SHECARE: Shared Haptic Environment on the Cloud for Arm Rehabilitation Exercises

by

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Abstract

It is well known that home exercise is as good as rehab center. Unfortunately, passive devices such as dumbbells, elastic bands, stress balls and tubing that have been widely used for home-based arm rehabilitation do not provide therapists with the information needed to monitor the patient's progress, identify any impairment, and suggest treatments. Moreover, the lack of interactivity of these devices turns the rehabilitation exercises into a boring, unpleasant task.

In this thesis, we introduce a family of home-based post-stroke rehabilitation systems aimed at solving the aforementioned problems. We call such applications: "Shared Haptic Environment on the Cloud for Arm Rehabilitation Exercises (SHECARE)".

The systems combine recent rehabilitation approaches with efficient, yet affordable skeleton tracking input technologies, and multimodal interactive computer environment. In addition, the systems provide a real-time feedback to the stroke patients, summarize the feedback after each session, and predict the overall recovery progress. Moreover, these systems show a new style of home-based rehabilitation approach that motivate the patients by engaging the whole family and friends in the rehabilitation process and allow the therapists to remotely assess the progress of the patients and adjust the training strategy accordingly.

Two mathematical models have been presented in this thesis. The first model is developed to find the relationship between upper extremity kinematics and the associated forces/strength. The second model is used to evaluate the medical condition of the stroke patients and predict their recovery progress depending on their performance history. The objective assessments, clinical tests, and the subjective assessments, usability studies have shown the feasibility of the proposed systems for rehabilitation in stroke patients with upper limb motor dysfunction.

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List of Acronyms

ADC: Analog to Digital Converter
ADL: Activity of Daily Living
AR: Augmented Reality
ARAT: Action Research Arm Test
ARIMA: Auto-Regressive Integrated Moving Average
ARMA: Auto Regressive Moving Average
CAMR: Computer-Assisted Motivating Rehabilitation
DOF: Degree Of Freedom
DTW: Dynamic time warping
FMA: Fugl-Meyer Assessment
FSR: Force Sensing Resistors
HMD: Head Mounted Display
JTHF: Jebsen Test of Hand Function
SHECARE: Shared Haptic Environment on the Cloud for Arm Rehabilitation Exercises
VHR: Virtual Home-based Rehabilitation
VR: Virtual Reality

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Finally, this dissertation is lovingly dedicated to all who are still seeking freedom in the whole world.

Chapter 1. Introduction

1.1. *Background*

A “stroke” is the damage of the neuraxis (the brain and the spinal cord) caused by disruption of the blood flow to the brain. There are two types of strokes: the ischemic stroke, and the hemorrhagic stroke. The former is the most common as 87% of strokes are classified as ischemic; it occurs due to an occluded blood vessel. The latter is due to a rupture of a blood vessel, which has a higher morbidity and mortality rate than ischemic strokes. Sudden dizziness, numbness of the face, leg, or arm, unconsciousness, and trouble with walking, speaking, and understanding, are all warning signs and symptoms of a stroke.

Worldwide, strokes are the second leading cause of death; 15 million persons suffer a stroke each year [1]. Although strokes do not discriminate based on age, gender, race, or even religion, they occur more often in women than in men, in blacks than in whites, and in elderly than in young. In North America, statistics reveals that stroke is the third leading cause of death, just coming after cancer and heart diseases, and it is the first leading cause of disability (33% of stroke patients experience a permanent disability). In Canada alone there are about 315,000 Canadians that live with the effects of stroke [2]. They cost the Canadian economy more than 3.6 billion dollars a year in hospitals and rehabilitation centers. Moreover, the patients spend more than 639,000 days in acute care in Canadian hospitals and 4.5 million days in rehabilitation centers [3].

Therapists coordinate with stroke patients and families for the therapy sessions, which commonly occur five or six days a week for inpatients and three days a week for outpatients. Moreover, both, in and out patients spend several hours completing exercises during each rehabilitation session with the same intense treatment program. Therapists, who are specialized in stroke rehabilitation, usually supervise the patients during their rehab program.

They perform a special predesigned set of exercises in front of the patients to teach them how to improve their upper limb motor function. Moreover, the therapists are also responsible for assessing the progress of the patients and recommending suitable rehabilitation exercises. However, both the patients and the therapists face many challenges during the course of rehabilitation. These will be considered in detail, next.

As we have stated before, stroke patients are admitted to an intensive rehabilitation program in order to improve their motor functions. The duration, capacity, and effectiveness of the rehabilitation program have a huge impact on the patient's progress. Such program is a continuum; it starts when the patients are admitted to the hospital and continues for several years depending on the severity of the stroke attack. However, rehabilitation centers with qualified professionals are usually located in cities, far away from patients that live in rural areas. This makes it very difficult for the patients that live in rural areas, and are in the early stages of their treatment, to get to these centers and receive proper treatment. They might not even receive any additional treatment after they have been discharged from the hospital.

Stroke patients depend on their therapists in getting exercise instruction so they can perform it correctly. It is crucial to have enough well trained therapists that can accommodate the increasing numbers of stroke patients. Moreover, and with the invention of new rehabilitation devices, the rehabilitation units should be expended and new rehabilitation centers should be established. However, and in most cases, there is a lack in the number of therapists and in the number of rehabilitation facilities in the crowded cities. This is another reason why stroke patients may not get adequate number of rehabilitation sessions.

In general, there are three ways to assess the affected upper limbs of a stroke patient in clinics and rehabilitation centers, namely measures of dysfunctions, improvement, and self-evaluation reports. The source of information about the patient's status can be provided by a direct observation from the therapist, by a report from the person that is taking care of the patient (e.g. a family member), or by the patient him/herself. Patients in home-based rehabilitation programs usually use passive devices in which self-performance evaluation is the only practical assessment that therapists can depend upon. Such a method is easy to apply, but the given information cannot be fully trusted because stroke patients may be suffering from deficiency in memory and concentration, or they may simply exaggerate the advances in their performance [4, 5]. For all of the above mentioned reasons, it is very crucial to have a systematic, accurate and objective assessment module that helps therapists to make correct clinical decisions when evaluating the progress that their patients are undergoing in a home-based rehabilitation program.

One of the main reasons that a group of patients with the same pathology respond differently to a rehabilitation program is motivation. In fact, many previous researchers have proved that motivation is a significant factor in the determination of the patient's outcome in a rehabilitation program [6, 7]. Family and close friends are a very important factor when it comes to stroke patients' motivation. Indeed, for stroke patients, the love and care that they receive from their loved ones empowers them to fight back, and motivates them to continue their treatment. This means encouragement and motivation are very crucial issues in the rehabilitation system design. Besides family and close friends, showing the real progress to the patient is another significant motivating factor. This can increase patient's self-satisfaction, engagement, and enjoyment [8]. Many time-series matching algorithms have been used to compare kinematics data obtained from patients and those obtained from healthy people [9, 10]. However, those algorithms are used in the systems where the user is required to wear a garment which is a difficult task for most stroke patients.

Patients use various types of assistive devices during their rehabilitation program. Most of these devices are available in rehabilitation centers in which professional therapists operate them. Stroke patients usually have a tedious and unpleasant experience when dealing with such devices due to their bulky shape. Moreover, the complexity of installation and the high cost of these devices make them unsuitable for home-based rehabilitation programs [11]. A simple, light weight, easy to operate, and cost-effective rehabilitation device is an urgent need for home-rehabilitation.

There is strong evidence that repetitive and intensive rehabilitation exercises may improve the recovery progress of stroke patients [12-14]. However, such exercises are boring and difficult to perform by stroke patients who usually suffer from fatigue due to post-stroke muscle weakness. Moreover, therapists need to be working on a one-to-one basis with patients in order to monitor their progress and motivate them while they are performing the required task which is not always possible especially with the increase number of stroke patients that need long term rehabilitation. Nevertheless, the limited area of the rehabilitation centers and the big size of the rehabilitation devices have forced the researchers to look for alternatives that can be used at home and are less expensive and smaller in size than those which are used in rehabilitation centers.

1.2. *Motivation*

Home-based rehabilitation has become an important component of the whole rehabilitation regime. However, there is a lack of rehabilitation systems that motivate the patients by engaging the whole family and friends in the rehabilitation process and allow the therapists to remotely assess the progress and adjust the training strategy accordingly. Moreover, new algorithms are needed to automate the evaluation process of the patients’ medical conditions, and hence, predict the recovery progress during the course of rehabilitation.

Stroke patients have difficulties putting on the rehabilitation devices on the affected hand. New body tracking sensors have been adopted by stroke rehabilitation researchers that can help capture the kinematic measurements of the stroke patients. Affordability and controller-free aspect are the main advantages of such tracking sensors. However, to the best of our knowledge, these sensors are not able to capture the forces/strength of the tracked muscles. Therefore, a specific correlation matrix is required that relate the kinematics of the stroke patients with their muscles strength.

During the early stages of conducting the experiments in the rehabilitation center, I have excluded some patients that have had a severe stroke attack which prevents them from moving their affected hands. Such patients need a very special rehabilitation program that is usually available in hospitals or professional centers. Therapists train the affected hand of such patient by using special robotic devices, or sometimes by taking the affected arm of the patient and stretching it for him/her. Moreover, in this case, the body tracking sensors are useless. There is nothing to be tracked since the patient cannot move the impaired hand at all. Nonetheless, after an extensive research in this matter, we have not found any research which tackles this problem, and hence, a novel home-based rehabilitation technique is required.

1.3. *Research Problem*

Although many researches have shown the importance of virtual reality home-based rehabilitation systems, current systems are still limited in the degree to which they provide patients with effective and adequate course of rehabilitation regardless of the magnitude of the stroke impact. Moreover, these systems, in general, provide the patients with one type of rehabilitation therapy. Therefore, developing a virtual reality home-based rehabilitation system that combines the benefits of existing frameworks and adapts with the individual needs of each stroke patient will be a valuable addition for Virtual Reality rehabilitation systems. The developed framework should satisfy the following requirements:

- **Provide real-time multi-modal performance feedback:** Having multi-modal performance feedback is as important as the rehabilitation process. Therefore, the developed framework should give the users a real-time statistical evaluation of their performance.

- **Adapt with stroke patient's needs:** The framework should support access to rehabilitation exercises regardless of the stroke patients medical status. In other words, the framework should provide therapy to the patients whether they can move their impaired hand or not or whether they can wear a glove on their affected hand or not.
- **Monitor and predict recovery progress:** Allow the users (patients, family, and therapists) to monitor the progress of the patient over the course of rehabilitation.
- **Remotely control rehabilitation:** Enable the therapists to remotely assess the progress of the patients and adjust the training strategy depending on the summarized feedback data of the rehabilitation sessions.
- **Engage family and friends:** Provide a multi-player gaming environment to motivate patient's adherence to the training program.
- **Maintain Cost-Effectiveness:** Minimize the cost of the rehabilitation treatment.
- **Simulate realistic environments:** Provide the patients with natural or real-life environments.
- **Minimize risks:** provide a safe training environment that minimizes the risks during rehabilitation sessions.

1.4. *Contributions*

The contributions of this thesis are:

- Modeling the relationship between the kinematics of the upper limb and the associated muscles.

- Developing an algorithm that automatically evaluates the medical status conditions of the patients given their kinematics measurements.
- Developing an algorithm that predicts the recovery progress of the stroke patients depending on their medical condition statuses history.
- Analysis of kinematics and forces signals that have been collected from healthy patients and deduce a ground-truth data.
- Develop a force-based glove to support the movement of the affected hand.
- Develop cloud-based serious games that motivate the patients to continue their rehabilitation exercises.
- Develop a haptic feedback glove that captures the forces exerted by the fingers and gives the patients a feedback about the weakly used fingers.

1.5. *Scholarly Achievements*

In the process of completing this work, the following publications have been submitted, accepted or published:

- Journal Papers:
    1. **Hoda, M.**, Hoda, Y., Alamri, A., Hafidh, B., & Saddik, A. E. (2015). A Novel Study on Natural Robotic Rehabilitation Exergames Using the Unaffected Arm of Stroke Patients. International Journal of Distributed Sensor Networks.
    2. **Hoda, M**., Hoda, Y., Hage, A., Alelaiwi, A., & El Saddik, A. (2015). Cloud-based rehabilitation and recovery prediction system for stroke patients. Cluster Computing, 18(2), 803-815.
- Conference Papers:

1. **Hoda, M.**, Hafidh, B., & El Saddik, A. (2015, June). Haptic glove for finger rehabilitation. In Multimedia & Expo Workshops (ICMEW), 2015 IEEE International Conference on (pp. 1-6). IEEE.
2. **Hoda, M**., Dong, H., & El Saddik, A. (2014). Recovery prediction in the framework of cloud-based rehabilitation exergame. In Universal Access in Human-Computer Interaction. Aging and Assistive Environments (pp. 256-265). Springer International Publishing.
3. **Hoda, M**., Dong, H., Ahmed, D., & El Saddik, A. (2014, July). Cloud-based rehabilitation exergames system. In Multimedia and Expo Workshops (ICMEW), 2014 IEEE International Conference on (pp. 1-6). IEEE.
4. **Hoda, M**., Alattas, R., & El Saddik, A. (2013, December). Evaluating Player Experience in Cycling Exergames. In Multimedia (ISM), 2013 IEEE International Symposium on (pp. 415-420). IEEE.

1.6. *Thesis Organization*

The thesis is organized as follows:

- Chapter 2 provides the related work for the various topics tackled in this work,
- Chapter 3 discusses the SHECARE rehabilitation framework along with its various components,
- Chapter 4 describes the recovery progress prediction algorithms, also in this chapter, a mathematical model is presented to find the relationship between the upper limb kinematics measurements and the strength of the associated forces,
- Chapter 5 introduces a proof-of-concept of the framework and illustrates the results,
- Chapter 6 presents the experimental and clinical results,
- Chapter 7 provides limitations, conclusion, and future work.

Chapter 2. Background and Related Work

Training sessions conducted at hospitals and rehabilitation centers are very important for patients to improve their impaired limbs. However, adhering to strict guidelines of a long-term rehabilitation process might be cumbersome for many patients who do not have access to rehabilitation centers in their communities. Consequently, those people are required to travel a long distance to get treatment. In addition, a long-term rehabilitation process might be expensive and unaffordable for patients who do not have adequate public or private insurance.

Many therapists recommend patients to perform a daily life activity, such as preparing a cup of coffee, in order to improve their upper limb movements. Since such tasks might be dangerous for a patient with arm injury, researchers have developed and implemented virtual home-based rehabilitation (VHR) frameworks that can overcome the aforementioned problems. Moreover, the effectiveness of using VHR over conventional rehabilitation therapy has been proved in many studies [15-19]. In this chapter we present a brief summary of the currently available frameworks along with their classification, advantages and disadvantages. Moreover, we provide our home-based rehabilitation framework classification along with a literature review of the state-of-the-art. However, before we start our survey, we should first state the definition of the virtual reality (VR) in the rehabilitation field.

2.1. *Definition of Virtual Reality in the Rehabilitation Field*

Virtual reality is the use of the computer’s software and hardware to build a multi-sensory environment that simulates the real-world. Virtual reality in rehabilitation is the used of VR technology as a rehabilitation tool for stroke patients.

2.2. *Effectiveness of Virtual Reality in Rehabilitation*

Many reviews have been conducted to evaluate the effectiveness of using virtual reality in stroke rehabilitation. One of these early reviews in this field has predicted that virtual reality would become an essential tool in stroke rehabilitation in the future [20]. Rose et al. [20] assessed the effect of using virtual reality on the major disabilities that could have been caused by stroke. Patients suffered from executive dysfunction, the first disability they assessed, showed a better performance in the sequencing and organization tasks with VR-based test than those who did not use it. However, there was no improvement in the memory impairments, the second disability they assessed, in most of the studies they had reviewed. The assessment of the rest of the disabilities, namely spatial ability impairments, attention deficits, and unilateral visual neglect, suggested that the effectiveness of the VR on those impairments was limited but encouraging to continue researching using VR in rehabilitation.

In another review, Crosbie et al. [21] concluded that virtual reality rehabilitation had in general, a positive effect on stroke patients. However, the results of the 11 papers that had been studied in the review were inconsistent. In fact, the virtual reality interfaces that had been used by the patients during their rehabilitation exercises had significant impact on the results. Moreover, the differences of the types and qualities of the provided feedback by the virtual reality rehabilitation systems, which were under study, had also played a role in the inconsistency of the results.

Henderson et al. [14] reviewed 20 virtual reality rehabilitation papers in order to investigate whether the immersive and non-immersive VR-based stroke rehabilitation systems were better than conventional therapy or no therapy of the upper limb. The results showed that the patients who had immersive VR therapy were significantly improved over those with conventional therapy or no therapy. However, there was no clear evidence that the level of immersion, the type of exercise performed in the rehabilitation program, and the type of feedback had provided additional benefit to the overall progress of the patients.

A later survey [22] covered 12 immersive and non-immersive VR-based stroke rehabilitation studies concluded that VR could be a promising tool in rehabilitation which had a great potential when combined with conventional therapy. In fact, 91.6 % of the reviewed studies showed that virtual reality alone had a significant effect on the recovery progress status of the patients. However, the recovery progress was not homogenous throughout the different disabilities which the stroke patients suffered from. Indeed, the improvement in motor function of the stroke patients was better than the improvement of the motor impairment. Although the results were very promising, large scale randomized clinical trials were needed to confirm their conclusion.

In [23], two studies used off-the-shelve commercially available VR gaming systems out of the 19 papers that Laver et al. had explored. Again, the results were in line with the previous studies that had tackled the effectiveness of customized virtual reality exergames. Moreover, the improvement of the upper limb motor function was statistically significant as reported in 7 other studies. However, there was no clear evidence on the effectiveness of the VR in stroke rehabilitation when all papers in the review statistically analysed together.

The previous review [23] has been recently updated to investigate more studies and reach conclusive evidence that whether VR can improve the motor function of a stroke patient or not. The updated review [24] was published in May 2015 and it included the result of analyzing 37 papers with 1019 participants which was almost double the number of papers (19 papers) and participants (565 participants) that had included in the previous review). Although the number of participants was relatively small in each trail that was under study, the authors could reach conclusive evidence that VR could improve the motor function of the upper limb as well as the general activity of daily living (ADL) function of a stroke patient.

However, the results of the review as to the effect of the VR on the grip strength, or global motor function were inconclusive.

In conclusion, with the advances of the VR technology, there are more evidences that VR-based rehabilitation systems can improve the motor function of the stroke patients. The evidences are clear when it comes to improvement in the ADL functions, but still unclear when it comes to the strength or flexibility of the upper limb of the stroke patient.

2.3. *Types of Virtual Home-based Rehabilitation Frameworks*

The wide and diverse spectrum of technology used in virtual stroke rehabilitation lead to difficulty having a unique classification of the current frameworks. However, three main classifications can be found in the literature. In the first classification the rehabilitation frameworks are categorized depending on whether they are (a) standalone, (b) providing feedback, or (c) adaptive. The second classification is depending on the input and display devices. This has led researchers dividing the rehabilitation frameworks into (1) fully immersed, and (2) non-immersed. In the third classification, the rehabilitation frameworks have been divided into three categories (i) virtual-reality based frameworks, (ii) haptic-based frameworks, and (iii) augmented-reality frameworks. It is worth pointing out that frameworks may contain one specific property or a combination of specific properties. For example, some virtual stroke rehabilitation systems are standalone and adaptive, others are providing haptic feedback and fully immersed and so on.

In this thesis, Virtual Home-based Rehabilitation (VHR) frameworks are divided into three categories, namely (1) virtual reality (VR) frameworks, (2) VR frameworks with haptic feedback, and (3) VR frameworks with assistive devices (Figure 2.1). VR takes advantage of the advances in the capturing and tracking sensors technology to build an artificial environment that enables users to interact with it. VR rehabilitation frameworks are divided into two more subcategories depending on whether they are off-the-shelf or customized. VR frameworks with haptic feedback enable the users to experience the sense of touch while they are interacting with the virtual objects in the artificial environment. VR rehabilitation frameworks with assistive devices are the most popular among the other rehabilitation frameworks. The three categories along with their sub-categories will be explained in the next sections.

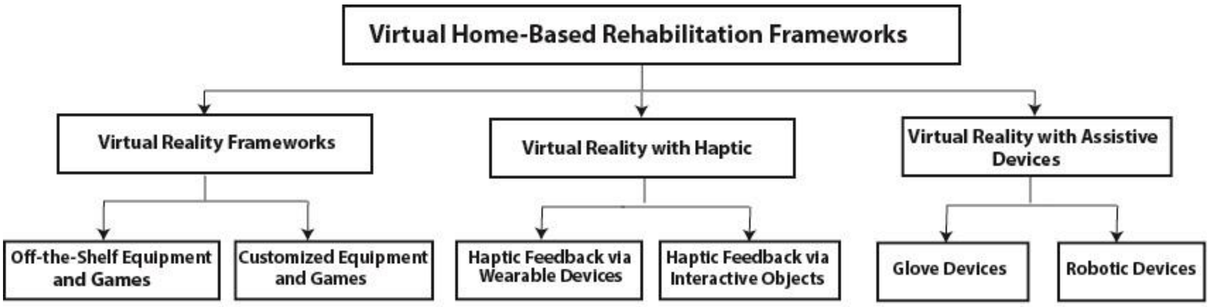


Figure 2.1 Classification of virtual home-based rehabilitation

2.4. *Virtual Reality Rehabilitation Frameworks*

Virtual reality games have been used to help stroke patients gradually regain some of their lost motor functions. These games allow patients interacting with virtual objects in a safe and controlled environment. The users place a head mounted display on their eyes for simulation of 3D viewing or simply they can interact with the objects through special input devices just like the standard computer games. Sony PlayStation, Nintendo Wii, and Microsoft Kinect are just examples of the new video gaming systems that have been used for rehabilitation.

Perhaps the oldest use of VR in stroke rehabilitation is due to Holden et al. [25]. They have recreated a “mailbox” scene used for stroke patients training. The patients had to pick up an envelope and place it in the mailbox. A virtual world of the real hand movements was created on a computer screen using a special application prototype. Although the number of the subjects were very limited (two stroke patients), the patients showed a significant improvement in reaching ability in virtual environment as well as in real world. Such result encouraged other researchers to investigate more the feasibility and the effectiveness of VR rehabilitation systems. In [26], Bach-y-Rita et al. developed a computer-assisted motivating rehabilitation (CAMR) system for stroke patients. A ping pong computer game was developed with a controlled joystick. CAMR was tested on one patient for ten hours. The evaluation showed improvements in the eye-hand coordination, objects reaching and grasping, and daily activity performing. More advanced tracking and controlling video gaming systems were used by in [27-31]. In [27, 28], the commercially available Sony Eyetoy on PlayStation 2 was tested in order to evaluate its effectiveness in stroke rehabilitation at home. Flynn et al. [27] simulated the essential aspects of functional movements with 23 different games. The system was tested on one stroke patient for 60 to 75 minutes each day, five days per week for two weeks. The system (Sony Eyetoy) was evaluated again in [28] by twenty patients over two weeks for six sessions but this time with give games. Each session lasted for 30 minutes. The results of all the aforementioned studies, along with other studies [29, 30] were very encouraging in a way that some patients preferred the low-cost off-the-shelf video games over the conventional therapy.

A spatial augmented reality (AR) system for rehabilitation of upper limb was proposed by Hondori et al [32]. They augmented a user’s view of the real world with a set of virtual objects that have been displayed in front of him on a table. Four tasks were designed to keep patients engaged in their rehabilitation program. In task 1 the users were asked to reach virtual melody boxes displayed by a projector on the table. In task 2, the users had to hold and tilt a mug to gradually pour virtual water. Task 3 was targeting patients that had problems with flexion/extension of their wrist, while task 4 was targeting patients that were suffering from weakness in their muscles strength. The system was tested on two healthy subjects and an encouraging feedback was provided. AR was also used in [33] by Bruke et al. in which two AR games for upper limb stroke rehabilitation were developed. A Brick ‘a’ Break game was developed to help improve reach and grasp movements of the upper limb. A player held a real object and used it to rebound a ball. When the ball hit a brick the brick would disappear and the ball would reverse its direction and move towards the real object. The game ended when the player cleared all the bricks. In the second game, Shelf Stack, a set of virtual objects that have been created in corresponding to a set of real objects. The player had to move the virtual objects to a designated place on the shelf. With each move, the user would train his upper limb to reach, grasp, lift, and release the object. He would also increase his cognitive skills by choosing the accurate spot on the shelf to place the object.

The usability of Microsoft Kinect as a tracking sensor in exergames rehabilitation exercises was studied by Chang et al [31], Lange et al. [34], Obdrzalek et al. [35] and Clark et al. [36]. In [31], a rehabilitation system using Kinect (Kinerehab) was tested on two patients namely, Peter who suffered from severe cerebral palsy and Sherry who suffered from muscle atrophy. By the end of the study, results showed that the correctness of the performed exercises increased with the use of the proposed rehabilitation system. Moreover, the patients were motivated by the virtual environment which was provided by the rehabilitation system and they showed an interest to continue their rehabilitation program using the Kinerehab system.

In [34], Lange et al. proposed an interactive gaming system using Kinect that helped stroke patients improve their balance ability. They used the Unity3D engine to develop a virtual reality game which used the Kinect sensor to capture the depth information of the users and mapped it as a virtual avatar on the screen. Although the initial calibration for the patients’ arms and their limits of stability was difficult, and the depth perception provided by the Kinect sensor was a new concept for most of the patients, the results were very encouraging.

Moreover, the feedback obtained from both, the patients and the physicians suggested that the proposed system had a great potential to improve the motor functions of the stroke patients.

Later studies evaluated the correctness of the obtained 3D positions of the body joints from Kinect [35, 36]. The evaluation was done by comparing the values captured by Kinect to those captured by an advanced multiple-camera 3D motion tracking. In [35], 43 markers were placed on a human body and tracked by nine cameras. The obtained points were connected together to form a skeleton. Another skeleton was estimated by using the Kinect sensor. Results showed that Kinect could replace high-cost tracking systems for controlled body exercises. However, it suffered from occlusion when the subjects were performing the exercises while they were sitting in a wheelchair. Clark et al. [36] have reached similar results when they tested Kinect pose estimation with twelve camera Vicon MX motion tracking.

Most of these video games systems were standalone. They did not connect the patients with their doctors. Stroke tele-rehabilitation was first proposed in [37] for the use of telemedicine in the form of video-teleconferencing to maximize the number of patients given effective acute stroke treatment. The system was not intended to support patients at home while they were conducting the rehabilitation exercises. In [38], Hoda et al. developed an intelligent, low-cost cloud-based rehabilitation gaming system using Microsoft Kinect sensor. They implemented two goal-oriented exercises that target the rehabilitation of patients with chronic upper limb motor dysfunction. While they were designing the games, they emphasized on the collaboration between family/friends and stroke patient in the post-stroke rehabilitation process. The games included moving a ball into a net (basketball game) in the vertical plane and reaching a cup (reaching game) in the horizontal plane. In addition, accurate performance measures were provided for each exercise to quantitatively evaluate the effectiveness of the treatment plan for each patient. The implemented system increased user motivation to participate in the rehabilitation program, accelerated the recovery of the muscles, and offered the therapists the ability to assess the patients' progress. Kinect camera was also used in [39] to track patients' body movements while they were performing four developed motion sensing exercises. The proposed gaming application, "Kinect-o-Therapy", was tested on six patients and their response were very good. However, no quantitative or clinical assessment tests were reported by the authors. More recently, nonrandomized and randomized controlled [40, 41] trails were systematically reviewed to determine the effect of tele-rehabilitation interventions on the motor functions of the stroke patients. The results showed that the patients' motor functions significantly improved after six months of the start of the experiment.

2.5. *Virtual Reality with Haptic*

Although the new games' controllers are considered to be intuitive, they are not suitable for all patients with upper limb impairments [15]. Moreover, the scores that are provided by the games are not adequate to evaluate the patients' progress. Many researchers have reported that adding the sense of touch to the virtual reality enhances the patient's sense of presence within the rehabilitation program [42]. In addition, it provides the therapists with important data that helps them asset the rehabilitation status of the patients. In many studies, Ruters Master II-ND (RMII-ND) haptic glove has been used as a standard input haptic device for exergames [43-45]. The glove was proposed in 2002 as a replacement of another haptic robotic arm called PHANToM, the most haptic interfaced that had been used at that time [46]. Perhaps the first use of RMII-ND was reported by Merians et al. [43] in which it was connected to a VR rehabilitation system and tested on three patients. In addition to the RMII-ND, the developed rehabilitation system consisted of another hand input device namely, a CyberGlove and personal computer. Four exergames were developed to improve the range of movement, improve the speed of movement, improve the fractionating of the fingers, and improve the strength of the movements. All the developed exercises were targeting the upper limb of the stroke patients. In [44], Adamovich et al. used almost the same system (PC + CyberGlove + Rutgers Master II-ND), with a different set of games that were dedicated to help patients improve the range of motion, the speed, the independence and the strength of their affected fingers. The VR system was tested on eight subjects for two to two and one half hours each day over thirteen days. The same rehabilitation system was used by Boian et al [45] with a set of exercises that targeted four fingers injuries: range of motion of the finger, speed of motion of the finger, degree of independence of the finger, and the strength of the finger. The results of the three VR systems [43-45] were very encouraging. In fact, in [43] two of the three patients showed a significant improvement in their ADL tasks. In [44], six out of eight patients showed significant increase of their overall fingers motor functions, while in [45] three of the four stroke patients showed a good degree of improvement. Jebsen Test of Hand Function (JTHF) was also used to evaluate the progress of the stroke patients in the real-world. The results confirmed the fact that improvement of motor functions in the virtual world was reflected to the real-world. Another VR system with haptic feedback device was also developed by Reinkensmeyer [47]. A customized haptic joystick was used as a controller device of the exergames. The joystick played a dual role during the rehabilitation exercises. It could physically assist or resist the movement of the patients while they were playing the game. The system was implemented using Java programming language along with ASP and HTML. It consisted of two components: a client component, and a server component. The importance of such VR system was that it considered being the first home-based rehabilitation system that connected stroke patients to their therapists through the internet. The system was tested on only one patient. The results showed that the subject improved on the Chedoke-McMaster Upper Extremity Scale, but did not improve on the Functional Test of the Upper extremity.

A new version of PHANToM hapic device was used by Broeren et al. [48]. They developed a virtual reality environment to investigate the effect of using the sense of touch in a 3D environment in rehabilitation on stroke patients. The rehabilitation environment consisted of a computer game, haptic device, and stereoscopic shuttered glasses. The stereoscopic was used to give the users an illusion of 3D virtual environment that they would interact through the hapic device. The system was tested on 5 stroke patients over a period of 5 weeks. They collected three sets of measurements from each patient at three different periods. Results showed significant improvement of the patient's upper-limb kinematics, however, four of the five patients showed no improvement in performing their activities of daily livings (ADLs).

CyberGrasp is another important haptic device that has been used as an interface with virtual environment rehabilitation systems [49-52]. Alamri et al. [49] used the CyberGrasp device with five virtual reality exergame to build an upper limb rehabilitation framework. The games were developed under the supervision of occupational therapists at the General Hospital of Ottawa and they were based on JTHF. Each game contained an exercise that was designed to help patients improve the strength and the range of motion of the affected upper limb. The proposed five exergames were evaluated by ten subjects and a usability study showed a great acceptance of the rehabilitation framework. Moreover, the analysis of the collected data helped the therapists effectively evaluate the patients' medical status. In [50], McLaughlin et al. designed a set of virtual reality exergames for hand reaching and grasping exercises. CyberGrasp was used to capture the position and the orientation of the user's hand while he was performing the tasks. The virtual environment could be displayed on a PC monitor or head mounted display. A very similar system was reported in [51]. A subjective assessment of the systems by two stroke patients showed an overall satisfaction of the whole rehabilitation experience. Another haptic/virtual environment rehabilitation system was proposed by Adamovich et al [52]. One of the main advantages of the developed system was that it used intelligent algorithms to control the level of difficulty of the exergame and provide an adaptive haptic assistance to the patients. As a proof of concept, a virtual piano exergame was implemented to train an individual finger of the paralyzed hand at each exercise and provide the user with auditory and visual feedback. The system was tested on four patients for ninety minutes per day in nine sessions. Two of the four patients had shown improvement of their aggregate time in completing the task on the JTHF and three patients had shown improvement in Wolf Motor Function test.

A new trend of haptic interaction devices for stroke rehabilitation in virtual reality was introduced by Alamri et al. [53] They mounted a tangible object, a cup in their case, with vibrotactile actuators and lightweight, inexpensive, and low power consumptive pager motors. By doing that, they changed the concept of wearable haptic interfaces which used to interact with static objects in the virtual world into a free-hand interaction with reactive objects that provided the haptic feedback. The virtual world contained a set of tasks that was suitable for stroke patients with different level of injuries. Eleven stroke patients evaluated the proposed system. A set of suitable tasks had been chosen by an occupational therapist for each patient. Each patient performed every chosen task for one hour. A usability questionnaire had been asked by the end of the experiments that showed a general satisfaction on the proposed system. However, two patients were frustrated during performing the tasks, and two other patients felt fatigue in their upper limb. The authors reported that was due to the weight and bulky shape of the proposed reactive object. Khademi et al [52] proposed another rehabilitation system with reactive object to monitor the stiffness of patient’s arm. The system consisted of a webcam, projector, a PC, and a smart mug (reactive object). A reaching game was designed to test the effectiveness and the accuracy of the system. Although the results for the reaching task were effective and accurate, they were not reliable because the experiment was conducted on only one healthy subject.

2.6. *Virtual Reality with Assistive Devices*

As we have mentioned before, many studies have suggested that repetitive training of the upper limb is very helpful in the rehabilitation course. However, stroke leaves the affected side of the body very weak in which training exercises become frustrating and tedious task. Many assistive devices have been introduced to help stroke patients interacting with virtual reality during their rehabilitation regime [54-58]. Jack el al. [54] used CyberGlove with virtual reality exergames to train the fingers of the injured hand after stroke. CyberGlove is a commercial glove that has been used for capturing fingers movement data. It is mounted with 18 piezo-resistive sensors that are used to measure the angles of the fingers, palm arch, wrist flexion, and wrist abduction/adduction [59]. However, Jack et al. used the data captured by the two bend sensors on each finger to measure the angles of the thumb and fingers. Two virtual reality rehabilitation games have been developed which targeted the range-of-motion and the speed-of-motion of the fingers. The system was tested on three stroke patients for nine days. All the three patients showed substantial changes on JTHF. In fact, one of the patients could button his shirt in the second week of the training program. Moreover, a subjected evaluation of the system showed a positive feedback from all the patients. All the patients agreed that the program was effective in which they felt that the movement of their fingers improved with the exercises. In [56], Connelly et al. designed and implemented a pneumatic glove (PneuGlove) for stroke rehabilitation that could be used for training grasp movements with real or virtual objects. One of the main advantages of the PneuGlove is that it can be used to assist the fingers extension while allowing the patients to fully move their affected arms. A head mounted display (HMD) is used to display the virtual environment that has been developed for stroke rehabilitation. The environment consists of a room in which the user can see his/her hand and the virtual objects inside it. Fourteen patients were recruited from the Rehabilitation Institute of Chicago Clinical Neuroscience Research Registry to test the proposed system. The subjects were randomly divided into two groups. The first group used the PneuGlove in their rehabilitation tasks while the second group used a shadow glove with the virtual environment. The rehabilitation program lasted for six weeks, three sessions a week with one hour training in each session. The Fugl-Meyer Assessment (FMA) test showed that there was an improvement of the clinical status of both groups, but even though the group using the PneuGlove showed a greater mean improvement than the second group, such improvement was not statistically significant. A similar glove was developed by Luo et al. [58] in which it could be used to measure the angles of the index finger and the middle finger. A HMD is used to display the virtual scene which consists of a set of virtual objects. The user is instructed to grasp-and-release the displayed objects while the speed and the maximum displacement of the fingers being monitored. The system was tested on three stroke patients for six weeks, three sessions a week for half an hour training in each session. By the end of the rehabilitation program, the patients showed some improvement in the angular speed and angular displacement of finger’s extension. Moreover, both the therapists and the patients have reported that the rehabilitation environment was easy to deal with. Another low cost P5 glove developed by Essential Reality was used in [57]. Morrow et al. designed and implemented two games that helped in improving the velocity and the range of motion of the fingers. The raw data captured from the glove finger sensors were calibrated in order to get valid data that could be used for further analysis. Although the system is significantly inexpensive when it is compared to other systems, it is still unclear whether it would be beneficial for stroke rehabilitation since no real tests have been conducted on real patients to evaluate its effectiveness.

Robotic devices are getting an increasing interest for stroke rehabilitation to help patients improve motor recovery. Many studies have suggested that using robotics devices in rehabilitation have improved the overall motor function of the patients [60-63]. More recently, robotic devices have been used in conjunction with virtual reality to provide patients with encouraging and entertaining environment that could help them continue their rehabilitation program [61].

The first interactive robotic device with 2-DOF was introduced by Hogan et al. [64] which allowed the therapists to monitor and control the rehabilitation of multiple patients without the need of the physical presence of the therapists. Several games were developed to motivate patients while they were conducting the exercises. Moreover, the patient's performance was recorded during the exercises for later evaluation. The proposed robotic device was evaluated on 96 stroke patients for two weeks, five days a week and one hour per day. The exercises were targeting to improve the range of motion, force, direction and dexterity control of the patients. By the end of the study, patients showed a significant improvement in performing their daily life activities. Moreover, they gained strength in their shoulder and elbow muscles[65-67].

In another study, Takahashi et al. [68] developed a 3DOF robotic device therapy to determine whether it would improve the motor functions of stroke patients. The device was used to assist the hand in grasp and release tasks. A computer software was implemented to enable real-time virtual environment fingers movements. Thirteen patients participated in the study for fifteen days. The patients were divided into two groups in which the first group (8 patients) had the robot in active assist mode for all the treatment period, while the second group (7 patients) had it for half of the treatment period. Significant improvement in grasp was found in group one which received robotic assistance in all sessions over group two which received robotic assistance in half of the sessions. However, the results suggested that there was no significant improvement in the supination/pronation of the hand by the end of the study.

The effect of combining 3D video games with robotic devices on reaching in stroke patients was studied by Acosta et al. [63]. They used a 6 DOF robotic arm and developed computer software to track the positions of the arm, and hence find the maximum reaching point. Seven stroke patients participated in the experiment. They asked to perform the reaching exercises in two different setting; while they were playing a video game and while they were reaching a specific targets and getting a visual feedback via a 3D avatar. Results showed reaching distances achieved by the patients in the avatar visual feedback setting were larger than those in the playing game setting. However, the results were not confirmed because, in certain conditions, the reaching distances in game playing setting were much better than the avatar setting.

In a recent study, Sale et al. [69] conducted a study on fifteen stroke patients to determine long-term and short-term changes in their motor functions. They used the ReoGo robot device which had an arm with a platform to stabilize the patient’s forearm. To motivate the patients, a user-friendly interface was developed with 3D objects display. The study was conducted on 15 stroke patients over four weeks, five days a week for forty-minutes a session. The results showed that the patients had accepted the proposed robotic stroke therapy. Moreover, a statistically significant improvement of the patients’ overall motor functions was found in the clinical assessment tests by the end of the study.

Robot-assisted stroke rehabilitation devices took advantage of low-cost new tracking technologies to track real objects while patients were performing their rehabilitation exercises. In [70], Loconsole et al. used Microsoft Kinect to identify and track generic objects which were going to be moved by stroke patients. A robotic arm exoskeleton was used to assist patients reaching and moving these objects. Although the proposed system (Kinect + robotic arm) were not tested on stroke patients, the results showed that the system was robust to occlusions and light variations. Moreover, it was accurate in identifying and tracking the generic objects. However, further studies are necessary to validate the correctness of the proposed system.

2.7. *Cloud-based Applications*

Cloud Computing along with emerging technological advancement including wearable devices, Body Area Networks (BANs), and ubiquitous wireless networks allows the development of healthcare services, information, and products which can benefit patients and medical experts. But before we dive into the world of cloud, I feel it is necessary to define the cloud from a technical perspective.

2.7.1. *What is Cloud Computing?*

The word cloud is a metaphor for the internet [71], hence the phrase cloud computing is defined according to National Institute of Standards and Technology (NIST) as follows:

> *Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction* [72].

2.7.2. *Why Cloud Computing?*

There are several advantages of adopting cloud computing as an IT solution in industry. Although the advantages vary depending on the size of company, the following advantages almost apply to all companies:

1- Cost-effective. In fact, Ingo Elfering, Vice President of Information Technology Strategy, GlaxoSmithKline said that 30 % of the IT operational costs had been reduced after adopting the cloud computing technology.

2- Almost unlimited processing and storage capacity. Indeed, many cloud computing providers (Amazon, Google, etc.) offer unlimited storage capacity with a very high processing speed.

3- Quick deployment of hardware and software assets. In fact, deploying a new server inside a company can take up to seven weeks while with the use of cloud computing it could be available online in two or three minutes.

4- Easy access to information from anywhere at any time.

5- Enables automatic software integration and update.

2.7.3. *Cloud-based Healthcare*

Generally, sensors and broadband communications enable constantly collection and transmission of patients’ medical to remote centers. The medical information then is used for real-time analysis to check critical signs and identify emergency conditions by medical professionals. Therefore, employing the so-called technologies allows building health information systems that assist medical experts instantly monitoring patients’ health information while reducing on-side consultations. However, the development of such systems poses some challenges that should be tackled. Cloud-computing address some of these issues including resources scarceness [73, 74], scalability, and cost restrictions [75-77]. Firstly, many mobile healthcare applications require real-time processing of health monitoring data collected from sensors. This demands intensive computing and storage resources which put limitations for the development of these applications for low- resources mobile devices. Cloud computing address this problem by hosting the data storage and execution of such applications outside of the device on remote intensive-resource computers. Besides, scalability is essential feature for efficient monitoring and analysis of patients' data in a large scale. Cloud-based infrastructure provides high volume of storage and computation capabilities for facilitating huge loads. Moreover, cloud infrastructures are geographically scalable which allows the usage of healthcare systems in distributed geographic areas [75]. Further, cloud users are charged according to a pay-as-you-go model [76] which is associated with the use of computation, network, and other related costs to the cloud services. Therefore, these services are less expensive than property services

Many researchers proposed and developed cloud-based healthcare applications and infrastructures. For instance, Cheng et al [78] designed a mobile cloud-based depression diagnosis. Using the mobile system, the user was able to check whether a person was depressed or not. In addition, Pandey et al [75] developed a real-time health monitoring system on the cloud for ECG data collection, storage, and automatic analysis. Furthermore, a cloud-based context middleware for ambient assisted living was introduced by Forkan [79]. This infrastructure aims at facilitating disabled people's daily lives and those who have critical health conditions by providing pervasive health-monitoring and -assisting services.

2.7.4. *Cloud-based Rehabilitation*

Many researchers have taken advantage of the numerous advantages of cloud computing and developed cloud-based rehabilitation systems. It is a new trade of medical services which offers stroke patients (along other patients) with effective rehabilitation program at their comfort. Exergames are the first main component of such rehabilitation program. They are deployed on the cloud for helping stroke patient preforming their rehabilitation exercises and hence, improving their motor function. Moreover, cloud-controller or cloud service is the second main component of the cloud-based rehabilitation systems. It acts as a mediator between different components of the system and stores and backups patients' data. The description of other components of cloud-based rehabilitation systems will come later.

Pham et al. [80] developed a cloud-based rehabilitation framework for helping monitoring and assessing the motor function of patients' hands. They used Creative Senz3D, an optical sensor that can track the depth and the gesture of human body. To examine the performance of the system, Pham et al. conducted a usability study on 40 patients. Results showed that the system had a high level assessing accuracy compared to the assessment conducted by the therapists.

A mobile cloud-based home rehabilitation system for stroke patients was developed by Raiz-Zafra et al. [81]. The system consisted of: (1) a mobile phone that had a frontal camera and a bluetooth connection, (2) a heart rate sensor, (3) a cloud mobile application, (4) and a cloud website interface. The purpose of the proposed system was to reduce the number of displacements of the patients from home to the rehabilitation centers. For this reason, the system did not provide any sort of entertaining exergames that could motivate the patients performing the required exercises. However, the propose system could reduce the number of displacement of the patients by monitoring their heart rates and capturing video of the performed exercises and sent them to the rehabilitation centers via the cloud.

Microsoft Kinect is also used in cloud-based rehabilitation systems [38, 82, 83]. Li et al. [82] developed a home-based rehabilitation system that consisted of two Microsoft Kinects, one at the patient side and another one, which is optional, at the therapist side, a computer, and a set of exercises that could be designed by the therapists depending on the patients' conditions. Kalman filter was used to build a ground truth motion model which would be used as a reference model to patients' motions while they were performing the rehabilitation exercises. The system was fully implemented on the cloud and tested on three healthy users. Although the results showed that the users' performance improved with the increase of the number of trails, more tests on a larger number of subjects were needed to reach such conclusion. Moreover, and in order to have realistic results, the system should have been tested on real patients for a significant period of time.

2.8. *Summary of the Literature Review*

Classification	**Virtual Reality (VR)**						**VR with Haptic**						**VR with Assistive Devices**					
	Holden et al [25]	Bach-Rita et al [26]	Flynn et al. [27]	Reinthal et al. [30]	Burke et al. [33]	Hoda et al. [38]	Merians et al. [43]	Adamovich et al. [44]	Reinkensmeyer et al. [47]	Alamri et al. [53]	McLaughlin et al. [50]	Khademi et al. [84]	Jack et al. [54]	Morrow et al. [57]	Luo et al. [58]	Hogan et al. [64]	Takahashi et al. [68]	Sale et al. [69]
Quantitative Feedback	√	X	X	√	√	√	√	√	√	√	X	√	√	√	√	√	√	√
Remote Rehabilitation	X	X	X	X	√	√	X	X	√	X	X	X	X	X	X	√	√	X
Cost-Effective	√	√	√	√	√	√	X	X	√	X	X	√	X	√	X	X	X	X
Motivating	√	√	√	√	√	√	√	√	√	√	√	X	√	√	X	X	X	√
Real-time Adaptation	X	X	X	√	X	X	X	X	X	X	X	X	X	X	X	√	√	X
Fits Patients with Severe Deficit	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	√	X	√
Predict Recovery Progress	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Overall Software Controlling	X	X	X	√	√	√	√	X	√	X	√	X	√	√	X	√	√	√

Figure 2.2 Summary of the literature review

Chapter 3. The SHECARE Framework

The Shared Haptic Environment on the Cloud for Arm Rehabilitation Exercises (SHECARE) framework is described in this chapter. I will first start with a top overview of the framework, and then I will explain in detail every component of the proposed framework. In order to complete the picture of the proposed framework, a set of interaction diagrams will be also provided for the sub-systems.

3.1. *SHECARE Overview*

SHECARE is a cost-effective, entertaining, and motivating home-based upper limb rehabilitation system which has the ability to adjust with the patients need. The framework provides a real-time feedback to the patients, summaries the feedback after each session, and predicts the rehabilitation performance. In addition, the framework proposes a new style of home-based rehabilitation approach that motivates the patients by engaging the whole family and friends in the rehabilitation process and allows the therapists to remotely assess the progress of the patients and adjust the training strategy accordingly.

The proposed framework consists of two major components namely, the client component and the cloud component. The former, as its name indicates, is software that enables the users (patients, therapists, and caregivers) exploiting the rehabilitation services. Therapists setup a set of games that are suitable for a specific patient. They also monitor the overall rehabilitation process. The patients connect to the predefined games in order to start the training sessions. Family members and friends can participate in the training sessions. The difficulty level of the games changes depending on whether the player is a patient or a healthy person. The latter, the cloud component, is where the rehabilitation services are stored and managed. Moreover, the cloud component is responsible for allocating the needed resources, monitoring the patient's performance, and controlling the game level depending on patient's profile. Usually, the cloud system is hosted on dedicated servers to provide the post stroke rehabilitation services for the patients.

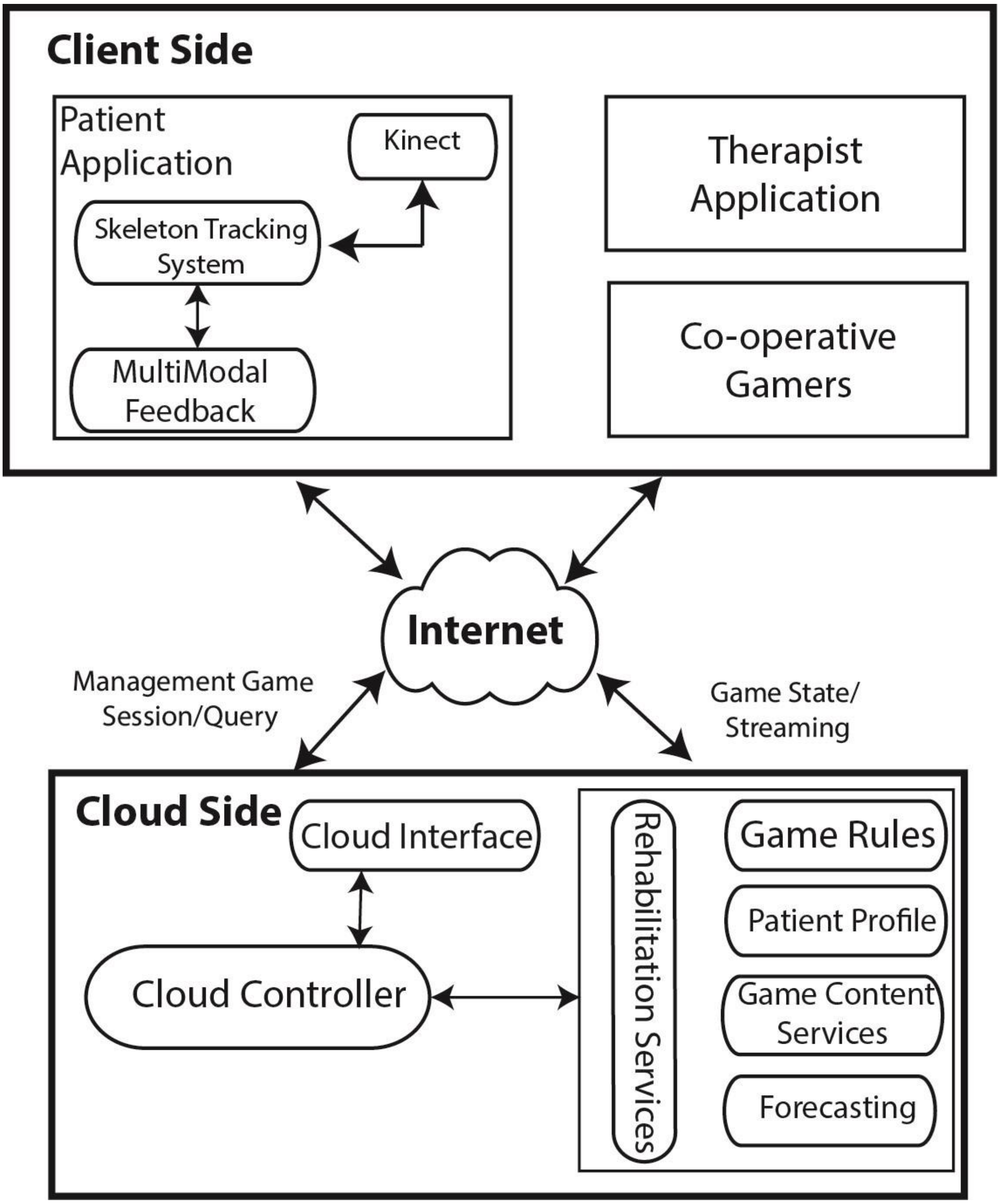


Figure 3.1 SHECARE Framework

3.1.1. *Client Side*

Patient Software: Patients are the primary users of the rehabilitation framework. Patients login to the framework through a graphical user interface. A set of games is loaded depending on the patient's profile. The patient's software checks the input devices that are going to be used by the patient. We have four types of input devices: the Microsoft Kinect sensor, the glove that mounted with FSR sensors for the affected hand, the glove that mounted with FSR sensors for the unaffected hand, and the glove that provide a haptic feedback. The Kinect sensor is going to be discussed in the next section. However, the rest of the devices are going to be discussed later in this chapter. The software has the ability to connect to other input devices depending on the patient's need. Moreover, whenever a patient login into the system, he/she has an option to send SMS messages to the family members and the caregivers asking them to participate in the exercise. Different types of feedbacks (auditory, visual, haptic, and numerical) are provided to the patients depending on their performance during the exercise.

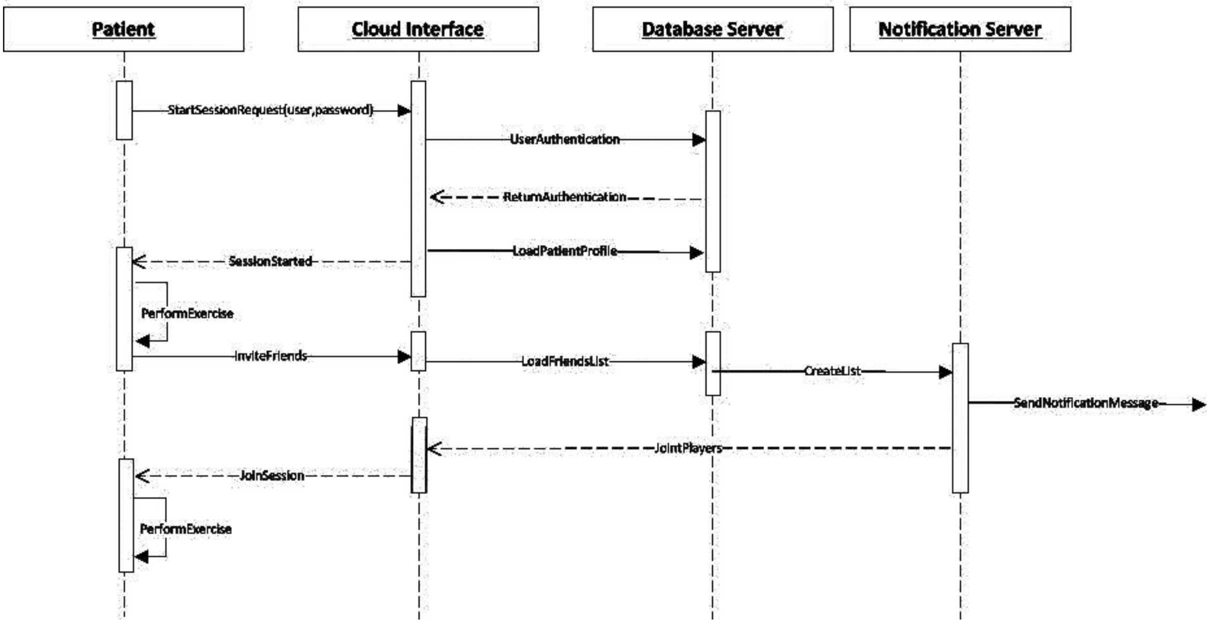


Figure 3.2 Sequence Diagram for patient and software interaction

In addition, in every session ten minutes of video recording are captured and uploaded to the cloud in which the therapist can evaluate the performance of the patients. The level of the difficulty of rehabilitation exercise that the patient has reached along with his/her rehabilitation status are to be stored on-line (cloud) and off-line (inside the application itself) in which the patient is able to perform the rehabilitation exercises without the need to be connected to the internet. The sequence diagram for interaction between the patient and the software is shown in figure 3.2.

Co-operative Gamers: The co-operative gamers' software is very similar to the patients' software except for two aspects: the level of difficulty of the games and the input devices. Since there are no saved profiles for the co-operative gamers in the database, the difficulty levels of the games are standardized for normal people. Kinect, a skeleton tracking input device by Microsoft, is used as an input sensor to the co-operative gamers software. Kinect is a new type of game controller which combines contemporary software and hardware technologies. The hardware is comprised of an infrared light source, a color camera to capture the RGB data, and a monochrome CMOS sensor to detect the depth data. The RGB camera supports a maximum resolution of 1280 x 960 pixels at low frame rate, while the depth camera supports a maximum resolution of 640 x 480 pixels at 30 Hz and with an extended range of 0.7 – 6.0 m. The novelty of Kinect is that it completely frees the hands of the players, and it is able to detect not only the position of the players, but also the depth in a 3D space. Basically, the players move and the game progresses in the same way. In a new study [85], it has been found that the Kinect interface has advantages over the Nintendo Wii and Sony PlayStation Move interfaces. Kinect detects users as well as the surrounding environment, which means an augmented reality is formed where the players can interact with virtual and real objects. Moreover, different kinematics measurements can be obtained for these objects.

Therapist Software: The therapist software consists of set of analysis tools that help the therapists in monitoring, evaluating, and adjusting the rehabilitation program. The therapists receive notification messages about the new rehabilitation sessions conducted by the patients. More information can be viewed when the therapists click on these messages. Moreover, the software provides the therapists with a list of the patients that are exercising simultaneously and gives them the ability to switch from one patient to another. In addition, and besides the general descriptive statistical analysis that the system provides, the system is able to quantify the rehabilitation status of the patients and forecast their recovery progress.

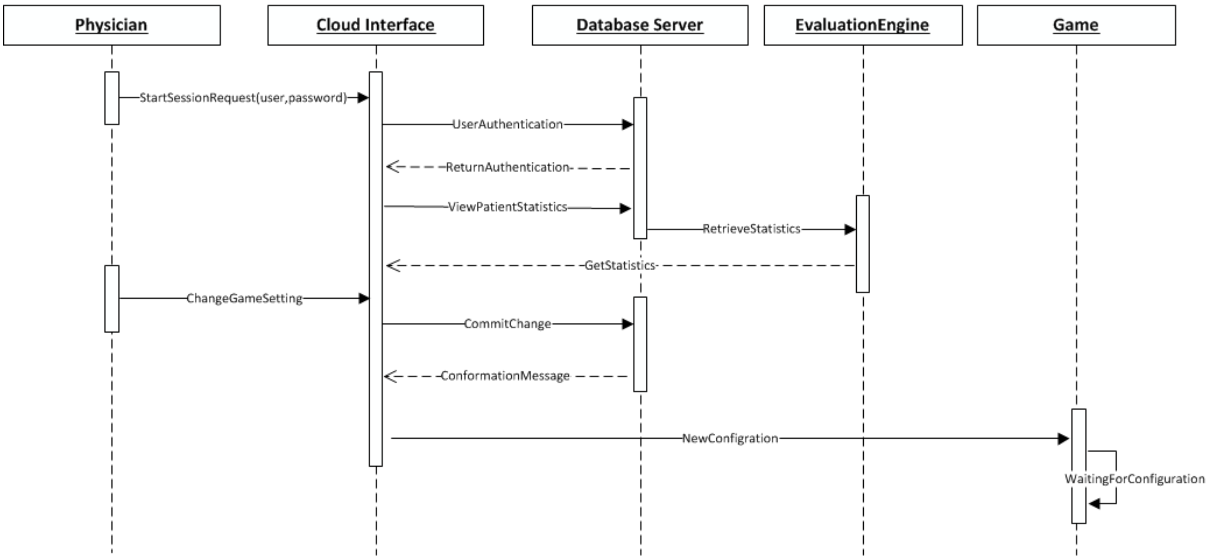


Figure 3.3 Sequence Diagram for therapist and software interaction

3.1.2. *Cloud Side*

Rehabilitation Services: The rehabilitation services cover various exergame related services such as the game content server and the game engine. The content server saves all game related information with the help of a game database. It also saves basic patient information along with relevant medical data. In addition, it maintains connections among all gamers (i.e. both patients and co-operative gamers), and delivers updated data and messages when necessary. It should be noted that the game engine also performs logical operations and is responsible for synchronization.

Cloud Controller: This is the core component of the proposed framework and is responsible for instantiating a game session. Like a facilitator, this enables the communication between gamers and exergame servers. The cloud controller provides several services such as: authentication, profile and activity management, game statistics, notification management, and others, in order to manage the whole exergame framework. The difficulty level of the game is automatically adjusted at real-time to adapt with the patient's performance. During each exercise, the game controller keeps track of the patient’s progress time and compares it to a predefined threshold value. When the patient starts experiencing difficulties, the time needed to finish the exercise increases. If the time exceeds the threshold value, the game controller automatically changes the reach distance that the patient’s upper limb has to travel in order to complete the task. In other scenarios, the game controller examines the time to finish the exercise along with other tracking parameters (angle, jerkiness, etc) and takes actions depending on whether they have exceeded their predefined threshold values. All game related information are saved with the help of the game content server.

Performance Monitor: The performance of the patients is evaluated by analysing the data captured by different sensors during the rehabilitation exercises. Dynamic time warping (DTW) algorithm is applied to compare the movement pattern of a patient subject with the movement pattern of a healthy subject. Two types of model matching approaches are applied: (1) real-time model matching that is used when the patient competes against another healthy subject, and (2) on-line model matching that is used when the patient competes with other patient or he/she is performing the rehabilitation exergame alone. In the first approach, we compare the time series of the patient and the healthy subject in real-time and adjust the difficulty level of the game for both according to the patient’s performance. In some cases, when the patient subject has difficulties in completing the exergame task, a message is sent to the healthy subject asking them to slow down. In the second approach, the performance of the patient is compared to the reference movement pattern of a healthy subject that has already been stored in the system. The rehabilitation status is calculated and the difficulty level of the game changes accordingly. Next, auto-regressive integrated moving average (ARIMA) is utilized to forecast the rehabilitation progress of the patients based on their performance history. Further details about this will be included in the next chapter.

3.2. *Assistive Devices*

Three assistive devices have been developed to help patients in their rehabilitation program. The patients use these devices along with the Kinect camera whenever the therapists need to evaluate the strength of the muscles of the upper limb of the patients.

3.2.1. *Affected Hand FSR Glove*

Five Force Sensing Resistors (FSRs) are mounted on the fingertips of a glove as illustrated in figure 3.2. This type of sensors is widely used in data gloves [49][86], because its force sensitivity is optimized for the use in human touch control of electronic devices [50][87]. As shown in figure 3.3 the FSR response approximately equals the inverse power-law characteristic (roughly 1/R, where R is the output resistance of the FSR). The glove is also equipped with a Picaxe 14M2 microcontroller and a BlueSmirf bluetooth modem. The microcontroller receives eight analog input voltages, corresponding to the amount of pressure on each FSR sensor, through eight Analog to Digital Converter (ADC) channels, processes, and sends a relevant serial output raw data to the computer through the Bluetooth modem. The modem passes this data with a baud rate of 9600 with a sample rate of 29 samples per second. The glove circuit is powered by a 3.3 V rechargeable battery.

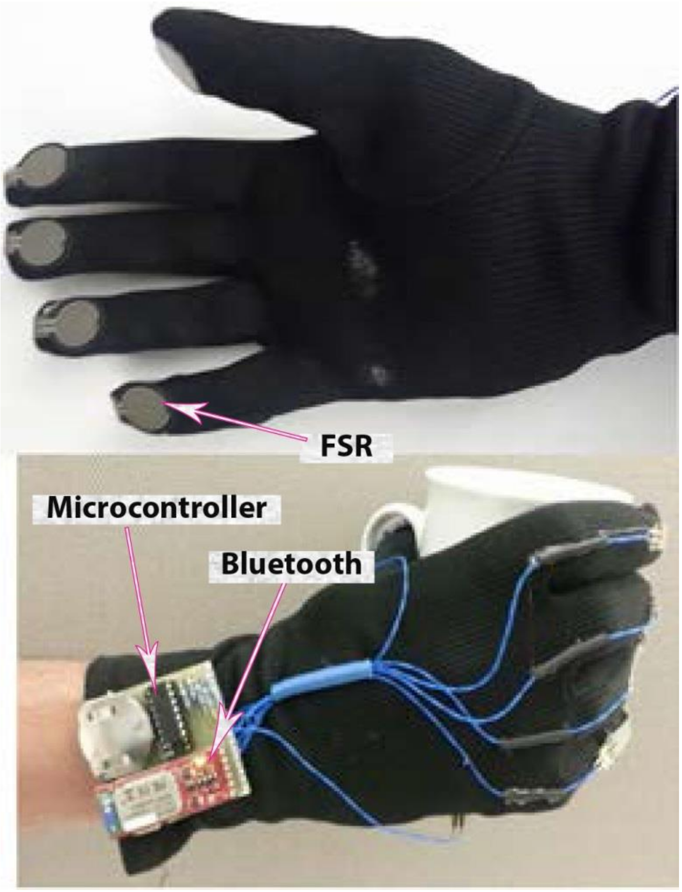


Figure 3.4 Five FSR sensors mounted on finger tips of a glove.

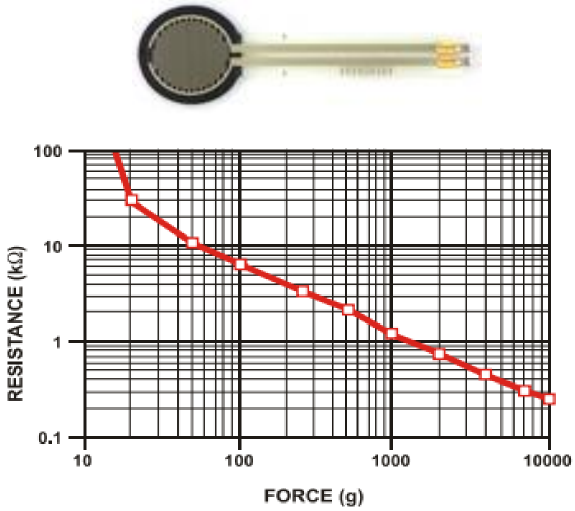


Figure 3.5 The FSR and its characteristics.

3.2.2. *Unaffected Hand FSR Glove*

The glove is a lightweight, inexpensive measurement device designed to find the force exerted by the affected hand on the unaffected hand. The novelty of this glove is that it is to be worn on the unaffected hand that acts as a natural robotic arm during the rehabilitation session. The glove is equipped with eight FSR sensors, five in which are mounted close to the middle of the fingers and three are mounted on the palm (figure 3.3). The rest of the design is similar to the one that appeared in above section.

Figure 3.6 The sensor glove.

For the glove to provide a reliable reading, the sensors should be placed in particular positions that give a weight measurement close to the actual weight of the affected hand. An artificial arm (hand + forearm) with a known weight is used in our study. We started changing the positions of the sensors on the glove and compared the force exerted by the stick on the hand that wore the glove. It is worth to note that, we followed the guidelines recommended by the therapists; we placed the sensors on a way that they read the exerted force naturally without adding the grip force of the fingers. That would allow the blood to circulate normally in the arm; the patients would not be at risk at any time.

3.2.3. *FSR Strap*

Twenty FSR sensors are placed on two hook and loop straps (ten FSR sensors on each). Each strap is 29 cm long and 2 cm wide as shown in figure 3.7. Half centimeter is the distance that separates two consecutive FSR sensors. The design is very similar to the one found in [88] except that we have added two extra sensors in order to get the measurements of most of the muscles that are engaged in the experiment.

Figure 3.7 The FSR Strap.

3.2.4. *Haptic Glove*

The designed haptic glove composed of five Force Sensitive resistors (FSRs) for measuring the amount of grip force on each finger. It also composed of five small vibro-tactile actuators (shaft-less vibratory motors). These actuators are mounted on the finger nails positions as shown in the figure 3.8. These sensors and actuators are connected to a control board. This board consists of a (Arduino pro-mini) Microcontroller, Motor drivers (SN754410 H-Bridge) and Bluetooth (Linvor_HC06) modem. The board is supplied by a 3.3V from a Polymer Lithium rechargeable battery. This board performs the following tasks:

1. Reads the analog voltage from each sensor. These values represent the measuring grip force by each finger.
2. Converts these measured values into digital form using 10-bit ADCs.
3. Stores and process the data.

4. Runs the actuators. The vibration intensity applied to the actuators depends on the amount of grip force of the corresponding finger.
5. Sends a row data wirelessly through Bluetooth (with a baud rate 9600) to the software interface that maps the physical grip force on each finger.

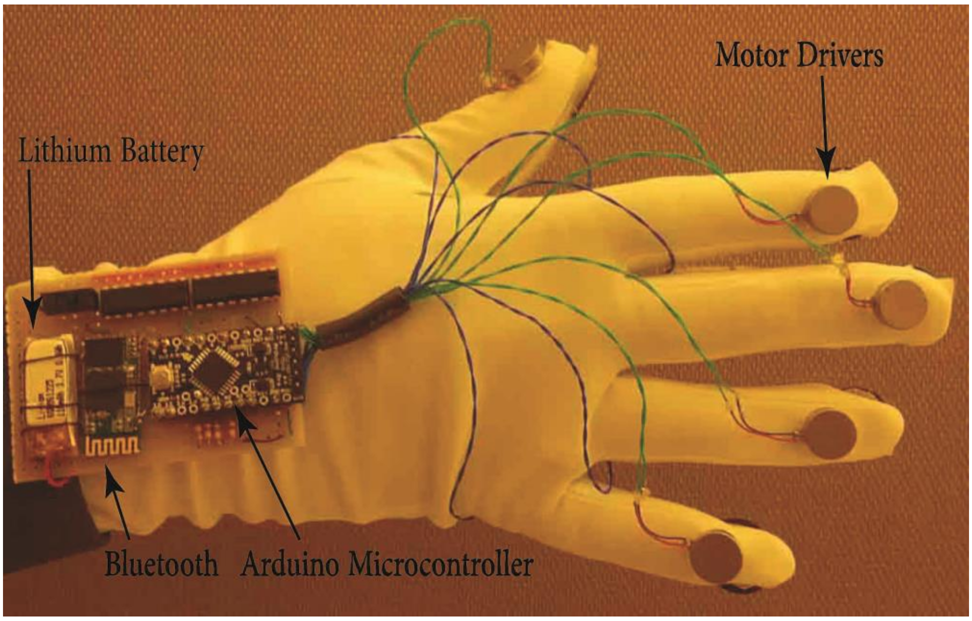


Figure 3.8 The Haptic Glove.

3.2.5. *Summary*

In this chapter we have presented a general overview of the SHECARE framework. The two main components of the framework, namely the cloud component and the client component, have been described in a way that showed the interaction between patients, therapists and caregivers. Moreover, we have discussed the different assistive devices that have been used to support the patients while they are performing the rehabilitation exercises.

Chapter 4. Predicting Recovery Progress under SHECARE

This chapter presents a set of algorithms used to track, evaluate, and predict the recovery progress of the stroke patients. The captured data that has been used as input parameters to these algorithms is briefly discussed in this chapter as well. We have applied a well-known optical alignment technique, dynamic time warping, to compare the time series kinematics patterns of stroke patients with those of healthy subjects. Moreover, we have addressed the relationship between the kinematics of their upper limbs and the strength of the corresponding muscles. This is considered a main contribution of this thesis because it allows us to estimate the strength of the forces by merely using the Kinect camera.

4.1. *Benchmarking*

There is no single standard measurement for the function of the upper extremities of patients with motor deficiencies. One of the main reasons for this is that therapists have not agreed on the definition of the word "function" [89]. Many researchers have developed quantitative tests in order to assess the improvement of the patients. For each test there is a set of normative values that have been taken from normal people with different categories. In this study, we have chosen several interrelated kinematic expressions of hand motions to describe the word "function". We refer to the process of finding ground truth measurement of these kinematics for the Kinect camera (which will be used in stroke rehabilitation) as "benchmarking." Benchmarking is the basic step in understanding and evaluating the progress of patients during recovery from their disabilities. It is achieved by applying benchmarks, or simply markers, that will form the basis of comparison between the data that has been gathered from the stroke patients and the benchmarking data that has been drawn from healthy individuals. The importance of benchmarking has been shown in many studies

[90-96]. Jebsen [95] provided the standard deviation, but not the norms, of seven tests used to assess the hand functions of two male and two female groups. The Australian version of the Jebsen test contains the norm and the standard deviation of eight tests for men and women within different aging groups, ranging from sixteen to ninety years [96]. Nagasaki [91] used an arm-rotator to find the kinematics measurements of human arm movements. The results of the benchmarks of four healthy men suggest that the asymmetric velocity and acceleration of the arm produced a minimum jerk and a smooth movement. In [97] a set of haptic-based hand exercises were created for use in stroke rehabilitation. The information gathered from five healthy subjects was used by occupational therapists to evaluate the progress of the patients under rehabilitation. Kim et al. [94] proposed a seven DOF robotic system (UL-EXO7) for stable post-stroke patients. Fifteen individuals were asked to play eight games that involved direct interaction with UL-EXO7. For each game the angles of the joints were recorded and new conventional metrics were proposed in order to help therapists in the assessment process for their patients' progress. A stress ball mounted with an accelerometer, gyroscope, and a magnetometer was used to find the angular tilting movements and their speeds, and the rotation around the z axis was used in [93]. The data was gathered from twelve healthy persons, and information about velocity, acceleration, jerk, and frequency was extracted. Such information is important for home-based rehabilitation due to the lack of benchmarks for wrist kinematics.

4.2. *Evaluated Parameters*

We have provided a set of measurements of the most important kinematics parameters that have been found in the literature of post stroke rehabilitation [90, 91, 94, 98]. These measurements will serve as a ground truth which the therapists can depend on in their evaluation process. It is worth to note that this set of parameters changes depending on the rehabilitation exercise.

4.2.1. *Direct Distance and Total Distance*

The movement of the human hand is, in general, a point to point displacement. The trajectory is roughly a straight line, but in some cases, especially if there is a hidden deficiency in the upper limb, the trajectory will be a set of connected up and down lines. In such cases, the distance covered is not equal to the length of the straight line that connects the starting point of the experiment with the ending point, but rather a total distance that is the sum of all the short unsteady movements of the user. By comparing the values of these two parameters, the user can discover different impairments during the therapy in the early stages of the rehabilitation program.

4.2.2. *Velocity*

The velocity of the hand is an important factor in assessing its strength. Despite the fact that many performance evaluation tests, such as the Purdue Pegboard Test and the JHFT [95, 99], offer different normative data to accurately assess hand functions, they all agree about the significance of hand speed being a key factor in the evaluation process [100]. It has been shown in previous studies that the trajectory of the hand velocity in the real world tends to be bell-shaped [101]. The velocity of the upper hand in the x-direction is obtained by equation 1.

$$v = \frac{\Delta x}{\Delta t} \tag{1}$$

where $\Delta x = x_2 - x_1$ is the change in the displacement between t_2 and t_1, and $\Delta t = t_2 - t_1$.

4.2.3. *Acceleration*

Acceleration is defined as the rate of change of velocity (equation 2). It is well known that there is a strong correlation between the acceleration of the upper limb and the observed movement by an individual. Moreover, therapists can use accelerometry measurements to distinguish between persons with normal and impaired upper limbs [102]. The acceleration is calculated in all three planes, but it is more sensitive to the x-y and y-z planes when the patient moves the affected hand in the horizontal and the vertical planes respectively. The magnitude of the acceleration vector is obtained by combining the values of accelerations at each axis and applying root-mean-square. The maximum acceleration is also extracted from the obtained data.

$$a = \frac{\Delta v}{\Delta t} \tag{2}$$

where $\Delta v = v_2 - v_1$ is the change in the velocity between t_2 and t_1, and $\Delta t = t_2 - t_1$

4.2.4. *Jerkiness*

The jerkiness, or the change of acceleration with time, is used to measure the smoothness of movements. The smaller the value of jerk is, the smoother the movement of the arm. In previous studies [91, 103], the jerkiness equation was studied in order to generate the smoothest trajectory between two points. In medicine, jerky movements can be caused because of many diseases and conditions, namely, Angelman syndrome, movement disorders, primary dystonia, spastic paraparesis and more. Researchers have found that “Jerk Cost,” the time integral of the squared magnitude of the hand jerkiness, is more effective in identifying the smoothness of the arm movement in the space [104]. The cost of jerkiness is shown in equation 3:

$$J = \frac{1}{N}\sum_{i=1}^{N}(\frac{1}{2}\times \int_{0}^{T} a'^{2}\,(t)dt) \tag{3}$$

Where J is the jerk cost, N is the number of times the user has performed the movement, T is the time interval, and a'(t) is the rate of change of acceleration. In this thesis, the zero-line cross will be taken into consideration as another indication of the smoothness of the hand motion. When the motion of the upper limb is controlled, then both jerkiness and zero-line cross should be in their optimum values.

4.2.5. *Joints Angles*

The joints create angles that need to be calculated in real-time when the user is moving the hands, the wrist, elbow and shoulders. In order to calculate the angle between the three joints that represents essentially three vectors, the performance efficient equation 4 that uses only one acos() method call is employed.

$$\begin{gathered} uv = P_{j1} - P_{j2} \\ wv = P_{j2} - P_{j3} \\ \theta = \mathrm{acos}(2 * \left(\frac{\frac{\overline{(\overrightarrow{uv}.\overrightarrow{wv})^{2}}}{\overrightarrow{uv}^{2}}}{\overrightarrow{wv}^{2}} \right) - 1) \end{gathered} \tag{4}$$

Equation 4 can be obtained by a simple derivation of the dot product formula between two vectors, where P_{j1} is the position of joint one, P_{j2} is the position of joint two, and P_{j3} is the position of joint three.

4.3. *Model Matching*

For the evaluation of patient's recovery progress we need a time series algorithm that computes the similarity between two time series regardless of their lengths. Moreover, the time complexity of the algorithm should be reasonable in which the output could be obtained at real-time when the size data input is small.

4.3.1. *Existing Model Matching Algorithms*

Researchers have developed a variety of algorithms in order to find the distance between two time series. Most of these algorithms are based on dynamic programming in which the tackled problems are divided into simpler subproblems. Dynamic Time Warping (DTW) [105] and Levenshtein Distance are the most popular algorithms that have been used to find the distance between two signals.

Dynamic Time Warping (DTW) is a well know algorithm that is widely used to find the similarities between two temporal sequences. It was introduced in the sixties [106], and extensively used for data mining and speech recognition after that [107, 108]. Nowadays, DTW is used in a variety of domains, including computer vision [109], gestures recognition [110], DNA sequence alignment [111] and much more.

Consider two time series sequences X and Y of lengths n and m respectively.

$$X = x_1, x_2, \dots, x_i, \dots x_n$$

and

$$Y = y_1, y_2, \dots, y_j, \dots y_m$$

The smaller the distance between two different points x_i and y_j, the more similar they are.

Let c be defined as the local cost distance (Euclidian distance) between x_i and y_j such that:

$$c: X * Y \to \mathbb{R}$$

To find the alignment path, we first build a cost matrix in which each element in the matrix represents the distance between two different points from the two series. Then we find the shortest path that connects the starting and the ending points of the minor diagonal of the matrix (figure 4.2). However such alignment path should satisfy the following boundary conditions:

1) Monotonicity: $x_i \leq x_{i+1}\ and\ y_i \leq y_{i+1}$.
2) Continuity: The alignment path should advance one step at a time. This step could be towards taken in the right, up, or diagonal directions.
3) Boundaries: The alignment path starts at the bottom left point and ends at the upper right point of the matrix.

Taking into consideration the three previous constraints, the total cost P of the alignment path can be defined as:

$$P(n,m) = c(x_n, y_n) + \min\{P(i-1,j), P(j-1,j-1), P(i,j-1)\}$$

We consider the movement pattern of a healthy subject (e.g., replacement, velocity, acceleration, jerkiness) as a template and the variance between the patient's movement pattern and this mentioned template indicates the recovery status of the patient. We can include the angles, the angular velocities, and other parameters to our template depending on the parameters captured during the exercises. Given a healthy subject's movement pattern (H):

$$H = \begin{cases} R_{healthy} = \left[R_{healthy,1} \cdots R_{healthy,m}\right]^T \\ V_{healthy} = \left[V_{healthy,1} \cdots V_{healthy,m}\right]^T \\ A_{healthy} = \left[A_{healthy,1} \cdots A_{healthy,m}\right]^T \\ J_{healthy} = \left[J_{healthy,1} \cdots J_{healthy,m}\right]^T \end{cases}$$

and the patient’s movement pattern (P):

$$P = \begin{cases} R_{patient} = \left[R_{patient,1} \cdots R_{patient,m}\right]^T \\ V_{patient} = \left[V_{patient,1} \cdots V_{patient,m}\right]^T \\ A_{patient} = \left[A_{patient,1} \cdots A_{patient,m}\right]^T \\ J_{patient} = \left[J_{patient,1} \cdots J_{patient,m}\right]^T \end{cases}$$

we want to find a correspondence matching between these two patterns:

$$\begin{aligned} &\Theta(Healthy\ Subjec's\ Pattern, Patient'sPattern) \\ &= \left[\Theta\left(R_{healthy}, R_{patient}\right)\Theta\left(V_{healthy}, V_{patient}\right)\Theta\left(A_{healthy}, A_{patient}\right)\Theta\left(J_{healthy}, J_{patient}\right)\right]^T \end{aligned}$$

where $R_{healthy}$, $V_{healthy}$, $A_{healthy}$, and $J_{healthy}$ are the replacement, velocity, acceleration, and jerkiness of the healthy subject. $R_{patient}$, $V_{patient}$, $A_{patient,}$ and $J_{patient}$ are the replacement, velocity, acceleration and jerkiness of the patient subject. T is the transpose operator. The optimized correspondence relation $\widehat{\Theta}$ is the minimum distance between the corresponding patterns [9]. In other words, the smaller the distance between two corresponding patterns, the more similarities they have in common.

$$\widehat{\Theta} = argMin \begin{bmatrix} \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(R_{healthy,i}, R_{patient,j}\right)p_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} p_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(V_{healthy,i}, V_{patient,j}\right)q_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} q_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(A_{healthy,i}, A_{patient,j}\right)r_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} r_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(J_{healthy,i}, J_{patient,j}\right)k_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} k_{i,j}} \end{bmatrix}$$

By using the above optimization criteria, we could conclude that we need to minimize the cumulative distance representing the unmatching part $D_{unmatch}$ which can be stated as:

$$D_{unmatch} = \begin{bmatrix} \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(R_{healthy,i}, R_{patient,j}\right)p_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} p_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(V_{healthy,i}, V_{patient,j}\right)q_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} q_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(A_{healthy,i}, A_{patient,j}\right)r_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} r_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d\left(J_{healthy,i}, J_{patient,j}\right)k_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} k_{i,j}} \end{bmatrix}$$

Then the patient's rehabilitation status is modeled as a combination of the elements of $D_{unmatch}$, as shown in equation 5:

$$\begin{cases} S_{rehab} = w_1.D_{unmatch}[1] + w_2.D_{unmatch}[2] + w_3.D_{unmatch}[3] + w_4.D_{unmatch}[4] \\ w_1 + w_2 + w_3 + w_4 = 1 \end{cases} \quad (5)$$

4.4. *Predicting with ARIMA*

The rehabilitation status index gives the therapists an indication about the current status of the stroke patient, but it does not help them answering a simple, yet important question that usually the patients and the caregivers ask: How long does stroke rehabilitation last? We know that such a question is not easy to answer, because successful recovery differs from one patient to another depending on so many factors (the severity of the stroke, the motivation of the person, support of family and friends, etc.). Most researchers use statistical methods that depend on specific achievements of the patients [112]. In our study, we used the ARIMA model to forecast the progress rate of the patients which proved to have a high forecasting accuracy as we would see later.

In general, a regression relation can be written as: $y = f(a, b, c, \dots)$ where y is the dependent variable and $a, b, c, \dots$ are the independent variables. An auto-regressive relation $y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \dots)$, is a relation between a dependent variable and itself but at different periods of time. In our case, the rehabilitation status $\{S_t\}$ is the dependent variable that have been collected over time t. An auto regression of first and second order, $AR(1)$ and $AR(2)$, can be expressed as:

$$S_t = \phi_1 S_{t-1} + \varepsilon_t \tag{6}$$

$$S_t = \phi_1 S_{t-1} + \phi_2 S_{t-2} + \varepsilon_t \tag{7}$$

where ϕ_1 and ϕ_2 are constants and ε_t is the error between the estimated and the real values. The auto regression model of order p, $AR(p)$, can be written as:

$$S_t = \sum_{j=1}^{j=p} \phi_j S_{t-j} + \varepsilon_t \tag{8}$$

where $\{\phi_j\}$ are called the auto regressive parameters.

An Auto Regressive Moving Average model $ARMA(p,q)$ is defined as:

$$S_t = \overbrace{\phi_1 S_{t-1} + \phi_2 S_{t-2} + \cdots + \phi_p S_{t-p}} + \overbrace{\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}} + \varepsilon_t \tag{9}$$

Where $\{\varepsilon_t\}$ is the residual series which has a zero average and with uncorrelated terms. Equation 9 consists of two main parts, the auto regressive part that contains p terms and the moving average part that contains q terms.

The $ARMA(p,q)$ model is a special case of $ARIMA(p,d,q)$. In fact, $ARMA(p,q)$ is $ARIMA(p,0,q)$, where p equals the number of auto regressive terms, and d equals the order of differencing, and q equals the number of moving average terms.

Since we could have infinite number of models depending on the values of p, d, and q, we are going to choose the model with the least square error. This implies the minimization of the residual terms or the moving average terms $\{\varepsilon_t\}$. Our predication approach is as follows:

1. Divide the values of S_t into two groups, the training group and the validation group.
2. Use the testing group to estimate the parameters of different models.

3. Use the model that is under testing to forecast the series one step ahead.
4. Find the mean square error of each model.
5. Choose the model with the smallest mean square error value for forecasting.

4.5. *Correlation between Strength and Kinematics*

Several studies have shown that there is a correlation between the strength and the kinematics of the upper limb movements [113, 114]. The relationship between the strength of the upper extremity and the throwing speed were investigated in [115]. The results suggested a direct relationship between, in particular, the strength of the elbow extension and wrist extension movements and throwing speed. Moreover, Cohen et al. [113] showed the serve's speed of elite tennis players could be increased by strengthening the muscles of their upper limb. The relationship between the kinematics and dynamics of nineteen upper limb's daily activities were generated in [114]. More recently, Xiao et al. [88] captured the force myographic data signals of the forearm and used them to predict the upper-extremity posture in real-time. Although these studies suggest that such relationship between the strength of muscles and the kinematics of the upper extremity exist, further investigations are needed to confirm the results. The reason is that most of the experiments were conducted on professional athletes that knew how to coordinate their upper extremity with lower extremity and truncate activity while they were performing the tasks [113, 115]. Moreover, after an extensive research in this matter, we could not find any research on the correlation between the kinematics of the upper limb of stroke patients and the strength of their muscles. In addition, to our knowledge, there were no attempts on finding the strength of the muscles using a camera tracking sensor (Kinect).

4.5.1. *Least-squares Regression Matrix*

Correlation techniques based on least square regression procedures are one of the most commonly used methods that deal with multi-input multi-output systems' problems. Such systems usually have more equations than unknowns in which an exact solution cannot be found. However, we can use the least squares technique in order to find an estimation of the solution with minimum sum of squares of errors.

Consider the system shown in figure 4.1. It has three kinematics inputs, $\boldsymbol{K} = (Velocity\ V, Acceleration\ A, Jerkiness\ J)$, and twenty five muscles' force outputs (ten from each strap and five from the glove), $\boldsymbol{F} = (f_1, f_2, \dots, f_{25})$. The mathematical model of the system can be described by the following set of equations:

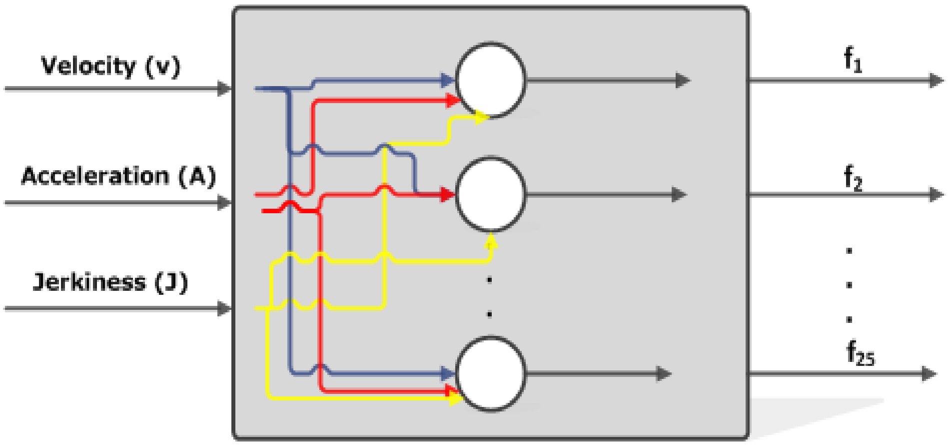


Figure 4.1 Mapping Kinematics to Forces.

$$\begin{cases} f_1 = b_{1,1}V + b_{1,2}A + b_{1,3}J \\ \dots \\ f_{25} = b_{25,1}V + b_{25,2}A + b_{25,3}J \end{cases} \tag{10}$$

Or in a vector form:

$$\boldsymbol{F} = \boldsymbol{BK} \tag{11}$$

where:

$$\boldsymbol{F} = [f_1, \dots, f_p, \dots, f_{25}]^T \tag{12}$$

$$\boldsymbol{K} = [V, A, J]^T = [k_1, k_2, k_3]^T \tag{13}$$

and

$$\boldsymbol{B} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ b_{25,1} & b_{25,2} & b_{25,3} \end{bmatrix} \tag{14}$$

The p^{th} row of equation 10 can be written as follows:

$$f_p = \boldsymbol{K^T b_p} \tag{15}$$

Where

$$\boldsymbol{b_p} = \left[b_{p1} b_{p2} b_{p3}\right] \tag{16}$$

Let n be the number of measurements of the forces f_p and the kinematics k_q where $p = (1, \dots, 25)$, and $q = (1,2,3)$ such that $n \geq \max(q) + 1$; in our case n should be greater than or equal to four. Moreover, let us further define the following two matrices:

$$\boldsymbol{\mathcal{F}_p} = \begin{bmatrix} x_{i(1)} \\ \vdots \\ x_{i(p)} \\ \cdot \\ \cdot \\ x_{i(n)} \end{bmatrix} \tag{17}$$

$$\Bbbk = \begin{bmatrix} V_{(1)} & A_{(1)} & J_{(1)} \\ \vdots & \vdots & \vdots \\ V_{(p)} & A_{(p)} & J_{(p)} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ V_{(n)} & A_{(n)} & J_{(n)} \end{bmatrix} = \begin{bmatrix} \boldsymbol{K^T_{(1)}} \\ \vdots \\ \cdot \\ \boldsymbol{K^T_{(n)}} \end{bmatrix} \tag{18}$$

The bracketed subscript (p) denoting the p^{th} set of measurement $p = (1, \dots, n)$. Consequently, the above n sets of measurements satisfy for the i^{th} output:

$$\begin{array}{ccc} x_{i(1)} & = & \boldsymbol{K}^{\boldsymbol{T}}_{(\mathbf{1})}\boldsymbol{b_i} \\ \vdots & \vdots & \vdots \\ x_{i(p)} & = & \boldsymbol{K}^{\boldsymbol{T}}_{(\boldsymbol{p})}\boldsymbol{b_i} \\ \vdots & \vdots & \vdots \\ x_{i(n)} & = & \boldsymbol{K}^{\boldsymbol{T}}_{(\boldsymbol{n})}\boldsymbol{b_i} \end{array} \tag{19}$$

Or in matrix form

$$\boldsymbol{\mathcal{F}_i} = \Bbbk\boldsymbol{b_i} \tag{20}$$

Since we cannot find the exact element of $\boldsymbol{b_i}$ of equation 20, we are going to assume $\widehat{\boldsymbol{b}_i}$ to be an estimate of $\boldsymbol{b_i}$. Equation 20 can be rewritten as:

$$\widehat{\boldsymbol{\mathcal{F}}_i} = \Bbbk\widehat{\boldsymbol{b}_i} \tag{21}$$

where $\widehat{\boldsymbol{\mathcal{F}}_i}$ is the estimation of $\boldsymbol{\mathcal{F}_i}$.

The sum $\boldsymbol{S}$ of the squared errors can be defined in the estimation as follows:

$$\boldsymbol{S} = \left(\boldsymbol{\mathcal{F}_i} - \Bbbk\widehat{\boldsymbol{b}_i}\right)^{\boldsymbol{T}}\left(\boldsymbol{\mathcal{F}_i} - \Bbbk\widehat{\boldsymbol{b}_i}\right) = \mathbf{tr}\left[\left(\left(\boldsymbol{\mathcal{F}_i} - \Bbbk\widehat{\boldsymbol{b}_i}\right)\left(\boldsymbol{\mathcal{F}_i} - \Bbbk\widehat{\boldsymbol{b}_i}\right)^{\boldsymbol{T}}\right)\right] \tag{22}$$

where $tr[M]$ is the trace of matrix M .

The best estimate of $\boldsymbol{b_i}$, in a least square regression sense, must satisfy the following expression:

$$\frac{\boldsymbol{\partial S}}{\boldsymbol{\partial b_i}} = \mathbf{0}, \forall\, \boldsymbol{i} \in (1,2,3) \tag{23}$$

Equation 21 is obtained by applying the techniques of matrix calculus of trace functions to the above expression:

$$\Bbbk^{\boldsymbol{T}}\Bbbk\widehat{\boldsymbol{b}}_{\boldsymbol{i}}^{*} = \Bbbk^{\boldsymbol{T}}\boldsymbol{\mathcal{F}_i} \tag{24}$$

where $\widehat{\boldsymbol{b}}_{\boldsymbol{i}}^{*}$ is the best estimate of $\boldsymbol{b_i}$ such that:

$$\widehat{\boldsymbol{b}}_{\boldsymbol{i}}^{*} = (\mathbb{k}^{\boldsymbol{T}}\mathbb{k})^{\boldsymbol{-1}}.\,\mathbb{k}^{\boldsymbol{T}}\boldsymbol{\mathcal{F}}_{\boldsymbol{i}} = \left(\widehat{\boldsymbol{b}}_{\boldsymbol{1i}}^{*}, \widehat{\boldsymbol{b}}_{\boldsymbol{2i}}^{*}, \widehat{\boldsymbol{b}}_{\boldsymbol{3i}}^{*}\right) \qquad (25)$$

Note: The experimental study with real patients of the mathematical techniques that have been described above will be explained in detail in chapter 6.

4.6. *Complexity of DTW*

Consider two sequences X: (x_1, x_2, …, x_n), and Y: (y_1, y_2, …, y_m). In order to measure the difference between the two sequences, a cost matrix has to be formed in which the Y sequence represents the rows and the X s sequence represents the columns. The algorithm checks the difference between x_i and y_j and advances in a diagonal path if there is no difference between them. However, if there is a difference between the two compared elements the algorithm advances in the horizontal or vertical axis depending on the minimum difference between the two moves. Considering the previous discussion, the time needed to find all the paths using the DTW algorithm is $O(3^n)$, where n is the number of the elements ($n = m$ in this case), and the algorithm is limited to three moves, diagonal, horizontal, and vertical moves. In other words, we have to move n steps and at each step we have three possible choices. The time complexity, $O(3^n)$, of the DTW algorithm is infeasible, however this time can be decreased dramatically to $O(n^2)$ if we assume that the cost difference for any pair or elements only depends on that pair of elements. This means the total cost for completing the algorithm is equal to adding up a set of independent terms which represent the cost differences for the pair of elements under comparison.

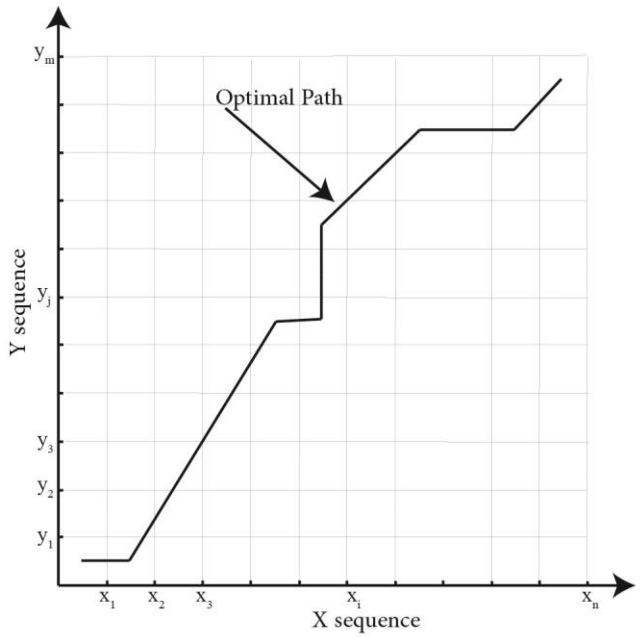


Figure 4.2 Optimal path between the two sequences.

4.7. *Summary*

In this chapter we presented a rehabilitation status model that is based in the DTW algorithm. The features that have been used to determine the progress of the patients are also discussed in this chapter. Moreover, we proposed a prediction recovery model that predicts the progress of the patients during their rehabilitation program. The model depends on a well-known forecasting algorithm (ARIMA) that uses a time-series data in order to predict future information. Our forecasting model uses the rehabilitation status of each patient to predict his/her recovery progress. In addition, a muscle strength estimation model has been discussed at the end of this chapter. The model is based on the least-square correlation method. It first builds a relationship between the strength of the muscles of the patients' upper limb and the corresponding kinematics. When such relationship is established, the model uses this relationship to estimate the strength of the muscles from the kinematics of the upper limb. In the last section of this chapter, the time complexity of the DTW has been illustrated.

Chapter 5. Proof-of-concept of SHECARE framework

The proposed framework serves a wide variety of stroke patients that have different medical conditions. In order to adequately evaluate the user's experience of our framework, we have tested it on different groups of stroke patients. During each phase of testing, a ground truth of reference data is captured from healthy subjects. The reference data, as its name indicates, is compared with the data measurements taken from the patients. In this chapter we will present a proof-of-concept of the SHECARE framework, describe the set of exergames that have been developed for rehabilitation.

5.1. *Proposed Exergames*

Unlike a typical video game, designing exergames for rehabilitation requires close coordination and cooperation between therapists and game developers. For this reason we have had brain-storming sessions with a therapist in order to design simple, yet effective games. The games need to be easy to play as stroke patients have physical limitations and may not be able to stand up for the entire game session. Moreover, the users should be able to perform the exercises while they are standing up or sitting down, though for capturing more accurate data, standing is better than sitting. Two exergames have been designed and implemented, the Basketball game, and the Touching Cup game.

5.1.1. *Basketball Game*

The Basketball game is designed to measure the mobility of the upper limb of the patient in the vertical direction. The users see themselves standing in front a ball and a net. The user has to grab a ball and move it vertically to the net, as shown in figure 5.1. The ball is placed at 45 degrees below the horizontal plane while the net is placed at 45 degrees above the plane, giving a total movement of 90 degrees. The goal of this game is to train the patient on a simple repetitive exercise that does not require any cognitive challenge. The timer starts the moment the user touches the ball and stops when he/she reaches the net. During this period we calculate the values of different parameters such as: direct distance, total distance traversed, velocity, angular velocity, acceleration, and jerkiness of the hand/arm. The game provides the users a real-time feedback about the stability of their hand movements.

Figure 5.1 A subject playing the Basketball game using the Kinect camera.

5.1.2. *Touching Cup Game*

The Touching Cup game is designed to help stroke patients restore the function of their upper limbs so that they can perform their daily activities. The game is divided into several levels that correspond to essential physical tasks (horizontal and vertical movement) for stroke patients, such as attempting to reach for an object, opening a pill box to retrieve pills, and so forth. The first level includes the challenge of reaching the pill bottle. In the second level, the patients have to flex the fingers of the opened arm and grasp the box. Each level contains additional challenges so by the end of all levels the user will be able to take his/her medications independently. The participants were asked to follow the line connecting the ball with the virtual cup (figure 5.2). Whenever a new level starts, the trajectory line varies fifteen degree from the previous level till it becomes ninety degrees with the horizontal. A timer is started at the moment the participant touched the real cup and ended when the real cup reached the virtual one. A more detailed description of the game and its implementation can be found [38].

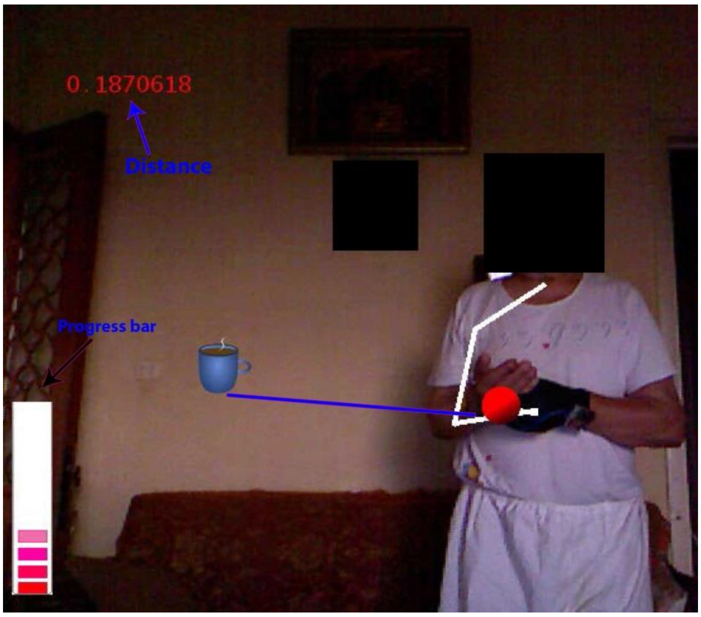


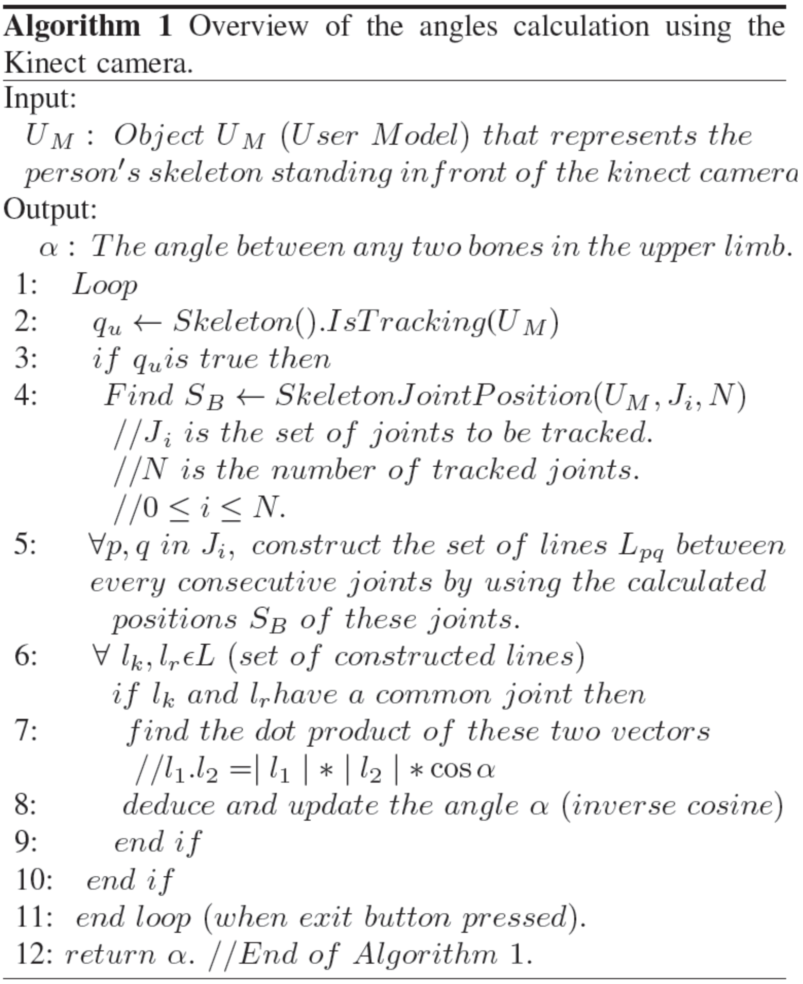
Figure 5.2 A subject playing the Touch Cup game at home.

5.2. *Developed Algorithms*

Capturing accurate and reliable data at real-time are two key features for successful performance evaluation of the rehabilitation status of stroke patients. For this purpose, two algorithms are developed to capture, at real-time, the time needed to complete the task, the displacement, the velocities, the accelerations, the jerkiness, and the angles measurements of the paralysed upper limb of the stroke patients. The extracted values are to be used in further analysis such as providing the appropriate feedback to the users, evaluating their progress, and recommending new level of rehabilitation exercises.

5.2.1. *Angles Calculation*

Algorithm 01 calculates the angles between two sequential bones in real-time. The importance of extracting the angles is two-fold. First, the angles measurements are used in advanced levels of the games, along with the other parameters, to determine the rehabilitation status of the patients. Second, these measurements are used to modify the level of difficulty of the game when the patient exceeds pre-set angles threshold values. To describe the working process of the algorithm, the joint detection and joint angle determination data are presented. Every three consecutive joints of the upper limb form two vectors with the middle joint as the intersection point between them. A simple, yet effective, way to find the cosine angle between the two vectors is by using the dot product of them. In our framework, we have calculated in real-time, the angles of the wrist, the elbow, and the shoulder when the users moves their upper limb. An analysis of these angular results is further mapped with the game interaction commands.



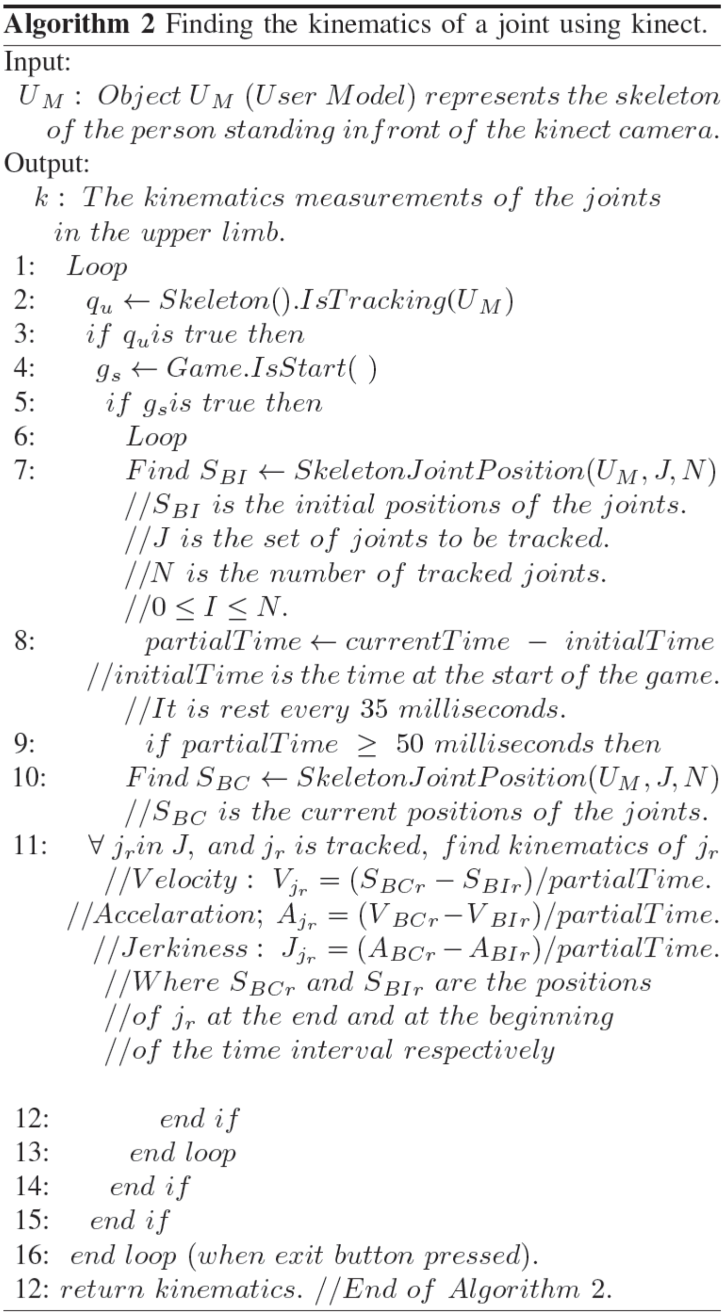
Algorithm 1 Overview of the angles calculation using the Kinect camera.

```
Input:
  $U_M$ : $Object\ U_M\ (User\ Model)\ that\ represents\ the$
  $person's\ skeleton\ standing\ infront\ of\ the\ kinect\ camera$
Output:
  $\alpha$ : $The\ angle\ between\ any\ two\ bones\ in\ the\ upper\ limb.$
Loop
  $q_u \leftarrow Skeleton().IsTracking(U_M)$
  $if\ q_u is\ true\ then$
    $Find\ S_B \leftarrow SkeletonJointPosition(U_M, J_i, N)$
    $//J_i\ is\ the\ set\ of\ joints\ to\ be\ tracked.$
    $//N\ is\ the\ number\ of\ tracked\ joints.$
    $//0 \leq i \leq N.$
  $\forall p, q\ in\ J_i,\ construct\ the\ set\ of\ lines\ L_{pq}\ between$
  $every\ consecutive\ joints\ by\ using\ the\ calculated$
    $positions\ S_B\ of\ these\ joints.$
  $\forall\ l_k, l_r \epsilon L\ (set\ of\ constructed\ lines)$
    $if\ l_k\ and\ l_r have\ a\ common\ joint\ then$
      $find\ the\ dot\ product\ of\ these\ two\ vectors$
      $//l_1.l_2 = \mid l_1 \mid * \mid l_2 \mid * \cos\alpha$
      $deduce\ and\ update\ the\ angle\ \alpha\ (inverse\ cosine)$
    $end\ if$
  $end\ if$
$end\ loop\ (when\ exit\ button\ pressed).$
$return\ \alpha.\ //End\ of\ Algorithm\ 1.$
```

Algorithm 1: Finding the Angle between two consecutive bones.

5.2.2. *Kinematics Calculation*

Algorithm 02 calculates the basic parameters that are used to indicate the rehabilitation status of the patient. It extracts the kinematics by finding the coordinates of the tracked joints every 35 milliseconds which we found enough to capture the joints coordination. After that, all what we have to do is to apply the basic kinematics functions to determine the velocity, acceleration and the jerkiness.



Algorithm 2 Finding the kinematics of a joint using kinect.

```
Input:
  $U_M$ : $Object\ U_M\ (User\ Model)\ represents\ the\ skeleton$
      $of\ the\ person\ standing\ infront\ of\ the\ kinect\ camera.$
Output:
  $k$ : $The\ kinematics\ measurements\ of\ the\ joints$
      $in\ the\ upper\ limb.$
  $Loop$
    $q_u \leftarrow Skeleton().IsTracking(U_M)$
    $if\ q_u is\ true\ then$
      $g_s \leftarrow Game.IsStart(\ )$
      $if\ g_s is\ true\ then$
        $Loop$
          $Find\ S_{BI} \leftarrow SkeletonJointPosition(U_M, J, N)$
          $//S_{BI}\ is\ the\ initial\ positions\ of\ the\ joints.$
          $//J\ is\ the\ set\ of\ joints\ to\ be\ tracked.$
          $//N\ is\ the\ number\ of\ tracked\ joints.$
          $//0 \leq I \leq N.$
            $partialTime \leftarrow currentTime\ -\ initialTime$
      $//initialTime\ is\ the\ time\ at\ the\ start\ of\ the\ game.$
          $//It\ is\ rest\ every\ 35\ milliseconds.$
            $if\ partialTime\ \geq\ 50\ milliseconds\ then$
          $Find\ S_{BC} \leftarrow SkeletonJointPosition(U_M, J, N)$
          $//S_{BC}\ is\ the\ current\ positions\ of\ the\ joints.$
    $\forall\ j_r in\ J,\ and\ j_r\ is\ tracked,\ find\ kinematics\ of\ j_r$
      $//Velocity:\ V_{j_r} = (S_{BCr} - S_{BIr})/partialTime.$
  $//Accelaration;\ A_{j_r} = (V_{BCr} - V_{BIr})/partialTime.$
    $//Jerkiness:\ J_{j_r} = (A_{BCr} - A_{BIr})/partialTime.$
      $//Where\ S_{BCr}\ and\ S_{BIr}\ are\ the\ positions$
      $//of\ j_r\ at\ the\ end\ and\ at\ the\ beginning$
      $//of\ the\ time\ interval\ respectively$

            $end\ if$
          $end\ loop$
        $end\ if$
      $end\ if$
  $end\ loop\ (when\ exit\ button\ pressed).$
  $return\ kinematics.\ //End\ of\ Algorithm\ 2.$
```

Algorithm 2: Finding Kinematics of the tracked joints.

5.3. *Games Sequence Flow*

In this section we will describe the flow chart sequence diagram’s state of the Touching Cup game. We also will describe in details various chart states along with their connectivity with the whole system.

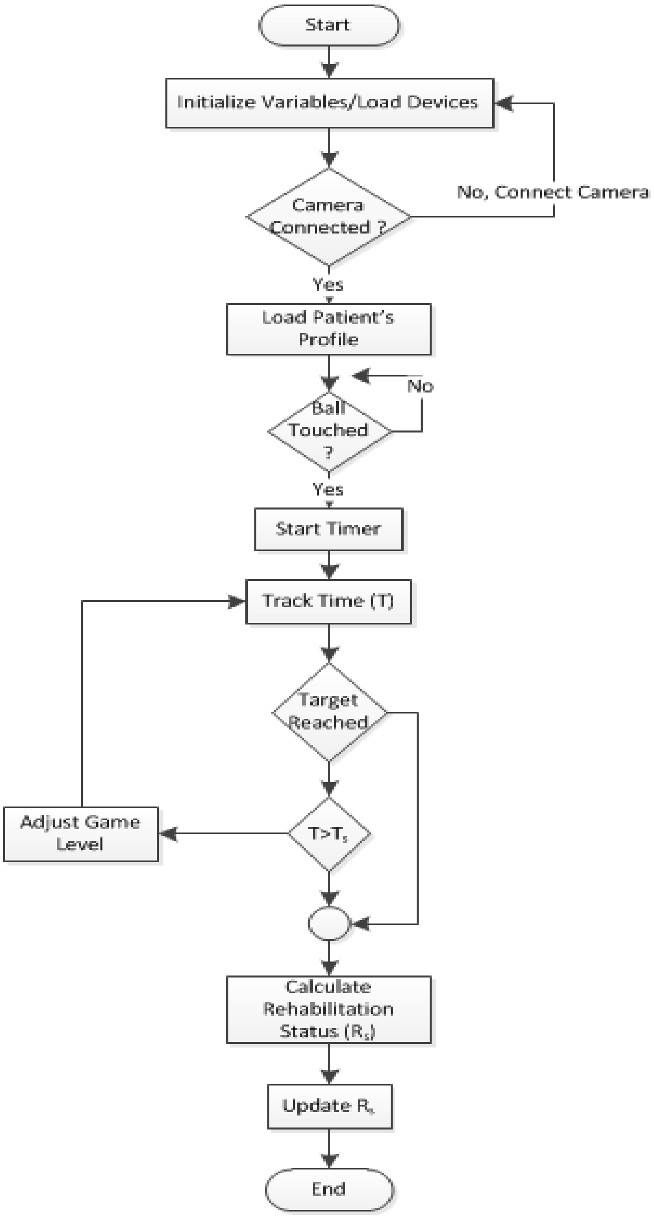


Figure 5.3 A Flow diagram of the Touching Cup game.

5.3.1. *Initialize Variables/Load Devices*

The first basic step of the Touching Cup flowchart is to initialize different variables that the game needs for its operation. These variables may include the threshold time of the exercises (T_s), the rehabilitation status (R_s), and the game difficulty level. After the initialization of the variables, the framework starts identifying and loading the connected devices. Since all exercises require the Kinect camera to be connected to the computer in order to work, the framework checks whether the camera is connected or not. In case the camera is not connected, a message is prompt on the screen asking the user to connect the camera in order to operate the rehabilitation tasks. The framework continues loading the drivers of other assistive devices if they are connected to the rehabilitation framework. Moreover, patient's profile is retrieved from the database at this stage of the initialization process.

5.3.2. *Start/Track Timer*

The timer starts when the user touches a red ball which indicates the beginning of the exercise. The program tracks the timer and checks whether the user has touched the cup. As we have mentioned before, the positions of the joints are recorded every 35ms. The timer stops when the patient reaches the cup. To motivate the patient, the time is displayed on the screen while the patient performs the exercise.

5.3.3. *Adjust Game Level*

The game controller that has been discussed in section 3.1.2, compares the time that the patient needed to finish the exercise with a predefined threshold time (T_s) and when the time exceeds T_s the game's level adjusted to meet the new patient's performance. A more on this can be found in the previously mentioned section.

5.3.4. *Calculate Rehabilitation Status (R_s)*

When the user reaches the cup, the captured data is analyzed and the rehabilitation status (R_s) is calculated. By using equation 5 (chapter 4), the displacement, the velocity, the acceleration, and the jerkiness are used to assess the overall performance of the patient. By the end of each exercise, the rehabilitation status is updated and saved on the patient's profile.

5.4. *System Usability*

One important aspect of usable interface design is the ability of users to communicate with systems easily and smoothly. Efficient communication between a system and users can be achieved through an easy and simple interface design. Studying the interface design usability allows to determine audience and know what end-users want and even need from the system. This way ensures what elements the interface should have and that these elements should be easy to understand, access, and use to perform different tasks of the system. More importantly, a usable interface of the system allows users to build a mental model of the system so they can use it easily on their own. In this work, we designed two interactive exergames. Two usability concepts were considered for their interfaces design: (1) Interaction Design that helps users to effectively communicate with the system in order to perform its tasks, (2) Visual Design that attracts users to be engaged with the system and build an interest in it.

5.4.1. *Usability of Basketball Game*

We chose to simulate the well-known game 'basketball' for two reasons. First, it serves the purpose of this study which requires patients to virtually hold an object, by hands, and move it from one position to another. Note that the stroke patients have physical limitations. Second, we want to reduce the cognitive effort to its minimum so that patients do not need to think too much when performing the rehabilitations’ tasks. Instead, they are familiar with the way the basketball game is played and hence they can easily build a mental model of how the game works.

To interact with the basketball game, users will see themselves in front of a ball and a basket through a Kinect camera (as shown in Figure 5.1). The users need to use their hands to virtually pick and hold the ball and then move it vertically until it reaches the basket. The users will see themselves holding the ball and can track their hand movement through a drawn line that simulates the movement on the screen. All the hands movements should be rendered in real time and the users should not feel any delays between hands movements and the corresponding displayed movements on the camera. Also, the system provides the users with a real-time feedback about the stability of their hand movements in form of a short-meaningful text message displayed on the screen.

Regarding the visual design, the ball and basket objects were designed carefully in a way that matches the real appearance of the ball and basket of the basketball game. Preattentive features such as color, shape, and position of the objects on the interface, were taken into consideration while designing the game. This way ensures that the Gestalt of the game design will be very clear to the end-users as they will perceive the system as a whole not as individual element.

5.4.2. *Usability of Touching Cup Game*

We designed this game to simulate a daily routine of drinking a cup of coffee so that we avoid extra cognitive effort required from the patients. The same method and usability concepts used in the Basketball game were applied to the design of this game as well. Users need to virtually pick an object and move it from where it was picked until they touch a real cup of coffee. The users will see themselves, through a Kinect camera, in front of a ball, a cup of coffee, and a straight line connecting both objects. The interaction with the game will be by touching the ball and move it until the users touch the cup. The users need to follow the straight line as the path for the movement. The game provides the users with a real-time feedback about the stability of their hand movements in a form of arrows pointing to where the hands and the ball should be repositioned to be on the straight line. The game also provides the patients with a real-time feedback on their progress during playing the game. It is important to mention that system's delay is not accepted while the patients are playing the game. The progress feedback is visualized into a progress bar displayed on the left bottom on the interface, in order to makes it easier for the patients to know the current status of their performance and therefore helping them making proper adjustments. The progress bar shows two main statuses: good and bad. For this, we use two colors: red and green. Color red indicates that the patients are not doing well while color green indicates a good status of the patients' progress. Different color saturations are used to show different levels of the same main status. The choices of red and green colors were based on the common knowledge that color red is used to indicate an error state while color green is used to communicate a successful state.

All the visual objects were designed in a way that their shapes, colors, positions on the screen are familiar to what end-users have experienced in real life.

User-computer interactions for both games were designed based on three interaction concepts:

1. Choice Reaction Time: where users should react upon seeing a signal. In our case, the game real-time feedback about the stability of hands movements in which prompt the users to adjust the position of hands movements.
2. Two-Dimensional Positioning: where users move an object from one point to another on the screen. We take into consideration the iterative process of hand-eye coordination while moving the object. In this case, the real hands movements

should be synched with the corresponding virtual movements on the screen so that adjustments can be made based on the visual feedback showing the hands position.

3. Control Compatibility: we choose the movement controls to be easy to learn based on users' previous knowledge and familiar experiences. For example, when users move their hands from left to right causing the virtual object to be moved from left to right on the screen. This previous knowledge of moving from left to right directions makes it easier for users to learn the system easily. Another example can be seen in the basketball game where users are familiar with how it works. They have a prior knowledge or experience that a ball needs to be hold and put inside a basket.

Users opinions are important in order to evaluate the proposed games. We interview the users after the experiment session seeking their opinions about the easiness and acceptance of the games.

5.5. *Summary*

In this chapter we described the proposed exergames along with the algorithms which was developed to capture the parameters needed in the assessment process. Moreover, a set of flow sequence diagrams of the exergames was depicted in flow charts and explained in details.

Chapter 6. Experimental and Clinical Results

A clinical assessment test, namely the Action Research Arm Test (ARAT) has been taken by all the stroke patients that have been participated in this thesis. Moreover, a new scoring technique has been introduced to evaluate the recovery progress of the stroke patients while they are performing their rehabilitation exercises. In this chapter we will present the clinical and the experimental results of the SHECARE rehabilitation framework. Moreover, we will assess how strong the relationship between the clinical assessment tests and the rehabilitation status index.

6.1. *Clinical Test*

Prior to these experiments, an orthopedic doctor and a professional physiotherapist have evaluated the severity and impact of stroke on the stroke patients. ARAT is considered being a strong and accurate assessment test because it assesses upper limb functioning through observation in contrast to other available outcome measures that tend to rely on questionnaires answered by patients. ARAT has excellent intra-rater (ICC=0.0989), and inter-rater (ICC=0.0995) reliability [99], [116] and great evidence of criterion validity comparable to the upper limb test of Fugl-Meyer Assessment and Motor Assessment Scale, making it a recommended outcome measure by professional association groups, such as Stroke Taskforce (StrokEdge) for chronic stroke. In addition, it is suitable to detect the progress of the patients over time [117].

The test was divided into four subtests: grasp, grip, pinch and gross movement. Each subtest contained an ordered items that were graded from 0 to 3: “3”, the highest grade which means the subject has performed the task normally; “2” means the subject has completed the task but with some difficulties; “1” that the subject could not complete all the parts of the task; and “0” that the subject has failed to complete any part of the task. The total number of items of the test is nineteen with a total score of fifty seven which indicates the arm is functioning normally.

6.2. *Rehabilitation Protocol*

The rehabilitation exercises took place mainly in rehabilitation centers with a little exception for some severely injured patients. In the following, descriptions of the rehabilitation protocol are illustrated.

6.2.1. *General Requirements*

1. A Kinect Camera.
2. A laptop (at least 4g RAM).
3. A room with minimum area of 4x4 m^2.
4. A cup.
5. Small set of shelves (Three shelves of height 1m, 1.4m and 2.0 m).
6. A consent form to be filled by the subject.

6.2.2. *Qualitative Test Protocols*

1. The test subject should see a prerecorded video that describes the tasks that he/she is going to do.
2. The minimum distance between the test subject and the camera should be 1.2m, while the maximum distance should be 3.5m.
3. Allow several minutes for the test subject to use the system before starting the official task. This would be an appreciate time to talk to with the test subject; to explain the different steps of the test, the importance of his/her cooperation, and to demonstrate some of the exercises.

4. If at any time during the test, the subject feels tired or uncomfortable, we should stop the test and repeat it at another time, may be in another day.
5. The test subject should be facing the camera at all times.

6.2.3. *Quantitative Test Protocols*

1. The average set of kinematics (speed, acceleration, jerkiness, etc,...) of each joint under testing shall be determined by taking the average kinematics of the all trials in each day.
2. The overall average is then determined by taking the average of the final data of each day.
3. The angles of the body joints under testing should be tracked at real-time and saved to a database every 35 millisecond.
4. A statistical model should be provided by the end of the test that shows the performance of the patient during the rehabilitation exercises.

6.3. *Experiment One*

In this experiment, we have designed and implemented a cloud-based rehabilitation system that helps stroke patients enhancing their motor functions. Forty five healthy persons (18 females and 27 males) and three stroke patients have volunteered to participate in our experiment. The derived data from the healthy subjects is served as motion normative data that can be used for accurate assessment of hand function. We have applied a well-known optical alignment technique, dynamic time warping (DTW), to compare the time series kinematics patterns of stroke patients with those of healthy subjects. The prototype of this system is tested on three patients for ten weeks.

6.3.1. *Subjects*

Forty five healthy volunteers (18 females and 27 males; aged 39 ± 13.7 years) and three stroke patients (1 female and 2 males; aged 65 ± 12.5 years) with corrected-to-normal vision participated in this study. The patients (table I) were having chronic stroke (> 8 months) with no serious cognitive problems, not fully bounded to a wheelchair, and had not been hospitalized for 24 hours a day during the time of conducting the experiments (they were out patients). All patients were giving a copy of the informed consent form to take home and read it carefully and to decide whether to sign it or not. The study was performed at Dr Mohamad Khaled Foundations, Department of Physical Therapy, Ozzaai, Beirut, Lebanon. We made sure that all the informed consent forms had been signed by the patients before we started the experiments. Moreover, the research was approved by the local ethics committee in the rehabilitation center.

Table 6.1 Stroke Patients Statistics

Patient	**Stroke Side**	**Age**	**Stroke Date**	**Dominant Hand**	**Action Research Arm Test***	
					Week 1	**Week 8**
Patient One	Right	52	Feb 05, 2013	Right	Bet. 25 & 29	Bet. 27 & 32
Patient Two	Right	77	June 07, 2012	Right	Bet. 13 & 19	Bet. 22 & 27
Patient Three	Left	66	Aug 01, 2013	Right	Bet. 13 & 19	Bet. 22 & 27

**Maximum score of this test is 57*

6.3.2. *Clinical Study*

The ARAT was applied to evaluate the arm and the hand motor functions of the stroke patients. The clinical test was conducted just before the first session of the rehabilitation program took place and right after the end of the last session. The results of the clinical test of the patients at week one and week eight are shown in table 6.1.

6.3.3. *System Setup and Experimental Protocol*

The client component of the developed software (figure 6.1) was used by the patients during the rehabilitation regime. The protocol used in the experiment was similar to the one described in section 6.2. More precisely, the exercises were taken place in a 5m x 7m room inside the rehabilitation center. The distance from the patient to the Kinect camera was 2.2 meters. The patients had four sessions every week within seventy days. Each session lasted for 30 minutes. In addition, the patients conducted the exercises while they were standing to avoid induce problems of Kinect that might occur while the patients are sitting. Finally, all arm motions started and ended at the same point. The Basketball game and the Touching Cup game described in section 5.1 were used by the patients to perform the required tasks.

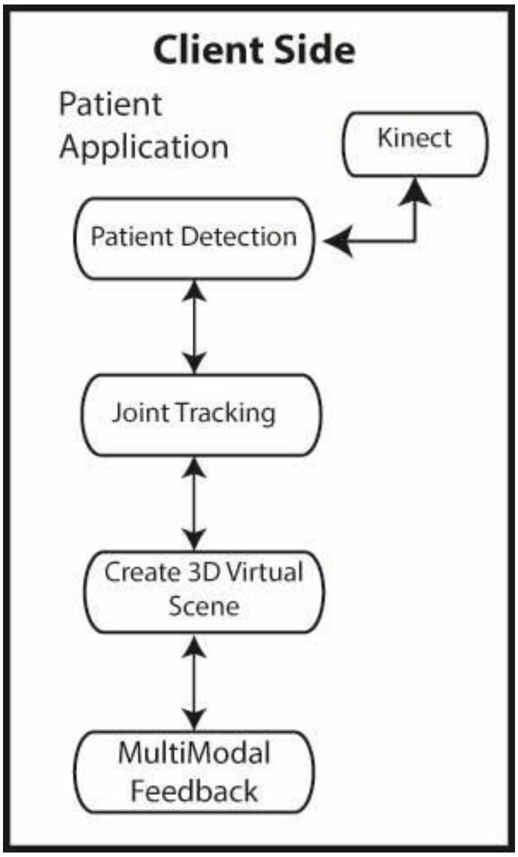


Figure 6.1 Patient’s Software Component.

6.3.4. *Results of Experiment One*

The average time (Time in milliseconds) needed to reach the target, the total distance (Distance in cm) covered from rest-to-rest, the ratio of the total distance to the direct distance (Ratio which is dimensionless), the maximum velocity (Max Vel. in cm/ms), the maximum acceleration (Max Acc. in cm/ms^2), the jerkiness (Jerkiness in cm/ms^3), and the number of zero-line cross (Z which is dimensionless) are shown in table 6.2. Although the young healthy people (age between 20 and 35) tend to have least values of kinematic parameters (table 6.2), a Tukey test revealed that there is no significant difference between the young, middle, and old groups as shown in table 6.3 (all p values > 0.05).

Table 6.2 Kinematics of Healthy Subjects of the Three Age Groups

Age	Time	Distance	Ratio	Max Vel.	Max Acc.	Jerkiness	Z
20 - 35	900 ± 65	64.7 ± 0.12	1.06 ± 0.014	0.11 ± 0.006	$2.75 * 10^{-4}$	$1.07 * 10^{-11}$	5
36 - 55	950 ± 71	66.2 ± 0.14	1.08 ± 0.013	0.10 ± 0.030	$2.61 * 10^{-4}$	$1.10 * 10^{-11}$	7
56 - 66	1050 ± 86	66.7 ± 0.17	1.10 ± 0.010	0.10 ± 0.005	$2.58 * 10^{-4}$	$1.10 * 10^{-11}$	7

Ratio: *is the ratio of the actual distance to direct distance (dimensionless).* ***Z:*** *is the number of Zero-line cross (dimensionless).* ***Time:*** *is in milliseconds (ms),* ***Distance*** *is in centimeter (cm),* ***Velocity*** *is in cm/ms,* ***Acceleration*** *is in* cm/ms^2*, and* ***Jerkiness*** *is in* cm/ms^3*.*

Table 6.3 ANOVA Test Results of the Healthy Subjects

(I) Group	(J) Group	Velocity	Acceleration	Jerkiness
Young	Middle	$9.51 * 10^{-1}$	$9.50 * 10^{-1}$	$9.49 * 10^{-1}$
	Old	$1.41 * 10^{-1}$	$1.40 * 10^{-1}$	$1.42 * 10^{-1}$
Middle	Young	$9.51 * 10^{-1}$	$9.50 * 10^{-1}$	$9.49 * 10^{-1}$
	Old	$2.43 * 10^{-1}$	$2.38 * 10^{-1}$	$2.42 * 10^{-1}$
Old	Young	$1.41 * 10^{-1}$	$1.40 * 10^{-1}$	$1.42 * 10^{-1}$
	Middle	$2.43 * 10^{-1}$	$2.38 * 10^{-1}$	$2.42 * 10^{-1}$

Young*: age between 20 & 35.* ***Middl****e: age between 36 & 55.* ***Old****: age between 56 & 66.*

Unlike the healthy subjects, the variation of the velocities of the stroke patients were statistically significant ($F(2,153) = 10.75$, $p < 0.001$). In particular, the Tukey test has showed that there is a statistically significant difference between patient one and patient three, and patient two and patient three, but there is no statistically significant difference between patient one and patient two as shown in table 6.4.

Table 6.4 ANOVA Test Results of the Stroke Patients

(I) Patient	(J) Patient	Velocity	Acceleration	Jerkiness
One	Two	$9.98 * 10^{-1}$	$9.23 * 10^{-1}$	$7.50 * 10^{-1}$
	Three	ˆ$1.0 * 10^{-3}$	$9.09 * 10^{-1}$	$6.08 * 10^{-1}$
Two	One	$9.98 * 10^{-1}$	$9.23 * 10^{-1}$	$7.50 * 10^{-1}$
	Three	ˆ 0.000	1.000	$9.75 * 10^{-1}$
Three	One	ˆ $1.0 * 10^{-3}$	$9.09 * 10^{-1}$	$6.08 * 10^{-1}$
	Two	ˆ 0.000	1.000	$9.75 * 10^{-1}$

ˆ *Means there is a statistically difference between the patients.*

An example of the model matching results between healthy and patient subjects is shown in figures 6.2 and 6.3. The vertical signals (y-axis) in the figure represent the healthy subject's kinematics, while the horizontal signals (x-axis) represent the patient's. In details, Figures 6.2a and 6.2e depict the DTW distance between the healthy and the patient displacement signals while the DTW of the velocity signals are depicted in figures 6.2b and 6.2f. In addition, figure 6.3c and figure 6.3g depict the acceleration signals while the jerkiness signals are depicted in figures 6.3d and 6.3h. To satisfy the constraints of the DTW, a global alignment of the two signals is required. The resulting curve represents the minimum cumulative cost of the matched signals between healthy and the patient subjects. We used equation 25 in chapter four to find the rehabilitation status index $S_{rehabilitation}$ of the patients in each week. The units of the kinematics measurements are: cm for displacement, cm/sec for velocity, cm/sec^2 for acceleration, and cm/sec^3 for jerkiness, knowing that the units used in figures 6.2, 6.3, and table 6.5 are cm per milliseconds for velocity and cm per milliseconds square for acceleration and cm per milliseconds cube for jerkiness (a simple unit conversion is needed). The values of the coefficients of equation 4 in chapter 4 (w1, w2, w3, and w4) are found by using trail and improvement/error method, and they have been best estimated to be equal to 0.03, 0.09, 0.18, and 0.7 respectively. The rehabilitation status index of patient one (for example) in week one is equal to:

$$\begin{aligned} S_{\text{rehabilitation}} &= 0.03 * 154.76 + 0.09 * 70 + 0.18 * 0.376 + 0.7 * 0.0296 \\ &= 11.031. \end{aligned}$$

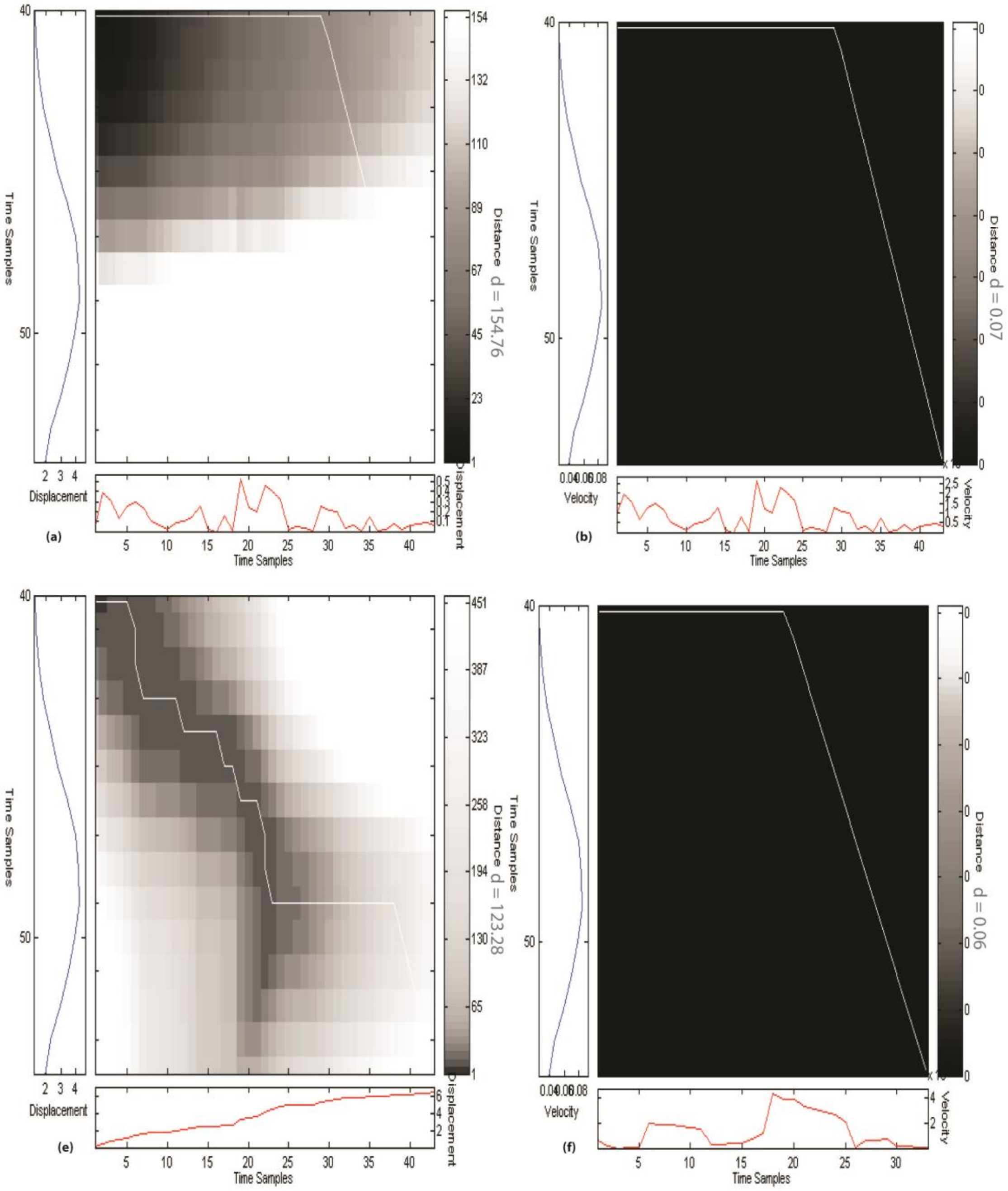


Figure 6.2 DTW Distance. The x-axis represents the patient’s data, and the y-axis represents a healthy subject’s data. The lines inside the graphs represent the distances between the healthy and patient’s data. The calculated distance is represented by **d**. (a) and (e) represent the displacement, (b) and (f) Velocity.

Table 6.5 Kinematic Values of the Patients at the First and the Last Week of the Study

Patient	**Before**				**After**			
	Dis.	**Vel.**	**Acc.**	**Jer.**	**Dis.**	**Vel.**	**Acc.**	**Jer.**
One	154.8	$7.0 * 10^{-2}$	$3.76 * 10^{-7}$	$2.96 * 10^{-11}$	123.3	$6.0 * 10^{-2}$	$3.7 * 10^{-7}$	$2.9 * 10^{-11}$
Two	164.4	$7.2 * 10^{-2}$	$3.94 * 10^{-7}$	$3.05 * 10^{-11}$	155.3	$6.8 * 10^{-2}$	$3.6 * 10^{-7}$	$2.9 * 10^{-11}$
Three	177.9	$7.7 * 10^{-2}$	$3.86 * 10^{-7}$	$2.99 * 10^{-11}$	154.9	$6.8 * 10^{-2}$	$3.9 * 10^{-7}$	$3.0 * 10^{-11}$

The values of the rehabilitation status during the eight weeks of the study are illustrated in table 6.6. These values are fed to ARIMA(0,1,0) model to forecast the rehabilitation status index of the patients in the next two weeks (week nine and week ten) and compared it to the actual values obtained from equation 4. The forecast values (the model predicted values for the forecast period), the fit values (the model predicted values for the estimation period), and the observed values (the observed values of the dependent series) of the three patients are shown in figure 6.4. The percentage of error of the forecasting model is less than 2.0 % for patient one and patient three, and 10.35 % for patient two. It is important to note that we have calculated the average of the four sessions in each week for ten weeks, but we have used the values of the first eight weeks in our analysis. The values of the last two weeks were used in forecasting.

In order to assess the acceptance level of the proposed framework, we conducted a usability study to evaluate the users' quality of experience. At the end of the rehabilitation sessions, the patients were asked to determine whether the system was entertaining, motivating and intuitive. They were asked to describe the whole system in one word, and to choose, according to their personal experience, whether the system was entertaining, motivating and intuitive. The results showed that the patients were satisfied with our proposed rehabilitation system (table 6.7). Moreover, the therapists' feedback was very encouraging. The system provided them with adequate information that helped them assessing the clinical status of the patients.

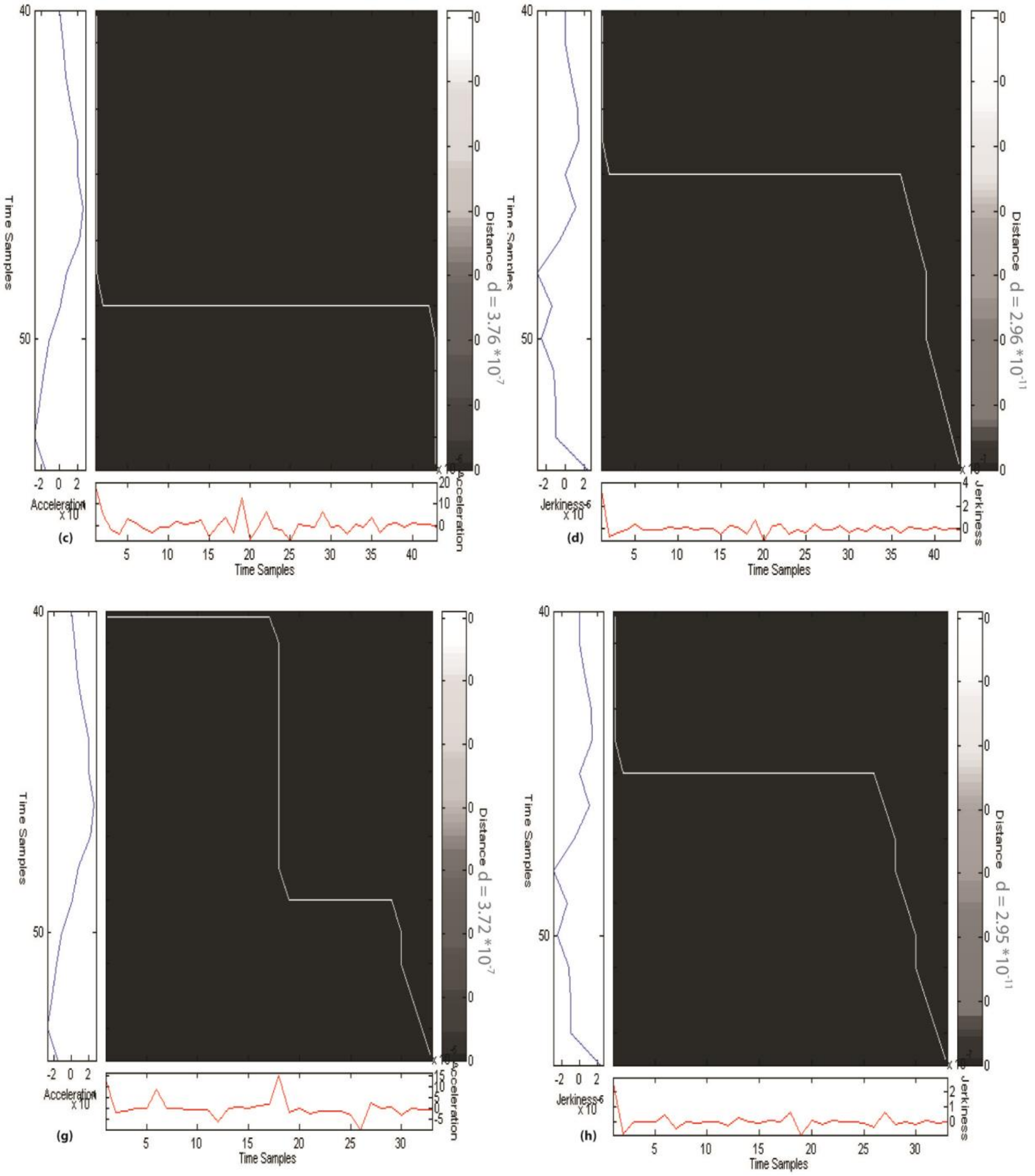


Figure 6.3 DTW Distance. (c) and (g) Acceleration, (d) and (h) Jerkiness.

Table 6.6 Rehabilitation Status Index

Patient	WK1	WK2	WK3	WK4	WK5	WK6	WK7	WK8
One	11.031	11.002	10.820	10.117	10.303	09.650	09.307	09.186
Two	11.503	11.418	11.350	11.086	10.917	10.942	10.891	10.865
Three	12.358	12.114	11.802	11.802	11.341	11.010	10.915	10.860

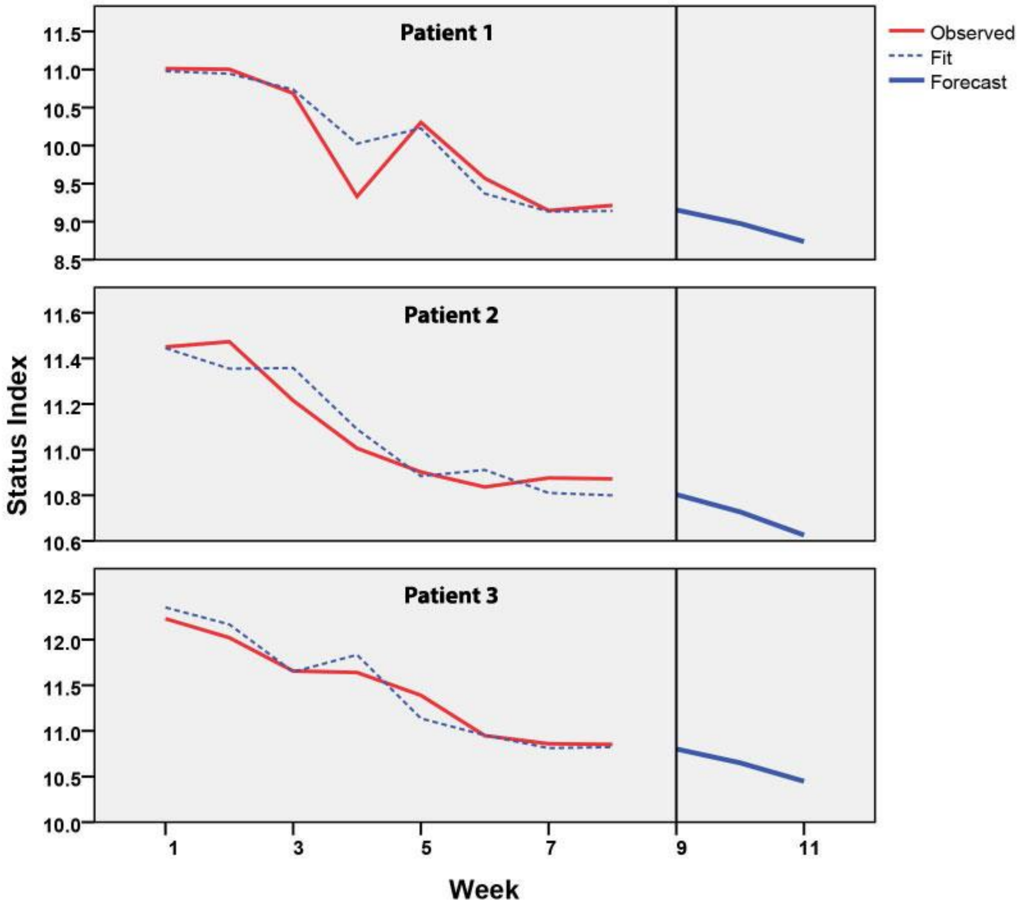


Figure 6.4 Forecasting the Rehabilitation Status index of the Patients.

Table 6.7 Results of the Usability Study

Patient	Entertaining	Motivating	Intuitive	Overall Acceptance
One	Strongly Agree	Strongly Agree	Agree	Great
Two	Strongly Agree	Strongly Agree	Agree	Awesome
Three	Agree	Strongly Agree	Agree	Excellent

6.3.5. *Discussion of the Results of Experiment One*

In experiment 1 we designed and implemented a cost-effective, entertaining, and intuitive upper limb rehabilitation and recovery prediction system for stroke patients. The influence of age of the healthy subject on the kinematics measurements was not statistically significant, and hence it was legitimate to compare the kinematics of the upper limb of healthy subjects with those kinematics of stroke patients though the difference between the mean ages in the two groups was big (age of healthy subjects is 39 ± 13.7, and the age years of stroke patients is 65 ± 12.5). Although the patients took more time to finish the exercise than the healthy subjects, both had similar kinematics curves shape whereas the patients' curves had more isolation. From this we could conclude that the movement of the upper limb of the stroke patients was not smooth. Moreover, the instability of the patients' upper limb could be easily noticed by examining their jerkiness curves (the number of peaks and valleys are much larger than those of healthy subjects.

The results of the clinical assessment confirmed our results. In the first week, and as it shown in table 6.1 and table 6.6, patient one has scored better than patient two and patient three in both the clinical and the kinematics measurement exercises. It is obvious that there is a correlation between the clinical assessment results and the proposed; the smaller the rehabilitation value, the larger the ARM test results. Although the rehabilitation status index of patients two and three were different (the values indicated that patient three had more severe attack than patient two) and the clinical assessments were the same, the rate of progress of patient three was higher than that of patient two. This would explain why both patients had very close rehabilitation status index by the end of week eight.

The distances between the signals of the patients and the signals of the healthy subjects have decreased during the course of rehabilitation (see figure 6.2, figure 6.3 and table 6.6). The number of the peaks has been also decreased. The patients have been clinically assessed again at week eight by using the action research arm test. The obtained clinical results also showed that the three patients have improved (patient one scored between 27 and 32, patients two and three scored between 22 and 27). This confirms previous studies [42], [7], [43] that proved the number of peaks of the kinematic signals decrease with the improvement of the stroke patient.

The values of the rehabilitation status index were not stationary; ARIMA(0,1,0), with d = 1. The absolute error between the observed and the fit signals was very small. Moreover, the level of accuracy of the forecasted values is significant. However, further study is required to increase the level of confidence of the obtained results.

6.4. *Experiment Two*

In this experiment, we present a low-cost virtual environment rehabilitation glove system for stroke patients. The system helps those patients with severely damaged upper limb to decrease the dysfunction. The novelty of this glove is that it is to be worn on the unaffected hand that acts as a natural robotic arm during the rehabilitation session. The glove is equipped with FSR sensors that measure the forces exerted by the affected hand on the unaffected hand. Results show that patients have significantly improved over the course of the rehabilitation program. Moreover, the patients themselves gave a positive feedback about the whole system; wearing the glove on the unaffected hand made their life easier and let them enjoy the rehabilitation sessions.

6.4.1. *Subjects*

The experiment was approved by the Ethical Committee of the Hamshary Hospital in Lebanon, and a consent form was signed by each participant. Three post-stroke patients of average age years were recruited to take this experiment. All patients (Table 6.8) were diagnosed with chronic stroke (<10 months). Exclusion criteria were serious cognitive problems, ability to move the affected hand without the support of the unaffected hand, fully bounded to a wheelchair, and in patients (the patients had not been hospitalized for 24 hours a day during the time of conducting the experiments). Patients did not attend any other rehabilitation treatment during the entire study; the only form of treatment that they got was provided by our proposed rehabilitation system.

Table 6.8 Patients Statistics

Patient	Stroke Side	Age	Stroke Date	Dominant Hand	Gender
One	Right	79	Jan 05, 2014	Left	Male
Two	Left	67	March 20, 2014	Right	Male
Three	Left	60	Jan 10, 2014	Right	Female

Patient's one description is as follows: a 79-year-old male who had a left Middle cerebral artery (MCA) ischemic stroke six months prior to the start of the experiment. Mr. S was sitting close to a chimney, drinking his cup of tea in a cold night of the winter of 2014. Suddenly, he felt dizzy, and both his face and right arm were numb. When he tried to stand up, he fell on the floor. Mr. S had hypertension and he was on medication during that time. Mr. S arrived to the hospital; he was diagnosed with ischemic stroke on the right side of his body. The right arm became very weak to the extent that he could not move it or control in any more. The stroke did not affect his cognitive abilities. Mr. S had not had stroke previously.

Patient's two description is as follows: a 67-year-old male who had a right middle cerebral artery (MCA) ischemic stroke four months prior to the start of the experiment. Mr. M was practicing some exercises and when he turned his head down he suffered from intense and sudden headache with blurry vision. Few hours later, Mr. M started to feel numbness in his left side. He had not suffered from migraine or any other disease before, so he thought it was a temporary symptom and it was going to fade soon. The next day, Mr. M woke up in the morning with his left side of his body paralyzed. He did not lose consciousness, but he could not speak properly nor had a clear vision. Mr. M was diagnosed with ischemic stroke and stayed in the hospital for three months.

Patient's three description is as follows: a 60-year-old female who had a right middle cerebral artery (MCA) ischemic stroke six months prior to the start of the experiment. Mrs. F was suffering from diabetes and she was a heavy smoker too. In the night, she had a stroke and she was feeling dizzy whenever she tried to walk. She woke up at four in the morning to go to the washroom. She moved one step from her bed and collapsed. Mrs. M’s son rushed her to the hospital where she was diagnosed with severe ischemic stroke. Mrs. F could not move her left upper limb prior to the time of the start of the study.

6.4.2. *FSR Glove*

The design of the FSR glove that was used in this experiment had been discussed thoroughly in section 3.2.2 (chapter 3). In nutshell, the glove is mounted with eight FSR sensors that have been placed on the glove under the supervision of an orthopedic physician in which the blood circulates normally in the patient’s arm.

6.4.3. *Virtual Environment System*

The proposed virtual environment system consisted of three main components: upper limb tracking unit, motion analysis unit, and multimodal feedback unit (Figure 6.5). The system combines recent rehabilitation approaches with efficient, yet affordable skeleton tracking input technologies, and multimodal interactive computer environment. Kinect, a skeleton tracking sensor from Microsoft for Xbox, is used as a 3D motion capturing and tracking of the upper limb. Affordability and controller-free are the main advantages of the Kinect sensor. The motion analysis unit evaluates the received data by comparing it with the data previously taken from the same patient. Therapists depend on this evaluation in order to assess the progress of the patient and determine the effectiveness of the treatment paradigm. The motion analysis unit sends requests to the game controller system to update the difficulty level of the exergame whenever needed. The system also provides the users with both visual feedback and auditory feedback. The visual feedback is represented by a predefined visual path that guides the user during the rehabilitation exercises. Moreover, a progress bar is displayed on the left bottom of the screen that shows the progress of the patients depending on the real-time data received from the glove (red means the unaffected hand is doing all the job and green means the affected hand is performing the exercise without the need of the support of the unaffected hand). The auditory feedback depends on the events that are taking place during the exercise and the data measurement received from the glove. At the end of the exercise the system plays an audio clip from pre-recorded audio clip list. The program chooses a clip to play that reflects the overall performance of the user.

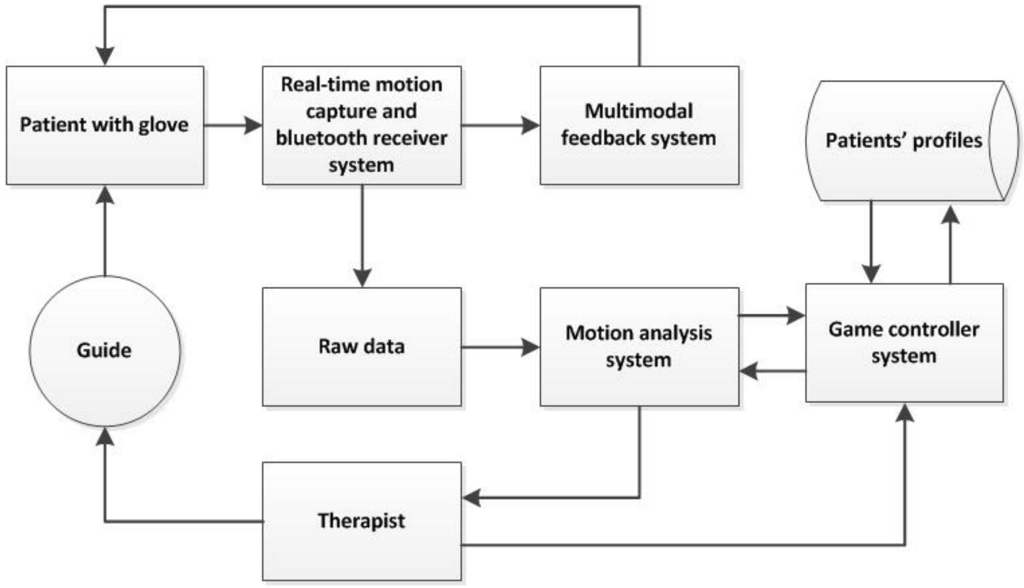


Figure 6.5 Rehabilitation System.

6.4.4. *Data Capturing Setup*

The recorded analog signals by eight sensors were converted into digital signals and their average value was sent to the computer. The sample rate of the data was 29 samples per second where the baud rate was 9600. The captured data is synchronized by a virtual cup that when it is touched, it triggers a signal to a specific module which opens a file and starts saving both the kinematics values and the force values.

During each task, we captured the values of five parameters: the displacement, the velocity, the acceleration, the jerkiness, and the exerted force of the affected hand on the unaffected hand. At the beginning of the first session, we took baseline measurements of these parameters and we used them to monitor the progress of the patient. The parameters were calculated according to the following formulas:

$$f = \frac{g * r}{255},$$

$$v_i = \frac{d_i - d_{i-1}}{t_i - t_{i-1}},$$

$$a_i = \frac{v_i - v_{i-1}}{t_i - t_{i-1}},$$

$$J = \frac{1}{N}(\frac{1}{2} * \int_0^T a'^2(t)dt),$$

where f is the equivalent force of the value captured by the glove, g is the gravity force (9.8 Newtons), is the actual reading of the glove, d_i is the position of the joint at time t_i, v_i is the velocity in cm/sec, a is the acceleration in cm/sec^2, J is the jerkiness cost, N is the number of times the user has performed the movement, T is the time interval, $a'(t)$ and is the rate of change of the acceleration.

6.4.5. *Clinical Study*

In this experiment, we have used the ARAT to evaluate the motor functions of the affected and the unaffected hand. We wanted to make sure that the severity of the stroke had no impact on the unaffected hand. The results of the ARAT for both the affected and unaffected hands are shown in table 6.9.

Table 6.9 Result of ARAT at the Beginning of the Study

Patient	Affected Hand	Unaffected Hand
One	Between 3 and 7	Between 51 and 55
Two	Between 3 and 6	Between 53 and 55
Three	Between 5 and 8	Between 54 and 57

[*] *Maximum score of this test is 57*

6.4.6. *Method*

Patients had four rehabilitation sessions per week for six weeks. Three of these four sessions were conducted at home under the supervision of a certified physiotherapist. One session per week took place in the rehabilitation center. Patients were free to stand or sit while they were performing the exercises. The therapists helped the patients wearing the glove on their unaffected hand. After that, the therapists asked the patients to stand at 2.2 meters from the Kinect camera. The therapists did not count the first few trails of the exercise during each session; they wanted the patients to get ready before they perform the official counted task. The patients could ask to end the rehabilitation session whenever they felt tired or uncomfortable. The experiment lasted for thirty minutes at each session.

A moving cup experiment was designed to help patients restore function in their affected upper limbs. The game is divided into several levels that differ by the movement distance, as well as, the trajectory line. The participants were asked to follow the line connecting the ball with the virtual cup. Whenever a new level starts, the trajectory line varies fifteen degrees from the previous level till it becomes ninety degrees with the horizontal. A timer is started at the moment the participant touches a virtual ball and ended when the ball reaches the virtual cup. A more detailed description of the game and its implementation can be found on our previous work [38].

6.4.7. *Results*

At week one of the study, the force exerted by the affected hand on the unaffected hand was almost constant (Figures 6.6(a), 6.6(e), and 6.6(k)). During the same week, the velocity curves exhibited bell shape with one peak, except for patient one whose velocity curve exhibited two peaks (Figures 6.6(c), 6.6(g), and 6.6(m)). Moreover, the small number of zero cross of accelerations and jerkiness curves indicated that the movement of the hand was steady. However, at the end of the study, the applied force of the affected hand on the other hand varied a lot, the velocity curves had more peaks than the velocity curves at week one, and the number of zero crosses of the accelerations and jerkiness curves were significant. Moreover, the time needed to finish the exercise was significantly longer at week six (2.44 ± 4.7 seconds), with a factor greater than 1.5 compared to week one (1.62 ± 2.2 seconds).

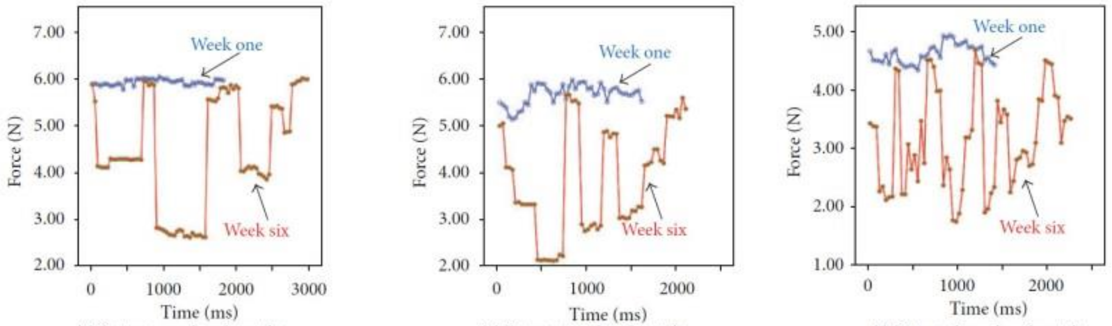
The variations of the movement velocities of the patients at the end of the study were not random; they changed with the change of the exerted force. Whenever the patients depended more on their affected hand to perform the exercise, the force measured by the unaffected hand, which acted here as a natural robotic arm, decreased and hence the velocity of the hand decreased too. This can be clearly seen in Figures 6.6(a) and 6.6(b) for patient one, Figures 6.6(e) and 6.6(f) for patient two, and Figures 6.6(k) and 6.6 (l) for patient three, where the velocities change in the same intervals the forces change.

Despite the smaller difference between the means of the forces applied on the glove at the beginning and the end of the study, the measurement values of the forces were statistically significant (table 6.10). The same argument can be applied to the velocity and the mean difference is small, but the paired samples -test succeeded to reveal a statistically reliable difference between the mean value of velocity of the patients at the beginning of the study and the mean value of the velocity at the end of the study. However, there is no statistically

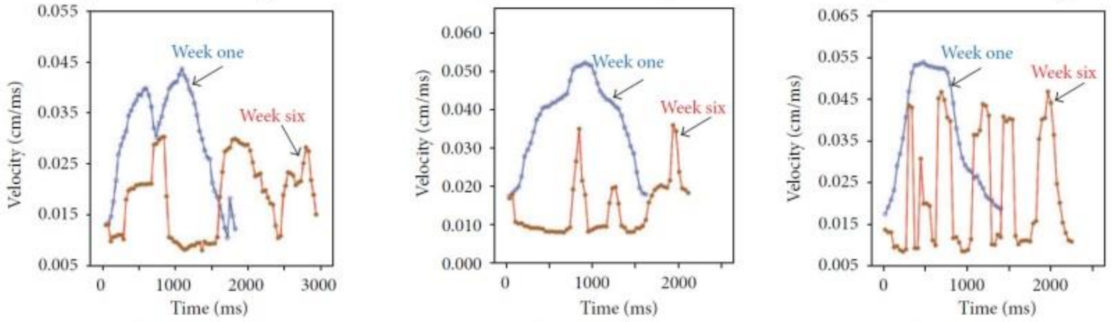
Table 6.10 Paired t-test of the Three Patients

Patient	**Paired Differences**											
	F1 – F2			V1 – V2			A1 – A2			J1 – J2		
	Mean	**Std**	**Sig**	**Mean**	**Std**	**Sig**	**Mean**	**Std**	**Sig.**	**Mean**	**Std**	**Sig.**
One	-1.14	.062	0^{*}	.011	.002	0^{*}	$-9.6E^{-6}$	$1.2E^{-4}$	.56	$-8.8E^{-8}$	$4.0E^{-6}$	.87
Two	1.86	-0.9	0^{*}	.026	.011	0^{*}	$-9.6E^{-6}$	$1.7E^{-5}$	.81	$-3.2E^{-8}$	$4.1E^{-6}$	.95
Three	1.14	-0.06	0^{*}	.014	.017	0^{*}	$-9.6E^{-6}$	$3.7E^{-4}$	.89	$-501E^{-9}$	$1.5E^{-5}$	.99

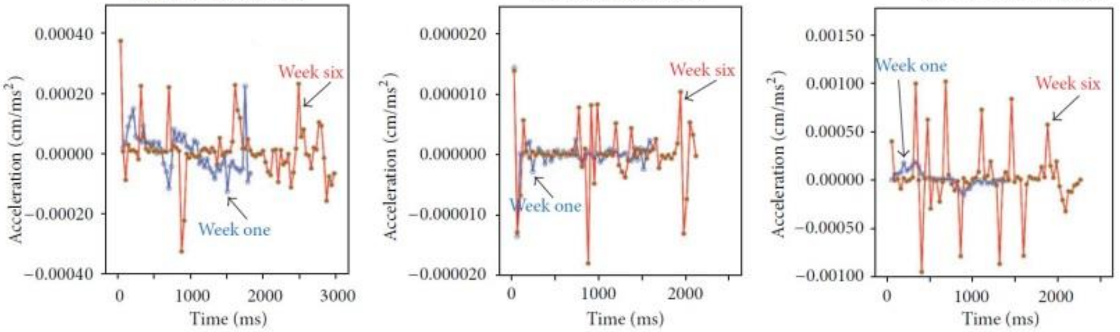
**Means there is a statistically difference between the values*



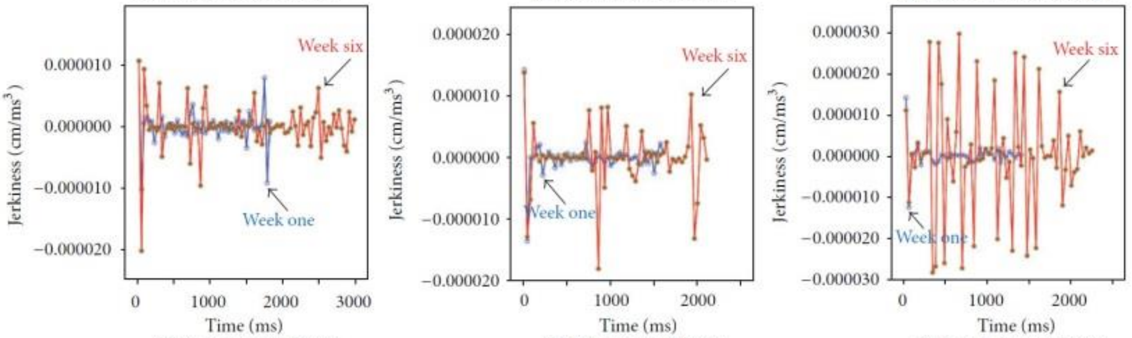
(a) Patient one: hand weight (e) Patient two: hand weight (i) Patient three: hand weight



(b) Patient one: velocity (f) Patient two: velocity (j) Patient three: velocity



(c) Patient one: acceleration (g) Patient two: acceleration (k) Patient three: acceleration



(d) Patient one: jerkiness (h) Patient two: jerkiness (l) Patient three: jerkiness

Figure 6.6 Captured Parameters at week one and week six.

reliable difference between the acceleration and the jerkiness at the beginning and at the end of the study.

The clinical assessment (ARAT) score at the end of this study showed an improvement of hands, the affected and the unaffected (table 6.11). The results of the clinical test were correlated with the outcome measurements obtained from the glove and the camera. The level of progress of the upper limb motor function was inversely correlated with force exerted on the unaffected hand and inversely correlated with the speed of the hand's movement. This indicates that the smaller the values of the force and the velocity, the less the arm motor impairment.

Table 6.11 Result of ARAT at the end of the Study

Patient	**Affected Hand**	**Unaffected Hand**
One	Between 8 and 11	Between 52 and 56
Two	Between 6 and 9	Between 53 and 57
Three	Between 8 and 12	Between 55 and 57

**Maximum score of this test is 57*

The overall evaluation of the system (glove + virtual environment) by the patients was satisfactory (table 6.12). Patient one, the oldest one among the other patients and who had no previous experience with 3D environment, found the 3D computer game environment enjoyable to be in; however, he needed more time to get used to it. Moreover, the three patients agreed that the system was comfortable to use, fun, and entertaining. In addition, they showed an interest in continuing their rehabilitation program using our proposed rehabilitation system, and they would highly recommend replacing the conventional home-based rehabilitation program with our system.

Table 6.12 Result of the Usability Study

Patient	Comfort of Use	3D Environment	System Feedback	Entertaining
One	Agree	Enjoyable	Excellent	Agree
Two	Strongly Agree	Normal	Excellent	Strongly Agree
Three	Strongly Agree	Fun	Satisfactory	Strongly Agree

6.4.8. *Discussion*

In this experiment, we designed and implemented a low-cost rehabilitation glove that meets the needs of stroke patients that could not or barely could, move their affected upper limb.

The bell-shaped trajectory of the hand movement during the first weeks indicated that the whole work is done by unaffected hand. This result confirms previous researches that have studied the trajectory of a normal hand of healthy subject moving from one point to another [118]. However, these trajectories look like a combination of the trajectories of health subjects and stroke patients together. It is obvious that when the patients fully depend on their unaffected hand, the curve looks like the curve of healthy subject, but when they put an effort and use their affected hand, the curve looks like the curve of stroke patient. Moreover, less variation of jerkiness at the beginning of the experiments indicates that the stroke had no impact on the unaffected hand of the patients.

Although the patients could not reach a zero force, which means the affected hands were not in fully control at any time, the significant variation of the forces between week one and week six shows clearly the progress of the patients. The clinical assessment confirms these results. Moreover, using the unaffected hand as a leading natural robotic arm of the affected hand made the unaffected hand stronger than before. The bigger the difference between the time needed to finish the exercises at week one and week six, the more the patients, were depending on their affected hand. For example, patients one and three, who have clinically progressed more than patient two, have registered bigger time difference than patient two.

Our results are compatible with previous researches that have been conducted by Cirstea and Levin [118], Turolla et al. [18], and Lambercy et al. [119]. In [118], the time needed to complete a rehabilitation exercise by the stroke patients was significantly larger than that of healthy subjects. Moreover, the measurement values of the velocities of the stroke patients were characterized by a larger degree of variation than the healthy subjects. Furthermore, the clinical test has revealed a significant correlation between the severity of the stroke and the kinematics of the affected hand. In [18], stroke patients were allocated to two treatments groups. Virtual environment was used along with the conventional treatment in the first group, while the other group was receiving the conventional treatment only. By the end of the study, stroke patients that received virtual environment rehabilitation recovered more than those who had the conventional therapy only. The feasibility of robot-assisted therapy on the upper limb recovery after stroke was shown in [119]. Patients have shown a significant improvement of their upper limb motor function six weeks after the end of the therapy.

Finally, the affordable price of the overall system, along with the comfortability of use and effectiveness in the rehabilitation process of the stroke patients, supports the concept that such system can help stroke patients with severely damaged upper limb restore some aspects of motor performance.

6.5. *Experiment Three*

This experiment investigates the relationship between kinematics and forces of the upper limb. A solid mathematical model (the least-square regression matrix) is used to find such relationships. The most innovative component, in addition to the correlation matrix, is the ability to derive the strength of the muscles from the kinematics values through the least square regression matrix.

6.5.1. *Clinical Study*

Before we conducted the experiment, an orthopedic doctor and a research physiotherapist had tested the physical abilities of the patients. The Action Research Arm test developed by Lyle [99] was used to evaluate the arm and the hand motor functions. The test was divided into four subtests: grasp, grip, pinch and gross movement. Each subtest contained an ordered items that were graded from 0 to 3: “3”, the highest grade which means the subject has performed the task normally; “2” means the subject has completed the task but with some difficulties; “1” that the subject could not complete all the parts of the task; and “0” that the subject has failed to complete any part of the task. The total number of items of the test is nineteen with a total score of fifty seven which indicates the arm is functioning normally. The results of the clinical test of the patients at week one, week eight, and week seventeen are shown in table 6.13.

Table 6.13 Result of ARAT at Weeks 1, 8, and 17.

Patient	First Visit (WK1)			Second Visit (WK8)			Third Visit (WK17)		
	Score Between			Score Between			Score Between		
One	35	…	43	38	…	46	40	…	48
Two	25	…	28	29	…	34	31	…	37
Three	35	…	43	38	…	46	41	…	47
Four	10	…	16	15	…	20	19	…	23
Five	10	…	16	16	…	19	19	…	23

**Maximum score of this test is 57*

6.5.2. *Experiment*

Eight healthy volunteers (mean age: 31 ± 10.9; mean forehand circumference: 28.2 ± 2.1; mean biceps circumference: 28 ± 1.6) and five stroke patients (mean age: 52.4 ± 20.8; mean forehand circumference: 26.56 ± 1.3; mean biceps circumference: 26.78 ± 1.7) participated in the experiment. The healthy volunteers, (table 6.14) were divided into two groups, the basic persons (five subjects) who do not practice on a weekly basis and the average persons (three subjects) who practice regularly every week. The patients (table 6.15) were having chronic strokes (> 8 months) with no serious cognitive problems, not fully bound to a wheelchair, and had not been hospitalized for 24 hours a day during the time of conducting the experiments (they were out patients). All patients were given a copy of an informed consent form to take home and read carefully, and to decide whether to sign it or not, and hence take part in the experiment. We made sure that the informed consent forms had been signed by the patients before we started the experiments. Moreover, the experiment was approved by the local ethics committee in the rehabilitation center. Finally, to ensure the reliability of the obtained results, the medical conditions of the patients were unknown to the experimenting team.

Table 6.14 Healthy Subjects Statistics.

Subject	Fitness	Age	Forearm Circumference (cm)	Arm Circumference (cm)
One	Basic	29	28.0	27.0
Two	Basic	55	24.0	25.5
Three	Basic	39	30.0	28.0
Four	Basic	26	29.0	30.5
Five	Basic	23	29.0	28.0
Six	Average	25	26.5	27.0
Seven	Average	24	30.2	28.0
Eight	Average	27	29.6	30.0

The exercises took place in a 5m x 7m room inside the rehabilitation center. In the following, descriptions of the test protocols are illustrated.

1. Prior to the first virtual-reality rehabilitation session, all the patients were asked to watch a pre-recorded video that describes the task they were going to perform.
2. As per Kinect requirement to be between 2 - 3 m from the subject, 2.2 meters was the distance from the patient to the Kinect camera.
3. The patients had tested the system before they performed the official task. That was the right time for us to talk to the patients; to discuss the different steps of the task, and to emphasize the importance of their cooperation.
4. The patients had four sessions in each week for a period of 24 weeks. Each session lasted for 30 minutes. However, we stopped some sessions before the planned time, because the patients were tired or got uncomfortable.
5. The data collected between week one and week seventeen was used to build the regression matrix, while the rest of the collected data was used in the validation process.

A moving cup experiment was designed to investigate the relationship between the kinematics of a moving hand and its strength. The participants were asked to reach and move a real cup in the vertical direction (figure 6.7).

Table 6.15 Stroke Patients Statistics.

Patient	Stroke Side	Age	Stroke Date	Forearm Circumference	Arm Circumference
One	Right	44	July 11, 2010	28.0 cm	28.8 cm
Two	Right	52	Feb 05, 2013	27.4 cm	26.4 cm
Three	Left	23	Feb 02, 2013	27.0 cm	28.0 cm
Four	Right	77	June 07, 2012	25.0 cm	26.1 cm
Five	Left	66	Aug 01, 2013	24.8 cm	24.3 cm

An augmented reality environment was formed that contained a virtual cup and a vertical straight line. The straight line represented the moving path between the start and the end points that the user would follow. A timer was started at the moment the participant touched the real cup and ended when the real cup reached the virtual one.

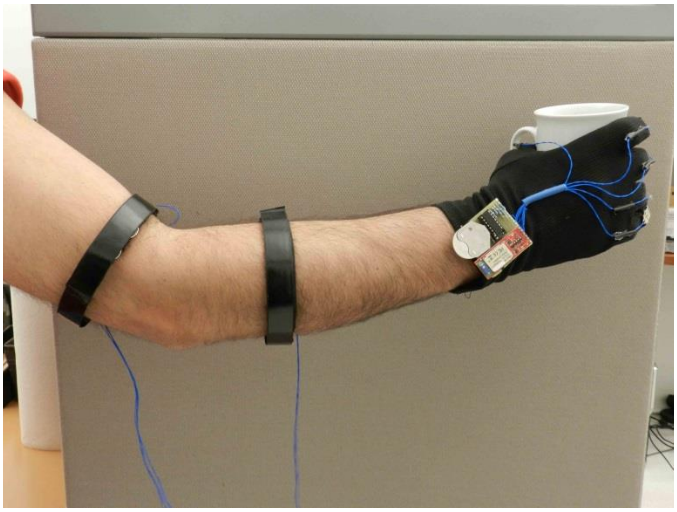


Figure 6.7 A Healthy Subject Conducting the Experiment

6.5.3. *Statistical Analysis*

Statistical analysis were conducted by using SPSS version 19 [120] and the mean difference was set to be significant at the 0.05 level. Separately for each participant, the average values of the kinematics and the forces were calculated and used to represent his/her overall performance. The ANOVA test was used to investigate the significant difference between the kinematics values and the forces values of the two groups of the healthy subjects (basic and average). The same test (ANOVA) was also used to determine the significant difference between the calculated parameters (kinematics and forces parameters) at the first and the seventeenth week of the stroke patients. Changes over time in the strength of the forces and the kinematics of the patients were evaluated by using the paired t-test.

The regression between the kinematics of the upper limb and the extracted forces for both the stroke patients and healthy participants were calculated using the least square regression technique. The resulted regression matrices were normalized for each individual at the first, the eight, and the seventeenth weeks. Moreover, we calculated the correlation between corresponding columns of the matrices that obtained from the same patients in week one and week seventeen.

6.5.4. *Results*

In this experiment, the least square regression matrix consists of three columns and twenty five rows (from the multiplication theory of matrices, our matrix should have the same number of columns of the kinematic matrix - three kinematic variables - and the same number of rows of the sensors matrix - twenty five data sensors - see equation 25). Before we discuss the calculated regression matrices of the stroke patients, it is worth to state that the variance of the obtained matrices of the same healthy subject were statistically significant ($P = 0.001$), and hence we could not find a unique relationship between the kinematics and the corresponding muscles of the healthy subjects.

Let M1, M2, and M3 be the least square regression matrices at week one, week eight and week seventeen respectively. We have conducted Pearson correlation to find the strength of association that exists between the three matrices M1, M2, and M3. As shown in table 6.16, M1, M2, and M3 are highly correlated and hence, we could use any of them in order to calculate the values of the forces. However, after testing the three matrices, the minimum error between the real values captured by the sensors and the calculated values of the upper limb forces was found by using M3.

Table 6.16 Correlation between the Regression Matrices M1, M2, and M3

Correlation	**WK1 & WK8**			**WK1 & WK17**			**WK8 & WK17**		
Patient	Vel. (col.1)	Acc. (col.2)	Jer. (col.3)	Vel. (col.1)	Acc. (col.2)	Jer. (col.3)	Vel. (col.1)	Acc. (col.2)	Jer. (col.3)
One	0.85	0.98	0.99	0.71	0.86	0.93	0.88	0.97	0.97
Two	0.80	0.94	0.96	0.6	0.73	0.93	0.79	0.93	0.96
Three	0.81	0.95	0.96	0.66	0.78	0.93	0.86	0.94	0.97
Four	0.97	0.98	0.99	0.92	0.95	0.97	0.91	0.96	0.98
Five	0.99	0.99	0.99	0.94	0.95	0.97	0.92	0.98	0.98

The average values of the measured forces of the arm, the forearm, and the fingers were greater than those derived using equation 25 (figure 6.8). However, there were no statistically significant difference in the measured values of the forces and the calculated ones (P = 0.234 for arm; P = 0.224 for forearm; and P = 0.349 for fingers). The smaller difference between the measured values and the calculated values of the forces was recorded at week18, whereas the larger difference was recorded at week 19.

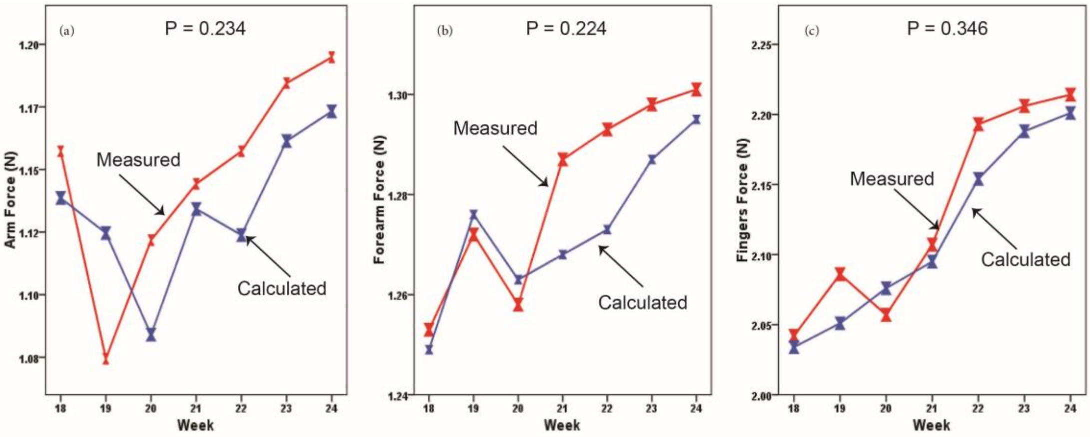


Figure 6.8 Mean Forces of the Upper Limb Measured between Weeks 18 and 24

The average force of each finger of the healthy participant followed the same trend over the four sessions during the first week; the forces dramatically increased at the beginning of the contact between the sensors and the cup, and then they almost reached a stable value (figure 6.9a). The minimum registered force (mean 2.21 N) was exerted by the little finger, while the thumb exerted the maximum force (mean 4.54 N). Although the forces exerted by the fingers of the stroke patients were not uniform, the minimum force (mean 0.61 N) and the maximum force (mean 1.81 N) were, just like the healthy subjects, registered by the little finger and the thumb respectively as depicted in figure 6.9d. The obtained results indicated that the mean values of the fingers of the healthy subjects were significantly different than those of stroke patients ($P < 0.001$). As compared with the strength of the fingers at week one, strength of the grooming, middle and ring fingers of the patients at week seventeen reported a non-significantly variance in the captured forces ($P = 0.21$). However, there were a statistically significant difference between the thumb and the little finger of the patients in week one compared to week seventeen ($P < 0.02$).

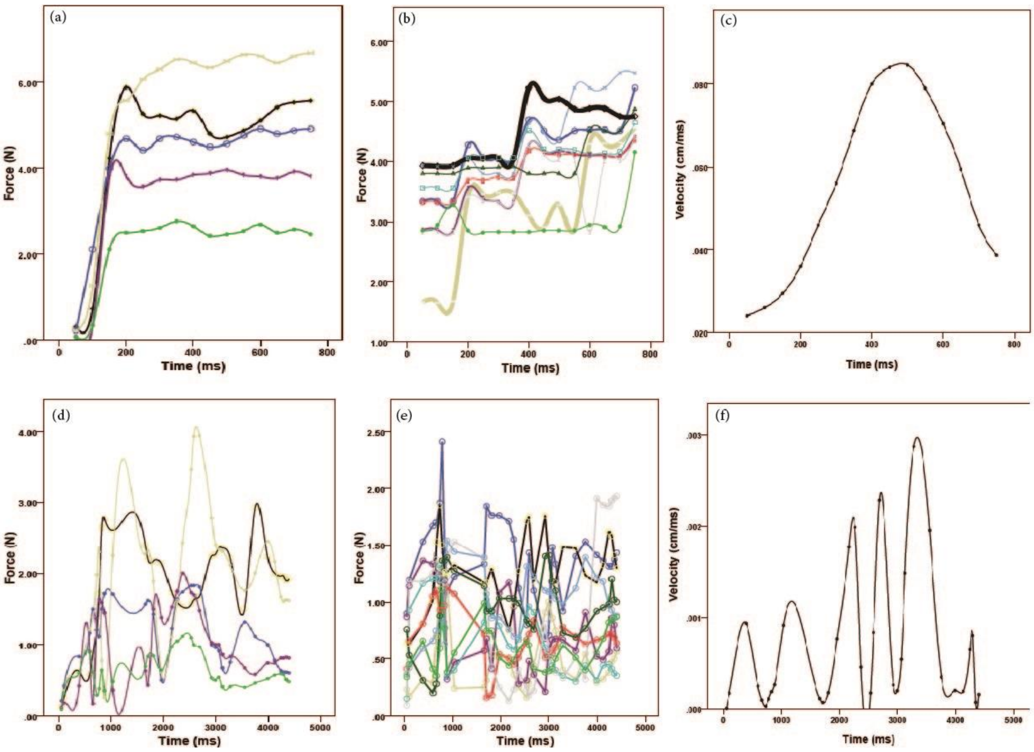


Figure 6.9 Muscles Forces and Hand Velocity Versus Time.

The forces generated by the healthy subjects' arm muscles have, to a certain extent, a certain pattern depending on the location of the sensor on the muscle (figure 6.9b). On the other hand, the curves of the forces of the stroke patient at week one are irregular; they do not follow a certain trend or pattern (figure 6.9d). After seventeen weeks of rehab the curves look smoother and a certain form of pattern can be detected and the overall forces exerted are greater in the seventeenth week than that in first week.

The corresponding velocity curves for the healthy and patients participant are shown in figure 6.9c. The velocity profile for the healthy subjects shows slightly negative skewed bell-shaped curve (single peak); the maximum velocity (v = 0.084 cm/ms) is registered a 500 ms and the total duration of time is 750 ms. However, in week one the velocity profile of the stroke patient has multiple peaks and the maximum velocity is lower (v = 0.0029 cm/ms). In week seventeen, the number of the peaks decreased while the maximum velocity increased (v = 0.0046 cm/ms). Although the mean velocities of all the patients increased, the amount of change was not statistically significant between week one and week seventeen. However, when the t-test was conducted on the jerkiness and zero-cross values of week one and week seventeen, it was found that the group of patients were associated with statistically significant mean difference (table 6.17).

Table 6.17 Summary of Different Variables

Patient	**First Visit (WK1)**			**Second Visit (WK8)**			**Third Visit (WK17)**		
	Time Needed	Max Velocity	Zero Cross	Time Needed	Max Velocity	Zero Cross	Time Needed	Max Velocity	Zero Cross
One	4.4	0.0029	56	2.8	0.0041	42	2.3	0.0046	31
Two	8.4	0.0026	103	6.9	0.0028	86	6.4	0.0034	78
Three	4.1	0.0024	60	3.4	0.0035	48	2.9	0.0041	41
Four	10.2	0.0027	135	9.5	0.0018	122	9.2	0.0025	112
Five	12	0.0051	181	10.1	0.0027	144	9.3	0.0037	126

The increase of the kinematics and the forces measurements was consistent with the results obtained from the clinical tests (table 6.13, and table 6.17). Moreover, such consistency was emphasized when we conducted the clinical test again at the end of the study (week 24).

6.5.5. *Discussion*

In this study we found the relationship between kinematics and strength of upper limb of stroke patients. The velocities of the hand movement of stroke patients were characterized by a larger degree of variation than those of healthy subjects. Moreover, the time needed to finish the task by the patients was longer than that of healthy subjects. The collected measurement data show that the trajectories of the movements of the patients were not smooth and precise. Indeed, the large number of both, the peaks of the jerkiness and the zero-cross of the patients' curves confirms that (see table 6.15). The kinematics values obtained from the patients were highly correlated with the severity of the stroke attack. In particular, data from patients with high severe attacks indicate less velocity, less acceleration, but more variations in the jerkiness.

Most studies show that the performance of the upper limb stroke patients is correlated with the severity of the stroke attack [31, 34]. Patients who had a severe stroke attack suffer from muscle weaknesses which lead to decrease of the kinematics. As expected, we found that there was a significant relation between the strength of the muscles of the fingers, forearm, arm and the kinematics of the upper limb. Moreover, our study has suggested that the strength of the muscles of the fingers and that of the forearm were significantly correlated during the first 500 ms of the task (time needed to start moving the cup in the vertical direction). After that, the forces of the muscles of the arm started to increase with overall values larger than those of the forearm. This indicates that the forearm muscles are more engaged in the grasping activity than the arm muscles. This result confirms a previous study by Sara et al. [32] who showed that there was no significant change in the arm muscles activity at the beginning of the task. However, during the object transport in the vertical plane maximum activity of the arm muscles was recorded.

The large variation in jerkiness measurements of the upper limb of the same patient is due to the lack of muscle strength in the group muscles of the fingers, forearm, and arm. Indeed, as shown in figures 6.9, the values of the forces exerted by the muscles of the fingers are very small compared to those exerted by healthy subjects. Moreover, the inconsistency of these values (note the lack of a trend in the obtained data) indicates that there is difficulty planning, coordinating, and controlling the movements of the upper limb. Such difficulty is significantly related to the severity of the stroke. In addition, we have noticed that there is a significant variation between the groups of data obtained from the different patients. For example, the magnitude of the standard deviation (3.5 seconds) of the time needed to complete the task is clinically significant. By the same token, the magnitude of the standard deviation (53) of the number of zero-cross is also clinically significant. In contrast, the kinematics measurements (including jerkiness) as well as the values of the muscles' forces of the healthy subjects were consistent during the entire upper limb analysis session. Our results are compatible with previous researches that have been conducted by Stewart et al. [33] and Xiao and Menon [25]. In [33] the time needed to complete a task of moving a cup was relatively small, and the trajectory profile of the velocity was a bell-shaped. In [18], eight FSR sensors mounted on a strap and placed around the forehand of a healthy subject. The captured forces of the muscles of the forehand exhibited patterns that can correctly classify six postures associated to a drinking task.

Finally, the least square correlation matrix showed to be a good tool in calculating the forces of the muscles giving the upper-limb's kinematics of the stroke patients. The same result could not be proven when it comes to healthy subjects. In fact, and since the rehabilitation exercises in this study require a little effort to perform, the healthy subjects could control the kinematics and the strength of their muscles at their will (they could change the measurement values of the forces without changing the kinematics and vice versa). Back to the regression matrix of the patients, we could notice that the more severe the stroke is, the higher is the correlation between the corresponding columns of the M1, M2 and M3. For example, patients four and five, with the most severe stroke patients in our study, have the largest correlation between the matrices obtained at week one, week eight, and week seventeen (table 6.16 and table 6.17). The correlation increases between the corresponding columns as we move from right to left (table 6.16).

The small difference between the measured values of the forces and the calculated values indicates that we could use an unobtrusive device, Microsoft Kinect camera in our case, to find the strength of the forces of the upper-limb of a stroke patient. To the best of our knowledge, this is the first work that finds the regression matrix between the kinematics and the associated forces for stroke patients. The majority of the current approaches so far have used the wearable-based systems to measure these forces. However, our approach will not cause discomfort to the patients while they are preforming their rehabilitation exercises because they do not have to wear tracking devices or forces measuring devices and yet the values of the forces can still be estimated.

6.6. *Summary*

In this chapter we described the experimental evaluation of the proposed framework. Three clinical studies have been conducted over a course of several months. In the first experiment, a recovery prediction model was evaluated by conducting the proposed algorithms on three stroke patients. In the second experiment, a novel rehabilitation glove is tested on three stroke patients with severe conditions. Finally, in the third experiment, a mathematical model is used to predict the strength of the upper limb muscles using a Kinect camera. The model is tested on five stroke patients. The results of the three experiments were very encouraging and indicated a great potential of Kinect as a rehabilitation tool.

Chapter 7. Conclusion, Limitations, and Future Works

In this thesis, we have presented our effort towards building and implementing a virtual reality home-based cloud post-stroke rehabilitation framework. The framework consisted of two sides, a client side and a cloud side. In the client side, a set of tools has been developed that allowed a simple interaction between the patients and the software. In the cloud side, the developed tools were responsible for analyzing, evaluating and predicting the progress of the patient. Moreover, it facilitated the patient-therapist communication in which the therapist could remotely evaluate and control the level of intensity of the rehabilitation regime.

Three of the main disadvantages of the robotic and haptic devices are their (1) bulky shape, (2) heavy weight, and (3) being very expensive. In this proposal, we have developed two lightweight, inexpensive measurement glove assistive devices. The first glove is designed to find the force exerted by the affected hand on the unaffected hand. The novelty of this glove is that it is to be worn on the unaffected hand that acts as a natural robotic arm during the rehabilitation session. The second glove is designed to measure the strength of each finger during grasping movements.

From a social perspective, we believe that this work can help post-stroke patients in particular and patients with upper extremity impairments in general to get a cheaper and beneficial treatment from the comfort of their homes. In addition, it will help reduce the burden on the health care system by requiring less therapist intervention. On the other hand, I believe that this research would contribute to innovations in theory, design and implementation of smart environments for medical purposes.

Though we have used a clear methodology to reach our results, our study has some limitations. First, the number of games that are provided for the stroke patients is limited.

Some patients may lose interest in performing their rehabilitation exercises because they like to play a specific game which may be not available. Second, estimating the strength of the forces from kinematics has facilitated the pre-setup of the exercises, however, such estimation valid for a certain period of time. Moreover, the estimation is not unique for all stroke patients. Third, Kinect is a revolutionary tacking sensor; however, the detection and tracking of the upper limb of the stroke patients is not accurate when they are bounded to the wheelchairs. That was why we made sure that the patients were standing while they were performing the rehabilitation exercises. Finally, we believe we should increase the number of patients and the number of rehabilitation sessions in order to have conclusive evidences about the effectiveness of the proposed framework.

In my future work, I am going to address the above limitations. In addition, I am aiming to investigate the use of neural networks, fuzzy logic, and other models in the rehabilitation environment and study their effects on the adaptation process and on the training efficiency.

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