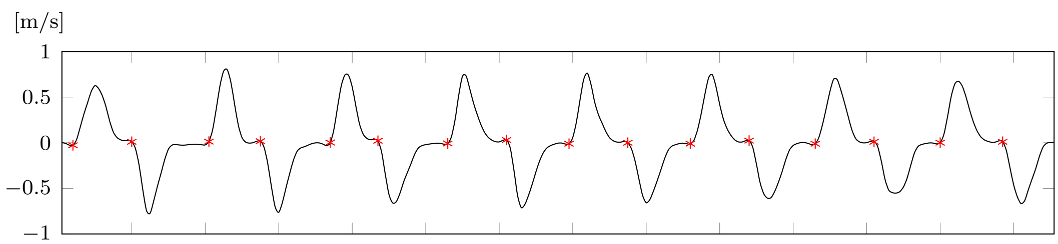


Figure 4.6: Zero-crossing of the velocity of the CoM.

4.3 Features extraction

The ReMoVES system records each game session along with the name of the game played, instant start and end times, final score and other game parameters for quick database querying. In addition to patient prescription, the features of interest can be classified as:

1. Instant Features,
2. Dynamic Features.

After the signal segmentation step, the automatic localization of the instantaneous time referring to some specific positions of the subject, the precise measurement of each joint constitutes the Instant Feature that allow one to understand the posture and compare it with the one indicated by the exergame.

Dynamic Features describe the kinematic movement that the subjects performed and refer to the Range of Movement in a given period of interest, the actual temporal displacement of the joints, or the change of angles during a specific movement.

Base Features are the joints position at an instant point which are directly accessible by signal punctual value. Even though coordinates in the 3D space are available for each joint at each time, much often their position in only one axis can be required.

Starting from Base Features, Derived Features are extracted by processing and combining the joint signals.

Some basic trigonometry concepts will be given below to introduce the calculation of angles in the case of human movement.

4.3.1 Angles computation

Vector

From a geometric point of view, a vector is an oriented segment characterized by a direction and a magnitude. The direction passes through the extremes, from the tail to the head of the vector; while the magnitude represents the length or intensity of the vector.

In general, a vector is indicated by a letter with an arrow above it. If v is a generic vector, then the notation to use will be:

$$\vec{v} \tag{4.28}$$

while the magnitude of the vector will be indicated with the notation:

$$\|\vec{v}\| \tag{4.29}$$

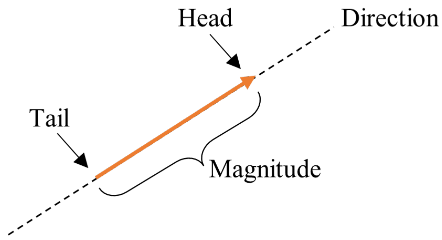


Figure 4.7: Graphic representation of a vector.

A unit vector is a vector of length 1 which is used to characterize other vectors by identifying a specific direction. Given a vector $\vec{v}$, the unit vector is defined as the ratio of $\vec{v}$ to its magnitude $\|\vec{v}\|$:

$$\hat{v} = \frac{\vec{v}}{\|\vec{v}\|} \tag{4.30}$$

Representations in a Cartesian coordinate system

Consider a system of orthogonal Cartesian axes and an applied vector $\vec{v} = \overrightarrow{OA}$ with the origin of the reference plane as its point of application. The Cartesian components of the vector $\vec{v}$ are the Cartesian coordinates of the point A and they are indicated by v_x and v_y, respectively for the component of $\vec{v}$ along the x-axis and along the y-axis.

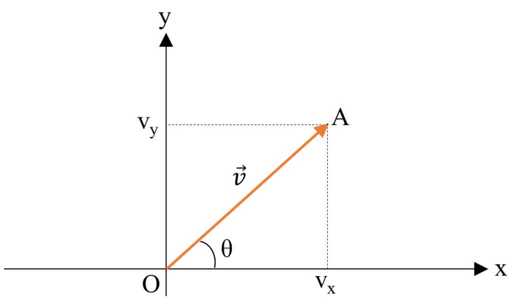


Figure 4.8: Cartesian representation of a vector in the plane.

Cartesian components can be used to define $\vec{v}$ with the following notation:

$$\vec{v} = (v_x, v_y) = v_x\vec{i} + v_y\vec{j} \tag{4.31}$$

where $\vec{i}$ and $\vec{j}$ are unit vectors representing the directions of the coordinate axes, and the algebraic formulas of the components v_x and v_y are given by:

$$\begin{cases} v_x = v\cos(\theta) \\ v_y = v\sin(\theta) \end{cases} \tag{4.32}$$

In a similar way, in three dimensional Euclidean space, vector $\vec{v}$ is identified with triples of scalar components:

$$\vec{v} = (v_x, v_y, v_z) \tag{4.33}$$

Operations between vectors

Dot product

The dot product of two vectors $\vec{v}, \vec{u} \in \mathbb{R}^n$ is denoted by $\vec{v} \cdot \vec{u}$ and is defined as:

$$\vec{v} \cdot \vec{u} = v_1 u_1 + v_2 u_2 + ... + v_n u_n \tag{4.34}$$

whose result is a scalar.

The dot product can also be defined by the angle formed between the vectors $\vec{v}$ and $\vec{u}$:

$$\vec{v} \cdot \vec{u} = \|\vec{v}\| \|\vec{u}\| \cos(\theta) \tag{4.35}$$

Magnitude

The magnitude or length of the vector $\vec{v}$ can be computed with the Euclidean norm:

$$\|\vec{v}\| = \sqrt{v_1^2 + v_2^2 + ... + v_n^2} \tag{4.36}$$

Similarly, the magnitude of the vector $\vec{v}$ can be expressed also in terms of dot product:

$$\|\vec{v}\| = \sqrt{\vec{v} \cdot \vec{v}} \tag{4.37}$$

Cross product

The cross product is only meaningful in three dimensions. The cross product denoted as $\vec{v} \times \vec{u}$, is a vector perpendicular to both $\vec{v}$ and $\vec{u}$ and is defined as:

$$\vec{v} \times \vec{u} = \|\vec{v}\| \|\vec{u}\| \sin(\theta) \vec{k} \tag{4.38}$$

where θ is the angle between $\vec{v}$ and $\vec{u}$, and $\vec{k}$ is a unit vector perpendicular to both $\vec{v}$ and $\vec{u}$ obtained with the right-handed system.

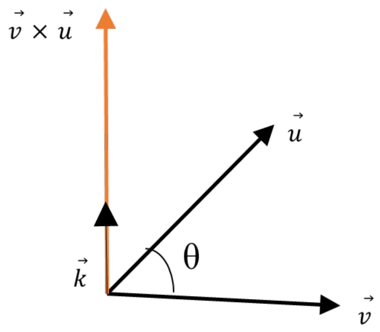


Figure 4.9: Cross product between the vectors $\vec{v}$ and $\vec{u}$.

Body Kinematics

Kinematics defines body motion without taking into account the forces that cause it to move. Firstly, to describe the position of a point in a 3D space, the reference system must be defined. The system used is the Cartesian coordinate system, defined as follows and shown in Figure 4.10. The direction of the X-axis corresponds to the horizontal direction of motion. The Y-axis is orthogonal to the X-axis, pointing vertically upwards, while the Z-axis is perpendicular to the X-Y plane in the outward direction.

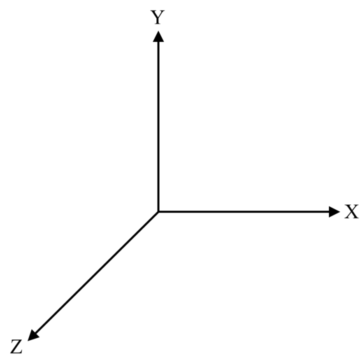


Figure 4.10: Cartesian coordinate system.

The human body is composed of several segments connected to joints. Although human motion involves movement in a 3D space, basic primitive motion can often be studied in a single plane. The three anatomical planes are thus defined [208] and displayed in Figure 4.11 [209]:

- Sagittal plane, which divides the body into two halves right and left. Movements in this plane occur around a medial-lateral axis and are called flexion and extension.

- Frontal or coronal plane, which divides the body into anterior and posterior sections. The movements described on the frontal plane have an anteroposterior axis as their fulcrum and are called abduction and adduction movements.
- Transverse plane, which divides the body into upper and lower halves. The movement described takes place on a vertical axis and is defined as rotation.

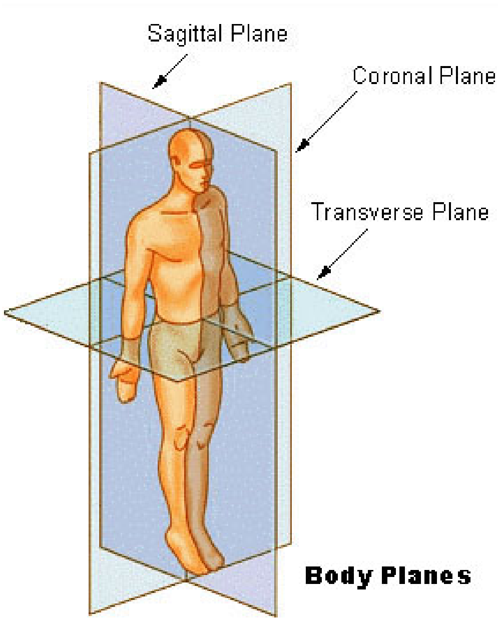


Figure 4.11: Reference anatomical planes.

With respect to the reference Cartesian system defined previously, the X-Y plane represents the Frontal plane, the Y-Z plane represents the Sagittal plane and finally, the X-Z plane the Transverse one.

In the literature, the study of the angles between two body segments and the Range of Motion of a particular joint is tackled with numerous approaches, sometimes equivalent to each other. The three most significant and used approaches will be illustrated below, comparing the strengths and weaknesses of each in the application context of this thesis.

Law of cosine

In trigonometry, in any triangle, the square of one side is equal to the sum of the squares of the other two sides decreased by the double product of these two sides multiplied by the cosine of the angle they form. Using notation as in Figure 4.12, the law of cosines states:

$$a^2 = b^2 + c^2 - 2bc\cos\alpha \tag{4.39a}$$
$$b^2 = a^2 + c^2 - 2ac\cos\beta \tag{4.39b}$$
$$c^2 = a^2 + b^2 - 2ab\cos\gamma \tag{4.39c}$$

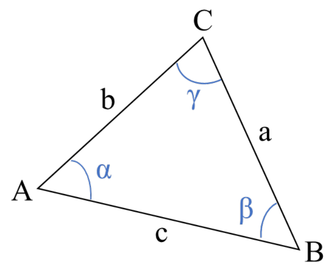


Figure 4.12: A triangle, whose sides are a, b, and c and the angles are α, β and γ.

This theorem is used to find one of the angles of the triangle if the three sides are known:

$$\gamma = \arccos\left(\frac{a^2 + b^2 - c^2}{2ab}\right) \tag{4.40}$$

From a physiological point of view, the Figure 4.13 shows an example of application of the cosine law to obtain the angle of the knee joint. The hip-knee and ankle-knee body segments are considered, plus an imaginary segment from the ankle to the hip.

In the literature, the Cosine theorem has been used by some papers to compare the angles calculated on the basis of Vicon and Kinect tracking data [210] or to check the posture of some exercises in an home environment [211] and to evaluate the Range of Motion of the shoulder joint [212].

Angle between vectors

The convex angle between two vectors $\vec{v}$ and $\vec{u}$ is defined starting from the formula of the dot product:

$$\cos(\theta) = \frac{\vec{v} \cdot \vec{u}}{\|\vec{v}\|\|\vec{u}\|} \tag{4.41}$$

from which it derives:

$$\theta = \arccos\left(\frac{\vec{v} \cdot \vec{u}}{\|\vec{v}\|\|\vec{u}\|}\right) \quad \theta \in [0, \pi] \tag{4.42}$$

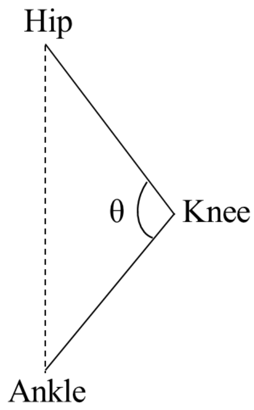


Figure 4.13: Visualization of the knee joint angle using the Cosine theorem.

The authors of the article [53] analyzed and studied the movement and the Range of Motion of the upper limb to monitor musculoskeletal disorders.

The formula derived from the dot product, however, can lead to less accuracy if the angle between the two vectors is small, and can also lead to rounding errors if the two vectors are parallel or opposite. An alternative could be to use the arctan function, which is more robust than the arccos, in handling small angles [213]:

$$\theta = \arctan\left(\frac{\|\vec{v} \times \vec{u}\|}{\vec{v} \cdot \vec{u}}\right) \tag{4.43}$$

Absolute and relative angles

The absolute angle is defined as "the angular orientation of a body segment measured consistently in the same direction with respect to a single, fixed line of reference, either vertical or horizontal" [214]. The relative angle is "the angle at a joint formed between the longitudinal axes of the body segments adjacent to the joint" [215].

There are numerous variations for calculating these angles [31, 216], the notation used will be explained below.

By convention, the absolute angles are measured in a counterclockwise direction, starting with the horizontal equal to 0°. In Figure 4.14, the calculated absolute angles with respect to the horizontal are marked in red, while the relative angle of the knee joint is marked in blue. To determine absolute joint angles the following trigonometric relationship can be used:

$$\theta_{shank} = \arctan\left(\frac{y_{proximal} - y_{distal}}{x_{proximal} - x_{distal}}\right) \tag{4.44}$$

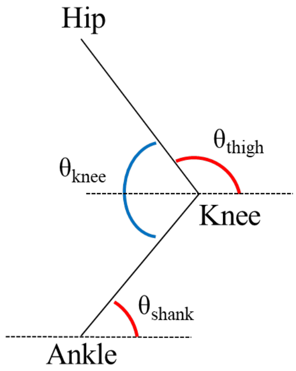


Figure 4.14: In red, the absolute angles of the thigh and the shank joints. In blue, the relative angle of the knee joint.

where $(x_{proximal}, y_{proximal})$ are the coordinates of knee joint and (x_{distal}, y_{distal}) are the coordinates of the ankle joint. Relative angles can be determined from the absolute angles, i.e., for the knee angle:

$$\theta_{knee} = 180^\circ + \theta_{shank} - \theta_{thigh} \tag{4.45}$$

4.3.2 Dynamic Time Warping

The result of segmentation allows the temporal comparison of specific movements. A rigid matching between the signals referring to some repetitions is meaningless and an elastic matching is then proposed through the Dynamic Time Warping (DTW) method.

DTW is a technique used in pattern recognition and time series analysis, mostly employed for assessing and evaluating the distance between two time sequences [217]. When the two sequences have different lengths or they present time shifts, speed variations, or other distortions, this approach can still determine the optimal alignment between them. As a result, a cost is calculated that quantifies how dissimilar they are, with a low DTW value suggesting greater similarity. Two signals from the same joint j are given:

$$y_j(kT_s)|M_{a,f} \tag{4.46}$$

$$y_j(kT_s)|M_{a,g} \tag{4.47}$$

respectively referring to two repetitions f and g of the same movement M_α, starting respectively at time T_f and T_g, whose length is FT_s and GT_s. They are at first temporally aligned at the starting time:

$$s_f(\phi) = y_j(\phi \cdot T_s - T_f) \cdot \Pi\left(\frac{(\phi - F/2) \cdot T_s - T_f}{F \cdot T_s}\right) \tag{4.48}$$

$$s_g(\gamma) = y_j(\gamma \cdot T_s - T_g) \cdot \Pi\left(\frac{(\gamma - G/2) \cdot T_s - T_g}{G \cdot T_s}\right) \tag{4.49}$$

The $F \times G$ cost matrix C is constructed whose $(\phi - th, \gamma - th)$ element is the distance between $s_f(\phi)$ and $s_g(\gamma)$, where ϕ being an index from 0 to $F-1$ and γ from 0 to $G-1$.

An alignment warping path π of length K is a sequence of index pairs (ϕ_k, γ_k) with the following properties:

1. *Boundary condition:* $\phi_0 = \gamma_0 = 0$ and $\phi_{K-1} = F-1$, $\gamma_{K-1} = G-1$.
2. *Monotonic condition:* $\phi_k \geq \phi_{k-1}$ and $\gamma_k \geq \gamma_{k-1}$.
3. *Continuity condition:* $\phi_k - \phi_{k-1} \leq 1$ and $\gamma_k - \gamma_{k-1} \leq 1$.

The cost $C_\pi(s_f, s_g)$ of a warping path π is then defined as:

$$C_\pi(s_f, s_g) = \sum_{k=0}^{K-1} C(s_f(\phi_k), s_g(\gamma_k)) \tag{4.50}$$

where $C(s_f(\phi_k), s_g(\gamma_k))$ is the Euclidean distance:

$$C(s_f(\phi_k), s_g(\gamma_k)) = \sqrt{(s_f(\phi_k)^2 + s_g(\gamma_k)^2)} \tag{4.51}$$

The Dynamic Time Warping (DTW) distance is finally defined as the total cost of the optimal warping path π^*. Then the similarity (distance) feature measurements becomes an optimization problem and an algorithm based on dynamic programming is implemented:

$$D(\phi, \gamma) = C(\phi, \gamma) + min\{D(\phi-1, \gamma-1), D(\phi-1, \gamma), D(\phi, \gamma-1)\} \tag{4.52}$$

where D define the $F \times G$ accumulated cost matrix.

The signal shape is here of interest, more than the specific absolute amplitude or a rigid timing of successive elementary movements. To face this problem a normalization procedure of the signal amplitude before the actual application of the DTW algorithm is needed. The normalized signals are therefore:

$$s'_f = \frac{(s_f - min(s_f))}{(max(s_f) - min(s_f))} \tag{4.53}$$

$$s'_g = \frac{(s_g - min(s_g))}{(max(s_g) - min(s_g))} \tag{4.54}$$

whose value is in the [0,1] interval.

In order to use DTW as a descriptive feature, the reference joint signals for each movement of interest has been defined. The best performed repetition pattern associated to the most precise movement has been used as the reference model:

$$s_f(\phi \cdot T_s)^* = y_j(kT_s)|M^*_{a,f} \tag{4.55}$$

4.4 Adopted solution

The solution adopted in this thesis for the processing of received signals and data is schematized in Figure 4.15. The raw data is acquired from the ReMoVES system, these signals are filtered with different techniques to deal with all the possible problems that could affect a signal coming from the Kinect sensor. Then, depending on the exergame considered, the signal is segmented into small portions to consider only the primitive movement. Subsequently, the features are extracted, which will then be analyzed individually also with statistical methods to compare the performance of the patients with the group of healthy subjects. In this way, conclusions will be drawn regarding the main features that help distinguish between the two groups. As regards angular features, the different techniques discussed in Section 4.3.1 give similar results. Therefore, in a similar way to what described by the authors of the study [218], in this work the relative angles of a body joint calculated with Equations 4.40 and 4.43 will be considered; while the inclinations of a body segment will be analyzed through the computation of the absolute angles seen in Equation 4.44.

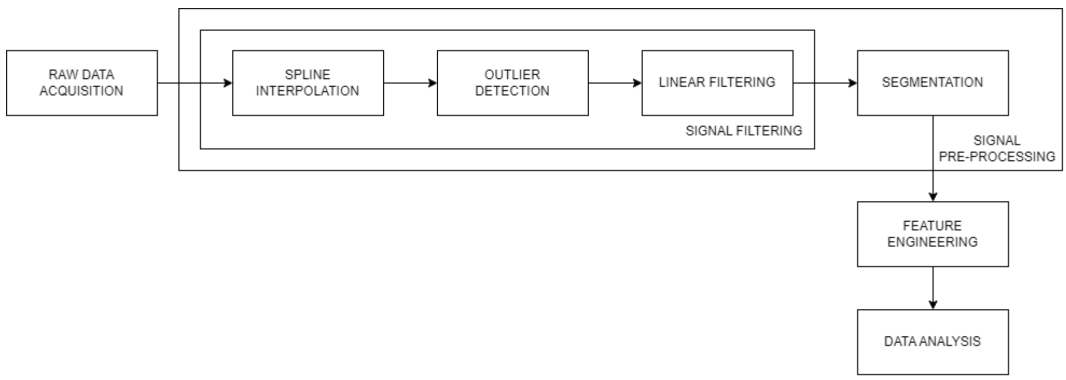


Figure 4.15: Flow chart of the proposed approach.

4.5 Extracted Parameters

At the end of each game session, the parameters useful for investigating the player's performance are collected in a JSON file and provided for the analysis. The positions of the joints recorded by the Kinect device will be used to reconstruct the movement performed, using the angle formulas described in the previous paragraphs. In the following description, the coordinates of the Kinect joints numbered as in the Figure 4.5 will be taken as reference, taking into account that the x, y, and z represent the mediolateral, vertical, and anteroposterior directions, respectively.

Below the indicators and parameters extracted based on the application or type of exergame analyzed in this thesis will be described.

4.5.1 Sit-To-Stand

A first direct indicator regarding the patient's performance after the execution of the STS is the number of sit-up occurrences (NSU) during the 30 seconds duration of the activity. This is computed by analyzing the trajectory of the spine middle joint (joint 7) along the vertical axis. Each peak of such a trajectory represents a sit-up. After the segmentation phase illustrated in Section 4.2, the movement features are separately computed in the ascending (Up) and descending (Down) phases in order to provide a fragmented and specific analysis of the patients' sessions. Two different studies were conducted, applying different methodologies for calculating the indicators.

For the first study, the definition of the considered features was inspired by works in the literature such as [219, 220].

The upper-body flexion angle (UBFA), represents the angle of flexion of the trunk and is computed as:

$$UBFA = \arctan \frac{z_2 - z_7}{y_2 - y_7} \tag{4.56}$$

The UBFA is maximal when the player is in a standing position, and reaches values of approximately 90° when sitting. For standing up, the player should move forward, which results in a decrease in sitting UBFA.

Similarly to the UBFA, the indicator of the lower-limb flexion angle (LLFA) represents the knee angle, and can be computed for both the left and the right limb. It is defined as:

$$LLFA = 180^\circ + \theta_{femur} - \theta_{tibia} \tag{4.57}$$

where $\theta_{femur} = \arctan \frac{z_{20} - z_{19}}{y_{20} - y_{19}}$, $\theta_{tibia} = \arctan \frac{z_{22} - z_{20}}{y_{22} - y_{20}}$ for the left limb and

$\theta_{femur} = \arctan \dfrac{z_{21} - z_{17}}{y_{21} - y_{17}}$, $\theta_{tibia} = \arctan \dfrac{z_{24} - z_{21}}{y_{24} - y_{21}}$ for the right limb.

Variation in this angle for both the left and the right limb is similar to the trajectory of the spine middle joint (see Section 5.2.1).

During this activity, patients may adopt erroneous behavior such as moving the shoulders or hips. Hence, it is important that therapists supervising the rehabilitation are informed about these compensatory movements. Regarding shoulder movement, the upper-body twist angle (UBTA) depicts the angle of the line joining the shoulders on the axial plane:

$$UBTA = \arctan \frac{y_5 - y_3}{x_5 - x_3} \tag{4.58}$$

Hip displacement is calculated on the basis of the anteroposterior and mediolateral displacement of the center of mass (COM) defined as in Equation 4.27. Hence, center-of-mass anteroposterior movement (COM AP) and center of mass mediolateral movement (COM ML) indicators depict COM positions on the axial plane.

To conclude, upper-frame velocity (UfV) is the velocity of motion in either the ascending or descending phase. For one ascending phase, it is computed as:

$$UfV_{up} = \frac{z_{peak} - z_{localmin}}{time_{peak} - time_{localmin}} \tag{4.59}$$

Similarly, in the descending phase, it is:

$$UfV_{down} = -\frac{z_{localmin} - z_{peak}}{time_{localmin} - time_{peak}} \tag{4.60}$$

During the second study, some angular features were calculated with a different approach compared to the first study. Furthermore, other useful indicators have been added for a more complete analysis.

The internal angle at the knee is calculated as a relative angle because it corresponds to an articulation between three joints. The formula used is the following:

$$\theta_{knee} = \arctan\left(\frac{\|\vec{v} \times \vec{u}\|}{\vec{v} \cdot \vec{u}}\right) \tag{4.61}$$

where $\vec{v}$ and $\vec{u}$ are the knee-hip and knee-ankle vectors, respectively.

The trunk flexion angle, in the sagittal plane, is defined as the absolute angle of the segment linking Spine Base with Spine Shoulder joints with respect to the antero-posterior axis in the body frontal direction and can be measured as:

$$\theta_{flexion-trunk} = 180 - \theta_H = \arctan\left(\frac{\Delta y}{\Delta z}\right) \tag{4.62}$$

Other angles depicting the deviation with respect to the required vertical or horizontal directions are computed in terms of absolute angles as well. For instance, compensation movements are observed through lateral body angles or shoulder rotations. The angle of the trunk in the frontal plane with respect to the vertical axis takes into account lateral deflection during the movement and is computed as:

$$\theta_{lateral-trunk} = \theta\left(\frac{y_{spine-shoulder} - y_{spine-base}}{x_{spine-shoulder} - x_{spine-base}}\right) \tag{4.63}$$

Shoulder angle in the frontal plane takes into account inclination of the line joining right and left shoulders with respect to the horizontal line (up and down shoulders):

$$\theta_{shoulder\_up} = \arctan\left(\frac{y_{shoulder-right} - y_{shoulder-left}}{x_{shoulder-right} - x_{shoulder-left}}\right) \tag{4.64}$$

where if $\theta_{shoulder\_up} > 0$, the right shoulder is higher than the left.

Shoulder twist angle takes into account the rotation of shoulders:

$$\theta_{shoulder\_twist} = \arctan\left(\frac{z_{shoulder-left} - z_{shoulder-right}}{x_{shoulder-left} - x_{shoulder-right}}\right) \tag{4.65}$$

where if $\theta_{shoulder\_twist} > 0$, the right shoulder is further forward than the left.

The main Instant Features of interest at rest positions are the torso and knees angles. At the standing position the knee extension (Max) angles, and upper body extension angle are defined. Instead, at the sitting position the knee flexion (Min) angle, and the upper body extension angle are computed.

Dynamic Features are relate to complex or single movements. Referring to the segmented Up and Down phases described in Section 4.2, some specific features are of clinical relevance. The min trunk angles and displacements during the ascending and descending phases explain the flexion required for a correct execution of the whole movement. Ascending and descending times were also considered. Features related to undesired compensatory movements are easily evaluated through ROM computed both as displacement and angle variations. Some compensatory motions must be avoided such as the medio-lateral inclination of the trunk, since it is requested to preserve the vertical position. The rotation of the shoulder axis as compared with the horizontal required position and the shoulder rotations in the transverse plane are also computed. Finally, the average of the DTW measured when comparing each segment of a session with the reference model is obtained.

4.5.2 Upper limb motion

Patients data have been analyzed both with 3D coordinates of Kinect joints and through 2D data obtained by the exergame itself. Two studies were carried out on upper limb rehabilitation using two different approaches to calculate the angles and ROMs of the shoulder, elbow and trunk.

For the first study, the computed indicators are the range of motion of the shoulder and elbow in the coronal plane, and the range of motion of the trunk in the sagittal plane. In particular, let us consider a fixed time, and define the shoulder and elbow angles in the coronal plane, and the trunk angle in the sagittal plane as:

$$\theta_{shoulder} = \arctan \frac{z_8 - z_5}{x_8 - x_5} \tag{4.66}$$

$$\theta_{elbow} = \theta_{shoulder} - \arctan \frac{z_8 - z_{16}}{x_8 - x_{16}} \tag{4.67}$$

$$\theta_{trunk} = \arctan \frac{z_4 - z_7}{y_4 - y_7} \tag{4.68}$$

respectively. Notice that shoulder ad elbow angles have been defined with respect to the right arm; the definition for the left arm is straightforward. Hence, the Range of Motion of the shoulder and elbow in the coronal plane, and the range of motion of the trunk in the sagittal plane are defined as:

$$ROM(\theta_{shoulder}) = \max \theta_{shoulder} - \min \theta_{shoulder} \tag{4.69}$$

$$ROM(\theta_{elbow}) = \max \theta_{elbow} - \min \theta_{elbow} \tag{4.70}$$

$$ROM(\theta_{trunk}) = \max \theta_{trunk} - \min \theta_{trunk} \tag{4.71}$$

respectively.

For the second study, the Range of Motion feature was computed for the elbow and shoulder joints in the three anatomical planes and in 3D space. An example of the equations used to compute the elbow angle in the coronal plane are the following:

$$a = \sqrt{(x_5 - x_8)^2 + (y_5 - y_8)^2} \tag{4.72}$$

$$b = \sqrt{(x_{16} - x_8)^2 + (y_{16} - y_8)^2} \tag{4.73}$$

$$c = \sqrt{(x_5 - x_{16})^2 + (y_5 - y_{16})^2} \tag{4.74}$$

where the joints 5, 8, and 16 are respectively for right shoulder, right elbow, and right wrist. From these equations the θ_{elbow} is derived:

$$\theta_{elbow} = \arccos \frac{a^2 + b^2 - c^2}{2ab} \tag{4.75}$$

Moreover, the tilt and twist of the trunk, i.e., lateral and antero-posterior inclinations on coronal and sagittal planes and trunk rotation on the transverse plane, are considered. For this kind of rehabilitation, these movements are an undesired strategy adopted by the patient during the execution of the arm flexion–extension and abduction–adduction exercises.

In addition to angles and ROMs, also other indicators are analyzed, such as:

- Target: the number of cans correctly positioned on the shelves.
- Angle between trajectories: the three specific tasks of Shelf Cans, referring to the differently colored cans, are split. Then, the straight line connecting starting position and targets is computed, and will be hereinafter referred to as the *optimal trajectory*. In addition, the so-called *approximate trajectory* performed by the patient during the game session is computed as the regression line of hand-game positions during the considered task. The lower the angle between the two lines, the better and controlled movement was done by the patient. Indeed, small angles shows that the approximate fitted path is similar to the optimal one. Conversely, large angles are typical of trajectories which are far from the optimal one. The linearity of scope-oriented movement is usually valued during physical therapy for patients affected by pathologies of motor learning such as cerebellar stroke. The importance of such an indirect analysis relies on the fact that it allows for quantifying the degree of improvement of the pathology which has caused the deficit of movement, and also to quantify the motor learning.
- Hand-Shoulder distance: the Euclidean distance between the hand and the shoulder joints while performing the movement is evaluated in order to assess whether the patient reaches the targets by performing a correct flexion–extension or abduction–adduction movements or makes a compensatory motion with the trunk instead, implying that in the latter case the Hand-Shoulder distance will be lower. The equation is the following, where joint 15 is for the right hand:

$$d = \sqrt{(x_5 - x_{15})^2 + (y_5 - y_{15})^2 + (z_5 - z_{15})^2} \tag{4.76}$$

- Time: the three specific tasks required by the exercise are split. The time taken to place the can on the shelf is calculated.

4.5.3 Unilateral Spatial Neglect indicators

In the traditional "paper and pencil" version of the Albert's test the fundamental indicators are:

- the number of correctly identified targets;
- the overall time to complete the test.

In the digital version additional indicative parameters can be extracted, by memorizing the patient's touch on the screen, saved as spatial coordinates:

- the covered area index defined as:

$$Covered\ Area\ Index = \frac{A_{explored}}{A_{max}} \tag{4.77}$$

where $A_{explored}$ is the area of the smallest rectangle containing the crossed lines, and A_{max} is the area of the smallest rectangle containing all the lines (see Figure 4.16);

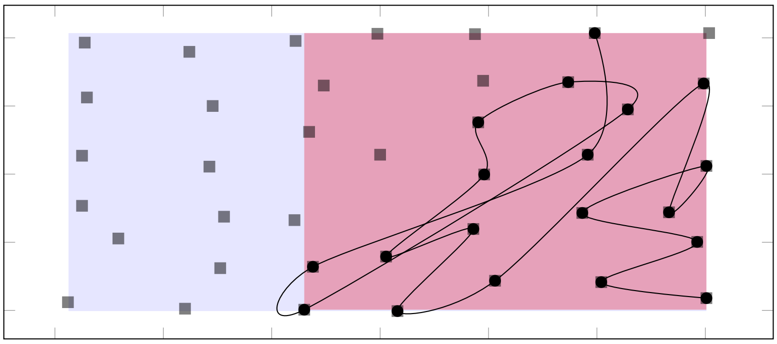


Figure 4.16: Red area represents the area explored. The total area containing all the lines is in blue color.

- the center of gravity (CoG) coordinates are the mean value of x and y coordinates of the crossed out lines;
- the execution order or spatial trajectory;
- the average distance between correctly identified targets;
- the average time between correctly identified targets.

Chapter 5

Results

Multiple diseases have been the focus of several studies, and therapists created specific care and rehabilitation treatment plans for each one based on the characteristics of the patients. This chapter will present the results of the work involving ReMoVES, including:

- studies on Unilateral Spatial Neglect conducted in collaboration with La Colletta hospital in Arenzano;
- the balance assessment, carried out in conjuction with the Prof. Giovanni Regesta of Gruppo Fides (Genova);
- studies of the movement of the upper limb, conducted in collaboration with Dr. Carlo Trompetto of Policlinico San Martino hospital and with Dr. Marina Siminoni of La Colletta hospital;
- the preliminary feasibility study with some children taken care of by the ASL3 clinic in Fiumara (Genova);
- the preliminary study of the results of the STORMS project, conducted with the San Martino hospital.

5.1 Unilateral Spatial Neglect assessment

5.1.1 First study

The first study [177, 221, 222] involved 12 patients suffering from post-ictus USN hospitalized at La Colletta hospital. In particular, ten of them have right lesions, thus a left-sided neglect and two of them have left lesions, thus corresponding to a right-sided neglect. For a further comparison, a preliminary control group of 14 healthy subjects is also considered. Data was collected during the first therapy session, and all patients performed the traditional Albert's test first and then the digital one.

Digital-traditional versions coherence

First of all, the correlation between standard test and the digital version is computed. For each patient and for each version, the percentage of crossed out targets in each column is collected into a 1×7 vector, called p_t and p_d for the traditional and digital version respectively. Then, the correlation coefficient (Pearson's coefficient) between p_t and p_d is calculated. The resulting average correlation coefficient is $corr = 0.82$, thus denoting a good concurrent validity of the digital version with respect to the standard one. This average value derives from high correlations in cases where patients have crossed out about the same targets in both versions, and from low correlations when there is some discrepancy between targets erased on paper and those erased in the digital version. Figure 5.1 depicts the crossed out target percentages in both the traditional (blue) and digital (red) version of the test. In general, blue and red crosses are very close for each patient, thus confirming the assumption of good correspondence between the traditional and digital versions. Taking a deeper look to the graph one can notice that patient 5 erases more targets in the digital test, while patient 6 performs better in the paper test. This is due to the difficulty in holding a pen and in using the touchscreen they have respectively.

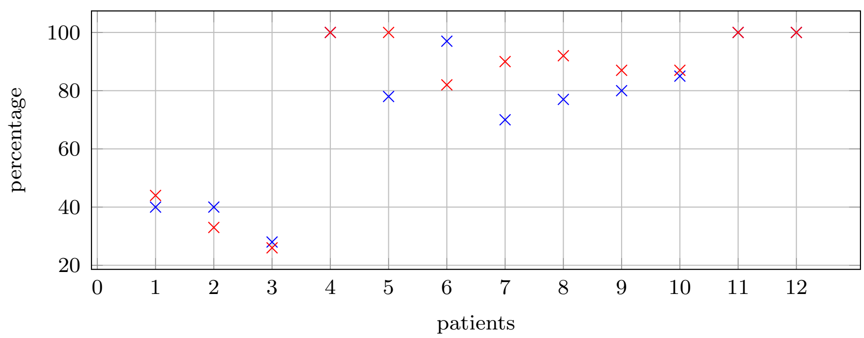


Figure 5.1: Crossed out target percentages, blue is for the standard version of the test, red is for the digital one.

In order to investigate the sessions based on the ignored hemispace, in Table 5.1 only ten patients with left neglect are considered. The average percentages of crossed target are lower in the first sections, and larger in the last ones, thus confirming the left-sided neglect. Furthermore, one can also notice the similarities between the percentages of the two versions of the test.

Table 5.1: Average percentages of targets erased in the seven sections, in both traditional and digital version of Albert's test.

	Traditional test	**Digital test**
Section 1	42%	58%
Section 2	62%	65%
Section 3	68%	70%
Section 4	72%	82%
Section 5	78%	92%
Section 6	90%	92%
Section 7	98%	96%

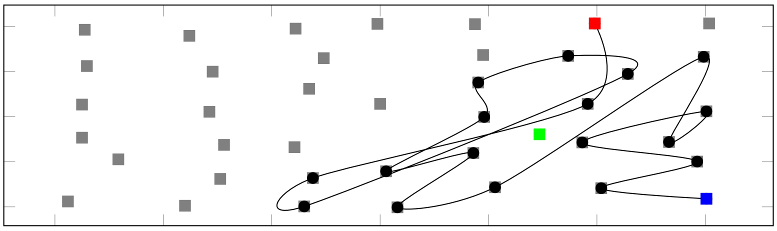
In order to assess the homogeneity of the available population, an Analysis of Variance (ANOVA) test is performed on erased targets. The result of the ANOVA test is the rejection of the null hypothesis and this denotes inhomogeneity in the population for both the results of the digital and traditional tests. Actually, it is an expected result because the population is made up of patients with both severe and minor injuries. For this reason, the population is split in two different groups according to the criteria suggested in [223]: in the contralesional part, a rate of more than 40% of omission was considered an index of severe neglect. Conversely, a rate of less than 40% of omission was taken as an index of mild/moderate form of USN. Respectively, the first group A consists of three patients and the others belong to group B. As a counterproof, two ANOVA tests are performed for each group formed and the results are the acceptance of null hypothesis (with $\alpha = 0.05$), meaning that the two groups are homogeneous, based on the results of the digital and traditional tests. To sum-up, both the correlation study and the outcomes from the ANOVA tests prove that traditional and digital versions are interchangeable for the population under analysis.

Performance analysis

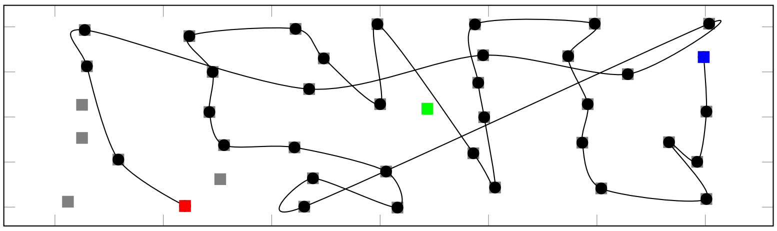
In addition to the information on the canceled targets, which can also be found in the paper version of the test, the parameters studied in the digitized version of the Albert's test are the spatial exploration method through the order of execution, the accuracy, the location, the type of errors and the erasing speed. The analysis and comparison of the trajectories performed by the subjects with USN and the healthy population allows to visualize the number and order of the deleted targets and the distribution area, providing information about the spatial exploration modality.

First of all, the trajectories followed by the patients are compared with the one followed by a healthy subject. In Figure 5.2 three types of point are highlighted:

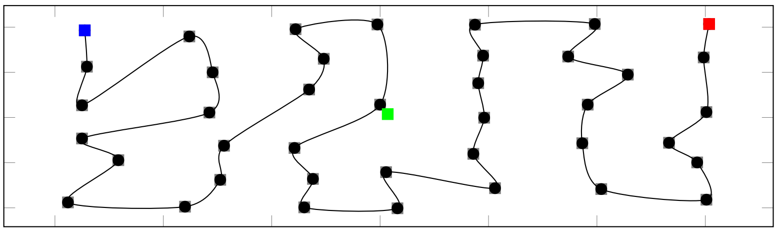
the blue ones indicate the start; the red ones indicate the final point; and the green points indicate the CoG. It is worthy to mention that the CoG position is in agreement with the left- or right- sided neglect diagnosis, for each patient. Furthermore, the plots provide a feedback of the different strategies adopted to crossed out the targets. In general, healthy subjects performed regular paths, i.e. from left to right or from top to bottom. Subfigure 5.2b represents the trajectory performed by a patient belonging to group B, that denotes a more regular path compared to the path tracked by a patient of group A (Subfigure 5.2a). Moreover, both patients have a left-sided neglect, in fact, the right side of the game area is the one from which patients started the test and that have explored more in depth.



(a) Trajectory of a patient of group A.



(b) Trajectory of a patient of group B.



(c) Trajectory of an healthy subject.

Figure 5.2: Trajectories followed by one subject for each group. The blue points are the starting points, the red points are the final ones, and the green points are the CoG's.

From the digital version one can also acquire information related to the times between two target cancellations and the distance between two consecutive crossed out targets. For what concerns the average time, it is 3.63 sec for patients in group A, 2.00 sec for group B, and 0.47 sec for healthy subjects. As one could suppose, the average time directly depends on the disease severity, thus it can be an informative indicator for the USN assessment. Similarly, the average distance between two crossed targets is 3.09 cm for patients in group A, 2.81 cm for group B, and 2.38 cm for healthy subjects. The trajectory, and hence the cancellation strategy adopted by patients in group A seems pretty random, and that is reflected on the average distance extracted from their sessions. Conversely, group B follows a more regular path, which is denoted by the smaller distance between consecutive targets, and so by the average time value which is close to the one by the healthy subjects. Recall that high values of distances or times can also mean that patients have explored some part of the ignored area, where indeed they had difficulty in finding targets.

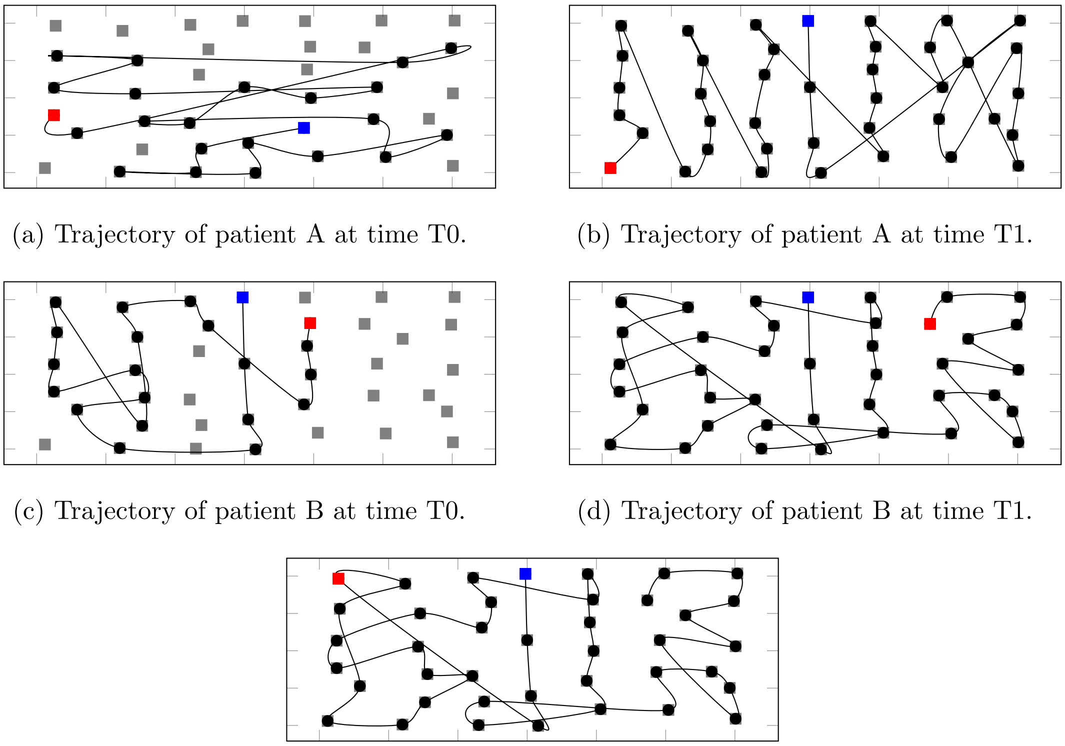
An attempt was made to evaluate whether the healthy group was homogeneous with respect to the two parameters extracted using the ANOVA statistical test. The group of healthy subjects is more homogeneous in relation to the distance index than the time indicator ($p-value << 0.01$). Furthermore, on both parameters the ANOVA statistical test was performed which shows a significant difference between the healthy and the patient groups ($p - value < 0.01$).

5.1.2 Second study

In the second study [178] a control group of fourteen healthy subjects, part of the La Colletta hospital's clinical staff, was considered. Participants were 9 females and 5 males aged between 27 and 61 years. These subjects performed all the digital test twice (at time points T0 and T1); between the two instants of time there was no change in the state of the subjects. Subsequently several patients affected by USN were involved. Two example patients will specifically discuss. Patient A has a right hemisphere lesion and patient B has a left hemisphere lesion. After hospitalization patients were contacted for a neuropsychological evaluation, performing the tests both in digital and paper format (time T0). After about a year, the same patients were again recalled from the facility for a new re-evaluation of their cognitive-motor status (time T1).

Spatial analysis

The analysis and comparison of the trajectories performed by the subjects with USN and the healthy population (Figure 5.3) allows to visualize the number and order of the deleted targets and the distribution area, providing information about the spatial exploration modality. For patient A, the digital Albert's test at time T1 highlights a new attentive attitude compared to time T0, since the patient has detected all the targets, but primarily has followed an organized trajectory, with a vertical observation trend. Patient B maintained the vertical exploration trend, succeeding in detecting all targets at time T1.



(a) Trajectory of patient A at time T0.

(b) Trajectory of patient A at time T1.

(c) Trajectory of patient B at time T0.

(d) Trajectory of patient B at time T1.

(e) Trajectory of one of the healthy subjects.

Figure 5.3: Trajectories followed by patient A, patient B and one of the healthy subjects, at times T0 and T1. The blue points are the starting points, the red points are the final ones.

Through the other indicators it is possible to trace the clear improvement of the total and average time compared to the digital test at time T1 performed by the subjects: for patient A the total time was reduced by about three times going from 92.33 seconds to 33.28 seconds, while patient B had an improvement of about half going from 111.68 seconds to 60.26 seconds. The results obtained on the average times and average distances between consecutive canceled targets are shown in Tables 5.3 and 5.4. The reduction in the average distance indicates a more effective exploring strategy and a more uniform erasing pattern.

Statistical analysis

For the statistical analysis, the average distance between two correctly identified targets and the average time between two correctly identified targets were considered. The minimum values of the parameters indicate an improvement or the absence of disability. First, the characterization of the control sample was performed in order to estimate the mean and deviation values of the indicators. In particular, the variations over time of the aforementioned characteristics are considered taking into account the instant T0 and T1, let's name P0 and P1 respectively. For a better understanding of the given situation, the Bland Altman graph is analyzed for both parameters. Subsequently, two patient is compared with the control group for an evaluation of any improvements.

After the 14 healthy subjects repeated Albert's test at time T0 and time T1, the mean ratings on the distance and time parameters and their differences Δ were observed as reported in Table 5.2.

Table 5.2: Mean values of distance and time parameters in time T0 and T1, and their difference Δ for the control group.

Distance [cm]			**Time [s]**		
μ_{T0}	μ_{T1}	μ_{Δ}	μ_{T0}	μ_{T1}	μ_{Δ}
2.31	2.27	0.037	0.45	0.44	0.015

Patients also repeat Albert's test at time T0 and time T1. Patient A and B achieved respectively the results shown in Tables 5.3 and 5.4.

Table 5.3: Mean values of distance and time parameters in time T0 and T1, and their difference Δ for patient A.

Distance [cm]			**Time [s]**		
X_{T0}	X_{T1}	X_{Δ}	X_{T0}	X_{T1}	X_{Δ}
3.64	2.91	0.73	5.04	0.83	4.21

Table 5.4: Mean values of distance and time parameters in time T0 and T1, and their difference Δ for patient B.

Distance [cm]			**Time [s]**		
X_{T0}	X_{T1}	X_{Δ}	X_{T0}	X_{T1}	X_{Δ}
2.71	2.50	0.21	6.11	1.57	4.54

Statistical test on differences The variation of the index $P0 - P1$ is expected to be very small for the control group where the subjects repeat Albert's test at time T0 and T1. Let's define μ_Δ the mean of this variation observed in the control population. S is the corrected estimate of the standard deviation. From a statistical point of view, to verify if the results of a patient at time T1 have changed significantly with respect to time T0, a test of differences was used.
Two patients are then evaluated who also repeat Albert's test at time T0 and time T1. Each subject is tested against the reference population. The patient variation is the X_Δ variable. The null hypothesis $H0$ assumes that the difference between the results at time T1 (P1) and the results at time T0 (P0) is small as for the control population and therefore the variation on the index is not significant. The alternative hypothesis $H1$ considers that the difference between P0 and P1 is large (in absolute value) and therefore significant.

$$\begin{aligned} \text{Hypothesis H0:} \quad & P0 - P1 = \mu_\Delta \\ \text{Hypothesis H1:} \quad & |P0 - P1| > \mu_\Delta \end{aligned} \tag{5.1}$$

With a small sample size ($n < 30$) a t-Student's bilateral statistical test of differences is applied:

$$T = \frac{X_\Delta - \mu_\Delta}{S}\sqrt{n} \tag{5.2}$$

where T is a t-Student variable with $(n-1)$ degrees of freedom, X_Δ the patient parameter (variation $P0 - P1$) to be compared with μ_Δ, i.e., the population mean of healthy subjects.

As already described, the average distance between consecutive targets is considered as the former parameter to be evaluated. For patient A, the statistics of the difference test is $T = 10.39$ and leads to the certain rejection of the null hypothesis $H0$, i.e., there is an extremely large difference between the value obtained at time T0 and that at time T1 . Hence the test is highly statistically significant, with a $p - value \to 0$.
In the second case, for patient B, the obtained value of $T = 2.59$ concludes that the test is partially significant. We get $p - value = 0.022$ so the test rejects the null hypothesis if $\alpha = 0.05$, but the null hypothesis is not rejected if $\alpha = 0.01$; therefore the test is weakly significant. Finally, in both cases, since the T value is positive, it can be concluded that there was an improvement in the parameter considered, between time T0 and time T1.

Now, the average time taken to cancel consecutive targets is considered as the latter parameter to evaluate. For both patients, an extremely high T value is obtained which leads to the certain rejection of the $H0$ hypothesis. The $p - value$ is so small that the test is significant for any value of α. As a conclusion both patients had a highly significant improvement with respect to the time parameter considered.

Statistical test on means In the case of improvements in a patient's indicator, a statistical test on the mean (right side) was applied to verify if the patient value at time T1 is statistically close to the mean of the healthy population. As previously described, no variations between instant T0 and instant T1 were observed in the healthy population, therefore only the values at instant T1 are taken as reference. The mean on the control population is μ_{T1}. Each patient is tested against the reference population (variable X_{T1}). The null hypothesis $H0$ assumes that the patient's value at time T1 does not differ from the mean of the control group, and therefore may belong to that population. The alternative hypothesis $H1$ assumes that the value at time T1 of the subject is significantly larger than the mean of the control group, and therefore the patient does not belong to the reference population.

$$\begin{aligned} &\text{Hypothesis H0:} \quad X_{T1} = \mu_{T1} \\ &\text{Hypothesis H1:} \quad X_{T1} > \mu_{T1} \end{aligned} \tag{5.3}$$

Also in this case the test statistics is a t-Student's distribution, having used the variance estimate and being n small:

$$T = \frac{X_{T1} - \mu_{T1}}{S}\sqrt{n} \tag{5.4}$$

where T is a t-Student variable with $(n-1)$ degrees of freedom, X_{T1} is the patient parameter at time T1 to be compared with μ_{T1}, i.e., the population mean of healthy subjects.

Considering the average distance between consecutive targets as a parameter, for both patients, the values obtained for T lead to reject the hypothesis $H0$, therefore the two subjects do not belong to the reference population. The $p-value$ is so small that the test is significant for any value of α.

Also for the cancellation time between targets, for both subjects a very high value of T is obtained which leads to the rejection of the hypothesis $H0$, with $p-value \rightarrow 0$. Therefore the subjects do not belong to the reference population.

Bland-Altman plot The Bland-Altman plot is a scatter plot that allows the evaluation of the agreement between two quantitative assessments. The vertical axis shows the differences between the two measurements. On the horizontal axis the arithmetic means of the two measurements are given. On this graph, in addition to the points representing the individual statistical units, there are also horizontal

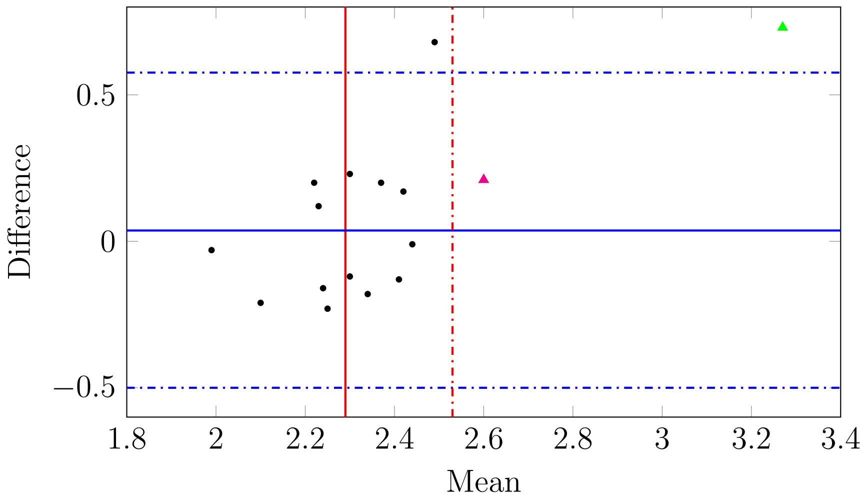


Figure 5.4: Modified Bland-Altman plot related to distance parameter. The continuous lines are the biases. The dotted lines are the upper and lower limits with respect to the corresponding line. Black dots represent distance values of the control group. Pink triangle is the distance value for patient B and green triangle is the distance value for patient A.

lines. In particular, the center line represents the mean of the differences between the measurements, whereas the two dotted lines at the top and bottom delimit a band that represents the limits of the 95% confidence interval of the mean of the differences. A modified version of the Bland-Altman plot is devised in which vertical lines are added. One lies at the global mean (i.e., mean bias); the others are the limit of the 95% confidence interval. Two vertical limits appear for bilateral tests; a single line for the one-sided test as in the present case.

To better visualize the statistical results obtained, the Bland-Altamn plots are analysed. Figure 5.4 is related to the distance parameter. Black dots represent the distance values of the control group. The blue horizontal line represents the bias over the difference between T0 and T1 (difference bias) equal to $\mu_\Delta = 0.037$. The blue dotted horizontal lines are the upper and lower limits as regards to the difference bias equal to $\mu_\Delta \pm 2.16\frac{S}{\sqrt{n}}$. In addition to the classic plot, the limit relating to the mean between values obtained at T0 and T1 have been included, represented by the red dotted vertical line in relation to the red vertical line (mean bias), calculated as $2.29 + 1.77\frac{S}{\sqrt{n}}$.

Results related to the average time between two consecutive target is shown in Figure 5.5. In this case, the blue continuous horizontal line i.e., the difference bias between T0 and T1 is equal to $\mu_\Delta = 0.015$. In a similar way to what was seen for the first parameter analyzed, the blue dotted horizontal lines are the upper and lower limits as regards to the difference bias equal to $\mu_\Delta \pm 2.16\frac{S}{\sqrt{n}}$. Lastly, the limit relating to the mean bias between values obtained at T0 and T1 is equal to $0.45 + 1.77\frac{S}{\sqrt{n}}$.

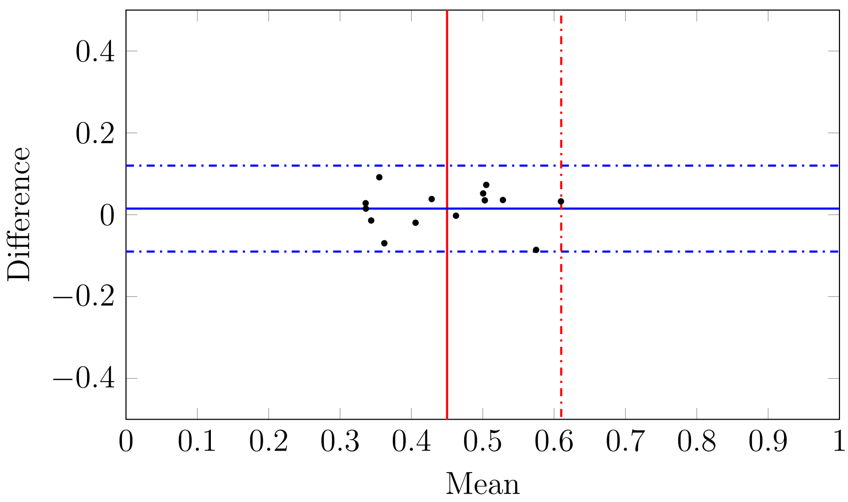


Figure 5.5: Modified Bland-Altman plot related to time parameter. Continuous lines are the biases. The dotted lines are the upper and lower limits with respect to the corresponding line. Black dots represent time values of the control group

.

From the plot in Figure 5.4 it can be deduced that patient B (pink triangle) had a small difference between T0 and T1 on the distance parameter, falling within the limits of healthy subjects. Conversely, patient A (green triangle) had a more significant difference between T0 and T1 because he is beyond the upper limit. On the other hand, compared to the mean, both patients are beyond the upper vertical limit and this denotes that they do not fall within the healthy population.

As discussed in the previous paragraphs, if the average time between the cancellation of consecutive targets is considered (Figure 5.5), for both patients the difference between T0 and T1 is very high compared to the group of healthy people and this also implies that on average the parameter value of the patients differs greatly from those of the healthy, not making them belong to this population.

5.2 Balance assessment

5.2.1 First study

The study [179] involved 13 frail elderly people referred to the Centro di Riabilitazione, Gruppo Fides (Genova). The population consisted of 6 females and 7 males with an average age of 82.3 ± 6.2 who participated several times to the rehabilitation sessions via ReMoVES, performing the Sit-to-Stand activity. Data were collected over a period lasting up to 2 months and up to twice a week, and admission to each game session was determined on the basis of the judgment of the physiatrist, who assessed the willingness to participate and the general conditions of the patient at that particular time.

Participants reported that they felt safe while playing the game, and there were no adverse events while playing. Most of the patients stated that they enjoyed this extra activity, asking the clinical staff to participate more frequently. An interesting social interaction developed among the participants, who enjoyed watching others carry out the activities.

Implicit Activity Analysis

The implicit analysis of the activity performed by the involved patients is presented. Mean values of the proposed indicators described in Section 4.5.1 were collected, and their coherence with already published results was statistically tested. In addition, aimed at enabling deeper analysis of each game session, a graphic visualization of the indicators along the time dimension is shown. Such graphs are provided to therapists via the application layer, so that clinical staff analyze both summary statistical indicators and patient performance during the whole session. In this fashion, even some erroneous movements or loss of energy, which may be limited to a short period of time, can be noted by the medical specialists, leading to a complete and deep clinical picture of the patients.

The average features of the available population are summarized in Table 5.5. Negative values for the UBTA indicate that the left shoulder was put forward while practicing the activity.

To address the coherence of the derived data with respect to the literature, the results of [219, 220] were considered for the discussion. In [219], the indicators standing and sitting COM AP, standing and sitting COM ML, UfV_{up}, and UfV_{down} were calculated with respect to a population of healthy elderly individuals (mean values were 0.01, 0.03, 0.03, and 0.04 cm, and 0.78 and 0.71 m/s, respectively). Hence, a statistical test was performed to verify the assumption that the indicator values in [219] depicted a better general health condition than the ones deduced for the population under analysis. A one-tailed t-test was used,

Table 5.5: Mean feature values. NSU, number of sit-up occurrences; UBFA, upper-body flexion angle; LLFA, lower-limb flexion angle; COM, center of mass; AP, anteroposterior; ML, mediolateral.

Feature	**Mean Value**
NSU	4.5 ± 1.5
Stand UBFA range (deg)	79.92 ± 6.71
Sit UBFA range (deg)	79.35 ± 8.15
Stand LLFA (deg)	131.16 ± 17.28
Sit LLFA (deg)	134.31 ± 16.94
Stand UBTA (deg)	-0.67 ± 1.91
Sit UBTA (deg)	-0.59 ± 1.91
COM stand AP (cm)	0.36 ± 0.09
COM sit AP (cm)	0.52 ± 0.61
COM stand ML (cm)	0.08 ± 0.02
COM sit ML (cm)	0.07 ± 0.03
UfV_{up} (m/s)	0.12 ± 0.06
UfV_{down} (m/s)	0.07 ± 0.02

and the assumption was confirmed with p value < 0.01.

In addition, the authors in [220] showed mean values for the range of UBFA in both the ascending and descending phases in a population of frail elderly persons. Via a two-tailed t-test, the assumption that the mean ranges of UBFA in [220] and in the present work were equal was verified with p value < 0.01.

Graphs on Therapist Client

As anticipated, therapists were also provided with graphs depicting all game sessions, delivering more comprehensive informative content than that in the mean or range indicators. An example of the graphic representation available on the therapist client is shown in Figure 5.6. In particular, Figure 5.6a depicts the trajectory of the COM and peaks; hence, corresponding standing positions were visible. In particular, parts with a light-gray background are for the ascending phase, and parts with a dark-gray background represent the descending phase. Figure 5.6b shows UBFA values during the session. Figure 5.6c shows LLFA values for both the right and the left limb during the session. The trend of this chart is very similar to that of the COM. A standing position also requires limbs to be fully extended, corresponding to the peaks of the LLFA indicators. Figure 5.6d presents the shoulder twist on the axial plane during the session. Lastly, COM AP and COM ML displacements are depicted in Figure 5.7 on the transverse plane. Reduced lateral displacement in the second graph with respect to the first suggests that the patient stabilized themselves while playing.

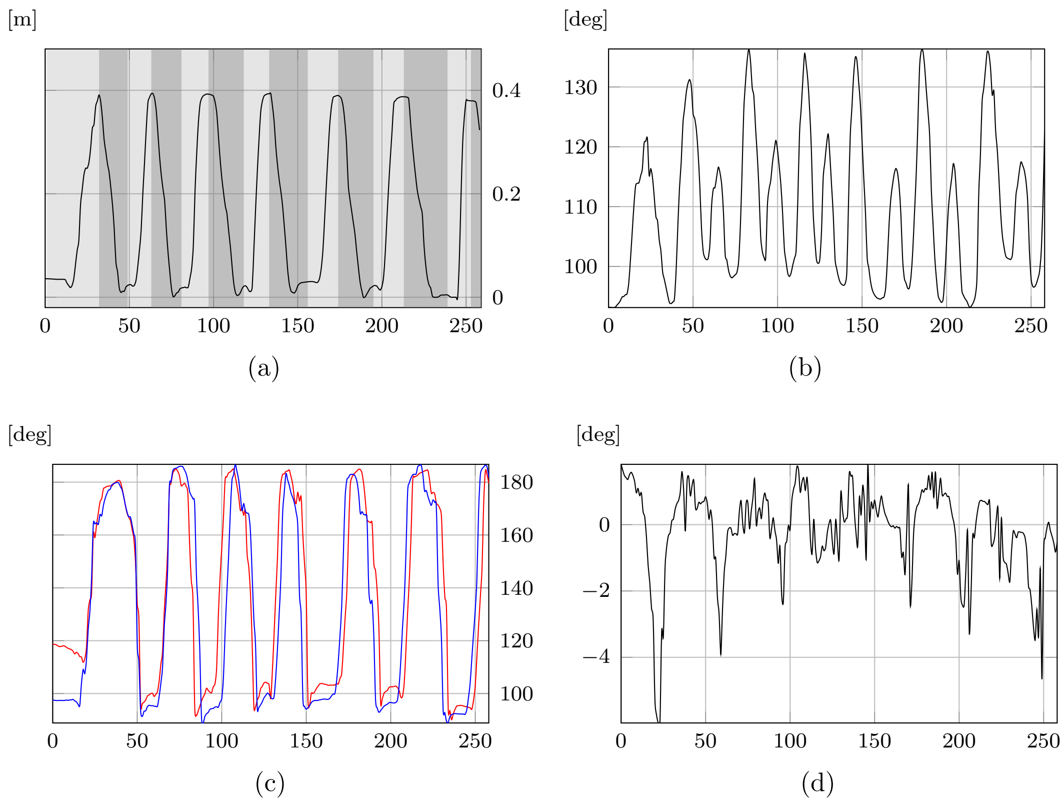


Figure 5.6: Graphs from Equilibrium Paint exergame. These graphic representations are available for clinical staff, so that deeper analysis is enabled throughout the whole session. (**a**) COM; (**b**) UBFA; (**c**) LLFA; (**d**) UBTA.

The COM trajectory in Figure 5.6a shows that the patient performed a smooth movement with no particular pauses. The resulting regular path means that the patient did not experience particular fatigue and managed to control their motion. So, by only considering such a graph, a therapist would say that the patient's performance was fairly good. However, Figure 5.6b,c, for UBFA and LLFA, respectively, depict incomplete movement. Indeed, the patient is supposed to reach maximal extension while standing, namely, the maximal values of UBFA and LLFA (corresponding to COM peaks) should reach approximately 180°. While LLFA satisfies such a requirement, meaning correct leg extension, the maximal values of UBFA were around 130°, denoting that the patient remained bent forward when standing. Figure 5.6d for UBTA depicts that shoulder rotations were very small, denoting correct movement (the patient is required to preserve shoulders in the frontal plane, i.e., without trunk rotations).

To conclude, graphs in Figure 5.7 depicting AP and ML movements show

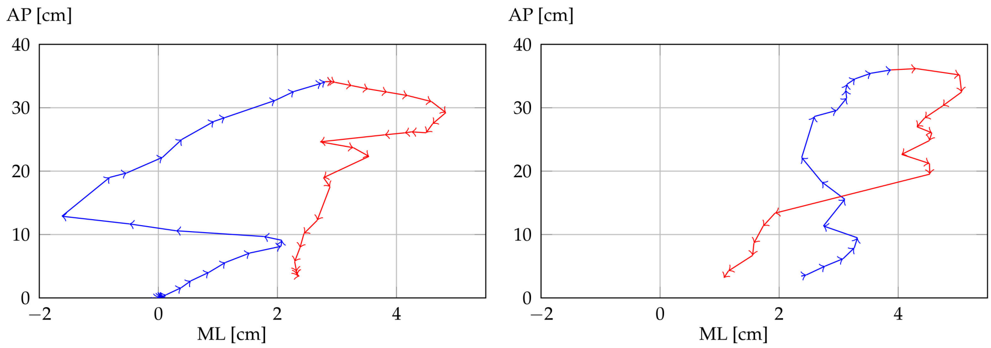


Figure 5.7: Representations of anteroposterior (AP) and mediolateral (ML) movements of center of mass in two consecutive ascending and descending phases. Blue lines, ascending phases; red lines, descending phases.

that the patient was not laterally significantly displaced (about 2 cm), confirming the correct execution of the exercise apart from the vertical trunk extension.

5.2.2 Second study

A control group of sixteen healthy subjects was considered. They are clinical specialists from La Colletta Hospital in Arenzano (Genova, Italy) and engineering students that performed the exercise at the Numip laboratory of University of Genoa. The participants were 9 female and 7 male aged between 27 and 61 years, with an average age of 38.62 ± 12.95. Some of them performed the STS exergame several times, for a total of 26 sessions. The control group sessions are used to define the benchmark values for further comparisons, based on the most significant indicators. With the methodology proposed in this study it is possible to evaluate the performance of patients suffering from different pathologies. About a hundred sessions were analyzed, in particular adult patients involved were mainly affected by stroke, scoliosis, frailty of the elderly, and orthopedic complaints. In this work, the results obtained with 2 groups of patients will be described, homogeneous in terms of age, pathology, place and type of hospitalization.

Group A is made of 2 post-stroke patients hospitalized at La Colletta hospital. After dehospitalization, thanks to ReMoVES, they performed a series of prescribed exercises remotely, at home. Thanks to the simplicity of the system, in both cases no technical intervention was necessary for the installation which was carried out by the patient and his family. During that time, a total of 65 sessions were recorded for the STS activity, accessible via the appropriate ReMoVES therapist client.
One patient was a 60-year-old man and performed the prescribed exercises for

Table 5.6: Values of the considered features for the control and patient groups.

Features		Mean ± STD		
Instant Features		**Control**	**Stroke**	**Elderly**
ψ_0	Repetitions (NSU)	8.42 ± 2.18	8.71 ± 2.79	4.03 ± 1.96
ψ_{1R}	Standing Right Knee Angle [°]	173.30 ± 5.29	170.35 ± 8.08	173.14 ± 6.91
ψ_{1L}	Standing Left Knee Angle [°]	172.53 ± 5.68	169.2 ± 8.39	174.67 ± 5.64
ψ_{2R}	Sitting Right Knee Angle [°]	86.61 ± 10.71	85.94 ± 7.23	84.75 ± 15.37
ψ_{2L}	Sitting Left Knee Angle [°]	85.89 ± 9.96	84.96 ± 7.47	85.80 ± 17.54
ψ_3	Standing Trunk Angle [°]	95.88 ± 7.21	90.28 ± 8.67	86.84 ± 6.79
ψ_4	Sitting Trunk Angle [°]	91.39 ± 10.01	88.83 ± 9.97	86.57 ± 11.75
Dynamic Features				
ψ_5	Flexion Trunk ROM UP-phase [cm]	16.93 ± 4.98	12.47 ± 3.88	23.76 ± 7.41
$\psi_{5\theta}$	Flexion Trunk Angle UP-phase [°]	73.96 ± 5.84	76.94 ± 7.87	64.84 ± 7.73
ψ_6	Flexion Trunk ROM DOWN-phase [cm]	20.65 ± 6.93	15.50 ± 6.05	32.72 ± 10.12
$\psi_{6\theta}$	Flexion Trunk Angle DOWN-phase [°]	74.36 ± 6.99	77.27 ± 8.20	63.83 ± 10.32
ψ_7	ML Trunk ROM [cm]	5.35 ± 1.42	11.04 ± 3.46	14.02 ± 22.51
$\psi_{7\theta}$	ML Trunk Angle [°]	5.58 ± 1.97	11.1 ± 6.94	13.4 ± 6.12
ψ_8	ML Shoulder Angle [°]	7.38 ± 3.19	10.7 ± 4.67	13.5 ± 15.33
ψ_9	Shoulder Twist [°]	7.82 ± 2.56	15.4 ± 5.19	20 ± 17.90
ψ_{10}	Ascending Time [sec]	1.51 ± 0.39	1.51 ± 0.59	4 ± 2.49
ψ_{11}	Descending Time [sec]	1.73 ± 0.46	1.69 ± 0.66	4.09 ± 2.28
ψ_{12}	Ascending DTW	1.14 ± 0.77	1.69 ± 0.96	2.57 ± 1.52
ψ_{13}	Descending DTW	1.97 ± 0.89	2.36 ± 1.04	4.55 ± 2.20
ψ_{14}	Knee Correlation	0.9988 ± 0.0014	0.9732 ± 0.0503	0.9960 ± 0.0032

upper and lower limb for a period of 39 days. A total of 24 sessions of the STS activity have been executed. The second patient was a 79 year old man and followed rehabilitation therapy with ReMoVES for 49 days for a total of 41 STS sessions.

Group B is made of twenty frail elderly people presenting several clinical pictures, with various pathologies and different levels of disease. In addition, some of them presented fractures and orthopedic problems affecting the lower limbs. They are hosted at two nursing homes (Gruppo Fides and Residenza Felice Conio, Genova, Italy). They are 8 female and 12 male with an average age of 82.5 ± 3.4. These subjects also repeated the STS several times, for a total of 34 sessions.

The present study was conducted retrospectively and following the principles of the Declaration of Helsinki. Also, an informed consent was obtained from all subjects involved in the study.

Reliability and meaningfulness

The features extracted and analyzed for the considered groups are reported in Table 5.6.

Given the small sample size, the normality of the distribution was assessed via the Shapiro–Wilk test. The results of the test showed the acceptance of normality condition ($p > 0.01$) for all parameters computed from the control group sessions. The test showed rejection of the normality hypothesis for most of the parameters, with $p < 0.001$ for both groups of stroke patients and elderly, with a few exceptions. Flexion knee angles are normal for both groups, extension and flexion trunk angles are normal for elderly group, along with shoulder rotation for stroke sample.

In healthy subjects the correlation between the instantaneous angle of the right and left knees has been taken as an index of the feature consistency. The correlation coefficient (Pearson) evaluated for the control group was found to be equal to $\rho = 0.9988$, proving the strong robustness of the feature, as one might have expected from the above considerations on the measure error. Surprisingly, when computing the same correlation index also for the other groups a $\rho = 0.9732$ and $\rho = 0.9960$ were found, respectively for the stroke and elderly patients. One explanation is the fact that the patients considered, despite their age or the outcome of neurological events, have a high degree of autonomy and are in good physical condition.

Since normality is not always true, with the purpose of discussing statistical differences between the groups, the non-parametric Mann-Whitney U test for independent samples is applied. For all tests, the null hypothesis H_0 assumes that the patient's value of a given parameter does not differ from that of the control group. However, depending on the parameter considered, three different alternative hypotheses H_1 were defined:

1. Some features have to be maximized, then the alternative hypothesis H_1 is: $X_{patient} < \mu_{control}$.

2. On the contrary, some features (such as those related to compensatory movements) should be minimized, therefore the alternative hypothesis H_1 is $X_{patient} > \mu_{control}$.

3. For all other parameters, a two-tailed test can be considered and therefore hypothesis H_1 is: $X_{patient} \neq \mu_{control}$.

Dealing with intra-rater reliability, similarity of movement pattern from among repetitions of a single session has been evaluated for the control group, through the variance of the DTW values obtained by the single repetitions within a session.

Control group characterization

After the segmentation step, for each game session the values of the parameters of interest (knee angles, antero-posterior trunk angles, and times) were calculated for each single repetition and then the values were averaged on the NSU number.

Instead, in the movements of the trunk and shoulders that are considered to account for compensatory motions, the range of the parameter is considered in the place of the average value. In fact, they must have low values for the entire duration of the session. As reported in previous works, the number of repetitions in the 30-second STS [224, 225] mainly depends on age, in addition to physical prowess, reaction times, etc.

Figure 5.8 shows the instantaneous knee angle for both the right (blue line) and left (red line) limbs during one session performed by one of the healthy subjects. The standing position requires that the legs be fully extended (at the peaks of angle signal) and in fact they reach approximately $170 - 180°$ at the point of standing position, signed with the green triangle. When the person is seated this angle is about $80 - 90°$ (orange triangles are at the sitting times).

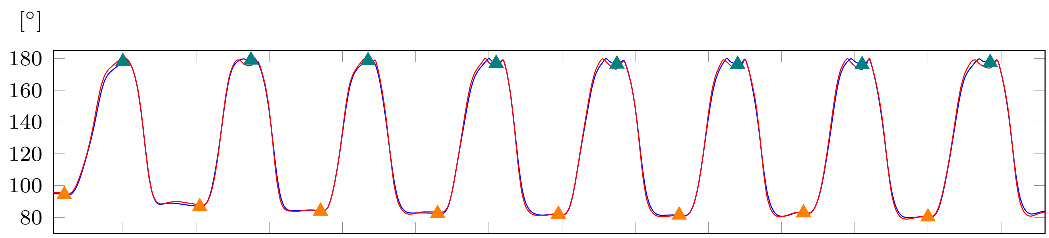


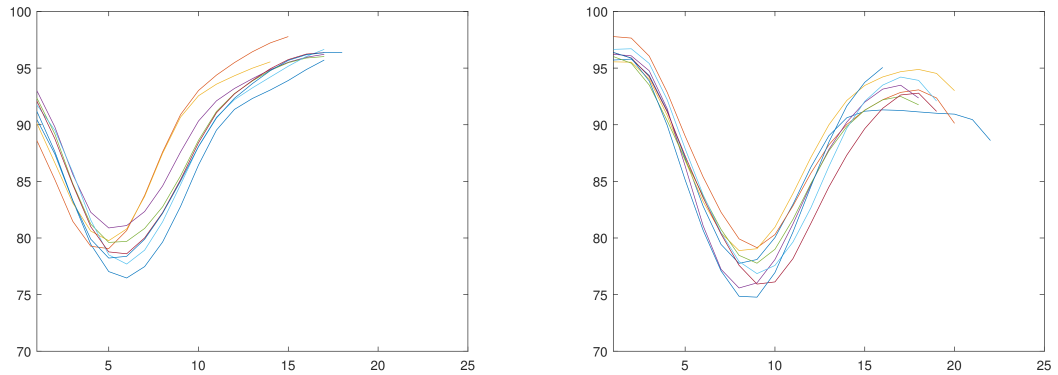
Figure 5.8: The signal of instantaneous knee angle during a session of a healthy subject. Red line is for left limb, blue line is for right limb. Green triangles are times of standing positions, orange triangles are for sit positions.

In the STS exercise, the subject is required to preserve shoulders in the frontal plane i.e., without trunk rotations or inclinations. Indeed, in the control group, the shoulder displacement in sagittal and transverse plane were very small, denoting a good control of the standing and sitting movements, performed without any compensation. Similarly, the lateral shift of the trunk must also have small values.

In the healthy group, the pattern of the antero-posterior trunk angle is fairly regular as can be observed in Figure 5.9 where the flexion trunk angle variation is reported for each Up and Down movement respectively in (a) and (b). The various repetitions give rise to very similar patterns in both cases. When the subject is in the sit position (left part of plot 5.9a) the trunk angle is approximately 90°; when the subject is standing (i.e., left extreme of plot 5.9b) the trunk angle is observed to be slightly larger, as also reported for feature ψ_3 in Table 5.6.

During the ascending and descending phases, the flexion of the trunk bending causes these angles to decrease to around $70° - 80°$. These movements show a strong repetitivity both for the relative measures and the absolute values.

As described in Section 4.3.2, the DTW value is computed for each game session by taking into account the most representative repetition. This parameter is well homogeneous in the control group, both in ascending and descending phases, as one can notice in the blue histograms of Figure 5.10.



(a) (b)

Figure 5.9: Motion of trunk angle in the sagittal plane of an healthy subject during (a) ascending and (b) descending phases.

As an important outcome of this analysis, an empirical description of the correct execution of the movement required by the exergame can be defined. The features values computed as the average on the control group are the reference model to be used for comparison with other subjects and patients. It is possible to monitor the activity of patients, evaluating whether a person is correctly performing the required movement, their deviations, etc. Such a possible application is described in the following paragraph with respect to the sample groups A and B.

Patient analysis

The Mann-Whitney U-test is applied for each feature. The null hypothesis H_0 is that the patient's value does not differ from that of the control group, where the mean value is taken as a reference $X_{patient} = \mu_{control}$. The test is repeated for each feature for group A (stroke patients) and group B (elderly) and the results obtained are summarized in Table 5.7.

Table 5.7: Mann-Whitney p-values for the elderly and stroke patient groups.

Alternative Hypothesis	**Feature**	**Mann-Whitney**	
		p-value Stroke	**p-value Elderly**
$X_{patient} < \mu_{control}$	Extension Right Knee Angle	0.083	0.636
	Extension Left Knee Angle	0.059	0.955
$X_{patient} \neq \mu_{control}$	Repetitions	0.553	<0.001
	Flexion Right Knee Angle	0.645	0.394
	Flexion Left Knee Angle	0.689	0.819
	Standing Trunk Angle	0.003	<0.001
	Sitting Trunk Angle	0.392	0.116
	Min Standing Trunk Angle	0.013	<0.001
	Min Sitting Trunk Angle	0.045	<0.001
	Ascending Time	0.195	<0.001
	Descending Time	0.370	<0.001
$X_{patient} > \mu_{control}$	Lateral Shoulder Inclination	<0.001	0.001
	Shoulder Rotation	<0.001	<0.001
	Lateral Inclination Trunk Angle	<0.001	<0.001

When looking to the average number of repetitions in the stroke group, it is very similar to the one of healthy subjects ($p - value = 0.553$). On the contrary, the test shows a significant difference with the control group only for group B of frail elderly people, with a $p < 0.001$, predicting a higher risk of falls.

Considering the time to stand up and the time to sit, stroke patients behave like healthy subjects. Instead, for elderly people there appears to be a significant difference, with $p < 0.001$. One can also notice from Table 5.6 that time for standing are generally shorter than times for sitting in all groups (features ψ_{10} and ψ_{11}).

For the majority of patients, flexion and extension angles of the legs are comparable with respect those of healthy subjects. The minimum $p - value$ is 0.059 related to the fact that stroke patients tend to have less extended legs when standing, as can also be noticed in Table 5.6 (feature ψ_1).

From Table 5.6 one can notice how patients tend to show similar trunk extension angles when standing and sitting, unlike healthy people who extend their torso more when they stand. When comparing with the control group, when considering the trunk angle during sit rest position there are no significant differences for both groups. Indeed, the trunk angle during standing position is partially significant in group A ($p - value = 0.003$) and significant ($p - value < 0.001$) in group B.

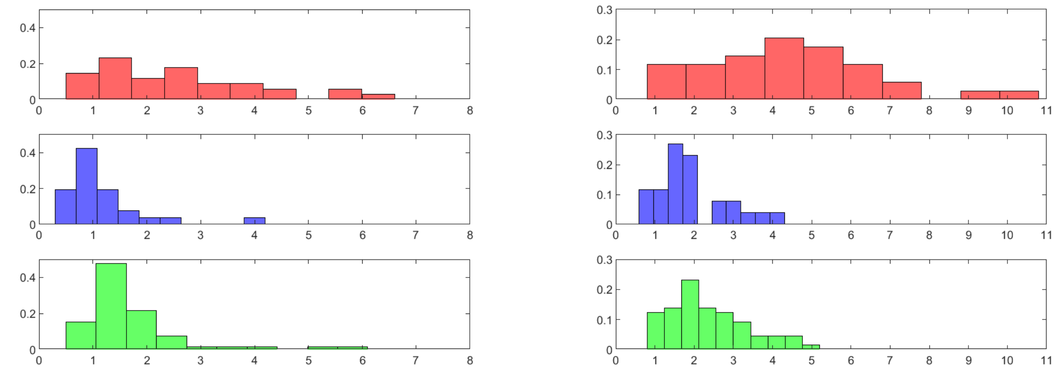
Dealing with Dynamic Features, the movement during ascending and descending phases in the repetitions of a single session are analyzed for the patients, as already done for the control group. Elderly patients tend to flex the trunk more during the ascent and descent phases, to help the movement and to compensate for the legs weakness (absolute trunk angle with respect to the horizontal plane around 64°).

It has been observed that stroke patients generally follow a pattern quite similar to that of healthy subjects; on the contrary, frail elderly people usually perform fewer repetitions and the movements deviate significantly from the standard. In Figure 5.12 an example of the trunk flexion angle during ascending and descending phases is plotted with different colors for each repetition of a session. The upper plots show a very confused and incorrect pattern ($DTW = 2.61$ and $DTW = 4.22$, respectively); the lower ones refer to the movement performed and repeated by a patient with good characteristics ($DTW = 0.79$ and $DTW = 1.67$, respectively).

The DTW is evaluated by comparing the patient signal with the reference signal that was extracted from the control group. The histogram of the DTW values in ascending and descending phases for the groups is reported in Figure 5.10. Blue are healthy subjects, green are stroke patients, and red are elderly subjects. One can see that the stroke patient of the considered group have a behavior very similar to that of the control group (with a maximum DTW value equal to 5 as compared with the maximum value equal to 4 of control subjects). In the elderly sample, a large number of sessions have been performed correctly, but a large session number have larger DTW distance. In particular, large values are observed for up phase reflecting the larger difficulties of standing up due to leg weakness. During the down phase there is also a worst DTW but less evident than that in the up phase.

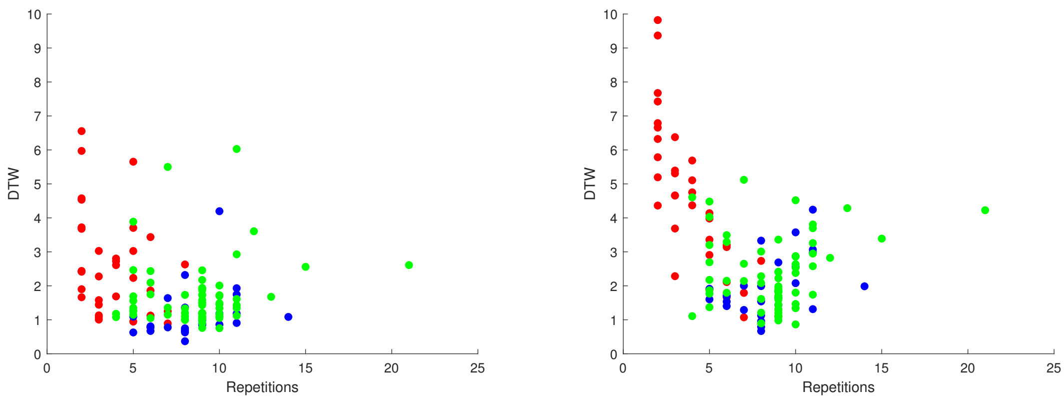
Figure 5.11 is a scatter plot of repetition numbers with respect to DTW distance. Control and group A are well overlapped in such feature space. A good separation with group B is observed. One can also notice a high negative correlation between the number of repetitions and the DTW result for the descent phase ($corr = -0.80$) in the elderly group.

From Table 5.6, it can be seen that patients showed significant differences in shoulders alignment during the entire duration of the exercise. This is mainly due to two reasons. The former is that patients considered presented asymmetric impairments due to either post-stroke outcomes or orthopedic impairments on the lower limbs. As a result, both standing and sitting movements were impaired and asymmetric, as they weighted more on the dominant limb and hemi-body part, yielding to a shoulders displacement in the coronal plane. For both groups the hypothesis H0 was rejected with $p < 0.001$, therefore this feature seems of interest in remote patients observation.



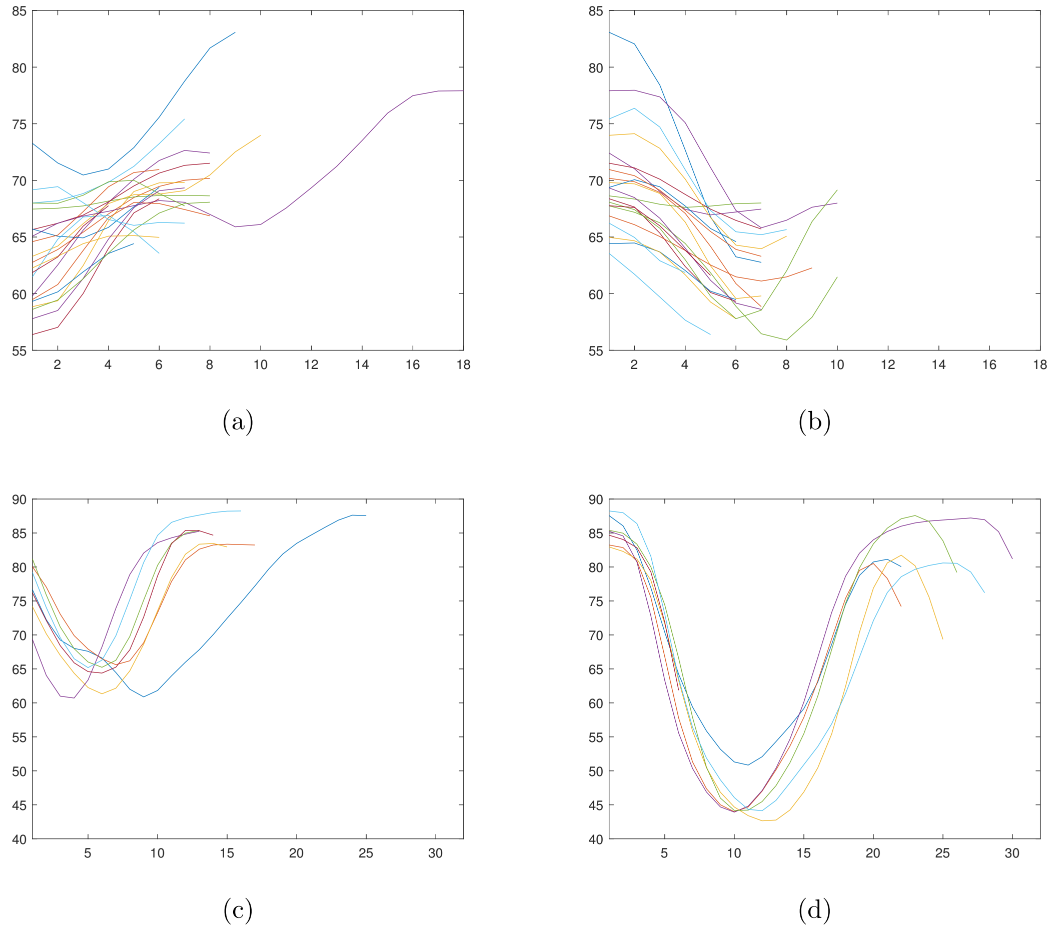
(a) (b)

Figure 5.10: Histogram of the DTW values in (a) ascending and (b) descending phases. Blue are healthy subjects, green are stroke patients, and red are elderly subjects.



(a) (b)

Figure 5.11: Scatter plot of the DTW values with respect to repetitions in (a) ascending and (b) descending phases. Blue are healthy subjects, green are stroke patients, and red are elderly subjects.



(a) (b) (c) (d)

Figure 5.12: (a) bad and (b) correct motion of trunk in the sagittal plane of two patients during ascending and descending phases.

5.3 Upper limb rehabilitation

5.3.1 First study

The first study [180] involved two patients. Patient A was a 49-year-old man, who suddenly experienced unsteadiness of gait, incoordinate movements of the right limbs, blurred vision and diplopia. The neurological examination showed a severe right ataxia and a bilateral gaze evoked horizontal nystagmus. Standing and gait were ataxic and broad-based. Brain MRI revealed a right cerebellar infarction. Two weeks later, the cerebellar signs improved moderately.

Patient B was a 59-year-old man who presented with sudden headache, nausea, speech disturbances and unsteadiness of standing and walking. The neurological examination revealed a moderate axial and right limb ataxia, together with slurry speech. Brain MRI showed a right cerebellar hemorrhage. After ten days, a slight improvement of the cerebellar signs and symptoms was observed.

After the acute phase of the disease, both patients were admitted to the Neurological Rehabilitation Unit of Ospedale Policlinico San Martino IRCCS of Genoa. The Scale for the Assessment and Rating of Ataxia (SARA) [226] was utilized to evaluate the severity of the cerebellar disorder. SARA values range from 0/40 (no ataxia) to 40/40 (most severe ataxia). Patient A scored 24/40 and Patient B scored 13/40. The Activity-Specific Balance Confidence Scale (ABC) [227] was also employed to assess the subjective confidence of balance (0% not safe at all, 100% completely safe). Patient A had 60%, while Patient B reported 74.3%. In conclusion, it is worth underlining that the two patients were similar in height and weight.

For each patient, two sessions of Shelf Cans exergame were considered, namely with and without weighting the involved upper-limb. Indeed, according to Bhanpuri et al. [99] a cerebellar damage likely causes an inertial mismatch between an internal representation of body dynamics and the actual body dynamics. On this base, a hypometric and a hypermetric cerebellar patient would respectively underestimate or overestimate their limb's inertia. Adding mass to the affected limbs can have beneficial effect on such a mismatch. Some other authors, however, failed to replicate the beneficial effects of such a strategy, especially for multi-jointed reaching movements [100]. The patient played the exergame while sitting, in order to reduce trunk and arms oscillation in the standing position, which could negatively affect the collected data. Here, the effect of weighting the limb is quantified in order to provide the clinical staff with such objective data. The weight amounts of one kilo, and was placed on the wrist of the used limb. The Microsoft Kinect sensor was place in front of the players, at a distance of three meters. The duration of the game session is 90 seconds. In order to avoid the influence of the order in using or not the weight for the activities, two hours time distanced the first and second session, so that they can be considered independent. In addition, some training session had been performed the days before these trials, for familiarizing with the system.

Case-studies application

Values of the indicators extracted from both the sessions with and without the strategy are summarized in Tables 5.8 and 5.9, and the graphs referring to the indirect analysis can be visualized in Figures 5.13, 5.14. In Figure 5.16 values of the ROM are depicted.

The weighting strategy yielded a more precise movement in the performance of Patient A, which is denoted by the decreased angle between the estimated and

Table 5.8: Angles between the approximate and optimal trajectories.

	Red can	**Orange can**	**Green can**
Pat. A no weight	7.18	63.77	13.96
Pat. A weight	6.25	5.28	2.32
Pat. B no weight	4.70	49.37	11.49
Pat. B weight	5.82	1.89	12.80

Table 5.9: ROMs of shoulder, elbow and trunk.

	Shoulder ROM	**Elbow ROM**	**Trunk ROM**
Pat. A no weight	14.66	54.86	17.01
Pat. A weight	149.47	108.25	7.72
Pat. B no weight	128.56	24.54	5.47
Pat. B weight	132.03	3.76	3.39

optimal trajectories, and also by the increased range of motion of both shoulder and elbow. In addition, the reader can notice that the range of motion of the trunk decreases when patient A has a weight on the limb. This is probably due to a major control on its arm that is enabled by the strategy.

The same strategy resulted less efficient for Patient B, where, apart from the angle between the estimated and optimal trajectories when handling the orange can, no other significant better performance could be detected. In general, indicators values are better for patient B, and his better general condition is likely the reason for a less visible effect of the strategy on the performance.

Aimed at favoring comparisons with healthy subjects, a control group of six persons was considered and took part to the same treatment as patients. The values of the indicators extracted from both the sessions with and without the weight are summarized in Tables 5.10 and 5.11. Also, an example of graph about the indirect analysis is depicted in Figure 5.15. In general, it is worth noting how the adoption of the weight strategy did not yield to relevant difference for healthy subjects.

In general, this analysis is conducted to be delivered to the clinical staff, in order to help them in defining a personalized plan of care, and also to support patients in acquiring or reacquiring faculties to employ in daily life activities.

5.3.2 Second study

In the second study [181], new methods and signal processing algorithms were applied, thus allowing a more detailed analysis. This work was done in collaboration with La Colletta hospital of Arenzano (Genova). A group of healthy people and

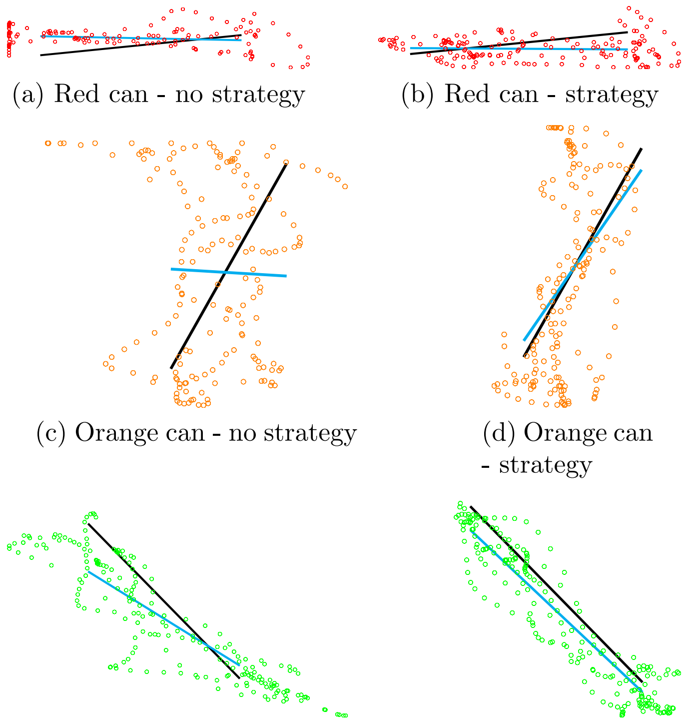
Table 5.10: Angles between the approximate and optimal trajectories in the control group.

	Red can	**Orange can**	**Green can**
Sub. 1 no weight	6.29	1.75	4.55
Sub. 1 weight	5.02	2.02	5.69
Sub. 2 no weight	4.25	19.11	3.13
Sub. 2 weight	5.85	15.65	1.48
Sub. 3 no weight	4.21	28.26	1.15
Sub. 3 weight	6.57	13.29	2.69
Sub. 4 no weight	7.52	0.54	2.98
Sub. 4 weight	2.60	2.87	0.16
Sub. 5 no weight	0.42	0.35	0.92
Sub. 5 weight	1.24	1.03	0.60
Sub. 6 no weight	5.20	9.23	2.22
Sub. 6 weight	6.01	3.33	5.01
Avg. healthy no weight	4.65	9.87	2.49
Avg. healthy weight	4.55	6.37	2.61

Table 5.11: ROMs of shoulder, elbow and trunk in the control group.

	Shoulder ROM	**Elbow ROM**	**Trunk ROM**
Sub. 1 no weight	179.71	97.76	3.68
Sub. 1 weight	179.21	140.48	4.89
Sub. 2 no weight	179.58	168.21	10.64
Sub. 2 weight	178.72	139.03	12.73
Sub. 3 no weight	179.22	72.48	5.54
Sub. 3 weight	179.74	92.56	5.23
Sub. 4 no weight	179.43	68.34	3.71
Sub. 4 weight	179.95	36.12	3.18
Sub. 5 no weight	179.49	46.30	3.75
Sub. 5 weight	178.45	45.65	3.22
Sub. 6 no weight	179.80	79.77	16.33
Sub. 6 weight	178.77	74.65	12.70
Avg. healthy no weight	179.54	88.81	7.28
Avg. healthy weight	179.14	88.08	6.99

one patient are involved. In particular, twelve healthy subjects, among physiotherapist, nurses, and doctors, perform Shelf Cans activity at the hospital. The participants were 8 female and 4 male aged between 27 and 61 years.
The patient involved was a 62-year-old man who suffered from motor disability as a result of an expansive left fronto-parietal lesion. His plan of care was to perform exercises for upper and lower limbs and to improve equilibrium. For the early days, he performed the exercises at the hospital, then he was de-hospitalized



(a) Red can - no strategy

(b) Red can - strategy

(c) Orange can - no strategy

(d) Orange can - strategy

(e) Green can - no strategy

(f) Green can - strategy

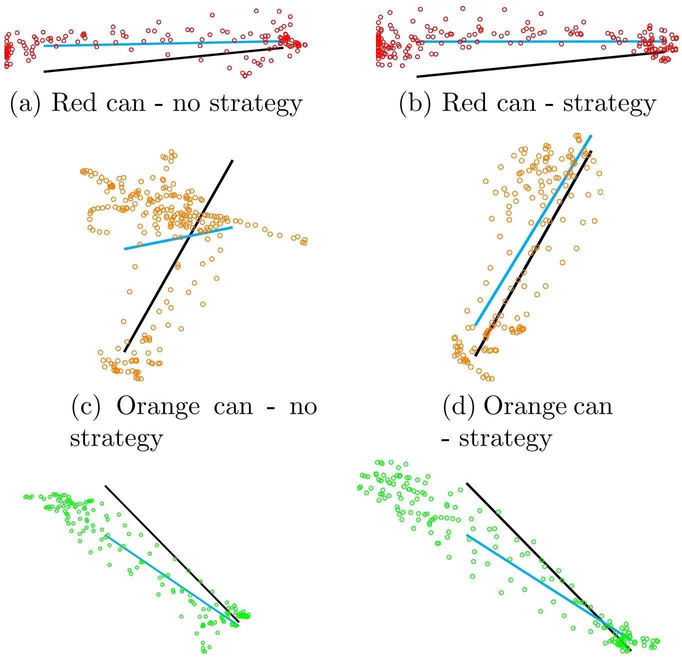
Figure 5.13: Patient A, approximate (light blue) and optimal (black) trajectories, and hand positions, based on the can color (dots).

and he finished his rehabilitation treatment after about twenty days at home. All participants were right-handed.

Signal filtering and segmentation

The procedure described at Section 4.1 is applied. The signals acquired by the sensor appear to be stationary with respect to the mean, and devoid of useful information at high frequencies. For signal regularization, after few tests a 4^{th} order Butterworth filter with cutoff frequency of 1.5 Hz was implemented.

Figure 5.17 depicts the motion segmentation applied to the right hand signals. As can be seen, the colored portions correspond to the movement performed by bringing the corresponded colored can to the shelf. The positive and negative variations on the X and Y axes of the Kinect, are consistent with the motion performed and with the positions of the three shelves. In fact, the positive values of x correspond to the movements performed to right of the origin, (i.e., the orange colored portions). Conversely, the negative values of x correspond to the movements



(a) Red can - no strategy (b) Red can - strategy

(c) Orange can - no strategy (d) Orange can - strategy

(e) Green can - no strategy (f) Green can - strategy

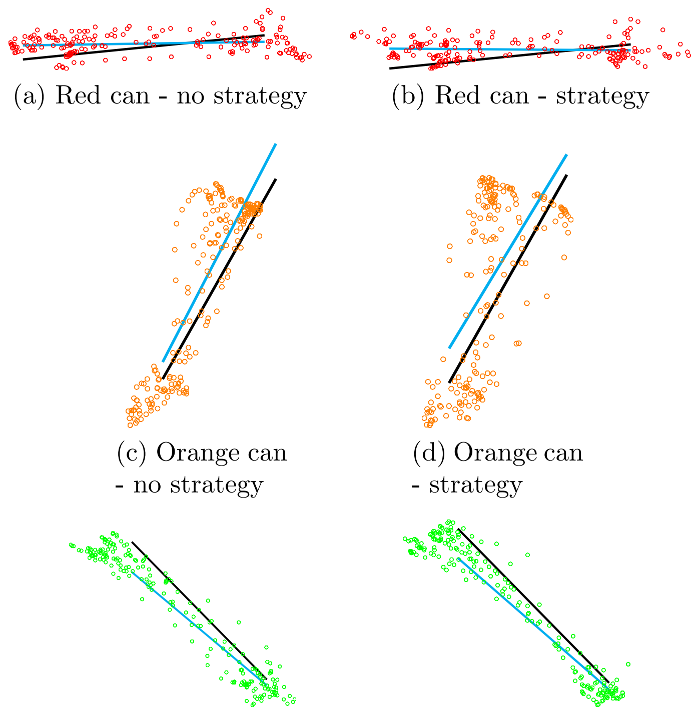
Figure 5.14: Patient B, approximate (light blue) and optimal (black) trajectories, and hand positions, based on the can color (dots).

performed from right to left (i.e., the green and red colored portions). Similarly, the positive y correspond to movements performed from the bottom upwards (i.e., orange and green portions), while the negative y values correspond to movements performed downwards (i.e., red portions).

Patient monitoring over time

The patient considered in this study had a personalized treatment plan in which he had to perform more repetitions per exercise, and for the exercises of the upper limbs, he had to alternate the playing hand. In this section the evolution of the main features of Shelf Cans activity executed with the pathological right hand will be analyzed, dividing the patient's monitoring period into 3 phases:

- phase 1: period in hospital, where the patient was able to try the exercises with the help of a physiotherapist (days 1-7);
- phase 2: first period at home (days 8-18);
- phase 3: last period at home, which shows a constancy in the game performances (days 19-30).



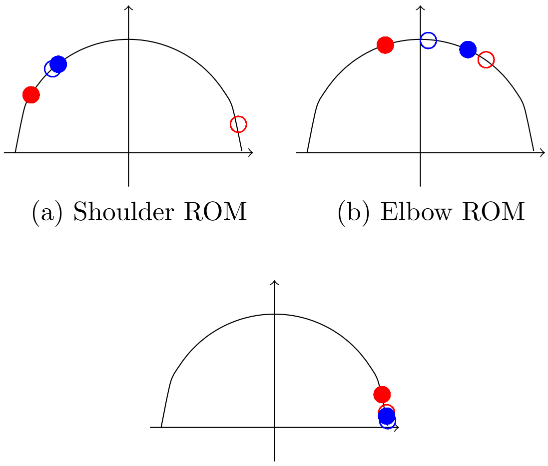
(a) Red can - no strategy
(b) Red can - strategy
(c) Orange can - no strategy
(d) Orange can - strategy
(e) Green can - no strategy
(f) Green can - strategy

Figure 5.15: Subject 1, approximate (light blue) and optimal (black) trajectories, and hand positions, based on the can color (dots).

The first analysis concerns the number of cans placed on the correct shelf, as shown in Figure 5.18. During phase 1, in the hospital, it can be seen that the number of targets is much higher than the session period at home, this better trend is normal, because the clinic is basically an environment prepared for physiotherapy and rehabilitation, and the patient was constantly followed, guided and stimulated by therapists. On the other hand, during the period at home, there was an initial worsening due to the change of location and conditions, and due to the lack of stimuli. The physiotherapist was able to provide timely a feedback to the patient as a result of this continuous monitoring, thus he improved his motions and attained constancy in performance throughout phase 3.

The subsequent analyzes will cover in detail the amplitude of the movement performed, the precision in following the trajectory and the values of the other features, explained in Section 4.5.2. These values will be compared with the performance of a group of healthy subjects, who performed the same exercise.

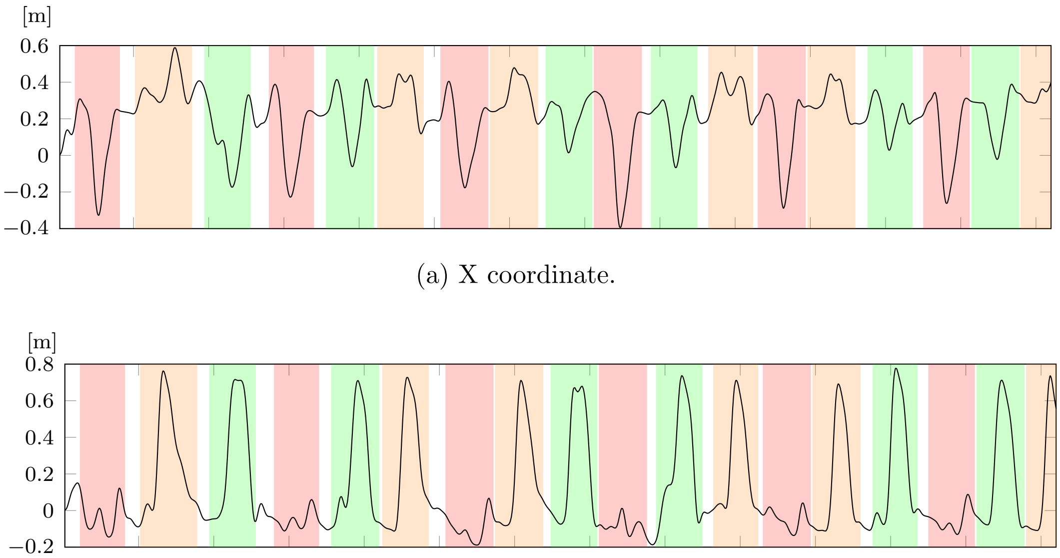
Referring to the upper-limb movement, the Range of Motion of elbow and shoulder joints were computed in 3D space and in the three anatomical planes



(a) Shoulder ROM (b) Elbow ROM

(c) Trunk ROM

Figure 5.16: Patients A and B shoulder, elbow, and trunk ROMs visualizations. Red marks refer to Patient A, blue marks refer to Patient B. Empty circles are for sessions without adopting the weighting strategy, full circles are for sessions where the weighting strategy was adopted.



(a) X coordinate.

(b) Y coordinate.

Figure 5.17: Signals segmentation of X and Y coordinates of the right hand joint.

i.e., coronal, sagittal and trasverse planes. The reference average values of healthy subjects are summarized in Table 5.12, while the values obtained for the patient,

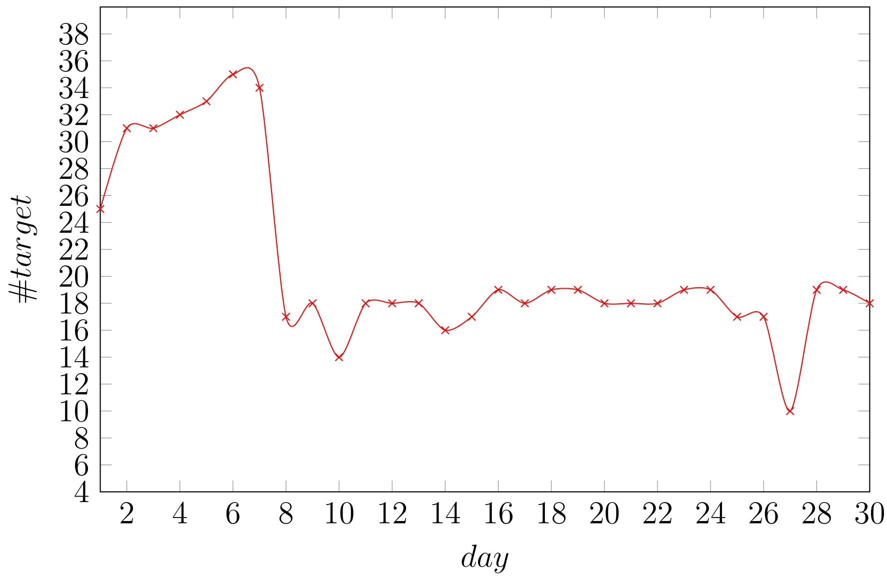


Figure 5.18: Number of cans placed correctly over the period of time considered.

in the three time phases considered, are summed up in Tables 5.13 and 5.14 for the shoulder and elbow ROMs respectively.

Table 5.12: ROMs of shoulder and elbow in the healthy group.

	Coronal plane	**Sagittal plane**	**Trasverse plane**	**3D space**
ROM shoulder	131.02	124.14	107.04	89.34
ROM elbow	178.67	129.99	114.90	98.81

Table 5.13: ROMs of shoulder.

	Coronal plane	**Sagittal plane**	**Trasverse plane**	**3D space**
Phase 1	122.42	83.08	86.86	77.76
Phase 2	138.47	71.95	102.52	81.82
Phase 3	134.32	91.69	112.43	77.48

The recorded values denote a difficulty in shoulder movement greater than 90 degrees during the first phase of rehabilitation at the hospital. In the first period at home, a worsening of the amplitude of the movement was noted, for reasons

Table 5.14: ROMs of elbow.

	Coronal plane	**Sagittal plane**	**Trasverse plane**	**3D space**
Phase 1	176.82	92.89	101.26	89.52
Phase 2	176.55	85.32	91.81	86.96
Phase 3	176.97	88.66	121.24	112.83

similar to those mentioned above. Finally, an improvement or a constancy of the ROM values can be noted with regard to the last treatment period.

For what concerning the compensation and strategy movement adopted by subjects when performing the exercise, on the part of healthy group low values of medio-lateral and antero-prosterior tilt are denoted respectively 8.99° and 20.53°, while on the transverse plane it was obtained on average 93.94° of trunk twist. Such a high value may be due to the movement of adduction to bring the red can to its shelf, which therefore involves a torsion of the body. The values obtained by the patient are summarized in Table 5.15. In this case, over the time, the patient decreased the compensatory movement he made with the trunk. These very high compensation values can explain why some ROM values of the shoulder and elbow are better than those of the healthy subjects.

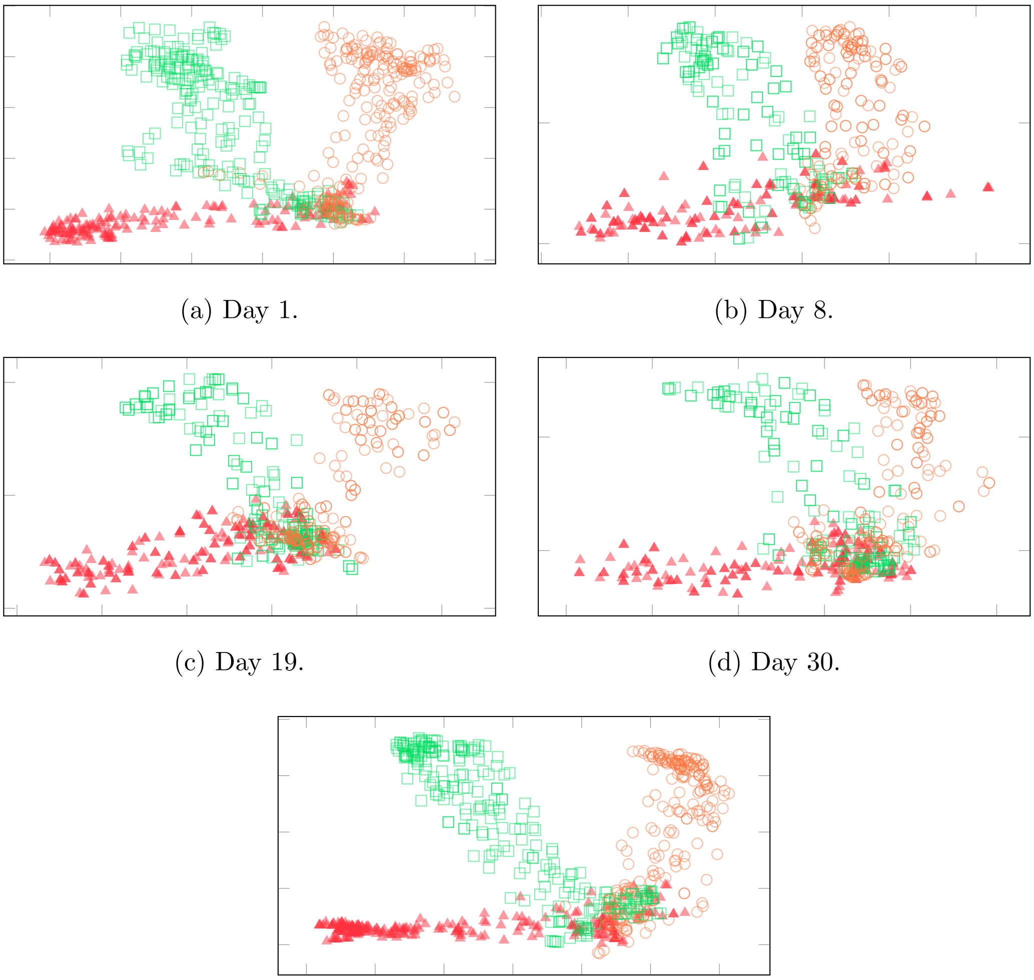
The Hand-Shoulder distance is an another indicators of compensatory motion, indeed the values obtained was 0.44 cm for healthy people and an average of 0.40 cm over the three phases for the patient (0.46 - 0.39 - 0.37 cm for phase 1, 2 and 3 respectively).

Table 5.15: ROMs of trunk.

	Lateral Tilt	**Antero-Posterior Tilt**	**Twist**
Phase 1	10.71	28.51	130.87
Phase 2	12.95	22.53	143.33
Phase 3	12.08	24.38	120.41

Figure 5.19 shows the evolution of the performance of the patient compared to the trajectory followed by an healthy subjects. This temporal analysis shows that, over the time, the subject has managed to control the arm motion with rather precise movements, always leading the can towards the shelf of the corresponding color without much hesitation.

Figure 5.20 offers an overview of the results in terms of angles between the optimal trajectories and the trajectory performed by patient. The horizontal colored lines indicate the values obtained for healthy group for each can. In detail, angles



(a) Day 1. (b) Day 8.

(c) Day 19. (d) Day 30.

(e) Healthy subject.

Figure 5.19: Each point corresponds to the temporal position of the can on the screen. Orange circles, red triangles, and green squares refer to orange cans, red cans, and green cans respectively. The temporal evolution of the movement control is provided in comparison with that performed by an healthy subject.

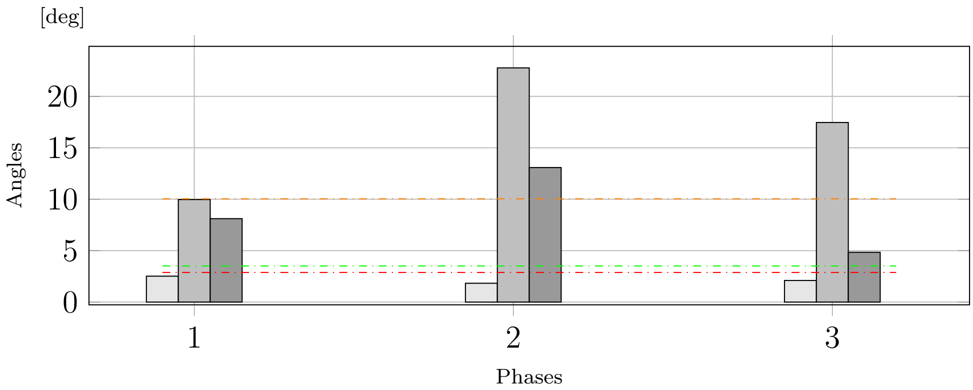


Figure 5.20: Overview of patient performance. The movement precision is calculated with the angles between trajectories. The bins represent the three shelf positions, in order for red, orange and green cans. The horizontal dotted lines indicate the standard performance of healthy subjects for each can.

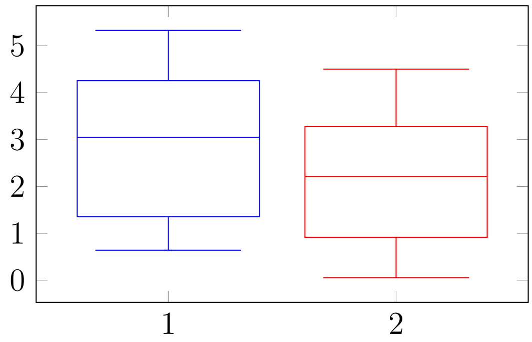
of 2.88°, 10.04°, and 3.51° was computed for red, orange and green cans respectively. Another display example for such indicator is represented by the box plots in Figure 5.21. As for the red trajectory, the box plots of the patient (in red) and of the healthy group (in blue) appear to be very similar and both show a certain symmetry of the data. For what concerns the orange and green trajectories, the patient's box plots have some outliers, as well as a median values higher than those of healthy subjects.

Lastly, the time indicator is computed to denote the time taken to perform the movement by subjects. In Table 5.16 are shown the time values in seconds, for the healthy group and for the patient. The time is computed making an average of the times found to execute the trajectories divided by task.

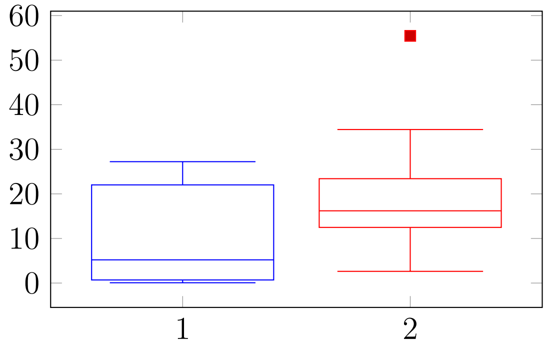
Table 5.16: Time feature, in seconds, for the healthy and patient subjects.

	Red can	**Orange can**	**Green can**
Healthy group	2.89	5.94	8.77
Patient phase 1	2.72	6.36	9.54
Patient phase 2	2.86	8.11	13.49
Patient phase 3	2.73	7.84	13.18

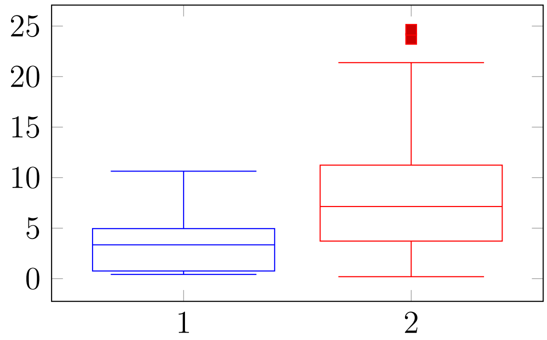
The time required to execute the trajectory that brings the red can from the center to its shelf is much less than that required to perform the other two tasks. In general, the time to perform the green can task is longer than the others, even for healthy subjects. This time increases significantly for the pathological subject when performing the exercise at home.



(a) Red trajectory.



(b) Orange trajectory.



(c) Green trajectory.

Figure 5.21: A comparison between patient and healthy group's values of trajectory's angles through box plots representation. In blue, the box plots of the healthy subjects; in red, the patient's box plots.

In conclusion, the evaluation and interpretation of these data must be considered in the clinical context by a specialist. In this case the patient, despite a long period of treatment, did not reach the performance of phase 1 again because the pathology from which he suffered is of an evolutionary type and this therefore leads to a progressive worsening.

5.4 Preliminary studies on Cerebral Palsy

The experimental phase began as part of the Rotary project "Medicina Digitale per la prevenzione e la cura" and involved 6 children being treated at the Fiumara ASL3 clinic. The children were at least 5 years old and had been diagnosed with mild cerebral palsy, even bilateral, and in some cases they also suffered from hemiparesis. They had no particular cognitive problems.

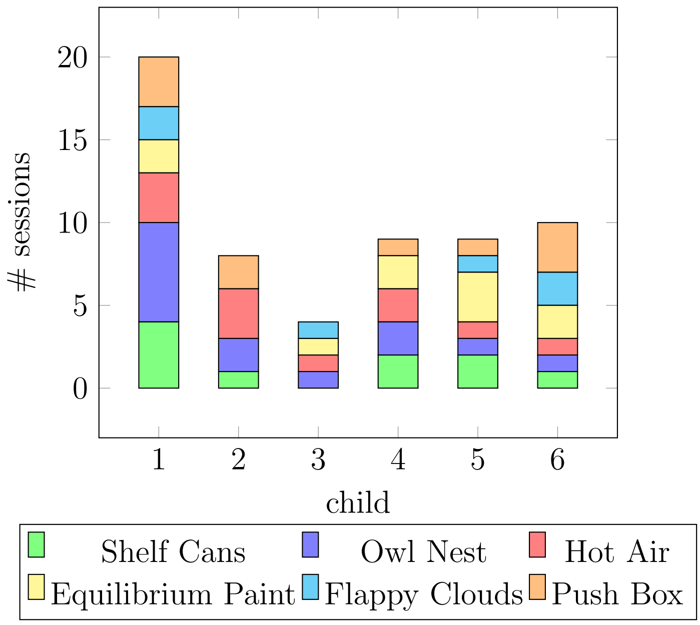


Figure 5.22: Number of sessions perfomed by children at Fiumara ASL3 clinic.

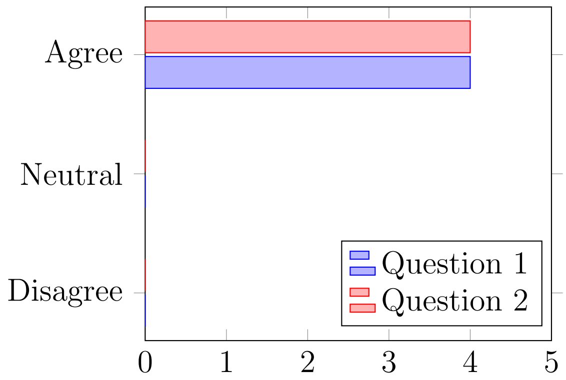
The physiotherapists of the clinic followed the children while they carried out some ReMoVES activities; in the Figure 5.22 it can see an overview of how many sessions they played for each Kinect exergame. Child 1 is the one who played several times, even with Leap Motion exergames, thus giving a complete feedback on all the activities. A lot of comments has been received both from children and from the specialists involved, in general the ReMoVES system is certainly fun for children and teenagers, thus combining rehabilitation with pleasure. The games that seemed most interesting were those dedicated to balance (Flappy Clouds and Hot Air) and for the upper limb (Owl Nest and Shelf Cans). Families were also given a questionnaire to find out their point of view on these new rehabilitation activities. Only 4 out of 6 families filled out the questionnaire; it may be useful to mention the answers given to some questions, including:

1. Was the child able to easily understand the task to be carried out?
2. Has the child shown interest in this type of activity?
3. Do you think it could be useful to carry out exercises following the instructions of a videogame, in addition to traditional rehabilitation therapy, even in the absence of medical/health personnel?
4. Do you think it is useful for the doctor or physiotherapist to be able to view the carried out activities on the computer to verify correct execution or provide suggestions?
5. Would you like the child to be able to perform this type of exercise at home?
6. Did you know that the rehabilitation guidelines also include the use of videogames as a rehabilitation activity?

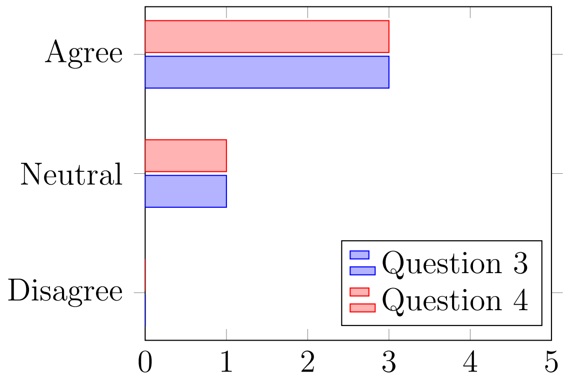
The score varies from 1 (Disagree) to 5 (Agree).

Analyzing the answers obtained, displayed in the graphs of Figures 5.23 and 5.24, it can be seen that the children were able to understand the purpose of the different activities proposed and showed very engagement. Families have shown enough interest in using videogames for rehabilitation purposes and believe it is useful for the doctor to be able to remotely see the results and performance of the exercise. Finally, families showed enough interest in continuing therapy with ReMoVES and not everyone was aware that the new guidelines on telerehabilitation also recommend the use of exergames.

This feasibility study shown that the system can also be a useful tool for children population. It would be preferable to integrate these activities at the clinic and then take the system home with the family's permission, keeping in mind the numerous school and extracurricular responsibilities that children and parents may have. Based on the comments received, it was determined that the current games, which are developed for an adult population that is less prone to technology and videogames, need to be improved primarily in terms of graphics. Children, in fact, require more stimulation as well as more engaging and dynamic activities. Therapists also have specific needs for what outcomes to investigate (for example, how the child maintains the wrist during upper limb games), and for this kind of disorder, it is critical to keep track on compensatory torso motions.



(a)



(b)

Figure 5.23: Results of the first 4 questions of the questionaire.

5.5 Multiple Sclerosis application

Within the STORMS project, the ReMoVES system was tested at the San Martino hospital with some patients affected by MS. First, a feasibility study was conducted with four patients who took the system home. In the absence of specific prescription, patients were allowed to carry out the exercises they found most enjoyable. However, this led to a greater utilization of the easier activities or those that the patients favored, at the expense of the more challenging or cognitively significant ones. As a matter of fact, the patients outperformed the basic exergames rather than improving their skills by progressing up the levels. In Section 5.5.1 some results of a 49 year old patient who kept the ReMoVES system at home for almost a month will be presented.

For the second study, it was decided to take a different approach, prescribing a patient with a precise and personalized weekly treatment plan, with activities distributed from Monday to Thursday. The patient has 56 years and took the

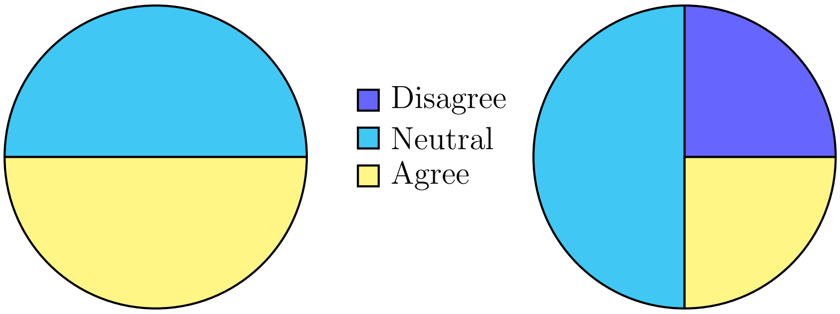


Figure 5.24: Results of the questions 5 and 6 of the questionaire.

system home for 4 weeks. At the end of each week, a brief report detailing the outcomes of the activities was compiled so that the therapists could adjust the therapy schedule for the next week. In Section 5.5.2 the results obtained on a weekly basis will be analyzed and the prescriptions will be compared with the actual sessions played by the patient. As the present study is still ongoing, in the end possible future analysis of the results are discussed.

5.5.1 First study

The Table 5.17 summarizes the number of sessions played for each exergame. As can be seen, the patient played mainly at the first level of each activity, focusing more on the basic ones (Shelf Cans and Hot Air). The sessions of Shelf Cans exercise will be analyzed below.

Table 5.17: Number of sessions performed by the patient for each exergame.

Exergame	**Level**	**# Session**
Shelf Cans	-	26
Owl Nest	1	23
Numbers	1-2	4
Supermarket	1	3
Business By Car	1	3
Hot Air	-	52

Shelf Cans analysis

In this first analysis, the cognitive results achieved by the patient and his precision and speed in performing the movement will be described. Figure 5.25 shows the learning curve obtained from patient when playing Shelf Cans exergame. A low score is expected in the initial sessions and a subsequent steady improvement during the final sessions.

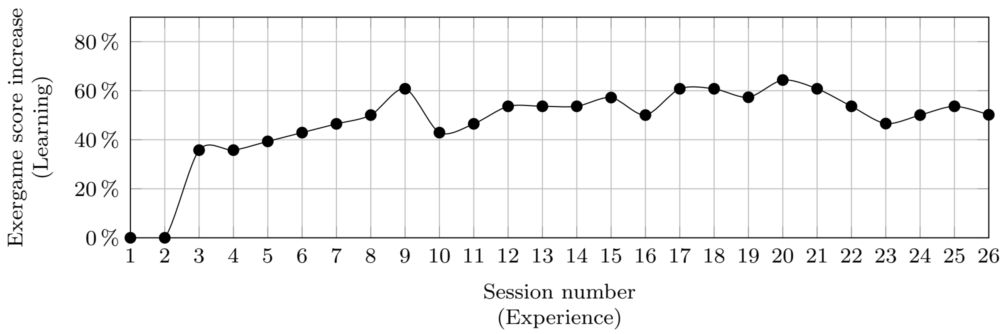


Figure 5.25: Learning curve in the context of Shelf Cans activity. On the vertical axis, it is evaluated how gaming performance improves with more experience (number of sessions). The game performance is defined as a percentage increase compared to the initial session.

Figure 5.26 offers an overview of the results in terms of angles between the optimal trajectories and the trajectory performed by patient and the times elapsed in bringing the colored cans to the corresponding shelf. From the graphs it can be seen an improvement in the times for each trajectory, which therefore denotes a greater speed of execution of the movement. On the contrary, the angles between the optimal trajectory and the one performed by the patient, which indicate the precision of the movement, increased for the trajectory of the red can or remained constant or decreased for the trajectories of the orange and green cans, respectively.

Therefore, one can notice a correlation between the angles (precision of the movement) and the times (speed of execution). For the red can, the faster he went, the less accurate he was (negative correlation of $\rho = -0.48$). For the orange can there is a low correlation of $\rho = -0.10$. For the green can there is a positive correlation of $\rho = 0.53$, therefore he was able to be both quick and precise in his movement.

Finally, a comparison between patient and a group of healthy subjects is represented throughout the box plots relating to the indicator of the angle between the trajectories (Figure 5.27). Regarding the red and green trajectories, the box plots of the patient (in red) and the healthy group (in blue) appear to be very similar and both show a certain symmetry of the data. As for the orange trajectory, the patient's box plots have some outliers, which correspond to the mistakes he made in getting those cans to the wrong shelves.

5.5.2 Second study

The exercise recommended for each week are provided in Table 5.18, along with the minimum number of times she was required to play each day. Instead, Figure 5.28 shows the patient's adherence to the prescription.

Table 5.18: Plan of care of the activities prescribed for 4 weeks.

Week	Exergame	Level	Prescription/day
1	Shelf Cans	-	4
	Owl Nest	1	4
	Owl Nest	2	5
	Supermarket	1	4
2	Owl Nest	3	5
	Owl Nest	4	4
	Supermarket	1	5
	Business By Car	1	4
3	Supermarket	1	5
	Business By Car	1	4
	Numbers	1	5
	Numbers	2	2
4	Supermarket	1	5
	Supermarket	2	5
	Business By Car	2	4
	Numbers	2	5

Although she did not follow the prescription in the first week, the patient achieved good results in the activities she had to perform. In fact for the second week, the therapists prescribed more advanced levels of Owl Nest and the addition of a new exergame. In the first two weeks, the Owl Nest and Shelf Cans exergames were played a lot and the patient does not seem to have encountered any particular problems or difficulties. Therefore in the last two weeks these games have not been prescribed anymore. On the contrary, the therapists wanted to add activities in which the patient seemed to have more difficulty, in order to entice her to greater concentration and cognitive recovery.

Overall though, over the weeks it can be noted that the patient did not completely follow the prescription and also performed several more advanced activities that were not requested. Also, in weeks three and four, she never played the Numbers exergame. One may also notice a dramatic decrease in the number of sessions performed over the last week.

Comparison between actual and prescribed gaming sessions revealed a significant discrepancy. This gap can be attributed to a number of factors that contributed to influencing the patient's participation in the context of the different activities and prescriptions she had. The need to combine multiple activities may have affected her willingness and motivation to regularly participate in rehabilitation sessions. To optimize future interventions, one might consider optimizing patient participation with a broader approach balanced that takes into account the individual needs and various prescribed activities. Addressing the factors that influence participation can help ensure greater consistency in carrying out exercises and achieving results desired.

Business By Car analysis

For the Business By Car exergame, progress in cognitive and motor skills was assessed through specific parameters and indicators.

The histogram representing the correct and incorrect paths per session offers a detailed view of the patient's motor skills during the gaming sessions. Correct paths reflect the patient's ability to correctly follow the path established by the game, while incorrect paths indicate any deviations or errors committed. In Figure 5.29, it can be seen how the number of wrong paths varies based on sessions. Fluctuations can be indicative of different factors, such as the complexity of the path, the level of concentration or the progressive adaptation to the challenges. Sessions with a high number of wrong paths they could suggest moments in which the patient faced greater difficulties in following the predefined path also due to a higher level of play. On the contrary, sessions with fewer wrong routes may indicate a greater ability to manage the motor challenges proposed by the game.

The histogram inf Figure 5.30 regarding correct and incorrect answers per session provides an analysis of the patient's cognitive abilities. Correct answers reflect the ability to provide accurate answers to the questions posed at the end of the game, while incorrect answers indicate any errors or inaccuracies in the answers provided. The trend of correct and incorrect answers can offer a perspective on the evolution of the patient's cognitive abilities during the game program. Sessions with a high number of correct answers could highlight moments of greater understanding and concentration, while those with a greater number of wrong answers could signal situations in where the patient encountered difficulties in processing information.

5.5.3 Future development

The analysis of indicators containing features concerning attention, working memory, speed of processing information about the environment or situation simulated by the serious games and those concerning the movements performed to reach the goal, defines a complete picture of the physical and mental state of the patient allowing then to monitor more accurately the course of symptoms highlighted by the disease. In future development, the main indicators and graphs will be analyzed from a cognitive and motor point of view. In fact, although the focal point of the STORMS project is cognitive rehabilitation, it is also necessary to study the movement performed by the patient, predict any errors or compensations, as well as analyze the precision and speed of the gesture itself.

For a cognitive point of view, the Mini-Mental State Examination (MMSE) perfomed by therapist before and after the rehabilitation treatment, will be used to assess the state of impairment and/or deterioration of cognitive efficiency. The results obtained with MMSE test could be correlated with the data collected by the Removes system to ascertain the capacity of cognitive functions of MS patients.

Lastly, the tool to measure the disability status of patients with MS will be the Expanded Disability Status Scale (EDSS). The inclusion criterion considered will include patients with a score lower than 6. The expected trends will be learning curves that will include information related to motor performance obtained in multiple gaming sessions. For each exergame, the correct joints will be tracked in order to detect and evaluate the patient's movement patterns. Possible motor indicators could be the amplitude of the movement (ROM) of the shoulder and elbow and compensations with the trunk.

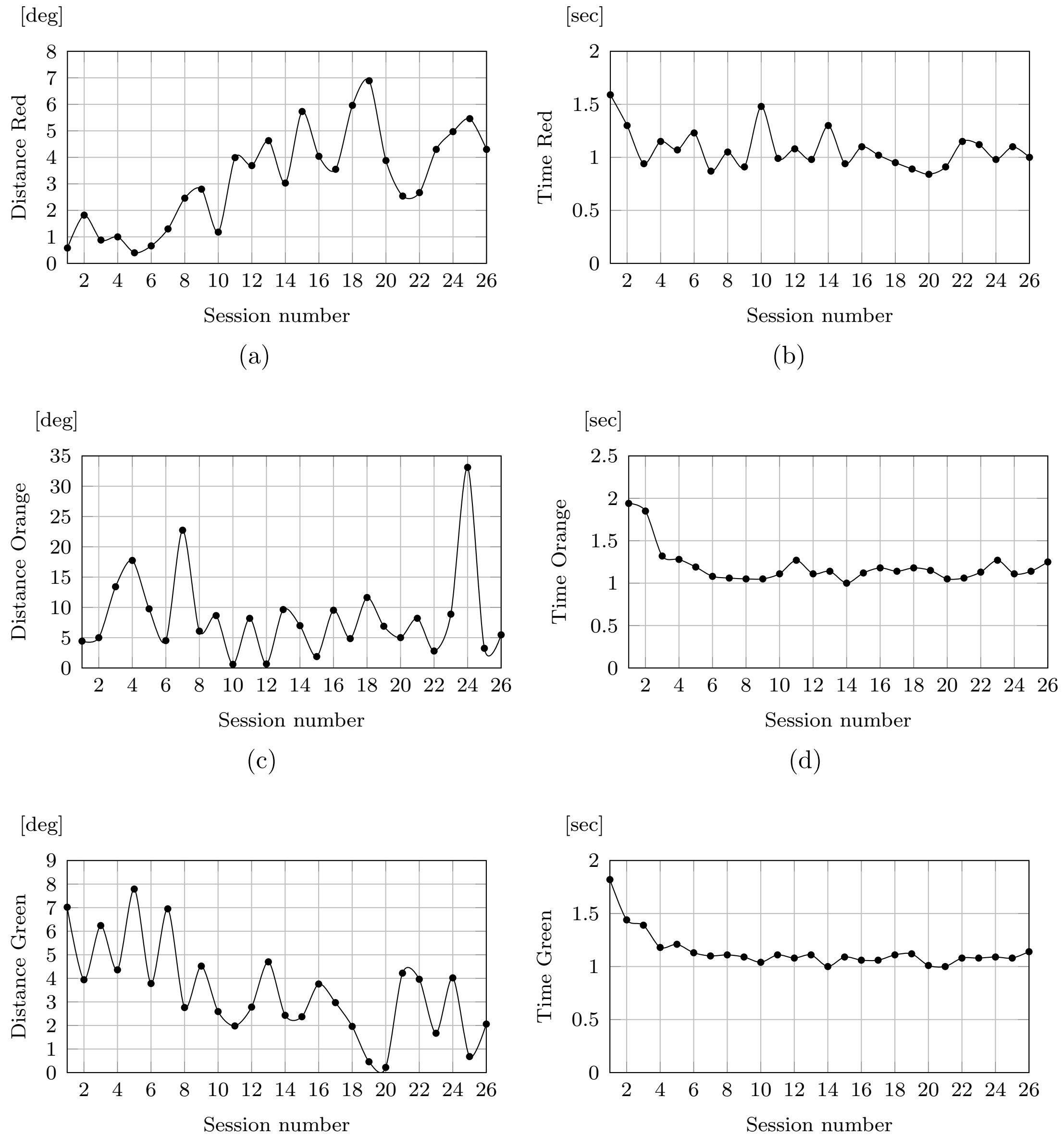
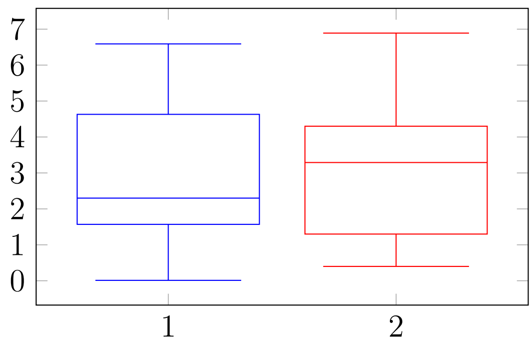
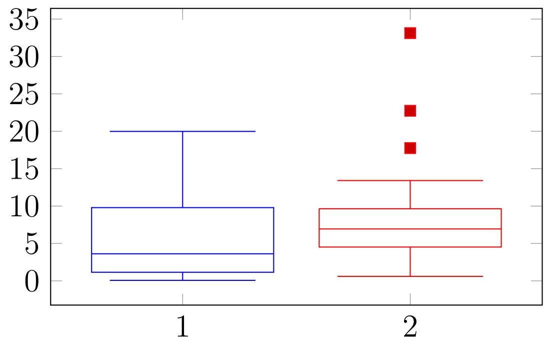


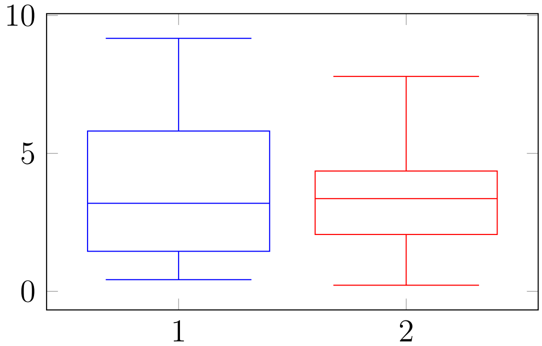
Figure 5.26: The graphs on the right relate to the angles between the optimal trajectory and the one performed by the patient. The graphs on the left represent the times to perform the required movement. From top to bottom the results for the red, orange and green trajectories are shown respectively.



(a) Red trajectory.

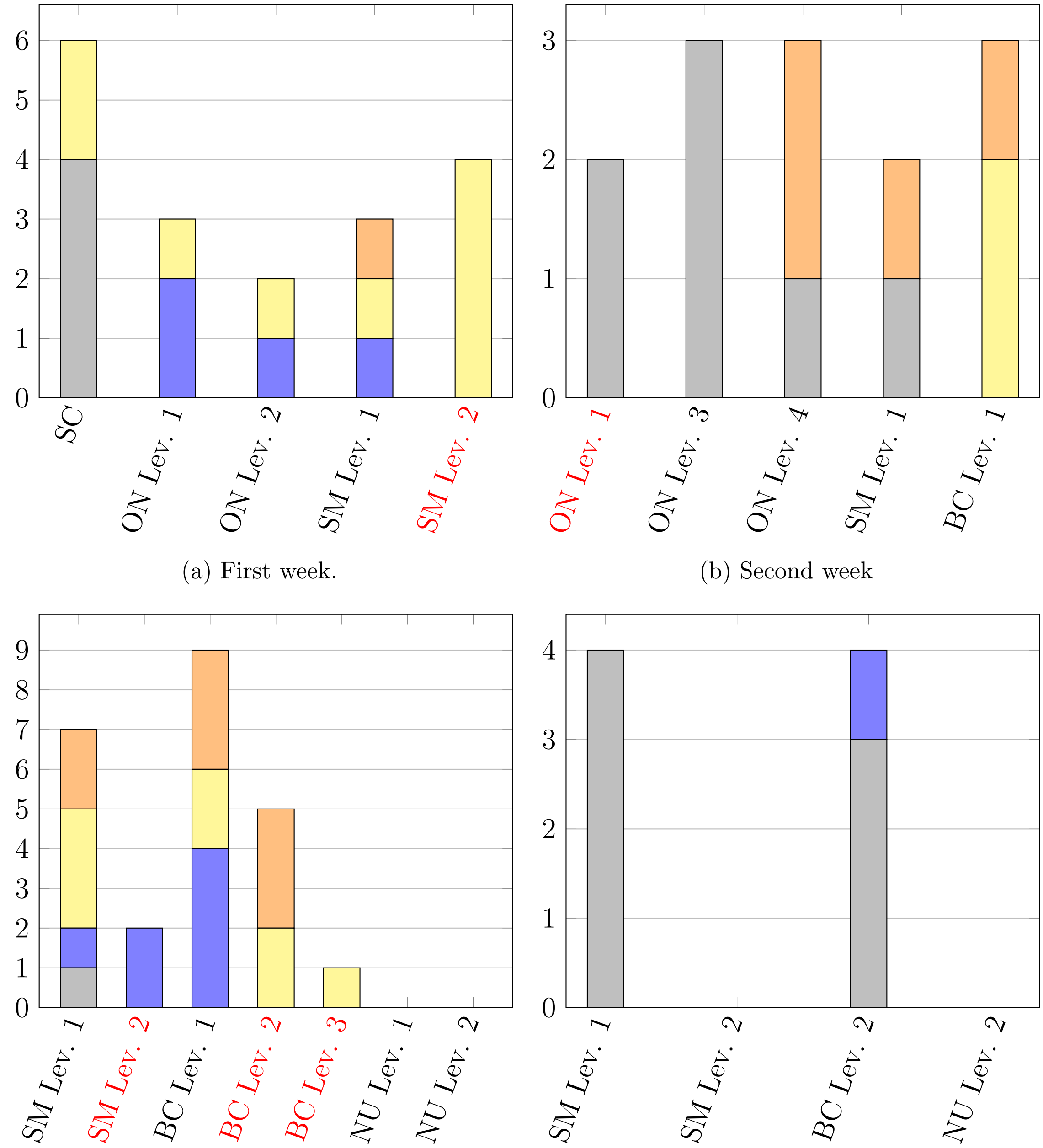


(b) Orange trajectory.



(c) Green trajectory.

Figure 5.27: A box plot depiction of the values of trajectory angles between the patient and healthy group. In blue the box plots of the healthy subjects; in red the patient's box plots.



(a) First week.

(b) Second week

(c) Third week.

(d) Fourth week.

Figure 5.28: Number of sessions performed each week. In gray are the sessions performed on the first day, in blue those of the second, in yellow the third and in orange the fourth day. The exercises in red highlight the execution of non-prescribed activities.

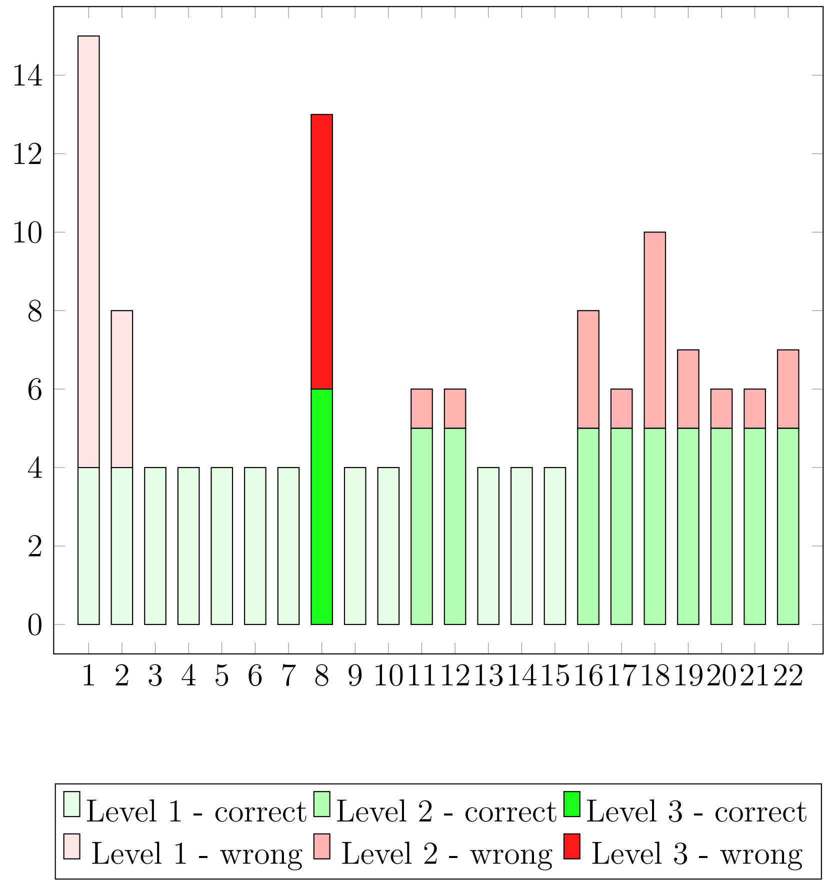


Figure 5.29: Number of correct and incorrect paths per session.

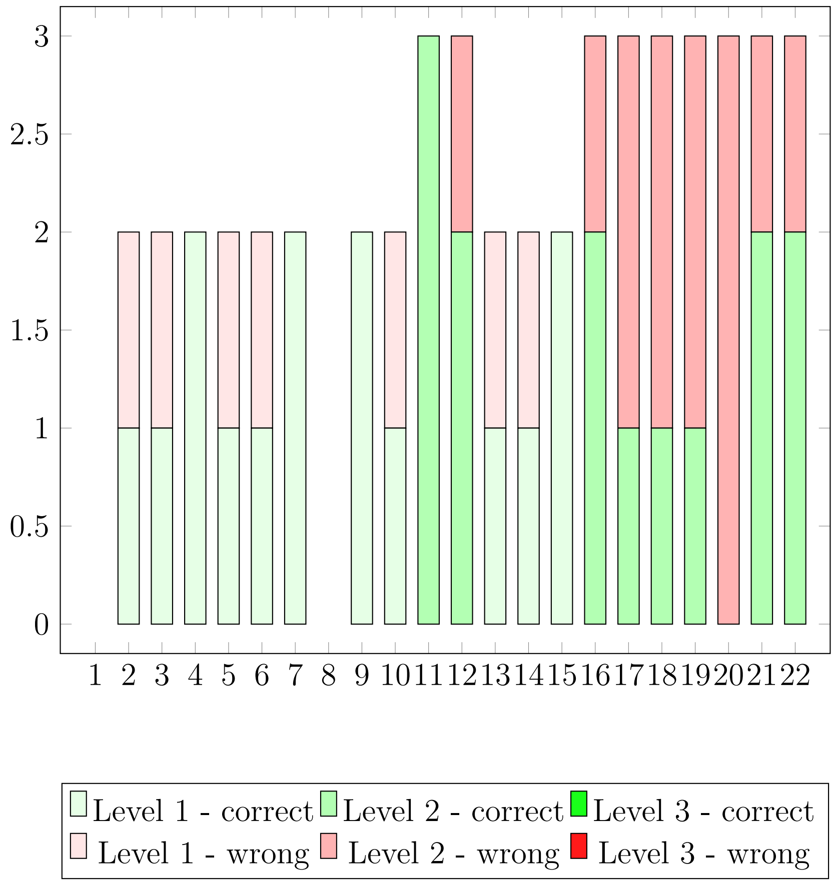


Figure 5.30: Number of correct and incorrect paths per session.

Chapter 6

Conclusion

This thesis focused on the application of the IoT system ReMoVES, which administers exergames for motor and cognitive activities, in the context of various diseases. Even when patient activity is carried out autonomously of therapist observation, it may still be tracked by using affordable, easily accessible components and an intuitive user interface. Furthermore, those who are unfamiliar with new technologies can still follow their tailored plan of care and perform the activities that are recommended. All of this enables remote clinical staff monitoring of the patient's behavior and the continuation of care following dehospitalization. The possibility to avoid wearable devices in favor of sensors such as depth cameras allow for expanding the use of such a system even without the need for therapists or caregivers to attend to patients. Moreover, measurement accuracy is satisfactory for remote monitoring, as pathological movement can be detected from the data, and sessions can be analyzed and discussed as in Section 5.

The most important theoretical contribution is the definition of indicators that drive feature-extraction and data-processing operations in future studies. The reliability of data and concordance with respect to the literature enable the development of data-analysis and artificial-intelligence techniques for supporting clinical practice. For instance, due to the sequential nature of rehabilitation data collected by ReMoVES, in a future perspective long short-term memory (LSTM) recurrent neural networks (RNNs) can be used for data analysis.

Even though acceptability towards IoT/ICT solutions for telerehabilitation and telemedicine is continuously increasing, it is still rare that such technologies are guaranteed and covered by national health services. For instance, in several Italian regions, the local health service has recently been operating in such a direction, recognizing the benefit that the people may have from technologies such as the one described here.

There are three main contributions for what concerns practical and social implications of the present work. First, from a clinical point of view, patients benefit from the use of ReMoVES in terms of help for dehospitalization, continuity of care, the personalization of plans of care, and engagement in activities. Second, from an operative point of view, telerehabilitation helps clinical staff to also follow several patients when they cannot physically attend to them. In the end, there were interesting social interactions among participants while practicing ReMoVES activities in the facilities. Patients enjoyed the experience both when playing themselves and when watching others carrying out the activities, thus promoting social inclusion. This may be the context of a stimulating future social experiment aimed at evaluating whether such a friendly atmosphere induced by ReMoVES activities can bring some sort of unexpected benefit.

The most challenging aspect of this work was acquiring data. It is common problem, particularly in the medical and rehabilitation fields, to identify enough patients with specific traits or diseases, or healthy people, who can complete the exercise correctly, to use as models. Automatic classification techniques may be used in the future, potentially in conjunction with methods to address the issue of imbalanced datasets with small sample sizes, as proposed by the authors of [228]. Concerning other future developments, the next objective is the improvement of technical ReMoVES potential, for instance, by deploying the new Azure Kinect sensor, developing novel exergames, and including biometric sensors. At the same time, the spectrum of diseases of which treatment also involves ReMoVES will be expanded.

Appendix A

PhD activities

A.1 Publication record

A.1.1 Journal papers

- M. Trombini, F. Ferraro, G. Iaconi, L. Vestito, F. Bandini, L. Mori, C. Trompetto, and S. Dellepiane, “A study protocol for occupational rehabilitation in multiple sclerosis,” Sensors, vol. 21, no. 24, p. 8436, 2021.
- M. Trombini, F. Ferraro, M. Morando, G. Regesta, and S. Dellepiane, “A solution for the remote care of frail elderly individuals via exergames,” Sensors, vol. 21, no. 8, p. 2719, 2021.
- M. Trombini, F. Ferraro, E. Manfredi, G. Petrillo, and S. Dellepiane, “Camera color correction for cultural heritage preservation based on clustered data,” Journal of Imaging, vol. 7, no. 7, p. 115, 2021.

A.1.2 Conference papers

- F. Ferraro, G. Iaconi, M. Simonini, and S. Dellepiane, “Signal processing for remote monitoring of home-based rehabilitation support activities,” in 2022 IEEE International Conference on E-health Networking, Application & Services (HealthCom), pp. 192–198, IEEE, 2022.
- F. Ferraro, M. Trombini, R. Truffelli, M. Simonini, and S. Dellepiane, “On the assessment of unilateral spatial neglect via digital tests,” in 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER), pp. 802–806, IEEE, 2021.
- M. Trombini, F. Ferraro, A. Nardelli, L. Vestito, G. Schenone, L. Mori, C. Trompetto, and S. Dellepiane, “On the performance assessment during the

practice of an exergame for cerebellar ataxia patients," in 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 5747–5751, IEEE, 2021.

- M. Trombini, F. Ferraro, and S. Dellepiane, "On the use of boundary gradient for the analysis of mr wrist bones volumes segmentation," in 2021 3rd International Conference on Intelligent Medicine and Image Processing, pp. 27–32, 2021.

A.1.3 Conference Proceedings

- F. Ferraro, G. Iaconi, G. Genesio, R. Truffelli, R. Amella, M. Simonini, S. Dellepiane. (2023, September). "Spatial Exploration Indicators in the Remote Assessment of Visual Neglect". In International Conference on Image Analysis and Processing (pp. 552-563). Cham: Springer Nature Switzerland.

- G. Iaconi, F. Ferraro, M. Balletto, D. Solarna, M. Trombini, G. Moser, and S. Dellepiane, "Graph-based segmentation and markov random field for covid-19 infection in lung ct volumes," in Advances in System-Integrated Intelligence (M. Valle, D. Lehmhus, C. Gianoglio, E. Ragusa, L. Seminara, S. Bosse, A. Ibrahim, and K.-D. Thoben, eds.), (Cham), pp. 43–52, Springer International Publishing, 2022.

- F. Ferraro, M. Trombini, M. Morando, M. Doveri, G. Bianchi, and S. Dellepiane, "Exergames for systemic sclerosis rehabilitation: A pilot study," in Advances in Computer Vision and Computational Biology, pp. 281–291, Springer, 2021.

A.1.4 Abstract and Posters

- M. Simonini, R. Truffelli, F. Ferraro, M. Trombini, and S. Dellepiane, "Riflessioni sull'utilizzo in clinica degli indicatori del Test di Albert digitalizzato." 49° Congresso Nazionale SIMFER Le Radici del Futuro, Milano 28-31 Ottobre 2021.

- R. Truffelli, M. Simonini, F. Ferraro, M. Trombini, and S. Dellepiane, "Test di albert in forma digitale. Indicatori e caratterizzazione di un campione di soggetti sani.," XX Congresso Nazionale SIRN La Neuroriabilitazione ai Tempi del Covid, Roma 23-24 Settembre 2021.

- M. Doveri, M. Trombini, F. Ferraro, R. Galli, A. L. Bargeri, S. Rando, S. Dellepiane, and G. Bianchi, "Towards systemic sclerosis rehabilitation via videogames," in ARTHRITIS & RHEUMATOLOGY, vol. 72, WILEY 111 RIVER ST, HOBOKEN 07030-5774, NJ USA, 2020.

- M. Doveri, M. Trombini, F. Ferraro, R. Galli, A. L. Bargeri, S. Rando, S. Dellepiane, and G. Bianchi, "Sclerodermia e videogiochi: un possible nuovo approccio riabilitativo," 57° Congresso Nazionale SIR, 25-28 Novembre 2020.

A.2 Attendance at Conferences and Events

- ICIAP 2023 - International Conference on Image Analysis and Processing, 11-15 September 2023, Udine, Italy.
- Healthcom 2022 - IEEE International Conference on E-health Networking, Application & Services, 17-19 October 2022, Genova, Italy.
- SysInt 2022 - 6th International Conference on System-Integrated Intelligence, 7-9 September 2022, Genova, Italy.
- EMBC 2021 - 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1-5 November 2021, Virtual.
- NER 2021 - 10th International IEEE EMBS Conference on Neural Engineering, 4-6 May 2021, Virtual.

A.3 Awards

- Project STORMS - Solution Towards Occupational Rehabilitation for Multiple Sclerosis, awarded for Premio Innovazione Digitale nella Sclerosi Multipla 2020 sponsored by Merck.

A.4 Scientific collaborations

- IRCCS Ospedale Policlinico San Martino, Clinica di Neuroriabilitazione - Carlo Trompetto, Laura Mori, Lucilla Vestito.
- Ospedale La Colletta, ASL3, Struttura Complessa Recupero e Rieducazione Funzionale - Marina Simonini, Romina Truffelli.
- Ospedale La Colletta, ASL3, Struttura Complessa di Reumatologia - Gerolamo Bianchi, Marica Doveri.
- Centro di Riabilitazione Gruppo Fides - Giovanni Regesta.

- Department of Chemistry and Industrial Chemistry (DCCI), Università degli Studi di Genova - Prof. Giovanni Petrillo.
- Department of Neurosciences, Rehabilitation, Ophthalmology, Genetics, and Maternal and Children's Sciences (DINOGMI), Università degli Studi di Genova - Prof. Carlo Trompetto, Prof. Laura Mori, Lucilla Vestito.

A.5 Educational and training activities

- Deep Learning and Computer Vision School certificate, 2023.
- Environmental sustainability of ICT, 2022.
- Deep Learning Specialization, Coursera certificate, 2021.

A.6 Didactic activities and supervision

- Assistant and Subject Expert for the course Digital Image Processing (Master of science course in Internet and Multimedia Engineering, Master of science course in Electronic Engineering).
- Assistant and Subject Expert for the course Comunicazioni Elettriche (Bachelor of science course in Biomedical Engineering).
- Assistant and Subject Expert for the course Elaborazione digitale delle immagini storico-artistiche (Master course in Art history and valorization of the cultural heritage).
- Co-supervisor of 18 Bachelor of science Theses in Biomedical Engineering.
- Co-supervisor of 1 Master of science These in Internet and Multimedia Engineering.

A.7 Scientific societies

- ACM - Association for Computing Machinery.
- CNIT - Consorzio Nazionale Interuniversitario per le Telecomunicazioni.
- CVPL - Associazione Italiana per la ricerca in Computer Vision, Pattern recognition e machine Learning.

- IEEE - Institute of Electrical and Electronics Engineers.
- IEEE EMBS - Engineering in Medicine and Biology Society.
- IEEE GRSS - Geoscience and Remote Sensing Society.
- IEEE SPS - Signal Processing Society.

A.8 Participation to other project

- Rotary Club project: Medicina Digitale per la Prevenzione e la Cura, demonstration day of tele-rehabilitation activities, 28 April 2023, Campo Ligure (GE), Italy
- Rotary Club project: Medicina Digitale per la Prevenzione e la Cura, demonstration day of tele-rehabilitation activities, 17 March 2023, Savignone (GE), Italy
- Rotary Club project: Medicina Digitale per la Prevenzione e la Cura, demonstration day of tele-rehabilitation activities, 17 February 2023, Rovegno (GE), Italy
- Rotary Club project: Medicina Digitale per la Prevenzione e la Cura, demonstration day of tele-rehabilitation activities, 27 January 2023, Torriglia (GE), Italy

Appendix B

Other works

In this appendix, the other works developed during the Ph.D., but not described in the present thesis are introduced.

B.1 Cultural heritage preservation

The present section briefly discloses the work in [229].

Cultural heritage preservation is a crucial topic for our society. When dealing with fine art, color is a primary feature that encompasses a great information content related to the artwork conservation status and to the pigments composition. As an alternative to more sophisticated devices, analysis and identification of color pigments may be addressed via a digital camera, i.e., a non-invasive, inexpensive, and portable tool allowing for studies on large surfaces. The present work proposes a new supervised approach to camera characterization based on clustered data, in order to address the homoscedasticity of the acquired data. The experimental phase is conducted on a real pictorial dataset made of 117 tiles from the database of diagnostic analyses of The Foundation Centre for Conservation and Restoration of Cultural Heritage "La Venaria Reale" (in collaboration with the National Institute of Metrological Research and Laboratorio Analisi Scientifiche of Regione Autonoma Valle d'Aosta) [230]. Figure B.1 shows some of the selected parts of tiles involved in the study. The dataset under analysis is clustered according to two different criteria, i.e., according to chromatic appearance and the chemical composition, with reference to the central metal atom.
Among the different approaches studied in the state-of-the-art, a polynomial regression allowed to obtain the best results on both the proposed clustering criteria. Thus, while the correlation between characterized photographic and colorimetric data remains high both when considering the entire dataset or the single clusters,

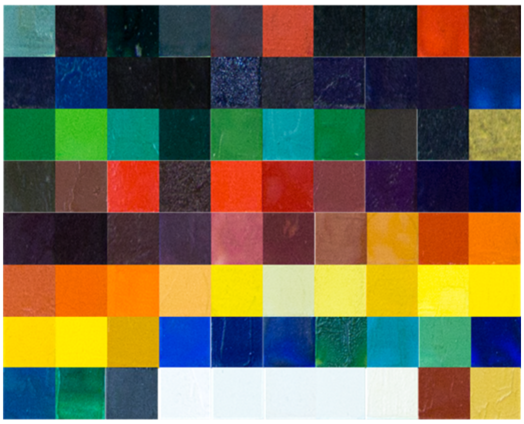


Figure B.1: A subset of tiles samples involved in the study.

in the last case notable improvements can be seen on the three types of parameters considered to test the efficacy of the characterization (i.e., RMS, ΔE_{00}, and Δ). In addition, the work introduces a way to deal with organic pigments in a quantitative visual approach.

B.2 Unsupervised evaluation of image segmentation

The present section briefly discloses the works on image processing in the context of Magnetic Resonance (MR) volumes [231] and Computer Tomography (CT) scans [232], respectively.

Image segmentation partitions a digital image into regions of interest, by taking into account the information content and local properties of homogeneity and topological connectivity. The evaluation of segmentation quality is usually based on supervised ground-truth images, which are provided by experts and used for comparison with segmented images. Indeed, intra-rater and inter-rater reliability affect the accuracy of such reference information. In addition to subjectivity, the skill of the experts and their knowledge could lead to bias. To achieve an objective performance measure, an automatic method for unsupervised evaluation of volume segmentation is proposed, which aims at finding a repetitive and user-independent evaluation of segmented results. The proposed approach leverages on the integration of volume- and boundary-based analysis. The quality of the segmentation is estimated on the basis of gradient properties, measured in the volume and focused on the voxels of the border. The segmentation is evaluated through a simple fuzzy index based on the resulting gradient. The experimental phase is conducted on a set of Magnetic Resonance volumes of the wrist district.

Most of the papers in the literature concerning the detection and evaluation of particular features from medical images (i.e., trauma, infections, etc.) are based on supervised techniques that always require large amounts of annotated data. On the contrary, in this work a completely unsupervised method is proposed, inspired by a previous 2D approach to segmentation, reformulated and extended to the case of 3D tomographic images. The method uses a flooding algorithm for the extraction of regions in the lung area, followed by the association with the corresponding statistical model by parametric estimation. A maximum a posteriori estimate of the 3D label map is obtained by modeling the image as a Markov Random Field that includes space-contextual information by means of a simple local proximity model for inter-voxel dependence. At this level, the problem is reformulated in terms of energy minimization, which is addressed using the α - β swap graph-cut algorithm. The proposed method was tested on 3D lung images in order to delineate infections from CT scans of the chest. A set of COVID-19 confirmed patients was then considered, and the results obtained showed accurate detection ability and remarkable robustness to the heterogeneity of CT scans considered.

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