FATIGUE-AWARE GAMING SYSTEM FOR MOTOR REHABILITATION USING BIOCYBERNETIC LOOPS

Maria Fernanda Montoya Vega
Master in Electrical Engineering

Supervisors: Ph.D Oscar Alberto Henao Gallo
Ph.D John Edison Muñoz Cardona

Universidad Tecnológica de Pereira
Human-Computer Interaction
HCI Group
Maestría en Ingeniería Eléctrica

Contents

Abstract

Physical rehabilitation therapies are mechanisms of physical recovery used to improve people's motor skills after an injury, an accident, or while suffering a motor disease. The rehabilitation process is carried out by a clinician and is well-established in health centres around the world. Despite its effectiveness, physical rehabilitation has several difficulties in engaging patients in the multiple therapeutic sessions required to obtain measurable results. The lack of timely feedback and an uninterrupted collection of variables that allows measuring therapeutical results are widely known problems in conventional rehabilitation. Researchers in the area conclude that motivation is the most influencing variable in the therapy progress with low rates ending up in the withdraw of the rehabilitation process. Novel technologies that use gamification strategies to encourage patients to "play" during the rehabilitation session have popularized in the last decade instead of count repetitions. The motivation provided by the goal-oriented nature of gaming applications, the visual and auditory cues that provide the narrative, rewards, and feedback related to progress, and the novelty of these interventions, attracted the attention of engineers and clinicians as a complementary approach to restore and maintain motor capabilities of people. Although investigations have been revealing positive benefits, there is a need for a greater understanding of the relationship between the different characteristics of these systems (influence of the virtual environment, measurement variables, rehabilitation protocol) and the impact with the physical therapy aided by gaming systems.

Therefore, this thesis aims to propose a complementary rehabilitation therapy based on human-computer interaction (HCI) paradigms that explore i) virtual rehabilitation techniques, integrating sophisticated and (nowadays) accessible virtual reality (VR) technologies, ii) low-cost physiological sensors, namely armband-like surface electromyography (sEMG) and iii) system intelligence through biocybernetic adaptation techniques, to provide a novel virtual rehabilitation technique. First, following medical advisory, we designed and developed a "serious" videogame for upper limbs rehabilitation of patients diagnosed with a motor disorder. Second, we integrated physiological muscle fatigue detection through collecting sEMG signals; thus, the gaming system changed the game's difficulty to maintain the player in a recommendable state of fatigue while performing muscle contractions. Two pilot studies were developed in order to prove the feasibility of using the physiological system as complementary rehabilitation therapy. The first aimed at investigating the effects of using the designed game with immersive VR systems (e.g., Head Mounted Displays) once compared with conventional flat screens in terms of system usability, game performance and perceive player's fatigue. A second study was developed to prove the feasibility of using the designed videogame to complement a conventional physical therapy of people affected with monoparesis/hemiparesis (M/H). Finally, pattern recognition algorithms were used looking at classification techniques that allowed an accurate and quantitative measurement of the player's performance during the interaction with the videogame by using machine learning approaches.

We proved the feasibility of using the fatigue-aware gaming system as a complementary tool to conventional motor therapies, as well as quantified the improvements in patient's motivation, game user experience and game performance. We also revealed the differences in specific outcomes in physical therapy (e.g., perceived fatigue) and game experience between the immersive VR system and the game displayed in conventional flat screens. Furthermore, we found that the use of support vector machines as a classifier of a database of sEMG signals of impairment subjects combined with game variables may be the most suitable algorithm to be implemented as a measurement of the player's performance.

Keywords: Motor rehabilitation therapy, physiological computing, sEMG, serious videogames design, muscle fatigue, virtual environments.

1. Justification and State of the art

1.1 Justification

The muscles produce a distribution of electrical potential over the skin and the record of this signal is called surface electromyography (sEMG). During sustained or intermittent contractions, the sEMG signals undergo changes that are referred to as mechanical and myoelectric manifestations of muscle fatigue [1]. There are many definitions of muscle fatigue; physiologically, low intracellular muscle pH has traditionally been considered the dominant factor causing fatigue, and acidosis caused by the accumulation of lactic acid was thought to cause fatigue in active skeletal muscle [2], [3]. Nevertheless, myoelectric manifestations of muscle tiredness are defined as changes in features of the sEMG during sustained muscle activity [1]. Those changes can be measured through parameters and algorithms used to process the sEMG signal in both time and frequency domains [4]. In the time domain, it uses the RMS (Root Mean Square) value, which is the square root of the average energy of the signal. From the beginning of the study of the SEMG signal, a consistent increase in the amplitude of the EMG signal collected with surface electrodes was observed. Pioneers in this area have attributed this increase to the recruitment of additional motor units. They believe that as a contraction progresses, additional motor units are required to maintain a constant level of force [5]. sEMG signal amplitude itself is rarely used as an indicator of muscle fatigue. It is used in combination with other signs, often with parameters of the spectral analysis. In the other side, the frequency domain has two primary fatigue descriptors that have been widely used, the mean frequency (MNF) and medium frequency (MDF) of the power density spectrum [4], [6], [7]. During isometric contractions, the shape of the motor unit action potential (MUAP) is affected by the pH changes related to fatigue. Because of it, the velocity of conduction over the muscular fibers decreases. Therefore there is a decrease of the MNF and the MDF and a compression of the power density spectrum of the sEMG signal.

Although fatigue is a well-known physiological phenomenon in physical rehabilitation [1], [6], [7] its measuring process to improve therapy's personalization in regular routines possesses several challenges regarding real-time physiological signal processing and the associated hardware economic costs [4]. When the patient practices resisted training, the physician must be alert to signs of fatigue, which can lead to the change of exercised muscles or lead to injury. The dose of resisted exercise is often limited to the fatigue supported by the patient: *the point at which a patient must interrupt the activity or sacrifice the way they execute it* [8]. In general terms, to produce fatigue states, sustained contractions have durations of two minutes long that should be performed at certain intensity levels. The contraction's intensity can be measured as a percentage of the maximum voluntary contraction (MVC) [9]. For instance, specialists recommend exerting at rates higher than 30% of the MVC but lower than 70%, to stress the muscles and produce measurable results without leading to exhausting fatigue levels [8].

Additionally, the 30% to 70% exertion range for isometric MVC should be performed in time intervals of 20-30 seconds. These levels are particularly recommended in the case of isometric contractions (both joint angle conservation and muscle length) that are sustained over time and do not alter the range of limb mobility. Isometric exercise is a valuable rehabilitation tool when joint movement is uncomfortable or contraindicated during immobilization or when there is a weakness of the underlying tissues to the injured area [8], [10]. However, due to many physical conditions and psychological factors present in conventional rehabilitation scenarios, the therapies typically failed in accomplishing active monitoring of muscle fatigue levels and providing adherence to treatment [10]. For that, novel human-computer interaction (HCI) paradigms that explored virtual rehabilitation techniques have been developed. The paradigms integrate sophisticated and (nowadays) accessible VR technologies, interactive sensors (e.g., motion trackers, haptics, wearable sEMG) and multimodal physiological sensors for active monitoring of the therapeutic effects [11].

Rojas and colleagues [12] point out three critical factors for virtual rehabilitation:

i) Enjoyable repetition process employing integrated interactive technologies that improve the execution of motor skills;
ii) ii) Feedback to produce intense and massive stimuli of the interaction;
iii) iii) Motivation and/or presenting the therapy pleasantly and attractively.

Also, virtual rehabilitation provides a very controlled way to deliver the therapy allowing high levels of content personalization. Virtual rehabilitation has become a significant area of research due to advances in game development and computer graphics [13]. Thanks to the advancement of physiological computing technologies, some virtual rehabilitation systems that use body signals have been developed in recent years [14]. These types of virtual activities integrated with physiological sensing provide players with feedback on their session performance as well as constitute a mechanism for quantifying significant physiological responses during the interaction. However, only a few research approaches have used physiological information as a dynamic adaptation strategy in the so-called biocybernetic loop construct [14].

Mainly, sEMG signals have been widely used in biofeedback therapies [15], although examples of biocybernetic applications based on muscular electrical activity are scarce [14]. Thus, although pioneers in physiological computing have developed many physiologically adaptive games, they have not explored the combination with VR environments for rehabilitation therapy enhancement. While biofeedback uses physiological signals to mirror inner states and physiological self-regulation, the biocybernetic loop technology proposes a more sophisticated use of this information via modulating the virtual therapy activities with detected human states, such as fatigue or workload [16]. In the next section, we provide a theoretical framework of relevant concepts related to this research and a literature review in the field of virtual protocol rehabilitation that uses sEMG parameters to either mirroring physical states (biofeedback). Furthermore, to extend HCI communication pathways or to enhance the therapy personalization employing biocybernetic adaptation [16].

1.2 Theoretical Background and State of the Art

1.2.1 Human-computer interaction

The concept of Human-Computer Interaction (HCI) involves the design, implementation, and evaluation of interactive systems in the context of a task and the user's work. By user refers to an individual user, a group of users working together, or a sequence of users dealing with a job. By computer refers to a technology in the range of an embedded system, as a personal or desktop computer. By interaction refers to the dialogue between the two previous agents that allows control and feedback through the development of the task. The purpose of interactive systems is to help the user achieve a goal within the domain of an application. The use of interaction models allows researchers to understand what is happening in the interaction and identify possible difficulties[17].

1.2.2 Physiological Computing Systems

Computational physiology is a term used to describe a technological system that can monitor human physiology directly and transformed it into a control input for a computer system [18].

1.2.2.1 Biofeedback

It is appropriate to say that biofeedback is the grandfather of computational physiology systems. Biofeedback is the technique of making unconscious processes of the body perceptible to the senses. In this process, the physiological signals of the users are measured by sensors and processed in information about their body, and then they are returned to the user in different ways, auditory, visual, haptic, or multimodal [14].

1.2.2.2 Biocybernetic Loops

A category of computational physiological systems is concerned with the self-perception of dynamic processes that occur within the body and contribute to the awareness of the physiological state [14]. Within this category are adaptive systems, within these are biocybernetically adaptive systems, called biocybernetic loops, focused on monitoring brain and body states to improve performance for well-being or a specific task [16].

The biocybernetic control loop describes the closed curve system that receives psychophysiological data from the player, transforms it into an automated response, which then shapes the future of the player's response [16]. This system works in a closed control associated with an actual state; therefore the system has a specific goal and is designed to influence the user's psychophysiology to set that objective state. Not only serve as an adaptation tool for improving the levels of fun and attractiveness of a videogame, but also a tool for the exploitation of computer-assisted and mediated therapies through video games. Therefore has attracted the attention of multiple research centers in an area called Serious Video Games for Health.

1.2.3 Muscle Interfaces

Currently, many technologies in HCI are well established. Between the different phases of HCI, the researchers in brain-computer interaction (BCI) are the most popular; however, in recent years, a new HCI area is focused on muscle-computer interfaces (muCIs). A muCI is an interface where the user uses the electrical activity of the muscle as an input while is performing several tasks. In other words, in such interaction, people can control a device using its myoelectric signals recorded through surface electromyography (sEMG)[19].

Although the term muCI is relatively new, the use of myoelectric devices that use sEMG electrodes has a long history. The term muCI was first conceived by Saponas et al. [20] while they were demonstrating the feasibility of a muCI using forearm electromyography. According to them, muCI is an “interaction methodology that directly censuses and decodes human muscle activity beyond referring to the device’s performance."

1.2.3.1 Surface Electromyography

The myoelectric signal is the electrical manifestation of neuromuscular activation associated with a muscular contraction [6]. Electromyography is the recording and interpretation of muscle action potentials [7]. Nowadays, surface electromyography (sEMG) is a specialized field in using electronic devices to measure muscle energy, analyze data, and bring reliable results.

The sEMG has many applications, including assisted treatment, evaluation of progress results, rehabilitation, ergonomic design, sports training and research [1]. The use of sEMG has many advantages. Data collection with sEMG provides safety, ease and a non-invasive method that allows objective quantification of muscle energy. It is not necessary to penetrate the skin and record the motor unit to obtain useful and meaningful information regarding muscle [7]. It is important to remember that sEMG is not a measure of strength, neither the amount of effort or the length of a muscle. It is merely a measure of the electrical activity understood as the intracellular action potential and its propagation.

1.2.3.2 Muscular Fatigue Detection using sEMG

It is known that during contractions at a constant force, the factors that affect the features of the signal can be reduced to fatigue indicators, such as the change in amplitude and frequency spectrum [6].

The main component of fatigue analysis through the measurement of the muscular electrical signal is the identification of prominent features of the sEMG data. In the literature two main components are established and presented as biomarkers of fatigue in time and frequency the RMS (Root Mean Square) value, which is the square root of the average signal energy, and the average frequency (MNF) and the median frequency (MDF) values of the power density spectrum of the frequency curve [4], [6].

Generally, before doing the primary signal processing, a pre-processing step is always applied, consisting of the filtering of the signal. For the sEMG signal, the following filters have been established [1], [21]:

- A reject-band Notch filter between 59Hz and 61Hz, as the rejection of the power line frequency
- A Passband filter, usually Butterworth, of minimum second-order, between 10Hz and 300Hz, where the highest signal energy is found. However, Depending on the sensor's sampling frequency, which can vary from 200Hz to 1000Hz, the amplitude of the passband may vary.

In the post-processing, it is found temporary, time-frequency, frequency and non-linear analysis techniques. In the time domain, the main changes in the single-channel sEMG signal are the modulation of the standard deviation of the signal (RMS) and spectral changes due to muscle strain or fatigue. As the muscular effort increases, the amplitude of the signal grows. However, the RMS value is rarely used alone as an indicator of muscle fatigue. Generally, its extraction is done through sliding windows, characterized by having overlap between each iteration of the window. The windowing of a signal in the time domain results in smoothing it [1].

If the contraction of a muscle is sustained strongly enough for an extended period, the conduction velocities of the action potentials along the muscle fibers are reduced and the muscle potential begins to discharge less frequently. During the first part of the contraction, the median frequency of the spectrum can be slightly above 100 Hz, while during muscle fatigue, the power density spectrum suffers a downward shift in its shape, and this frequency can be found at approximately 55 Hz [7].

The power density spectrum (PDS) of the sEMG is used in the frequency domain. The PDS shows the curve's height at any given frequency and indicates how predominant is the energy of the muscle in that frequency. For instance, when a muscle gets contracted, a filter between 20 Hz and 300 Hz will represent almost all the energy in the muscle spectrum, if a filter between 100 Hz and 200 Hz is used, only a portion would be represented [7].

The measurement of this frequency contraction can be done with different methods. The method based on the Fast Fourier Transform (FFT) is the most used. Finally, it was decided to use the medium frequency of the PDS as the main feature of the spectrum since it is less sensitive to noise, to aliasing (phantom signals), and in most cases, it is more susceptible to biomechanical and physiological factors that occur in the muscle [6].

1.2.3.3 Pattern recognition of sEMG signals

The non-stationary and stochastic nature of sEMG signals is especially considered in the classification task. Nevertheless, in isometric contractions, it has been shown that in short intervals of the signal, this can be assumed quasi-stationary [4], [6], [7]. Therefore, the temporal and frequential features are used to describe the behavior of this signal, and features that can better characterize patterns of muscular activity play a key role in classification tasks. Feature selection and extraction can be used to speed up the learning process, incentive the classification accuracy, improve model generalization capability [22]. The extraction of these relevant features can be developed through different methods. The Principal Component Analysis PCA is one of the most used, which seeks a space of lower dimensionality, known as the principal subspace [22]. The

goal is to represent data in a space that best describes the variation in a sum-squared error sense [23].
On the other hand, RELIEFF (a Relief-based feature selection algorithm) is considered one of the most successful algorithms for assessing the quality of features due to its simplicity and effectiveness. It is a classical supervised feature selection algorithm in the filter model [24]. The main goal is to accomplish the attributes estimation according to how the values distinguish among instances that are near each other. For that purpose, RELIEFF for a given instance searches for its two nearest neighbors: one from the same class (called nearest hit) and the other from a different class (called nearest miss) [24]. The evaluation of the classifiers is often used to find the best one. This evaluation is made using the accuracy, defined as how many times the classification method was right with the prediction of the classes [22], [25].

On the other hand, the use of classifiers of the signal sEMG has been widely used to study patterns of neuromuscular disorders [26], as well as for the diagnosis of fatigue states in combination with other optimization methods, and the creation of human-computer intuitive interfaces[27]. The tool most used by researchers is the support vector machines (SVMs), which have demonstrated high precision in the classification of this type of signal for differentiation of hand and arm gestures [28]. Although the classifiers for sEMG signal had been worldwide studied, there is no evidence of which type of classifier could be the best for sEMG muscle fatigue descriptors in together with videogame variables taken under protocols of virtual rehabilitation.

1.2.4 Virtual Rehabilitation and Serious Games for Health

1.2.4.1 Serious Games

Serious games is a term that has been used to describe video games that have been designed specifically for training and education [29]. Since early years for this century, the serious games for health area has been in development, where initial research proved the efficacy of games to change essential health behaviors, suggesting that the strengths of these tools should be seriously considered when designing interventions in health care [29].

Within the serious video games for rehabilitation, two large groups can be found: for cognitive rehabilitation and physical rehabilitation. The latter includes rehabilitation of upper and lower limbs, spatial and perceptual training, balance, wheelchair mobility, functional activities and daily. The latest reviews developed by [30], [31], specify the design and therapeutic recommendations to create this kind of videogames, highlighting the importance of taking into account for whom is being developed the system and the final goal of therapy.

Thanks to the advance of computational physiology, in recent years, some serious video games that use body signals have been developed. Such videogames provide users with feedback on their activities and provide a mechanism for quantifying physiological performance during the interaction [32]. Some of these systems are used in controlled environments, such as clinics or rehabilitation centers; however, new systems seek to enable their use outside these environments.

1.2.4.2 Virtual Reality (VR)

In simple terms, VR can be defined as a virtual or synthetic environment that gives a person a sense of reality. This definition can include any artificial environment that provides a person with the feeling of "being there." VR generally refers to computationally generated environments.

The recent success of the integration of VR with the field of medicine and rehabilitation shows the technological potential to allow patients to face challenging, safe and ecologically accepted environments [12]. Although VR systems depend on hardware and software, its use in the context of rehabilitation requires clinicians to make decisions about appropriate interventions for the patient, the implementation of the treatment parameters, and the progression through different levels of tasks or games.

1.2.4.3 Virtual Rehabilitation and Motor Disorders

Hemiparesis and monoparesis are the main sequelae of different neuromuscular disorders, such as stroke, cerebral palsy and muscular dystrophy; as they also derive from brain trauma and heroin addiction. These motor disorders are caused by damage to the upper motor neurons and are known as the superior motor neuron syndrome (MNS)[33]. The motor impairment derived from these disorders is caused by a characteristic known as muscle spasticity, which refers to "*a motor disorder characterized by a speed-dependent increase in the tonic stretch reflex (muscle tone) with exaggerated tendon pulls, as a result of hyper-excitation of the stretch reflex*" [34]. There is a causal relationship between spasticity and people's independence and activity limitations; it is also claimed that spasticity leads to contractures, pain and weakness.

Given the increase in low-cost systems that use VR technology for the rehabilitation of major diseases from which spasticity derives, such as stroke, the treatment with virtual rehabilitation has been explored in the last decade. In [35] used VR combined with transcranial stimulation to treat spasticity in children with cerebral palsy and improve motor control in gait. In [36] used gestural therapy with simple games in VR to improve neuronal reorganization in motor rehabilitation in people with stroke, proving that this type of treatment generates functional changes associated with the recovery of motor skills. Furthermore, it is relevant to mention the work done by Da Silva Ribeiro et al. [37], where using the Wii console and its traditional games, the authors performed motor rehabilitation activities in patients with hemiparesis after suffering stroke. Moreover, they compare the improvement resulting from these activities against the improvement with conventional therapy activities. Using a randomized blind protocol with 30 patients, the authors assessed sensorimotor function and improved quality of life, finding that both therapies are effective for the treatment of people with hemiparesis. Finally, it is worth mentioning initial works such as those by Juarez et al. [38], where they evaluated the effectiveness of electromyographic biofeedback in reducing spastic hypertonia in a hemiplegic patient. They showed a significant reduction in the degree of spastic hypertonia due to learning obtained through exposure to the electromyographic signal.

Similar to what it is proposed to develop in this thesis, in recent years, different investigations have explored VR therapy together with physiological sensors as a successful alternative for motor rehabilitation. Like in [39] the authors developed a systematic review of VR therapy aimed at physical rehabilitation of older adults, where it is found that most of them are based on balance and flexibility exergames. Those games use motion capture data delivered by sensors such as the Wii, Kinect and pressure platforms to evaluate the improvement of functions such as postural control and gait.

The review and analysis performed by Levac et al [40] of the use of VR as a therapy tool reveal the components of this technologies that support and improve the rehabilitation process, for instance the motivation, repetition and feedback, components that also can be found in works as [12], [41]. Furthermore, those researchers in VR environments point to three critical factors for its application in rehabilitation: 1) Repetition to improve the execution of motor skills. 2) Feedback to produce intense and massive interaction stimuli. 3) Motivation, presenting the therapy pleasantly and attractively. The applications of the sEMG signal in virtual environments have not been left behind. Thus, in [42], the authors design a system based on MoCap, sEMG and VR, where they develop a VR videogame that uses the myoelectric signal as the control of objects within it. In [43], they study a videogame developed to perform basic tasks and the authors analyzed their effect on the subsequent use of a prosthesis in activities of daily living. The tasks were oriented to caught objects of different sizes and fragilities. They concluded that all subjects undergoing training with the video game performed better in the use of the prosthesis than those who did not perform the training. This study demonstrates the effects of the transfer of a serious videogame to activities of daily living.

2. Research Problem and Research Questions.

This project is proposed as a solution to the effectiveness problem of physical therapy in patients with muscle disorders in the upper limbs, particularly the adherence of patients to rehabilitation programs. The lack of timely feedback and an uninterrupted collection of variables that allow quantification of the results of therapy are widely known problems in conventional rehabilitation [44]. Based on the above, this research seeks to evaluate the effectiveness of an intervention that combines traditional rehabilitation with assisted rehabilitation with the called Force Defense (FD) videogame and the adaptative system created with it (currently version uses conventional TV-LED and VR-Glasses). On the other hand, to our research is also essential to find variables searching for objective quantification of the therapy progress. Therefore, the following research questions are established:

1) What are the methodological aspects that should be considered to design a serious videogame for motor rehabilitation in upper limbs?
2) How do the virtual environment features, as immersion and visualization mode, influence player's game perception and their performance?
3) How does the player's interaction with the serious videogame FD, influence rehabilitation therapy in terms of game experience and perceive muscle fatigue?
4) What is the effect over measured and perceived fatigue on users with (M/H) by a motor rehabilitation program based on the FD videogame?
5) Is there any measurable change in upper limbs mobility in patients with M/H after a rehabilitation program based on the FD videogame?
6) Is there a pattern recognition classifier that can be used to quantify therapy improvement by using sEMG and game variables?

Hypothesis

1) A mixed methodology, which combined well know videogame design guiding, the therapeutic requirements for motor disorders, and physiological adaptation, contain the appropriated aspects to create a serious videogame for motor rehabilitation of upper limbs.
2) The immersive feature and the virtual scenario in which the videogame FD is played can improve the player's game experience, as well as directly influence their muscle fatigue perception.
3) The variables, within the videogame, can affect the positive or negative user experience when interacting with the videogame.
4) The fatigue perceived by users, both healthy and impairment, will be reduced when interacting with the game, thanks to the characteristics of motivation and immersion of it.
5) The rehabilitation therapy supported by the interaction with the videogame will make impairment subjects diagnosed with M/H improve their degree of spasticity according to the Ashworth scale and will achieve an improvement of 5% in their range of motion according to the mobility test.
6) The literature review suggests that the Support Vector Machines (SVMs) are the appropriate pattern recognition algorithms to be used in classifications task for sEMG signals and should work appropriately combined with game variables.

This project is approached by a research that aims to improve the classic virtual rehabilitation games by using advanced physiological computing techniques. Firstly, we described the methodology used to design a serious videogame for upper limbs motor rehabilitation. Secondly, are presented two pilot studies where we proved the feasibility of using the created system as a complementary tool for motor rehabilitation. Finally, it is described a classifier based on pattern recognition to establish a metric to quantify users' performance to understand the effects of the therapy better.

The designed system allows the collection and evaluation of the sEMG signal in order to know the levels of muscle fatigue of players within the VR system in order to customize and improve the patient's motivation in physical rehabilitation sessions. Moreover, the system allows to assist the clinician in the evaluation of the recovery process and eventually may be used for telerehabilitation therapies.

2.1 Contributions

The contributions of the thesis in the fields of HCI, virtual rehabilitation, serious games and physiological computing are described as follows:

- We presented a designed methodology used for the creation of a serious videogame for motor rehabilitation of upper limbs that used sEMG as the human-computer interface to control the game, to monitor and react accordingly, the players' fatigue levels
- We reveal significant insights for engineers, physical therapists, and game designers to create more personalized and adaptive solutions for motor rehabilitation using low-cost wearable sensors and physiological computing techniques (e.g., biocybernetic adaptation).
- Using the principles of physiological adaptation, we created a biocybernetic loop that was integrated into the videogame and used sEMG signals to adapt the game difficulty and influence directly the muscle perceived fatigue of players.
- We revealed new perspectives about the effects of VR and highly immersive environments on perceived and measured muscle fatigue, and how these technologies might enhance immersion, engagement, and flow in virtual rehabilitation therapies.
- We prove the high usability of virtual environment setups, thus demonstrating the feasibility of the low-cost solution provided, which can be further explored by clinicians in motor rehabilitation therapies.
- Together with physical therapists, we designed a combined therapy that integrated the biocybernetically adaptive game into conventional therapies, proving its potential of being used in upper-limb rehabilitation of people with M/H.
- This research includes the use of pattern recognition algorithms as a method to quantify the therapy progress and the patient's performance, finding the SVM as the appropriate technique to classify information of sEMG signals combined with videogame variables.

3. Game Design for Motor Rehabilitation

This chapter exposes a design methodology used for the creation of a serious videogame for motor rehabilitation of upper limbs using surface electromyography (sEMG) as the human-computer interface to control the game and monitor the players' fatigue levels. By utilizing an adaptation mechanism from the physiological computing field, called biocybernetic adaptation, the videogame can adapt the game difficulty based on measured fatigue levels. The game design was also informed with therapeutic recommendations and followed an iterative design process.

3.1 Designing a fatigue-aware videogame for upper-limb rehabilitation

Due to the complexity of the pathologies, the recovery is not performed by a single therapist. In order to have a holistic approach to a particular patient, a team of clinicians is needed to provide different points of view of an individual pathology [11]. The development of serious games requires a similar healthcare team, often a physiotherapist or a clinical expert (e.g., physiatrist, Kinesiologist), complemented with game designers, software developers, and biomedical engineers. The clinical expert and exercise therapists provide the information related to the clinical aspects to consider while the game design team carried out the gamification of the medical intervention. Our process was developed with the primary goal of defining how the mechanics, technology, story, and aesthetics of a game work together to create a player experience capable of entertaining patients while providing an effective rehabilitation process [45]. In this section, we present our design process from the elicitation of therapeutic requirements to the final design of the balancing layer for physiological adaptation.

3.1.1 Therapeutic requirements

The main control signal to interact with the videogame was chosen to be the sEMG signals since the therapeutic goal was based on the stimulation of muscle contractions [7]. A physiatrist medical expert and two exercise therapists were included in early stages to define the system requirements in terms of therapeutic benefits clearly; they are listed as follows:

3.1.1.1 Complementary instead of alternative

The proposed system was thought of as a complementary intervention to conventional physical therapies [44]. Due to the complexity of the therapeutic intervention, the rehabilitation videogame is developed to be used at the start of conventional therapy. The patients can interact with it for 10 minutes for each arm, which is the typical time used to constantly exercise a single muscle, in our case, the biceps [10].

3.1.1.2 The relevance of fatigue in rehabilitation processes

Healthcare professionals were very persistent in highlighting the importance of muscular fatigue in motor rehabilitation processes. Although physicians should be alert to signs of fatigue, this is not always possible since conventional sEMG sensors are very cumbersome for clinical settings. Fatigue can lead to damages of exercised muscles or lead to an injury. The rehabilitation process should be aware of fatigue levels [10].

3.1.1.3 Isometric instead of isotonic contractions

Isometric exercise is a valuable rehabilitation method when joint movement is uncomfortable or contraindicated after an injury or a surgery. These isometric contractions are exerted at sub-maximum levels between 30% and 70% of the maximum voluntary contraction (MVC) with a duration between 20 to 30 seconds, and the same time to rest, following the recommendation for first stages of physical rehabilitation [10]. According to the therapist advisory, for patients with a motor disorder, the proper range of MCV is 40%, a maximum 70%, and the periods of muscle work should be equal to the periods of rest. That is why we choose to design an exercise of 15s of contraction and 15s of rest, starting at 40% of the patient MVC. Nevertheless, due to the game could also be used for healthy people, we also establish an exercise for this requirement, with a contraction time of 15s and a rest period of 10s, starting at 60% of the MVC. Moreover, the quality of the sEMG signal collected on isometric contractions allows performing the signal processing searching for the muscle fatigue index that will be used as a physiological state for a feedback mechanism in the videogame [6], [7].

3.1.1.4 Therapy quantification and calibration stage

A quantitative evaluation of the therapy progress is needed. Both subjective and objective metrics should be considered to quantify the possible benefits of the serious game designed accurately. Finally, a calibration stage should be defined where individual capacities can be considered before the game starts. Moreover, the game should implement mechanics and strategies that ensure a player performance quantification.

3.1.2 Iterative Game Design

3.1.2.1 State of the art.

An extensive revision of the literature was performed searching for previous work related to sEMG controlled videogames, videogames for motor rehabilitation, and exercise type of task to control videogames. The main common feature found was the simplicity of the proposed interaction to control the game elements [42], [46]–[48]. Although daily life activities have been widely used, we believe transporting players to magical words and monster-like enemies can be beneficial to improve patient's engagement and motivation. All in all, we wanted to design a game more than a simulation. Moreover, the simplicity of activity is need due to in early stages of physical therapy the contractions required to gain muscle force are isometric ones, and those contractions do not require much joint movement.

3.1.2.2 Brain Storming sessions

Working together with a senior researcher in videogames for health, a physiatrist medical expert and two exercise therapists, we concluded that the interaction in the virtual environments should be based on simple actions such as throw, catch, defend, hit, or shoot [43]. The chief game mechanic proposed was a power-up that will reward users' desired muscular physical intensities

3.1.2.3 Elemental tetrad.

Proposed by Schell [49] is a game design methodology that suggests synergies between four game elements called game mechanics, aesthetics, story and technology. Our game design process was strongly influenced by a clear definition of those elements and their interconnected interactions inside the game. The tetrad elements are defined as follows:

Game Mechanics. Establish the goal of the game, and what happened if the player achieves it. In our case, the mechanics are defined based on the therapeutic requirements and the use of power-ups. In this element of the tetrad, we defined:

- Space: where the actions will take place, in our case, an abstract circular space with two small circles that represented the spaces for the main player and his enemy was envisioned.
- Time: A dimension to define the duration of game scenes and states, for instance, how many times will the enemies attack, how much time will take the character to die. In our case, the muscle contraction duration and the rest duration were the key factors to have in mind.
- Objects: the elements which will mediate the interaction, in our game, the characters, the powers of the characters and the control signal were the main objects to consider.

- Actions: the verbs that defined the game mechanics, for instance, to attack, to defend, to win, to die.
- Rules: the rules establish the consequences of game actions. The rules in our case were chosen following Parlett's rule analysis [49]. This model (Figure 3.1) considers fundamental rules; for instance, the game can only be played if a calibration stage has been made. In figure 3.1 can also be seen the operational rules, such as the constant muscle contractions required to users, and behavioral rules, for instance, reduce the user's life if the muscle contractions are not performed.

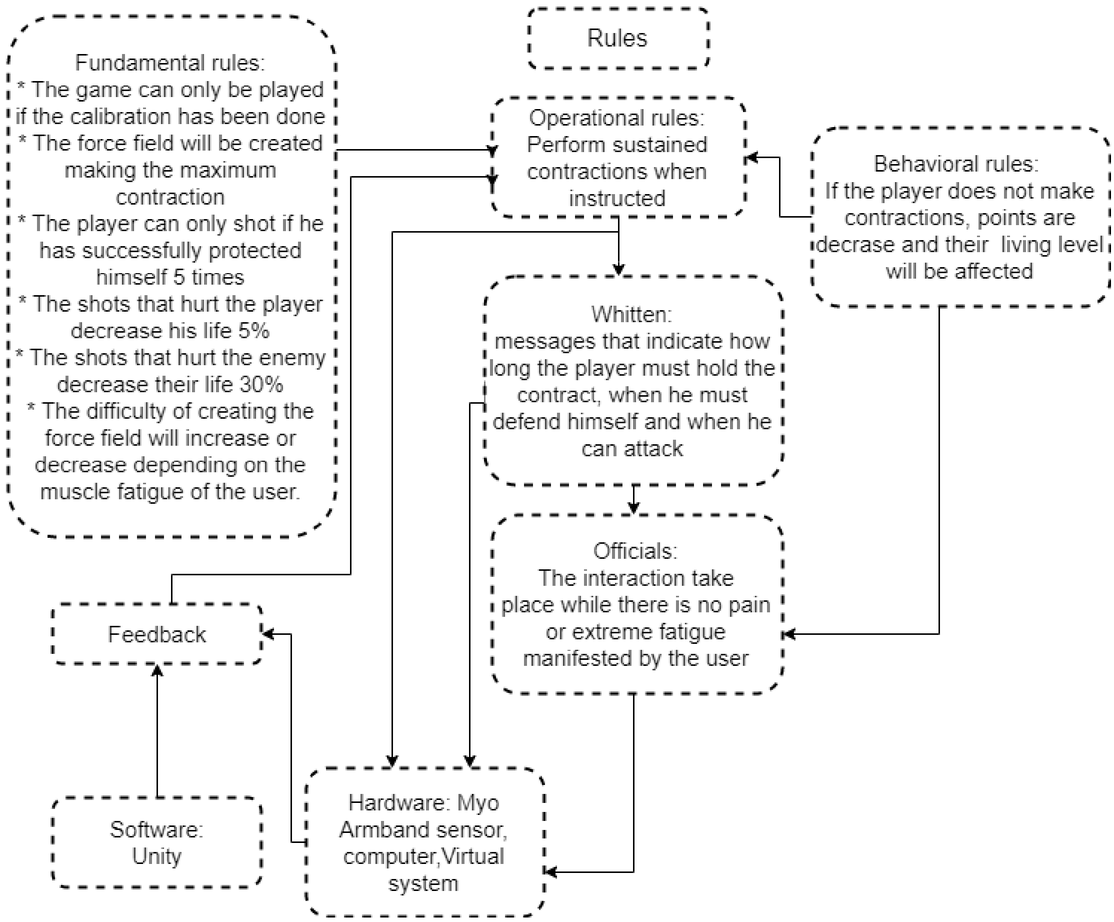

Figure 3.1. Rules according to the Parlett's model: Fundamental rules, operational rules, behavioral rules, written and officials. The rules are accomplished through the hardware and software that allows data collection and audiovisual feedback. VR is optional.

Aesthetics: This feature refers to how the game sounds, feels and looks, and has had the closest relationship with the player's experience. We decided to check the freely available scenarios, modeling tools, and graphical assets in the game engine stores, due to the time limitation to model the virtual environments. An extra-planetary environment with mountains and lakes was chosen to recreate our virtual environment and characters.

Story: Initially, the game was defined in a fictional world where the main role character is trapped in the middle of a lake. The character must defend himself/herself of a monster who is constantly attacking, and the way to do it is through creating a force shield that will allow counterattacks. The player is introduced to the fictional world and is encourages to defeat the monster to save himself and scape the world.

Technology: It is related to the materials and interactions that make the game possible, is the medium in which the aesthetics take place[shell]. After analyzing different game platforms and wearable sensors for interfacing the EMG signals, the Myo Armband was chosen as a physiological sensor and Unity3D as the game engine. The Myo Armband [21], [22], is a wearable bracelet that includes eight dry electrodes to record sEMG signals at 200 Hz sampling frequency. Moreover, Unity3D is free, has a very active developer community, has a plugin for the Myo connection and allows the use of C# as a programming language. The game was designed to be run and visualized on a personal computer and also in the HTC Vive VR system.

3.1.2.4 Storyboarding.

It is a pre-planning of the storytelling made by sketches [50]. A sequence of sketches was built considering the different scenes where the user should interact with the game objects. According to the concept found in [20], the storyboard for the muscular controlled videogame was developed following a sequence that can be seen in figure 3.2.

Figure 3.2. Storyboard of the videogame. A)First Scene. B) Calibration Scene. C) Arm Choosing. D) The monster is shooting the main character. E) Elements in the screen: points, life, power. F) First-person view. G) The monster receiving an attack.

3.1.3 Dual flow model

Several studies suggest that repetitions while giving feedback and motivating the patients during the training process, while providing feedback and motivating the patients during the training process, can have a significant effect on the patients' skills recovery [51]. Research has shown that a psychological status called flow reflects the enjoyment that game playing produces and it has a positive influence on motivation and learning [3]. By following the classic flow theory, Sinclar et al. [52] developed an extended model for Exergaming Exergames that encompasses an additional flow dimension called effectiveness, which balances player's fitness levels with the Exergame intensity. We used this dual flow model in the game design process as a mechanism to control the challenge through the biocybernetic adaptation technique [16], as used before, through cardiovascular sensing in Exergames for older adults [53].

3.1.3.1 Physiological Adaptation

By using physiological computing principles, the biocybernetic loop construct allows the integration of an artificial software intelligence layer: physiological awareness. In our case, we are interested in detecting fatigue levels of players unobtrusively to, therefore, adapt game variables to maximize physical performance. Thus, the purpose of the biocybernetic loop is two-fold: i) control the users' contraction levels by influencing players to exert at the recommended levels and ii) react to the users' fatigue states to minimize its impact on the game performance.

The creation of the biocybernetic loop to provide physiological intelligence was developed following the stages proposed by Fairclough and colleagues [16] and are described below and resume in figure 3.3.

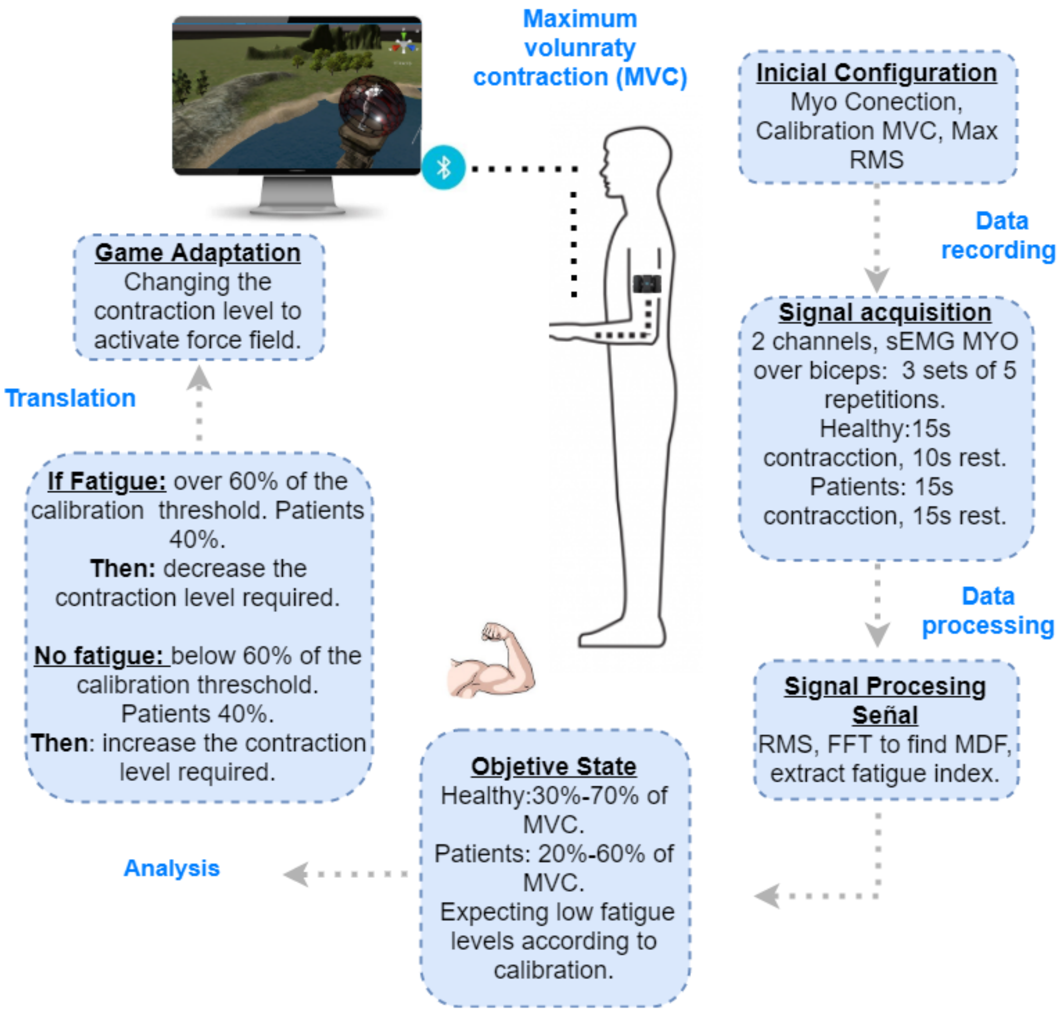

Figure 3.3 Model of the biocybernetic loop created for the physiological adaptative videogame. MVC: maximum voluntary contraction. RMS: Root Mean Square value. FFT: Fast Fourier Transform. MDF: Median frequency of the power spectrum.

Therefore, the biocybernetic adaptation was designed to control the intensity of the muscle exercise according to the clinical recommendations; this is exerting at the desired levels of MVC (healthy people 30%-70%, patients 20%-70%). Figure 3.3 describes the biocybernetic loop design for the physiological adaptation designed for the videogame. The initial configuration stage considers the calibration scene where the player exerts an MVC and with these levels, the initial values of the difficulty are established. The signal acquisition stage is aware of the muscle contractions received through 2 channels from the Myo sensor, where the contractions for healthy people configuration are of 15 seconds with 10 seconds of rest. For people with motor disabilities, the setting is 15 seconds of work out and 15 seconds of resting. During this time a signal processing is developed, looking at the fatigue index, which, depending on the value, will modulate the game difficulty, persuading players to exert in the desired targeted zones.

1) Conceptual Model
The psychophysiological state to detect is muscle fatigue. Following the clinical requirements, it is desired to maintain the player's fatigue at a level that will stress the muscles without over-exercising them. This may be achieved by requesting healthy users to perform contractions between 30% and 70% of the MVC, and impairment users between 20% and 70% of the MVC, for 15 seconds [8]. The biocybernetic loop uses 60% or 40% as a threshold to define whether the fatigue exists or not (defined by experimentation). The calibration process will allow the definition of each individual's MVC values, thus guaranteeing that the adaptation will consider both inter and intra subject variability.

2) Psychophysiological inference
The physiological measure to represent the state of the user is the sEMG signal collected by the Myo Armband sensor. This signal will be processed looking for two specific fatigue biomarkers, the RMS value and the MDF [6], [54]. Previous research revealed the feasibility of the Myo Armband to measure fatigue biomarkers under strict protocols of isometric contractions in biceps brachii [55], [56].

3) A quantified model of the user state
The fatigue state is defined as the values of sEMG biomarkers equal to or higher than 60% of its calibration levels. The non-fatigue state is defined as the values of sEMG biomarkers less than 60% of its calibration level.

4) A real-time model of the user state
During the game interaction, signal features looking for muscle fatigue will be computed after each repetition. The sEMG signal processing is done by following standardized methods [1], [7]. Once the biocybernetic software is calibrated and the thresholds defined, the adaptive system will decide whether to reduce or not the game difficulty level to create the force field. If the variables are above the threshold the game difficulty level will be reduced by 10%, if the variables are over the limit the difficulty level will increase by 10%, being careful to always keep players in the range of 30% -70% or 20%-70% of MVC, if it is a healthy player or an impairment player, respectively.

5) Design of the adaptive interface
The biocybernetic loop adaptation will dynamically modify the game difficulty via tuning the force needed to activate the shield. The modification will be shown with bars that give visual feedback about the real-time force levels.

3.2 Force Defense (FD) Videogame: Final Implementation

FD is a rehabilitation videogame created to provide interactive sessions of physical rehabilitation in upper limbs. The game uses a wearable bracelet as an interface to encourage players to perform multiple controlled isometric contractions while detecting the player's fatigue levels and adapting accordingly. The goal of the game is to survive the attacks of an enemy monster that is constantly shooting acid balls. While creating a protection field through controlled isometric contractions, players can reject their enemy attacks and attack back as a response.

The videogame starts with a short animation that visualizes the scene details such as mountains, the lake, the platform where the monster is stood, and the platform where players are positioned

(Figure 3.4A). Here the player has to choose the game mode, healthy player, or impairment player, due to the difficulty and the interaction is different for each mode. A calibration stage (Figure 3.4B) is used to define initial parameters that will determine the thresholds of the biocybernetic system. Mainly, the game requires players to hold a biceps' contraction for 15 seconds (Figure 3.4C). The maximum contraction level reached in this stage will moderate the contraction level in the main scene.

The user interface elements are over-imposed in a first-person view of the game including i) a life bar that will decrease every time players receive a shoot (Figure 3.4C), ii) a power bar that will increase or decrease proportionally to the strength of the contraction, iii) a point-coin counter that will increase every time players can activate the power-up (Figure 3.4D), and iv) a countdown of 15 seconds that indicates the periods where the players have to perform contractions or rest. During the resting period, the monster will not attack (Figure 3.4E), and players are allowed to relax their muscles while is waiting for the next attacks.

The game ends if the player is killed by the monster, or when players manage to defeat the monster. Finally, the points awarded and the received attacks are shown to the player as can be seen in figure 3.4F. Data logging features were added to record game events and sEMG signals. These signals are kept into an array to be used in diverse statistical states for monitoring the subject´s perseverance into the intervention with serious videogames. The final demo of the videogame can be seen **here**.

Figure 3.4 Force Defense designed in Unity 3D. A) introducing scene, game mode. B) calibration scene. C) the first-person view of the screen elements: points, life bar, and power bar. D) creation of the force field.E) Monster. F) Information about the interaction.

4. Effects of Immersive and non-immersive virtual environments over rehabilitation

The previous game was evaluated to establish how the virtual environment influences users and find the best scenario to generate adherence and motivation to rehabilitation therapies. The experimental protocol considered two different visualization modalities: the non-immersive, which uses conventional screens to display the game and the immersive condition, which utilizes novel VR headsets as an interaction medium. The comparison between the modalities was made in terms of game variables, muscle fatigue perceived, system usability and game experience. We hypothesized that the immersive condition could produce lower levels of players' perceived fatigue and a better game user experience compared with the non-immersive version.

4.1 Methods

4.1.1 Subjects

Twenty-four subjects (12 females and 12 males, Ages 28 ± 5) volunteered for the experiment. Two groups of 12 subjects were created, each group was exposed just to one of the conditions. All subjects were right-handed, and 10 of them had past experiences with body-based interaction videogames. None of the subjects claimed any motor disorder or disability, and everyone was previously informed about the experimental procedure and its associated risks, signing informed consent. The experiment was carried out in two different research facilities, one group of 12 subjects in Portugal, and the other group of 12 subjects in Colombia, under controlled situations. Both groups are homogeneous in terms of age and mental workload, due to all the subjects are university students or university researchers.

4.1.2 Instrumentation

The Myo Armband wearable bracelet that includes eight dry electrodes to record sEMG signals at 200 Hz sampling frequency was used as a physiological interface. The Myo Armband was used due to its portability and non-invasiveness. The signals collected by this sensor were previously compared with the signal of a sensor of standard features in a muscular fatigue protocol and showed comparable accuracies [55]. Depending on the experimental condition (immersive or non-immersive), the videogame was displayed either in a flat-screen or a VR headset (Figure 4.1):

1) The Non-immersive condition: It used an LCD screen of 21.6 inches with wireless headphones.
2) The Immersive condition: It used the HTC Vive VR headset with headphones.

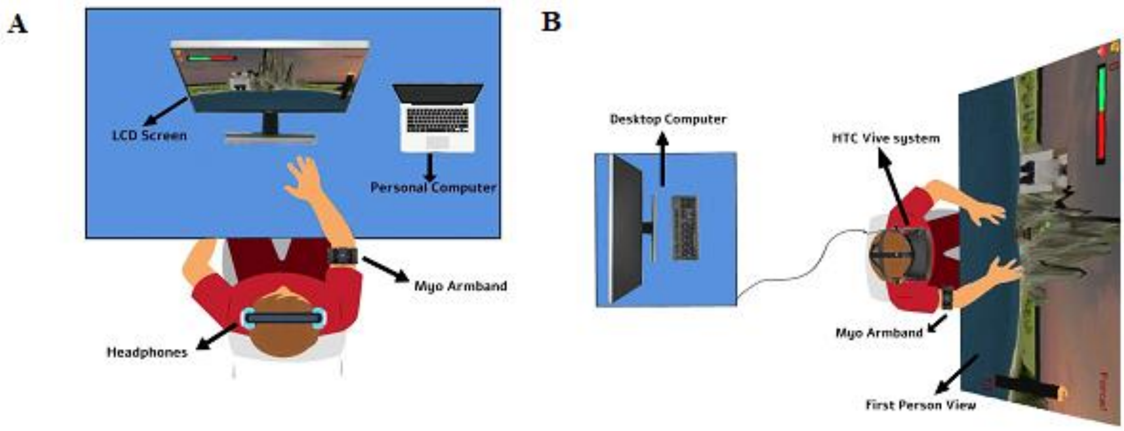

Figure 4.1 A) Figure depicting the non-immersive condition that uses an LCD screen (14 inches), a laptop, the player wearing headphones and the Myo Armband. B) Figure showing the immersive condition setup that uses a desktop computer, the HTC Vive headset that included headphones and the player with the Myo Armband.

4.1.3 Questionnaires and performance metrics

The following questionnaires were applied to the subjects of both groups just after they finished the exposition to the videogame, to ensure the direct correlation between what they experienced with the videogame and the questionnaires responses.

4.1.3.1 Muscle Fatigue Perception

A 0-10 Borg's scale was used to quantify the player´s perceived fatigue levels [57]. The numbers are related to expressions as follows: 0-Nothing at all, 0.5-Extremely weak, 1-Very weak, 2-Weak, 3-Moderate, 5-Strong, 7-Very Strong,10-Extremely strong. This scale was previously used in muscular fatigue protocols [58].

4.1.3.2 Game Experience

The core and post-game modules from the Game Experience Questionnaire (GEQ) [59] were used to investigate players' impressions and opinions about the game experience. The GEQ core module measures seven categories: immersion, flow, competence, positive and negative affect, tension, and challenge. The GEQ post-game module focuses on how the gamer feels after playing the game and measures four aspects: positive and negative experience, tiredness and returning to reality. The last item assesses how hard it is to come back to the real world after having experienced high levels of flow and immersion.

4.1.3.3 System Usability

The System Usability Scale (SUS) is a scale of 10 items for which it was used to evaluate whether the users consider that the system serves the purpose for which it was designed or not [60].

4.1.3.4 Players' performance

The FD videogame was programmed to store in-game data considering a set of variables that reflected users' performance, such as the awarded points, received shots and successful attacks. Overall, players' performance is defined as the ratio between the points awarded and the sum of the points awarded with the received attacks as shown in (1).

$$PlayerPerformance = \frac{Points\ Awarded}{Points\ Awarded + Attacks\ recieved} * 100\%, \qquad (1)$$

4.1.4 Physiological Fatigue

The sEMG signal processing was carried out following the suggestions found in the literature [1], [6], [55], [56]. There is a pre-processing stage covering a normalization phase and a filtering phase using a Butterworth passband filter of fourth-order between 10 Hz and 90 Hz. The main processing is performed using the Discrete Fourier Transform (DFT) to find the fatigue index suggested by the literature, the MDF, which is supposed to decrease with fatigue conditions. Moreover, an amplitude analysis is developed to find the RMS values, also used as a fatigue index.

The signal was stored and analyzed online during the calibration stage, looking for the RMS and MDF values corresponding to the 100 % of MVC. This stage ensures a sEMG signal baseline for each subject; hence the next stages will depend on it. The biocybernetic loop that was created in the previous chapter (section 3.1.3) was used as the difficulty adaptation. Thus, a threshold was established with the healthy people configuration, as 60% of the MDF measured in the calibration stage. Therefore:

1) Under the threshold: fatigue is not detected, then the difficulty of creating the force field will increase in one unit, meaning that the player will have to exert 10% stronger in the next interaction period to be able to create the force shield.
2) Above the threshold: fatigue is detected, then the difficulty in creating the force field will decrease one unit, meaning that the player will be able to exert 10% less intense in the next interaction period to generate the force field.

4.1.5 Experimental Procedure

The study was carried out under controlled conditions. The interaction scenarios were established using the non-immersive or the immersive setups (Figure 4.1). Seated players used the Myo Armband sensor on his/her dominant arm, specifically over the biceps brachii. Guided by the researcher, participants performed a five-minute stretching session focused on the upper limbs. The goal of the FD videogame was explained together with the game mechanics. During the calibration stage, players were asked to relax their arms for 10 seconds before performing a biceps MVC at 90° of elbow flexion for 15 seconds. After the calibration, players were free to interact with the game objects in the main scene. Besides guiding users through the calibration process after every set of 5 contractions, the researcher requested players to rate the subjective fatigue level by using the Borg's scale.

The game experience ended when a) the player won, b) the player lost or c) the player manifested a fatigue level over nine on the Borg's scale. After finishing, responses for the game user experience modules as well as the SUS were collected.

4.2 Results

4.2.1 Perceive Muscle Fatigue

Data from the perceived muscle fatigue reported with the Borg scale was averaged over each set of 5 contractions as can be seen in figure 4.2B. Generally, the immersive condition reported lower values for perceived muscle fatigue. Nevertheless, both groups tend to report higher values as time progresses. Significantly higher scores were reported in the non-Immersive condition ($M=3.3$, $SD=0.87$) compared with the immersive condition ($M=2.2$, $SD=0.72$), using an independent T-test analysis, $t(22)=0.004$, $p<0.05$ (see figure 4.2A).

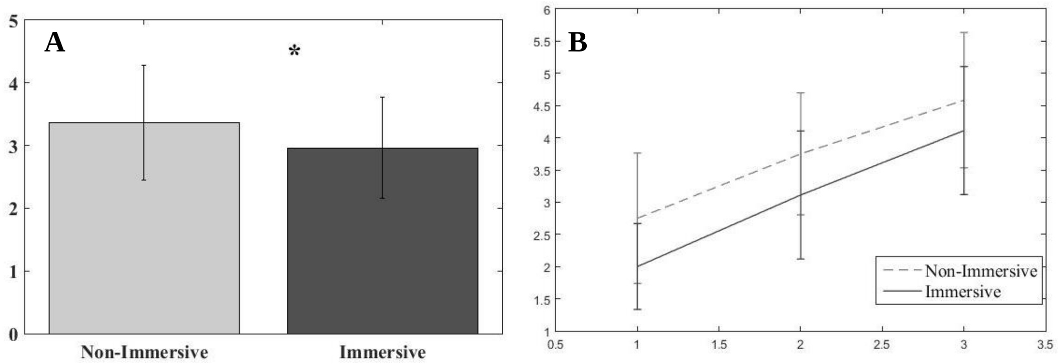

Figure 4.2 A) Averaged values of the Borg’s fatigue scale reported during the *immersive* and *non-immersive* conditions. (*significance p<0.05). B) Averaged scores of the Borg's fatigue scale reported every 5 contractions during the entire interaction for the *immersive* and *non-immersive* conditions.

4.2.2 Game experience Questionnaire

The core module of the GEQ questionnaire was analyzed and compared between conditions (see figure 4.3). As expected, significantly higher values of immersion were found for the immersive (M=2.7, SD=0.51) condition compared with the non-immersive (M=2.0, SD=0.83), t(22)=0.019 p<0.05.

Moreover, positive affect was also significantly higher during the immersive condition (M=3.2, SD=0.46) compared to the non-immersive (M=2.7, SD=0.54), t(22)=0.025 p<0.05. Similarly, negative affect was much lower during the immersive condition (M=0.21, SD=0.29) compared with the non-immersive (M=0.62, SD=0.58), t(22)=0.033 p<0.05. Interestingly, higher values of competence (M=1.9, SD=0.71) and flow (M=3.0, SD=0.76), and lower values of tension (M=0.28, SD=0.34) and challenge (M=1.5, SD=0.59) were reported in the immersive condition compared with the non-immersive counterparts (competence: M=1.6, SD=0.66, flow: M=2.7, SD=0.91, tension: M=0.59, SD=0.64, challenge: M=1.8, SD=0.66), although non-significant effects were found in these domains.

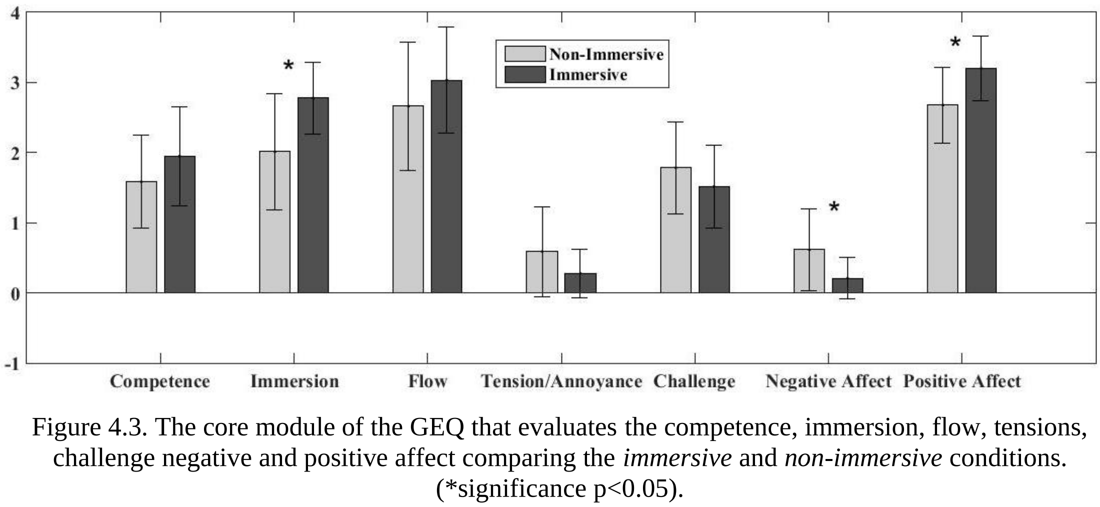

Figure 4.3. The core module of the GEQ that evaluates the competence, immersion, flow, tensions, challenge negative and positive affect comparing the *immersive* and *non-immersive* conditions. (*significance p<0.05).

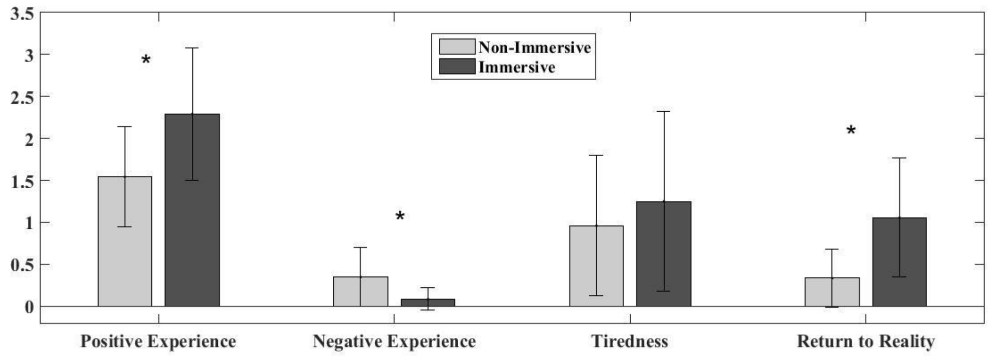

Figure 4.4. Independent T-test GEQ Post-Game Module that evaluated the positive experience, negative experience, tiredness and return to reality in both conditions, non-immersive and immersive. (*significance $p<0.05$)

Results for the GEQ Post-Game module are presented in figure 4.4. Statistical analysis showed overall better values for the immersive condition than the non-immersive. Similar results to the previous questionnaire were obtained, showing that positive experience in the immersive condition ($M=2.3$, $SD=0.79$), $t(22)=0.016$ $p<0.05$ was significantly higher compared to the non-immersive condition ($M=1.5$, $SD=0.59$) as well as the return to reality domain in the immersive ($M=1.1$, $SD=0.71$), $t(22)=0.0041$ $p<0.05$ compared to the non-immersive ($M=0.33$, $SD=0.35$). Moreover, Negative Experience was significantly lower in the immersive condition ($M=0.83$, $SD=0.13$), $t(22)=0.024$ $p<0.05$ compared with the non-immersive experience. ($M=0.35$, $SD=0.35$).

4.2.3 SUS Questionnaire and player's performance

The SUS questionnaire showed higher scores in the immersive condition ($M=87$, $SD=9.1$) compared with the non-immersive ($M=85$, $SD=10$) although the difference was not significantly different, $t(22)=0.55$ $p>0.05$ (see figure 4.5A). Moreover, the non-immersive group showed lower values of the performance index ($M=40\%$, $SD=16\%$) than the Immersive group ($M=54\%$, SD 17.2%) (Figure 4.5B), although again non-significant.

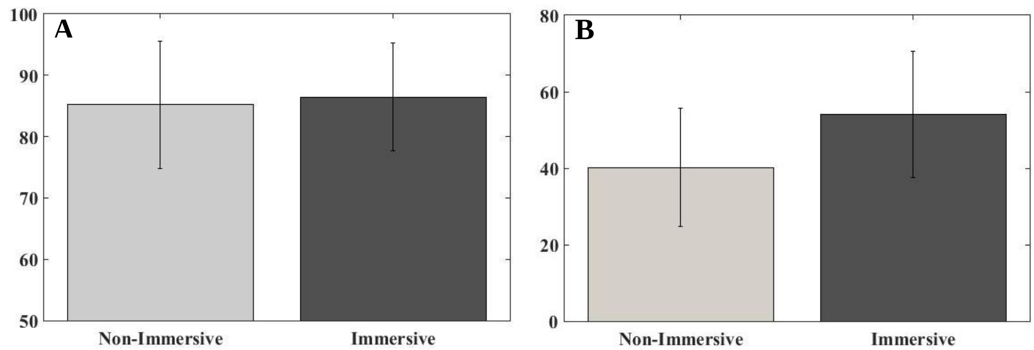

Figure 4.5 Evaluation of non-immersive and immersive conditions. A) the SUS. B) The Performance Index.

4.3 Discussion

In this paper, we presented a feasibility study to evaluate a biocybernetic system designed as an intelligent adaptation layer in a virtual training game created for upper-limb rehabilitation. The novelty of the system resides in its awareness with muscle fatigue levels measured through sEMG signals using a low-cost, non-invasive wearable sensor. From our initial hypothesis, we demonstrated how immersive experiences could significantly modify the player's perceptions of game experience and physiological factors.

Firstly, perceived fatigue levels were lower during the immersive condition compared with the non-immersive reflecting how novel immersive VR technologies can produce meaningful and measurable changes in real physical factors during virtual rehabilitation processes. This can potentially aid technology adoption and therapy adherence, two critical points for widely spreading the use of these technologies in real healthcare scenarios [61]. This experience enhancement was supported by the GEQ results which showed how significant factors such as competence, flow, and positive affect were higher in the immersive experience compared with the conventional non-immersive media. Moreover, the negative affect was also lower during the immersive experience compared with the non-immersive, again reinforcing the idea of a more pleasant and engage-able experience. These results were expected due to past research findings that pointed out that, via immersive and interactive activities, participants might partially ignore negative feelings such as pain or fatigue [62]

The GEQ Post-Game module aimed at measuring how people felt after they have stopped playing. In our experimental design, the categories Positive and Negative experience showed significantly better scores for the immersive condition. The SUS showed no significance between the setups. The system evidenced close means SUS values for both conditions, proving that the system's usability is not significantly affected by the setups. On the other hand, the performance index suggested that an immersive environment could encourage players to achieve better in-game performance, thus boosting the benefits of virtual rehabilitation through self-competitive strategies. This can be an exciting phenomenon to investigate where players being in a flow state can push themselves to continually improve their game performance producing a very desirable reinforcement strategy for virtual rehabilitation [32].

The lack of a baseline condition in this experiment is a clear limitation that prevents reaching more conclusive insights. Although efforts to homogenize both groups were carried out for this experiment in order to reduce possible physiological effects from demographic factors, the inclusion of a control or baseline condition in a future experiment would aid a better quantification of the biocybernetic adaptation benefits. Therefore, some of the post-gaming differences cannot be uniquely attributed to the immersivity provided by the condition but other factors should be also considered (e.g., previous mood, initial perceived fatigue, etc.). Since the main goal of this paper was to prove the hypothesis suggesting that changes on player's performance were due to the display modality (e.g., immersive vs. non-immersive), any control or sham condition was discarded. Due to no control condition was used to quantify the muscular and game user experience responses of players after gameplay without physiological adaptation, more research is needed to disentangle the isolated role of biocybernetic systems in improving not only the gaming experience but also the rehabilitation effectiveness through immersive technologies. However, as the non-immersive condition is commonly used to play videogames, this group can be considered as a "control" or conventional group.

Our findings bring new perspectives about the effects of VR and highly immersive environments on perceived and measured muscle fatigue, and how these technologies might enhance immersion, engagement, and flow in virtual rehabilitation therapies. Moreover, we presented a methodology to integrate biocybernetic adaptation into muscle-based interaction paradigms, enabling the detection of fatigue levels and real-time adaptations to maximize muscular performance. This novel tool can be used for clinicians to compare measured versus perceived levels of fatigue during exercises with isometrics contractions, usually used for physical rehabilitation (e.g., rehabilitation after injuries). The physiotherapists can compare the fatigue levels found by the loop with the fatigue levels perceived by the users, and then make the decision whether to continue or stop the exercise using the quantitative information provided by the adaptive system. Additionally, fatigue patterns and profiles can be obtained from each rehabilitation session, thus aiding the process of patient progress reporting.

4.4 Conclusions

The physiologically adapted FD videogame was evaluated with 24 healthy subjects to establish the feasibility of immersive VR and biocybernetic adaptation for upper-limb rehabilitation. In a comparison of immersive against non-immersive conditions, the first showed reduced levels of perceived fatigue and better game user experience compared with the non-immersive condition. These outcomes confirm the hypothesis that immersive VR technologies can produce better experiences, having an impact on important human factors as perceived fatigue and motivation. Results also confirmed that the usability of both the immersive and non-immersive setups was consistently high, thus demonstrating the feasibility of the low-cost solution provided, which can be further explored by clinicians in motor rehabilitation therapies. The physiological adaptation modulated by measured muscle fatigue levels proved to be an important characteristic of the system, supporting its feasibility since the measured fatigue levels compared favorably with the fatigue levels reported by the users. Based on our findings, we encourage more extensive use of novel physiologically adaptive systems in immersive virtual rehabilitation as a strategy to deliver a more personalized therapy and as an objective tool to customize difficulty levels based on physiological performance.

5. Pilot Study of the FD physiological system with Patients suffering from pyramidal syndrome

The main goal of this thesis is to test the feasibility of using the interactive system (videogame + computer physiology system) as a complement to a physical rehabilitation program. The pilot study aims to evaluate the impact of the combined rehabilitation program using the FD videogame on patients with M/H in the upper limb according to:

- The game experience (e.g., positive versus negative feelings, game performance)
- The perceived fatigue levels during the interaction with the videogame
- The functionality of the elbow and shoulder joint.

A rehabilitation program combining normal exercise routines (swimming routines in this case) with training using the FD videogame was designed for this pilot study.

5.1 Methods

5.1.1 Subjects

Seven subjects from a local rehabilitation centre volunteered for the intervention. The subjects were diagnosed with M/H in upper limbs derived from stroke, heroin addiction, cerebral palsy or muscular dystrophy (Table 5.1). Two subjects withdraw the study due to health issues. The university ethics committee previously approved the study; the general overview of the intervention and the experimental procedure was explained to each participant before they signed informed consent. Rehabilitation sessions were carried out in two different places of the rehabilitation centre: i) a small room prepared for connecting the videogame and preparing the participant for the training session and ii) an adapted pool where the conventional therapies were performed.

Table 5.1. Subjects diagnosis of motor disorder.

Subject	Diagnosis
1	Upper left limb Monoparesis derived from a Heroin overdose
2	Left Hemiparesis derived from a Heroin overdose
3	Right Hemiparesis derived from Cerebellar Ataxia
4	Upper left limb Monoparesis derived from Stroke
5	Left Hemiparesis derived from Muscular Dystrophy

5.1.2 Training Program

An exercise program of 4 sessions carried out along one month (1 session per week) lasting 60 minutes was used as a training program. The sessions consisted of combined training using 20 minutes of virtual rehabilitation (using the FD game) and 40 minutes of conventional therapy using a swimming pool. During the traditional therapy, participants performed an exercise routine, including walking and basic swimming exercises involving movements of the upper limbs. In all sessions, subjects started with some movements of upper limbs warming up for 5 minutes and subsequently played with the videogame.

5.1.3 System Setup

Interactive system: the FD videogame was used to provide exercise training sessions as a complementary routine for the rehabilitation therapies. Although the videogame has been adapted to be used with novel immersive VR systems, due to the in-situ characteristic of the pilot study, a conventional PC screen (15" screen, ADM A10 Radeon processor, 16GB RAM, Windows operative system) was used. Additionally, participants were wearing the Myo Armband to collect the sEMG signals, whereas headphones were used to hear game events such as attacks, background music, and rewards (Figure 5.1).

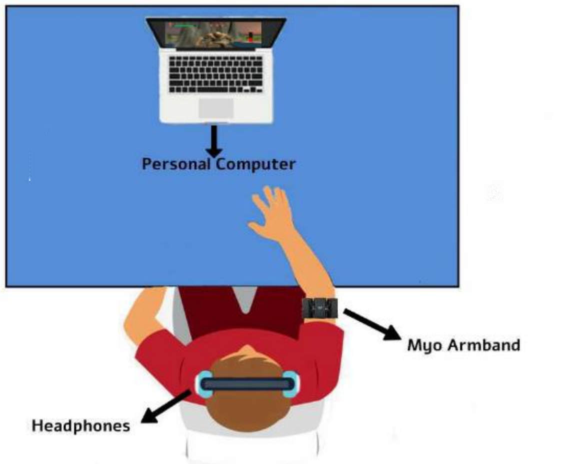

Figure 5.1. Facility condition to the interaction with the videogame: The subject sitting in front of a personal computer using the Myo Armband and headphones.

5.1.4 Outcome measurements

5.1.4.1 Game experience and Performance Evaluation

The following two questionnaires were administered to the participants at the end of the first session. Due to in previous chapters were explained, this section will only be mentioned.

- **Game Experience Questionnaire (GEQ):** Core module and Post-Game module [59].
- **The performance index:** the index proposed to evaluate the game performance of the subjects with the game variables.

$$PlayerPerformance = \frac{Points\ Awarded}{Points\ Awarded + Attacks\ recieved} * 100\%, \qquad (1)$$

5.1.4.2 Usability and acceptability:

- **The System Usability Scale (SUS)** [60] The SUS assesses three main usability domains: effectiveness (users achieving their objectives), efficiency (users' efforts and resources are spent in achieving those objectives) and satisfaction (users' experience is satisfactory).

5.1.4.3 Fatigue Measurement and Evaluation

- Muscle Fatigue Perception: The Borg’s scale was used to quantify the player´s perceived fatigue levels [57].
- Superficial electromyography: During all the interaction with the videogame the user worn the Myo Armband sensor. The signal delivered by this sensor allowed to establish the muscular fatigue evidenced by the users during the interaction with the game. The signals from all sessions were saved to the post-process. The signals and the markers of muscle fatigue extracted were compared with those evidenced in the video game.

5.1.4.4 Clinical Evaluation
The following tests were conducted one session before the first intervention and one session after the last intervention.

Range of Motion test (ROM): This is the measurement of movement around a specific joint [63]. With the help of a goniometer, a voluntary ROM of the elbow and shoulder joints will be performed. This test consists in measuring the angle at which the person can voluntarily flex and extend the elbow and the shoulder (Figure 5.2).

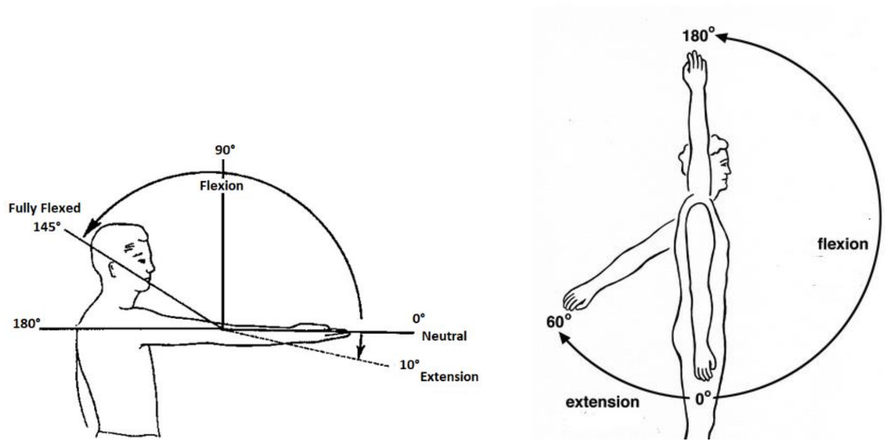

Figure 5.2. ROM of elbow flexion and shoulder flexion.

- **Modified Ashworth Spasticity Test:** It is a widely used scale where the contraction and personal muscle tone is measured [64]. The participant is asked to make a voluntary contraction of the brachial biceps and the physiotherapist evaluates according to a 0 to 5 scale as follows: 0 – no increase in muscle tone, 1 – slight increase in muscle tone, manifested by a catch and release, 2 – slight increase in muscle tone, manifested by a catch, followed by minimal resistance, 3 – more marked increase in muscle tone, but affected part (s) can easily be moved, 4 – considerable increase in muscle tone, passive movement difficult, 5 – affected part (s) rigid in flexion or extension.

5.1.4 Experimental Procedure

Before the first training session, the physiotherapist evaluated the motor function of each subject using the Ashworth test [64] and the mobility range test. The interaction was developed as can be seen in Figure 5.1;The subjects were wearing the Myo Armband over the biceps as well as the headphones. The researcher started the game and guided the subject during the entire experience asking and registering the Borg's scale at the end of every five contractions. Each subject played the videogame with both arms, approximately 10 minutes for each arm, for a total time of 20 minutes of playing. When the interaction with the videogame was finished, each subject continued immediately with the conventional therapy for 40 minutes more, guided by the physiotherapist. The GEQ and SUS were used at the end of the first training session.

5.1.4 Data Processing

The personal information of the participants was collected in a demographic registration document. The video game evaluation information was collected through the questionnaires proposed in the last section. The data delivered by the videogame was automatically saved in a .csv file after each interaction session. Using the SPSS software, a dependent T-test was developed between the game sessions of each subject. On the other hand, it is desired to find a correlation between the variables of the videogame with the Ashworth spasticity test and the mobility test, for which an ANOVA unilateral correlation test was applied.

5.2 Results

The four weeks of intervention was carried out with the subjects without any trouble. Although in previous chapters we proved that VR environments show better results on immersiveness, due to the displacement troubles of patients and to the rehabilitation center facilities, the environment condition was outdoors, as can be seen in figure 5.3, but conserving the setting proposed in figure 5.1.

Figure 5.3. Final facility condition to the interaction with the videogame.

5.2.1 Game Experience and System Usability

The core module and the post-game module from the GEQ were applied to the subjects after the first session. As can be seen in figures 5.4, the higher scores of the core module were obtained in the Competence (M=3.00, SD=0.46), Immersion (M=2.73, SD=0.65) Flow (M=3.04, SD=0.38) and Positive Affect (M=3.72, SD=0.62) categories. The categories Tensión (M=0.4, SD=0.72), Challenge (M=1.24, SD=0.53) and Negative Affect (M=0.30, SD=0.41) obtained lower scores.

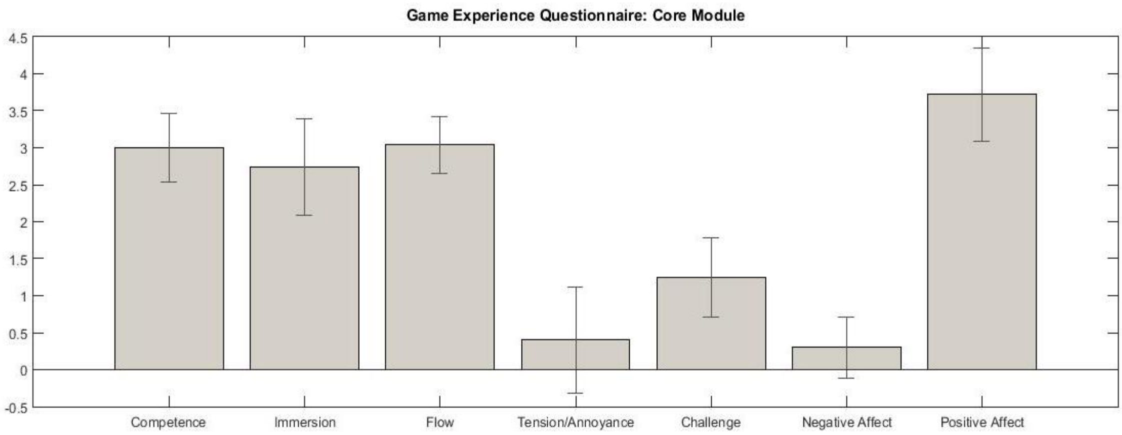

Figure 5.4. The core module of GEQ evaluates the competence, immersion, flow, tension, challenge, negative and positive affect.

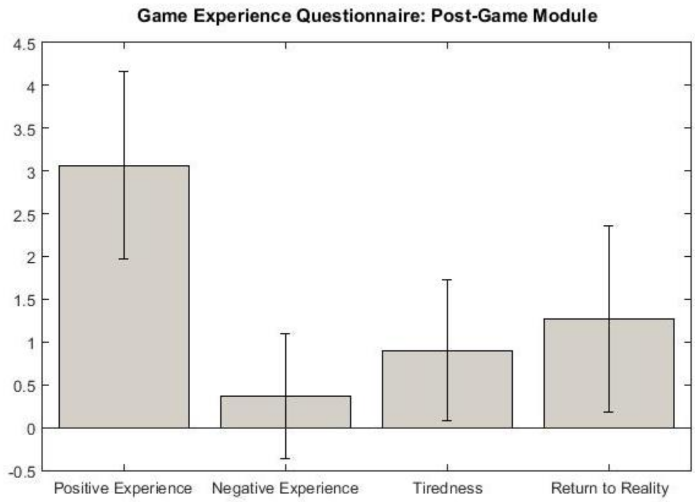

Figure 5.5. The post-game module of GEQ evaluates the negative and positive experience, tiredness and return to reality.

Figure 5.5 shows the results for the post-game module. Negative Experience (M=0.37, SD=0.73) and Tiredness (M=0.90, SD=0.82) scored lower than Positive experience (M=3.07, SD=1.09) and Return to Reality (M=1.27, SD=1.09).

Finally, the system usability was assessed with the SUS. The SUS scale had a final score of M: 78.33, SD: 14.11. As shown in figure 5.6, regarding confidence using the system (M=4.8, SD=0.45) expectations for using the system again (M=5, SD=0) obtained the highest scores.

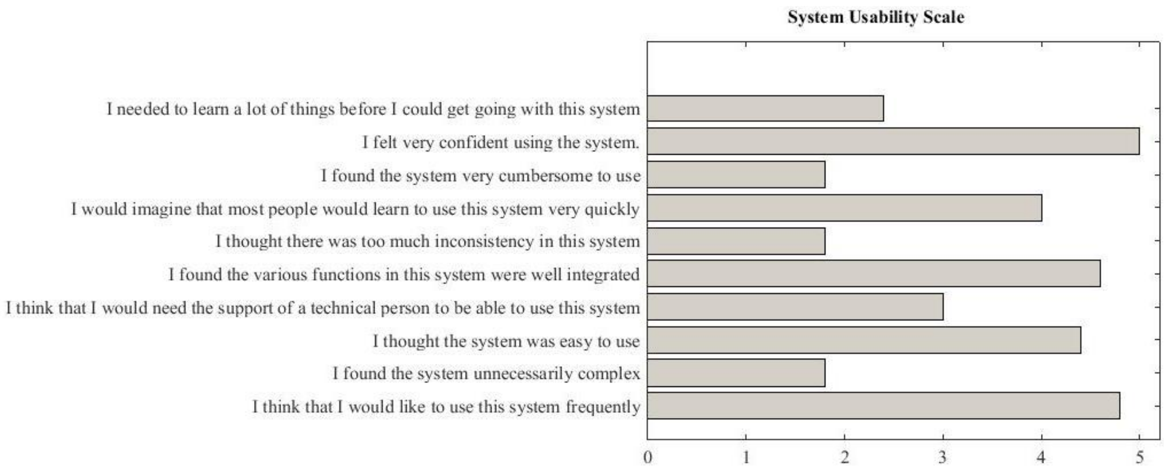

Figure 5.6. The SUS scores for each question from the scale. Final score M: 78.33, SD: 14.11.

5.2.2 Game Performance and Perceived Fatigue

The performance indexes for each session are shown in figures 5.7 and 5.8. Four of the five subjects (X-axis) improved their final right arm's index with respect to the first session. On the other hand, three of the five subjects grew their final left arm's index concerning the first session.

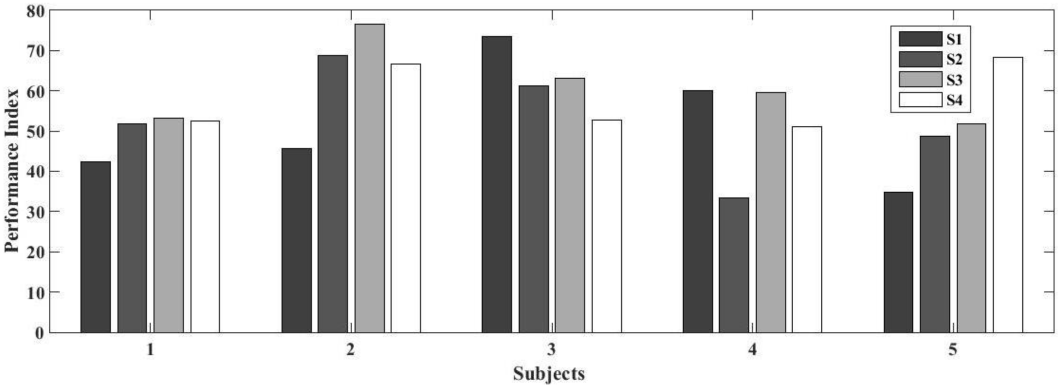

Figure 5.7. Left arm's performance index for each subject. S1: first session, S2: Second session, S3: third session, S4: fourth session

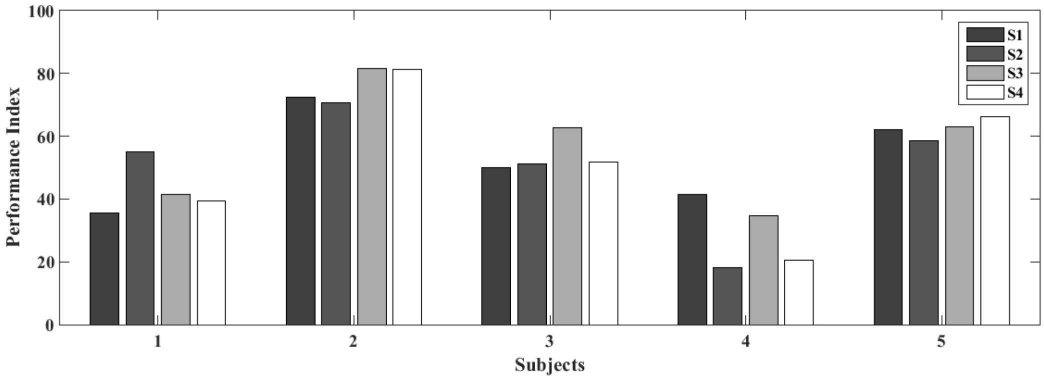

Figure 5.8. Right arm's performance index for each subject. S1: first session, S2: Second session, S3: third session, S4: fourth session.

5.2.3 Perceived Fatigue

Figures 5.9 and 5.10 shows the mean perceived fatigue for both the left and right arms of each subject for each session. In all the subjects, the perceived fatigue of the left arm measured in the last session was lower than the perceived fatigue measured in the first session. Similar results were found for the right hand, where four subjects manifested lower perceived muscle fatigue in the last session once compared with the first one.

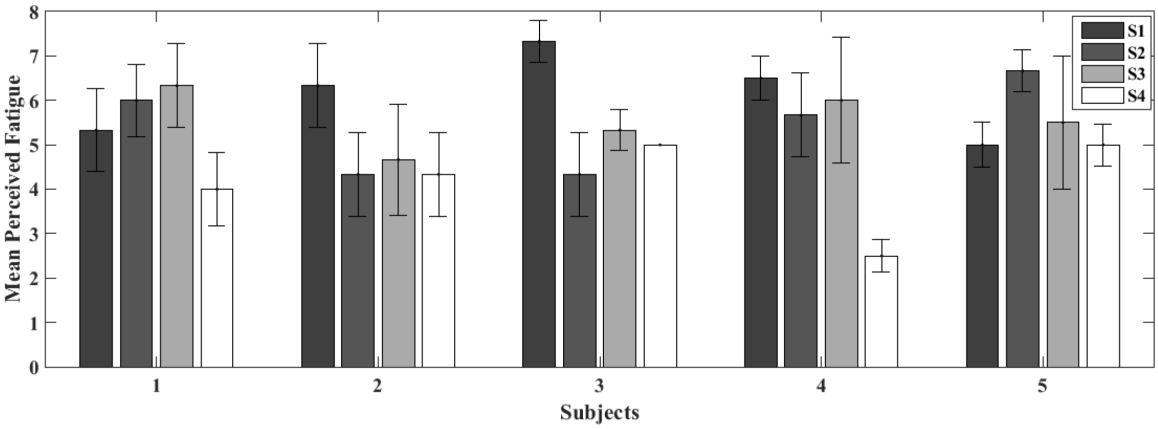

Figure 5.9. Left arm's Perceived Fatigue of each subject for each session. S1: first session, S2: Second session, S3: third session, S4: fourth session

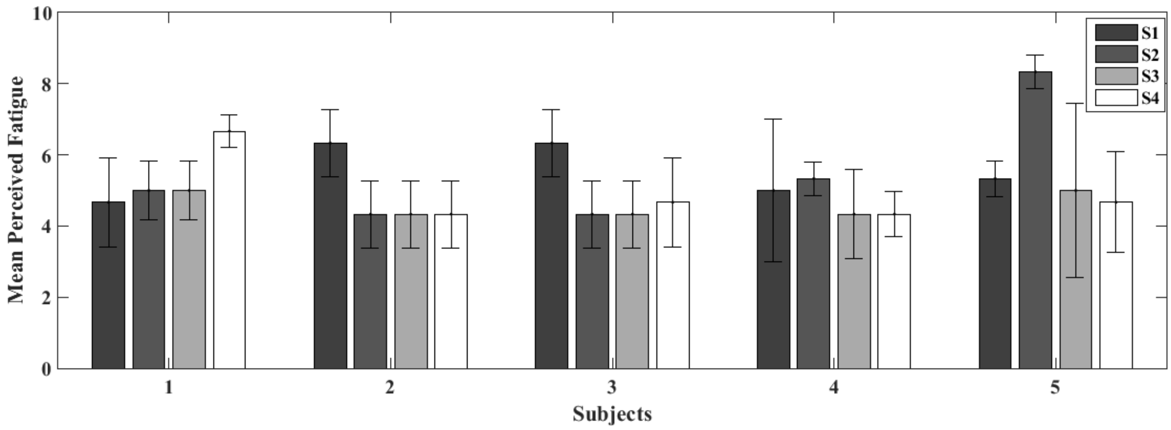

Figure 5.10. Perceived Fatigue of each subject for each session. S1: first session, S2: Second session, S3: third session, S4: fourth session

5.2.4 Functional Mobility in Upper Arms


Figure 5.11 Mobility range test using an analogical goniometer.

The Ashworth test and the ROM were developed before the first session and after the last session. (Figure 5.11). Table 5.2 resumes the results of the measured differences in both the mobility range test and the Ashworth test for each subject, considering the Pre and Post evaluations. The most noticeable improvements in average were the left shoulder (M: 24°, SD: 33°) and right shoulder (M: 9°, SD: 8°) in the mobility range test after the training program. It is worth noticing that subject number 5 had the greatest improvement in mobility range. On the other hand, the spasticity improvement was notable for the right arm (M: -0.8, SD: 0.4), the negative values mean that the subjects reduce the level of spasticity, where the participant two reported the greatest improvement in the Ashworth scale.

Table 5.2. Angle improvement in the subject's range of mobility and spasticity improvement of the subject's in the Ashworth scale.

	The angle of mobility improvement of each joint (°)				Spasticity improvement of each joint			
Subject	Left Elbow	Right Elbow	Left Shoulder	Right Shoulder	Left Elbow	Right Elbow	Left Shoulder	Right Shoulder
1	5	0	10	0	-1	-1	-1	-1
2	3	0	10	0	-1	-1	-1	-1
3	0	0	10	15	0	0	-1	-1
4	0	0	0	10	0	-1	0	-1
5	5	0	90	20	0	0	0	0

5.2.5 sEMG and Muscle Fatigue

A signal processing of muscle contractions recorded from the interaction with the videogame was computed for each subject. Figure 5.12 shows an example of the pre-processing stage: normalization-rectification-detrend- filtering. A passband third-order Butterworth filter between 10Hz and 95 Hz and a Notch filter in 60Hz were applied to the signals, following previously found literature [55], [56]. It is essential to consider that the signal amplitude provided by the Myo Armband sensor is codified in a numeric value in a range of [-127,127] [65].

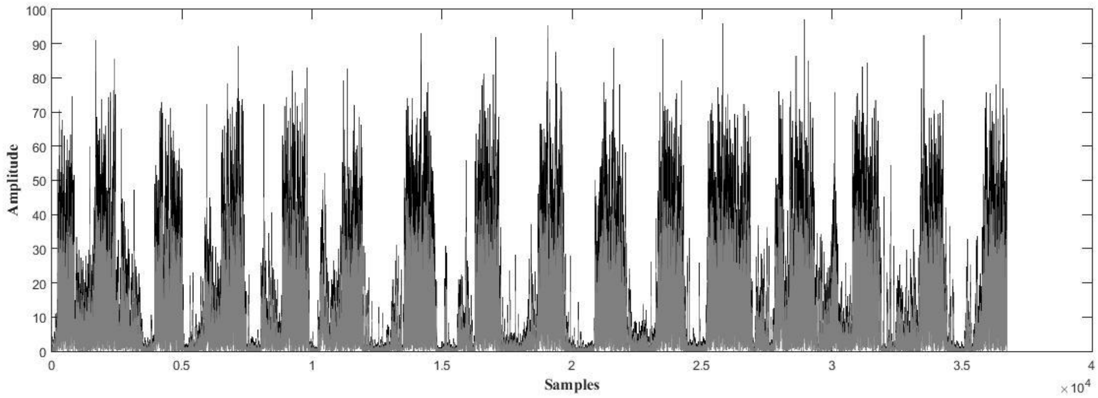

Figure 5.12. Pre-processing of the sEMG signals collecting during the videogame. Black line: raw signal; grey line: processed signal.

The core of the signal processing was to find the fatigue indexes.; namely, the RMS tendency value and the MDF tendency value in a single electrode channel (the one over the biceps) for each contraction, considered in an entire interaction with the videogame. In order to find the RMS tendency value, a moving average window with a length of 200 samples and an overlap of 50 samples was applied to the signal. On the other hand, the FFT was applied to find the MDF.

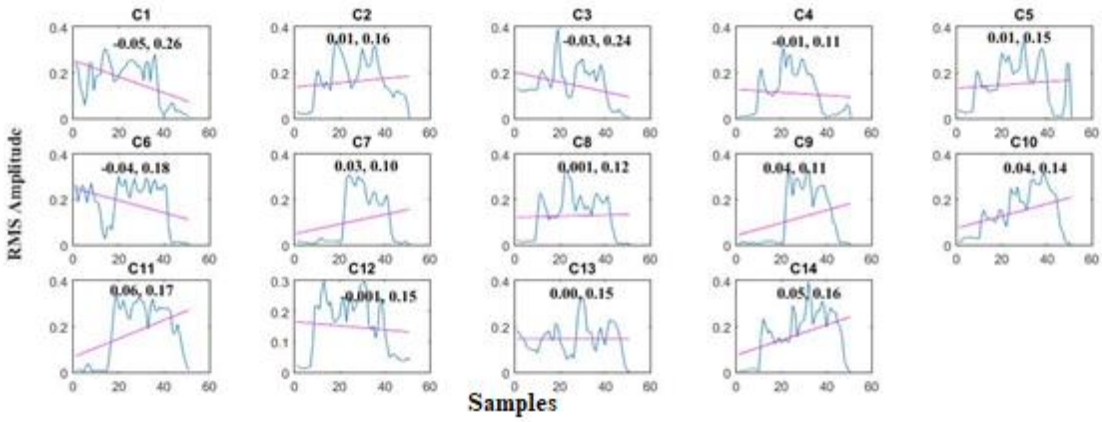

Figure 5.13. Processing of the sEMG signals collecting during the videogame. RMS index for each contraction of an individual interaction of a subject. C1: contraction number 1; C2 contraction number 2, and so on.

In order to illustrate what can be found after using this processing pipeline, we applied it to one of the datasets we have (one user, one game session). For instance, figures 5.13 and 5.14 shows the indexes for each muscle contraction of the left arm extracted from one session of the subject 5. The data shows the participant who improved the most in terms of ROM after the therapies.

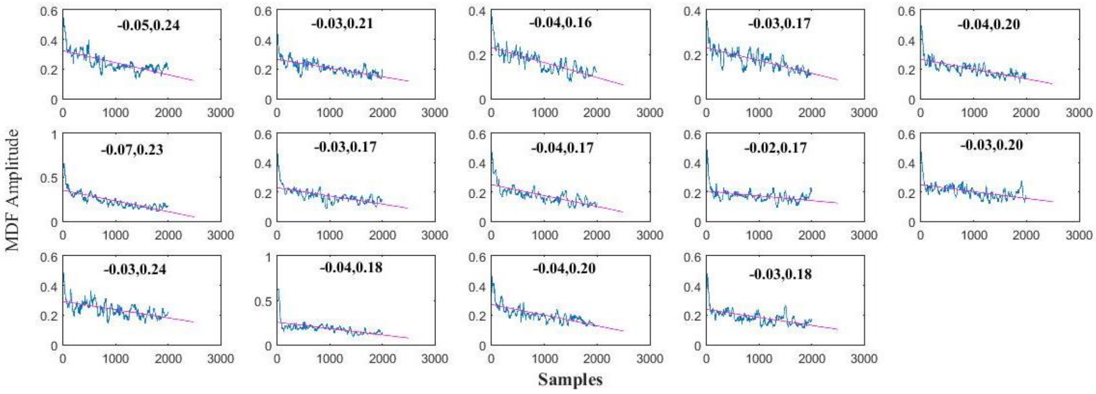

Figure 5.14. Processing of the sEMG signals collecting during the videogame. MDF index for each contraction of an individual interaction of a subject. C1: contraction number 1; C2 contraction number 2, and so on.

Finally, figure 5.15 shows time series of the fatigue indexes and the difficulty threshold. This figure is analyzed to understand how the game difficulty changes can influence the fatigue indexes. For instance, it is noticeable that in the middle of the interaction, a difficulty adaptation took place (discontinuous black line), producing lower values for the RMS (grey line) and a few higher values of the MDF (continuous black line), indicating a negative fatigue state. On other hand, at the end of the game, the threshold sustained in the higher value produced a higher score for the RMS and lower score for the MDF, indicating a positive state of fatigue.

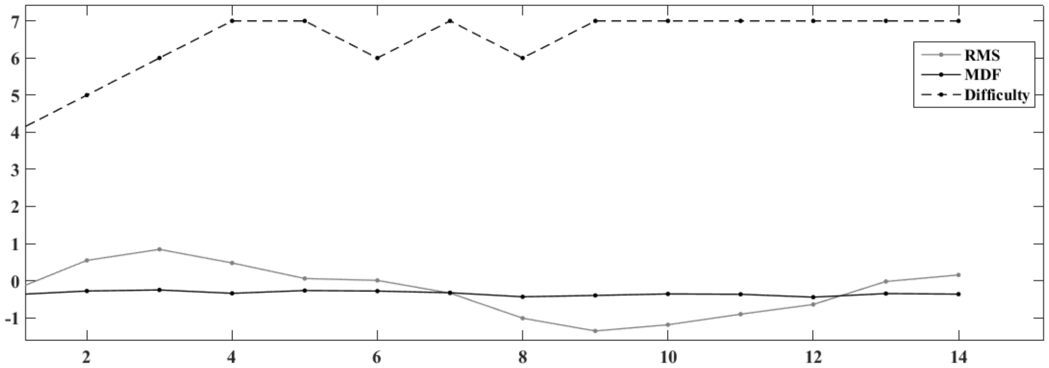

Figure 5.15. Influence of difficulty changing over the fatigue indexes. Grey line: RMS tendency value. Black line: MDF tendency value. Discontinuous black line: difficulty threshold.

5.3 Discussion and Conclusions

The ultimate goal of the feasibility study was to evaluate the impact of the proposed combined rehabilitation therapy in patients diagnosed with monoparesis or hemiparesis. The conventional motor therapy combined with the adaptative system designed was expected to positively influence the rehabilitation processes in terms of motor functionality and users' perception of the exercise. Due to the growing evidence showing that videogames and VR/VE applications can successfully be employed for early detection and monitoring of physical and cognitive impairment [31], [40], [66], we expected to find positive results towards confirming the evidence. Firstly, the GEQ showed a subject's positive perception of the videogame. The categories Positive Affect in the core module and Positive Experience in the post-game module were the highest in both tests, as well as the Negative Affect and the Negative Experience were the lowest in the respective questionnaires. The categories Competence and flow highlighted in the core module GEQ, evidencing a high motivational component in the videogame.
Moreover, the Immersion category was high despite the outdoor facility. On the other hand, the SUS score proves that the system is highly usable, and their functions are well integrated for the

purposed that was made. The subject's responses suggest that they would like to use the system frequently and they felt very confident using it (Figure 5.6)

Secondly, the goal of using the performance index as a metric to quantify the improvement of the therapy could not be well established. Indeed, in most of the cases, the final performance index improved concerning the initial, being the performance index of the right arm the most stable. Nevertheless, it had a non-linear improvement in every session, and the reason for it could not be established due to limitations such as i) non-controlled environmental variables in the development of the therapy and ii) the small sample size.

Thirdly, despite that the perceived fatigue in both arms did not seem to have an identifiable pattern, three of the five subjects manifested overall lower levels of perceived fatigue in the right arm and all the subjects manifested lower fatigue in the last session for the left arm. These results might suggest that the biocybernetic loop for fatigue adaptability in the game is working properly and the subjects are reacting to it. Likewise, the decrease in perceived fatigue could be an indicator of mobility improvement.

Finally, the results of the clinical evaluation, before the protocol and after the protocol, evidence a motor functionality improvement of all the subjects. Although a notable improvement was only found in the right shoulder's clinical evaluation, all the joints with motor deficits presented improvements in the Ashworth spasticity test and in the range of mobility test (Table 5.2). Although our sample size is very small, these preliminary results show the potential of combining physiological adaptation with games empowered with sEMG signals to complement physical rehabilitation therapies. Thus, the biocybernetic loop acted as a mechanism to boost game effectiveness in delivering customized experiences for individuals with motor impairments. Moreover, the post-processing developed as an example of the information that can be found in the collected sEMG signals, suggests that the difficulty adaptation performed by the biocybernetic loop influences the fatigue indexes, and the analysis of the signals from all subjects needs to be developed.

Based on the results of this pilot study can be concluded that the combined therapy proposed has the potential of been frequently used in patients with monoparesis/hemiparesis for the improvement of their motor capabilities. Furthermore, the positive perception of the subjects for the combined therapy highlights the motivational component that was aimed to imply in the rehabilitation process. On the other hand, the study did not present a control group condition, due to the different difficulties of patients, as time, displacement and rehabilitation center facilities. Therefore, the effect's quantification of the proposed combined therapy against conventional therapies is out of the scope of the paper. Moreover, the easy and low-cost access to the system proposed, together with the partnership with the rehabilitation center and the positive preliminary results encourage us to create a more controlled and extensive study soon.

6. Therapy quantification through Pattern Recognition Methods

Although the classifiers for sEMG signal had been worldwide studied, there is no evidence of which type of classifier could be the best for sEMG muscle fatigue descriptors in together with videogame variables taken under protocols of virtual rehabilitation. That is why we want to find the best classifier for our databases, the database collected with healthy people in chapter 4, and the database collected with impairment subjects in chapter 5. Thus, this chapter is divided into two principal sections. The first one presents the cross-validation of a classifier for the database from the 12 subjects under the non-immersive condition in chapter 4. The second one shows the proof of the best classifier found in section one using the database collected in chapter 5. In both sections, the classification task is related to classifying the subjects as “good player” or “bad player”, due the videogame was designed to motor rehabilitation and the performance of each subject should be monitored.

6.1 Cross-validation of a classifier method for sEMG signals and game variables collected from healthy people playing a body interaction videogame.

6.1.2 Methods

A super-matrix was created with the data of each subject collected in the muscle fatigue experimental protocol already described. The information available for the study was the sEMG signal pre-processed, the muscle fatigue index, and the game variables, such as the point awarded, the attacks receive, the difficulty changes, and the subject’s life lost (Figure 6.1). This information was divided into contractions. The samples of every subject were added to the previous one until completing the entire super-matrix. Using Matlab as processing software, data matrix X was created, where every row, related to the features, was integrated as follow:

$$X_n = \text{FatigeIndex}(1{:}\,1001) + \text{points}(1002{:}\,2001) + \text{Life}(2002{:}\,3001), \qquad (1)$$

From row number 1 to row 1001, the fatigue index, from row number 1002 to row 2001 the points awarded by each subject during one contraction, and from row number 2002 to row number 3001 the life lost by each subject during one contraction.

The samples X_n were separated in every work period (contraction- rest), of all the signal of each subject. Having in mind that each subject had a different number of samples due to each one had different times of interaction with the game, for instance, some subjects lost the game faster than others, the total number of samples was 198. Finally, the matrix had a dimension of 198x3001, as can be seen in Eq. 2:

$$\begin{bmatrix} x_{n0,1} & \cdots & x_{n0,1001} & \cdots & x_{n0,2001} & \cdots & x_{n0,3001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1,1} & \cdots & x_{n1,1001} & \cdots & x_{n1,2001} & \cdots & x_{n1,3001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n2,1} & \cdots & x_{n2,1001} & \cdots & x_{n2,2001} & \cdots & x_{n2,3001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{ntot,1} & \cdots & x_{ntot,1001} & \cdots & x_{ntot,2001} & \cdots & x_{ntot,3001} \end{bmatrix}, \qquad (2)$$

Where n_1 is the number of samples of subject 1, n_2 the number of samples of subject 2, and so on until n_{tot} is the number of total samples, 198 for our case. For instance, subject 1 had 24 samples, so n_0=1 and n_1=24, then subject 2 had 6 samples, so n_2=30, and so on until 198 total samples.

A label vector was created using the performance index extracted in every contraction of each user as the ratio between the points awarded and the sum between the points awarded and the life lost (Eq. 3). The mean value of this vector was extracted, and the values above this mean were labeled as 2 "good player" and the values below the mean were labeled as 1 "bad player", and that is how the T label vector had a size of 198x1

$$Performance\ index = \frac{PointsAwarded}{PointsAwarded+LifeLost}, \qquad (3)$$

Using the software Matlab, the four classifications tasks previously named were carried out with the respective evaluation. The training set was the 70% of the data, and an analysis of selection and extraction of features was previously develop using PCA and Relieff. The cross-validation was made with 10 iterations and an analysis of the average of the set of iterations was perform with box diagrams. Moreover, nested cross-validation with 10 iterations was computed in the last two classifiers, in order to find the optimal parameters for our database. The KNN parameter that was changed was the number of k-neighbours using 1, 2,3,5,7,9,11 neighbours. In the SVM a RBF kernel was used, and the parameters that were changed were the kernel regularization parameter using 20, 40, 60, 70, 80, 90, 100, 120; and the misclassification error parameter using 1, 10, 100, 200, 400, 600, 800, 1000. To reduce the computational cost, the SVM was trained with the number of characteristics with better performance obtained using the KNN classifier. The named classifiers were evaluated using the minimum distance of the accuracy to a target accuracy of 100% and 0% of standard deviation.

6.1.3 Results

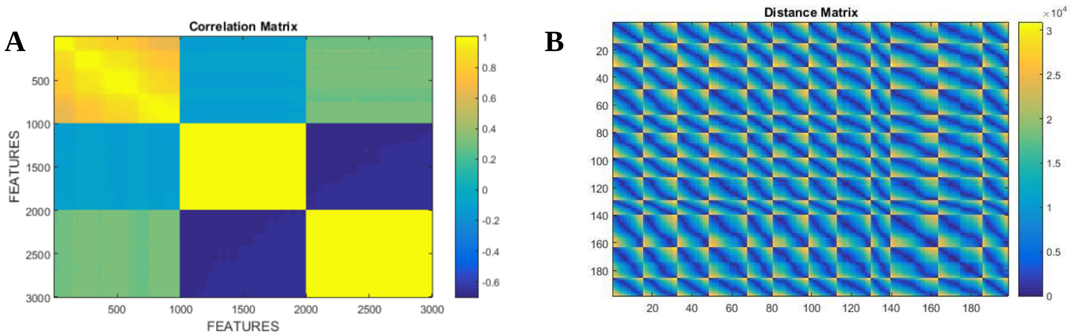

Figure 6.1. A) Correlation matrix of the features of the videogame database. The color bar represents the values of the correlation index. B) Euclidean distance matrix of the features of the videogame database. The color bar represents the distance values between features.

A first approach to the selection and extraction of features was developed using correlation analysis and a distance analysis. These two matrices can be seen in figure 6.1. The correlation matrix shows a low correlation between the characteristics, and this could mean that a low number of it could be ignored two reduce the dimensionality of our database. The Euclidean distance matrix shows a high similarity between most of the features; therefore the variance is low.

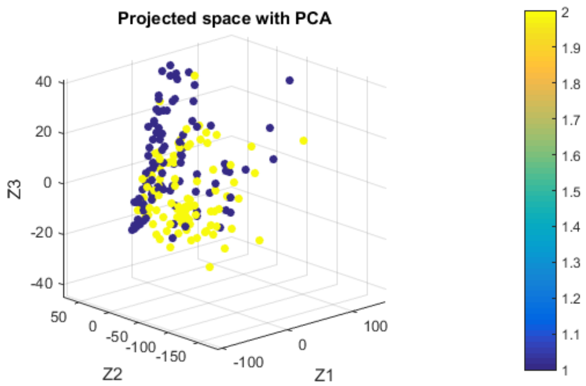

Figure 6.2. Projected space using the PCA method for the features of the videogame database. Z1, Z2 and Z3 are the coordinates in the projected space.

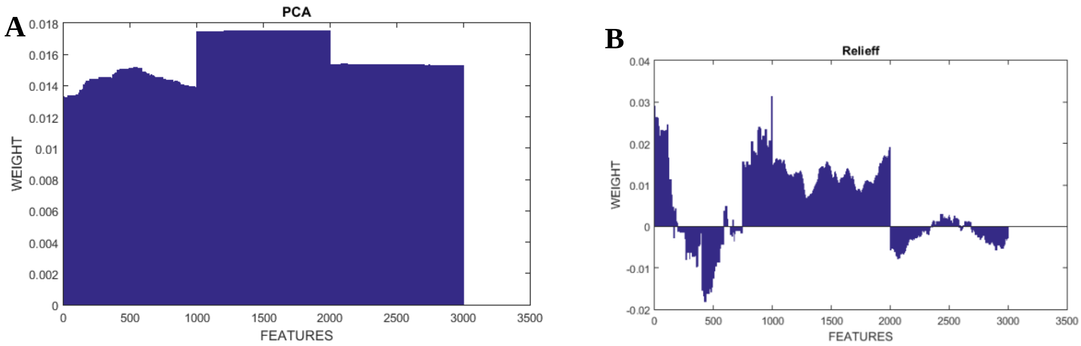

Figure 6.3. A) PCA relevance of features for the videogame database. B) The Relieff significance of features for the videogame database .

A PCA and Relieff analysis were computed to notice the relevance of features and avoid redundancy. As the variance of this matrix is low, the PCA method could be better than the Relieff. In figure 6.2 the projected space with PCA can be seen. In this region, the classes seem to be separable. The PCA relevance for each feature shown in figure 6.3A evidence that the awarded points and the lost life have higher weights than the fatigue index.

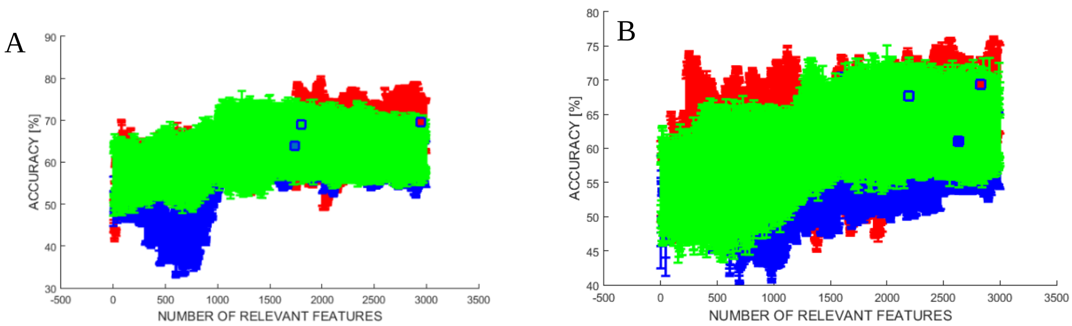

Figure 6.4. A) Box diagram of the percentage of accuracy of the classifiers using cross-validation with the extraction of features using PCA. Black line: Linear classifier, black dot: best accuracy. B) Box diagram of the percentage of accuracy of the classifiers using a cross-validation with the selection of features using Relieff. Black line: Linear classifier, black dot: best accuracy. Dark grey line: Quadratic classifier, dark grey dot: best accuracy. Light grey line: KNN Classifier, light grey dot: best accuracy.

The relevance shown in figure 6.3B was extracted using the Relieff method. According to this, some fatigue index features and the points awarded features are the ones with higher weights. The cross-validation of the Linear, Quadratic and KNN classifiers can be seen in figure 6.4, where they evidence a better performance with a higher number of characteristics. In both cases, the worst classifier was the Linear and the best was the KNN. The results are summarized in Table 1.

Table 1. Best accuracy using cross-validation of the Linear, Quadratic and KNN Classifiers. Number of features with the best performance, the percentage of accuracy and the respective standard deviation.

CLASSIFIER	**RELIEFF**			**PCA**		
	Number of Features	Accuracy (%)	Standard Deviation (%)	Number of Features	Accuracy (%)	Standard. Deviation (%)
Linear	2827	69,33	9,244	2948	69,33	6,806
Quadratic	2633	61,00	5,273	1740	63,99	7,944
KNN	2196	67,66	6,452	1804	69,00	4,116

As the best performance for KNN was found with 1804 features with PCA, these parameters were used to train an SVM. The result can be seen in the boxplot in figure 6.5, where the median was 81,66% with a standard deviation of 6.33%. The misclassification error parameter, chosen as the mode in the nested cross-validation, was 400. The kernel regularization parameter, selected as the mode, was 60.

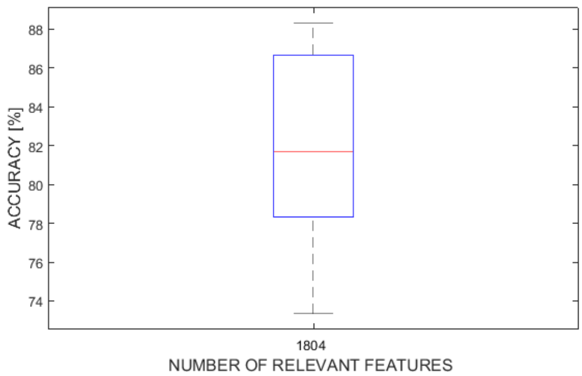

Figure 6.5. Cross-validation for SVM classifier using PCA with the same number of relevant features than the best performance for KNN. The median was 82,66%, with a standard deviation of 6.33%.

6.2 Classification of sEMG signals of patients with muscle disorders.

Due to the results in the previous section suggested that the best classifier for the sEMG signals combined with game variables was the proposed SVM, we decided to prove that classifier with the data collected from the experimental protocol in chapter 5. In order to implement a heuristic threshold into the adaptation of the videogame, it is important to establish if the same classifier used with the information of healthy people can also work properly with data from patients with motor disorders. On the other hand, the classifier can provide information about the performance of the players and complement the information about the rehabilitation improvement, since the classification task is related to distinguish between a good player and a bad player.

6.2.1 Methods

Similar to the methodology developed in chapter 5, a matrix of data was created for each subject. The matrixes contained the information of the four sessions of the subjects arranged in rows by samples. A sample is created with the information of every period of contraction-rest (30s). This means that the samples of each session of a single subject were added to the previous one until completing the four sessions. Using Matlab as processing software, data matrix X for each subject was created, where every row, related to the features, was integrated as follow (Eq. 4), taking into account that the frequency test was 60hz:

$$X_n = \text{FatigeIndex}(1{:}\,2001) + \text{points}(2002{:}\,4001) + \text{Life}(4002{:}\,6001), \qquad (4)$$

From row number 1 to row 2001, the fatigue index, from row number 2002 to row 4001 the points awarded by each subject during one contraction, and from row number 4002 to row number 4001 the life lost by each subject during one contraction.

The samples X_n were separated in every work period from the signals of a single subject in the four sessions. Each session had a different number of samples due to every time the subjects had different times of interaction with the game. For instance, subject number 1 lost the game in the first sessions, but in the four session won the game and completed all the work periods. Thus, the total number of samples was different for each matrix created for the subjects. Finally, the matrix had a dimension of n_{tot}x6001, as can be seen in Eq. 5:

$$\begin{bmatrix} x_{n0,1} & \cdots & x_{n0,2001} & \cdots & x_{n0,4001} & \cdots & x_{n0,6001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1,1} & \cdots & x_{n1,2001} & \cdots & x_{n1,4001} & \cdots & x_{n1,6001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n2,1} & \cdots & x_{n2,2001} & \cdots & x_{n2,4001} & \cdots & x_{n2,6001} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{ntot,1} & \cdots & x_{ntot,2001} & \cdots & x_{ntot,4001} & \cdots & x_{ntot,6001} \end{bmatrix}, \qquad (5)$$

Where n_1 is the number of samples of the first session of subject 1, n_2 the number of samples of the second session of subject 1, and so on until n_{tot} is the number of total samples of all the sessions of subject 1.

The label vector was created as in section 5.1, (Eq. 3) the performance index was extracted in every work period of all the sessions of each subject. The mean value of this vector was extracted, and the values above this mean were labeled as 2 “good player” and the values below the mean were labeled as 1 “bad player”, and that is how the T label vector was created.

Using the software Matlab, the classification task previously named was carried out with the respective evaluation. The training set was the 70% of the data, and an analysis feature selection was previously developed using PCA, due to the results found in chapter 5. The cross-validation was made with 10 iterations and an analysis of the average of the set of iterations was perform with box diagrams. The SMV was computed using a RBF kernel, and using a nested validation with 10 iterations the parameters of the kernel where changed in order to find a higher accuracy. The kernel regularization parameter was changed using 20, 40, 60, 70, 80, 90, 100, 120; and the misclassification error parameter using 1, 10, 100, 200, 400, 600, 800, 1000.

6.2.2 Results

The feature selection of each database was developed using PCA as can be seen in figure 6.6 and 6.7. Figure 6.7 shown the difficulty of the classification task of this database in the PCA space, due to both classes had a difficult separation in all the subjects’ databases.

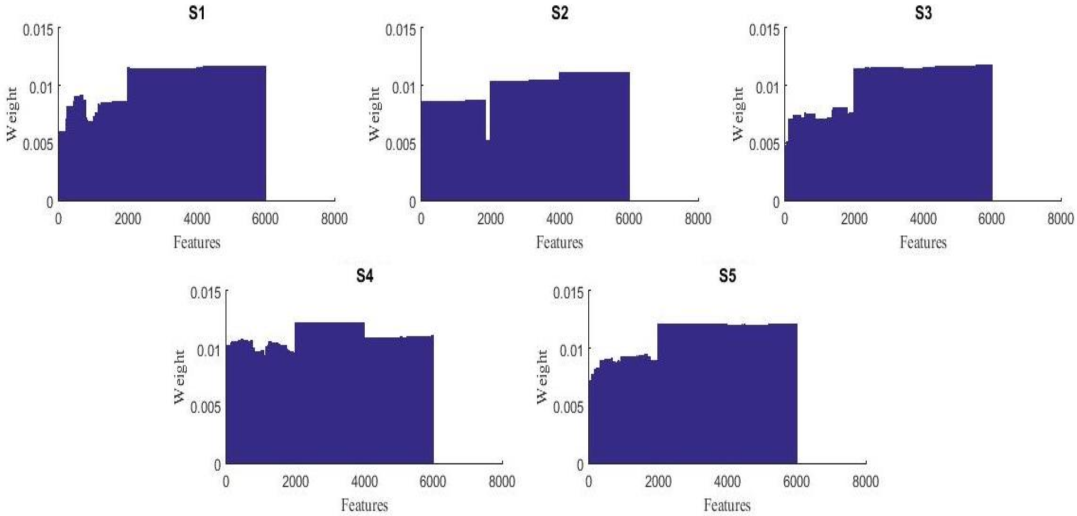

Figure 6.6. PCA relevance of features for each subject's database

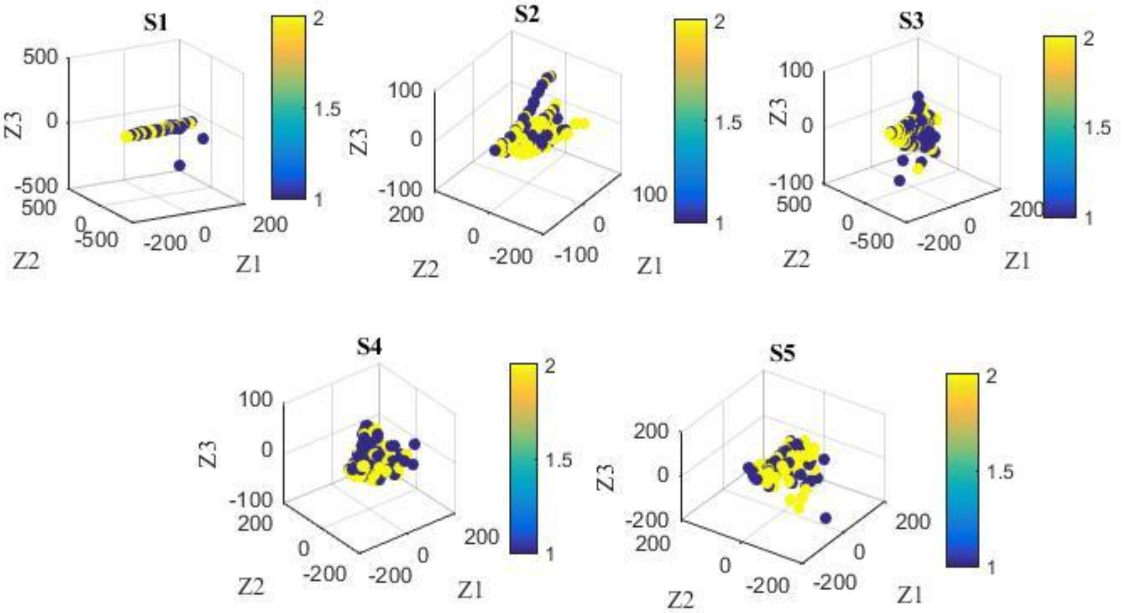

Figure 6.7. Projected space using the PCA method for the features of each subject's database. Z1, Z2 and Z3 are the coordinates in the projected space.

Due to the classifier was proved with the data of each subject, figure 6.8 resume the results found. The classifier's accuracy was higher for the data of subject 1(M=81,94%, SD=11.8%), subject 2 (M=79.31%, SD=9.05%), and subject 4 (M=74.9%, SD=6.01%); with similar results the data of subject 3 (M=70%, SD=9.98%), and subject 5 (M=72.92%, SD=11.54%) obtain the lower scores. Finally, the classifier accuracy for the data of the 5 subjects had a mean of M=75.81% and a standard deviation of SD=4.31%.

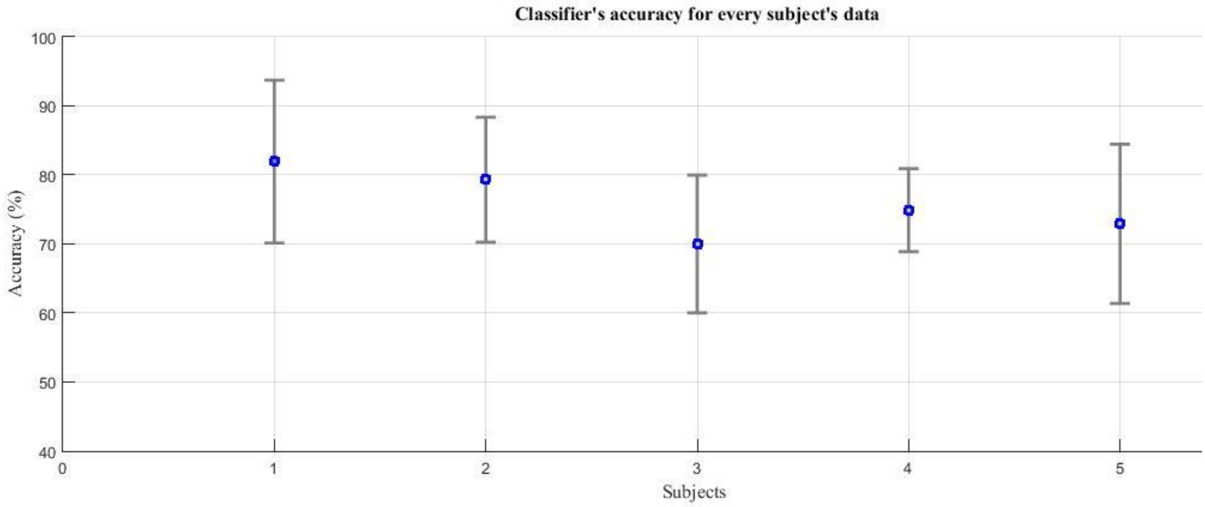

Figure 6.8. Classifier’s accuracy for each subject´s data

6.3 Conclusions

The classification task in pattern recognition is one of the most used techniques to analyze databases. In our case, the task to develop is to classify the users of a videogame as "good player" or "bad player" knowing their muscle index fatigue and their game variables. To have a better understanding of our database, in the first section of this chapter was developed a correlation analysis and distance analysis. The analysis found that the features had a low correlation and the dimensionally of the database will not be reduced too much, and that a PCA extraction of features could be more convenient due to the low variance and that the projected space show separable classes. Based on the results, this was confirmed, due to the three classifiers showed a better percentage of accuracy with PCA than with Relieff, and that the number of features using PCA was lower than using Relieff (table 1). Even though the Linear classifier with PCA had better accuracy than the KNN with PCA, this last one was chosen as the best due to the number of features used was lower at least for 1000 characteristics.

The SVM using the same number of features than KNN with PCA evidenced a higher percentage of accuracy, almost 10% more than the KNN. The KNN is sensitive to lousy feature selection because of the variance of the data; as was explained before, our database has low variance, so it was expected that the SVM had a better performance. On the other hand, the SVM method is known for being more robust than the others, is better with high dimensional data, since it will only use the most relevant points to find a linear separation.

The higher accuracy of the SVM for sEMG contractions is accorded with the literature [67], [68], where SVMs were used for classification tasks of muscle fatigue sEMG signal. Based on the results, the SVMs also showed to be the appropriate pattern recognition method to classify information of sEMG signals combined with videogame variables.

This classifier seems to be the best to be implemented on the videogame to provide information about the performance of each player during the interaction, and to record the progress therapy through the game's sessions. That is why in the second section of this chapter was decided to prove this classifier with the database collected in chapter 6, which contains the sEMG signal features and the game variables from subjects with motor impairments.

The classifier was cross-validated with 10 iterations and a nested validation for the kernels parameters of the SVM was also computed. The results of the accuracy of the classifier for the database of every subject were found to be acceptable with a score higher of 70% for every subject. The mean for the accuracy was M=75.81% and a standard deviation of SD=4.31%, lower than the one found for the database of healthy subjects that scored M=82,66% with a standard deviation of SD=6.33% (section 5.1.2). This lack of accuracy percentage can be related to the different building of the data matrix, due to the databased for healthy subjects contained all the subjects, and the database used for impaired subjects was built for each one. The matrix's building was decided due to the classifier was thought to be used in the subject's individual interaction, not in the interaction of the subjects as a group. On the other hand, as can be seen in figure 6.7, the classification task is difficult due to the separation of both classes is not evident; nevertheless, the SVM obtained good accuracy.

Further research is needed to improve the SVM working with the database collected from the interaction with the videogame. Figure 6.6 evidenced that the features from the Fatigue index extracted from the sEMG signal had the lower weights in the PCA feature selection, while the game variables always had higher scores. Other features from the signal, as the RMS, could have higher weights and improve the accuracy of the classifier.

Finally, although in the literature was not found evidence of robust pattern recognition methods, as neural networks (NN), working better than the SVM for sEMG signals, it could be interesting to prove if the NN could have higher performance for the combined videogame database.

7. Discussion, Limitations and Future Work

7.1 Discussion

7.1.1 Methodology for serious game design

The first stage developed in this research was to create an appropriate serious videogame for motor rehabilitation of upper limbs. Even though the literature provides the key factors to consider when designing videogames for healthcare, particular game mechanics to be used are still missing in the literature. Specific examples of using exergames in physical rehabilitation [29], [39], explain the factors related to i) the compatibility between game and motor disability, ii) the advice of how often (dose) it should be used [31], and iii) why videogames are effective for rehabilitation [30]. By using game design literature [49], and mixing it with the experience of experts in healthcare for physical rehabilitation, the FD videogame is presented as an interactive solution that uniquely balances attractiveness and effectiveness for motor rehabilitation.

The FD videogame was created using specific game mechanics designed to provide a natural interaction between the players and the game, while following the therapeutic recommendations appropriate for motor rehabilitation. The technology and the user interface (sEMG signal) were chosen to recreate the isometric muscle contractions that are often used in therapy, and more importantly, to be aware of the muscle fatigue states of players. Thus, a biocybernetic loop was integrated into the game's normal functioning with the ultimate goal of adapting the game's difficulty based on the muscle fatigue measured through the sEMG signal. Moreover, the final goal of the entire system was to generate an effective low-cost complementary activity to conventional therapy.

7.1.2 Impact of virtual environments on user's muscle fatigue perception

Despite the fact that we felt very confident about our game design methodology, in chapter 4, we presented an experimental procedure designed to prove the player's perception of the game. The results of the GEQ and the SUS confirmed our initial hypothesis, revealing a high acceptance of the system and a positive perceived experience when players interacted with the videogame. Moreover, the experimental procedure also considered a research question that has been previously explored in the Exergaming literature: How virtual environments influence rehabilitation therapy? [40], [69]–[72]. With the purpose of bringing some insights into this issue, we developed a protocol where the videogame was played using two different display modalities: a non-immersive (conventional flat screens) and an immersive one that used state-of-the-art VR systems. The fatigue perception of the players assessed by the Borg's scale during the interaction resulted that it was directly influenced by the virtual environment and the display mode. The muscle fatigue perceived in the immersive scenario was lower than the perceived in the non-immersive, suggesting that players with a higher sensation of being immersed in the virtual world were less sensitive to feel muscle fatigue, facilitating the rehabilitation process. Similar results have been found by researchers in the application of VR for pain management [62], [73], [74].

7.1.3 Therapy follow up through sEMG and game metrics.

The game mechanics designed in chapter 3 allowed to follow up upon the subject's performance since variables such as points or attacks completed have a direct relation with the quality of the muscle contractions. Using those variables, we created a game metric called the performance index, which was computed in the data analysis proposed in chapter 4 and was extracted during the rehabilitation protocol presented in chapter 5. Firstly, the performance index showed to be sensitive to the virtual environment differences, due to the mean score for subjects in the immersive condition was higher than those in the non-immersive condition. Secondly, in the study with patients with M/H, although the performance index was not consistent through the sessions, it showed an improvement while comparing the first session with the last session. Based on these results, we confirmed the feasibility of using game variables as a quantification of the rehabilitation progress.

On the other hand, the sEMG signal used for interfacing the game, demonstrated to be a powerful mechanism for balancing attractiveness and effectiveness since it acted as an adaptation medium to maintain subjects in a proper muscle fatigue state. These signals are rich in information; for instance, the close analysis of the amplitude for the muscle contractions (RMS value) could reveal the maintenance of the muscle's contractions quality. Moreover, as the RMS tendency value and the MDF tendency value, used as fatigue index, revealed the behavior of the muscle fatigue and how the biocybernetic loop was affecting it. Nevertheless, more clinically-friendly analysis is needed to facilitate the adoption of fatigue biomarkers in clinical settings.

7.1.4 Therapy quantification thought pattern recognition methods

The recorded information in the protocols developed in chapters 4 and 5 was used to test different pattern recognition methods looking for a confident variable to inform the subject's performance during the rehabilitation therapy, and also searching for an alternative way to adapt the game difficulty. The cross-validation of four classification methods: Linear, quadratic, KNN and SVM, reveal the SVM with a RBF kernel as the algorithm with higher accuracy to perform the classification task related to choosing between “good player” or “bad player” based on the MDF valued and game variables. Classifying players as good or bad is a direct indicator of their performance, and an easy way that clinicians might have of being aware of patients’ improvement. On the other hand, if we classify the subject's performance on every contraction period, the belonging class could work as a marker of the game difficulty, for example, if the player is classified as “good” after a contraction, the level of difficulty will increase to perform the next muscle contraction as well as if the player is classified as “bad” after a contraction, the level of difficulty will decrease to perform the next muscle contraction. In this manner, we could create an automatic threshold, different to the threshold provided by the clinician’s appreciations, which so far has worked very well.

This stage of the research was valuable since, in the literature review, we did not find automatic algorithms to solve classifications tasks with information related to physiological signals and game variables. Nevertheless, the accuracy of the SVM was lower when it was tested with individual information of impairments subjects, suggesting that more research is needed to confirm the usefulness of machine learning techniques in this field.

7.2 Limitations

Some of the identified limitations of this research are related to the factors listed below:

- The perceived muscle fatigue results of chapter 4 could not be attributable to the biocybernetic loop due to the lack of a control group, where subjects belonging to it played the videogame without difficulty adaptation. Then, a holistic influence of physiological adaptation could not be proved.
- The rehabilitation intervention proposed in chapter 5 was first thought to be implemented with the VR system, due to the results suggested in chapter 4. However, limitations in participant’s displacement to the research laboratory, limited the use of the immersive setup.
- The intervention time of the rehabilitation protocol proposed in chapter 5 was shorter than what was initially suggested by clinicians. A longer intervention over more subjects exposed to the system in a longer period of time could provide a better understanding of the effects of using the FD adaptive videogame in realistic scenarios.

7.3 Future Work

The combined rehabilitation therapy proposed and developed by this research work is now part of the rehabilitation process that can be used the patients who come to the rehabilitation centre in which we carried out this investigation. From September of the present year, we provided rehabilitation support using our gaming system, allowing patients to experience the videogame and become more aware of these rehabilitation technologies (figure 7.1). Despite the good acceptance of our system, we need to develop a more extended evaluation of it, one that can cover the limitations listed before. For this, it is decisive to continue with the well-established partnership between researchers, physiotherapists and clinicians to find better mechanisms for collaboration to carry out the interventions and to be able to extend the use of these technologies to more people in the city.

On the other hand, we want to develop a few videogames more with the design methodology used for FD creating more diversified options to complement the motor rehabilitation. Moreover, the integration of the algorithms of the biocybernetic loop on those games can be easily carried out, since the FD videogame was programmed in a modular and integrative manner.

Figure 7.1. FD system carried out as part of rehabilitation therapy at the rehabilitation centre.

Appendices

Appendix A: Publications

Chapter 3
Ongoing publication:
"Design of an Upper Limbs Rehabilitation Videogame with sEMG and Biocybernetic Adaptation"
REHAB 2019, September 11–13, 2019, Popayan, Colombia

ACM ISBN 978-1-4503-7151-3/19/08...$15.00
https://doi.org/10.1145/3364138.3364170

Contribution: The programming of the videogame was entirely developed by the author. The established methodology to design a serious videogame for upper arms rehabilitation was proposed by all the authors and the clinician's advisors.

Chapter 4
Accepted in IEEE Transactions on Neural Systems and Rehabilitation Engineering:
"Enhancing Virtual Rehabilitation in Upper Limbs with Biocybernetic Adaptation: The Effects of Virtual Reality on Perceived Muscle Fatigue, Game Performance and User Experience."

Contribution: The data collecting and processing was developed by the author, as well as the VR environments. All the authors contributed to the design of the experimental protocol and paper revision.

Chapter 5
Vega, M. M., & Henao, O. A. (2019, June). Cross-validation of a classification method applied in a database of sEMG contractions collected in a body interaction videogame. In Journal of Physics: Conference Series (Vol. 1247, No. 1, p. 012049). IOP Publishing.

Contribution: The data signal processing and the algorithms were by the author in Matlab. All the authors contributed to the paper revision.

Chapter 6
Under review in Sensors:
"Designing a fatigue-aware videogame using biocybernetic adaptation. A pilot study for upper-limb rehabilitation with sEMG"

Contribution: The experimental protocol was planned jointly with the supervisors. The data collecting, processing and analysis was developed by the author. The established methodology to design a serious videogame for upper arms rehabilitation was proposed by all the authors and the clinician's advisors. All the authors contributed to the revision of the paper

Appendix B:Questionnaires and measurement scales

System Usability Scale

Strongly disagree | Strongly agree

	1	2	3	4	5
I think that I would like to use this system frequently					
I thought the system was easy to use.					
I found the system unnecessarily complex.					
I think that I would need the support of a technical person to be able to use this system.					
I found the various functions in this system were well integrated.					
I thought there was too much inconsistency in this system.					
I would imagine that most people would learn to use this system very quickly.					
I found the system very cumbersome to use.					
I felt very confident using the system.					
I needed to learn a lot of things before I could get going with this system.					

Game experience Questionaire
Core Module
Please indicate how you felt while playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4

1 I felt content
2 I felt skillful
3 I was interested in the game's story
4 I thought it was fun
5 I was fully occupied with the game
6 I felt happy
7 It gave me a bad mood
8 I thought about other things

9 I found it tiresome
10 I felt competent
11 I thought it was hard
12 It was aesthetically pleasing
13 I forgot everything around me
14 I felt good
15 I was good at it
16 I felt bored
17 I felt successful
18 I felt imaginative
19 I felt that I could explore things
20 I enjoyed it
21 I was fast at reaching the game's targets
22 I felt annoyed
23 I felt pressured
24 I felt irritable
25 I lost track of time
26 I felt challenged
27 I found it impressive
28 I was deeply concentrated in the game
29 I felt frustrated
30 It felt like a rich experience
31 I lost connection with the outside world
32 I felt time pressure
33 I had to put a lot of effort into it

Post Game Module
Please indicate how you felt after you finished playing the game for each of the items, on the following scale:

not at all	slightly	moderately	fairly	extremely
0	1	2	3	4

1 I felt revived
2 I felt bad
3 I found it hard to get back to reality
4 I felt guilty
5 It felt like a victory
6 I found it a waste of time
7 I felt energized
8 I felt satisfied
9 I felt disoriented
10 I felt exhausted
11 I felt that I could have done more useful things
12 I felt powerful
13 I felt weary
14 I felt regret
15 I felt ashamed
16 I felt proud
17 I had a sense that I had returned from a journey

Borg's Scale

0	Nothing at all
0.5	5 Very, very slight (just noticeable)
1	Very slight
2	Slight
3	Moderate
4	Somewhat severe
5	Severe
6	
7	Very severe
8	
9	Very, very severe
10	maximal

Modified Ashworth Scale

0	No increase in muscle tone
1	Slight increase in muscle tone, manifested by a catch and release or by minimal resistance at the end of the range of motion when the affected part(s) is moved in flexion or extension
1+	Slight increase in muscle tone, manifested by a catch, followed by minimal resistance throughout the remainder (less than half) of the ROM
2	More marked increase in muscle tone through most of the ROM, but affected part(s) easily moved
3	Considerable increase in muscle tone, passive movement difficult
4	Affected part(s) rigid in flexion or extension

Appendix C: Informed Consent

Research Group in Physiology
Research Group in Automatic
Human Computer Interaction Group
Universidad Tecnólogica de Pereira (UTP)
Informed Consent

Pilot study for the evaluation of the Force Defense videogame as a virtual rehabilitation system for motor therapy

We are asking for your permission to participate in the validation of the Force Defense video game as a virtual rehabilitation system that responds to muscular fatigue in the biceps brachii (arm). This research is directed by PhD Oscar Henao, researcher and professor at UTP and PhD John Edison Muñoz, Postdoctoral researcher at the University of Waterloo, Canada. Likewise, there is the advice and follow-up of the Physiatrist and teacher of the UTP Dr, José Fernando López and the Physiotherapist and teacher of the UTP Felipe Gómez.

Research Objective:
Establish the viability in the use of the Force Defense videogame as a complementary therapy for rehabilitation processes in upper limbs. The system uses physiological adaptation features in order to adjust to the specific needs of the population (patients with Monoparesis / Upper Hemiparesis)

Research Justification:
Establish the viability of this rehabilitation system to be a complementary therapy to conventional rehabilitation therapy. This system is designed to create motivation in users, create adherence for physical therapy, at a very low cost, so that technology can be easily acquired by rehabilitation centers.

Procedures:
You will undergo a physical rehabilitation therapy that combines interaction with a video game and the physical therapy that you perform regularly. You will undergo this therapy once a week, for 8 weeks, where you will play in front of a computer using a sensor that allows interaction with the videogame. You will be accompanied and guided all the time by the principal investigator and by the physiotherapist.

Benefits:
This therapy is designed to improve muscle spasticity, with a motivating component for interaction with a videogame. You will be exposed to an innovative therapy with technology designed to improve your physical well-being. At the end of this study, an improvement in your joint mobility of the elbow and shoulder is estimated, as same as a positive perception of you towards this type of alternative therapy.

Factors and risks:
This is a minimum risk investigation. It is an intervention or intentional modification of physiological variables of people participating in the study, this physiological variable is muscle spasticity derived from the pathologies Monoparesis and hemiparesis. On the other hand, this study does not imply any physical or psychological risk for you, nor consequences for your financial situation, your employment or reputation. You have been selected for your condition and fitness. The only risks that could occur at the end of the process would be that you feel low satisfaction regarding the interaction with the videogame or some levels of muscle fatigue.

Response to concerns guarantee:
We will not disclose any information about you, or provided by you during the investigation. When the results of the research are published or discussed in conferences, information that may

reveal your identity will not be included. Your participation in this investigation is voluntary. At the time you request information related to the project, the researchers will give it.

Freedom guarantee:
Participation in the study is free and voluntary. Participants may withdraw from the research at any time they wish, without any consequence.

Information guarantee:
The electronic data collected, such as the information acquired in the surveys, will be managed and stored by the researchers. Only researchers will have access to them, with the only purpose of answering the research questions raised.No information will be disclosed that revealed your identity or affected your reputation. Participants will receive all significant information that is obtained during the study. At the conclusion of the study, the researcher along with the physiotherapist will make an informative presentation with the results of the study, in addition, each participant will be cited individually to reveal personal results and resolve concerns regarding their performance.

Confidentiality:
The names of the people and all information provided, will be treated privately and with strict confidentiality, these will be consolidated in a database as part of the research work. Only the overall information of the investigation will be disclosed, in a report in which the proper names of the people from whom information is obtained will be omitted. In addition, each participant will be left with a copy of this informed consent document.

Economic resources:
In case there are expenses during the development of the research, they will be paid with the research budget.

Contact:
Principal researcher:
Maria Fernanda Montoya Vega, mf.mv@utp.edu.co, +573157020072

I certify that I have read the above information, that I understand its content and that I agree to participate in the investigation. It is signed in the city of _____________ on ____ days, of the month _______________ of the year 2019

___________________________________	________________________________
Informed Name Signature / ID number:	Informed Footprint
___________________________________	________________________________
First Witness name ID number:	First Witness signature
___________________________________	________________________________
Second Witness name ID number:	Second Witness signature
___________________________________	________________________________
Informant Name ID number:	Informant Signature

Appendix D: Bioethics Committe approval

Universidad Tecnológica de Pereira

UNIVERSIDAD TECNOLÓGICA DE PEREIRA

COMITÉ DE BIOÉTICA

NOTIFICACIÓN DE APROBACIÓN DE PROYECTO CON RIESGO

Pereira, 10 de junio de 2019

Señor(a)
Investigador Principal

Referencia: proyecto "Clasificador de señales sEMG con características de fatiga muscular recolectadas en línea para el control de un videojuego de interacción corporal para rehabilitación física".

El Comité de Bioética de la Universidad Tecnológica de Pereira, ubicado en el edificio 1, oficina 1ª-404 en la carrera 27 #10-02 del barrio Los Álamos de Pereira, con teléfono (6) 3137114, en reunión ordinaria efectuada el día de hoy, según acta No. 10, punto 4.1, numeral 4.1.1, ha aprobado el proyecto ***"Clasificador de señales sEMG con características de fatiga muscular recolectadas en línea para el control de un videojuego de interacción corporal para rehabilitación física"***, clasificado como investigación con **RIESGO MINIMO**. El CBE-UTP deja constancia de lo siguiente:

- Los autores del proyecto están calificados para ejecutarlo.
- El proyecto posee las condiciones bioéticas y científicas adecuadas y justifica la relación entre los riesgos y los beneficios predecibles para los participantes.
- El consentimiento informado escrito contiene la información requerida y los autores establecen claramente cómo entregarán la información a los participantes.
- El proceso de selección e inclusión de los participantes queda claramente establecido.
- Los autores están comprometidos en que cualquier cambio substancial en el proyecto original o la aparición de un evento adverso serio debe ser reportado al CBE-UTP tan pronto como sea posible por el investigador principal, para las consideraciones y pronunciamientos pertinentes.

El CBE-UTP se acoge a las normas y estándares éticos, legales y jurídicos vigentes para la investigación en seres humanos (resolución 8430 de 1993, resolución 2378 de 2008 y Declaración de Helsinki). El CBE-UTP cuenta con **12** miembros activos y considera quórum a la presencia de la mitad más uno de sus miembros.

Atentamente,

Carlos Alberto Isaza Mejia
Presidente Comité de Bioética
Universidad Tecnológica de Pereira

NOTICE OF APPROVAL OF RISK PROJECT

Pereira, June 10, 2019
Mr. Principal Researcher
Reference: project "Classifier of sEMG signals with muscle fatigue characteristics collected online for the control of a physical interaction video game for physical rehabilitation"

The Bioethics Committee of the *Universidad Tecnológica de Pereira* , located in building 1, office 1-404 in race 27 # 10-02 of the Los Alamos neighborhood of Pereira, with telephone (6) 3137114, in ordinary meeting held on the day of today, according to act No. 10, point 4.1, paragraph 4.1.1, has approved the project "Classifier of sEMG signals with muscle fatigue characteristics collected online for the control of a physical interaction video game for physical rehabilitation" classified as research with MINIMUM RISK. The CBE-UTP records the following:

- The authors of the project are qualified to execute it.
- The project has the appropriate bioethical and scientific conditions and justifies the relationship between the risks and the predictable benefits for the participants.
- Written informed consent contains the required information and the authors clearly state how they will deliver the information to the participants.
- The process of selecting and including participants is clearly established.
- The authors are committed that any substantial change in the original project or the occurrence of a serious adverse event should be reported to the CBE-UTP as soon as possible by the principal investigator, for relevant considerations and pronouncements

The CBE-UTP adheres to the current ethical, legal and legal norms and standards for research in human beings (resolution 8430 of 1993, resolution 2378 of 2008 and Declaration of Helsinki). The CBE-UTP has 12 active members and considers quorum to the presence of half plus one of its members.

Sincerely,
Carlos Alberto Isaza Mejia
Chairman Bioethics Committee
Universidad Tecnológica de Pereira

References

[1] R. Merletti y D. Farina, *Surface electromyography: physiology, engineering and applications*. John Wiley & Sons, 2016.

[2] C. Juel, «Regulation of pH in human skeletal muscle: adaptations to physical activity», *Acta physiologica*, vol. 193, n.º 1, pp. 17–24, 2008.

[3] D. G. Allen, G. D. Lamb, y H. Westerblad, «Skeletal muscle fatigue: cellular mechanisms», *Physiological reviews*, vol. 88, n.º 1, pp. 287–332, 2008.

[4] M. Cifrek, V. Medved, S. Tonković, y S. Ostojić, «Surface EMG based muscle fatigue evaluation in biomechanics», *Clinical Biomechanics*, vol. 24, n.º 4, pp. 327–340, 2009.

[5] G. Venugopal, M. Navaneethakrishna, y S. Ramakrishnan, «Extraction and analysis of multiple time window features associated with muscle fatigue conditions using sEMG signals», *Expert Systems with Applications*, vol. 41, n.º 6, pp. 2652–2659, 2014.

[6] C. J. De Luca, «The use of surface electromyography in biomechanics», *Journal of applied biomechanics*, vol. 13, n.º 2, pp. 135–163, 1997.

[7] J. R. Cram, *Cram's introduction to surface electromyography*. Jones & Bartlett Learning, 2011.

[8] H. Carrie y B. Lori, «Ejercicio Terapéutico: Recuperación Funcional», *Editorial Paidotribo*, 2006.

[9] T. O. Bompa y C. Buzzichelli, *Periodization-: theory and methodology of training*. Human Kinetics, 2018.

[10] G. Puddu, A. Giombini, y A. Selvanetti, *Rehabilitation of sports injuries: current concepts*. Springer Science & Business Media, 2013.

[11] B. Bonnechère, *Serious Games in Physical Rehabilitation*. Springer, 2018.

[12] V. Gatica-Rojas y G. Méndez-Rebolledo, «Virtual reality interface devices in the reorganization of neural networks in the brain of patients with neurological diseases», *Neural regeneration research*, vol. 9, n.º 8, p. 888, 2014.

[13] P. L. T. Weiss, E. A. Keshner, y M. F. Levin, *Virtual reality for physical and motor rehabilitation*. Springer, 2014.

[14] S. H. Fairclough y K. Gilleade, *Advances in physiological computing*. Springer, 2014.

[15] O. M. Giggins, U. M. Persson, y B. Caulfield, «Biofeedback in rehabilitation», *Journal of neuroengineering and rehabilitation*, vol. 10, n.º 1, p. 60, 2013.

[16] S. Fairclough y K. Gilleade, «Construction of the biocybernetic loop: a case study», en *Proceedings of the 14th ACM international conference on Multimodal interaction*, 2012, pp. 571–578.

[17] A. Dix, «Human-computer interaction», en *Encyclopedia of database systems*, Springer, 2009, pp. 1327–1331.

[18] S. H. Fairclough, «Fundamentals of physiological computing», *Interacting with computers*, vol. 21, n.º 1-2, pp. 133–145, 2008.

[19] A. Chowdhury, R. Ramadas, y S. Karmakar, «Muscle computer interface: a review», en *ICoRD'13*, Springer, 2013, pp. 411–421.

[20] T. S. Saponas, D. S. Tan, D. Morris, y R. Balakrishnan, «Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces», en *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2008, pp. 515–524.

[21] C. J. De Luca, «Physiology and mathematics of myoelectric signals», *IEEE Transactions on Biomedical Engineering*, n.º 6, pp. 313–325, 1979.

[22] C. M. Bishop, «Pattern recognition and machine learning (information science and statistics) springer-verlag new york», *Inc. Secaucus, NJ, USA*, 2006.

[23] R. O. Duda y P. E. Hart, «Pattern classification and scene analysis», *A Wiley-Interscience Publication, New York: Wiley, 1973*, 1973.

[24] I. Kononenko, «Estimating attributes: analysis and extensions of RELIEF», en *European conference on machine learning*, 1994, pp. 171–182.

[25] K. P. Murphy, *Machine Learning: A Probabilistic Perspective. Adaptive Computation and Machine Learning*. MIT press, 2012.

[26] J. Yousefi y A. Hamilton-Wright, «Characterizing EMG data using machine-learning tools», *Computers in biology and medicine*, vol. 51, pp. 1–13, 2014.

[27] Q. Wu *et al.*, «Hybrid BF–PSO and fuzzy support vector machine for diagnosis of fatigue status using EMG signal features», *Neurocomputing*, vol. 173, pp. 483–500, 2016.

[28] A. Alkan y M. Günay, «Identification of EMG signals using discriminant analysis and SVM classifier», *Expert Systems with Applications*, vol. 39, n.º 1, pp. 44–47, 2012.

[29] P. M. Kato, «Video games in health care: Closing the gap», *Review of general psychology*, vol. 14, n.º 2, pp. 113–121, 2010.

[30] I. of D. Media *et al.*, «Games for health for children—Current status and needed research», *Games for health journal*, vol. 5, n.º 1, pp. 1–12, 2016.

[31] V. Manera *et al.*, «Recommendations for the use of serious games in neurodegenerative disorders: 2016 Delphi Panel», *Frontiers in psychology*, vol. 8, p. 1243, 2017.
[32] K. Gilleade, A. Dix, y J. Allanson, «Affective videogames and modes of affective gaming: assist me, challenge me, emote me», *DiGRA 2005: Changing Views–Worlds in Play.*, 2005.
[33] C. B. Ivanhoe y T. A. Reistetter, «Spasticity: the misunderstood part of the upper motor neuron syndrome», *American journal of physical medicine & rehabilitation*, vol. 83, n.º 10, pp. S3–S9, 2004.
[34] A. Pandyan *et al.*, «Spasticity: clinical perceptions, neurological realities and meaningful measurement», *Disability and rehabilitation*, vol. 27, n.º 1-2, pp. 2–6, 2005.
[35] L. A. Collange Grecco, N. de Almeida Carvalho Duarte, M. E. Mendonça, M. Galli, F. Fregni, y C. S. Oliveira, «Effects of anodal transcranial direct current stimulation combined with virtual reality for improving gait in children with spastic diparetic cerebral palsy: a pilot, randomized, controlled, double-blind, clinical trial», *Clinical rehabilitation*, vol. 29, n.º 12, pp. 1212–1223, 2015.
[36] F. Orihuela-Espina *et al.*, «Neural reorganization accompanying upper limb motor rehabilitation from stroke with virtual reality-based gesture therapy», *Topics in stroke rehabilitation*, vol. 20, n.º 3, pp. 197–209, 2013.
[37] N. M. da Silva Ribeiro *et al.*, «Virtual rehabilitation via Nintendo Wii® and conventional physical therapy effectively treat post-stroke hemiparetic patients», *Topics in stroke rehabilitation*, vol. 22, n.º 4, pp. 299–305, 2015.
[38] F. Juárez y F. Contreras, «Biofeedback-emg y su aplicación en un caso de hipertonía espástica», *Clín. Salud*, vol. 5, n.º 2, pp. 219–228, 1994.
[39] K. I. Molina, N. A. Ricci, S. A. de Moraes, y M. R. Perracini, «Virtual reality using games for improving physical functioning in older adults: a systematic review», *Journal of neuroengineering and rehabilitation*, vol. 11, n.º 1, p. 156, 2014.
[40] D. E. Levac y H. Sveistrup, «Motor learning and virtual reality», en *Virtual reality for physical and motor rehabilitation*, Springer, 2014, pp. 25–46.
[41] M. F. Levin, P. L. Weiss, y E. A. Keshner, «Emergence of virtual reality as a tool for upper limb rehabilitation: incorporation of motor control and motor learning principles», *Physical therapy*, vol. 95, n.º 3, pp. 415–425, 2015.
[42] A. L. Rincon, H. Yamasaki, y S. Shimoda, «Design of a video game for rehabilitation using motion capture, EMG analysis and virtual reality», en *2016 International Conference on Electronics, Communications and Computers (CONIELECOMP)*, 2016, pp. 198–204.
[43] L. van Dijk, C. K. van der Sluis, H. W. van Dijk, y R. M. Bongers, «Task-oriented gaming for transfer to prosthesis use», *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, n.º 12, pp. 1384–1394, 2016.
[44] J. L. Pons y D. Torricelli, *Emerging Therapies in Neurorehabilitation*. Springer, 2014.
[45] R. Dörner, S. Göbel, M. Kickmeier-Rust, M. Masuch, y K. Zweig, *Entertainment Computing and Serious Games: International GI-Dagstuhl Seminar 15283, Dagstuhl Castle, Germany, July 5-10, 2015, Revised Selected Papers*, vol. 9970. Springer, 2016.
[46] B. Terlaak, H. Bouwsema, C. K. van der Sluis, y R. M. Bongers, «Virtual training of the myosignal», *PloS one*, vol. 10, n.º 9, p. e0137161, 2015.
[47] M. Ortiz-Catalan, N. Sander, M. B. Kristoffersen, B. H\a akansson, y R. Br\a anemark, «Treatment of phantom limb pain (PLP) based on augmented reality and gaming controlled by myoelectric pattern recognition: a case study of a chronic PLP patient», *Frontiers in neuroscience*, vol. 8, p. 24, 2014.
[48] M. A. Oskoei y H. Hu, «Adaptive myoelectric control applied to video game», *Biomedical Signal Processing and Control*, vol. 18, pp. 153–160, 2015.
[49] J. Schell, *The Art of Game Design: A book of lenses*. AK Peters/CRC Press, 2014.
[50] A. Jew, *Professional storyboarding: Rules of thumb*. Focal Press, 2013.
[51] N. Hocine, A. Gouaich, I. Di Loreto, y M. Joab, «Motivation based difficulty adaptation for therapeutic games», en *Serious Games and Applications for Health (SeGAH), 2011 IEEE 1st International Conference on*, 2011, pp. 1–8.
[52] J. Sinclair, P. Hingston, y M. Masek, «Considerations for the design of exergames», en *Proceedings of the 5th international conference on Computer graphics and interactive techniques in Australia and Southeast Asia*, 2007, pp. 289–295.
[53] J. E. Muñoz, M. Cameirão, S. Bermúdez i Badia, y E. R. Gouveia, «Closing the Loop in Exergaming-Health Benefits of Biocybernetic Adaptation in Senior Adults», en *Proceedings of the 2018 Annual Symposium on Computer-Human Interaction in Play*, 2018, pp. 329–339.
[54] R. Merletti y P. A. Parker, *Electromyography: physiology, engineering, and non-invasive applications*, vol. 11. John Wiley & Sons, 2004.

[55] M. Montoya, O. Henao, y J. Muñoz, «Muscle fatigue detection through wearable sensors: a comparative study using the myo armband», en *Proceedings of the XVIII International Conference on Human Computer Interaction*, 2017, p. 30.
[56] M. Montoya, J. Muñoz, y O. Henao, «Surface EMG based muscle fatigue detection using a low-cost wearable sensor and amplitude-frequency analysis Detección de la fatiga muscular a través de un sensor wearable de bajo costo y análisis de amplitud y frecuencia de la señal EMG superficial», *Actas de Ingeniería*, vol. 1, pp. 29–33, 2015.
[57] G. Borg, *Borg's perceived exertion and pain scales.* Human kinetics, 1998.
[58] E. Borg, G. Borg, K. Larsson, M. Letzter, y B.-M. Sundblad, «An index for breathlessness and leg fatigue», *Scandinavian journal of medicine & science in sports*, vol. 20, n.º 4, pp. 644–650, 2010.
[59] W. A. IJsselsteijn, Y. A. W. De Kort, y K. Poels, «The game experience questionnaire», *Manuscript in preparation*, 2008.
[60] J. Brooke, «SUS-A quick and dirty usability scale», *Usability evaluation in industry*, vol. 189, n.º 194, pp. 4–7, 1996.
[61] M. Slater y M. V. Sanchez-Vives, «Enhancing our lives with immersive virtual reality», *Frontiers in Robotics and AI*, vol. 3, p. 74, 2016.
[62] V. C. Tashjian *et al.*, «Virtual reality for management of pain in hospitalized patients: results of a controlled trial», *JMIR mental health*, vol. 4, n.º 1, 2017.
[63] N. B. Reese y W. D. Bandy, *Joint range of motion and muscle length testing-E-book*. Elsevier Health Sciences, 2016.
[64] C. A. Agredo y J. M. Bedoya, «Validación de la escala ashworth modificada», *Arq Neuropsiquiatr*, vol. 3, pp. 847–51, 2005.
[65] S. Rawat, S. Vats, y P. Kumar, «Evaluating and exploring the MYO ARMBAND», en *2016 International Conference System Modeling & Advancement in Research Trends (SMART)*, 2016, pp. 115–120.
[66] D. Corbetta, F. Imeri, y R. Gatti, «Rehabilitation that incorporates virtual reality is more effective than standard rehabilitation for improving walking speed, balance and mobility after stroke: a systematic review», *Journal of physiotherapy*, vol. 61, n.º 3, pp. 117–124, 2015.
[67] C. Savur y F. Sahin, «Real-time american sign language recognition system using surface emg signal», en *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on*, 2015, pp. 497–502.
[68] Q. Wu *et al.*, «Classification of EMG Signals by BFA-Optimized GSVCM for Diagnosis of Fatigue Status.», *IEEE Trans. Automation Science and Engineering*, vol. 14, n.º 2, pp. 915–930, 2017.
[69] D. E. Levac y J. Galvin, «When is virtual reality "therapy"?», *Archives of physical medicine and rehabilitation*, vol. 94, n.º 4, pp. 795–798, 2013.
[70] M. K. Holden, «Virtual environments for motor rehabilitation», *Cyberpsychology & behavior*, vol. 8, n.º 3, pp. 187–211, 2005.
[71] K. Harris y D. Reid, «The influence of virtual reality play on children's motivation», *Canadian journal of occupational therapy*, vol. 72, n.º 1, pp. 21–29, 2005.
[72] L. Zimmerli, M. Jacky, L. Lünenburger, R. Riener, y M. Bolliger, «Increasing patient engagement during virtual reality-based motor rehabilitation», *Archives of physical medicine and rehabilitation*, vol. 94, n.º 9, pp. 1737–1746, 2013.
[73] K. M. Malloy y L. S. Milling, «The effectiveness of virtual reality distraction for pain reduction: a systematic review», *Clinical psychology review*, vol. 30, n.º 8, pp. 1011–1018, 2010.
[74] F. J. Keefe *et al.*, «Virtual reality for persistent pain: a new direction for behavioral pain management», *Pain*, vol. 153, n.º 11, p. 2163, 2012.