

CAHR: A Contextually Adaptive Rehabilitation Framework for In-Home Training

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Thesis submitted to the
Faculty of Graduate and Postdoctoral Studies
In partial fulfillment of the requirements
For the degree Doctor of Philosophy in
Electrical and Computer Engineering

School of Electrical Engineering and Computer Science
Faculty of Graduate and Postdoctoral Studies
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Abstract

Home-based rehabilitation has evolved in recent years as a cost-effective and convenient alternative to traditional clinical rehabilitation. Researchers have developed various types of sensors-based rehabilitation systems that incorporate Virtual Reality games aimed to offer the patient an entertaining and beneficial training experience from the comfort of home. This has consequently created the need to design reliable assessment and adaptation mechanisms that are able to measure and analyze the patient's performance and condition, and to accordingly make proper adjustments that conform to the abilities of the patient during the training.

In this dissertation, we introduce our context-based adaptive home-based rehabilitation framework (*CAHR*) that offers the patients a rehabilitation environment that can adapt based on their physical, physiological, and psychological context, while taking into consideration the environmental conditions that may hinder their progress. *CAHR* is a generic framework that can be implemented to fit any of the upper or lower extremity rehabilitation. However, in this dissertation, we base our modeling and analysis mainly on the wrist.

In *CAHR*, the physical condition of the patient is assessed by a fuzzy logic-based mechanism that uses the various kinematics captured during the training to provide a quantified value which reflects the Quality of Physical Performance of the patient. The rehabilitation task adaptation is achieved based on a special algorithm that defines how the physical training, psychophysiological responses, and environmental conditions must be

manipulated in order to match the desired performance target parameters set by the therapist. The simulation results have shown that the proposed adaptation engine can properly adjust the rehabilitation environment based on different simulated performance behavior that might be produced by a patient. In addition, training with a special game that has been designed based on the developed framework has shown improvement in the physical capabilities of two patients suffering from upper extremity impairments.

Acknowledgment

I would like first to thank the creator who gave me the will and the strength to fulfill this dissertation. Very special thanks go to my supervisors, Prof. Abdulmotaleb El Saddik and Prof. Wail Gueaieb for their advice and guidance throughout my studies. I was so lucky to have such great mentors, and they have definitely had the biggest impact on my academic journey.

I owe my deepest gratitude to the very special people in my life, namely my father Mohamad, my mother Jamal, my wife Ghazala, and my wonderful children Meriam and Eisa. Your support and patience was the key factor of my success.

I am so grateful to my dear colleagues, Dr. Mohamad Eid and Hussein Al-Osman. I will never forget the long hours of discussions we had during my doctoral studies. Finally, I would like to dedicate this work to my parents, family, and my dear friends in the Multimedia Communication Research Laboratory (MCRLAB).

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List of Acronyms

| | |
|-------------|---------------------------------|
| A/D | Analog to Digital |
| ADL | Activity of Daily Life |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| AR | Augmented Reality |
| BN | Bayesian Network |
| BPNN | Backpropagation Neural Network |
| CAE | Context-based Adaptation Engine |
| DAA | Dynamic Adaptation Adjustment |
| DDN | Dynamic Decision Network |
| DOF | Degrees of Freedom |
| EMG | Electromyography |
| FIE | Fuzzy Inference Engine |
| FIS | Fuzzy Inference System |
| FL | Fuzzy Logic |
| GUI | Graphical User Interface |
| HMD | Head-mounted Display |
| HTML | Hypertext Markup Language |

| | |
|-------------|-----------------------------------|
| IK | Inverse Kinematics |
| IMU | Inertial Measurement Unit |
| IR | Infra-Red |
| PPQ | Physical Performance Quantifier |
| QOP | Quality of Performance |
| QPP | Quality of Physical Performance |
| ROM | Range of Motion |
| SFQ | Short Feedback Questionnaire |
| SOAP | Simple Object Access Protocol |
| UML | Unified Modeling Language |
| VE | Virtual Environment |
| VHR | Virtual Home-based Rehabilitation |
| VR | Virtual Reality |

Chapter 1. Introduction

Physical injuries are common among post stroke patients, athletes, and workers of physically demanding professions. Statistics have revealed that following a stroke, almost 85% of patients who survive the disease are left with deficiencies in the hand [Parker et al., 1986], among them 20% suffer from what it is called “Foot-drop” symptom [Haudsroff and Ring, 2008]. On the other hand, upper and lower extremity injuries are also widely reported by construction workers [Choi et al., 2007], and people working in the manufacturing sector. Almost 4.7% of textile male workers suffer from chronic upper limb pain, while 16.7% of women working in metal manufacturing experience the same culprit [Palmer, 2003]. Furthermore, athletes also suffer frequently from several physical injuries. Research has also identified that chronic wrist pain is quite common among gymnasts [Difiori et al., 2006] and ankle sprains account for up to 21% of sports-related injuries [Saluta and Nunley, 2010].

Treating the aforementioned impairments is normally achieved through a physical therapy regime which is normally carried out at special clinics. Rehabilitation is a restorative process that aims to treat the disabilities and impairments in the injured limb in an attempt to hasten and maximize the recovery of the patient and to bring him/her back to pre-injury levels. It attempts to improve the patient's quality of life and to reintegrate her or him as much as possible into society [Karime et al., 2011a]. The expected outcome of such a regime is to develop strength, flexibility and proprioception in the injured body segment [Girone et al., 2001]. Nevertheless, to obtain satisfactory rehabilitation results, a patient needs to

undergo an adequate number of therapy sessions. During these sessions, the therapist conducts a series of exercises to the patient and assesses his/her performance based on a number of standard tests.

Research has revealed that the reduction in the duration of rehabilitation and the lack of timely interventions can have a negative impact on the patient's treatment [Popescu et al., 2000]. However, receiving a sufficient number of sessions is becoming a very challenging issue for both the patient and the clinician. On one hand, the growing number of patients and the lack of human and financial resources in many countries have led to a reduction in the amounts and duration of the therapy for the patients. For example, patients are receiving less therapy in the US due to the economic pressure on the health care system [Reinkensmeyer et al., 2002]. On the other hand, most of the rehabilitation training is done in special clinics or at hospitals and requires the presence of a therapist during these treatment sessions. As a result, patients living in rural areas might find it difficult to frequently travel back and forth to the cities where most of the rehabilitation centers are located. This might force many patients to skip some of the sessions or even stop the treatment which can greatly delay their recovery.

For those who are unable to receive clinical rehabilitation, home-based training could be an alternative or a complimentary method to continue their treatment. Passive devices, such as Elastic Bands, Foam Rollers, Wobble Boards, and Rubber balls were proven to have a good effect on the therapy and are recommended by therapists as affordable and beneficial tools for home-based exercise [Andersen et al., 2010, Nielson et al., 1996]. An Elastic Band [DM Systems, 2013] is a rubber tubing device that comes in different shapes that is used for strength training. A Foam Roller [Foam Roller, 2013] consists of a cylindrical cone of resistant foam. The roller can be placed between the body and the floor, or in other positions

for various types of exercise. A Wobble Board [Rehab Supplies, 2013] is a foot platform that is rectangular or circular in shape which sits on top of a ball-like structure that allows various degrees of axial tilt. A Rubber Ball [IMAK, 2013] is a squeeze ball that is normally used to strengthen the grip force of the hand. The main reason behind choosing these tools for home training is the fact that besides their health benefits, almost every patient is familiar with their usage and their prices are affordable for all classes of people. However, these tools suffer from two main drawbacks:

- Repetitive Nature: Patients are normally asked to train with these devices by repeating the same exercise for a number of times on a daily basis [Betker et.al, 2006]. On the long run, this repetition would result in boring the patient who might stop training.
- Storage Incapability: These devices cannot store any training information that enables the therapist to examine the patient's performance at the next visit to the clinic. Therefore, the progress and the quality of performance of the home-training are always unknown to the clinician.

The tremendous developments in the field of sensory and Virtual Reality (VR) technologies have drawn new boundaries for medical applications. Computerized home-based rehabilitation has evolved in recent years as a cost-effective and convenient alternative to traditional clinical rehabilitation [Ryu et al., 1991]. Patients have now the capability to train from home with special sensory interfaces that are coupled with VR tasks that run on their computers. The VR tasks can be designed to guide the patient during the training and to adapt to his capabilities. The therapist can monitor the progress of the patient by examining the collected data stored on a database. One way of making home-based rehabilitation

systems more appealing to the patient is by choosing intuitive interfaces and games that do not require technical knowledge or computer skills. Furthermore, an effective home-based rehabilitation system should provide means to measure the quality of patient's performance in order to help therapists easily monitor the patient's progress, identify any impairment, and suggest treatments (rehabilitation exercises). Potential benefits associated with home rehabilitation include improved empowerment (earlier return to home and family), reduced cost (home rehabilitation costs have been shown in some studies to be lower than hospital based in-patient rehabilitation [Von Koch et al., 2010]), and low therapist to patient ratio (since the patient requires minimum supervision). In Chapter 2, we provide a survey of the state-of-the-art works that have been achieved in this field.

1.1. Application Scenario

As an application scenario, consider the case of a post-stroke survivor suffering from impairments in his upper limb movements who was discharged from the hospital and prescribed by the doctors to undergo physical therapy three times per week for 6 months. The patient lives in the country side where there is no rehabilitation clinic, and the nearest specialized facility is about 70 kilometers away. In addition, the patient does not have a medical insurance that covers the costs of the therapy which is almost 70 dollars per session. To reduce the burden on the patient, the therapist suggests him/her to buy a computerized tele-rehabilitation system that enables the communication with the clinic through the internet.

The system is comprised of a software component that can be installed on the patient's computer and a hardware training device used for training the injured hand. The software

module consists of an application that enables the patient to perform various tasks, such as choosing a virtual exercise from a number of VR games, storing performance results, generating a training report at the end of an exercise, communicating messages to the therapist, including other options. All captured results and generated reports are stored on the cloud. Such a setup allows the user to ubiquitously access her or his training information. It also permits the clinician to monitor all persisted data. The hardware training tool consists of a sensory-embedded training device that can track the patient's motions during the training. The training device is very intuitive to use and allows the patient to easily control the games in a very natural manner. The device also generates vibro-tactile feedback based on specific states so that the training experience becomes more fun and the patient feels more immersed in the VE. In order to provide proper exercise for the patient tailored to his abilities, the VR games can automatically adjust based on the physical and physiological parameters of the patient during the exercise. In addition, the tasks take into consideration the limitations imposed by the clinician so that they do not exceed the patient's physical abilities. Figure 1.1 shows a high level model of a home-based rehabilitation system.

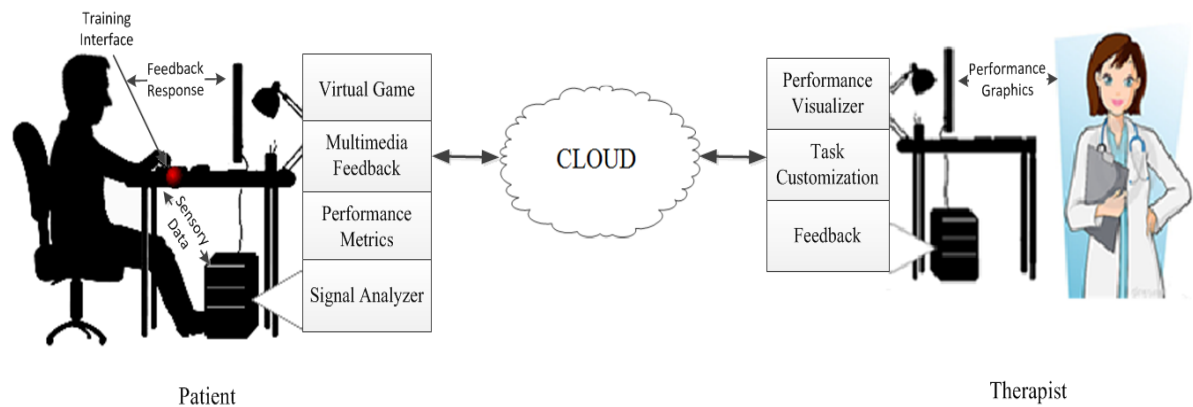


Figure 1.1: A model of a home-based rehabilitation system

Now on the clinician's side, an application is installed on the therapist's computer. The therapist's application enables him or her to track the performance of the patient through the cloud interface. The application includes many features that help the therapist to easily visualize the performance of the patient and to customize the difficulty levels of the games. Therefore, the clinician can easily find out where potential deficiencies lie and set training goals accordingly. The clinician's application also facilitates the configuration of the virtual environment and allows the therapist to communicate messages with the patient.

Based on the above scenario we derive seven major requirements that the rehabilitation framework should satisfy:

- **Online Adaptation:** The rehabilitation task should adapt to the physical and psychophysiological abilities of the patient by considering the past performance captured throughout the training. Adaptation should be applied online both in a per-trial (i.e., a trial is one set from a session) and a per-session fashion so that the over-time fluctuations in performance are well analyzed and the task is more accurately adjusted.
- **Multimodal Feedback:** Visual, audible, and haptic feedback are widely used in computerized rehabilitation applications because they assist the patient to feel more immersed in the virtual environment [Yeh et al., 2005, Karime et al., 2011b]. They are necessary to help the patient achieve the goal of the task accurately by providing feedback pertained to his performance. Finally, multimedia feedback can greatly reduce the boredom of the exercise by offering an entertaining gaming environment.
- **Quantitative Assessment:** In order for both the therapist and the patient to easily understand the outcome of the training, the system should possess a mechanism that

quantifies the captured training data and represents it in a way that is easy to comprehend.

- **Therapist customization and Control:** Any rehabilitation regimen cannot be successful without the expertise and the supervision of a specialized therapist. Thus, the home-based rehabilitation system must enable the specialist to customize the virtual environment and to control the adaptation of the task so it does not exceed the patient's physical abilities.
- **Physiology awareness:** The physiological condition of the patient, such as fatigue and stress, can greatly affect his/her training performance. For instance, a patient performing very well at the beginning of a training session might have his performance declining after a certain time due to fatigue. Therefore, the VHR system must be aware of the physiology of the patient so that the assessment of the performance is optimized.
- **Environment Awareness:** Environmental factors such as training location, time of the training, the atmosphere in the training room etc., can also have an influence on his/her performance. For instance, a noisy room might cause the patient to lose his or her concentration while exercising. Consequently, this context should be taken into consideration by the system when judging the training outcome.
- **Intuitive Interface:** The training interface that the patient is using is actually the core of the rehabilitation process. Since the patients come from different backgrounds and can have different types of impairments, it is very crucial that the training device be non-invasive and very simple to understand its functionality so that everyone is able

to use easily and intuitively without the help or the presence of an expert and with minimal learning.

1.2. Research Statement

Virtual Home-based rehabilitation (VHR) poses several challenges. First, being home-based, the rehabilitation system operates autonomously since the therapist is not present during the training session. Therefore, the possibility of aggravating the injury due to overtraining or because of generating inappropriate exercises by the system exists. Making the system adaptive could lead to a safer training environment and a more effective exercise generation that suits the patient's abilities. However, assessing the performance of the patient based on his physical abilities alone may not be always accurate since his physiological state and the environmental conditions of the training location can have a significant role on the overall performance. Consequently, this adds another level of challenge for home-based rehabilitation on how to make the rehabilitation system able to properly adapt to the overall psychological and/or physiological conditions of the patient while considering the environmental factors surrounding him/her.

To the best of our knowledge, none of the current home-based rehabilitation frameworks have actually considered psychological, physiological or environmental context when adapting the rehabilitation task to the performance of the patient. As a result, the adaptation algorithms were mostly based on examining mainly the physical performance of the patient during the training. In this dissertation, we define our research statement as the following:

“Developing a context-aware adaptation framework for a home-based rehabilitation system that can adjust the rehabilitation task (such as task difficulty, multimedia contents,

and interaction modality) by considering the quality of patient performance, physiological and psychological state, and environmental conditions of the patient in the previous tasks, by utilizing intuitive tangible interfaces”.

1.3. Contributions

The main objective of this dissertation is to elaborate on the design, modeling, and evaluation of a context-aware home-based wrist rehabilitation framework that incorporates VR tasks that can adapt to the patient’s performance in terms of their intensities and multi-media content. The thesis contributions can be summarized by the following:

1. The design and development of a generic context-aware adaptive virtual rehabilitation framework that enables home-based training with minimal therapist supervision. The framework can be implemented to fit any of the upper or lower extremity rehabilitation. However, in this dissertation, we have based our modeling and analysis on one limb, namely the wrist. The framework facilitates the capture, analysis, and representation of the collected training data and allows customization and control to the clinician.
2. The modeling and analysis of an adaption algorithm that takes into account the context of the patient, namely the physiological/psychological and the environmental factors, as well as his quality of physical performance to make decisions on the intensity of the subsequent exercises (tasks) and to adjust the multimedia content of the virtual game.

3. The modeling and analysis of a fuzzy logic inference engine that quantifies the captured training kinematics into a crisp representation which conveys the quality of physical performance of the patient.
4. The design and implementation of a sensory-embedded wireless rubber ball that is used as a tangible interface to capture the patient's performance with real patients when deployed in a home rehabilitation environment.

1.4. Scholarly Achievements

The following journals and conference papers are the outcome of this research:

Refereed Journal Publications:

1. **Ali Karime**, Mohamad Eid, Jihad Mohamad Aljaam, Abdulmotaleb El Saddik and Wail Gueaieb, "A Fuzzy-based Adaptive Rehabilitation Framework for Home-based Therapy", *IEEE Transactions on Instrumentation and Measurement* , 63(1), pp.135-144, 2014.
2. **Ali Karime**, Hussein Al-Osman, Jihad Mohamad Aljaam, Wail Gueaieb, and Abdulmotaleb El Saddik, "Tele-Wobble: A Tele-Rehabilitation Wobble Board for Lower Extremity Therapy", *IEEE Transactions on Instrumentation and Measurement*, 61(7), pp.1-9, 2012.
3. Basim Hafidh, Hussein Al-Osman, **Ali Karime**, Jihad Mohamad Aljaam, and Abdulmotaleb El Saddik, "SmartPads:"A Plug-N-Play configurable Tangible User Interface", *Multimedia Tools and Applications*, 2013.
4. Jihad Mohamad Aljaam, Ali Jaoua, Saleh AlHazbi, Ahmad Hasnah, **Ali Karime** , and Abdulmotaleb El Saddik, " An Assistive Computerized System for Children with

Moderate Intellectual and Learning Disabilities”, *International Journal of Emerging Technologies in Learning (iJET)*, Vol.6, pp.11-19, 2011.

5. **Ali Karime** , M. Anwar Hossain, ASM Mahfujur Rahman, Wail Gueaieb, Jihad Mohamad Alja'am, and Abdulmotaleb El Saddik, " RFID-based Interactive Multimedia Edutainment System for the Children”, *Multimedia Tools and Applications*, Springer, 59 (3), pp.749-774, 2011.

Refereed Conference Publications:

1. **Ali Karime**, Mohamad Eid, Hussein Al-Osman, Wail Gueaieb, and Abdulmotaleb El Saddik, "Capturing Ankle Benchmark Kinematics Using a Sensory Wobble Board", *IEEE International Conference on Multimedia and Expo (ICME)*, Workshop on Multimedia Services and Technologies for E-Health, San Jose, USA, pp.1-6, 2013.
2. **Ali Karime**, Mohamad Eid, Wail Gueaieb, and Abdulmotaleb El Saddik, "Determining Wrist Reference Kinematics Using a Sensory-Mounted Stress Ball", *IEEE International Symposium on Robotics and Sensors Environments*, Magdeburg, Germany, 2012.
3. Rajwa Alharthi, **Ali Karime**, Hussein Al-Osman, and Abdulmotaleb El Saddik, "Exerlearn Bike: An Exergaming System for Children's Educational and Physical Well-Being", *IEEE International Conference on Multimedia and Expo (ICME)*, the *International Workshop on Interactive Ambient Intelligence Multimedia Environments*, Melbourne, Australia, pp. 489-494, 2012.
4. Moutaz S. Saleh, Jihad M. Aljaam, **Ali Karime**, and Abdulmotaleb El Saddik, "Leaning Games for Children with Intellectual Challenges", *International Conference on Information Technology Based Higher Education and Training*, pp. 1-5, 2012.

5. **Ali Karime**, Basim Hafidh, Abdulmajeed khaldi, Jihad Mohamad Aljaam, and Abdulmotaleb El Saddik, "MeMaPads: Enhancing Children's Well-Being Through a Physically Interactive Memory and Math Games", *IEEE International Instrumentation and Measurement Technology Conference* ,Graz, Austria, pp. 2563-2566, 2012.
6. **Ali Karime** , ASM Mahfujur Rahman, Abdulmotaleb El Saddik, and Wail Gueaieb, "RehaBall: Rehabilitation of Upper Limbs with a Sensory-Integrated Stress Ball", *IEEE International Symposium on Haptic Audio-Visual Environments and Games (HAVE)*, Qinhuangdao, Hebei, China, pp. 24-28, 2011.
7. **Ali Karime** , ASM Mahfujur Rahman, Hussein Al-Osman, Wail Gueaieb, and Abdulmotaleb El Saddik,"E-Dumbbell: An Electronic Dumbbell with Haptic Feedback for Wrist Rehabilitation", *IEEE International Conference on Virtual Environments, Human-Computer Interfaces, and Measurement Systems (VECIMS)*, Ottawa, Canada, pp.1-4, 2011.
8. **Ali Karime** , Hussein Al-Osman, Wail Gueaieb, and Abdulmotaleb El Saddik," E-Glove: An Electronic Glove with Vibro-Tactile Feedback for Wrist Rehabilitation of Post-Stroke Patients ", *IEEE Workshop on Multimedia Services and Technologies for E-Health (ICME)*, Barcelona, Spain, pp.1-6, 2011.
9. **Ali Karime**, Hussein Al-Osman, Wail Gueaieb, Jihad Mohamad Alja'am, and Abdulmotaleb El Saddik, "E-Wobble: An Electronic Wobble Board for Ankle and Toe Rehabilitation ", *IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Bari, Italy, pp. 366-369, 2011.
10. **Ali Karime**, Hussein Al-Osman, Wail Gueaieb, Jihad Mohamad Alja'am, and Abdulmotaleb El Saddik, "Learn-Pads: A Mathematical Exergaming System for

Children's Physical and Mental Well-Being", *IEEE International Conference on Multimedia and Expo (ICME)*, Barcelona, Spain, pp. 1-6, 2011.

1.5. Thesis Organisation

This dissertation is organized as follows. In Chapter 2, we review the current state-of-the-art virtual home-based rehabilitation systems and compare each against the requirements we have defined in Chapter 1. In Chapter 3, we present our adaptive VHR framework and elaborate in details about each component incorporated within it. In Chapter 4, we present a preliminary study of the wrist kinematics and show how our findings were used to model the fuzzy logic-based *Physical Performance Quantifier* that assesses the *Quality of Physical Performance*. In Chapter 5, we discuss in details the *Context-based Adaptation Engine* model that is responsible of adjusting the rehabilitation environment and we present an analysis of its performance. In Chapter 6, we give a detailed description of the digital rubber ball design and the software proof-of-concept rehabilitation game. In Chapter 7, we present our usability study that was conducted with two patients suffering from upper limb impairments. Finally, In Chapter 8 we draw our conclusion and state possible future research directions.

Chapter 2. Literature Review

In this chapter, we briefly give an introduction about Virtual Rehabilitation and its applications at clinics and homes. We then state the main benefits of Virtual Home-based Rehabilitation and the challenges it is currently facing. Afterwards, we provide our classification of the current home-based technologies along with a literature survey of the state-of-the-art.

2.1. Background

Computerized rehabilitation is an important branch of e-health which relies on video games, namely Virtual reality (VR) to enhance specific skills through playing [Halton, 2008]. The use of Virtual Environments (VE) in computerized rehabilitation has been shown to be a promising technology and was found to have potential benefits as an assessment and training tool [Chen et al., 2006, Alamri et al., 2008]. Virtual Rehabilitation is able to provide a natural or real-life environment where patients have the chance to forget about their surroundings and to put all their focus on the simulated environment [Schultheis and Rizzo, 2001].

The term "Virtual Rehabilitation" has been used by researchers to emphasize the association of VE with the rehabilitation training within a system [Feasel et al., 2011, Connelly et al., 2010]. Virtual rehabilitation has been recently deployed in clinical settings and hospitals for aiding the specialists in training their patients and obtaining objective performance measures. For example, the commercial Biodex Balance System [Biodex, 2013] is

used for lower extremity rehabilitation in general. It consists of a circular platform that the patient steps on with both feet, and a small screen where the games and the related training information are displayed. Due to the medical costs and the inconvenience of traveling to rehabilitation facilities, researchers introduced a new therapy approach that consists of virtual reality systems specially designed to offer a home-based training that mimics the one performed in clinics but without the need of a therapist to be continuously present during the exercise.

Virtual Home-based Rehabilitation (VHR) is the process of combining the rehabilitation training performed at home with video games that aim to entertain, motivate, and lead the patient to perform the appropriate exercises that could potentially lead to a progress. The main goal of VHR is not actually to replace the conventional therapy performed in clinics but rather to provide an assistive means that can empower the patient to perform rehabilitation tasks conveniently at home in a portable, affordable, and potentially beneficial fashion.

2.2. Benefits of Virtual Home-based Rehabilitation

Virtual home-based therapy has various economical and physical advantages for the patients and the clinicians at the same time. These benefits could be summarized in the following points.

- **Reduced Costs:** Clinic-based rehabilitation can be a very expensive process for both patients and governments [Bach et al., 2002, Wielgosz et al., 2009]. For example, the cost of a 45 minute visit to a physiotherapist is about \$70 in Canada [TCSM, 2013]. Training from home with a minimal clinical supervision can greatly reduce the

economic burden on the medical sector and offer a cost effective alternative for patients without a proper medical insurance.

- **Reduced Travels:** One of the main inconveniences that many patients encounter is the distance that they might have to travel in order to receive their treatment. Most of the rehabilitation clinics and facilities are located in major cities such as downtowns. Consequently, patients living in the suburbs or in the rural areas need to frequently make long trips to reach those facilities. VHR can reduce the hardship of traveling by significantly reducing the number of visits to a therapy center.
- **Increased Training Sessions:** In a report published by the Ontario Stroke Evaluation in 2011 [Hall et al., 2011], it was found that post stroke patients were not receiving enough rehabilitation sessions after being discharged from the hospital. This problem can be avoided using virtual home-based rehabilitation which conveniently offers the capability to train from home on a daily basis and at the time of convenience.
- **Increased Motivation and Entertainment:** Rehabilitation is repetitive in nature; patients are required to perform the same exercise over and over again. This characteristic of repetitiveness results quite often in a loss of motivation for the patient who might become bored while proceeding with the training. The virtual reality games incorporated with the VHR offer a more realistic training experience and make the patient feel more immersed into the training environment, thus eliminating the lack of motivation normally experienced with the traditional therapy and shifting the exercise from a state of boredom to fun [Rizzo and Kim, 2005].
- **Easier Diagnosis and Performance Analysis:** Diagnosing the condition of the patient in a timely fashion is a vital aspect of the therapeutic procedure. A deficiency

discovered at an early stage could lead to a better rehabilitation output if the treatment starts at the right time [Fredericson, 1996]. Virtual home-based rehabilitation systems normally provide statistical and visual analyses that help clinicians easily track the progress of their patients after each training session. By examining the performance of the patient, clinicians might identify hidden impairments that might take a long time to diagnose by conventional medical methods.

2.3. Social Challenges

VHR poses several social challenges for its widespread adoption. The most important challenges can be summarized by the following:

- **Clinical Acceptance:** There are still lots of controversy in the medical community on the viability of virtual rehabilitation in improving the health condition of the outpatients. However, recent studies revealed some encouraging results, particularly with post-stroke patients who have shown a good progress after training with a VR environment even years after their traditional therapy had stopped [Burdea, 2003].
- **Patient Acceptance:** An interesting aspect of any new technology is how people perceive it. Patients come from various backgrounds and their interests might be widely different. For instance, patients who are exposed to video games might be very interested in adopting such a technology at home, while others who are computer illiterate might find it hard to understand the concept of virtual training and simply prefer an alternative rehabilitation option.
- **Equipment Cost:** When it comes to buying new equipment, cost always tops the interest of the consumer. The price of the equipment plays an important role in the

patient's decision of purchasing the technology. Home-based systems should be made affordable so that the majority of the patients can get it at home.

- **Deployment Logistics:** Patients come from different backgrounds, and many of them might not have good computer or technical skills. As a result, the tools and equipment of any VHR system should be simple to install and the operation theme should be made as simple as possible so that everyone is able to setup and configure the system.

2.4. Classification of Virtual Home-based Rehabilitation systems

The current VHR systems can be classified into three categories, (a) Stand-alone applications, (b) VHR systems with Feedback, and (c) Adaptive systems. The Stand-alone applications offer a passive mode of training in the sense that the system does not provide any guidance to the patient during the training. On the other hand, VHR systems with feedback can be considered as an interactive version of the Stand-alone applications. They consist of special hardware and/or software specially designed for rehabilitation purposes. These systems normally inform the patient about his/her progress either through multimedia feedback (e.g., haptics, auditory, text etc.) or by providing the patient and the therapist with quantitative assessment about his progress. Finally, the adaptive systems are patient-centered applications that are tailored to the patient's need and performance overtime by adjusting their level of challenge and environment to fit his/her abilities. In the following sections, we state some of the related works for each of the three categories.

2.5. Stand-alone Home-based Rehabilitation Systems

In general, most of the stand-alone rehabilitation systems use the commercialized interaction interfaces and consoles initially designed for entertainment and apply them into the therapy training. Since these consoles were not initially designed for rehabilitation exercises, they do not provide any performance feedback to the user.

Recently, the term "Wiihabilitation" or "Wiihab" has been frequently used in the field of computerized rehabilitation. The online Urban Dictionary has defined Wiihabilitation as "the use of the Nintendo's Wii video games system in rehab therapy for patients recovering from strokes, broken bones, surgery, and even combat injuries" [Urban, 2013]. Many researchers have used the prevalent Wii consoles as a rehabilitation training interface. For instance, Sugarman [Sugarman et al., 2009] used the popular Nintendo Wii Fit [WII Fit, 2013] for balance training with a stroke survivor suffering from gait disability. The authors picked 4 games that are included with the console to conduct the training experiments. Those games are the Table Tilt, Bubble Balance, Tightrope Tension and the torso and waist twist. The patient was asked to control each of those games either by shifting her weight without moving the feet, or by stepping on a special platform where the Wii Fit console was placed on the top of it. The outcome of the training with the console was assessed based on a number of standard rehabilitation tests, such as the Berg Balance Scale [Berg et al., 1992], and a questionnaire. The subject reported a joyful experience when training with the console.

The Wii remote has also been used in [Harley et al., 2011] for upper extremity training of stroke survivors. The authors have introduced a new input device that is composed of a Wii Remote IR camera mounted on the ceiling that tracks two infrared (IR) beacons attached to the patient's impaired arm. This configuration allowed a 2D tracking of the forearm by

using an inverse kinematic (IK) model of the human arm that can track its motion in a horizontal plane. The motion data were used to control a special game that was developed to encourage specific stroke rehabilitation arm exercises such as *Range of Motion* (ROM), precision, stability and tremor. A qualitative evaluation was conducted with one stroke survivor who expressed his interest in the system.

In a similar work that focuses on balance training, the authors in [Lange et al, 2011] deployed the Microsoft Kinect Camera [Kinect, 2013] to evaluate the usability of a specially developed rehabilitation game. The rehabilitation task was designed to elicit specific therapeutic motions when controlling the movement of a virtual avatar trying to achieve a specific goal. The game enabled the therapist to make choices about some settings within the environment in order to make the game appropriate to each of the patient's therapeutic needs. The authors conducted qualitative evaluations with twenty participants suffering balance problems due to various illnesses. Ten therapists provided their feedback on the application and each of the patients was interviewed and asked to provide his/her perception about the system. The data collected indicated that therapists and patients showed excitement and support of such technology however urged the need for quantizing the patient's performance.

In another work, Rand [Rand et al., 2008] studied the feasibility of using the Sony Playstation II Eye Toy [Eye Toy, 2013] with twelve post stroke survivors with upper extremity disabilities. All the subjects sustained a right hemispheric stroke and the severity of their impairments ranged between moderate and severe. Participants were asked to play with the Wishy-Washy and Kung-Foo environments that come with the console and their gaming experience were characterized by using the Short Feedback Questionnaire (SFQ) [Kizony et al., 2006] and the Borg scales [Borg, 1990]. The authors used only descriptive

statistics and reported that the Eye Toy might be feasible for patients with acute and chronic stroke.

2.6. VHR Systems with Feedback

This category of VHR consists of systems that capture and analyze various parameters collected during the training in order to present them to the therapist and/or the patient in the form of quantified performance metrics and/or multimedia feedback.

Boian [Boian et al, 2002] presented his haptic rehabilitation tool called “Rutgers Ankle” which is based on the six degrees of freedom Stewart platform. “The Rutgers Ankle” is aimed to help patients with foot impairments, specifically at the ankle, to exercise at home while being remotely monitored by a therapist. The Stewart platform is a closed loop manipulator made with six pneumatic cylindrical actuators that connect a six-DOF end-effector to a base platform through prismatic joints. The system incorporates a set of virtual reality (VR) games that deal with several types of ankle rehabilitation exercises, such as strength, flexibility, and balance. Depending on the state of the game, the patient receives a determined force feedback through six actuators that are controlled by an electro-pneumatic controller. A number of performance parameters such as target accuracy scores, maximum range of motions (ROMs), time, and the torques achieved by the patients, are collected and stored during the training. In the offline mode, the data are analyzed to extract performance metrics, such as the mechanical work and the power output. These data are then transferred to a remote database that can be accessed by the therapist.

Alamri [Alamri et al., 2010] developed an augmented-reality framework that adopts the concept of tangible objects as a means of interaction. Virtual objects are superimposed over a

real environment set up, and the patient is required to perform a certain rehabilitation task by manipulating a real cup in the Augmented Reality (AR) environment. The framework includes 2 reaching exercises that are derived from daily life activity, such as moving a cup to a virtual cupboard. During the training, data are captured to determine a number of performance parameters, namely task completion time, compactness of task, and the speed of hand movement. These parameters can be displayed on the therapist's interface (computer) in form of visual graphs.

Holden [Holden et al., 2005] introduced a telerehabilitation system that enables the patient to train at home while being monitored by his/her physiotherapist. The system uses an electromagnetic motion-tracking device to track the arm movements of the clinician who records a set of recommended arm training movements that are translated into VE animations. At home, the patient can perform his rehab exercise by imitating the VE recorded motions (exercises) of the therapist. A set of related data training feedback are displayed on the computer screen of the patient and transmitted at the same time to the therapist's computer through the internet.

Karime [Karime et al., 2012a] designed a sensory mounted wobble board to control a specially developed software golf game for training the ankle of post-stroke patients with foot-drop symptoms. The main idea of the system was to leverage the benefits of the passive wobble board that is widely used in rehabilitation by adding a number of sensory and actuating devices to the board, therefore taking it from a passive state to an interactive one. The system adopted a tele-rehabilitation framework that is comprised of two main components: a patient tier and a medical tier. The patient tier accomplishes a number of duties such as capturing the training data collected throughout the exercise, generating performance reports at the end of each session, and allowing the patient to view the

clinician's feedback. On the other hand, the medical tier enables the clinician to view a number of performance parameters that are of interest to the therapist such as, the session completion time, the ROMs or angles collected during the exercise, the performance errors, and the accelerations on each of the 4 ankle motions. The system was tested with a patient who showed an improvement after training for 2 weeks.

Hilton [Hilton et al., 2002] developed a virtual reality system that is based on the concept of performing a daily life activity, particularly the activity of making coffee. For this purpose, he used a tangible user interface approach which consisted of mounting the kitchen tools required for making coffee (such as spoons, cups, jars etc.) with sensors that enable the detection of the patient's actions. For instance, a light sensitive switch was mounted inside a coffee jar in order to detect the activity of opening the jar's lid. The tangible objects were associated with a virtual environment that represents virtually the same real objects. The actions performed by the patient are actually mapped with the virtual objects in the VE. The design of the VE coffee making activity was based on a hierarchical task analysis. The authors defined a number of steps (subtasks) that constituted the complete activity and built the virtual environment of the training activity around those steps. A set of verbal instructions delivered by a computer were triggered to lead the patient on how to proceed with the exercise. In case the patient performs an incorrect activity, the system responds by triggering a verbal correction and the patient will not be able to proceed until the correct action is taken.

Morrow [Morrow et al., 2006] exploited the high computational performance of the existing game consoles to design a VR hand rehabilitation system using an Xbox from Microsoft. Morrow's main goal was to use off-the-shelf cheap and efficient devices to develop a portable rehabilitation system that could be easily used in both clinics and homes. The author used an Xbox instead of a computer to run the virtual reality graphics by making

some hardware and software modifications to the console. A P5-glove [Mindflux, 2013] that measures the flexion of the fingers and the wrist position was connected to the Xbox instead of the regular joystick. Two games were developed to encourage two types of rehabilitation training: the finger ROM and the finger velocity games. In the finger ROM game, the patient has to uncover a screen that conceals an image by flexing his/her fingers, except the thumb. The image is uncovered in proportion to each finger flexing motion. Now in the finger velocity game, the patient has to flex his/her finger from a flat position to a fist as fast he/she can in order to meet a certain threshold that makes a virtual butterfly circling a palm flies away. The system provides numerical, auditory and visual feedback upon achieving certain performance goals during the play.

2.7. Adaptive Systems

In this Section, we first discuss the importance of adaptation in VHR systems and briefly explain its two modes (online and offline adaptation). We then survey some of the existing adaptive rehabilitation systems found in the literature.

2.7.1 Significance of Adaptation

It is commonly known that a player who frequently plays the same game becomes very familiar with the behaviour of that game, and therefore would require a higher level of challenge that keeps him enjoying it and willing to continue playing. On the other hand, if the game becomes very challenging and goes over the player's abilities, he/she might become frustrated and simply gives up playing. In essence, a game that is either too easy or too hard might simply result in the loss of the player's motivation. Consequently, the need for an

adaptation mechanism that can continuously match the difficulty level of the game with the varying skills of the user becomes really crucial in order to create a balance between entertainment and challenge.

Adaptivity attempts to maintain an appropriate level of challenge by dynamically adjusting game elements, such as the difficulty level and the environment within a game, according to the player's performance [Burke et al., 2009]. Adaptation of digital games is an active area of research that focuses on using Artificial Intelligence (AI) to create Dynamic Adaptation Adjustment (DAA) models that fit the player skills [Bakkes et al., 2009, Spronck et al., 2006]. The dynamic adaptation of the game elements can make it more player-centered and offer an experience that is more unique and personal [Lopes et al., 2011]. The advantages of incorporating adaptation algorithms within games have two main advantages. Firstly, it improves the player gaming experience since it can adapt to his or her abilities. Secondly, it can anticipate all the possible situations that might be encountered by the player, therefore reducing the development effort [Ram et al., 2007].

The necessity of incorporating adaptation in rehabilitation related games becomes even more significant. Not only keeping the patient engaged and excited does become a concern in VHR, but also making sure that the chances of getting pre-injured because of requiring hard tasks that go beyond the patient's abilities are reduced to a minimum [Burdea, 2003]. Furthermore, it is believed that effective adaptive systems can potentially shorten the recovery time since the training tasks are adjusted to efficiently address the deficiencies of the patient [Chen et al., 2007].

2.7.2 Modes of Adaptation

There exist two modes of adaptation, online and offline. Offline adaptation means that the adjustments of the environment and the intensity levels of a game or a system are made prior to starting a game play based on the user's dependant data. These data are normally collected either through asking the patient to fill up a profile before starting a new session or by starting a game at the easiest level and then adapting it after each session based on the performance data collected.

Unlike the offline adaptation which adaptive states are defined and known in advance, the transformed states in the online adaptation are unknown and depend on the learning and processing of the performance data of the previous states. Charles [Charles et al., 2004] stated that this sort of adaptation is the most interesting type. It is interesting because the output is unpredictable which make it hard for the player to learn manoeuvres or tactics that make him/her always reach the gaming goals easily. The online adaptation allows a per-trial adjustment of the challenge rather than a per-session adaptation, which makes the training highly dynamic for the patient.

2.7.3 Existing Adaptive VHR Systems

Despite its importance in VHRs, only few researchers have designed systems that incorporate adaptation algorithms [Pirovano et al., 2012]. One of these authors is Rossol [Rossol et al., 2011] who proposed a framework for self-adjusting adaptive training in Virtual Environment (VR) rehabilitation games that is based on Bayesian Networks (BN). The framework's main goal was to help therapists probabilistically assess the patient performance in a complex range of several skill areas by providing meaningful discrete

ranges. The BN network is modeled depending on the knowledge base of the clinician. This is done by allowing him/her to customize the network topology of the BN to include several numbers of skill areas (latents) and measured variables along with complex interaction between them. The appropriate training environment (game) that fits the ability of the patient is chosen by the clinician based on the probabilistically inferred values of the latent variables.

The use of an Artificial Neural Network (ANN) was examined in handling the dynamic difficulty level adjustment of an Artificial Intelligent (AI) computer game in [Wong, 2008]. The author suggested the use of an intelligent agent to represent each player in order to provide a personalized difficulty level adjustment system. Each agent was modeled by a Backpropagation Neural Network (BPNN) that is trained with a set of data recorded within a training data warehouse. The training data warehouse contains all the possible outcome behaviours of the AI game. This includes recorded data pertained to the successful and unsuccessful trials, as well as 18 individual databases (samples) that contains data samples for accuracies ranging from 5 to 95 percent with a step of 5 percent. The samples are actually formed from data collected about the trials by finding the ratio of successful and unsuccessful trials with a total number of 500 in each data base. Therefore, the BPNN can be trained to learn association between the inputs and outputs and store the data in the appropriate individual database based on the ratio inferred by the BPNN. An "Even Trigger Rules" database that contains predefined custom rules and parameters related to the difficulty adjustment triggers the adaptation of the game to meet the required difficulty level of the player.

Ma [Ma et al., 2007] developed an adaptive VR game for post-stroke patients with upper extremity deficiencies that aim to encourage movement and improve their accuracy and

speed. The game can be controlled through motion data captured by three sensors, Motion-Star Wireless, VR 1289 HMD, and the 5DT data glove that enable the detection of the position and orientation of the patient's hand. The game called "whack-a-mouse" requires the patient to hit a mouse that appears at a certain location within a particular time. The game can be adapted to automatically progress between three levels (easy, intermediate, and expert) by considering the time allocated for hitting the target and the position of the mouse (depending on the motor deficit). Adaptation is achieved by initially configuring the game based on the patient's profile, and then by automatically adjusting its intensity based on a simple accuracy test function that provides an accuracy ratio between the number of successful and missed hits. The increase or decrease in the difficulty level of the game is decided in accordance with the accuracy level of the patient by checking if it is higher or lower than a pre-defined threshold.

Chen [Chen et al., 20008] introduces a media adaptation framework that can be used in a multi-model biofeedback system [Chen et al., 2006] for stroke patients undergoing arm rehabilitation. The adaptation model is based on a pre-trained Dynamic Decision Network (DDN) that predicts the patient's performance and suggests an online optimal adaptation decision to the rehabilitation team (e.g., therapists, doctors, etc.). The model is thought to help the therapist makes the most appropriate decisions on how to adapt a biofeedback environment consisting of a large number of parameters in order to help a patient get a productive exercise that helps in improving his arm movements. The media adaptation in the framework refers to changes in audio and visual feedback within the virtual environment, as well as changes in the physical environment (e.g., table height). The model was applied on three adaptation scenarios: spatial accuracy, straightness of hand trajectory, and jerkiness of

hand velocity. The experiments yielded promising results on both performance prediction and adaptation decision recommendation when tested with 3 stroke subjects.

Adamovich [Adamovich et al., 2005] introduced an adaptation algorithm to control the level of difficulty of a number of VR games incorporated into a VR hand rehabilitation system that uses the commercially available CyberGlove [Cyber Glove, 2013] and the Rutgers Master II-ND (RMII) [Bouzit et al., 2002] force-feedback glove. The main idea of the algorithm consists of automatically calculating a target goal for each trial within a block of exercises (trials) based on the performance of the patient in the previous block. The targets for each trial within the block are chosen from a normal distribution around an average target which is computed by averaging the performance results of the patient in the previous block. In order to address the variations in patient performance from one day to another, the amount of target change is computed so that the success rate in each block would be between 70 and 90 per cent. The VR system was tested with eight subjects suffering from a right-hemisphere lesion to examine its impact on a number of performance parameters such as, Range of Motion (ROM), fractionation, and finger strength. Improvements in some parameters showed that the system might be a viable tool.

Pirovano presented a framework [Pirovano et al., 2012] for self-adaptive games for home based-rehabilitation that adopts the fuzzy Logic and Bayesian adaptive methods. The fuzzy theory was used to analyze the correctness of the exercise by properly choosing an appropriate set of rules and constrains specified by the therapist. The output of the fuzzy inference mechanism consisted of a quantified output that was translated into a number of alarming signs that notify the patient about his/her performance. The adaptation of the system was achieved through 2 probabilistic algorithms. The first algorithm was based on the implementations shown in [Jack et. al, 2001] and [Ma et al., 2007] and performs a simple

adaptation based on a patient's performance value computed as a ratio between the number of successful trials and the total number of trials. Subsequently, the ratio is compared with a pre-defined target performance level and the level of difficulty is adjusted accordingly. The second algorithm was built upon the Quest Bayesian adaptive approach [Watson and Pelli, 1983] used in psychophysics to adapt a psychometric threshold considering the results of the previous trials. The main goal is to continuously adapt a parameter value so that it converges to a predefined threshold (defined by the therapist) that guarantees that a target performance level is met in a certain trial based on the patient's actual status. The authors implemented the framework into a rehabilitation system that incorporates two types of interfaces The Wii balance board and the Microsoft kinect that control 2 specially developed games. A usability study conducted with a number of healthy participants showed that the system was able to adapt to the players' performances.

2.8. Summary

Table 2.1 summarizes the related work presented in the previous sections in the light of the 6 requirements discussed in Chapter 1. It is obvious that the stand-alone applications do not fulfil any of those requirements. This is because these systems mostly use gaming consoles that are primarily designed to entertain the players rather to promote training. Furthermore, the gaming environments of this category do not really enable the customization and the adaptation of the gaming environment. In addition, these consoles use input interfaces are not hard to understand and control for a large portion of patients, such as the elderly.

Another main thing that could be inferred from the table is that none of the applications have taken into consideration the effect of physiological and environmental factors on the

performance of the patient. Pirovano [Pirovano et al., 2012] mentioned in his paper that such information could be among the data collected within his framework, but he never really elaborated on how this could be handled or how these data could affect the adaptability of the system. On the contrary, our framework considers these aspects to make decisions that could substantially affect the level of the challenge within a session.

In the proposed framework, we address all these requirements first by adopting the concept of training through special intuitive interfaces that everyone is familiar with. In addition, we assist the therapist to make proper decisions on the gaming environment by providing him/her with a *Quality of Performance* (QoP) assessment that considers the physical, physiological, and environmental factors, therefore, reducing the therapist's effort to identify all the elements that affect the training of the patient. Finally, we consider the constraints and thresholds defined by the therapist to adapt the level of challenge not only within sessions, but also within trials.

| Features | Sugarman [Sugarman et al., 2009] | | | | Harley [Harley et al., 2011] | | | | Lange [Lange et al., 2011] | | | | Rand [Rand et al., 2008] | | | | Boian [Boian et al., 2002] | | | | Alamri [Alamri et al., 2010] | | | | Holden [Holden et al., 2005] | | | | Karime [Karime, et al, 2012a] | | | | Hilton [Hilton et al., 2002] | | | | Morrow [Morrow et al., 2006] | | | | Rossol [Rossol et al., 2011] | | | | Wong[Wong, 2008] | | | | Ma [Ma et al., 2007] | | | | Chen [Chen et al., 2008] | | | | Adamovich [Adamovich et al., 2005] | | | | Pirovano [Pirovano et al., 2012] | | | | Framework Herein | | | |
|-------------------------------------|----------------------------------|---|---|---|------------------------------|---|---|---|----------------------------|---|---|---|--------------------------|---|---|---|----------------------------|---|---|---|------------------------------|---|---|---|------------------------------|---|--|--|-------------------------------|--|--|--|------------------------------|--|--|--|------------------------------|--|--|--|------------------------------|--|--|--|------------------|--|--|--|----------------------|--|--|--|--------------------------|--|--|--|------------------------------------|--|--|--|----------------------------------|--|--|--|------------------|--|--|--|
| Classification | Stand-alone Applications | | | | VHR with Feedback | | | | | | | | Adaptive Systems | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Online Adaptation | X | X | X | X | X | X | X | X | X | X | X | X | X | √ | √ | √ | X | X | X | √ | √ | √ | √ | √ | √ | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Multimedia Feedback | X | X | X | X | √ | √ | √ | √ | √ | √ | X | X | √ | √ | √ | √ | X | X | √ | √ | √ | √ | √ | √ | √ | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Quantitative Assessment | X | X | X | X | √ | √ | √ | √ | X | X | √ | X | √ | √ | √ | √ | √ | X | √ | √ | √ | √ | √ | √ | √ | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Therapist customization and Control | X | X | X | X | √ | X | X | X | X | X | √ | X | √ | √ | √ | √ | √ | X | √ | √ | √ | √ | √ | √ | √ | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Physiology awareness | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Environment Awareness | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | X | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Intuitive Interface | X | X | X | X | X | √ | X | √ | √ | √ | √ | X | X | X | X | X | √ | X | X | X | X | X | √ | √ | √ | √ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Table 2.1: Summary of related work

Chapter 3. The CAHR Framework

In this chapter, we present the high level architecture of our context-based adaptive home rehabilitation framework (*CAHR*), and discuss the functionalities of the various components associated within it.

3.1. CAHR Overview

CAHR is a rehabilitation framework that aims to provide the patient with a virtual home-based training that could be adjusted to his or her physical abilities while taking into consideration his psychophysiological state and the environmental conditions of the training location. The architecture (Figure 3.1) makes use of abundant internet connectivity to provide a link between the patient and the medical practitioner overseeing her or his rehabilitation progress. It is composed of two collaborating systems, the Client and the Cloud Systems.

In a broader view, the framework serves two types of users, the patient and the therapist. The patient can have a computerized home-based rehabilitation system that is simple to grasp, natural to train with, and performance informative. The sensorized *Tangible Training Interface* incorporated offers a natural way to interact with the VR games that are specially developed to train affected limb in an intuitive manner. The *Patient Software Application* provides the patient with performance reports that are easy to comprehend and offers a simple means to communicate with the therapist.

From the clinician's perspective, the framework helps the therapist better understand the performance of the patient, get informed about his/her physiological and psychological state and the environmental conditions surrounding him/her , and to customize the adaptation of the virtual exercises. The *Physical Performance Quantifier* associated within the framework gives the therapist an insight on the *Quality of Physical Performance (QPP)* of the patient. The *QPP* is quantified in a way that reflects the physical performance of the patient in contrast to a healthy user's performance. The physiological, psychological, and environmental information makes the therapist aware of his/her patient's condition during the training, and help him/her determine what might affect the patient's progress. The framework's *Context-based Adaptation Engine (CAE)* enables the therapist to customize the adaptation of the exercise based on the contextual information already collected and analyzed, therefore making the adaptation more suitable to the overall condition of the patient.

3.2. The Client System

The *Client System* comprises the *Web Client Proxy*, the *Patient Interface*, the *Therapist Software Application* and the *Context Interface*. The *Client* is a software component that provides various stakeholders (such as the patient, therapist, or a third party) access to the home-based rehabilitation system over the web.

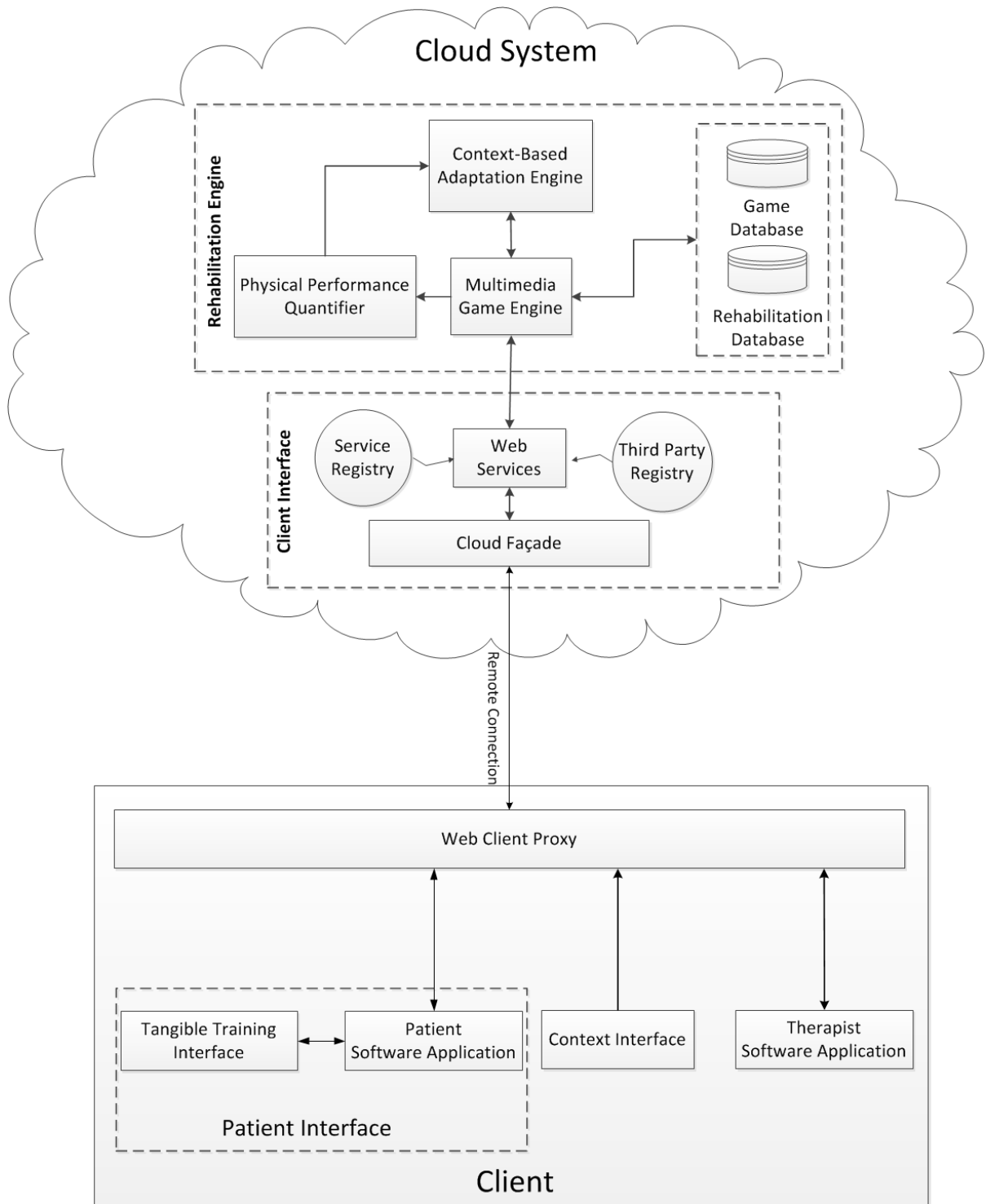


Figure 3.1: The CAHR framework.

3.2.1 Web Client Proxy

The *Web Client Proxy* is a software application that provides services for retrieving, presenting and traversing web contents on the World Wide Web (HTML interpreter and Simple Object Access Protocol (SOAP) for exchanging structured information via the Web). It also facilitates the communication between *the Client System* and the *Cloud System*.

3.2.2 Patient Interface

The *Patient Interface* provides the patient with the means to interact with the system (to facilitate personalization of home-based rehabilitation) or to communicate with the therapist. Patient Interfaces are classified as conventional input/output interfaces such as keyboard, mouse, or monitor (in case the patient can use them) and non-conventional interfaces such as intelligent tangible devices and haptic interfaces. The *Patient Interface* comprises two main components:

1. **Tangible Training Interface:** The *Training Interface* is the sensory device that is used by the patient to perform his/her training and to interact at the same time with the VR games. The framework can support any type of motion tracking training devices that can capture the hand kinematics, namely the accelerations and velocities of the wrist which are necessary to compute the *Quality of Physical Performance (QPP)*. Examples of training interfaces include but not limited to tracking cameras, and devices embedded with motion sensors such as accelerometers and gyroscopes (e.g., the Wii remote). However, in this thesis we design and utilize a tangible rubber ball interface that is equipped with an *Inertial Measurement Unit (IMU)* that enables capturing the motion kinematics of the wrist. The rubber ball interface is specially developed to offer intuitive home-based rehabilitation training. The ball

will be briefly discussed in Chapter 4 and its detailed description and implementation will be presented in Chapter 6.

2. Patient Software Application: The *Patient Software Application* is the patient's door to the framework. Upon successful login, the *Patient Software Application* checks information from the patient's treatment plan and displays the appropriate Virtual Reality games that are prescribed by the remote therapist. The application also integrates a number of features that aim to enhance the home-based rehabilitation experience. These features can be summarized by the following:

- **Well-being Questionnaire:** The questionnaire aims to check on the physical and the psychophysiological conditions of the patient prior to starting the therapy training session. Keeping in mind that the patient's initial states are always unknown at the beginning of a session, the data collected from the questionnaire helps the system to properly customize the initial task within a session so that it suits the patient's overall conditions.
- **Instant Messaging:** This feature aims to keep the patient in touch with the clinician by offering him/her a way to establish contact in real time with the physiotherapist either through short messages or via internet video conferencing.
- **Performance Self-Check:** Informing the patient about his/her progress in a simple way that he/she is able to understand might be very motivating during the therapy treatment. The *Performance Self-Check* feature offers that capability by providing the patient with an after-training progress report that displays his/her overall condition and the next level of performance that he/she should try to achieve. The results are

shown in a numerical format rather than graphical so that patients with different educational backgrounds are able to easily understand them.

3.2.3 Therapist Software Application

The *Therapist Software Application* enables the clinician to monitor the patient's performance by retrieving information extracted during the game sessions. In addition, it allows the therapist to customize the rehabilitation task by offering him/her the capability to define a number of performance thresholds that best fit the physical and physiological conditions of the patient. The features included in the therapist's GUI are the following:

- **The Desired Performance Matrix:** This matrix contains the therapist threshold parameters pertained to the physical, physiological, psychological, and environmental conditions. One of those thresholds is the one that defines the minimum *Quality of Physical Performance* that the patient should achieve. QPP_{Th} is the therapist's index of choice that represents the minimum *Quality of Physical Performance* that a therapist might require his/her patient to achieve in order to be considered within the normal range. The maximum value of this index could be 1; however, such value would mean that the patient should perform similar or even better than a healthy person in order to be considered progressing. This matrix will be explained in more details in Chapter 5.
- **Performance Correlation Matrix:** This matrix enables the therapist to define correlation among the various psychophysiological, physical, and environmental contextual parameters that could affect the performance of the patient. For instance, it is known that fatigue or stress can affect the abilities of the patient to properly per-

form a task. Therefore, judging his or her performance based on the physical aspect *QPP* only may not lead to a reliable assessment. Moreover, since the physical abilities of patients might be affected differently by these contextual parameters from one patient to another, the correlation among those parameters cannot be constant and rather should be personalized depending on the therapist's knowledge of the patient. Therefore, if the therapist knows that a particular patient's performance can be highly affected by stress or fatigue, the *Performance Correlation Matrix* allows him/her to easily transmit this knowledge to the system by simply setting different thresholds in the matrix.

- **Task Progress Step Size (S):** The *Progress Step Size* (S) controls the limit of increment and decrement of the difficulty (in degrees) among tasks so that the patient is always faced with reasonable challenges. In other words, S can be thought of as the maximum number of degrees that can increase or decrease from one task iteration to the next. For instance, supposing that the therapist has set S to 5° in a Supination exercise that requires the patient to achieve a reaching angle of 45° . Consequently, the angle of the next task would be incremented by a maximum of 5 degrees in case the patient had a normal performance.
- **Performance Analyzer:** This feature aims to facilitate the therapist's reading and analysis of the measurements collected during the training by displaying a set of graphs that reflect the performance of the patient.
- **Virtual Task Selector:** This feature allows the therapist to choose a virtual task that fits best the condition of his/her patient from a series of games incorporated within the framework.

3.2.4 Context Interface

The *Context Interface* provides the rehabilitation framework with information related to the patient's context. This interface can be any of the hardware and/or software components that enable the detection of the physiological, psychological or environmental context. An example of such interface is a watch, a light sensor, a heart rate sensor, a brainwave headband, among others. However, the context can be also more accurately detected by frequently asking the patient about his or her condition through simple questionnaire that can be answered within the training session.

3.3. The Cloud System

The Cloud System is composed of the Client Interface and the Rehabilitation Engine. It is an independent entity that manages various system functionalities (such as adaptation) and store relevant data (such as games and patient's performance data). The Cloud System can be hosted by an authorized entity to provide home-based rehabilitation services.

3.4. The Client Interface Module

The *Client Interface* module is located at the Cloud and provides abstract interfacing to individual clients. The client is typically located in a physically remote place. The *Client Interface* is composed of the following:

- **Web Services:** This component hosts a pool of web services that provide various functionalities for both the patient and the therapist (such as a web service to retrieve patient's performance information and provide a proper display, a web service to

facilitate real-time interaction between the game engine and the patient, a web service to perform signal conditioning, etc.).

- **Service Registry:** The *Service Registry* enables clients to discover and access web services by storing information about the services functionalities as well as their interfaces (how to access the web services).
- **Third Party Services:** These are services that are hosted by third party service providers to provide assistive functionalities (such as certain type of signal processing or graphics display web services).
- **Cloud Façade:** This interface has a similar functionality as the *Web Client Proxy*. It is a software application that implements HTML interpreter and SOAP messenger for exchanging structured information with the client.

3.5. Rehabilitation Engine

The *Rehabilitation Engine* is the unit where all the performance data is analyzed and the game state decisions are made. The *Rehabilitation Engine* is comprised of the *Physical Performance Quantifier*, the *Context-aware Adaptation Engine*, the *Multimedia Game Engine*, and the required databases for storing the training and game related information.

3.5.1 Physical Performance Quantifier

The *Physical Performance Quantifier (PPQ)* aims to assess the *Quality of Physical Performance (QPP)* based on the physical kinematics captured during the rehabilitation training. The main goal is to provide the rehabilitation framework and the therapist with a crisp value that reflects how well or bad the patient was able to achieve a particular task from

a physical perspective. To achieve this goal, benchmarks kinematics should be defined so that the *PPQ* can be modeled to assess the performance of the patient in contrast to a healthy user. The *QPP* is evaluated based on the *Fuzzy Logic* (FL) theory that is distinguished by its capability of reasoning in a human-like manner. In Chapter 4, we discuss in details the modeling of the *PPQ* based on an analysis performed over the human wrist.

3.5.2 Context-based Adaptation Engine

The *Context-based Adaptation Engine* (*CAE*) constitutes the core of the rehabilitation framework since it controls the intensity levels of the tasks and the multimedia content of the rehabilitation environment (e.g., screen brightness, recommendation messages, music etc.). The adaption is done in an online fashion (i.e., per-task) based on the aforementioned context parameters, as well as the physical context of the patient. We propose a context-aware adaptation algorithm that considers the context of the patient and the therapist performance thresholds to properly adjust the tasks within a rehabilitation session so they fit the physical, physiological, psychological abilities of the patient while considering at the same the environmental conditions. The detailed mathematical modeling and performance analysis is elaborated in details in Chapter 5.

3.5.3 The Multimedia Game Engine

The *Multimedia Game Engine* formulates and load the proper rehabilitation task for the patient based on the therapist's constraints, the patient's context, and the adaptation decisions made by the *Context-aware Adaptation Engine*. In addition, the engine provides multimedia feedback in the form of recommendations and vibro-tactile haptic feedback to

the patient depending on his/her training performance and the game's state. The recommendations are shown in the form of text messages on the patient's screen. These messages are triggered based on the therapist's customization once a particular threshold is surpassed. For instance, the system might recommend the patient to take a 10 minute break if his stress level is really high. On the other hand, the engine sends vibro-tactile commands to the Training Interface module upon achieving a particular goal during the task in order to make the rehabilitation session more entertaining and encouraging.

3.5.4 Game Database

The *Game Database* stores information regarding the rendering and the configuration of the various rehabilitation games incorporated in the framework (such as the games graphics and default settings).

3.5.5 Performance Database

This database stores the performance and motion data captured throughout the rehabilitation training. This includes the raw data captured using the tangible interface, performance parameters (such as grasping angle/velocity, jerkiness, tremor, etc.).

3.6. Summary

This Chapter presented a generic *CAHR* framework architecture that may be adopted for any type of physical rehabilitation. We have explained how the framework can offer the patient an appropriate home training that is planned in cooperation with the therapist. The *Physical*

Performance Quantifier and the *Context-aware Adaptation Engine* components, which are briefly described here, are both discussed in the two subsequent chapters. In addition, the design of a proof-of-concept system that is based on the framework is elaborated in Chapter 6.

Chapter 4. The Modeling and Analysis of the Wrist Behaviour

As was discussed in Chapter 2, adjusting the difficulty level of the virtual exercises of most of the rehabilitation systems was based on different adaptation heuristics. In general, the adaptation is normally done by comparing various performance measurements to pre-defined target values that are usually set by the clinician. However, it is not clear how the clinician himself would be able to determine what a proper target value for a specific application is. In other words, for each task, there must be a set of benchmark values (standards) that the clinician can refer to before defining a target level for the exercise. These benchmarks should reflect the normal behavior of the joint being trained.

CAHR is a generic framework that can be implemented to fit the physical rehabilitation of any of the upper or lower extremity limbs. However, throughout the rest of this dissertation, we will take the wrist as our limb of interest. Therefore, in this chapter, we first study the behavior of the wrist with healthy subjects when performing a number of virtual exercises with a specially designed digital stress ball. Then, we analyze the data captured to determine a set of game-specific performance thresholds that can help us model the wrist behavior with a *Fuzzy Inference System* (FIS) that estimates the *Quality of Physical Performance* (*QPP*) index.

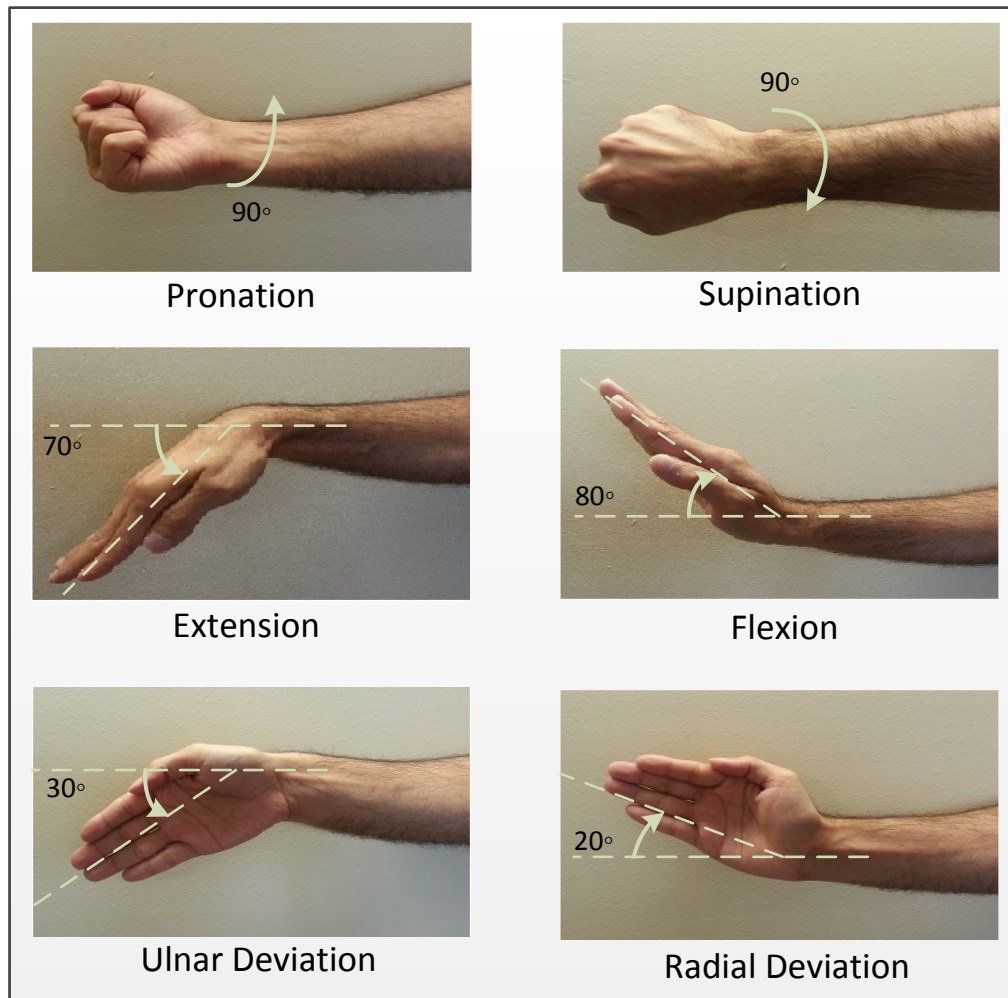


Figure 4.1: The six motions of the human wrist

4.1. The Wrist Anatomy

The human wrist is a complex part of the hand that is composed of multiple joints that form a complex structure capable of transmitting a large load to the upper extremity and provides a mobile base for the precision movement [Stuchin, 1992]. The wrist was found to have three degrees of freedom (Figure 4.1) which enables 6 motions on the x, y, and z coordinates. The wrist motions are the following:

1. **Pronation:** turning the forearm with the palm facing down.
2. **Supination:** turning the forearm with the palm facing up
3. **Wrist Extension:** bending the wrist to move the back of the hand towards the forearm.
4. **Wrist Flexion:** bending the wrist to move the palm of the hand towards the forearm.
5. **Radial Deviation:** side bending the wrist towards the thumb.
6. **Ulnar Deviation:** side bending the wrist towards the little finger.

4.2. Wrist Pattern Analysis

There have been previous efforts in the medical community to determine the ideal ranges of motion required to perform the activities of daily living [Murgia et al., 2004, Andel et al., 2008]. The studies in [Ryu et al., 1991, Han, 2009] have shown that the pattern of the wrist movement differs from one task to another, meaning that daily life activities such as hammering a nail or pouring from a cup necessitate different wrist kinematics requirements. Therefore, in order to help the clinician properly describe the wrist joint angles from a functional perspective, the virtual task that the patient must perform during the training should be first tested with healthy subjects in order to determine the movement standards (benchmarks) that can be used as an assessment reference.

In this section, we present an analysis for the performance metrics of the wrist kinematics captured with a number of healthy subjects while performing three different virtual tasks. We also derive a set of benchmarking thresholds that can be used to automatically measure the quality of wrist performance for wrist rehabilitation.

4.2.1 Methods

Fifteen participants, ages 22-55, all right-hand dominant males, took part of the experimental evaluations. Each subject was asked to sit on a chair and place his right hand on the chair arm, and play the games while keeping his/her hand as steady as possible on the chair's arm. We have developed three simple software games that focus on training the six wrist movements in an intuitive manner. The training input interface consisted of a sensory-integrated rubber ball which was specifically designed for rehabilitation purposes. Each subject was asked to perform 6 sessions (exercises) that are comprised of different number of tasks (trials). Each session targeted one type of wrist motions. The wrist kinematics were captured during each session, and the collected data were analyzed at the end of all of the 45 sessions. Below, we provide a description of each of the tasks, the rubber ball training interface, and the captured wrist kinematics.

4.2.2 Exercises 1 and 2: The Cup and the Plate

The first 2 exercises are based on the Activity of Daily Life (ADL) [Cohen and Marino, 2000] concept and require the patient to grasp a cup and place it on a plate (Figure 4.2). The user is asked to perform a set of *Pronation* movements in the first exercise (session) followed by a set of *Supination* movements in the second.

At the beginning of each session, a hand and a plate are displayed vertically at the center of the screen with a cup placed at an initial position of ± 10 degrees from the plate (e.g., +10 degrees when assessing *Pronation* performance and -10 for *Supination*). The plate is always fixed at a neutral position (e.g., at 0 degree) while the hand can move freely in a semi-circular pattern. To achieve the goal of the game, the user has to rotate his/her wrist in the

Pronation or *Supination* motion in order to reach the cup which can be grasped by exerting a certain amount of pressure on the ball. Then, the user should turn his/her wrist in the opposite motion in order to reach the plate where the cup must be released by simply reducing the amount of hand grip pressure on the ball. Upon successfully completing a task, a new cup is displayed with a 5 degree increment from the previous position. Each exercise is completed once the user achieves the full *Range of Motion* (ROM) on each motion, which is $+90^\circ$ for the *Supination* and -90° for the *Pronation*.

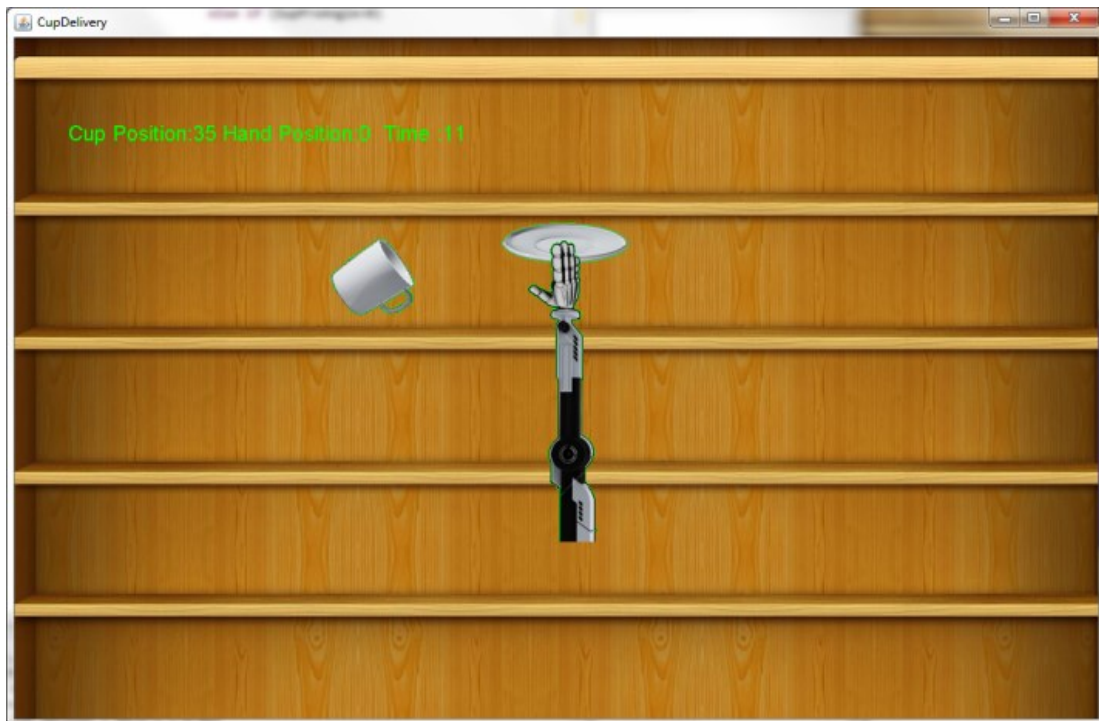


Figure 4.2: A snapshot of the Cup and Plate game while the cup was positioned at 35 degrees

4.2.3 Exercises 3 and 4: Horizontal Golf

The Horizontal Golf game consists of a ball that the user has to simply drag to a hole by turning his wrist in the *Flexion* (Figure 4.3 (a)) or *Extension* motion (Figure 4.3 (b)). Here,

the rotational movements of the wrist are mapped into translational displacements on the screen. Similarly to the Cup and Plate scenario, the hole is always fixed at the centre of the screen and the ball changes position at an incremental rate of 5 degrees every time a task is completed successfully. The first exercise (Flexion) ends when the user achieves 80 degrees while the other (Extension) is terminated when 70 degrees is reached.

4.2.4 Exercises 5 and 6: Vertical Golf

The Vertical Golf game is the same as the Horizontal with the difference that the ball moves in a vertical direction. Therefore, to move the ball, the user should move his wrist in the Radial or Ulnar deviations motion (Figure 4.3 (c) and (d)). These tasks end when the user achieves 20 degrees and 30 degrees on the *Radial* and *Ulnar Deviations* motions respectively.

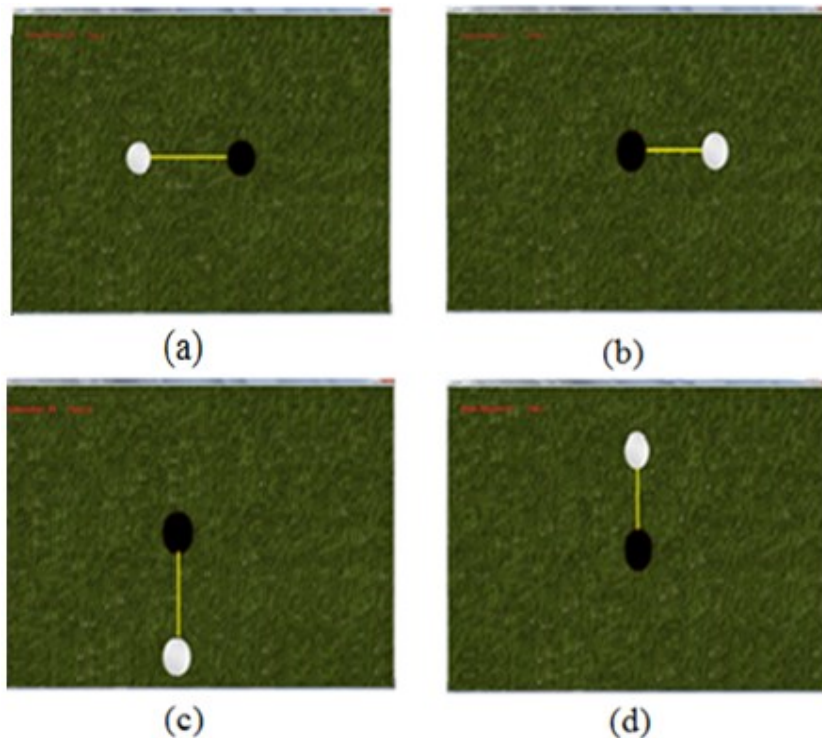


Figure 4.3: Snapshots of the Golf game, (a)-(b) the horizontal configuration (c)-(d) the vertical configuration

4.2.5 The Digital Rubber Ball

The digital rubber ball or as we call it the “*DigiBall*”, is a regular stress ball that is enhanced with the capability of tracking the hand motion of the user and producing a set of hand related performance data. The ball is embarked with a number of sensors that make it a tangible training interface that is easy to use and comprehend. The detailed implementation of the *DigiBall* is elaborated in Chapter 6.

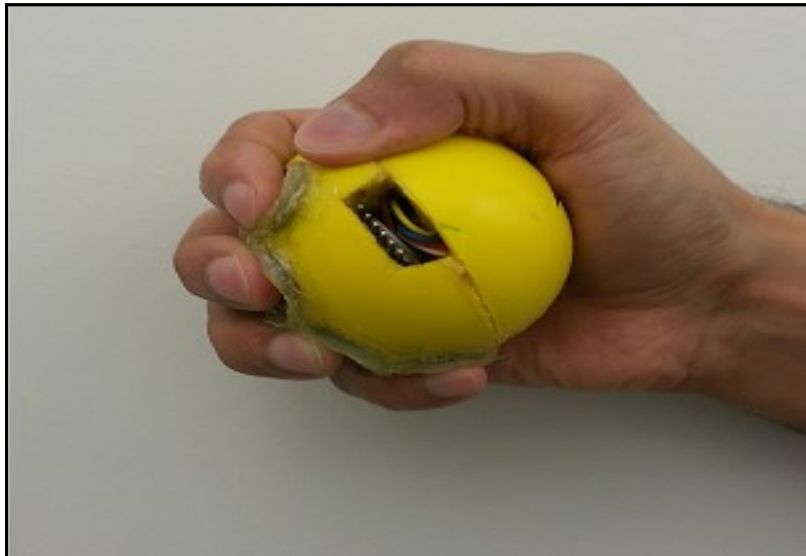


Figure 4.4: The Digital Rubber Ball

4.2.6 Performance Parameters

The *DigiBall* was designed to measure and provide three potential physical performance rehabilitation parameters that can quickly visualize potentially hidden deficiencies during the training. The following are the metrics captured during the exercises. More information about the importance of these parameters can be found in [Karime et al., 2012b].

1. **Reach Angle:** The *Reach Angle* (θ) is the angle that the patient is required to reach on one of the motions shown previously in Figure 4.1 in order to accomplish a particular exercise (task) within a session. The maximum value ($\text{Max } \theta$) achieved during a session represents the *Range of Motion* (ROM) of the patient's wrist on a particular motion.
2. **Average Angular Velocity:** The Angular Velocity ($\hat{\theta}$) of the wrist provides a good indication on the ability of a patient to perform his/her daily life tasks in a timely manner. Achieving a speed close to a healthy person can avoid any clumsiness in the patient's hand movements. Since the velocity while performing a task is not constant and varies in time, we consider instead the average angular velocity ($\bar{\theta}$) for a particular task. The average angular velocity was computed after cutting off the low insignificant values through a low pass filter. For simplicity, we refer to the average angular velocity simply as *Velocity* throughout this dissertation.
3. **Jerkiness:** By definition, *Jerkiness* (J) is the rate of change of acceleration and is used to indicate how smooth the velocity of the wrist is for a specific exercise. Therefore, in order to obtain a good wrist jerkiness result, the patient should perform the task without making frequent jerks or sudden abrupt movements. *Jerkiness* is a very well-known metric in biomedical engineering. The smaller it is, the smoother the wrist velocity.

4.3. Captured Data Results and Analysis

Figures 4.5 to 4.8 reveal the results obtained from our evaluations with the healthy subjects while performing the *Supination* and *Pronation* exercises. All participants were able to

achieve the full *Range of Motion* (ROM) on these 2 motions which is 90 degrees. The solid line in the curves presents the mean values of the angular *Velocity* and Jerkiness of all the participants after completing the 45 sessions. As can be seen, the range between 0 and 10 degrees on the *Reach Angle* axis is omitted here because it results in a very small wrist movement that is insignificant for such exercises.

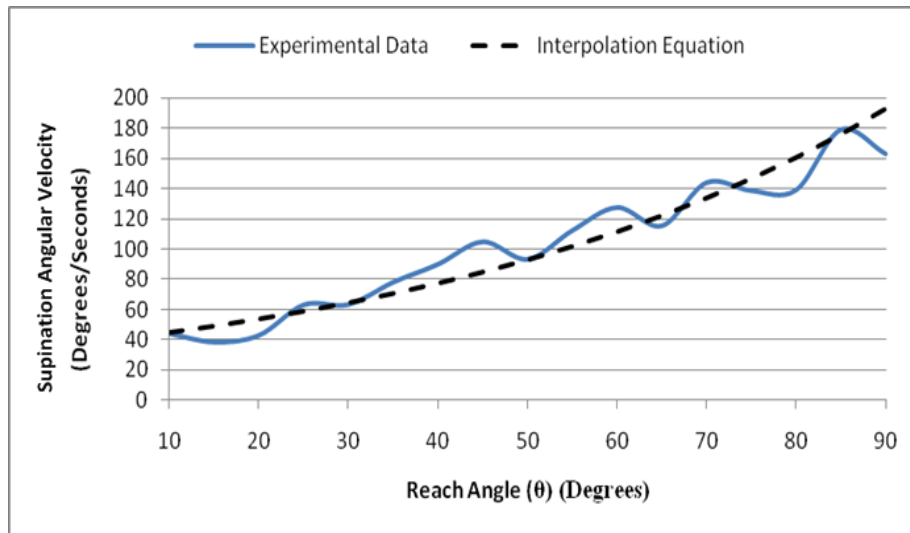


Figure 4.5: The peak Supination velocity over different tilting ranges

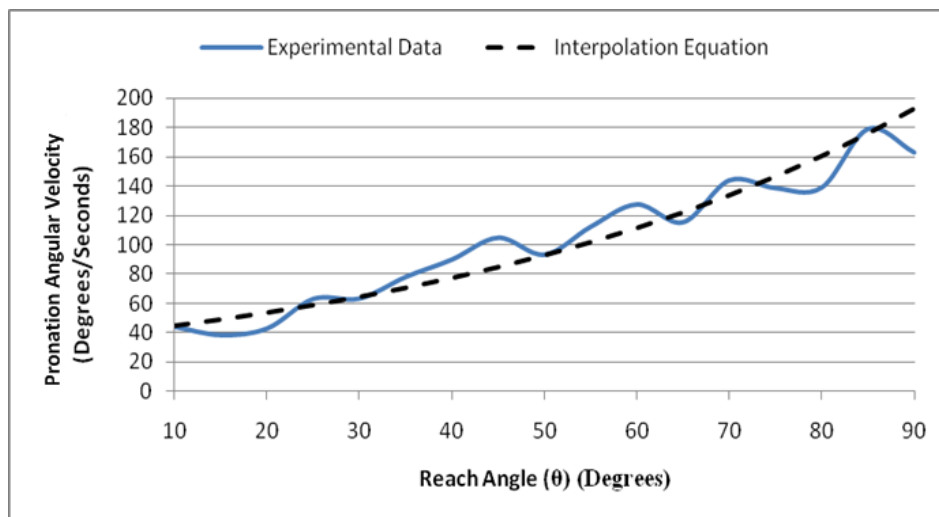


Figure 4.6: The peak Pronation velocity over different tilting ranges

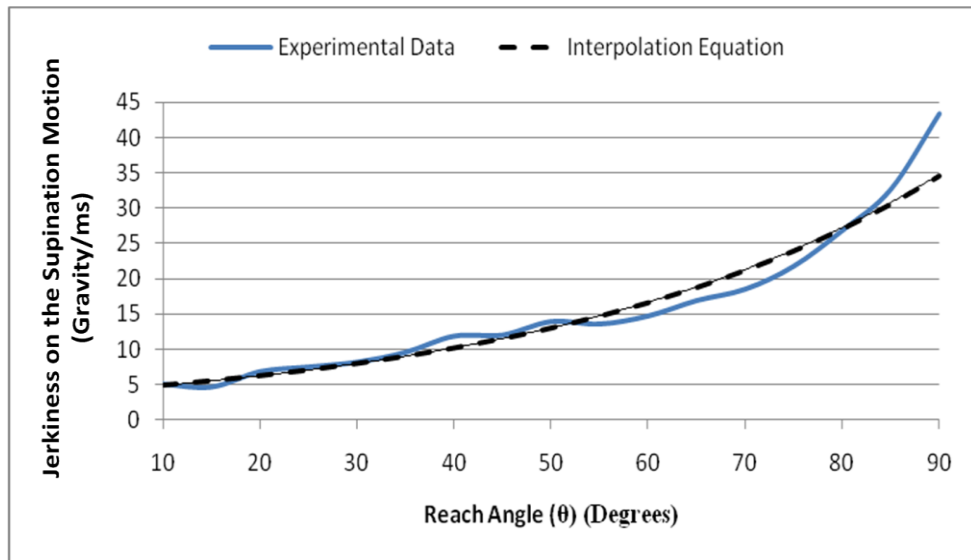


Figure 4.7: Jerkiness on the Supination motion

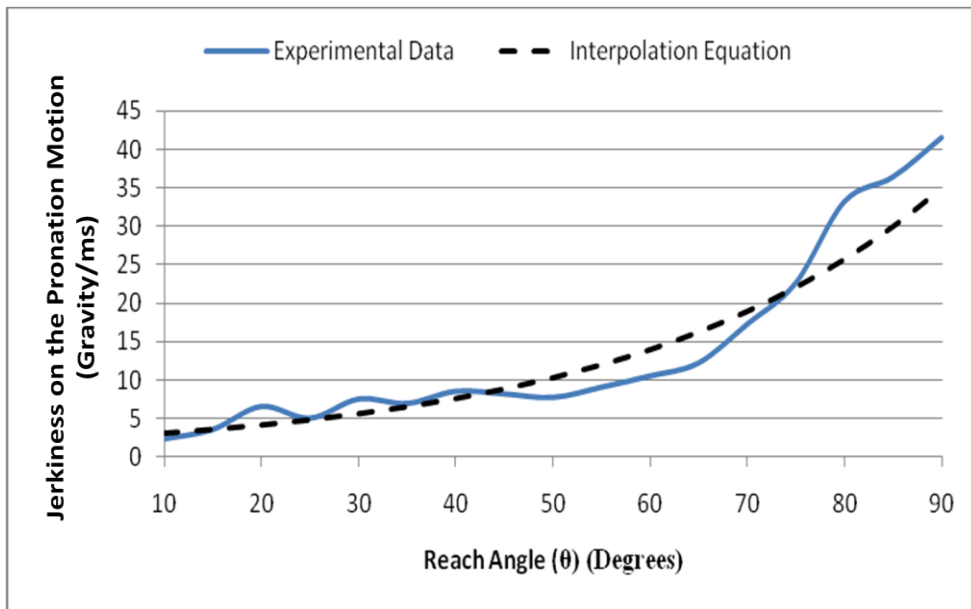


Figure 4.8: Jerkiness on the Pronation motion

It can be intuitively deduced from the experimental data in Figure 4.5 and 4.6 that the higher the *Reach Angle* (θ) the higher the *Velocity* ($\dot{\theta}$). This means that the subjects tended to move their wrists slowly during tasks with small task *Reach Angle* (θ), while their speeds increased during tasks with higher *Reach Angles*. Similarly, it can be seen that *Jerkiness* increases whenever *Reach Angle* (θ) increases. We can therefore conclude that whenever the *Reach Angle* (θ) increases, the user responds by moving his wrist faster which results in a less smooth movement, and therefore a higher jerkiness.

In order to have a good estimate on what a normal velocity and jerkiness is at intermediate points on the θ axis, we apply a regression analysis for each of the graphs. Therefore, with such technique, the therapist can always have an approximation on what a normal standard is at every *Reach Angle* (θ). We have approximated the points with different types of functions such as linear, logarithmic, polynomial and exponential. However, the exponential approximation was the one that best fit the curves.

The dotted curve represents the sketch of the resulting interpolation equation. We have also applied the same approach for all of the remaining exercises. The following are the general interpolation equations for both the *Velocity* and the *Jerkiness* metrics:

$$\dot{\theta}_M = \phi \cdot e^{\tau_M \theta} \quad (4.1)$$

$$J_M = \mu \cdot e^{\delta_M \theta} \quad (4.2)$$

where M is the type of motion (exercise), δ and τ are empirical coefficients, ϕ and μ are the velocity and jerkiness coefficients respectively.

Table 2 presents the values obtained after performing interpolation on the data captured from all the exercises along with the minimum and maximum values of the *Reach Angle*. We have noticed while performing *Radial* and *Ulnar Deviations* tasks that *Jerkiness* was almost constant in both cases and was not really affected by the increase in angular movements or velocity. The jerkiness values found were 0.21 and 0.73 for *Radial* and *Ulnar Deviations* respectively. The reason why these two values were found to be constant may be due to the small ROM nature of these two motions which prevented the users to perform jerky movements. The cases of the *Flexion* and *Extension* exercises were similar in their outcomes to those of the *Supination* and *Pronation* ones, meaning that the change in velocity and jerkiness were directly proportional to the change in the *Reach Angle*.

| Type of Motion (M) | ϕ | τ | μ | δ | Reach Angle Constrains |
|--------------------|--------|--------|-------|----------|--------------------------|
| Supination | 41.07 | 0.019 | 3.82 | 0.024 | $10 \leq \theta \leq 90$ |
| Pronation | 37.16 | 0.018 | 2.20 | 0.031 | $10 \leq \theta \leq 90$ |
| Radial Deviation | 23.62 | 0.037 | 0 | 0 | $5 \leq \theta \leq 20$ |
| Ulnar Deviation | 32.95 | 0.017 | 0 | 0 | $5 \leq \theta \leq 30$ |
| Flexion | 39.05 | 0.014 | 3.23 | 0.019 | $10 \leq \theta \leq 80$ |
| Extension | 36.14 | 0.016 | 3.15 | 0.028 | $10 \leq \theta \leq 70$ |

Table 4.1: Numerical values of the parameters of the velocity and jerkiness interpolation equations.

4.4. Wrist Behavior Modeling

In the previous section, we showed that there is a correlation among the *Reach Angle*, the *Velocity*, and the *Jerkiness* of the wrist. These findings could be consequently used by the clinician as a base to make his/her judgment on the physical performance of the patient. For instance, a patient performing a set of *Supination* tasks that require training the wrist between 30-40 degrees, would require velocities in the range between 72.6 and 87.8 degrees per second and a jerkiness values between 7.8 and 9.9 Gravity/ms in order to be considered in the healthy range (N.B the velocity and jerkiness ranges were obtained using Equation 4.1 and 4.2). However, how would a therapist assess the patient's condition if the velocities were much lower and/or the jerkiness values were much higher? The answer can be fuzzy since assessing the *Quality of Physical Performance* might differ from one therapist to another. The answer can be even more complex to a VHR system since it must assess the patient's performance after each task and session without the online supervision of the therapist.

In order to make the VHR system capable of providing a reliable estimate, it should be empowered with an intelligent mechanism that enables it to make decisions based on the knowledge of the therapist who should be able to update and modify this knowledge depending on what he/she thinks suits more the condition of the patient. Therefore, it is very sensible to have an intelligent decision maker that can mimic the human reasoning. Fuzzy set theory [Zadeh, 1965] has been developed to offer that capability and to fulfill that ambiguous goal. Figure 4.9 shows the *Physical Performance Quantification (PPQ)* Model that is based on the *Fuzzy Logic* theory.

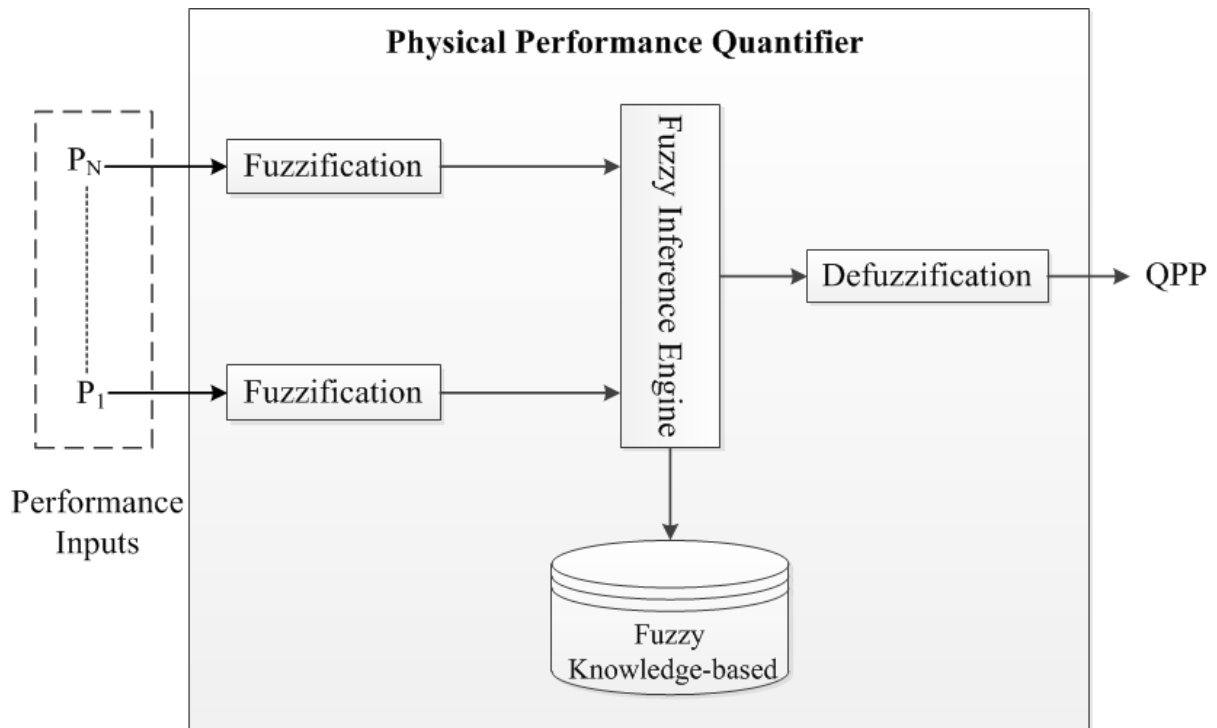


Figure 4.9: The fuzzy logic Physical Performance Quantification (PPQ) Model

4.4.1 Physical Performance Quantifier

The aim of the *Physical Performance Quantifier (PPQ)* is to decide on the *Quality of Physical of Performance (QPP)* of the exercise based on the three performance parameters, the *Reach Angle (θ)*, *Velocity ($\dot{\theta}$)*, and *Jerkiness (J)*. In other words, the *PPQ* gives a quantified value that describes how well a patient performed after accomplishing a certain task by producing a crisp value on a scale between 0 and 1.

4.4.2 Fuzzification and Defuzzification

Fuzzification is the process of transforming crisp values into fuzzy values. Since the inputs are captured in a scalar forms, they need to be first converted into a format that the *Fuzzy Inference Engine* can comprehend. This is normally done by assigning each input a

membership function that is used to associate a grade to each linguistic term. On the contrary, *Defuzzification* is the process of converting fuzzy values into crisp values using membership functions analogous to the ones used in the fuzzification process. In our case, the defuzzification is achieved using the centroid method (Please refer to [Karray and de Silva, 2004] for more details on defuzzification methods).

The fuzzification and defuzzification membership functions (Figure 4.10) are chosen as linear triangular membership functions for their higher computational efficiency. Then, an empirical analysis was performed to optimize these function parameters to improve the *PPQ* performance. The fuzzy labels *SM* (small), *AV* (average), *HI* (high), and *VH* (very high) are the linguistic terms of the membership functions. The universe of discourse of each membership function was standardized based on the previous benchmarks we defined in Table 4.1.

The *Fuzzy Inference Engine* (FIE) accomplishes the task of mapping the inputs to the outputs using the If-Then rules defined in the Fuzzy Knowledge-base. We have used the Mamdani fuzzy inference method [Mamdani, 1976] which is one of the most common methods used for this purpose.

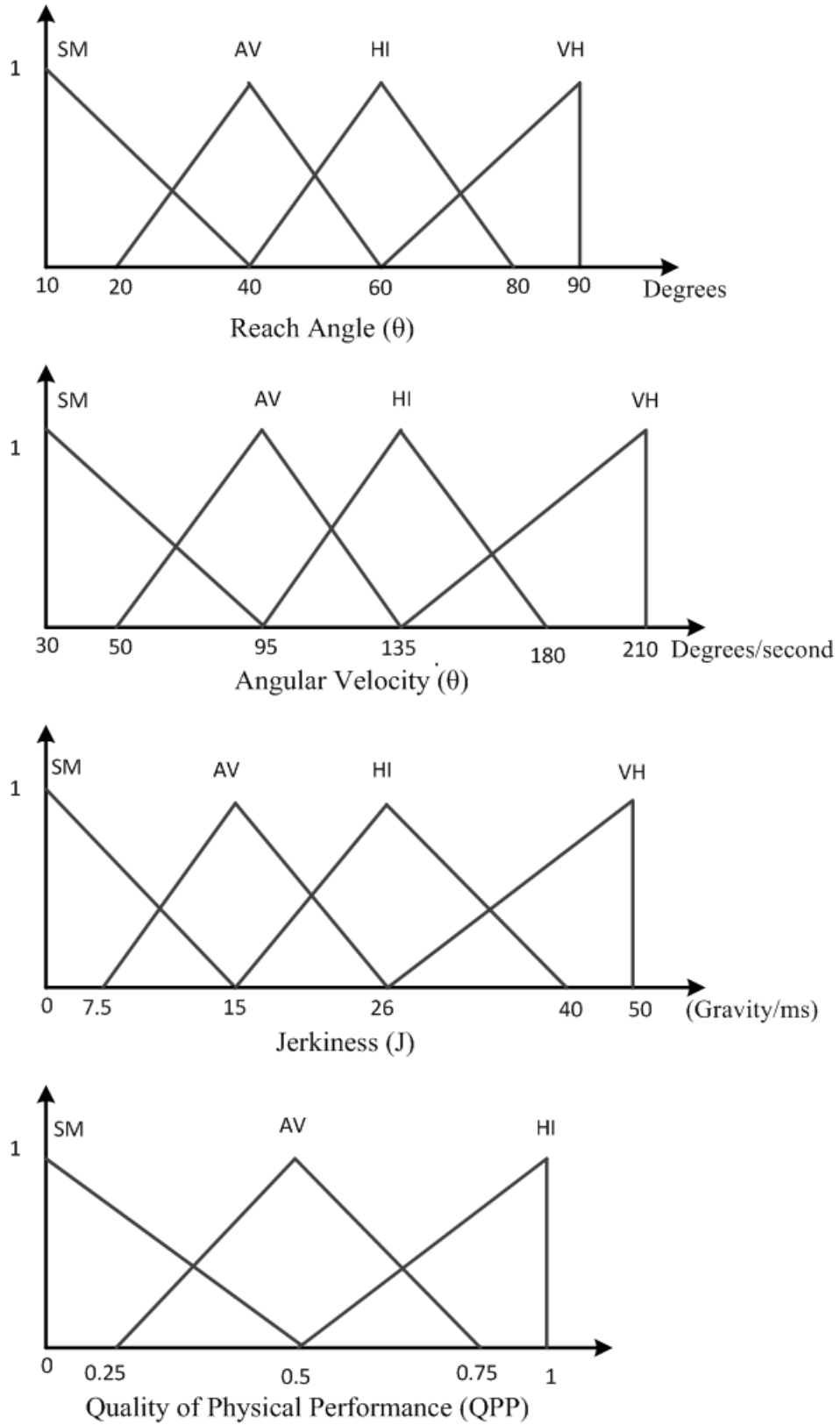


Figure 4.10: The inputs and output fuzzification and defuzzification membership functions

4.4.3 Fuzzy Knowledge-base

The Knowledge-base is comprised of the fuzzy rules associated within the *PPQ*. These rules which can be set by therapist were defined here to convey the logic that the *QPP* is considered *HI* (high) or close to *HI* (high) when both the *Velocity* and *Jerkiness* are "normal" or close to "normal" within a particular task angle. Here, the state "normal" would depend on the size of the task angle in effect (Please refer to Section 4.3 for more clarification). We have defined 41 rules of the form:

$$\mathbf{If} (\theta \text{ is } \theta_i \text{ and } \dot{\theta} \text{ is } \dot{\theta}_j \text{ and } J \text{ is } J_k) \mathbf{Then } QPP \text{ is } QPP_{ijk}$$

where $i=1$ to 4, $j = 1$ to 3, $k = 1$ to 4, and θ_i , $\dot{\theta}_j$, J_k and QPP_{ijk} can be any of the fuzzy labels defined on each variable's membership function.

4.5. Performance Analysis

The goal of the performance analysis is to demonstrate the ability of the *Physical Performance Quantifier (PPQ)* to adapt the *Quality of Physical of Performance (QPP)* index in accordance with the variations of velocity and jerkiness performance. The performance analysis includes a number of simulation scenarios that investigate various simulated patient behaviors (namely normal, decreasing, and increasing performances) and an experimental study where the simulation results are compared to experimental data captured with normal subjects. In order to verify the performance of the proposed *PPQ*, we simulate one motion only (rather than the 6 wrist motions), namely the *Supination*.

4.5.1 Simulation Set-up

The *Physical Performance Quantifier* was implemented using *XFuzzy* Fuzzy Logic Design tool on a Windows 7 environment. Then the resulting FIS was compiled to a Java function that enables us to use the model with Java Compilers. The simulation was implemented in Java using Eclipse IDE and performed on an Intel i7-2640M, 8 GB RAM PC. The *Physical Performance Quantifier* accepts the *Reach Angle* (θ), the *Velocity* ($\dot{\theta}$), and the movement *Jerkiness* (J), and returns *Quality of Physical Performance* (QPP).

4.5.2 Adaptation Scheme Simulation Analysis

In this simulation, various patients' performance scenarios are evaluated: normal performance, deteriorating performance, and improving performance (Figure 4.11). We have based the simulations for the three performances on one fixed *Reach Angle* (θ), namely $\theta = 45^\circ$, while the *Jerkiness* and *Velocity* values were manipulated in each scenario as follows.

- **Normal Condition:** For a normal condition, values for the *Velocity* and the *Jerkiness* are computed using Equations 4.1 and 4.2 respectively. Then small fluctuations (maximum 2 percent of fluctuations) are randomly introduced for each value at the first 40 iterations. The fluctuations are chosen to be small in order to keep the values within the normal range and to mimic what occurs in a real life training scenario. It is worth noting that an iteration can represent a task or a session. Algorithm 1 shown below explains the following scheme.

Algorithm 1: Simulation of a Normal Performance

Input: The Reach Angle, the Velocity, and Jerkiness values, θ , $(\dot{\theta}_{New})$ and (J_{New}) .

Output: The Quality of Physical Performance (QPP).

Initialize: $\theta = 45^\circ$, $\phi = 41.07$, $\tau = 0.019$, $\mu = 3.82$, $\delta = 0.024$

Begin

Loop while Iteration ≤ 100

 Compute the velocity

$$\dot{\theta}_M = \phi \cdot e^{\tau_M \theta}$$

 Compute the jerkiness

$$J_M = \mu \cdot e^{\delta_M \theta}$$

If Iterations ≤ 40

 Add 2 percent fluctuations for the velocity

$$\dot{\theta}_{New} = \dot{\theta}_M + rand(-2,2) * \dot{\theta}_M / 100$$

 Add 2 percent fluctuations for the Jerkiness

$$J_{New} = J_M + rand(-2,2) * J_M / 100$$

Else

$$\dot{\theta}_{New} = \dot{\theta}_M$$

$$J_{New} = J_M$$

 Compute QPP by the Physical Performance Quantifier (PPQ)

$$QPP = PPQ(\theta, \dot{\theta}_{New}, J_{New})$$

 Update Iteration number

 Iteration = Iteration + 1

 Return QPP

- **Deteriorating Condition:** This condition can be simulated by choosing *Velocity* or *Jerkiness* values that are below their normal thresholds found in Equations 4.1 and 4.2. However, in this particular scenario, we introduce an error, or what we call a deterioration factor (Δ_{Det}) in the *Velocity* only and keep the *Jerkiness* at the threshold level. The deterioration factor (Δ_{Det}) is meant to shift the Velocity down

from its normal value by -0.5% at every iteration, therefore decreasing it so that it is farther than the threshold. The following algorithm (Algorithm 2) explains this approach.

Algorithm 2: Simulation of Deteriorating Performance

Input: The Reach Angle, the Velocity, and Jerkiness values, θ , $(\dot{\theta}_{New})$ and (J_{New}) .

Output: The Quality of Physical Performance (QPP).

Initialize: $\theta = 45^\circ$, $\phi = 41.07$, $\tau = 0.019$, $\mu = 3.82$, $\delta = 0.024$, $\Delta_{Det} = 0$

Begin

Loop while Iteration \leq 100

 Compute the velocity

$$\dot{\theta}_M = \phi \cdot e^{\tau_M \theta}$$

 Decrease the Velocity by Δ_{Det}

$$\dot{\theta}_{New} = \dot{\theta}_M - \Delta_{Det}$$

 Compute the threshold value for Jerkiness

$$J_{New} = \mu \cdot e^{\delta_M \theta}$$

 Compute QPP by the Physical Performance Quantifier (PPQ)

$$QPP = PPQ(\theta, \dot{\theta}_{New}, J_{New})$$

 Update the deterioration factor

$$\Delta_{Det} = 0.5 * \dot{\theta}_{New} / 100$$

 Update Iteration number

$$\text{Iteration} = \text{Iteration} + 1$$

 Return QPP

- **Improving Condition:** In this scenario, we assume that the performance starts at one third of the threshold (very bad performance), and then starts to increase because of an improvement in the *Velocity* throughout the iterations. We introduce here a factor

of improvement (Δ_{imp}) that aims to increase the velocity by 0.5% at every iteration.

This approach is more elaborated in the procedure shown in Algorithm 3.

Algorithm 3: Simulation of an Improving Performance

Input: The Reach Angle, the Velocity, and Jerkiness values, θ , ($\dot{\theta}_{New}$) and (J_{New}).

Output: The Quality of Physical Performance (QPP).

Initialize: $\theta = 45^\circ$, $\phi = 41.07$, $\tau = 0.019$, $\mu = 3.82$, $\delta = 0.024$, $\Delta_{imp} = 0$

Begin

Loop while Iteration \leq 100

 Compute the velocity

$$\dot{\theta}_M = \phi \cdot e^{\tau_M \theta}$$

 Decrease the Velocity by 0.5% from the threshold

$$\dot{\theta}_{New} = \frac{1}{3} \dot{\theta}_M + \Delta_{imp}$$

 Compute the threshold value for Jerkiness

$$J_{New} = \mu \cdot e^{\delta_M \theta}$$

 Compute QPP by the Physical Performance Quantifier (PPQ)

$$QPP = PPQ(\theta, \dot{\theta}_{New}, J_{New})$$

 Update the improvement factor

$$\Delta_{imp} = 0.5 * \dot{\theta}_{New} / 100$$

 Update Iteration number

$$\text{Iteration} = \text{Iteration} + 1$$

 Return QPP

As shown in Figure 4.11, the *Quality of Performance* (QPP) has maintained almost a constant maximum value since the patient's performance is optimal. However, when deterioration in the average velocity and jerkiness was introduced, the patient's performance is decreased, and thus the QPP has decreased over the iterations. Finally, when an improvement is simulated (starting with low performance values for the average velocity and

jerkiness and change them towards normal conditions) the QPP has increased steadily. This behavior demonstrates the ability of the proposed system to adapt to various performance patterns.

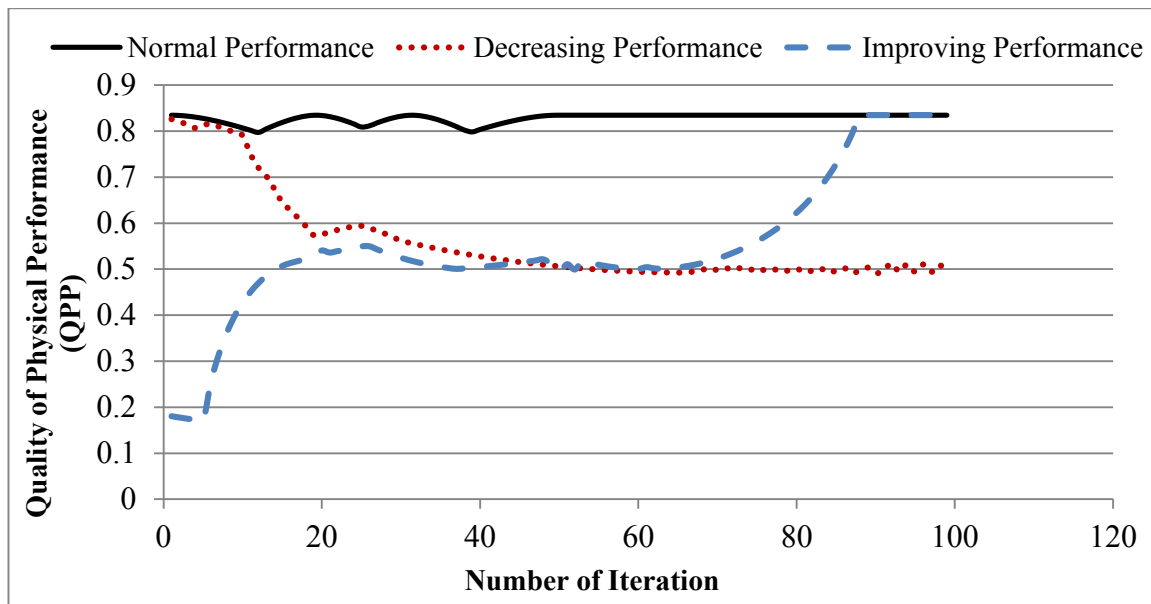


Figure 4.11: Adaptation under various conditions (improving, deteriorating, and normal performances)

4.5.3 Velocity Simulation Analysis

The goal of this simulation is to examine the effect of the velocity on the QPP under three different $Reach$ Angles while assuming a small constant $Jerkiness$ (optimal jerkiness). It can be clearly seen in Figure 4.12 that over higher $Reach$ Angles, higher velocities have to be reached so that the highest QPP possible is achieved (the highest QPP possible is 0.834). For instance, among the curves, the highest $Reach$ Angle (in green) required the highest velocity threshold in order to reach the optimal QPP . On the contrary, the lowest $Reach$ Angle (in blue) required the least velocity threshold in order to reach an optimal

performance. These findings correlate very well with the data in Table 4.1 which suggest that at higher *Reach Angles*, users tend to move their wrists much faster and vice-versa.

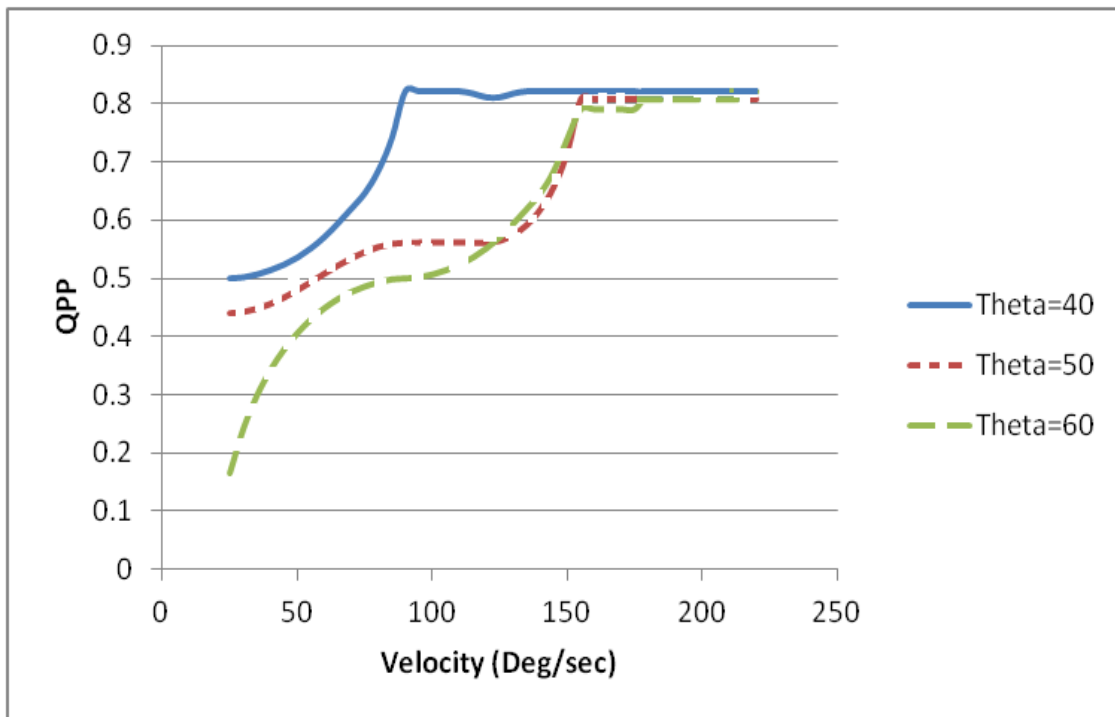


Figure 4.12: The effect of the velocity on the *QPP*

4.5.4 Jerkiness Simulation Analysis

Similarly to the velocity simulation case, in this scenario, we investigate the impact of the *Jerkiness* variations on the *QPP* under three different *Reach Angles* while assuming an optimal velocity. Looking at Figure 4.13, we notice that higher *Reach Angles* are more tolerant to high *Jerkiness* values than in the case of lower angles. This can be clearly verified when looking at the green curve that maintained almost an optimal *QPP* for a range of *Jerkiness* values as high as 28 Gravity/sec. Curves with lower *Reach Angles* were more sensitive to *Jerkiness* and their *QPP* values started declining much faster.

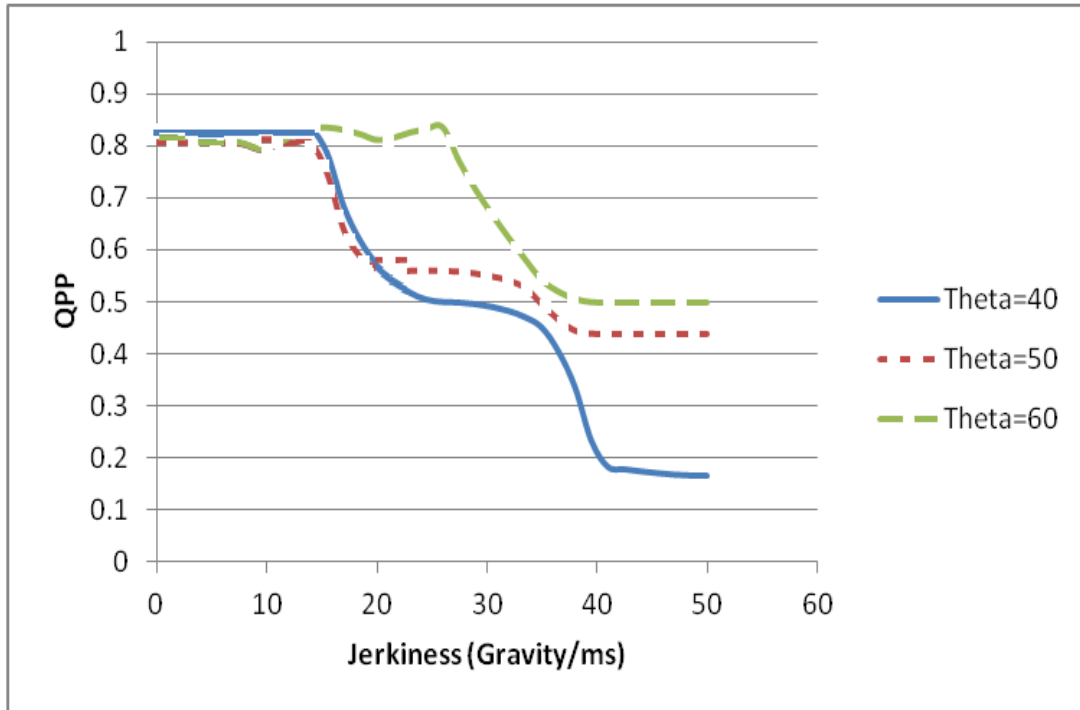


Figure 4.13: The effect of jerkiness on the QPP

4.5.5 Experimental Analysis

Twelve (12) right-hand dominant subjects took part in the experimental study (all males) with 5 trials each. The task assigned to the subjects was to play the Cup and Plate game (Figure 4.2) where the player should grasp a cup and place it on a plate using the tangible rubber ball interface (Figure 4.4).

The *Quality of Performance (QPP)* is computed for a total of 100 iterations per rehabilitation task, and then averaged over 45 trials (15 subjects multiplied by 3 trials each) so the results are statistically significant. Figure 4.14 shows a comparison between the experimental results and the simulated results for the QPP . Overall, the experimentally computed values has matched the simulated one and thus the performance of the proposed *Physical Performance Quantifier (PPQ)* functionality is verified with normal subjects.

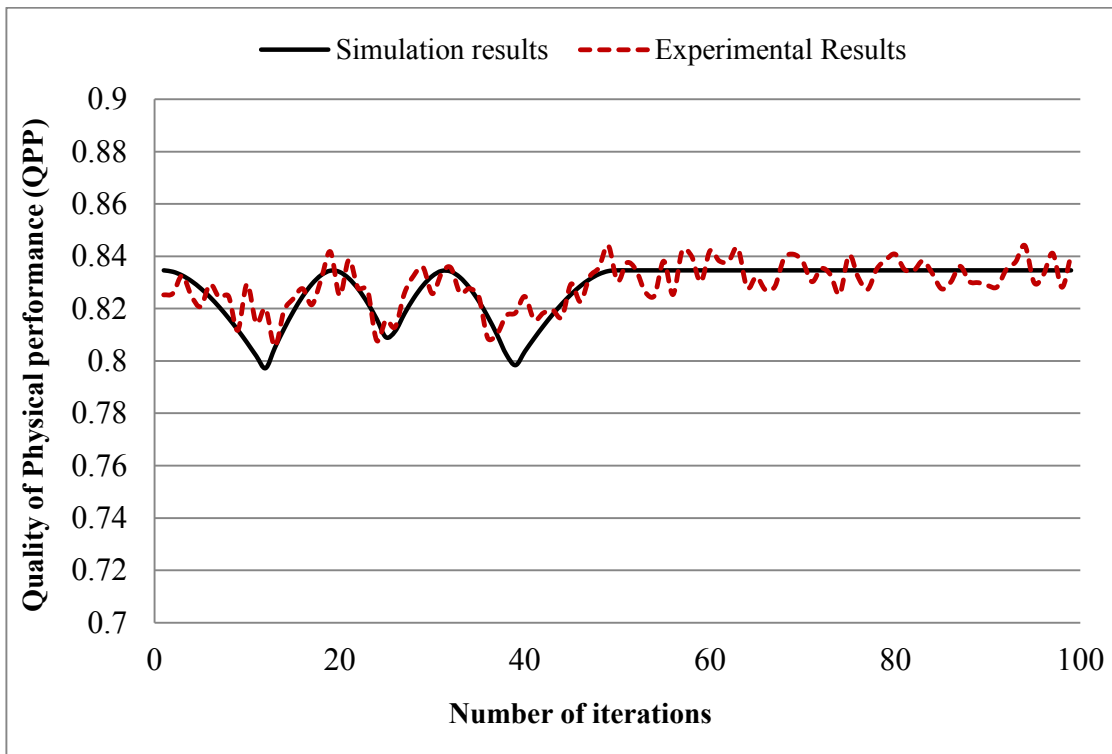


Figure 4.14: Experimental results as compared to simulation results

4.6. Summary

This chapter describes how the *Quality of Physical Performance* of a patient can be modeled using a Fuzzy Logic-based quantification model. Since the model is based on fuzzy set theory, its membership functions should be constructed based on the performance standards of the limb being rehabilitated. For this reason, we have provided a wrist analysis that enabled us to find the task-specific golden values that allow us to implement such model. Evaluations have demonstrated that the model is responding very well to the variations of three performance metrics, namely the *Reach Angle*, *Velocity*, and *Jerkiness*.

Chapter 5. Modeling and Analysis of a Context-based Adaptation Engine

As mentioned in Chapter 2, almost all of the current adaptive VHR systems have based their adaptability mainly on the physical abilities of the patient while neglecting other important contextual information that could greatly affect his/her performance. In this chapter, we present our mathematical model that explains in details how our adaptation engine handles the physical, psychophysiological, and environmental context information to make adaptation decisions that conform to both the patient's condition and the therapist's constraints.

5.1. The Model

Studies have revealed that physiological conditions, such as fatigue and stress, and psychological reactions, such as sadness or happiness, can significantly impact the human's performance to properly accomplish various tasks [Motowidlo et al., 1986, Matthews et al., 1998, Driskell and Salas, 1996]. Furthermore, environmental conditions such as time, location, and the ambient conditions (e.g., weather condition, ambient noise, etc.) affect both performance and the person's satisfaction in doing a task [Vischer, 2007]. The proposed model captures and utilizes the patient's physical performance, psychophysiological responses, and environmental conditions to provide an optimized adaptation for home-based

rehabilitation. Therefore, it takes into consideration the various contexts that may hinder the patient to progress during the rehabilitation training.

The model enables the clinician to select the contextual parameters that affect his/her patient and to define their correlations with the patient's ability to perform a task. This is done by assigning a weight between all of the context parameters. As a result, the model generates an adaptation matrix that defines how the psychophysiological responses and environmental conditions must be manipulated in order to accelerate the rehabilitation process.

5.1.1 Definitions

Three matrices define the proposed model: the Measured Conditions Matrix (M), the Desired Conditions Matrix (D), and the Correlation Matrix (C). The output of the mathematical model is the Adaptation Coefficients Matrix (α). Note that α_i represents the significance of the i^{th} condition towards the patient's performance, which can also be used to adjust the various conditions to optimize the rehabilitation process.

The patient's performance in the home-based rehabilitation system is modeled using the Measured Conditions Matrix (M) as shown in equation (5.1)

$$M = [M_1, M_2, \dots, M_N]^T \quad (5.1)$$

where M_i is the measured index for the i^{th} condition and N is the number of conditions to be considered in the adaptation model. The Desired Conditions Matrix D is defined according to Equation (5.2):

$$D = [\alpha_1 \times D_1, \alpha_2 \times D_2, \dots, \alpha_N \times D_N]^T \quad (5.2)$$

where D_i is the desired index for the i^{th} condition and α_i is the adaptation coefficient for the i^{th} condition. The Desired performance index D_i is set by the therapist to setup the optimal conditions for the patient to perform a rehabilitation task.

The Correlation Matrix C (Equation 5.3) is a $N \times N$ matrix that describes the mutual correlation between any two conditions. For instance the element at i^{th} row and j^{th} column describes the correlation between the i^{th} and j^{th} conditions (such as the correlation between stress and fatigue).

$$C = \begin{bmatrix} C_{i_1 j_1} & C_{i_1 j_2} & C_{i_1 j_3} \dots & C_{i_1 j_N} \\ C_{i_2 j_1} & C_{i_2 j_2} & C_{i_2 j_3} \dots & C_{i_2 j_N} \\ \vdots & \vdots & \vdots & \vdots \\ C_{i_N j_1} & C_{i_N j_2} & C_{i_N j_3} \dots & C_{i_N j_N} \end{bmatrix} \quad (5.3)$$

Note that the therapist defines the correlation matrix C for every patient in order to personalize the model's performance according to the patient's particular preferences and needs. The initialization of this matrix is done based on the therapist's knowledge about the factors that may affect his or patients. For instance, if the patient knows that the physical performance of a certain patient is affected by stress, then this knowledge can be transmitted to the framework by defining the proper correlation value between the physical parameter and the stress parameter.

5.1.2 Model Derivation

The ultimate goal of the proposed model is to match the Measured Conditions Matrix (M) and the Desired Conditions Matrix (D) by tuning the Adaptation Coefficients Matrix (α), which is the output of the adaptation model. The concept is illustrated in Figure 5.1.

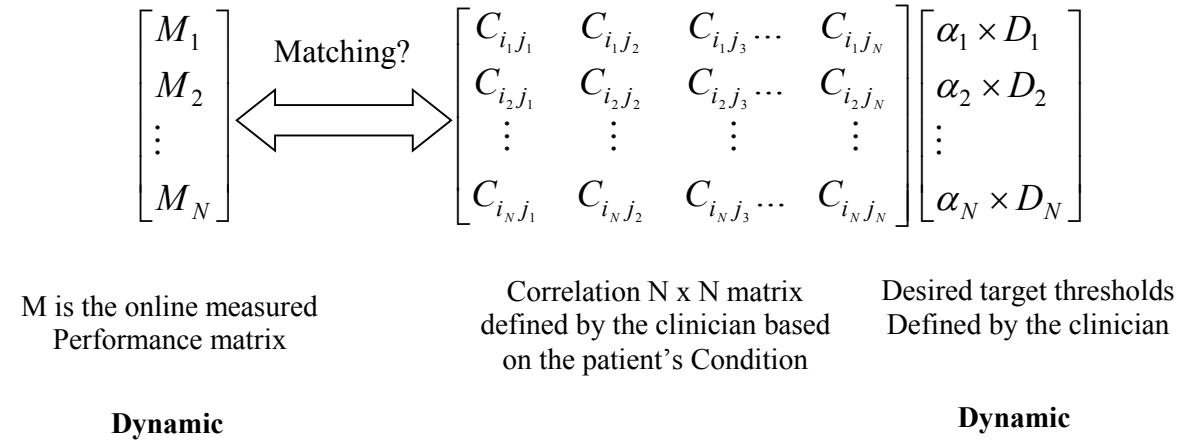


Figure 5.1: The proposed adaptation scheme

As the adaptation coefficient α_i ($1 \leq i \leq N$) is unknown, an estimate model corresponding with Figure 5.1 is defined according to the following equation:

$$M(t) = CD(t) = C \begin{bmatrix} \alpha_1 D_1 \\ \vdots \\ \alpha_N D_N \end{bmatrix} \quad (5.4)$$

In Equation (5.5), the updated Measured Conditions Matrix (\hat{M}) is computed by multiplying the Correlation Matrix (C) by the estimated Desired Condition Matrix (\hat{D}).

$$\hat{M}(t) = C\hat{D}(t) = C \begin{bmatrix} \hat{\alpha}_1 D_1 \\ \vdots \\ \hat{\alpha}_N D_N \end{bmatrix} \quad (5.5)$$

The idea is to update the adaptation coefficient $\hat{\alpha}_i$ ($1 \leq i \leq N$) by using the online data. The estimated Desired Condition Matrix (\hat{D}) can be obtained by minimizing the total error between the measured and the estimate model in the form of least-squares, as expressed in Equation (5.6).

$$\min \int_0^t e^{-\lambda \|M(r) - C\hat{D}(r)\|_2} dr \quad (5.6)$$

where $\lambda > 0$ is the forgetting factor, giving a weight of importance for the current measurements based on previous measurements. In other words, the forgetting factor (λ) represents the weight of the history of patient's performance on the adaptation of the next rehabilitation task. For example, the larger the value for the forgetting factor (λ), the faster the adaptation will occur as the history of performance has less weight and thus the adaptation decision will be mostly based on the current performance. This parameter can be defined by the therapist to realize a more personalized adaptive home-based rehabilitation system. Now, the update of (\hat{D}) can be derived as shown in Equation (5.7).

$$\dot{\hat{D}} = -PC^T (\hat{M} - M) = -PC^T (C\hat{D} - M) \quad (5.7)$$

where (P) is defined as the Gain Matrix and is defined according to Equation (5.8).

$$P = \left(\int_0^t C^T C dr \right)^{-1} \quad (5.8)$$

Therefore, the adaptation coefficients can be computed according to Equation (5.9).

$$\begin{bmatrix} \hat{\alpha}_1 \\ \vdots \\ \hat{\alpha}_N \end{bmatrix} = \begin{bmatrix} \hat{D}_1 / D_1 \\ \vdots \\ \hat{D}_N / D_N \end{bmatrix} \quad (5.9)$$

Notice that if $\hat{D}_i/D_i \approx 1$, this would mean that the patient has already achieved the target level of performance for parameter i .

In order to update the gain matrix (P) without the need to do matrix inversion, the property described in Equation (5.10) has been utilized

$$\frac{d}{dt}(PP^{-1}) = \dot{P}P^{-1} + P\frac{d}{dt}(P^{-1}) \quad (5.10)$$

where

$$\dot{P} = \frac{dP}{dt} = \frac{d}{dt} \left(\int_0^t C^T C dr \right)^{-1} \quad (5.11)$$

Now, since $\frac{d}{dt}(PP^{-1}) = 0$, we get

$$\frac{d}{dt}(PP^{-1}) = \dot{P}P^{-1} + P\frac{d}{dt}(P^{-1}) = 0 \quad (5.12)$$

therefore, this yields

$$\dot{P} = -P\frac{d}{dt}(P^{-1})P = -PC^T CP \quad (5.13)$$

Finally at the next iteration, \dot{P}_{New} , P_{New} , \hat{D}_{New} and \hat{D}_{New} can be updated using Equations 5.15, 5.16, 5.17 and 5.18 respectively.

$$\dot{P}_{New} = \lambda P_{Old} - P_{Old} C^T C P_{Old} \quad (5.14)$$

$$P_{New} = P_{Old} + K_g \dot{P}_{New} \quad (5.15)$$

$$\hat{D}_{New} = -P_{New} C^T (C \hat{D}_{Old} - M) \quad (5.16)$$

$$\hat{D}_{New} = \hat{D}_{Old} + K_u \hat{D}_{New} \quad (5.17)$$

where K_g and K_u are constants that yield faster convergence.

5.1.3 Execution Procedure

The mathematical model derived in Subsection 5.1.2 can be executed using the procedures shown below (note that step 1 and step 2 are initial setting whereas step 3 and step 4 are the iterative update).

The Executing Steps of the Adaptation Algorithm

Step 1: Initialization

- Initialize the matrix (P) with very large values, noted as $P(0)$
- Read values for Measured Conditions Matrix (M), and Desired Conditions Matrix (D).
- Initialize the Correlation Conditions Matrix (C)
- Compute Transpose of C (C^T)
- Initialize $\hat{D}(0)$ with Desired Conditions Matrix (D)
- Initialize forgetting factor λ
- Initialize convergence constants K_g and K_u

Step 2: First Iteration (e.g., first training task)

- Use Equation 5.13 to find \dot{P} .
- Update $P(0)$ using Equation 5.14.
- Find matrix $\dot{\hat{D}}$ using Equation 5.7.
- Compute matrix \hat{D} using Equation 5.16.

Step 3: Iterations Afterwards (e.g., second training task until the end of the training)

Loop while $\hat{D}/D < \text{Threshold}$

- Find \dot{P}_{New} using Equation 5.14.
- Update P_{New} using Equation 5.15.
- Compute $\dot{\hat{D}}_{New}$ using Equation 5.16.
- Update \hat{D} using Equation 5.17.
- Find $\hat{\alpha}$ using Equation 5.9.

Here, Threshold is a value defined by the therapist.

5.2. Model Performance Analysis

This section introduces a case study to demonstrate the merits of the proposed adaptive mathematical model for home-based rehabilitation.

5.2.1 Context-Adaptive Home-based Rehabilitation (CAHR)

The *Context-Adaptive Home-based Rehabilitation* framework (CAHR) can support an N number of context parameters. In this version, we will assume that the framework only incorporates four parameters to define the home-based adaptation: (1) The *Quality of Performance* (QPP) to quantize the patient's performance, (2) *Fatigue* as a physiological condition, (3) *Stress* as a psychological condition, and (4) *Noise* as an environmental condition. The objective here is to provide a more efficient rehabilitation experience.

- **The Quality of Performance (QPP):** The QPP is a task-specific parameter that measures the quality of performance for the patient while performing a rehabilitation task.
- **Physiological Fatigue:** *Fatigue* is a bio-behavioral state an individual is in that is induced by enduring task performance; and refers to the state of the patient after performing a rehabilitation task. Apparently, the patient's performance is directly related to the physiological fatigue they experience. EMG sensors may be used to measure physiological fatigue by monitoring the muscles activities over time.
- **Psychological Stress:** *Stress* is an innate response to an environmental threat or psychological distress that triggers chemical and hormonal reactions in the body. The

quality of patient's rehabilitation performance is directly related to the stress level. The adaptation system takes into consideration psychological stress in order to optimize home-based rehabilitation.

- **Environmental Conditions:** Such conditions include the ambient noise, ambient temperature, luminance, or any other ambient environment condition that might affect the quality of patient's performance for a home-based rehabilitation task.

Based on the four parameters described above, the proposed mathematical model can be described as follows. The *Measured Conditions Matrix* (M) becomes:

$$M = [M_1, M_2, M_3, M_4]^T \quad (5.12)$$

where M_1 is the measured probability density function for the *Quality of Physical Performance QPP*, M_2 is the measured fatigue parameter, and so on.

Now the *Desired Conditions Matrix* D becomes:

$$D = [\alpha_1 \times D_1, \alpha_2 \times D_2, \alpha_3 \times D_3, \alpha_4 \times D_4]^T \quad (5.13)$$

where α_1 is the adaptation coefficient for the *Quality of Physical Performance* index and D_1 is the *Desired Condition* for the *QPP*. The *Correlation Matrix* becomes:

$$C = \begin{bmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & C_{34} \\ C_{41} & C_{42} & C_{43} & C_{44} \end{bmatrix} \quad (5.14)$$

where C_{12} describes the correlation between *Quality of Physical Performance* and physiological fatigue, etc.

5.2.2 Simulation Setup

The *CAHR* model is implemented in C# and the experiments are run on a Pentium 4 machine with 4 GB RAM. The initial settings of the simulation were chosen as the following:

$$M = [0.6 \quad 0.8 \quad 0.7 \quad 0.5]^T$$

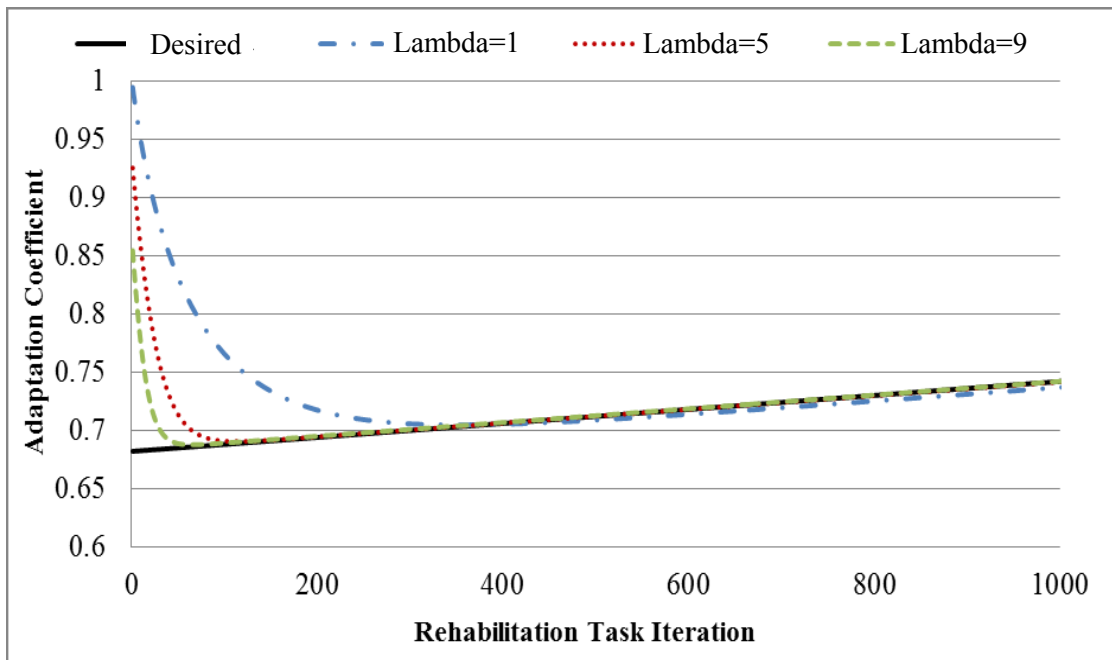
$$D = [0.9 \quad 0.8 \quad 0.75 \quad 0.7]^T$$

$$C = \begin{bmatrix} 1 & 0.7 & 0.4 & 0.5 \\ 0.7 & 1 & 0.3 & 0.2 \\ 0.4 & 0.3 & 1 & 0.3 \\ 0.5 & 0.2 & 0.3 & 1 \end{bmatrix}$$

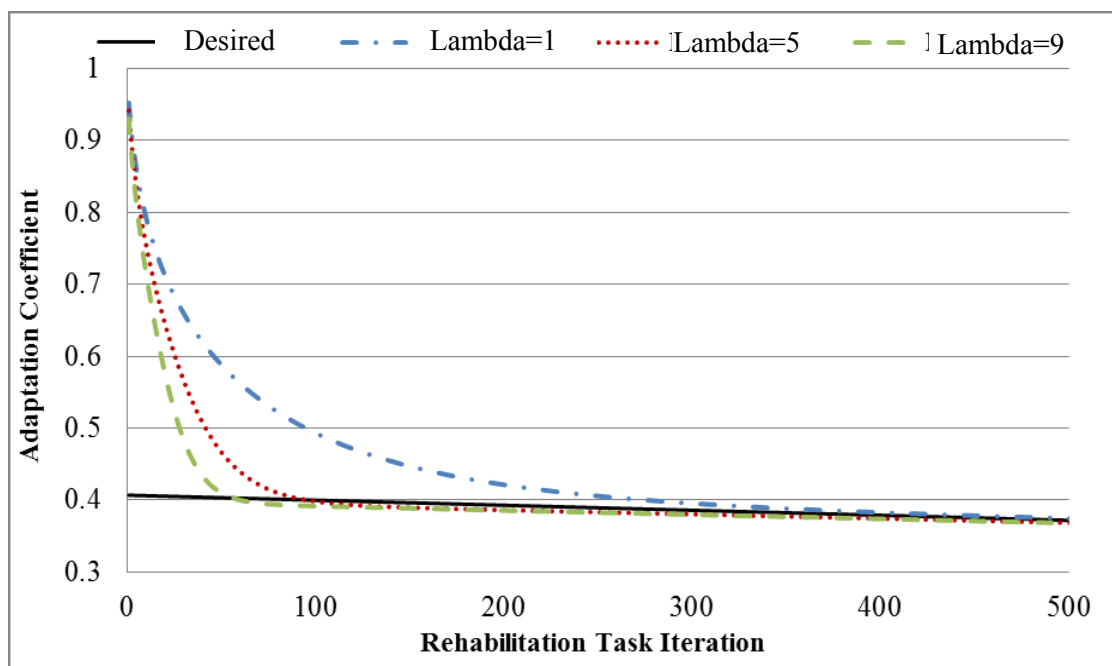
The initial values of the matrices were randomly chosen. However, during the simulation, only the correlation matrix *C* was kept constant while matrices *M* and *D* were changed at every iteration. For example, the measured matrix *M* was changed depending on the performance pattern being simulated. On the other hand, matrix *D* was computed at every iteration using Equation 5.7 shown previously in this chapter.

5.2.3 Simulation Results

Three simulation cases are considered: (1) A linear improvement or declination in the patient's performance. That is the Measured Conditions Matrix (M_1) is increasing or decreasing in a linear function of the rehabilitation task iteration, (2) a logarithmic improvement in the patient's performance, and (3) a sinusoidal fluctuations in the patient's performance.



(a)



(b)

Figure 5.2: (a) Adaptation when patient's performance is a linearly increasing function, and (b) Adaptation when patient's performance is a linearly decreasing function

Case 1: Linear Improvement

In this scenario, the patient's performance is assumed to be linearly varying in both directions. The results are shown in Figure 5.2 (a) for a linearly increasing simulation and in Figure 5.2 (b) for a linearly decreasing simulation. In both cases, the adaptation coefficients have been tuned in to match the desired and measured conditions. Furthermore, the forgetting factor (λ) is shown to have a significant impact on the speed of adaptability, as shown in Figure 5.2 (a) and Figure 5.2 (b). An increase of the forgetting factor (λ) results in a faster convergence of the measured conditions towards the desired conditions.

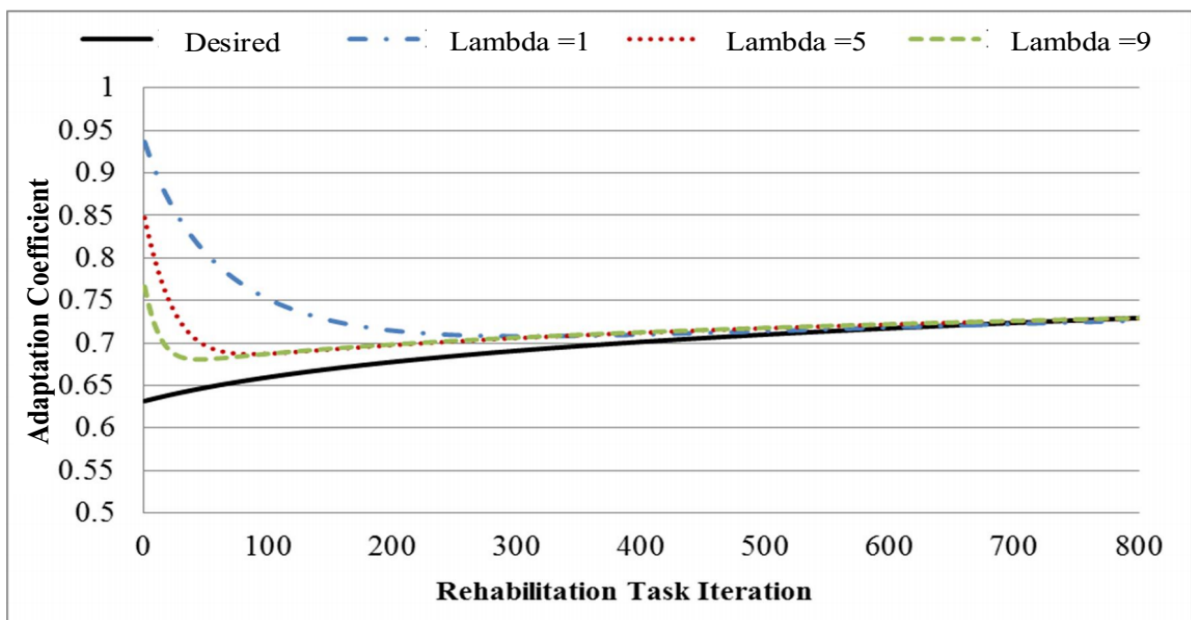


Figure 5.3: Adaptation when patient's performance is a logarithmic function

Case 2: Logarithmic Improvement

In this scenario, the patient's performance is modeled as increasing logarithmically as function of the rehabilitation task iterations. The results are shown in Figure 5.3 where again

the measured conditions have converged to the desired conditions, thanks to the adaptation model. Same impact of the forgetting factor (λ) has been experienced in this case.

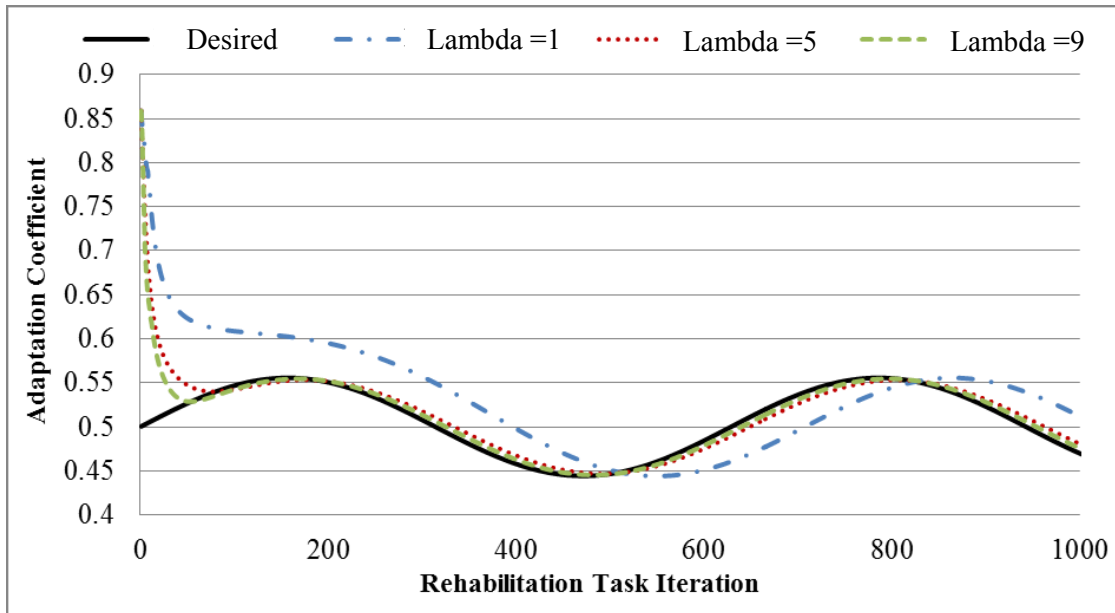


Figure 5.4: Adaptation when patient’s performance is a sinusoidal function

Case 3: Sinusoidal Improvement

In this scenario, the patient’s performance is modeled as an oscillating performance as a function of the rehabilitation task iterations. The objective of the scenario is to evaluate the ability of the adaptation model to cope with fluctuations in the patient’s performance. The results are shown in Figure 5.4 where the measured conditions converged to the desired conditions, except when the forgetting factor (λ) is equal to 1. The condition ($\lambda = 1$) implies that the adaptation model has experienced a latency to cope with higher frequency changes in the patient’s performance. Therefore, a conclusion can be drawn from this simulation result that a patient with a fluctuating performance should be assigned a higher value of the

forgetting factor (λ) to make sure the adaptive model can cope and respond to abrupt changes in the patient's performance.

5.3. Summary

In this chapter, we have presented an adaptation model for in-home rehabilitation that is based on the *least-square* method. The model involves the clinician in the adaptation process by enabling him or her to define target levels and to define the factors that might affect his/her patient's performance during the training. Consequently, the model uses the online training data of the patient to find the best match between the measured data and the therapist's desired thresholds by tuning a number of adaptation coefficients which reflect the overall performance condition of the patient at a particular task or session. In Chapter 6, we realize our *CAHR* framework by designing a proof-of-concept hardware and software system which will be used in Chapter 7 for testing with the patients.

Chapter 6. Proof-of-Concept Design of the CAHR Framework

In this Chapter, we present the hardware implementation of the proposed tangible training interface and the software interaction of the proposed *CAHR* framework. We elaborate on the different electronic components that were incorporated inside the ball. In addition, we give details on the way interaction is achieved between the therapist, the patient and the proposed framework.

6.1. DigiBall Design

One of the contributions of this dissertation is the development of a tangible training interface that makes the rehabilitation easy to perform at a home environment without requiring any assistance to operate and use. Passive devices have already been used in rehabilitation for many years and are very well known to both patients and therapists. A rubber ball is normally used by patients suffering from hand related injuries. To make such ball suitable for VHR applications, it must possess a means that enables motion detection and the storage of information. Sensors technology and microprocessing units can greatly transform the rubber ball from a passive state to an interactive one if properly deployed.

6.1.1 Hardware Implementation

Our proposed *DigiBall* (Figure 6.1) can be considered as an improved version of the passive stress ball that is widely prevalent in the market. On its outer surface, the ball was mounted with 5 *Force Resistive Sensors* that are positioned to go under each of the hand's fingers. The *Force Sensors* are 0.5 inches of diameter and can sense applied finger forces anywhere in the range of 100 grams to 10 kilograms. The battery of the ball can be charged through the *Charger/Programming Socket* that is also the terminal through which the microprocessing unit of the ball can be programmed.

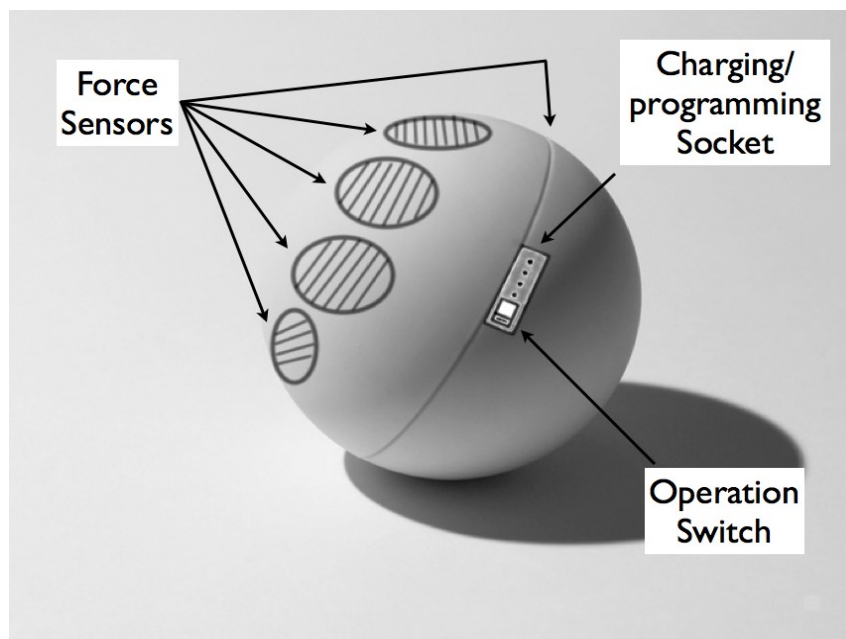


Figure 6.1: The outer surface of the proposed DigiBall

Figure 6.2 depicts how the various components that are integrated inside the ball. As can be realized, two hemispheres that are attached together to form the ball. Each component can be described by the following:

- *Inertial Measurement Unit*: The hand motion was captured using a 6 DOF *Inertial Measurement Unit* (IMU) that is comprised of a 3-axis ADXL 335 *Accelerometer* and an ITG 3200 *Gyroscope*. The data fusion of the 2 sensors allows the detection of the three motions of interest (pitch, roll, and yaw).
- *Microcontroller*: The *Microcontroller* consists of an *Arduino ProMini* that has a 10 bit *Atmega 328* processor running at a 16 MHz clock speed.
- *Actuator*: We have incorporated a small, low voltage (3V) vibration motor in order to produce a vibro-tactile feedback that aims to enhance the rehabilitation experience of the user and add more fun to the games.
- *Wireless Module*: The full-duplex communication between the ball and the computer is achieved by using a low power (1 mW) *XBee Transceiver* module with a transmission range as far as 120 meters (outdoor and assuming line-of-sight). In order to reduce the delay that can occur during data transmission, the baud was increased so that the interaction between the ball and the game appears very natural. After performing a number of tests with users, we have determined that a baud rate of 19200 bits per second would suffice for a realistic interaction.
- *Battery*: The power of the whole circuitry was supplied by a *Polymer Lithium Ion* (LiPoly) Battery that produces a nominal voltage of 3.7 Volts with a capacity of 2000 mAh (milli-amp-hour).
- *Battery Charger*: The battery charger consists of a USB LiPoly Charger that allows the charging of 3.7 V LiPo cells at a rate up to 500 mA.

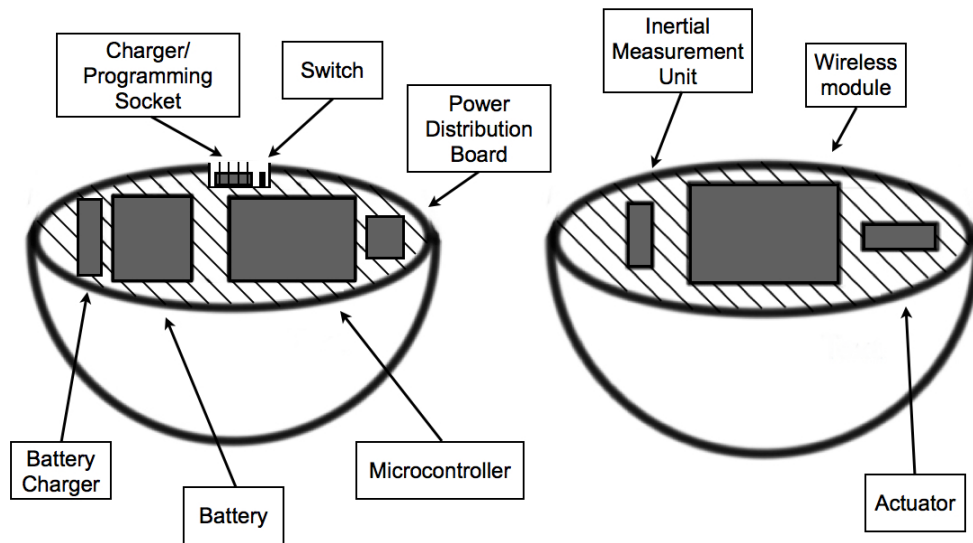


Figure 6.2: The various devices integrated in the inner surface of the proposed DigiBall

6.1.2 Signal Conditioning

Signal Conditioning refers to the process of analog to digital (A/D) Conversion, digital to analog Conversion (D/A), calibration, and filtering of the input and output signals of the DigiBall. The analog signals broadcasted by the IMU unit and the pressure sensors were digitized by the 10 bit A/D converter of the *Microcontroller* which produced digital values that range between 0 and 1023. On the other hand, command signals to the vibration motor were converted into analog signals through the *Pulse Width Modulation* (PWM) [Barr, 2001] technique which allows us to increase or decrease the intensity of the motor vibration by varying the PWM frequency (f_{pwm}).

The *Accelerometer* is known to be very sensitive to vibrations and mechanical noise while a *Gyroscope* drifts over time (rate of change does not go back to 0 when rotation stops). These factors might result in large errors which can greatly alter the readings of the IMU, and therefore proper calibration and filtering is required. In order to properly calibrate

the IMU, the direct current offsets need to be removed [Bouten et al, 1997]. This was achieved by removing the offset voltage from the output voltage supplied by the device using Equation 6.1.

$$V_{A(x,y,z)} = V_{out(x,y,z)} - V_{off(x,y,z)} \quad (6.1)$$

where V_A is the actual voltage obtained after removing the voltage offset on a particular axis, V_{out} is the voltage outputted by the device, and V_{off} is the offset voltage as specified in the device's datasheet.

After calibration, the signals of the IMU must be properly filtered in order to obtain a reliable reading of the accelerations and the velocities. There has been extensive work in the field of signal processing that seeks to introduce orientation estimation algorithms for proper IMU filtering [Kim and Golnaraghi, 2004, Won et al., 2010, Luinge et al, 2007]. A *Kalman* filter has become the basis for the majority of orientation algorithms [Marins et al., 2001]; however, its relatively heavy computational requirements prevent its implementation on low performance microcontrollers, such as an Arduino. For this reason, we deployed an open source filtering algorithm [Fusion Filter, 2013] that is accurate, yet fast and can be implemented on an Arduino. The algorithm is based on the work of Mahoney [Mahoney et al., 2006] which has been extended by Madgwick [Madgwick et al., 2011]. The filter uses the data fusion of the Gyroscope and the Accelerometer to compute the yaw, pitch, and roll motion with respect to the world frame. Discussing the details of this filter is out of the scope of this dissertation (for more information on this filter, please refer to [Varesano, 2011]).

6.1.3 Features Extraction

The proof-of-concept virtual exercise incorporates three types of training performance parameters, namely the *Reach Angle*, *Velocity*, and *Jerkiness* that feed the *Physical Performance Quantifier* module (See Section 4.4). These parameters were computed on the *Microcontroller* using the conditioned data of the IMU.

1. **Reach Angle:** The human wrist has 3 rotational Degrees of Freedom (DOF), pitch, roll, and yaw. To find these motions, the accelerations on the x, y, and z coordinates have to be first captured by the IMU. Then, the pitch (α), roll (β) and yaw (δ) motions can be computed using trigonometry by plugging the accelerations in Equations 6.2, 6.3, and 6.4 respectively.

$$\alpha = \tan^{-1} \left(\frac{A_x}{\sqrt{A_y^2 + A_z^2}} \right) \quad (6.2)$$

$$\beta = \tan^{-1} \left(\frac{A_y}{\sqrt{A_x^2 + A_z^2}} \right) \quad (6.3)$$

$$\delta = \tan^{-1} \left(\frac{\sqrt{A_x^2 + A_y^2}}{A_z} \right) \quad (6.4)$$

where A_x , A_y , and A_z are the accelerations on the three axes.

2. **Average Angular Velocity:** The Average Angular Velocity or simply *Velocity* was estimated by the following equation:

$$\dot{\theta} = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} v(t) dt \quad (6.5)$$

Here, t_1 is the starting time of the task, t_2 is the time when the reaching of an object is achieved.

3. **Jerkiness:** The Jerkiness of velocity was calculated using Equation 6.6. Please note that Jerkiness is measured in gravity per milliseconds throughout this thesis.

$$J = \int_{t_1}^{t_2} \sqrt{\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2 + \left(\frac{d^3z}{dt^3}\right)^2} dt \quad (6.6)$$

where x , y , and z are the 3D coordinates of the wrist.

6.2. Adaptive Cup and Plate Game Design

The Cup and Plate exercise was previously explained in Section 4.2 of Chapter 4. The main goal of the game is to rotate the wrist on the Supination or Pronation motion in order to grab a cup and release it on its plate. In Chapter 4, a non-adaptive version of the game was utilized to conduct our wrist analysis with healthy subjects. In order to test the game with real patients, we have developed an adaptive version of the game by implementing the *CAHR* framework architecture. Please note that we have only considered the physical, physiological and psychological context of the patient in the design process of the game. The game was developed using the Java programming language. The Java swing library was used to create the 2-dimensional graphics, while the rxtx library [RXTX, 2013] was used for serial communication with the *DigiBall*.

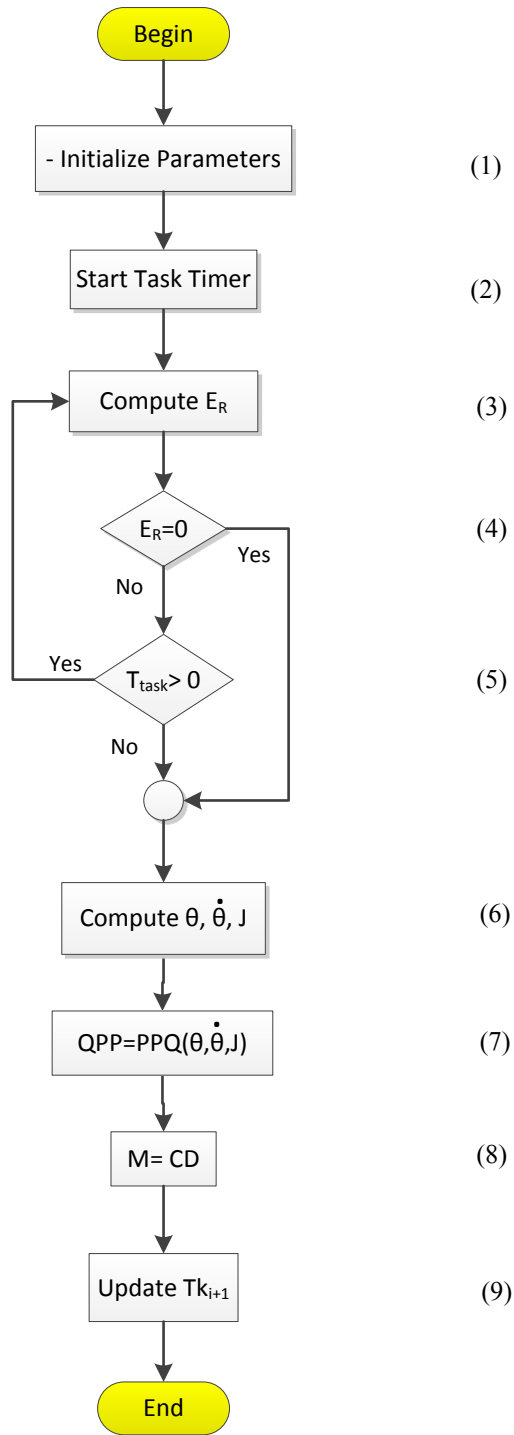


Figure 6.3: The Cup and Plate task flow diagram

6.2.1 Game Work Flow

Figure 6.3 shows the flow diagram of the overall functionalities accomplished during each task performed within a session. The overall process can be divided into 8 steps than can be explained by the following:

Step (1): The first step consists of initializing the different parameters that the framework requires for its operation. This includes defining the Desired Matrix (D), the threshold *Quality of Physical Performance* (QPP_{Th}), the Correlation Matrix (C), and the threshold stress and fatigue levels by the therapist. In addition, the fatigue and stress levels of the patient should also be initialized frequently throughout the training session.

Step (2): Once the game begins, the process starts by listening to a timer that expires at a custom time interval (T_{task}). The aim of the timer here is to make sure that the task is changed or stopped in case the patient is not able to reach the goal during the session. T_{task} is defined as:

$$T_{task} = T_{Th} - T_{current} \quad (6.7)$$

where $T_{current}$ is the current time within the task and T_{Th} is the therapist's task-expiry-time of choice. Note that T_{task} is higher than 0 as long as the patient's task play time does not exceed the therapist's predefined time interval.

Step (3): The Reach Error E_R is computed iteratively throughout the duration of the task. E_R (Equation 6.8) is the error between the *Reach Angle* (θ) to reach and the maximum reach achieved by the patient (θ_P). It indicates whether or not a patient is able to reach the cup.

$$E_R = \theta - \theta_p \quad (6.8)$$

E_R can be either 0 or a positive value. Obviously, if a patient successfully finishes a task the reach error is always 0 since he/she is able to achieve the goal (i.e., move the cup onto the plate). On the contrary, the reach error is a positive value if the timer expires while the patient is still attempting to finish the task. In this case, we assume that the wrist ROM capabilities is less than that required by the task (i.e., patient is not able to rotate his/her wrist to a particular degree).

Steps (4) and (5): The process goes on by continuously checking if the patient finishes the task ($E_R = 0$). If this is the case, the process jumps to Step (6); otherwise, if the task in effect is not finished and the timer is not expired, that is E_R and T_{task} are both positive values, the status is kept monitored until one of the two conditions changes. If either the timer expires or the task is finished, the process jumps to step (6).

Step (6): At this stage, the performance metrics previously discussed are computed. It is worth noting that these metrics are calculated even if the patient is not able to achieve the required goal.

Step (7): Once the performance metrics are determined, the *Quality of Physical Performance* (QPP) is estimated by the *Fuzzy Inference System* of the *Physical Performance Quantifier* (PPQ) of the model discussed in Chapter 4.

Step (8): Upon estimating the QPP , it is passed along with the fatigue and stress levels to the *Context-based Adaptation Engine* (CAE) discussed in Chapter 5. The CAE matches the performance matrix with the desired one and generates an adaptation coefficient matrix

(Equation 6.9) that reflects the performance of the patient taking into consideration his/her physical, physiological and psychological conditions.

$$\hat{\alpha} = [\hat{\alpha}_{QPP} \quad \hat{\alpha}_{FT} \quad \hat{\alpha}_{ST}] \quad (6.9)$$

where $\hat{\alpha}_{QPP}$, $\hat{\alpha}_{FT}$, and $\hat{\alpha}_{ST}$ are the *Quality of Physical Performance*, *fatigue*, and *stress* adaptation coefficients respectively. The closer the coefficients to 1, the better the patient's performance.

Step (9): The last step in the process consists of updating the *Reach Angle* of the subsequent task in a Session. We have defined these updates in collaboration with the therapist. The updates of θ_{New} is done using Equations 6.10:

$$\theta_{New} = \theta_{Old} + sign(\Delta Q)(\hat{\alpha}_{QPP} \cdot S) - E_R \quad (6.10)$$

Here, θ_{Old} is the *Reach Angle* of the previous task within a session, S is the *Task Progress Step Size* discussed in Section 3.5 of Chapter 3, and ΔQ is the *Performance Deficiency Distance*. A nil or positive value of ΔQ (equations 6.11) means that a patient has achieved or even exceeded the performance threshold; otherwise, the patient's performance needs to be improved. Now $sign(\Delta Q)$ (Equation 6.12) is a sign function that returns either +1 or -1 depending on the patient's deficiency distance. Such distance reflects how far the estimated *Quality of Physical of performance* (QPP_{Th}) is from the threshold.

$$\Delta Q = \hat{Q}_{PP} - Q_{Th} \quad (6.11)$$

$$\text{sign}(\Delta Q) = \begin{cases} +1 & \text{if } \Delta Q \geq 0 \\ -1 & \text{if } \Delta Q < 0 \end{cases} \quad (6.12)$$

Equation (6.10) boils down to the logic that the intensity of the physical exercise will increase by a factor of $(\hat{\alpha}_{OPP} \cdot S)$ degrees if the patient achieves the threshold set by his or her therapist; otherwise, the intensity will decrease.

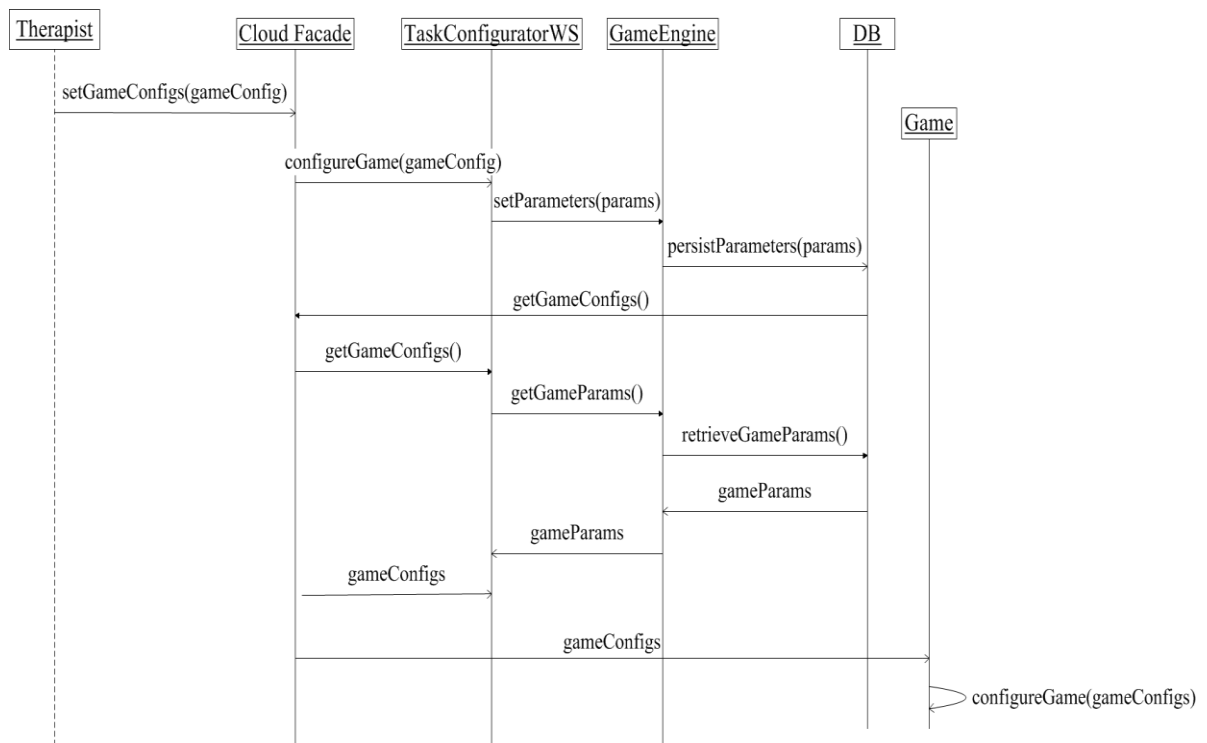


Figure 6.4: A UML sequence diagram for interaction between the therapist and the CAHR framework

6.2.2 Therapist-CAHR Software Interaction

Figure 3.2 reveals a UML sequence diagram that explains how the interaction is done between the therapist and the cloud-based *CAHR* framework. The application server *JBoss* was used to generate the web-service stubs as well to run the patient and medical web-services in its web container.

Prior to a particular training session, the therapist starts by setting the proper configuration of the exercise by interacting with the *CloudFaçade* through `setGameConfigs(gameConfig)` which is an object that contains information about the thresholds and the settings of the game. The *Cloud Façade* passes the configuration parameters through the object `configureGame(gameConfig)` to the *TaskConfiguratorWS* which a special web service that facilitates the communication of the configuration parameters with the *GameEngine* through `setParameters(params)`. Now the *GameEngine* stores the parameters in the *Database (DB)* by creating the object `persistParameters(params)`. Consequently, every time the patient starts a session, a `getGameconfigs()` object is created which enables polling the configuration settings from the cloud through the *CloudFaçade* which in turn applies these configurations to the *Game* (task) through `gameConfigs`.

6.2.3 Patient-CAHR Software Interaction

The software patient-framework interaction was implemented based on the UML sequence diagram presented in Figure 3.3. The interaction starts when the patient wants to begin performing a new task by acquiring the *Context* interface through `getContext()` about the physical and psychophysiological context of the patient. Upon receiving the contextual

information, the object `getAdaptationParams(taskResult)` is created and sent to the *CloudFacade* layer that requests the services necessary for adapting the content of the game through `calcAdaptParams(tasResult)`. Once the request for adaptation is received by the *AdaptationWS*, it is passed to *GameEngine* that polls the *PPQ* and the *ContextAdaptationEngine* for the Quality of physical Performance estimation and the Adaptation coefficients through `getQPP(physicalTaskResult)` and `getAdaptationParams(QPP,nonPhysicalContext)` respectively. Once the necessary adaptation parameters are received by the *GameEngine*, they are sent back to the *Game* where the proper media is loaded.

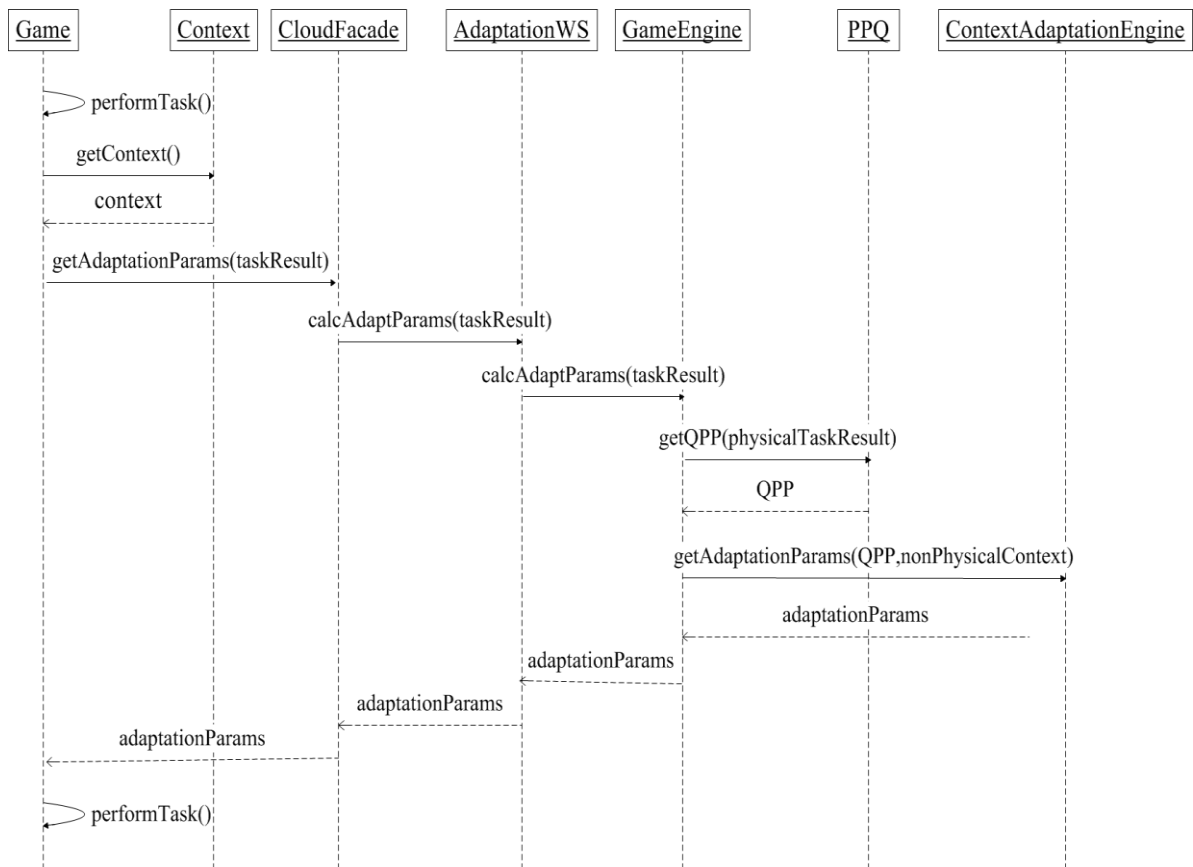


Figure 6.5: A UML sequence diagram for interaction between the Patient and the CAHR framework

6.3. Summary

In this chapter, we have revealed the hardware implementation and the software interaction details of the *CAHR* framework. In terms of hardware, we presented our digital rubber ball called the *DigiBall*, and discussed the various components incorporated along with the functionalities of each of them. On the other hand, we elaborated on how the proof-of-concept Cup and Plate game was designed by explaining the whole work flow of the game through flowchart and UML diagrams.

Chapter 7. Clinical Study: Evaluation with of CAHR framework with Patients

After simulating the *Context Adaptation Engine* and ensuring its stability and reliability in adapting to various performance behaviors, it became possible to test our framework with real patients in a true rehabilitation environment. In this chapter, we report the results of our evaluations conducted with two patients suffering from upper extremity deficiencies. The testing was limited to two subjects because of the rules in the rehabilitation centre which allowed only two patients.

7.1. Evaluation Procedure

The aim of the clinical study is to examine the impact of the *CAHR* framework on the rehabilitation outcome of patients suffering from wrist deficiencies. In other words, we wanted to explore if the adaptation decisions made by the framework can really help the patient acquire suitable training levels that may enhance his abilities, and therefore bring him/her to a reasonable recovery state.

7.1.1 Patient Information

The selection of the patients was a meticulous process. Since our *Physical Performance Quantifier (PPQ)* was modeled based on benchmarks computed from the data captured

from right dominant users aging between 22 and 55, we had to ensure that our candidate patients fall within this category so we can avoid any mismatch.

Two right-hand dominant males, ages 35-50, participated in this study. The first patient (ML) suffered a fracture at the forearm while the second patient (AS) had a hand fracture. Both patients had difficiencies in performing *Supination* and *Pronation* rotations and were unable to achieve the full *Ranges of Motion* on the two motions. In addition, both patients were at the early stages of a physical rehabilitation program when they participated in the tests.



Figure 7.1: A patient while exercising with the Cup and Plate game

7.1.2 Evaluation Set Up

The evaluations took place at a rehabilitation and senior home complex in the city of Tripoli in Lebanon in collaboration with Halimi and Kabbara physiotherapy center located in the

same city. Consent forms were signed prior to any tests. The tests were conducted in 10 sessions over the period of three weeks. The length of each session varied between 15 and 30 minutes depending on the physical and psycho-physiological state of the patient, as well as the recommendations of the therapist who was present during the experiments.

We have used a Pentium 4 Dell laptop to run our *CAHR* framework. Each patient was asked to sit on a chair and rest his hand on the seat's arm and try to be as steady as possible during the exercise. Figure 7.1 shows one of the patients while training with the Cup and Plate game.

7.1.3 Baseline Patient Evaluation

At the beginning of each session, patients were provided with a short questionnaire that aims to rate their physiological and psychological state. In order to properly confirm the physiological and psychological conditions of the patients, one method was to ask them to rate their conditions. Such a method would eliminate the need to attach any sensory devices on the patients' body and guarantee a very accurate assessment of their psychophysiological conditions. The patients were simply asked to rate their fatigue and stress levels on a scale of 10 so that we can take these values as a baseline of performance in order to implement the initial configurations. Since the status of a patient might change during the training, we have taken updates from the patients every 5 minutes through an electronic questionnaire that requires them to rate their physical and psychological conditions. Then, this information was fed to the system so that the measured matrix can be updated. It is worth noting that the environmental context was simply ignored throughout the evaluation sessions.

The *Quality of Physical Performance* of the therapist (QPP_{Th}) index was chosen by the therapist based on his knowledge about the patient. As previously explained, QPP_{Th} is the minimum level that the patient should attain in order to consider his/her performance as a good one. Table 7.1 shows the QPP_{Th} values that were fed into the *Context Adaptation Engine* of the framework prior to each training session. As can be seen, the thresholds of the QPP_{Th} for both patients were chosen by the therapist as low values and then were increased over sessions. This would mean that at the last few sessions, the patients were expected to perform better than at the beginning of the treatment.

| | Session | | | | | | | | | |
|---------------------------|---------|------|------|------|------|------|------|------|------|------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| QPP_{Th} for Patient AS | 0.42 | 0.42 | 0.42 | 0.42 | 0.42 | 0.52 | 0.53 | 0.56 | 0.56 | 0.6 |
| QPP_{Th} for Patient ML | 0.52 | 0.52 | 0.52 | 0.54 | 0.57 | 0.57 | 0.63 | 0.67 | 0.67 | 0.71 |

Table 7.1: The Quality of Physical Performance thresholds defined by the therapist prior to each session

7.1.4 Evaluation Metrics

Our *Physical Performance Quantifier* (PPQ) discussed in Chapter 4 was modeled based on three inputs: *Reach Angle* (θ) or *Range of Motion* (ROM), *Velocity* ($\dot{\theta}$), and *Jerkiness* (J). Therefore, our main goal was to monitor the progress of the patients specifically over these parameters. In addition to these metrics, we scrutinize the average *Task Completion Time*

(\overline{TCT}) so that we can find out if such rehabilitation training could have any effect on the ability of the patient to accomplish tasks faster.

7.2. Results and Discussion

In this section, we present the results obtained from the tests and discuss them in details.

7.2.1 Range of Motion Results

Figure 7.2 and 7.3 reveals the change in the *Range of Motion* over the supination and pronation motions for the two patients. Calculation of improvements or deterioration is based on the regression curves fit to the data.

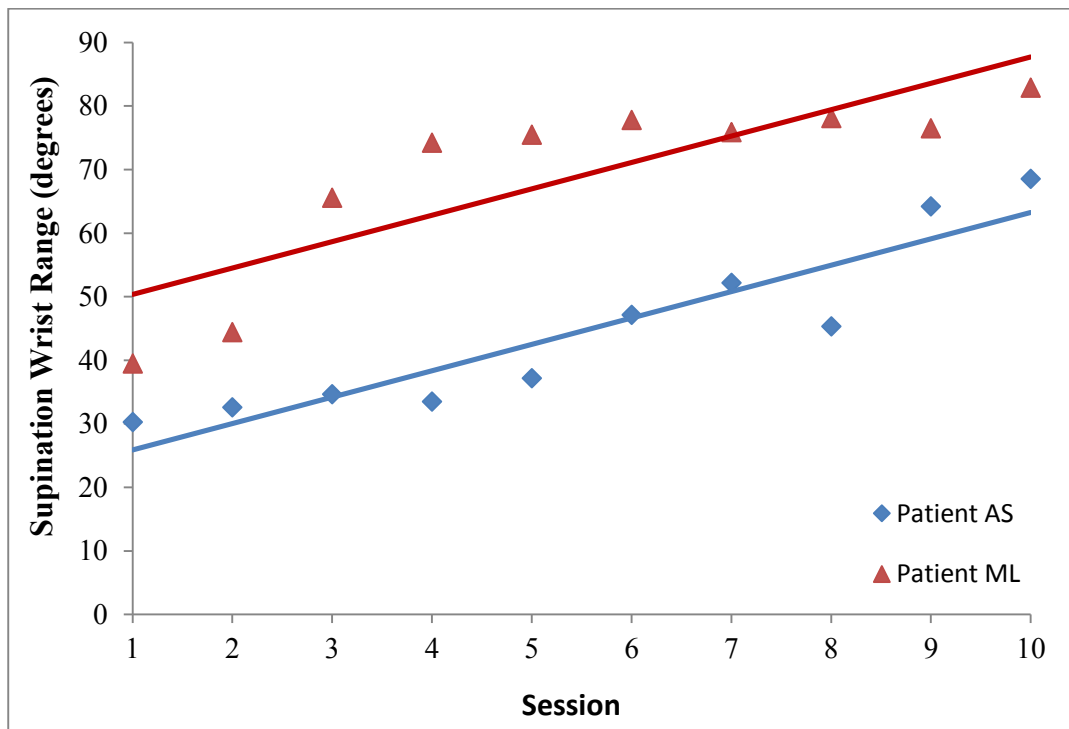


Figure 7.2: Range of Motion achieved on the Supination motion

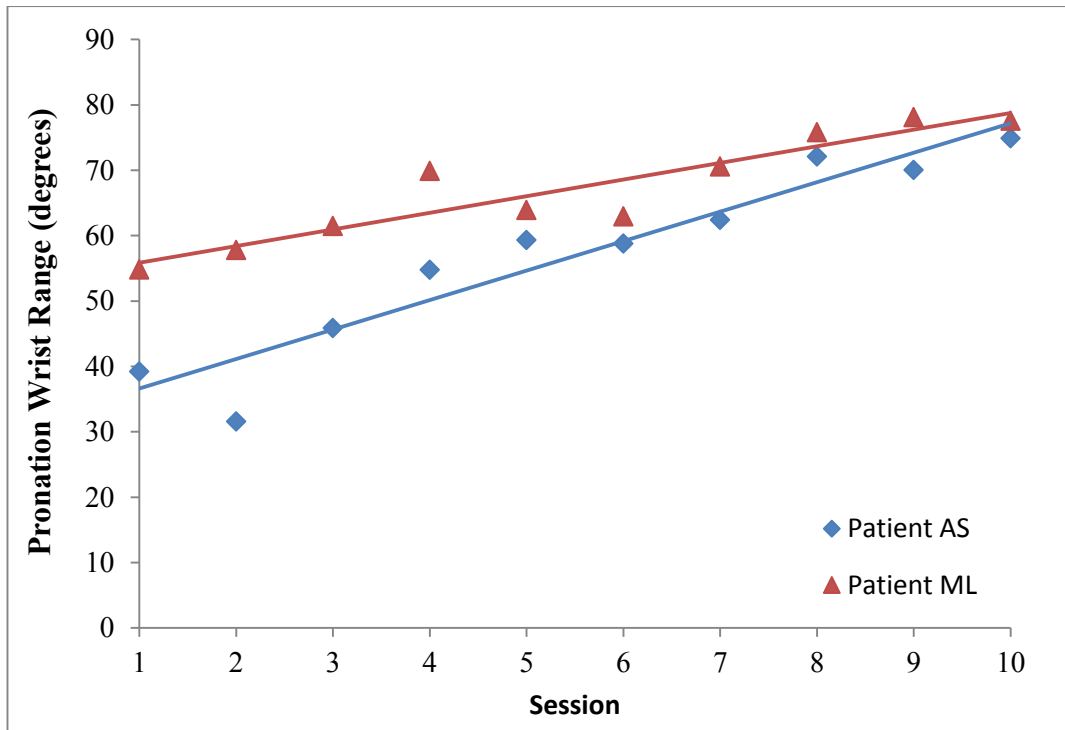


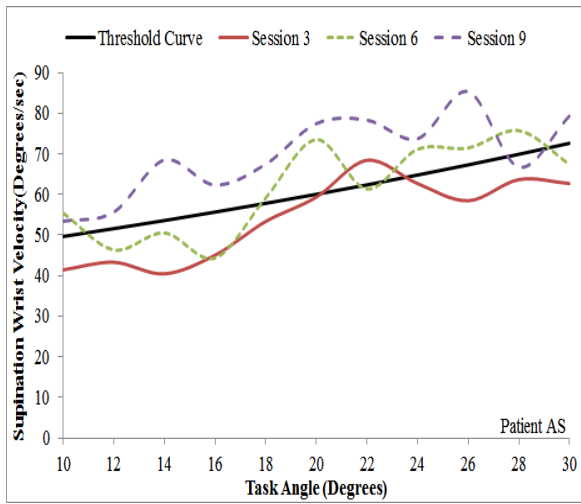
Figure 7.3: Range of Motion achieved on the Pronation motion

It can be clearly seen from the figures that both patients have shown improvement in their *Supination* and *Pronation Range of Motions*. Patient AS who had the least deficit on both motions had shown 43% improvement on the *Supination* movement and 48% enhancement on the *Pronation*. On the other hand, Patient ML has accomplished 48% improvement on the *Supination* motion and 26% on the *Pronation*. The largest improvement was realized on the *Supination* motion in Patient ML who has achieved 82 degrees of range and consequently was able to perform almost a full rotation on that motion by the end of the 10th session.

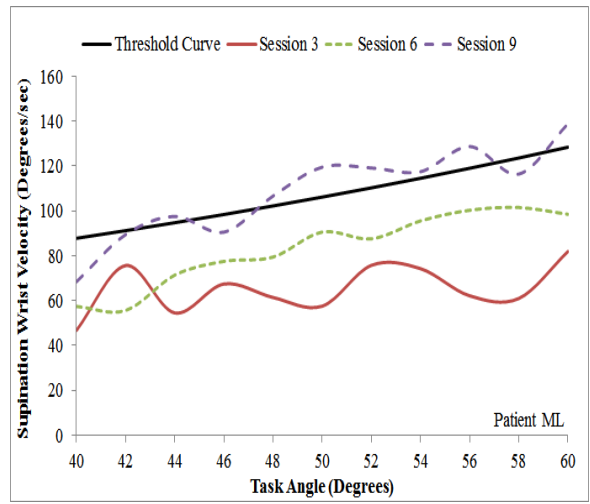
7.2.2 Wrist Velocity Results

In order to determine if there is any improvement in terms of wrist *Velocity* , we consider three data samples collected during three different sessions for every patient on each motion and study their behaviors with respect to the norms explained in Chapter 4. We limited our studies to 3 sessions only because it would really be inconvenient to graphically display all the results on one curve for analysis. In addition, the improvement of a patient does not normally change significantly in subsequent sessions.

Figures 7.4 and 7.5 show the velocity data collected during sessions 3, 6, and 9 for both patients while performing the *Supination* and *Pronation* set of tasks. The solid black curve represents the *Velocity Benchmark Equation* given in Section 4.3 of Chapter 4. Therefore, in order to notice a progress in performance, the velocity pattern(s) of the session(s) should either converge to the threshold curve or even exceed it. In order to determine the best performance among overlapping curves we compute the area under each of them. Table 7.2 presents the area corresponding to each session on the *Supination* and *Pronation* motion for each of the patients. The area under the curve can be therefore interpreted as the score that the patient has achieved after the training. Consequently, this would facilitate our analysis since the performances in the sessions could be simply compared with crisp values.

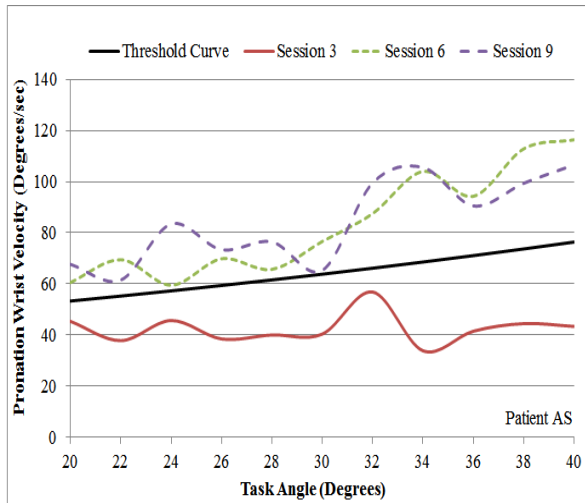


(a)

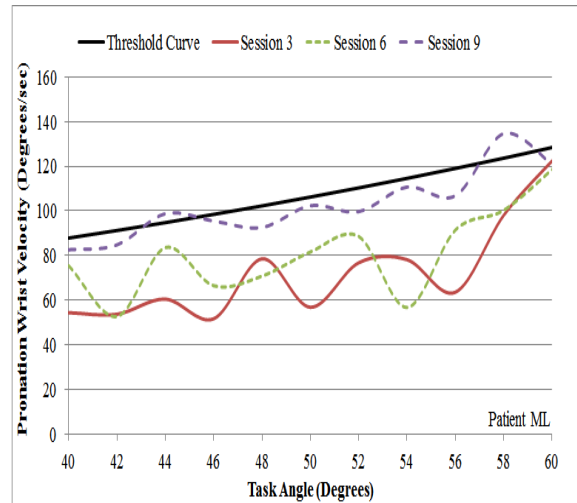


(b)

Figure 7.4: Supination velocity performance patterns over various sessions for (a) Patient AS, and (b) Patient ML



(a)



(b)

Figure 7.5: Pronation velocity performance patterns over various sessions for (a) Patient AS and (b) Patient ML

| | | Area Under Curve | | | |
|---------------------|------------|------------------|-----------|------------|-----------|
| Supination Velocity | Patient | Session 3 | Session 6 | Session 10 | Threshold |
| | Patient AS | 1197.68 | 1352.9 | 1536.68 | 1330.79 |
| | Patient ML | 1437.23 | 1831.24 | 2385.72 | 2353.2 |
| Pronation Velocity | Patient AS | 934.72 | 1832.88 | 1857.98 | 1412.36 |
| | Patient ML | 1588.56 | 1771.84 | 2257.78 | 2353.78 |

Table 7.2: The areas under the curves presented in Figure 7.4 and 7.5

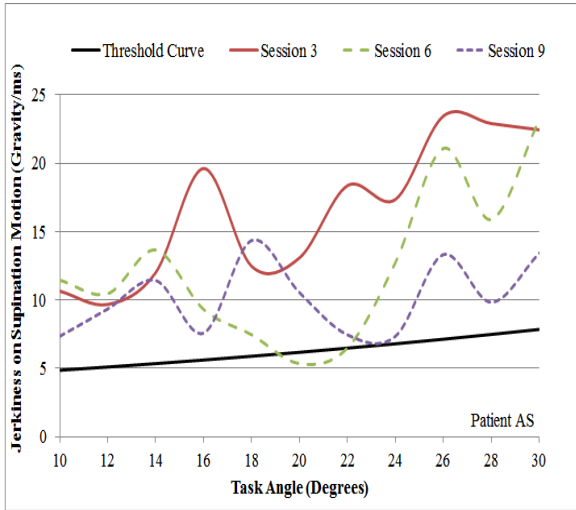
For Patient AS, we chose velocity data samples for Task Angles that range between 10 and 30 degrees. It can be deduced from Figure 7.4 (a) and Table 2.1 that the patient's performance on the *Supination* motion started to converge to the threshold by the end of Session 3 and clearly surpassed it by end of Session 10. In the case of Patient ML, we assess his performance based on velocity data samples for Task Angles that range between 40 and 60 degrees. The results in Figure 7.4 (b) show that Patient ML's performance on the *Supination* motion was below the threshold for both Sessions 3 and 6 but then managed to fluctuate around the threshold by the end of Session 10.

The curves in Figure 7.5 (a) and the data in Table 7.2 reveals that Patient AS was almost 33% below the threshold in Session 3. However, Session 6 and 10 shows around 96% improvement over Session 3. However, Patient ML's improvement was relatively slow. Even though Figure 7.5 (b) shows that ML's performance was improving over the sessions, his progress did not reach an acceptable level until Session 9 where he was only 4% away from the threshold.

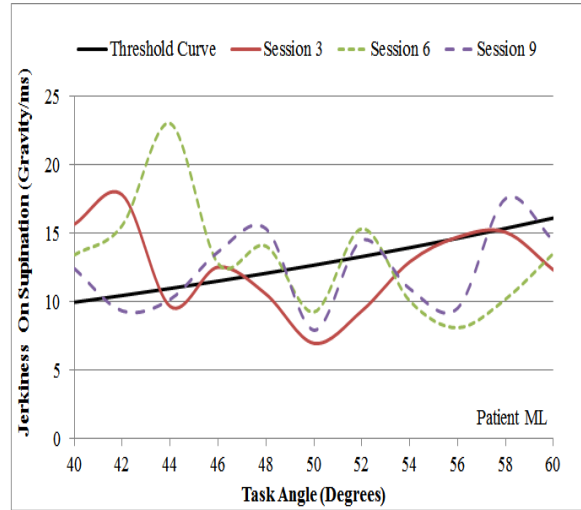
7.2.3 Wrist Jerkiness Results

The analysis of the wrist *Jerkiness* on both motions was done based on the same *Reach Angle* data samples that were used to analyze the velocity. The threshold curve for the *Supination* and *Pronation* motions were computed based on the *Jerkiness* Benchmark Equation given in Section 4.3 of Chapter 4. As was explained in Section 3.4 of Chapter 3, *Jerkiness* is the rate of smoothness of velocity. Therefore, the smaller the value of *Jerkiness* the smoother the hand velocity. Consequently, a patient's performance is said to be improving if the pattern of *Jerkiness* either converges to the threshold curve or goes below it (i.e., in this case the performance is better than the target threshold level). In terms of the area under the curve presented in Table 7.3, the area of a certain *Jerkiness* performance curve should be less than or equal to the area below the threshold.

Figures 7.6 and 7.7 reveal the results of the *Jerkiness* obtained on the *Supination* and *Pronation* motion respectively. We can deduce from Figure 7.6 (a) that Patient AS might need more training sessions before his *Supination Jerkiness* can improve since even after the 10th session, the patient did not achieve a decent progress. On the contrary, Patient ML did not have a problem with his *Supination Jerkiness* performance. We can clearly observe that his performance over the various sessions is below the threshold level. This can be easily realized from the curve areas presented in Table 7.3.

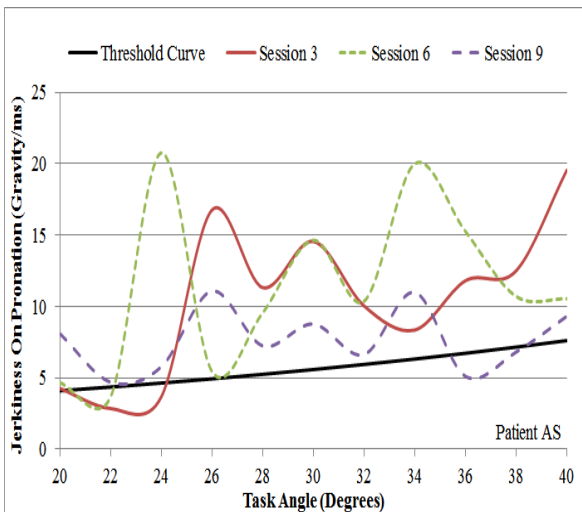


(a)

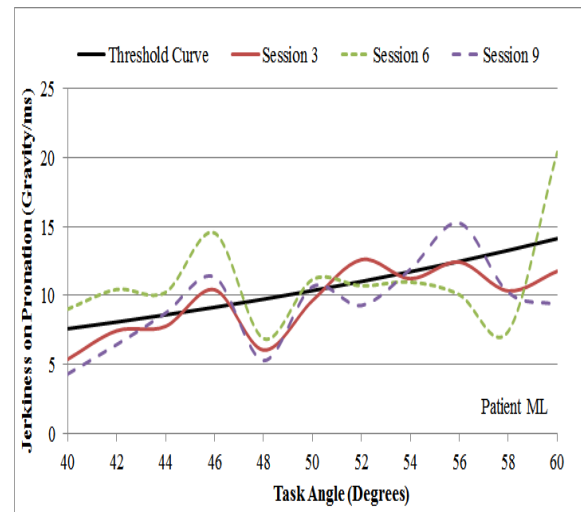


(b)

Figure 7.6: Supination Jerkiness performance patterns over various sessions for (a) Patient AS, and (b) Patient ML



(a)



(b)

Figure 7.7: Pronation Jerkiness performance patterns over various sessions for (a) Patient AS and (b) Patient ML

| | | Area Under Curve | | | |
|----------------------|------------|------------------|-----------|------------|-----------|
| | Patient | Session 3 | Session 6 | Session 10 | Threshold |
| Supination Jerkiness | Patient AS | 364.02 | 274.12 | 223.89 | 137.4 |
| | Patient ML | 275.30 | 290.90 | 271.80 | 282.25 |
| Pronation Jerkiness | Patient AS | 231.20 | 251.10 | 168.89 | 125.04 |
| | Patient ML | 210.24 | 243.70 | 205.66 | 232.44 |

Table 7.3: The areas under the curves presented in Figures 7.6 and 7.7

Now looking at the Pronation results of both patients, we realize that Patient AS had shown some improvement in Session 9 over the past sessions (i.e., see Figure 7.7(a)); however, the results did not reach the expected thresholds which means that the patient might need more sessions before optimal results are reached for this metric. On the other hand, Patient ML had no problem with his *Pronation Jerkiness* throughout the various sessions. Figure 7.7 (b) shows that the curves were always fluctuating smoothly around the threshold curve .

7.2.4 Task Completion Time Results

Even though the therapist did not define any time interval within which patients were expected to finish their tasks, monitoring the task completion time might give an indication about the patient's ability to perform tasks in a timely manner. For this reason, we have

calculated the average *Task Completion Time* (\overline{TCT}) after each session. Figures 7.8 and 7.9 reveal the \overline{TCT} of Patient AS and ML over the 10 training sessions.

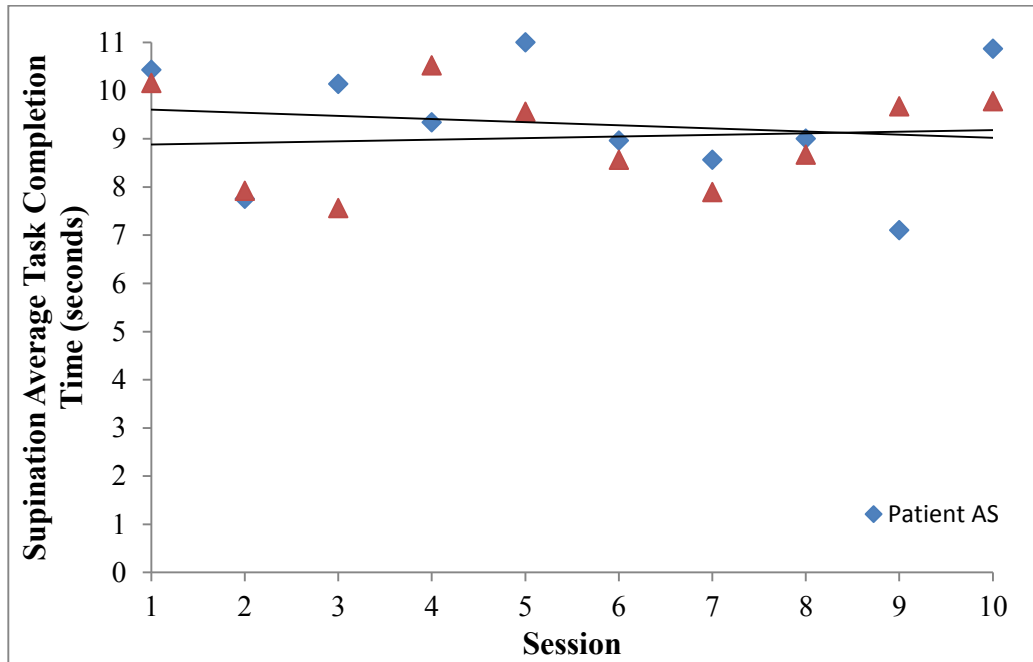


Figure 7.8: The average Task Completion Time on the Supination Motion

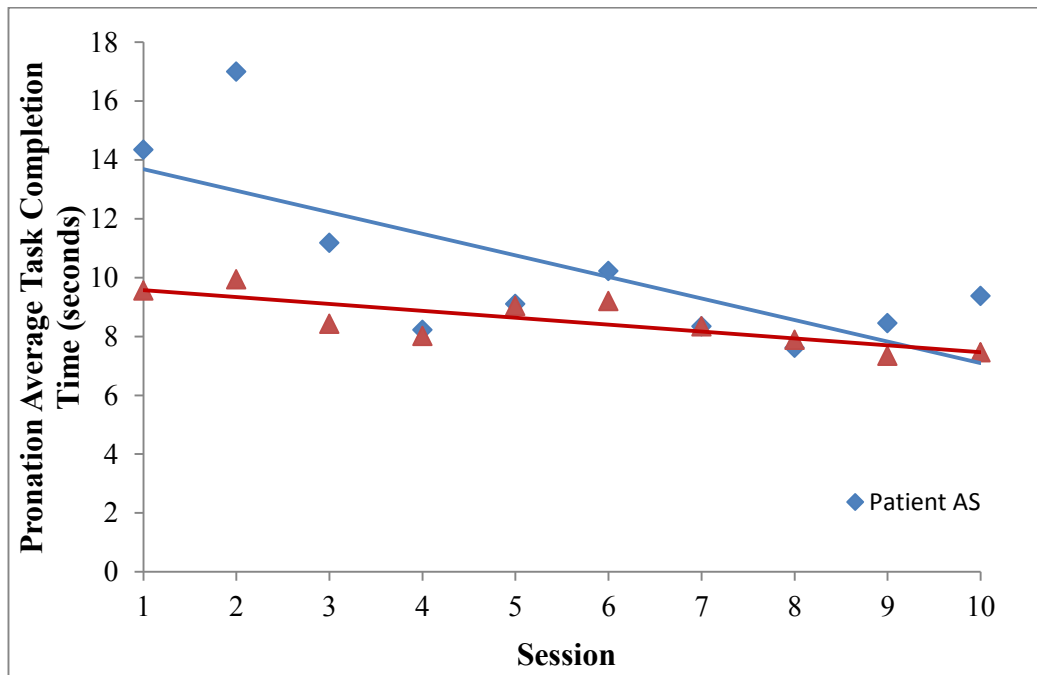


Figure 7.9: The average Task Completion Time on the Pronation Motion

The results reveal that the *Supination* \overline{TCT} of both patients was almost constant throughout the 10 training sessions. Figure 7.8 shows that Patient AS required an average of 10 seconds to finish a task while Patient ML needed around 9 seconds. An improvement in the \overline{TCT} can be however realized on the *Pronation* motion for both patients. Figure 7.9 shows Patient AS required an average of less than 14 seconds to finish a task while his time came down to 9 seconds by Session 10, therefore showing 75% improvement. Now Patient ML showed a slight improvement as well by being able to perform tasks with an average of 7.5 seconds in Session 10 while he needed almost 10 seconds in Sessions 1 and 2.

7.3. Summary

Chapter 7 revealed the experimental evaluations conducted with two male patients suffering from wrist impairments. The tests performed over the period of three weeks have shown that both patients have achieved a certain degree of improvement in terms of their *Range of Motions (ROMs)*, wrist *Velocities*, and *Jerkiness*. In addition, both patients have shown an improvement in terms of *Task Completion Time* especially over the *Pronation* motion.

Chapter 8. Conclusion and Future Work

Virtual Home-based Rehabilitation (VHR) aims to offer patients the ability to train from home with special sensorized training devices that are coupled with Virtual Reality games. In order to provide a safe and an optimized training experience for the patient, a VHR system should be able to assess the performance of the patient and to adjust the rehabilitation environment so that it fits his or her abilities and the constraints defined by his/her therapist. However, most of the VHR systems have focused on examining mainly the physical aspect of the patient and did not consider other factors that may greatly affect his/her performance, such as his/her physiological and psychological state.

8.1. Thesis Summary

In this dissertation, we have presented our adaptive VHR framework (*CAHR*) that aims to provide the patient with a rehabilitation environment tailored to his physical and psychophysiological needs while considering the environmental factors that could affect his/her performance.

The physical performance of the patient is assessed by a fuzzy logic quantification model that provides both the therapist and the adaptation engine with a crisp representation that reflects the *Quality of Physical Performance (QPP)* of the patient.

The adaptation engine adjusts the rehabilitation virtual task (environment) based on the *QPP* of the patient and the therapist's target levels. The ultimate goal of the proposed

adaptation model is to properly adjust the rehabilitation environment based on the patient's physical and psychophysiological conditions so that he or she safely and efficiently achieves the training threshold goals set by the therapist. The performance scenarios simulated through the Context-based Adaptation Engine have shown that the proposed model can properly adjust to fit the physical and psychophysiological needs of the patient.

In order to study the rehabilitation benefits of the *CAHR* framework, a special tangible training interface and a proof-of-concept software game were implemented to realize its functionalities. The series of simulations and experiments conducted with two patients have shown promising results, and therefore have led us to conclude that the *CAHR* framework may have strong potential benefits for patient seeking in-home rehabilitation.

8.2. Future Work

Although a significant progress has been made in this thesis, a multitude of challenges remains to be addressed. Apart from further testing and performance evaluation, here are two of what we deem as most important future research directions that we are planning to work on.

1. **Fatigue and Stress Detection:** The current implementation of the *CAHR* framework does not provide any technique on how the fatigue and stress levels of the patient could be detected while performing a rehabilitation task. Rather, it only uses the patient's personal assessment of these levels through questionnaires. Therefore, future research is needed to explore means of detecting these levels through the sensory information provided by the digital rubber only so that capturing such context is possible without the need for complex tools and equipment.

2. **Media Adaptation Recommender:** Stress and fatigue could be reduced during a task through proper media adaptation and recommendation. For example, reducing the stress could be done by playing a certain type of music, while fatigue can be decreased through changing the behavior of the virtual task. Therefore, we are planning to investigate and design a Media Adaptation Recommender system that provides recommendation on the optimal media changes that would result in reducing the fatigue and stress levels of the patient.

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