INTEGRATION OF MULTIMODAL SENSOR DATA FOR TARGETED ASSESSMENT AND INTERVENTION

by

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DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy at
The University of Texas at Arlington
August, 2017

Arlington, Texas

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ABSTRACT

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Physical and Occupational Therapy have been used for many years to help people who have suffered an injury of some kind. This injury could be caused by a physical injury, such as falling or breaking a bone, or a brain injury, such as a stroke. Traditional interventions involve having a therapist watch a patient perform any prescribed interventions to see if they are done correctly and to assess progress, or to have a patient perform exercises at home unsupervised. Patients, once discharged, do not always adhere to the prescribed intervention. They begin to not keep scheduled appointments and not complete the at home exercises. This limits the patient's chances for a full recovery.

Tele-rehabilitation is a potential answer to improve adherence and rate of recovery. By using gamification and Virtual Reality (VR), rehabilitation exercises can be turned into more engaging and entertaining activities called exergames. Patients show a preference towards these exergames over traditional interventions. The sensors required to gather input for these games often include motion tracking technologies.

These input modalities can be used to gather more information about a patient than just the score achieved in a game. Detailed information about the patient's motions can be collected. With new low-cost alternatives available, such as the Microsoft Kinect, Leap Motion, and HTC Vive, these types of tele-rehabilitation systems are becoming more affordable.

This research aims to develop a virtual recreation of an Occupation Therapy assessment using newer low-cost equipment. Data gathered from gameplay and from sensors are used to assess a user's performance. Evaluation of different types of gameplay will be done to find the best way to administer computerized or virtual versions of this Occupational Therapy task.

ACKNOWLEDGEMENTS

I would like to thank my supervising professor, Dr. Fillia Makedon, for her support throughout both my undergraduate and graduate careers. Her mentoring and encouragement has been extremely valuable. I would also like to thank my committee members Dr. Vassilis Athitsos, Dr. Heng Huang, and Dr. James LePage for their insight during my PhD studies. Thanks also goes to Dr. Gian-Luca Mariottini for the time he spent serving on my committee during the early phases of my studies.

Lastly, I would like to thank my fellow Heracleian Lab members, both past and present. Their guidance, mentoring, and support have been valuable. Working with them has been an extremely great pleasure.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Problem

During life, people may injure themselves or become injured by the actions of others. These injuries may cause people to become either temporarily or permanently disabled. People can also become disabled by cause of an illness or something else happening inside the body. Regardless of the cause, many disabled individuals undergo some type of therapy, whether that be physical, occupational, speech, vocational, or a combination of these. This thesis will focus primary on physical and occupational therapy applications, but can be extended into the others.

Physical Medicine and Rehabilitation (PM&R), according to the American Board of Physical Medicine and Rehabilitation, deals with the “diagnosis, evaluation, and management of persons of all ages with physical and/or cognitive impairment and disability,” [1]. Two roles in PM&R are those of Physical Therapists (PTs) and Occupational Therapists (OTs) [2]. The American Physical Therapy Association defines the role of a PT as someone “who diagnose(s) and treat(s) individuals … who have medical problems or other health-related conditions that limit their abilities to move and perform functional activities in their daily lives” and “examine(s) each individual and develop(s) a plan using treatment to promote the ability to move, reduce pain, restore function, and prevent disability” [3]. The American Occupational Therapy Association Inc. defines the role of an OT as someone who “help(s) people of all ages participate in the things they want and need to do through the therapeutic use of everyday activities (occupations), … helps people function in all of their environments, … and addresses the physical, psychological, and cognitive aspects of their well-being through engagement in occupation" [4].

PTs and OTs provide interventions to their patients in order to improve their patients' quality of life, strength and range of motion (ROM) in affected areas of the body, and ability to perform activities of daily living (ADL). Interventions are the "interactions and procedures used in managing and instructing patients" [3]. These interventions are customized for each individual patient based on their diagnosis, cause, and progress during the intervention. While the goal of Physical Therapy and Occupational Therapy interventions are similar, the means of which these goals are achieved are different. Physical Therapy interventions may involve stretching of muscles, applying weight and attempting to use the affected portion of the body, heat treatments, and many others but not limited to those detailed in [5] and [6]. Occupational therapy interventions may involve buttoning a shirt, picking up and placing various types of objects, feeding yourself, and others but not limited to those described in [7].

As the recovery process begins, patients are transitioned from a hospital to their house. These patients are expected to go to local clinics to perform interventions, as well as complete a home-based program. The goal of these interventions is to further aid in the recovery of patients once they leave the hospital and to learn how to function in their normal day to day lives.

This is where the issue of patient compliance and/or adherence begins to surface. Some patients do not complete their prescribed interventions (some studies report over 50% [8]), while some never attend appointments with PM&R staff [9]. There are many reasons for this noncompliance, including lack of time due a limited lifestyle, patients thinking something else is the cause of the pain or will solve their problem, patients finding the exercises too boring and repetitive, and many other detailed in [10].

1.2 Motivation

One of the many proposed ideas to solve this compliance issue is to use virtual reality to enhance traditional therapy techniques [11]. Virtual Reality (VR) can be defined as "the use of computer technology to create the effect of an interactive three-dimensional world in which the objects have a sense of spatial presence" [12]. VR therapy has already been successfully applied to the treatment of PTSD and to help people get over phobias [13,14]. VR exposes people to triggers of a psychological condition in a safe and controlled environment. These triggers can be changed or modified based on a person's reaction and progress through a recovery program.

VR can be applied to physical and occupation therapies in a similar fashion. A Virtual Environment (VE) can be created to mimic real world situations where a patient can perform any actions needed to complete a goal. The actions, goals, and all other aspects of the VE can be modified based on the current abilities and limitations of the patient to make it easier or harder. This happens under the supervision of a therapist which can make any necessary changes during the course of treatment and make sure a patient does not injure him/herself. VR interventions have been shown to have an increased compliance rate and an increased rate of recovery compared to traditional interventions [15]. Also, the opinions of the patients towards interventions have also improved when they are VR based [16].

Turning therapies into games have also been proposed, especially when developing interventions for children. Using game based, or "gamified," interventions have shown similar results to those using VR interventions. This has led to VR gamified interventions. Patients undergoing these interventions not only showed an increased compliance rate and rate of recovery [17], but also experienced less pain during these games [18].

The main concern with VR gamified interventions is that these interventions require expensive sensors, computers, and other equipment, many of which are connected to the patient. This poses two issues. The first is the cost of the equipment. Many hospitals and clinics cannot afford to purchase this equipment, making VR based interventions available to those who have access to those certain facilities. The cost would also prevent many patients from doing any VR home-based interventions. This would require all patients to do interventions at a hospital or clinic. This would be next to impossible for patients who live far away from these facilities or have busy lives. Also, PM&R staff would have to obverse all activity that takes place to make sure there is no damage to equipment, therefore increasing staff costs, only making VR interventions even more expensive.

The second issue is that the patient has to wear this equipment or have wires attached to them. This causes the patient to become encumbered with the extra weight of the equipment. The wires also limit the movement of patient. All of these may limit the effectiveness of Physical and Occupational Therapy. This would require extra care to be taken during interventions to make sure no harm comes to the patient.

In recent years, new low-cost off-the-shelf sensors have become available, many of which were initially designed for playing games. There are many examples of these. The Microsoft Kinect tracks human body movement in the form of a skeleton. The Leap Motion Controller tracks the movement of the hand and fingers. The Nintendo Wii has accessories that track human movement and infrared light. The Myo, by Thalmic Labs, tracks the movement of an arm while obtaining electromyography (EMG) data from the muscles to interpret hand gestures. Head Mounted Displays (HMDs), like the Oculus Rift, Samsung Gear, and HTC Vive, have made immersive VEs much more affordable and accessible to many individuals. Many of these sensors have already begun being used in various types of therapeutic interventions and are showing positive results [19, 20]. These sensors would allow the use of VR based interventions in a home environment, allowing a significant amount of data to be collected when a therapist is not present.

1.3 Proposed Work

In this dissertation, we present a framework for a Computerized Rehabilitation system using the different versions of the Box and Blocks Test. The goal of this system is to allow a patient to complete different versions this test in a home environment without a therapist present. A therapist would prescribe an intervention and send it to the patient via a hospital system. The patient would log in and see what exercises or games to do that particular day. The patient would then perform those exercises or play those games using various low-cost sensors, generating large amounts of multi-modal data. This data then goes though many types of computational analysis, such as data fusion, gesture recognition, activity performance evaluations, and many others in order to provide reports. These reports contain any necessary information in a readable form that the therapist and the patient need to further the recovery process. This information is saved to a database so that it can be viewed by both the therapist and the patient as needed. The patient would view their information in order to see visible progress of their rehabilitation, which would motivate them to perform even better and perform the interventions. The therapist would view this information in order to monitor patient progress and make changes to the intervention to help the patient recover faster. Figure 1.1 gives a general overview of the proposed cyber-physical framework.

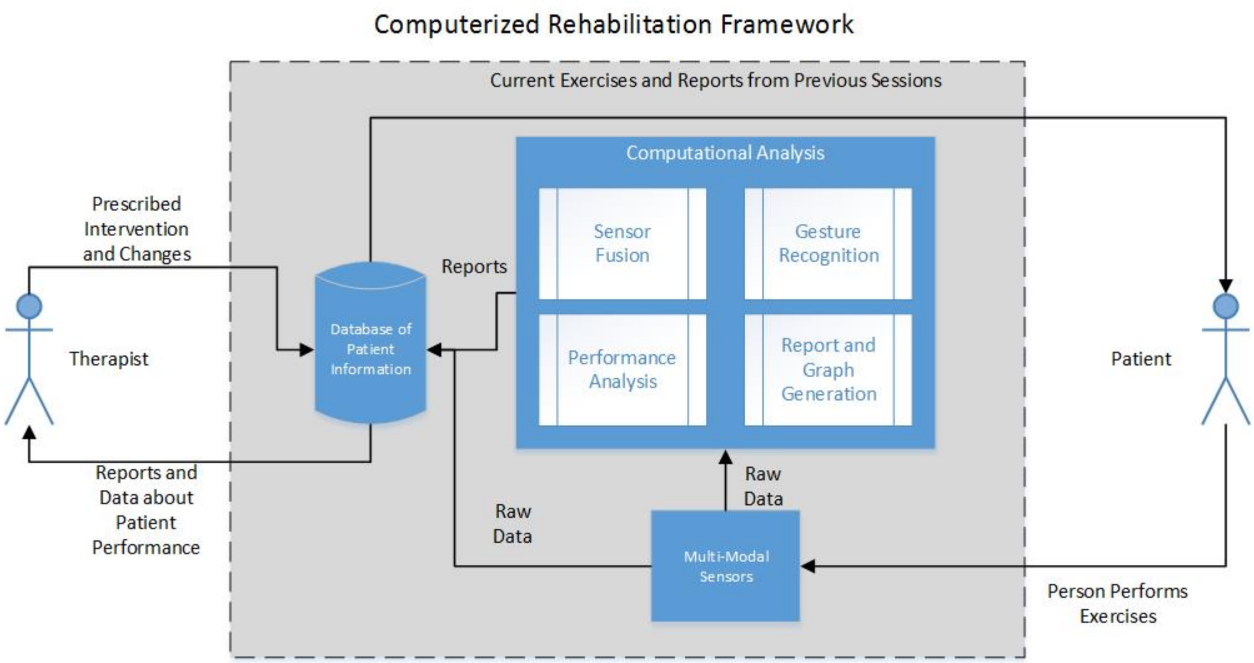

Figure 1.1 Architecture of Proposed Box and Blocks Rehabilitation Framework

This dissertation focuses on the sensor and computational analysis portions of the Box and Blocks Rehabilitation framework. The topics of this dissertation is organized in the following order. Chapters 2, 3 and 4 focus on sensor validation, including visualizing data obtained from sensors, determining error, and using the sensors in tasks to see if they would be useful for a more complicated task. Chapters 5 and 6 present games that may be used for physical or occupational therapy. Chapters 7, 8, and 9 present the Box and Blocks Test, 2 computerized versions of this test, user opinions of the different versions, and analysis of data obtained from the computerized versions. Finally, Chapter 10 will provide concluding remarks and a discussion of future work. Figure 1.2 provides a visual representation of this dissertation.

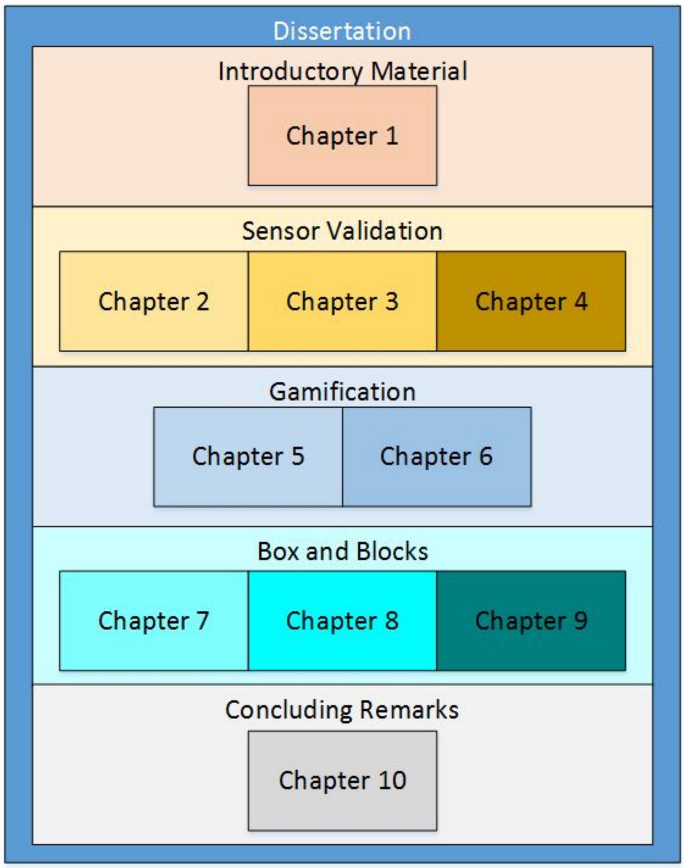

Figure 1.2 Structure of Dissertation

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CHAPTER 2

USING CAVE IN PHYSICAL REHABILITATION EXERCISES FOR RHEUMATOID ARTHRITIS

2.1 Introductory Comments

This chapter is the first chapter of the Sensor Validation section of this dissertation. If obtained sensor data cannot be easily visualized or explained to a health professional, then a case could be made that the sensor should not be used in rehabilitation. However, if the data obtained is combined with data from another sensor, or the results from computational analysis of that data, is something that can be easily visualized or explained, then it would be valid for rehabilitation.

This papers shows ways to visualize data obtained from motion tracking sensors. It also presents analysis tools on how to get useful and meaningful results from the data obtained. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, ran participants, performed analysis, wrote most of the paper
- Eric Becker: Supervised the study, assisted in study design, suggested analysis techniques, wrote some of the related works, helped edit the paper
- Fillia Makedon: Supervised the study, helped edit the paper

USING CAVE IN PHYSICAL REHABILITATION EXERCIESES

FOR RHEUMATOID ARTHRITIS[1]

Shawn N. Gieser, Eric Becker, and Fillia Makedon. 2013. Using CAVE in Physical Rehabilitation Exercises for Rheumatoid Arthritis. In *Proceedings of the 6th International Conference on PErvasive Technologies Related to Assistive Environments* (PETRA '13). ACM, New York, NY, USA, , Article 30 , 4 pages.

DOI=http://dx.doi.org/10.1145/2504335.2504367

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2.2 Abstract

Rheumatoid Arthritis is a chronic disease that leads to swelling and inflammation of the joints and even spread to surrounding tissues and blood vessels. Physical therapy has been used successfully to slow the effects of this degenerative disease. Patients, however, do not want to do these exercises due to the fact they are boring and repetitive. In this paper, we introduce the first steps in creating a virtual environment using a CAVE System for the physical therapy sessions where the user will be engaged and motived to complete the exercises prescribed by his or her doctor.

Categories and Subject Descriptors: I.4.8 [Image Processing and Computer Vision] Scene Analysis – Motion Tracking, J.3 [Computer Applications] Life and Medical Sciences

General Terms: Experimentation, Human Factors

Keywords: Rheumatoid Arthritis, CAVE, Motion Tracking, Physical Therapy

2.3 Introduction

Rheumatoid Arthritis (RA) is a chronic, systemic, inflammatory autoimmune disorder causing pain and swelling of both large and small joints and commonly presents in patients age thirty to fifty years of age [1]. RA can also spread to muscles, arteries, and internal organs, causing an increase in morbidity and mortality [2]. RA decreases the lifespan of an affected person by an estimated five to ten years [3].

Not only does RA decrease a person's lifespan, but it also decreases your productivity while they are working. A person will have a fifty percent probability of being permanently work disabled after a range of four and a half to twenty-two years, losing an average of thirty-nine days in the first year [4]. This loss of productivity, along with the chronic pain caused by RA, leads patients to become depressed, thirteen to seventeen percent of which are severe cases [5].

Patients were originally told rest and not exercise whenever possible, but that has changed over the past twenty years with studies focusing on the effect of exercise and outcome measures as diverse as fitness, muscle strength, bone density, functional scores, disease activity and joint damage [6]. Even though exercise helps, there is non-compliance with some patients when it comes to performing the prescribed exercises. The reason for non-compliance could be that they do not have time, find them to boring, or are just unable to do them [7]. In fact, less than fifty percent of patents continue performing the exercises when not supervised [8].

So this makes the question of "How do we keep patients involved in their rehabilitation exercises to where they want to complete them?" In this paper, we present our preliminary results in creating a virtual reality (VR) environment using a CAVE system for RA physical therapy in which patients will complete game-like activities to motivate them to complete their activities. More specifically, we will present a basic calibration sequence and what data can be represented with just a basic exercise from tracking the motion of the patient.

In this paper, we will first talk about related works done with VR and CAVE in other aspects of health care, as well as other technologies in motion tracking. Second, we will describe the calibration sequence and exercises that were done to capture data. Then we will show results of analysis done on the captured data and explain their significance. Lastly, we will describe our conclusions and future work for this work.

2.4 Related Works

2.4.1 Virtual Reality and CAVE in Rehabilitation

VR has been used in many different forms for rehabilitation. The main reason for this particular method is that VR can provide interesting and engaging tasks that are more motivating than formal repetitive therapy [9]. This brings the complexity of the physical world into the controlled environment of the physical. VR allows for the measurement of natural movement within natural complex environments. In fact, this particular method also allows us to create a synthetic environment with precise control over a large number of physical variables that influence behavior while recording physiological and kinematic responses. VR also provides the numerous strengths, which include stimulus control and consistency, real-time performance feedback, modifications of the program based on patient's abilities, the ability to distract the patient, and to motivate the patient directly while performing the exercises [10].

Using VR in rehabilitation has shown an improvement over regular rehabilitation techniques. Over seventy percent of patients in a VR rehabilitation group showed clinically significant improvements, while only forty percent of patients did who were in a traditional rehabilitation group. Also, the VR group had a higher enthusiasm towards the exercise programs, enjoyed the exercises more, and had an improved confidence level [9]. All these can cause long term compliance while rehabilitation takes place.

VR rehabilitation has been used in patients with Cerebral Palsy, patients recovering from surgery, and patients who have had a stroke [11]. Both [11] and [12] use VR for stroke rehabilitation using a glove for haptic feedback. [11] focuses more on the technical side showing an improvement in patient's use of hands. [12] shows that patients actually liked this exercise and that they would actually expect further improvement if people.

CAVE is very useful in VR rehabilitation. CAVE can track a patient's arm and represent it in the virtual world. In this case, a patient would have to actually move and reach into the virtual world in order to interact with objects and to perform his exercises. One can save this data and generate the joint angles for the arm. This data can be used to track range of motion over time and see improvements the patient is making [13].

2.4.2 Other Technologies in Rehabilitation

Other motion tracking technologies have been used in various rehabilitation exercises. VICON has been used in Cerebral Palsy rehabilitation therapies by tracking children while they are playing games such as Wii Sports and Dance Dance Revolution [14]. VICON was also used in determining balance of patients by having them stand on a tillable surface that would shake and the patients would have to regain balance [15]. While VICON is a good approach, the time it takes to connect all the reflective sensors or putting on a suit for motion caption would take too much time.

Nintendo Wiimotes have been used in motion tracking as well. This is used mainly in upper body rehabilitation since the Wiimote has to be held in a hand. The patient can use the Wiimote to interact with objects in the virtual environment. This requires the set up to have at least two Wiimotes and an infrared LED emitter. This was added into a CAVE environment [16].

Lastly, the Microsoft Kinect has become popular in the last few years. A system called RPLAY is using the Kinect for tracking the patient's motions. It uses a Dynamic Space-Time Warping algorithm to analysis 3-dimensional human motion. However, the accuracy of the Kinect is not perfect and can cause issues the tracking. Also, it does not allow the subject to be fully immersed in the environment [8].

2.5 Experiment

For this experiment, we used student volunteers to would simulate a patient by moving their arms in big circles while hitting certain target points along the circle's path. We used the IS-900 for capturing data. The two wrist sensors were worn by the student while the head sensor was placed on the ground to be used a reference point. The wand was not used for this experiment. The experiment consists of two stages. The first part calibrates the system for the current student. The second part is the data collection while the student performing the exercise.

2.5.1 Calibration

Before we can begin data collection, we have to calibrate the system for the student. The calibration process establishes the target points that the student would have reach. Figure 2.1 shows the six target points that each student had to calibrate, with each one given a code of one through six.

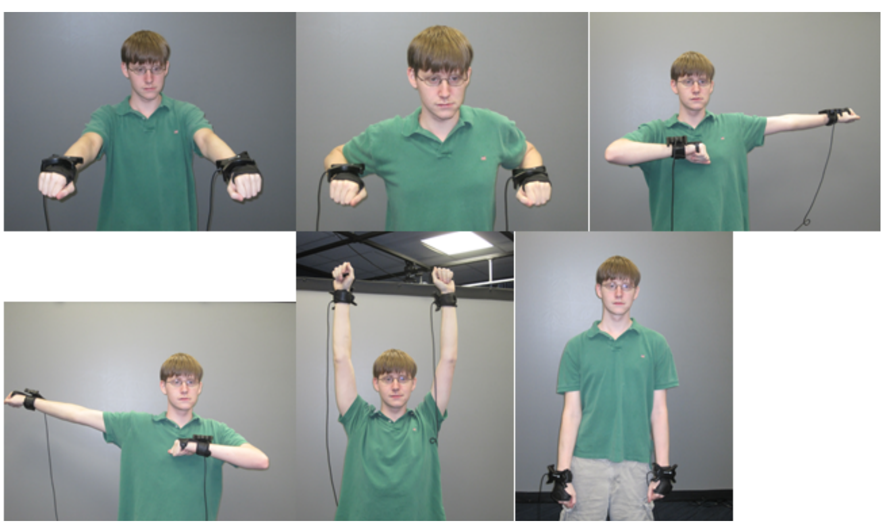

Figure 2.1 The target points that have to be targeted before data collection can begin. They are labeled (from top to bottom, left to right) forward (1), back (2), left (3), right (4), up (5), down (6).

Each student will require a different calibration due to the fact that each student has a different height, weight, and physical build. Calibration points could also differ on the same subject over different days. If the subject is not hurting, then the target points would be further out then on a day when he hurting and unable to extend his arms as much. After calibration is complete, an error is created around each target point. This is so that the participant only has to be close the target point, and not be perfect every time.

These target points are then saved for later use during both the data collection phase and the analysis.

2.5.2 Data Collection

The data collection part is where the student does the actual exercise. Each student had to do six different exercises, each thirty times. Each exercises required them to move their arms in circles to hit the various target points (Figure 2.1) for that exercise. The exercises are shown in Table 2.1.

Table 2.1 Exercises and Movement Path

Exercises	**Path of Points**
Vertical Clockwise	3, 5, 4, 6
Vertical Counterclockwise	3, 6, 4, 5
Horizontal Clockwise	3, 1, 4, 6
Horizontal Counterclockwise	3, 6, 4, 1
Side Circle Forwards	5, 1, 6, 2
Side Circle Backwards	5, 2, 6, 1

During the data collection, a sample is taken at a rate of fifty hertz. Each sample contains a sample number, current recognized target point (zero if no point recognized), and the x, y, and z coordinates of the three sensors. These samples are saved and are used for analysis later on.

2.6 Results

2.6.1 Data Visualization

With just the raw data, one can already see useful information. The motion in the depth (Figure 2.2), horizontal (Figure 2.3), and vertical directions (Figure 2.4) can be plotted with respect to time. Also, the full three-dimensional path can be plotted (Figure 2.5).

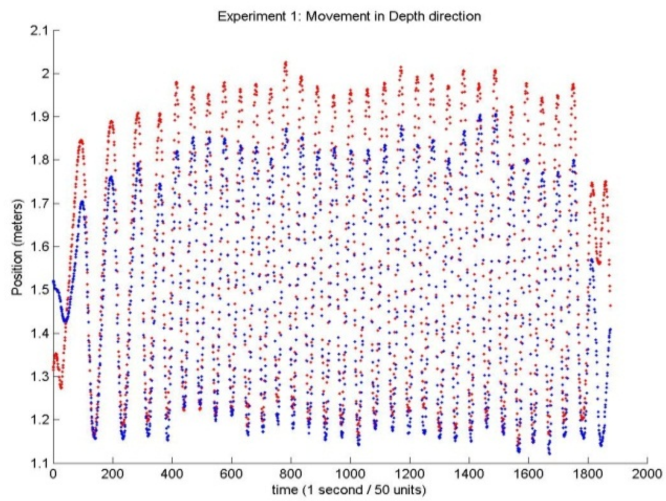

Figure 2.2 Position (m) in the depth direction with respect to time

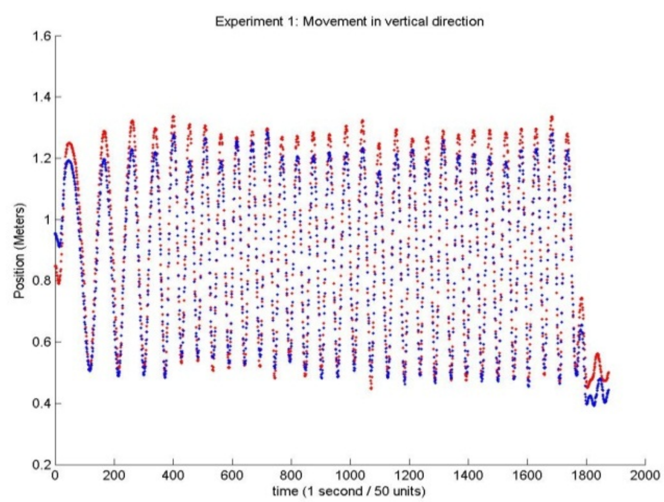

Figure 2.3 Position (m) in the vertical direction with respect to time

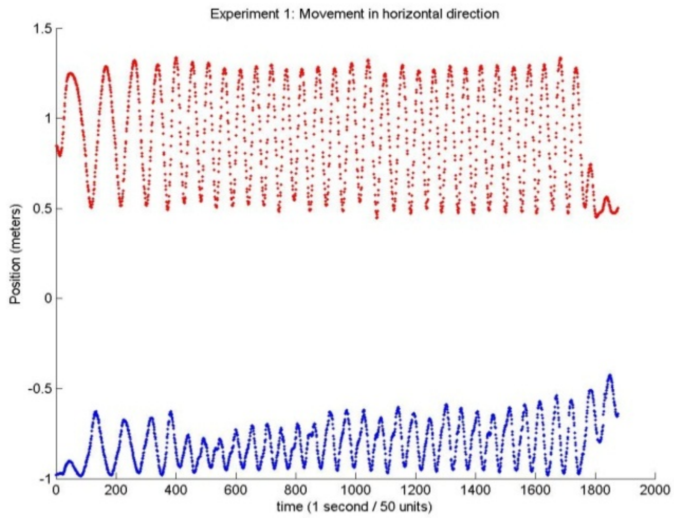

Figure 2.4 Position (m) in the horizontal direction with respect to time

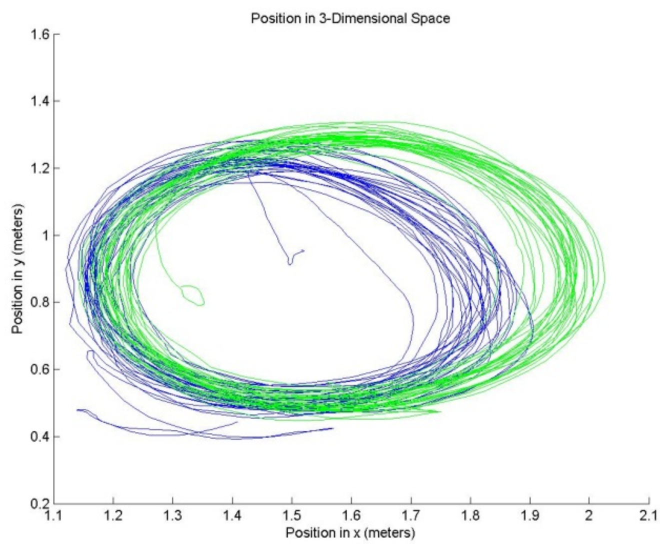

Figure 2.5 Position (m) in 3D space

2.6.2 Segmentation

Next, we break up the session into segments. Each segment is only circle during the session. This is relatively easy to accomplish. Since we know where the circle starts (say position 3), we can just look through the file and look for times when one circle ends and another begins (when it transitions form a 0 to a 3). Each of these segments can also be represented as a three- dimensional graph. These graphs can show us if a patient is struggling during a certain part of the exercise by a portion of the circular shape being concave compare to the rest of the circle.

2.6.3 Segment Analysis

One analysis that can be run on these segments is how consistent the patient is over time. To do this, we need to compare the radii of the different segments to each other. To compute the radius of a segment, we must find the center of the segment first. This can be done using the following formula:

$$(x_c, y_c, z_c) = (\frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n}, \frac{\sum_{i=1}^{n} z_i}{n})$$

where x_c, y_c, and z_c are the center of the segment, n is the number of points in that segment, and x_i, y_i, and z_i are the current point in the segment.

Now that we have the center of the segment, we can calculate the average radius of that segment. To do that, we can use the this formula:

$$Radius_{Avg} = \frac{\sum_{i=1}^{n} \sqrt[2]{(x_i - x_c)^2 + (x_i - x_c)^2 + (x_i - x_c)^2}}{n}$$

where x_c, y_c, and z_c are the center of the segment, n is the number of points in that segment, and x_i, y_i, and z_i are the current point in the segment.

We can now compare the average radii across multiple segments to see if a patient is struggling during the course of the exercise. This radius can also be compared to a target radius taken from target points. Example of struggling is show in Table 2.2. It shows that the subject is getting either worn out or is beginning to experience pain. If we take the average radius of the whole exercise, then we can see if the patient is improving or regressing over the course of time.

Table 2.2 Comparing average radius samples to target radius

Sample Number	Average Radius (m)	Target Radius (m)
1	0.35	0.35
10	0.33	0.35
20	0.32	0.35
30	0.30	0.35

2.7 Conclusions

In this paper, we have presented the first steps in creating a virtual environment for rheumatoid arthritis physical therapy treatments. We showed how to calibrate the system and to perform the exercises. This calibration process can be used to make the commands for the games. These commands would be the exercises so that the subject would not feel like he or she is doing rehabilitation but playing a game instead.

We then demonstrated what data can be obtained from the sensors, the visualization of the data, and any initial processing that cane be done. This data can be used by medical staff to show how much a subject is improving or degenerating over time. This will allow the medical staff to make changes to the games to incorporate different motions to better suit the patient.

2.8 Future Work

The next part of this project is to incorporate game-like activities so that patients will actually enjoy and become engaged in their exercises. Also, we need to find out any other useful data we can obtain and represent. Finally, we need to find the best way to visualize the data for the medical staff to make the best decisions.

2.9 Acknowledgements

Thank you to the four students that completed the exercises and generated the data sets: Prathibha Datta Kumar, Manan K. Mehta, Prathyusha Thummaluru, and Vishal Singh.

This work has been partially supported by NSF grants IIS: 1329119, IIS: 1258500, IIS: 1041637, and CNS: 1035913.

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CHAPTER 3

QUANTITATIVE EVALUATION OF THE KINECT SKELETON TRACKER FOR PHYSICAL REHABILITATION EXERCISES

3.1 Introductory Comments

This is the second chapter in the Sensor Validation section of this dissertation. Each sensor has its own accuracy issues. This can be caused by either an error created by the senor, or noise in the sensor data. This can be corrected by various means, such as sensor calibration, adjusting the position of the sensor, adjusting the data obtained to account for the error, or filtering out noise. Medical data needs to be as accurate as possible, so planning on how to deal with sensor error is a must when it comes to assessing a sensors validity for rehabilitation. If the error is minimal, or can be reduced or eliminated, then a sensor would be valid for rehabilitation. If the error cannot be reduced or rectified, then the sensor would not be valid for rehabilitation.

This chapter presents a way to determine the error by using a ground truth VICON system and discusses one technique to eliminate error from a Microsoft Kinect V1 sensor. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, collected data, performed analysis, wrote paper
- Vangelis Metsis: Assisted in study design, suggested analysis techniques, assisted in analysis, edited paper
- Fillia Makedon: Assisted in study design, edited paper

QUANTITATIVE EVALUATION OF THE KINECT SKELETON TRACKER FOR PHYSICAL REHABILITATON EXERCISES[2]

Shawn N. Gieser, Vangelis Metsis, and Fillia Makedon. 2014. Quantitative Evaluation of the Kinect Skeleton Tracker for Physical Rehabilitation Exercises. In *Proceedings of the 7th International Conference on PErvasive Technologies Related to Assistive Environments* (PETRA '14). ACM, New York, NY, USA, , Article 48 , 4 pages.

DOI=http://dx.doi.org/10.1145/2674396.2674429

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3.2 Abstract

Using video game technology in physical rehabilitation has shown many positive results in the past few years. The release of the Microsoft Kinect has presented many new opportunities for development in physical rehabilitation technologies. However, there have been questions about the Kinect's accuracy in actual experimentation. In this paper, we compare skeleton data obtained by a Kinect to that obtained by a VICON system in order to determine the accuracy of the Kinect while a tracked subject is moving their arm around. This is the first steps towards a much larger physical rehabilitation system.

Categories and Subject Descriptors: I.4.8 [Image Processing and Computer Vision] Scene Analysis – depth, range data, motion, tracking, J.3 [Computer Applications] Life and Medical Sciences – Health

General Terms: Measurement, Reliability, Experimentation, Human Factors, Verification

Keywords: Kinect, VICON, Motion Tracking, Physical Therapy

3.3 Introduction

Rehabilitation has two major goals: the enhancement of functional ability, and the realization of greater participation in community life. In terms of physical rehabilitation, the focus is to improve motor functions of various joins and limbs to improve the patient's daily life [1]. Game based physical therapy has been shown to be useful. Patients who had had experiences with Virtual Reality integrated with their exercises have found the exercises more entertaining and had higher rates of recovery [2]. Also, work with other types of gaming technology have shown to be useful as well, such as the Nintendo Wii and the Microsoft Kinect [3, 4]. These type of systems prove useful because they are low cost and highly accessible.

But now comes the question of “If these systems are low-cost, then is there any accuracy lost due to decrease in cost?” In this paper, we present a validation system to analyze the accuracy of the Microsoft Kinect. We use the Microsoft Kinect’s Skeleton Tracker to track a subject and compare it to a Vicon system that is tracking the subjects arm.

In this paper, we will first talk about some uses of the Kinect in other rehabilitation systems as well as other evaluation and validation techniques. Second, we will describe the equipment used and the experimental setup of how we collected data. Then, we will show the results of analysis done on the captured data between the two different systems. Lastly, we will describe our conclusions and future work.

3.4 Related Work

The Microsoft Kinect provides a low-cost, markerless motion tracking system. This is attractive to rehabilitation systems for many reasons. Because of its low-cost, it can be used by almost anyone who can afford it. There is not the hefty price tag that very accurate systems such as a Vicon system can provide. This makes it so it can be widely used in many places, not just a scientific or laboratory setting. Other marker based systems have the disadvantage of requiring a set up time and accurate placement of the markers. A markerless system allows for a faster experience for patients and does not hinder the patient’s movements in anyway [5].

The Kinect has already been used in a Kinerehab project [4, 6]. The purpose of this was to determine the number of correct motions made by a patient. Also, [7] uses a

Kinect while having subjects play games made for rehabilitation. The main issue with these approaches is that there is no validation of the data obtained using a ground truth as reference.

Work has also been done to validate the depth sensor of the Kinect [8]. The work done here has shown that the Kinect can do well at performing depth analysis. However, this work was only done on static objects and not done on actual people or used with objects in motion.

Evaluation work has also been done in gait assessment [5, 9]. One approach had the Kinect stationary, while the other had it placed on a mobile robot while following a person. Both show promising results with the Kinect while comparing against a Vicon system. However, these approaches focused on gait assessment and did not focus on upper body.

Also, validation work has also been done when focusing on postural control [10]. This work also shoes that the Kinect has the potential to be used in clinical settings. They did mention some drawbacks that were found. One of limitations found was lack of access to joint rotations in the subject's limbs. This limits the amount of angular data that can be obtained from the joints.

3.5 Experiment

3.5.1 Equipment

3.5.1.1 Vicon

The Vicon system is a motion capture system that was used as a ground truth in our experiments [11]. It is used for collecting highly accurate 3D coordinate positions of infrared (IR) reflective markers.

For this, we used the Vicon Tracker software to track markers placed on a subject's left shoulder, elbow, and wrist. Since Tracker only tracks rigid bodies, we made custom 3D printed mounts to place the markers in and taped them to the subject's body. They were placed in such a way to mimic joints in the Kinect SDK. Figure 3.1 shows the mounts and the placement on the body.

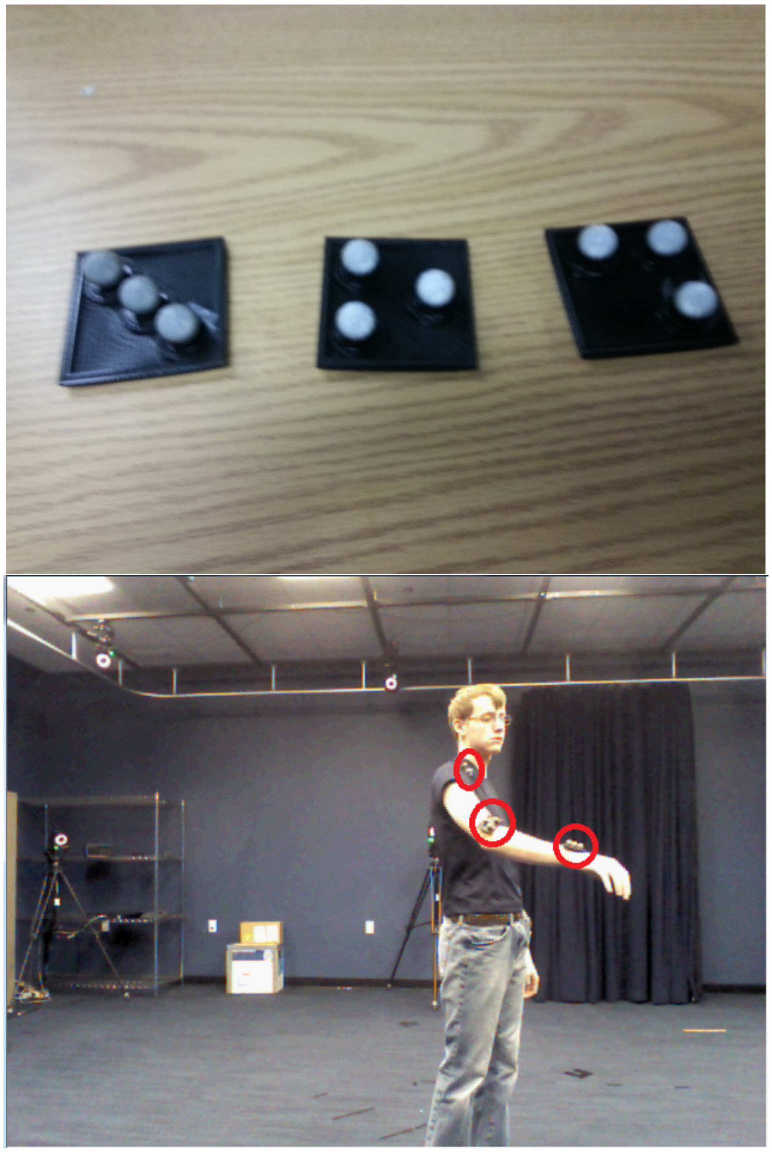

Figure 3.1 Top) Vicon markers placed in the 3D printed mounts. The left mount was placed on the wrist, the center was placed on the elbow, and the right was placed on the shoulder. Bottom) The mounts placed on the body.

3.5.1.2 Microsoft Kinect

The Microsoft Kinect, as shown in Figure 3.2, is a low-cost sensor that captures motion data from an IR camera and a regular RGB camera [12]. We are using the Skeleton Tracker from the Kinect SDK to obtain the joint positions of the subject in 3D. Figure 3.3 shows an example of the model produced by the skeleton tracker.

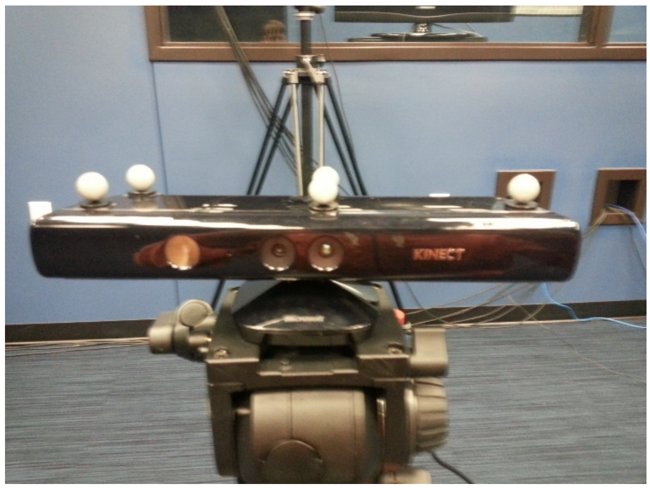

Figure 3.2 The Microsoft Kinect Sensor with Vicon markers placed on top

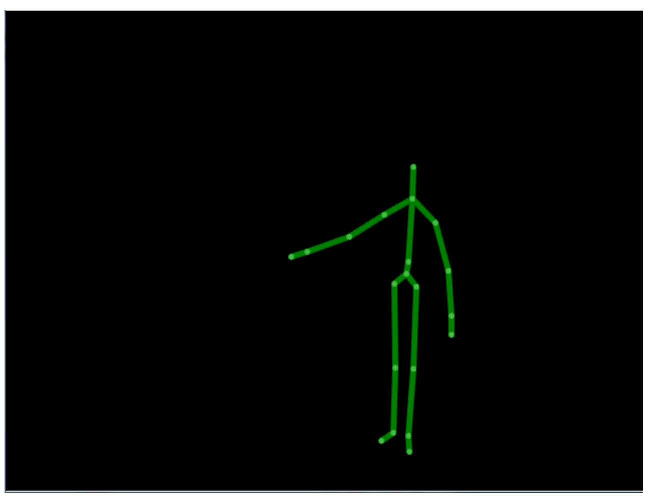

Figure 3.3 Skeleton Tracker Model produced from the Kinect SDK.

3.5.2 Experimental Setup and Data Collection

For the experiment, our goal was to compare data from the Kinect Skeleton Tracker to that of the Vicon system. To start, we placed Vicon markers on top of the

Kinect (Figure 3.2). This gives the position of the Kinect in the Vicon reference frame as well as the Rotation and Translation Matrices between the Kinect and Vicon reference frames. We then placed the Kinect on a tripod in a room with 16 Vicon MX cameras (Figure 3.4 Top). The subject then walked into the room with the markers attached to their arm. Figure 3.4 Bottom shows the view of the setup from Vicon Tracker.

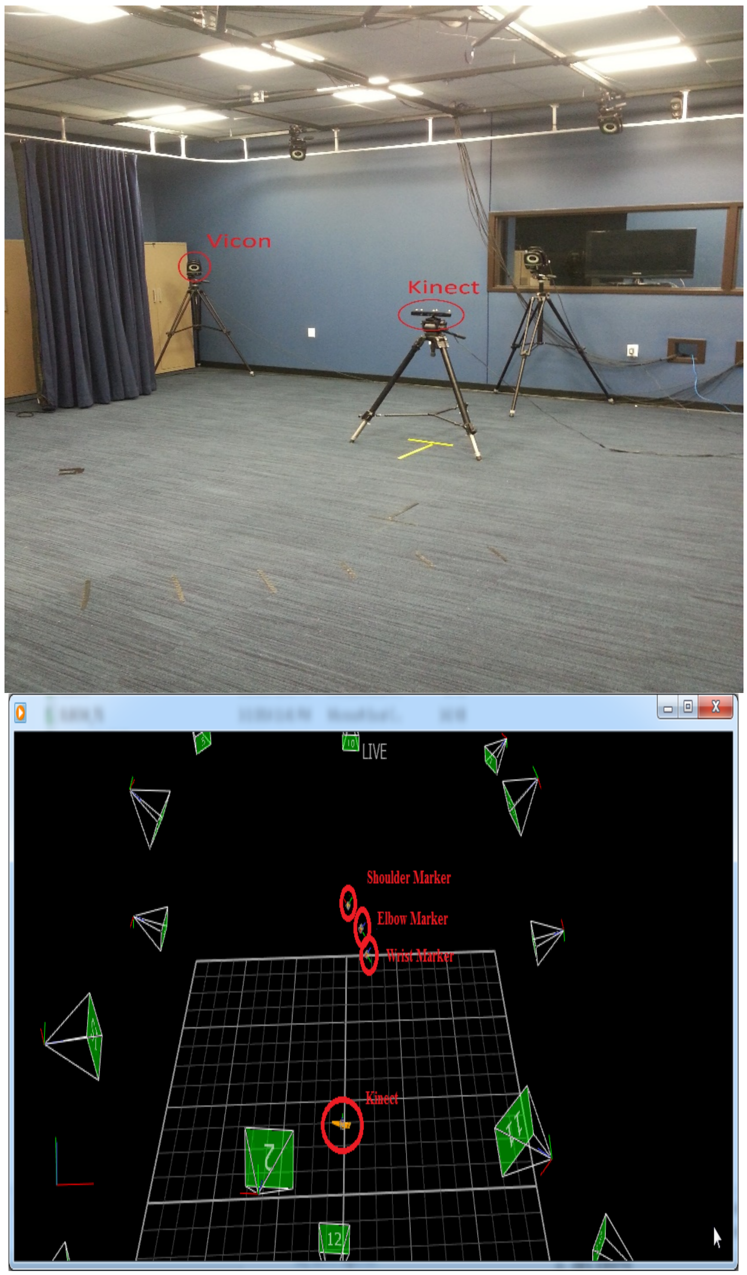

Figure 3.4 Top) Kinect placed in the Vicon Capture area. Bottom) Vicon Tracker view of the environment.

The subject walked into the room wearing the mounts on their arm. The subject was then asked to walk around and move their arm around to where the both the Kinect and Vicon would we the motion. The Kinect recorded all the X, Y, and Z coordinate position in meters, while the Vicon recorded the same values for the marker mounts. Timestamps of when the samples were taken were also recorded. This is because the Kinect records at 30 frames a second, and Vicon records at 100 frames a second. This allows us to find matching frames between the two systems.

3.6 Results

The first step in order to compare the Kinect and Vicon data is to convert from points obtained from the Kinect reference frame to the Vicon reference frame. The Vicon system gives the rotation and translation matrices between the two systems, making the transformation trivial. Figure 3.5 shows an example of the obtained arm position data from the two different sensors. We then calculated the difference between the two sets of samples. Figure 3.6 shows the difference between the Kinect and Vicon for each frame taken. The reason for the different number of samples for each joint is that the Vicon system did not capture all the mounts in each frame. The reason for this is that the markers that were placed too close together, particularly on the wrist mount. The system saw two markers as one and recorded the value for that mount at [0, 0, 0] for some frames. Those frames were excluded from all calculations. The spikes at the end of the graph were caused by walking away from the Kinect where the Kinect's error increases greatly.

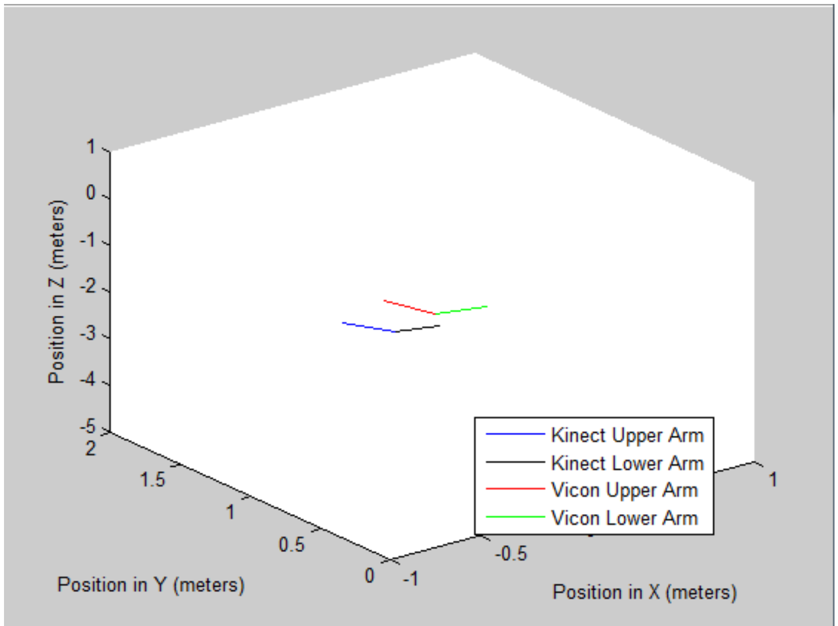

Figure 3.5 Visual comparison of the subject's arm from both Vicon and Kinect views.

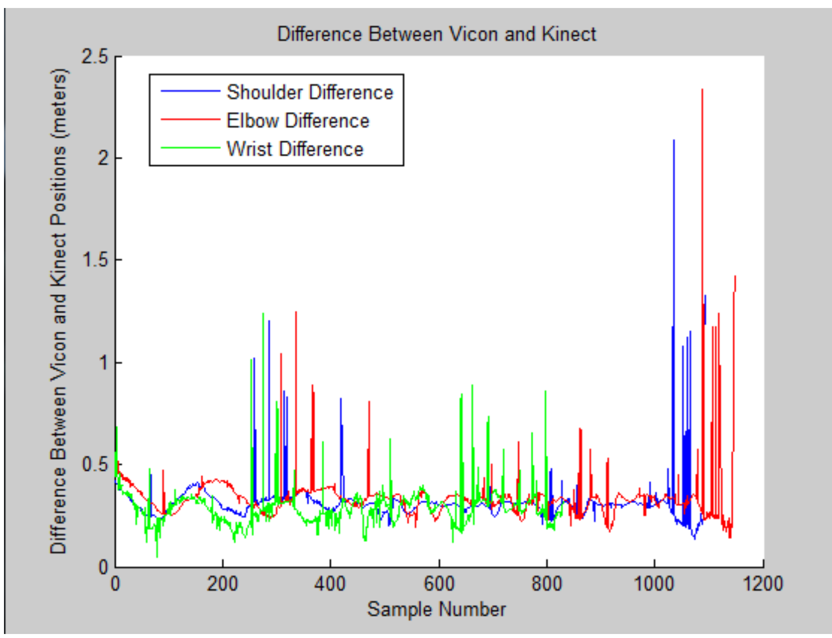

Figure 3.6 Difference of the joint positions between the Vicon and Kinect samples.

Table 3.1 shows the mean and the standard deviation of the joint positions between the two systems. There were some differences between the two, which were expected. This much of a difference was not. Other experiments that used Vicon for Kinect evaluation shown more promising results [5, 9, 10, 13]. Gait analysis has had average error of less 2cm [5]. [13] also tracked an subject's arm using a Kinect and a similar system to that of the Vicon. The error presented in their work was also significantly less than ours. All of these used markers placed on the body instead of using mounts. This has led us to believe that our issue with how the markers were placed on the body during our experiments. The fact that the markers were placed on top of the Kinect means that the Vicon system sees the Kinect slightly higher than where the principle point of the depth camera actually is. Also, the calculated center of the Kinect from Vicon may also not line up with the principle point. Another reason for the differences were that the mounts could have caused some deviation as well. While we tried to mimic the joint positions of the Kinect SDK Skeleton Tracker, the mounts may have been slightly off. Also, the mounts were a raised surface on the body, causing Vicon to see the mounts closer to the Kinect than the joint actually was.

Table 3.1 Mean and Standard Deviation of the Difference of Joint Positions between the Vicon and Kinect samples

Joint	Mean (m)	Standard Deviation (m)
Shoulder	0.302	0.138
Elbow	0.322	0.180
Wrist	0.284	0.178

Next we determined the above mentioned difference that was caused between these two systems and accounted for this. This significantly reduced our error, as shown in Table 3.2 and Figure 3.7. To remove the error, we measured the approximate distances between the position of the mounts and the Kinect joint locations, as well as the distance from the Kinect and the markers on top of the Kinect. When these were accounted for, we able to obtain much more promising results.

Table 3.2 Mean and Standard Deviation of the Difference of Joint Positions between the Vicon and Kinect samples after Correction

Joint	Mean (m)	Standard Deviation (m)
Shoulder	0.057	0.036
Elbow	0.079	0.061
Wrist	0.084	0.077

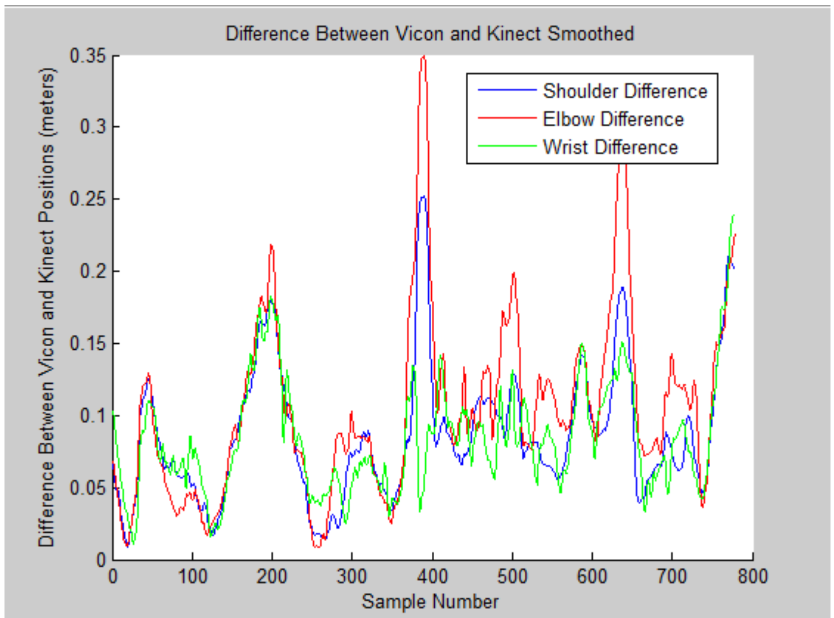

Figure 3.7 Difference of the joint Position between the Vicon and Kinect samples after error corrections.

3.7 Conclusions

In this paper, we have shown a way to validate data obtained from the Microsoft Kinect Skeleton Tracker. We also compared this data to that obtained from a Vicon system while tracking a subject's arm. The Vicon system was used as a ground truth in order to determine the accuracy of the Kinect. The results that were obtained were not exactly expected. The difference between the two systems was somewhat significant averaging at least 5cm per joint, but parts of this were caused by the experimental setup. The fact that there are still differences seen means that further work needs to be done in order to further reduce this difference.

3.8 Future Work

The first step that has to be taken is to figure out how much error was introduced by the set up. Also, different marker formation in the marker mounts have to be made so that less frames have to be dropped. Finally, this would have to be applied to the whole body instead of just an arm so that full body tracking can be validated.

3.9 Acknowledgements

This work has been partially supported by the following NSF grants: IIS: 1409897, IIS: 1258500, CNS: 1035913, IIS: 1041637, CNS: 1338118.

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CHAPTER 4

EVALUATION OF A LOW COST EMG SENSOR AS A MODALITY FOR USE IN VIRTUAL REALITY

4.1 Introductory Comments

This is the third and final chapter of the Sensor Validation section. If a sensor will be used for recognizing gestures in a game, that sensor should be able to recognizes gestures outside of a game. The same can be applied to Activities of Daily Living (ADLs) and exercises. A test using a sensor to perform basic tasks or classify simple actions should be done before incorporating it rehabilitation tasks or games. If the sensor can recognize the required gestures in simple activities or the desired motion outside of the game, then it would be valid to use in rehabilitation games. If the sensor cannot classify the gesture, then it would not be valid for use. Any results obtained from a low-cost sensor should be similar to a more accurate sensor.

This chapter presents an assessment of a low-cost EMG sensor by using data obtained for gesture classification. These classification results are compared to that of a more accurate sensor. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, collected data, decided analysis techniques, generated figures, annotated data, wrote paper
- Varun Kanal: Assisted in study design, collected data, developed data visualizer decided analysis techniques, performed analysis, generated tables, assisted in results section
- Fillia Makedon: Assisted in study design, edited paper

EVALUATION OF A LOW COST EMG SENSOR AS A

MODALITY FOR USE IN VIRTUAL REALITY[3]

Shawn N. Gieser, Varun Kanal, and Fillia Makedon. 2017. Evaluation of a Low Cost EMG Sensor as a Modaility for use in Virtual Reality. In Stephanie Lackey and Jessie Chen (eds.) *Virtual Augmented and Mixed Reality* (VAMR ’17). Lecture Notes in Computer Science, vol. 10280. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-57987-0_8

[3] In Press

4.2 Abstract

Virtual Reality (VR) is becoming more accessible to everyday users. Users of VR want realistic experiences, both in how it looks and in how to interact with the environment. Electromyography (EMG) is a possible tool to use to make VR more realistic, but in the past, has been considered too expensive to be accessible to the everyday user. New low-cost EMG sensors have become available in recent years that have made this technology more available to the everyday user. In this paper, we evaluate one low-cost EMG sensor to assess its usefulness as an input modality for VR. We will do this by assessing how accurately gesture recognition can be accomplished with the data acquired from the sensor. We will compare it to gesture classification done with data obtained from a higher cost EMG system that has a much higher sampling rate. If the classification results are similar, then low-cost EMG is a valid choice as an in- put modality for VR.

Keywords: EMG, Gesture Classification, KNN, SVM, Myo Armband, Trigno Lab

4.3 Introduction

Virtual Reality (VR) technology is becoming more and more accessible to everyday users. Just in the last two years, releases of multiple consumer versions of Head Mounted Displays (HMDs), such as the HTC Vive, Oculus Rift, Samsung Gear VR, Sony Playstation VR, and Google Daydream just to name a few, have increased the demand for this technology [1]. The people who use VR love how immersive the environment is and that tasks are accomplished by mimicking the motions needed to perform the task in real life [2].

VR tasks, however, sometimes do not properly mimic their real world counterpart. Once commercial example would be the game The Climb by Crytek [3]. In this game, one climbs a virtual wall using two controllers to represent their hands. Buttons are used for grabbing rocks and putting chalk on the virtual hands. In real rock climbing, one uses their hands, feet, and various muscle groups to climb a wall or rock face. There are no buttons to press to perform these tasks. Therefore, one could say that this virtual task does not have a high degree of interaction fidelity. Interaction fidelity is the objective degree of exactness in which real-world interactions can be reproduced in an interactive virtual environment [4].

One possible way to increase interaction fidelity is to add electromyography (EMG) as an input modality. Let us create an example task by requiring a user to push a heavy block in a virtual environment. With controllers, this task can be completed by navigating to the block, moving the controllers to the block, pressing a button to grab the block, then finally moving the controllers forward to push the block. This is a very simple list of actions to complete if this block really was heavy. With the addition of EMG, we could add one more requirement to the list of actions. In addition to moving the controllers forward, the user would have to flex the muscles in their arms and chest. This would make the task more similar to the real world counterpart since the virtual task now requires similar muscle activation to the physical task.

In this paper, we will be evaluating a low cost, off the shelf, EMG sensor in its use-fullness to classify gestures. We will be comparing the results with a full EMG system that has a higher sampling rate. If the low-cost sensor is useful in being able to classify gestures and has a similar success rate classifying gestures as the full EMG system, then it would also be useful as a modality in VR applications. We will begin by going over background information and related works, followed by our experimental setup and procedure. We will then talk about our analysis and discuss our results. Lastly we will present our conclusions and future work.

4.4 Related Work

There have been many different approaches for deciding how to handle input in VR. Text input has been attempted many times. Researchers have used various techniques such as speech, gloves, writing on tablets, chord keyboards, and gesture mapping [5, 6]. SteamVR uses a controller in which users point at a virtual keyboard and click which letters they want [7]. Drawing has also had various techniques applied to it. Haptic devices which have a pen or a stylus attached have been used [8]. Modern approaches however use controllers to accomplish this, such as what is used in Google Tilt Brush [9]. Others have focused on movement techniques in VR. [4] compares game movement techniques and its correlation to different levels of display fidelity. The two different movement techniques compared are keyboard input and a “human joystick” where the user’s position and distance from a central point effects direction and speed of movement in a game. The two different levels of display fidelity were a one wall of a six-sided CAVE and another version using four wall of the CAVE to create a full 360-degree environment. The situations that performed the best were either high levels of both interaction and display or low interactions of both. It has also been said that developers should focus on not developing mid-fidelity or semi-natural interactions techniques that do not resemble real world interactions [10]. Commercial examples of movement techniques vary between many different options, which include, but not limited to, an omni-directional treadmill and using a controller to point at a location and "teleport" to that location [11, 12]. All of these various techniques represent different degrees of interaction fidelity.

Gesture classification has been done by others using EMG. Most of these studies involve expensive equipment, or equipment put together in house. Various classification techniques have been used, including K-Nearest Neighbor (KNN) [13], Support Vector Machines (SVM) [14], Dynamic Time Warping (DTW) [15], and Bayes [16]. EMG gesture classification has been used for various applications as well. It has been used as an input device for games and computers [13, 17], as well as assisting the users with motor disabilities in navigating a wheelchair [18]. EMG has also been combined with accelerometers to get increased accuracy on motions and tasks that involve movement of the hand or arm [19]. EMG has been used in VR to train amputees how to control a prosthetic device so that they can become used to controlling the device before having it attached to their body [20]. These uses of EMG data show that EMG can serve as a modality in VR. With low-cost options becoming available, can these EMG sensors, that don't have as high of a sampling rate, serve in the same capacity?

4.5 Experimental Setup and Procedure

In this section, we will begin by describing the equipment that was used. This will be followed by the procedure, detailing the gestures used, sensor placement on the body, and how the study was conducted.

4.5.1 Equipment

We acquired data from two different EMG sensors. The first one was the Myo Armband developed by Thalmic Labs [21], seen in Figure 4.1 Left. It is a wireless sensor that communicates with a computer or smart phone via Bluetooth. It contains eight EMG sensors with a sampling rate of approximately 200 Hz [22]. It also has a nine axis IMU, a three-axis accelerometer, and a three-axis magnetometer, all with a sampling rate of approximately 50 Hz. For the sake of this study, all we are using is the EMG aspect of this sensor. The Myo Armband is relatively inexpensive when compared to that of medical grade EMG systems. The main issue with this sensor is that the sampling rate for the EMG sensor does not satisfy the Nyquist-Shannon Theorem. The Nyquist-Shannon Theorem states that the sampling frequency should be greater than twice the signal frequency [23]. Based off this theorem, the Myo Armband should only be able to pick up signals with a frequency of 99 Hz and lower. This then creates a potential issue, since most significant EMG activity happens in the 5 to 450 Hz range [24].

Figure 4.1 (Left) The Myo Armband (image from myo.com). (Right) Delsys Trigno Lab (image from delsys.com).

The second sensor was the Trigno Lab developed by Delsys [25], seen in Figure 4.1 Right. The Trigno Lab has a number of small sensors that communicate to a base station via an RF signal. Each sensor contains an EMG sensor with a sampling rate of approximately 1926 Hz and has a three-axis accelerometer with a sampling rate of approximately 148 Hz [26]. This EMG sampling rate easily satisfies the Nyquist-Shannon Theorem since it is over four times the maximum frequency of significant EMG activity.

Two different pieces of software were used for data collection. For collecting data from the Myo Armband, we used Unity [27]. We felt that it was a more realistic approach than specialized data collection programs. Since the goal was to see if the Myo Armband would be good for VR, it made sense to use a program that had built in functionality for game design and VR. For data collection from the Trigno Lab, we used EMG Works [28], a specialized piece of software developed by Delsys.

4.5.2 Experimental Procedure

To assess the validity of low cost EMG sensors as a modality for VR, we will be assessing how well we can classify gestures with just EMG data. This will be useful in recognizing what a user is trying to do in a virtual environment. For this study, we used eleven gestures. These gestures were resting, wave out, wave in, fist, fingers spread, double tap, pinching, holding up a block, pretending to hold up a block, pointing, and thumbs up. All these gestures, except for double tap, can be seen in Figure 4.2. Six of these gestures can be detected by the Myo Armband already, which are resting, wave out, wave in, fist, fingers spread, and double tap. As far as the authors have noticed, all other gestures are primarily classified as resting even though there is an unknown gesture reading available.

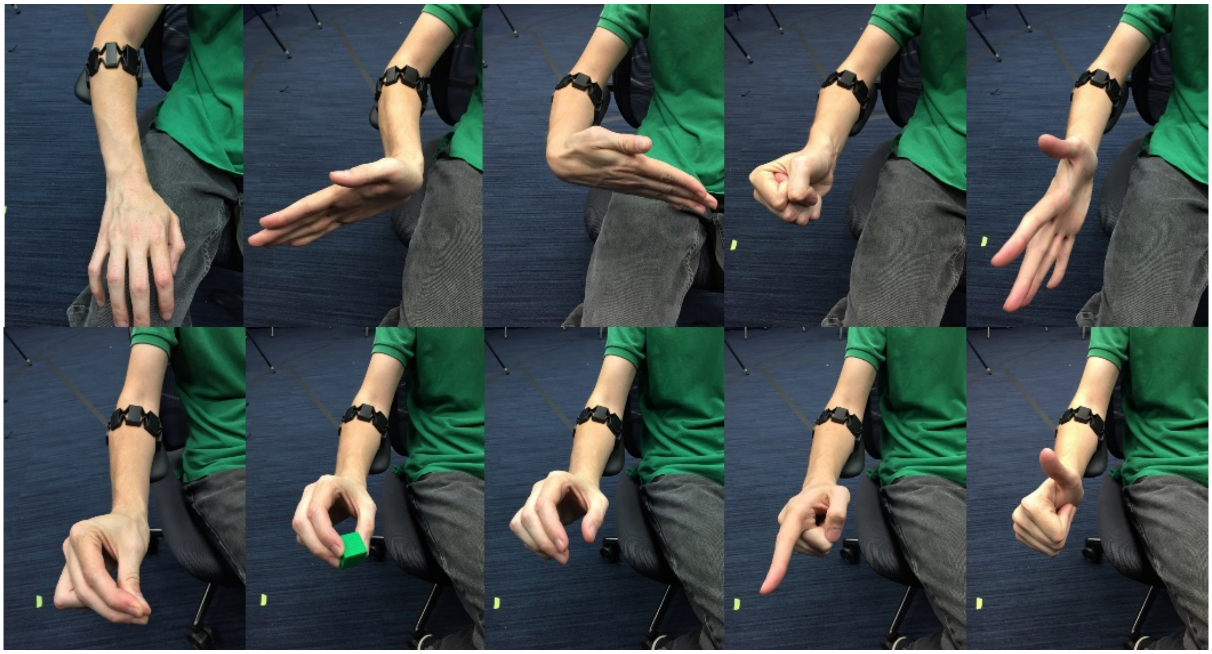

Figure 4.2 The gestures used during data collection. From Top-Left to Bottom-Right: Rest, Wave out, Wave in, Fingers Spread, Pinching, Holding a Block, Pretending to hold a Block, Pointing, and Thumbs up.

In order to get as similar readings as possible from the two different sensors, we attempted to place the sensors in the same position on the body. To do this, we first had each participant for the study place the Myo Armband on their arm following the instructions for the Myo Armband (Figure 4.3 Left). These were that the armband had to be placed on the widest part of the forearm with the USB port facing towards the hand. We additionally added that the sensor logo should be facing upwards when the arm is in a supinated position. We then marked where the top and bottom of the individual pods were positioned on the arm with a red marker (Figure 4.3 Center). The EMG sensors from the Trigno Lab were then placed in the areas marked (Figure 4.3 Right).

Figure 4.3 (Left) Placement of the Myo Armband. (Center) Markings from where the Myo was positioned. (Right) Placement of Trigno Sensors.

There were thirty-five participants for this study. Participants were recruited through one of the introductory courses in the Computer Science Department. There were no exclusionary criteria to prevent someone from participating in this study. The order of the sensors was alternated between participants to balance the study. The participants placed the Myo armband on first so that its position on the arm can be marked. The participant then either left the Myo Armband on, or took it off so the Trigno sensors can be put on. The participants made the eleven gestures three times each. The gesture was made before being recorded. Each gesture was held and recorded for approximately five seconds. After the first set of gestures were complete, the sensors were switched. If the Myo Armband was second, it was lined back up with the markings on the arm so that it can be in the same position it was before. Then the participants repeated the same gestures as before. Overall, each participant performed sixty-six gestures, thirty-three with each sensor.

4.6 Analysis and Discussion

The first component we looked at was the classification algorithm built into the Myo Armband's software. We wanted to see how the Myo Armband's classification algorithm looks at gestures it can already classify and what it's results are for the new gestures we added. Table 4.1 shows these results. These results were acquired through the IMU sensor of the Myo Armband which has a sampling frequency of 50 Hz. The Myo Armband sends the gesture classification results with the IMU data instead of with the EMG data. These results show what the Myo Armband classified each gesture as at each time the IMU sensor acquired a sample. These results were also acquired using the default calibration setting on the Myo Armband. Even though there is a custom calibration setting available, we chose to use default settings since this is what we were interested in most.

Table 4.1 Myo Self-Classification Results

	Myo Classification						
Gesture Made	**Rest**	**Fist**	**Wave In**	**Wave Out**	**Fingers Spread**	**Double Tap**	**Unknown**
Rest	13998	0	0	0	0	0	47593
Fist	14079	44308	1735	368	1178	0	1364
Wave In	17004	13433	21106	3	1330	88	8292
Wave Out	1170	5479	2187	51236	1762	66	0
Fingers Spread	14947	15775	1947	4178	26227	31	0
Double Tap	13252	405	216	262	416	853	0
Pinching	28788	14741	2510	6780	9552	0	0
Pick Up Block	35960	13877	2836	4541	4714	25	0
Pretend	34359	9634	5739	2396	10982	0	0
Pointing	48140	12375	1167	575	26	0	0
Thumbs Up	36695	21144	305	0	4544	0	0

As you can see in Table 4.1, the Myo Armband correctly identified a little over 50% of the gestures that it was supposed to. The individual gesture success rates are as follows: Rest – 22.727%, Fist – 70.294%, Wave In – 34.449%, Wave Out – 82.772%, Fingers Spread – 41.560%, and Double Tap – 32.380%. The classification results for Double Tap were presented differently in Table 4.1. For the other gestures, we showed what the Myo Armband classified each sample sent by the IMU sensor. However, Double Tap is only shown by the Myo Armband for a small period after the gesture has been completed. We examined all the classification results sent by the Myo Armband during the five second recording period to see if there was a Double Tap result. If there was, the whole gesture was determined to be a Double Tap. If not, we used whatever the most common classification result was. These low classification rates may have been caused by using the default calibration settings instead of creating a custom calibration profile for each participant. Using a custom calibration profile should greatly improve these results.

Looking at the added gestures, all five of them had one common element. These gestures all shared the Rest gesture as their highest classified gesture. Therefore, if you were building a classifier to support the Myo Armband, the Rest gesture can be used to determine if an additional classifier is even necessary for the current gesture or not. If the Myo Armband shows rest, then run the additional classifier. If the Myo Armband shows any other gesture, then the additional classifier would most likely not be needed in that case.

Figure 4.4 shows a sample of the raw data collected from the Trigno Lab and the Myo Armband. These plots show the data collected from each sensor or pod used. Two gestures are shown in the graph. The blue dashed line represents the data collected while a participant performed one of the “Pretend” gestures, and the red solid line represents one of the “Rest” gestures. These were plotted on the same graph to show the comparison of muscle activity between the two gestures. All other attempts for all gestures were plotted in this same way. One thing to note is that the Y-axis on Myo Armband graphs is not in Volts like traditional EMG data. This is because the data the Myo Armband SDK produces for the EMG sensors is unitless activation [29]. We have decided to label this “Myo Units.”

Figure 4.5 shows a frequency analysis done on the data previously shown in Figure 4.4. This was also done for all attempts for all gestures. To perform the frequency analysis, the signals obtained from both the sensors was decomposed into their individual frequencies. This was done by performing a Fast Fourier Transform (FFT) on the signal. FFT is a modification of the Direct Fourier Transform (DFT) for quicker results. The formula for DFT is:

$$Xk = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N}$$

where x_n is the data sequence and X_k is the DFT. Even though the data collected from the Myo Armband was unitless, we decided to perform the frequency analysis on the data to show a comparison between two data sets.

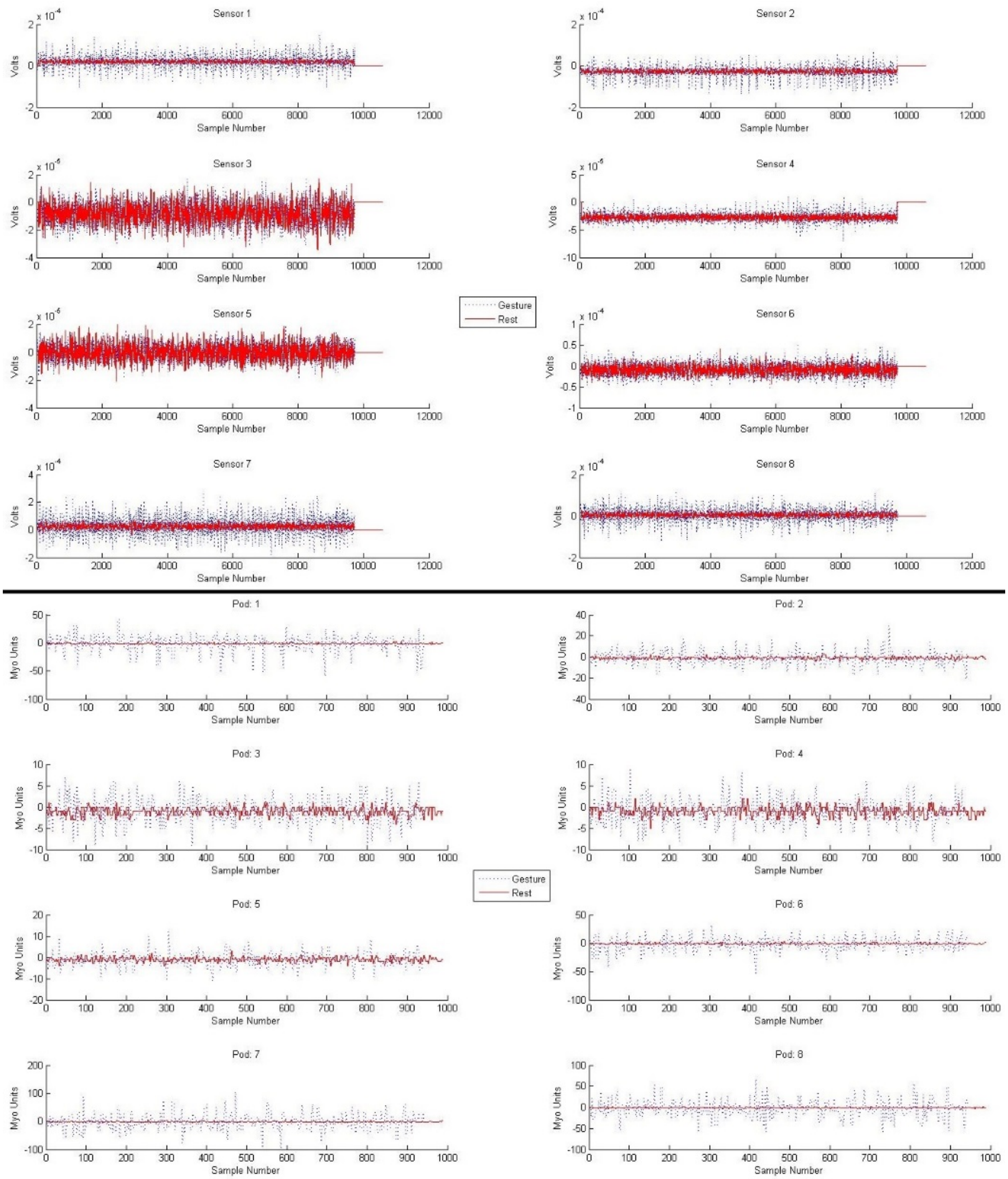

Figure 4.4 Sample of the raw data collected from the Trigno Lab (Top) and the Myo Armband (Bottom) EMG sensors for the "Pretend" Gesture compared to the "Rest" Gesture

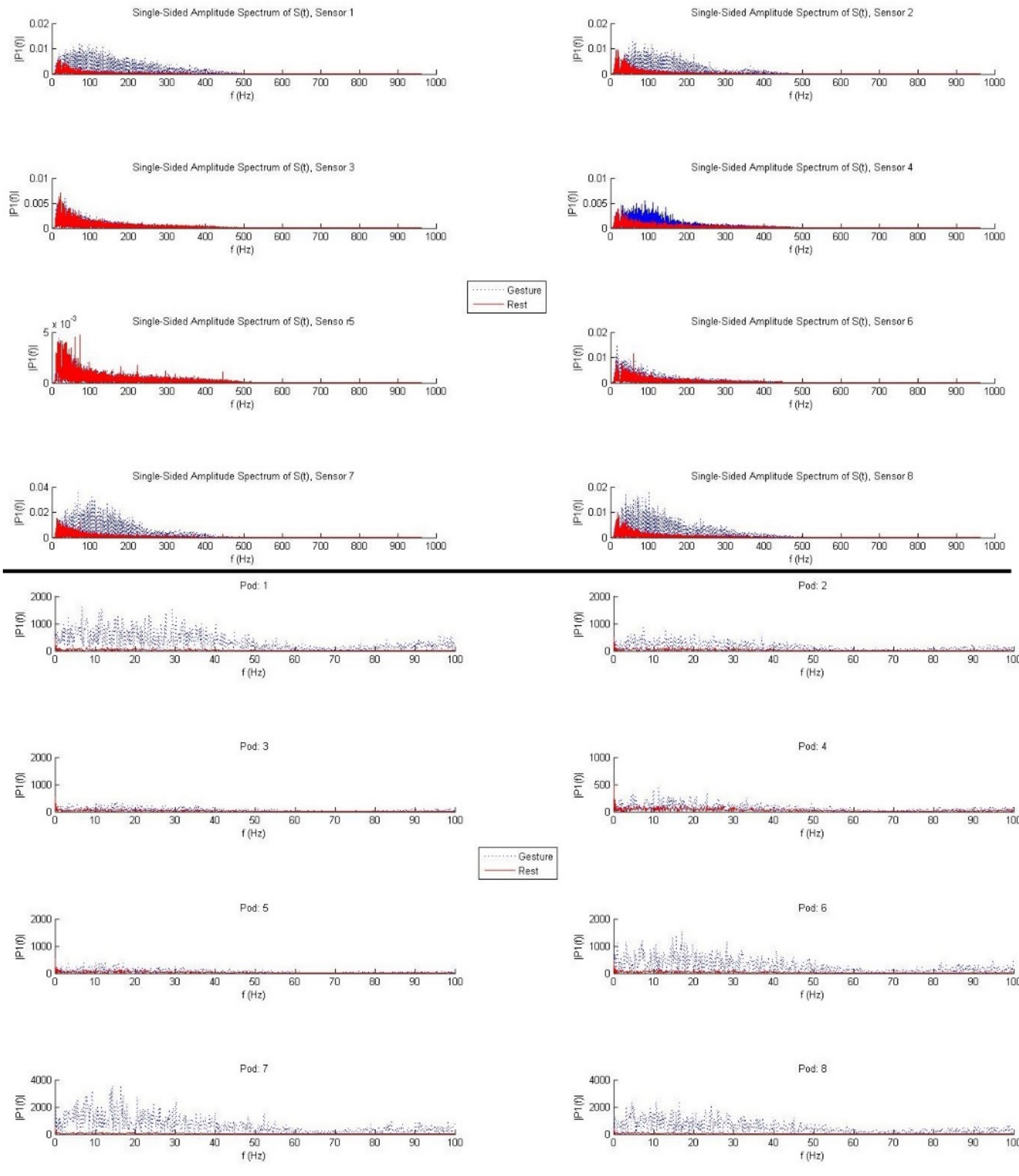

Figure 4.5 Frequency Analysis of data collected from Trigno Lab (Top) and Myo Armband (Bottom) EMG Sensors for the "Pretend" Gesture compared to the "Rest" Gesture

For gesture classification, we focused on using the data collected instead of the frequency analysis. This decision was made to make it simulate as if a program or game was getting a window of data at a time. For the Trigno Lab data set, we used filtered data. The filtering process was performed in 3 steps. First, the signal was passed through a high pass filter. The corner frequency for this filter was 10 Hz. Then, the filtered signal was passed through a low pass filter with the corner frequency at 500 Hz. Finally, the signal was passed through a notch filter at 50 Hz. The resulting signal has its frequency in the range of 10 Hz to 500 Hz. This removes any low frequency and high frequency noise. The filter used for this was a zero phase shift equiripple filter. We did not filter the Myo Armband data, since the data is unitless, and the Myo Armband has a small sampling rate.

To help with classification, each senor was given a weight of 1, 0.5, or 0 based on the graphs that were generated in the style of Figure 4.4. This weight was determined manually based on how different the “Non-Rest” gesture was compared to the “Rest” gesture. If the “Non-Rest” gesture’s EMG signal had significantly greater and/or easily distinguishable from the “Rest” gesture, then that sensor was given a weight of 1. If there was no difference, or the “Rest” gesture showed more activity, then it was given a weight of 0. If the EMG for the “Non-Rest” gesture was greater, but not significantly greater, then it was given a weight of 0.5. Figure 4.6 shows examples of how these were classified. Tables 4.2 and 4.3 show the averages of the weights given for each sensor separated by gesture.

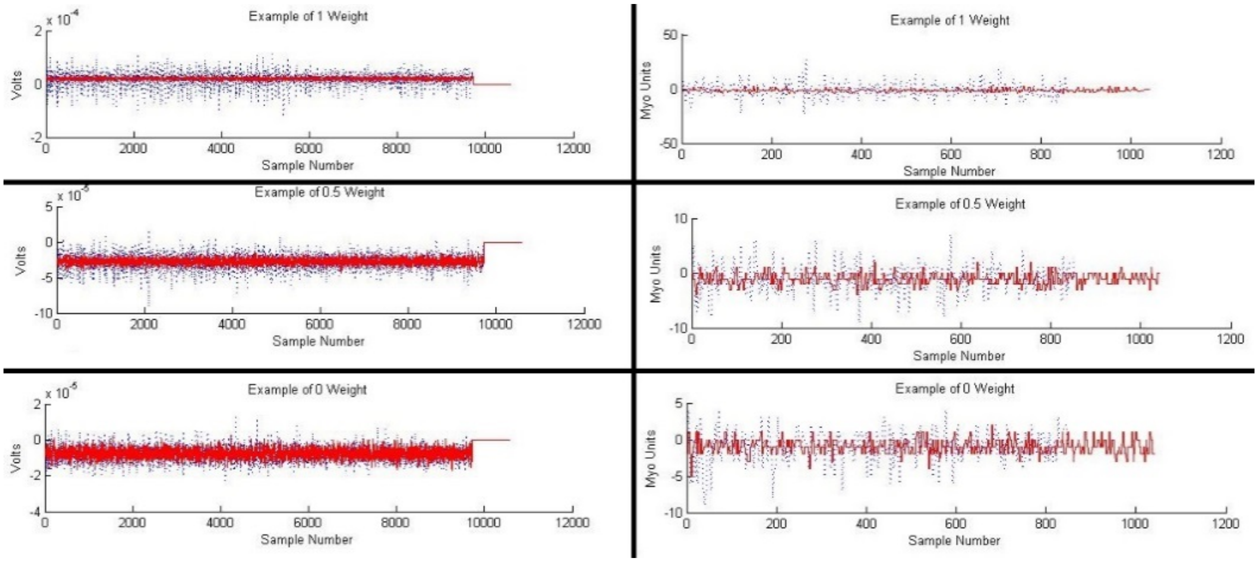

Figure 4.6 Examples of what was used for weight classification with Trigno Lab (Left) and Myo Armband (Right) for weights of 1 (Top), 0.5 (Middle), and 0 (Bottom)

Table 4.2 Trigno Lab Sensor Weights for each Gesture

	Trigno Lab Sensor Number							
Gesture	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Rest	0.6889	0.7111	0.5778	0.5000	0.6333	0.8556	0.6778	0.9222
Fist	0.5778	0.3556	0.1667	0.6111	0.7667	0.5889	0.5444	0.5889
Wave In	0.8222	0.7667	0.5000	0.5333	0.2333	0.2111	0.2333	0.6778
Wave Out	0.7667	0.6333	0.2667	0.3667	0.2556	0.6444	0.4778	0.5889
Fingers Spread	0.6333	0.7111	0.7444	0.5111	0.7444	0.7444	0.5333	0.4000
Double Tap	0.5333	0.5333	.3111	.2889	.1889	.2111	0.1667	0.4667
Pinching	0.5444	0.4111	0.2556	0.2333	0.1778	0.1889	0.3222	0.4556
Pick Up Block	0.5556	0.5111	0.1778	0.1889	0.1111	0.2356	0.2667	0.4556
Pretend	0.3333	0.2889	0.1333	0.2222	0.2000	0.3667	0.3111	0.3778
Pointing	0.6222	0.2667	0.1778	0.2778	0.2556	0.4111	0.4222	0.6889
Thumbs Up	0.6889	0.7111	0.5778	0.5000	0.6333	0.8556	0.6778	0.9222

The data was extracted from 8 pods from each sensor. The weights were used to narrow down the pods which was the most important for each sensor. The pod with the highest weight was used for classification. There were some cases where the highest weight for the pods was below 0.5, even in such cases the pod with the highest weight was used. Two classification algorithms were considered: K Nearest Neighbors (KNN) and Support Vector Machines (SVM) with a linear kernel. A 5 fold cross validation method was used to create the model. When creating these models, we focused on the gestures “Holding a Block” and “Pretend.” This was done so that we could apply this to previous work in VR. [30] shows a problem with interaction fidelity of picking up virtual blocks. One of the possible solutions was to consider other input modalities. These two gestures best represent the motions needed to pick up a block. Table 4.4 shows the classification results using these methods.

Table 4.3 Myo Armband Sensor Weights for each Gesture

	Myo Armband Sensor Number							
Gesture	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Rest	0.7476	0.8714	0.7667	0.7000	0.7190	0.8524	0.8714	0.8476
Fist	0.9429	0.3952	0.2905	0.6571	0.8000	0.7190	0.7333	0.6810
Wave In	0.9857	0.9524	0.8333	0.6762	0.5190	0.5190	0.7048	0.8333
Wave Out	0.9381	0.8238	0.5286	0.4143	0.5000	0.7952	0.8095	0.7571
Fingers Spread	0.9476	0.9524	0.8905	0.7905	0.9095	0.9286	0.7762	0.7143
Double Tap	0.8048	0.7952	0.6571	0.4000	0.5143	0.5224	0.5143	0.5810
Pinching	0.8286	0.7381	0.5143	0.3048	0.4810	0.2714	0.4000	0.6476
Pick Up Block	0.7714	0.6524	0.4714	0.3000	0.4095	0.4333	0.5333	0.6095
Pretend	0.5429	0.5048	0.2619	0.2095	0.4190	0.5238	0.6619	0.6333
Pointing	0.6810	0.5000	0.3238	0.2524	0.5714	0.6905	0.6905	0.7143
Thumbs Up	0.7476	0.8714	0.7667	0.7000	0.7190	0.8524	0.8714	0.8476

The results in Table 4.4 are not promising, which a highest classification rates on the Trigno Lab data set being 61.11% on KNN with the “Double Tap” gesture and the Myo Armband data set being 53.81% on KNN with the “Pinching” gesture. This initially led us to believe that not enough data was collected, or we did not consider enough sensors. We then started modifying our approach to classification to look at extracted features from the EMG data. There were 5 features extracted from the signal; Maximum value of the selected window, the Minimum value, the absolute Mean of the window, the Variance and the Root Mean Square (RMS) of the signal. These features are few of the common features that are used for signal analysis and have been known to be used in EMG gesture classification [31]. We used extracted features on both sets of data for comparison, even though the Myo Armband data was unitless. Table 4.5 shows the classification results using the extracted features.

Table 4.4 Classification Results: Filtered Trigno Lab Data and Myo Armband Raw Data

Gesture	Trigno Lab Filtered Data Set		Myo Armband Raw Data Set	
	KNN	SVM	KNN	SVM
Fist	50.00%	41.11%	26.67%	24.76%
Wave In	50.00%	43.33%	43.81%	45.24%
Wave Out	48.89%	45.55%	40.95%	41.91%
Fingers Spread	48.89%	42.22%	40.00%	39.05%
Double Tap	61.11%	43.33%	41.86%	41.43%
Pinching	50.00%	41.01%	53.81%	49.05%
Pick Up Block	50.00%	43.33%	48.57%	50.00%
Pretend	55.56%	38.89%	49.05%	49.05%
Pointing	53.33%	36.67%	38.57%	40.47%
Thumbs up	50.00%	38.89%	41.43%	40.48%

Table 4.5 Classification Results: Extracted Features from Trigno Lab and Myo Armband Data

Gesture	Trigno Lab Data Set		Myo Armband Data Set	
	KNN	SVM	KNN	SVM
Fist	86.66%	41.11%	95.24%	95.24%
Wave In	94.44%	52.22%	81.43%	81.90%
Wave Out	93.33%	48.89%	99.05%	98.57%
Fingers Spread	90.00%	46.67%	99.05%	96.67%
Double Tap	90.00%	50.00%	98.10%	98.10%
Pinching	83.33%	36.66%	86.19%	92.86%
Pick Up Block	75.56%	43.33%	87.62%	87.14%
Pretend	84.44%	44.44%	90.95%	92.38%
Pointing	73.33%	48.89%	77.62%	77.62%
Thumbs up	91.11%	43.33%	84.28%	85.24%

The Trigno Lab data set performed significantly during KNN classification using extracted features instead of filtered data. SVM classification only showed a slight improvement in success rates. The Myo Armband data set, however, showed significant improvements with both classifiers. This is very interesting since the Myo Armband data set is unitless. Even though this does look promising, further investigation is needed to explain why this result occurred. These initial results, however, do show that low-cost EMG sensors could have a place in VR and an input modality if used properly since the KNN classification results were similar between the Trigno Lab data set and the Myo Armband data set.

4.7 Conclusions

In this paper, we evaluated a low cost, off the shelf, EMG sensor for its potential use in VR. We decided that if this sensor can classify gestures, and we can classify gestures with a similar success rate to a sensor with a better sampling rate, then we can use it to trigger virtual interactions. We used KNN and SVM to classify the gestures. Our results show that using extracted features to classify gestures works significantly better than using raw data. Also, the classification results between the two different sensors were similar. With these results, we can conclude that, if used properly, then low-cost EMG sensors can be used in VR. We cannot fully support the use of extracted data with the Myo Armband yet until we have done further investigation.

4.8 Future Work

There are many future steps for this work. The first is to investigate how the extracted features affected the Myo Armband classification so much. This would help solidify our claim that this sensor is useful in VR. Also, we would need to expand the training set for our data so we can get more accurate weights. This will allow us to have a primary sensor with one or two secondary sensors to be considered as well. This will also allow us to get more accurate classification results. Lastly, we would look at to see how a custom calibration file effects the data collected, if at all.

The other major category for future work is using EMG in VR. We will expand on our previous work to improve gameplay and interaction with virtual objects [30]. This will then be expanded to future games as well. This should increase the interaction fidelity of virtual tasks. This will require user experience tests to be done to see if this does increase interaction fidelity as expected.

4.9 Acknowledgements

This work was partially supported by the NSF grant 1338118. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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CHAPTER 5

POT HUNTER: A VIRTUAL REALITY GAME FOR ANALYZING RANGE OF MOTION

5.1 Introduction

This is the first chapter of the Gamification section of the dissertation. This chapter presents a reaching game. This is meant to represent a task where someone is required to reach onto a high shelf and grab an object. We also show techniques of how to use gameplay to present useful data to a therapist of when a patient was reaching into the target area. These results make this a game that could be used for rehabilitation for analyzing gross upper arm range of motion. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed the study, assisted in game design, ran participants, performed analysis, wrote paper,
- Peter Sassaman: Assisted in study design, developed the game, ran participants, wrote equipment and game sections, helped edit the paper,
- Eric Becker: Assisted in study design, assisted in game design, suggested analysis techniques, assisted writing background and related sections, helped edit the paper.
- Fillia Makedon: Assisted in study design, helped edit the paper.

POT HUNTER: A VIRTUAL REALITY GAME FOR ANALYZING RANGE OF MOTION[4]

Shawn N. Gieser, Peter Sassaman, Eric Becker, and Fillia Makedon. 2015. Pot Hunter: A Virtual Reality Game for Analyzing Range of Motion. In *Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments* (PETRA '15). ACM, New York, NY, USA, , Article 3 , 4 pages.

DOI: http://dx.doi.org/10.1145/2769493.2769523

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5.2 Abstract

Patients undergoing physical therapy go through a series of sessions performing exercises to help improve the range of motion (RoM) in affected regions of the body due to disease or injury. However, patients find these tasks repetitive and boring and end up not completing the prescribed therapy program. It has been shown that game based therapy exercises have led to increased rates of compliance. In this paper, we provide a continuation of previous work in VR-based therapy and present Pot Hunter, and one type of RoM analysis for when a person reaches above their head.

Categories and Subject Descriptors: I.4.8 [Image Processing and Computer Vision] Scene Analysis – Motion, Tracking, J.3 [Computer Applications] Life and Medical Sciences

General Terms: Experimentation, Human Factors

Keywords: Range of Motion, CAVE, Motion Tracking, Physical Therapy

5.3 Introduction

Two main aims in physical rehabilitation are the enhancement of motor functionality of joints and limbs and exercise compliance, both of which improve Activities of Daily Living (ADL) [1]. One of the challenges is tracking the patient's range of motion and assisting during unsupervised exercises [2].

Using exergaming has helped improve compliance in traditional therapy [3]. A higher recovery rate was observed in patients using VR-based therapy when compared to patients undergoing traditional therapy; patients exhibited greater enthusiasm and a higher confidence level in being able to complete the program [4].

In this paper, we present a VR game, called Pot Hunter or PH for short, designed to help assess and analyze the range of motion in physical therapy. PT tracks a person playing the game in 3D space. Human motion data is collected and clustered into separate instances whenever the player reaches above his/her head. This will allow us to measure and visualize how far above the head the player is able to reach. In what follows, we first present related work, the equipment, the environment and the methods used to create and play PH. Then we provide an analysis and discussion of the results, followed by conclusion and future work.

5.4 Background

The authors of [5] analyze the strengths and weaknesses in using VR in rehabilitation.(SWOT). Some of the strengths include real- time performance feedback and gaming factors to enhance motivation. The real-time feedback is key for therapist to get real- time analysis of a patient while they are doing the exercise. Gaming factors make the patient feel motivated to complete tasks and help recover faster. Some of the weaknesses are wires, displays, and side effects the patient experiences. The introduction of wearable displays has eliminated such weaknesses. Side effects continue to be an issue (called “VR sickness”). VR brings to rehabilitation processing and graphics power as well as telerehabilitation. New technology in processors and graphics cards make it possible to develop VR technologies even cheaper and make them more immersive. Telerehabilitation has the possibility to increase compliance by allowing patients to do their exercises in more comfortable environments and still allow therapists to be involved.

A key feature for stroke victims involves the retraining of the upper limbs so they can partake of ADL. Games can be created such that the gameplay encourages the repetitive motion needed for subjects to overcome the results of the disability caused by the stroke. This gameplay is especially important because boredom becomes a key factor when doing this kind of exercise. For example, for older patients, history and trivia challenges worked better than an action style game [6]. In fact, even with the development and inclusion of inertial measurement units (IMU), the activity of the game play is usually not enough, and requires the flow of the activity to suit the player. The playing of the games with motions by themselves was not enough to encourage improvement in ADL. Thinking challenges and social interaction also need to be included in the design and structure of such virtual environments to encourage and promote rehabilitation [7]. In addition, as technology has improved, games and therapy can be moved to a home. In addition, the developers connected the game to key functions needed to resume ADL. Over the course of the study, patients using the system showed a marked improvement in their ADL, and started to show interest in their own progress and prognosis, showing real interest instead of boredom [8]. Further improvements included the implementation of a feedback loop. Incentives of scores and deterrents of loss of points would push the subjects to behave more normally, and to take the virtual environment sincerely. This extra reinforcement, both positive and negative, shaped the play in the virtual environment and the response of the subjects [9]. Making the subject want to do the exercise, wanting to do the repetition in order to retrain the neurological pathways of the brain is a key component of rehabilitation that virtual reality.

5.5 Related Work

Another aspect of keeping the subjects focused on their rehabilitation is by the application of new technologies to keep them performing their exercises regularly. One solution was the creation of a wearable baseball cap that had a pocket for a mobile device [10]. Augmented reality was used to keep young drivers focused on the traffic through a point system [11]. Another style of sensor is to have an actual tool that interacts with other objects in the real world to include adding physical stress on the hand and fingers [12].

New technologies are also in place that include, motion tracking, the Oculus Rift and Kinect. Oculus Rift is a wearable display device that projects the virtual environment on a pair of stereoscopic screens, while the Kinect can do a coarse-grain skeleton tracking of the human figure. Combined, these tools can be used to facilitate rehabilitation [13]. Another system uses the IMU with a wireless configuration to track a constrained arm or measure the rotation of a limb as it uses a steering wheel or similarly shaped device [14]. These newer technologies are cheaper and wireless.

Immersive virtual reality has the subject interact displays. One of these is MIME. It combines the head display with the hand and gesture recognition. The system is capable of recognizing the placement of the hand within the view of the subject. In addition, the system attempts to find the region of interest (ROI) of the subject, trying to find where the person is looking and devoting the system resources to improve that section of the system [15]. Gloves with actuators in the fingertips give the sense of touching a virtual object [16]. Magnetic fields are used in the Hydra unit to show hand position in a power wall situation [17].

Previous work [18] has shown that VR can be used for rehabilitation by having the subjects perform gestures that simulate traditional rehabilitation exercises. We visualized the collected data to enable the therapists better understand important information about the patient. However, an engaging interface was lacking. Also, the data set was just limited to positional data and did not include other types of data that can provide a better evaluation of the patient’s motion.

5.6 Pot Hunter

In this section, we discuss the development of the PH game providing the sensors and development environment that were used and the procedure for setting up and playing the game.

5.6.1 Equipment

Previous studies used specialized hardware to create immersive assessments. In our assessment we used a variety of devices to form a Computer Aided Virtual Environment (CAVE). The various hardware systems utilized to compose this CAVE system are the following. The Oculus Rift Head Mounted Display [19] which provides its user with a full field of view stereo three dimensional image while also providing low latency head tracking. These features combined allow their user to look around naturally in a visually convincing virtual environment. Second, we utilized the InterSense System [20] to accurately determine the position and orientation of each of the participant’s hands, head, and wand. It achieves this by emitting an ultrasonic sound from an array installed on the ceiling, which is picked up by microphones on each of the modules strapped to the user’s wrists and head. Third, we used the Fifth Dimension Technologies Data Glove 14 Ultra [21] with 14 flexure sensors on each of the gloves, they can accurately track each of the fingers on the participant's hands. A subject wearing all these sensors is shown in Figure 5.1 left. Finally, a Personal Computer was used to host all of these systems and to run the simulated environment.

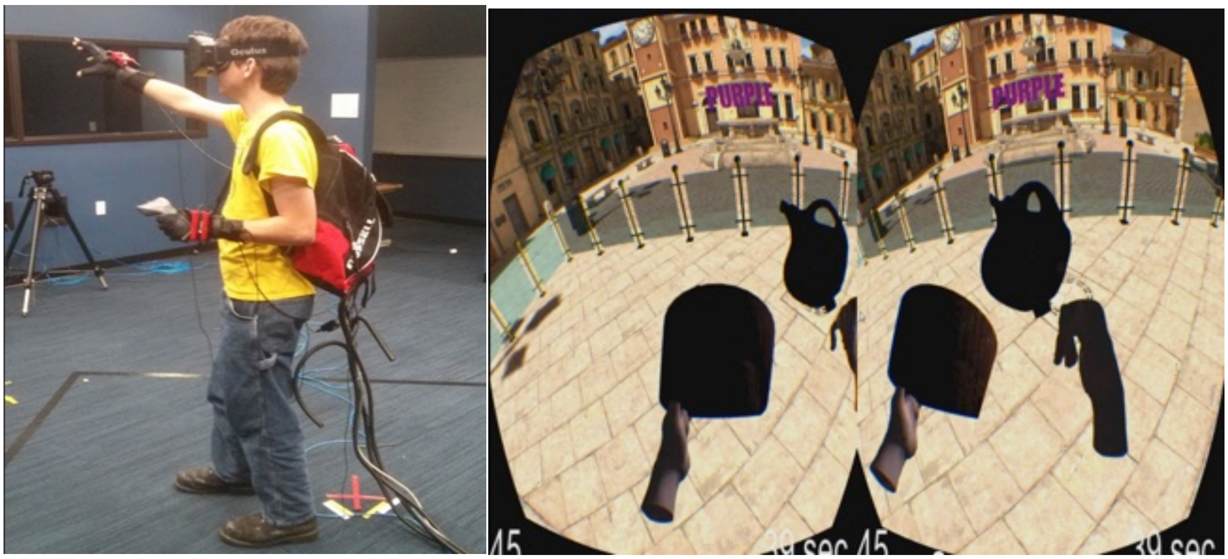

Figure 5.1 (Left) Subject wearing sensors for the PH Game (Right) Gameplay of PH seen from the Oculus Rift

5.6.2 Environment

To create a convincing and comfortable environment in which the participant could interact, several models were utilized which resemble realistic objects. First, was the scene itself which resembles an Italian Piazza. This resource came with the Vizard [22] software. Second, we utilized pots which were available for free download and use. The pots were textured to different colors for scoring pieces. Third, as a scoring bin of sorts, a basket was modeled and textured. The model was made in the Blender 3D [23] modeling software and the texture was made in the Gimp [24] art software. The texture was UV (ultra violet) mapped on the object and exported as a .dae (digital asset exchange) file type. The basket is tied in position and orientation to the physical wand sensor that is a part of the InterSense motion tracker. Finally, a barrier was modeled to discourage the participant from traveling outside the sensor boundaries. In order to prevent the barrier from obstructing the view of 3D text information in the world, the barrier was made to resemble a glass barrier. In order to achieve the convincing look of glass the reflection, refraction, and other physical properties had to be applied to the model in Blender.

5.6.3 Procedure

The procedure developed for our assessment includes the following: First, the appropriate lenses for a participant's vision strength are placed into the Oculus Rift. Second, the participant moves to the center of the room onto a cross marked with tape on the floor. Third, the data gloves, wrist trackers, wand, Oculus Rift, and head tracker are equipped by the participant. Fourth the Rift's optics are adjusted by the participant forwards or backwards to bring the image into sharp focus. Fifth, an inter-pupillary distance (IDP) test is taken. Sixth, the participant is asked to put their hands above their head, by their side, and in front of their face to calibrate where the scoring pieces should be placed in the environment. After this calibration the participant sees themselves in an Italian Piazza. Inside the Piazza is a grid of pottery in several different primary colors. 3D text appears showing the participant which color piece of pottery they should grab from the grid of pottery and place the virtual basket they are holding. The user's score increments of decrements depending the pot was of the collect color. The assessment concludes when all pots have been gathered. Figure 5.1 right shows a screenshot of the gameplay.

5.7 Analysis

We had eight subjects play the PH game ten times each. The data gathered from each sensor is shown in Table 5.1. For this paper, we are looking at the times when a player reached above their head. Therefore, only the data produced by the Intersense positional trackers were considered.

Table 5.1 Types of Data Collected from PH gameplay

Sensor	**Data Collect**
Intersense Positional Trackers (Head and Wrists)	X, Y, Z position in 3D Space, Roll, Pitch Yaw of Sensors
5DT Data Gloves	Amount of bend in each joint of the finger, Amount of abduction between fingers, Pitch, Roll
Oculus Rift	Angular Acceleration and Velocity

To find the times when a player reach above their head, we looked at the Y component of the wrist trackers in relation to the Y component of the head tracker obtained during the calibration process. The wrist tracker that was compared depends on the handedness of the player, left or right handed. Right handed players tended to reach for the pots with their right hand, while left handed players reached with their left. Whenever the dominant hand's wrist tracker was above the head tracker's calibration data, this was assumed to be a time when the player was reaching up to grab a pot.

Once the times when a player reached above their head were identified, we took the 3D positional coordinates and ran the K- Means clustering algorithm in order to group the data into separate instances of reaching up to grab a pot. Since there were only nine pots to grab during the game, we used k=9 for obtain a cluster for every instance a player reached to grab a pot. The centroid for each cluster is used as the average position of their hand and will be used in later work. We ran K-Means 10 times in and took the result that had the smallest sum of point to centroid differences. This allowed us to obtain a more accurate clustering and overcome some of the randomness of choosing the initial centroid positions.

We also looked at the timestamps when the data was sampled. If we only look at the times where a player reached above their head, we can easily cluster the positional data into different instances since there is a large time difference between last sample taken right before the hand came below the head and the first sample taken right after the hand rose above the head again compared to the time difference caused by the sample rate. This is compared to the clusters created by K-Means.

5.8 Analysis

Figure 5.2 shows the visualized Y component of each positional tracker with respect to time as well as 3D visualizations of the wrist position grouped by each instance the player reached above their head. From these, it is clear that the PH game can be used to analyze RoM when someone reaches above their head.

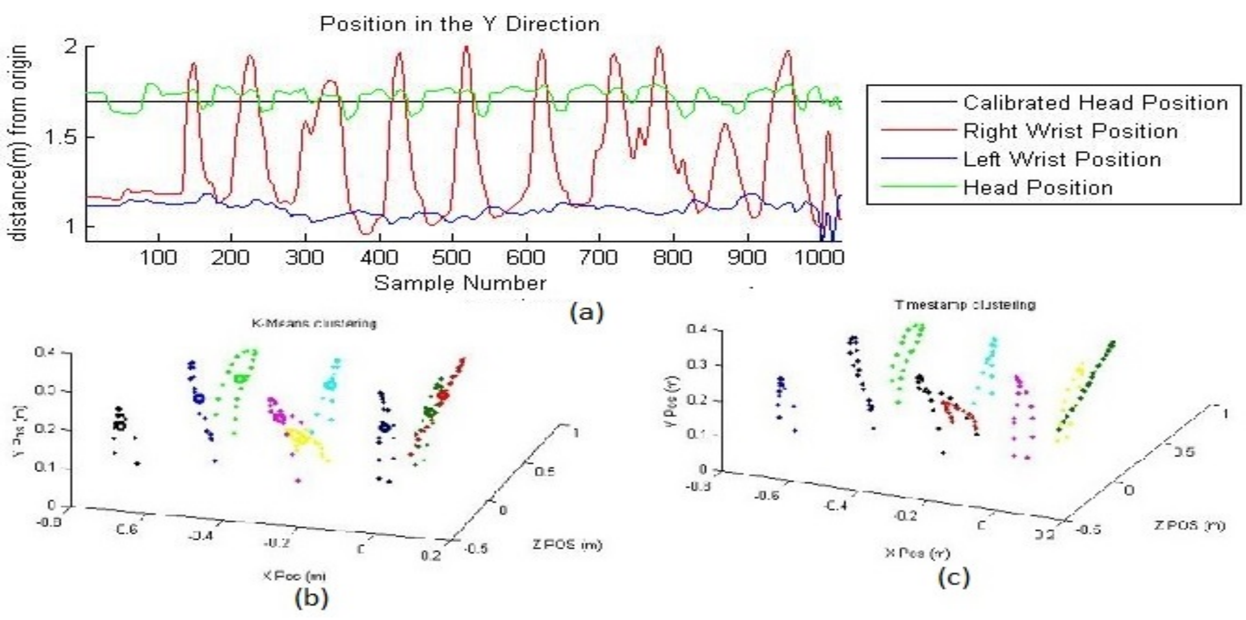

Figure 5.2 (a) Y positon of positional trackers, (b) K-Means clustering of a subject reaching 9 times above their head, (c) timestamp clustering of a subject reaching above their head.

However, there were three specific circumstances where the way the player collected pots caused problems during analysis. One of these cases is where the player very rarely brought their hand below their head. This caused the inaccurate clustering, because there were not nine distinct times where their wrist went above their head and came back down. This can be remedied in a two ways. The first is the instructing the player not raise the basket as high. The other way is to instead of looking at times when the user reached above their head is to look for local minima and maxima in the path of the wrist.

The second circumstance was when the player made wide arcs with their arms while reaching up to grab the pots. Even though there were nine distinct times where the user reached above the head, the wide arcing path made by the arm caused the wrist to intersect with previous paths when the player reached up for other pots. This caused an inaccurate clustering by K-Means since it was based on positional data and did not consider time. It did not affect the time-based clustering since that method was based solely on time. A solution to this would be to look at specific windows of the data and perform K-Means on smaller portions instead of analyzing the whole set at once.

The third is where the user reached above their head but did not grab a pot. This caused there to be more than nine instances where the player reached above their head. This caused issues in both the K-Means and time based clustering. A solution to this would be to combine the wrist data with the glove data to find times when the player reached up, closed their hand to grab a pot, and then lowered it. This would eliminate the extra times when the player reached above their heads.

5.9 Conclusion

In this paper, we presented the game PH, a continuation of the work in [18] aimed at increasing user engagement in exercise. The subjects showed increased interest in the activities to that of the previous work. We also used a similar calibration procedure to that of the previous work. We also showed that other forms of RoM analysis can be done using VR. We expanded from circular motions to that of reaching above the head and showed how traditional machine learning can be used to obtain valuable results. We showed that K-Means and timestamps analysis can be used to cluster data and perform segmented data analysis. This will allow therapists to easily monitor the progress of patients while comparing multiple sessions.

5.10 Future Work

The next phase of the PH game is to include multiple forms of analysis and the use of glove data in order to eliminate the problem described at the end of Section 6. Also, analysis of when the player reaches across their body will be analyzed as well. We will also look at the head orientation to know where the patient is looking in the virtual world. This will allow us to know when the patient looks at the pots or at the 3D text telling them what color pot to grab. This can be useful in measuring attention and memory based on how many times they look back at the text. Other algorithms for clustering and motion analysis will be analyzed to see if better results can be obtained.

We will also explore better ways to display the data to the therapist, using interactive graphs, comparing different sessions and determining how to best display the data. Finally, we will explore new ways to display the game objects for better engagement.

5.11 Acknowledgements

Thanks to Shane Hanlon for assisting in the development of the PH game and to Heracleia Lab researchers for volunteering to play the game. This work has been supported by the following NSF grants: CNS: 1338118, CNS: 1035913, and IIS: 1041637.

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CHAPTER 6

REAL-TIME STATIC GESTURE RECOGNITION FOR UPPER EXTREMITY REHABILITATION USING THE LEAP MOTION

6.1 Introduction

This is the second and final chapter of the Gamification section of this dissertation. This chapter presents a gesture matching game using the Leap Motion hand tracker. It also presents the methods used to collect data and train the gesture classification for the game. These gestures, which are used as exercises, were provided by an Occupational Therapist. This makes this game a gamified version of real Occupational Therapy exercises that could be used in a rehabilitation setting. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, collected data, performed analysis, designed game, wrote paper
- Angie Boiselle: Assisted in study design, provided gestures, wrote some background and related work, edited paper
- Fillia Makedon: Assisted in study design, edited paper

REAL-TIME STATIC GESTURE RECOGNITION FOR UPPER EXTREMITY REHABILITATION USING THE LEAP MOTION[5]

Shawn N. Gieser, Angie Boiselle, and Fillia Makedon. 2015. Real-Time Static Gesture Recognition for Upper Extremity Rehabilitation Using the Leap Motion. In Vincent G. Duffy (eds) *Digital Human Modeling. Applications in Health, Safety, Ergonomics, and Risk Management: Ergonomics and Health* (DHM '15). Lecture Notes in Computer Science, vol 9185. Springer, Cham. DOI: http://dx.doi.org/10.1007/978-3-319-21070-4_15

6.2 Abstract

Cerebral Palsy is a motor disability that occurs in early childhood. Conventional therapy methods have proven useful for upper extremity rehabilitation, but can lead to non-compliance due to children getting bored with the repetition of exercises. Virtual reality and game-like simulations of conventional methods have proven to lead to higher rates of compliance, the patient being more engaged during exercising, and yield better performance during exercises. Most games are good at keeping players engaged, but does not focus on exercising fine motor control functions. In this paper, we present an analysis of classification techniques for static hand gestures. We also present a prototype of a game-like simulation of matching static hand gestures in order to increase motor control of the hand.

Keywords: Gesture recognition, Leap Motion, Upper Extremity Rehabilitation, Gamification, Cerebral Palsy

6.3 Introduction

Cerebral palsy (CP) is a condition directly related to a lesion in the brain that occurs early in the life of a child. Children with cerebral palsy (CP) have permanent issues with posture and movement that impact participation in daily activities. They may also experience musculoskeletal changes, cognitive impairment, communication and behavioral concerns [1]. There are several subtypes of cerebral palsy based on the type of muscle tone (spasticity, dyskinetic, hypotonia, and mixed tone) and location of impairment (quadriplegia, hemiplegia, diplegia, and others) [2]. Hemiplegia is a type of CP where the child experiences limitations in posture and movement on one side of the body. A child with hemiplegia does not use the impaired arm as often as the unaffected arm due to repeated experiences of failure in using that arm. Human computer interaction (HCI) is a method that supplement traditional rehabilitation therapy, such as occupational and physical therapy, to create experiences and environments to provide children with successful opportunities to promote the use of their affected hand or limb without feeling a sense of failure. Research has shown that the use of specially designed computer games can motivate and help children to enhance the use the affected limb while also strengthening the muscles involved and any related affected functionality [3–5].

Introduction of low cost, off the shelf sensors, such as the Leap Motion [6], have increased the accessibility to and usability of equipment that was previously too expensive for many applications. The Leap Motion was specifically designed to detect hand motions and gestures. It operates over a small range and high precision due to its use of infrared optics. Rehabilitation therapists indicate that the Leap Motion has potential for rehabilitation and that it would be an effective motivational tool young people within a home environment without a therapist being present [7].

The purpose of this paper is twofold. First, we will compare three classification techniques, decision trees, Support Vector Machines (SVM) and k-nearest neighbors (KNN), to recognize and classify static gestures from the Leap Motion based on the position of the hand and fingers as well as the joint angles. Secondly, a game will be created to detect these gestures and will be evaluated by both student volunteers and occupational therapy experts in the field.

6.4 Background

Evidence for rehabilitation in the area of cerebral palsy has expanded in recent years due to new technologies and methodologies. Specific interventions have been researched to ensure efficacy, cost-effectiveness and safety [8]. In addition, the World Health Organization (WHO) has established the International Classification of Functioning, Disability, and Health (ICF) that is intended to serve as a collaborative global framework and scientific tool to measure health and disability. The ICF has shifted the focus from disability and impairment to that of function and participation within context of the social and physical environment [9]. It is for these reasons that it is important to develop rehabilitation interventions that are both evidence-based and consider contextual factors and participation.

Reference [8] completed a systematic review of smaller systematic reviews for interventions related to children with cerebral palsy. Therapeutic interventions that were found to have the strongest evidence included: bimanual training; Botulinum toxin (Botox) injections; context-focused therapy; goal-directed functional training using a motor-learning approach; therapeutic home programs; and Botox followed up by occupational therapy. Human computer interaction is an area within rehabilitation therapy that provides a new and innovative method for intervention. Virtual reality games are used in rehabilitation to promote movement and strengthening within a motivating environment [10]. Evidence is emerging to determine the efficacy of virtual reality and influence of functional outcomes related to children with cerebral palsy [11]. However, the principles of Virtual Reality (VR) support strong evidence because it can be designed to emphasize motor learning, bimanual training and goal-directed training within the home environment [10, 12]. The child's participation in rehabilitation through the use of highly motivational VR games within the context of their home also supports WHO initiatives.

Gaming systems such as the commercially-available gaming systems and robotic arm systems are most commonly used in the clinic setting. Children with CP are often unable to use commercially-available systems due to movement restrictions in the upper extremities. Additionally, they are not beneficial to the occupational therapist because they do not specifically measure small upper extremity movements such as finger extension, wrist extension, ulnar/radial deviation, and forearm supination [13].

6.5 Related Work

VR has been used in the treatment of CP with an increased success rate compared to conventional exercises. The authors of [4] show that children with and without CP found that VR exercises are more interesting than conventional exercises. These children also were able to hold exercises longer and showed an increased range of motion during VR exercises compared to conventional exercises. The parents for the children also noticed their children having more fun during VR exercises and believe that their children would continue the exercises at home. The authors of [14] also agree with this, stating that a VR training program has potential to improve reaching abilities and control in children with CP.

The Leap Motion controller has been used in game based physical therapy. Reference [7] evaluated the usefulness of the Leap Motion controller for a clinical environment by developing game-like versions of existing rehabilitation activities that were evaluated by clinicians. The results of their trial show that the Leap Motion does have potential to be used in place of some traditional techniques, especially in the home and for young people. Reference [15] focused on the responses from patients. The patients in this study said that the game presented to them was very engaging and addressing a need of practicing movements that are related to daily functions. Also, the patients said that they would play this game if provided as part of home therapy program.

Work has also been done with using the Leap Motion controller in terms of gesture recognition. Reference [16] shows classification techniques using the Leap Motion controller for both static and dynamic gestures. Reference [17] also presents a gesture recognition system using the Leap Motion control made for therapy applications, including a list of gestures created with the help of therapists. Both these systems, however, are lacking a game aspect to keep the patient involved. These present a good starting point, but missing the game component could lead to non-compliance similar to that of conventional therapy exercises.

6.6 Experimental Procedure

6.6.1 Equipment

This paper focuses on the use of the Leap Motion controller. As shown in Fig. 6.1, the Leap Motion consists of three infrared (IR) light emitters and two IR cameras. Since this system uses stereo vision, it can be categorized as an optical tracking system instead of depth based tracking system [18]. The Leap Motion controller provides detailed information about a user's hand, including the position of the wrist, palm, and finger digits in the Cartesian space, as well as the direction of the hand and finger digits. This information can be used to determine joint angles of the wrist and knuckles. The Leap Motion controller can also provide other information, such as what fingers are extended, the normal vector to the palm, information about the forearm and any tools being used within the Leap Motion controller's field of view.

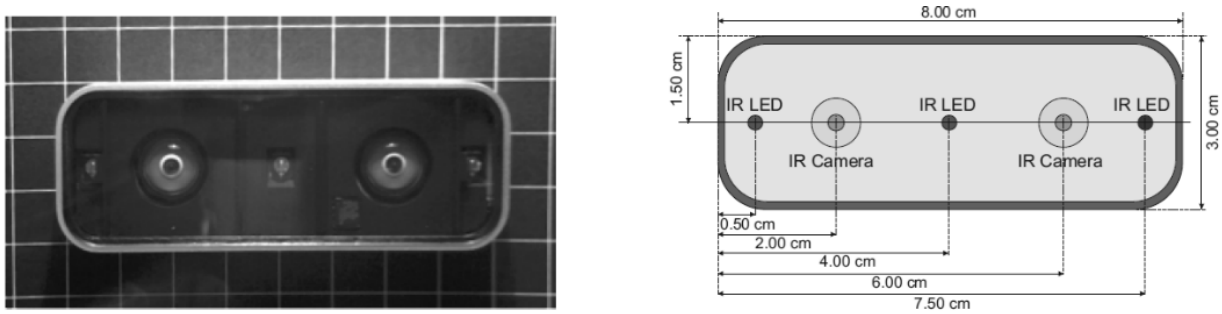

Figure 6.1 A view of the real (left) and the schematic (right) of the leap motion controller

6.6.2 Data Collection

A gesture library was created for this prototype with the help of an occupational therapist. The goal of this was to actually recognize gestures that are used as exercises. Figure 6.2 shows the gestures that were chosen for this library.

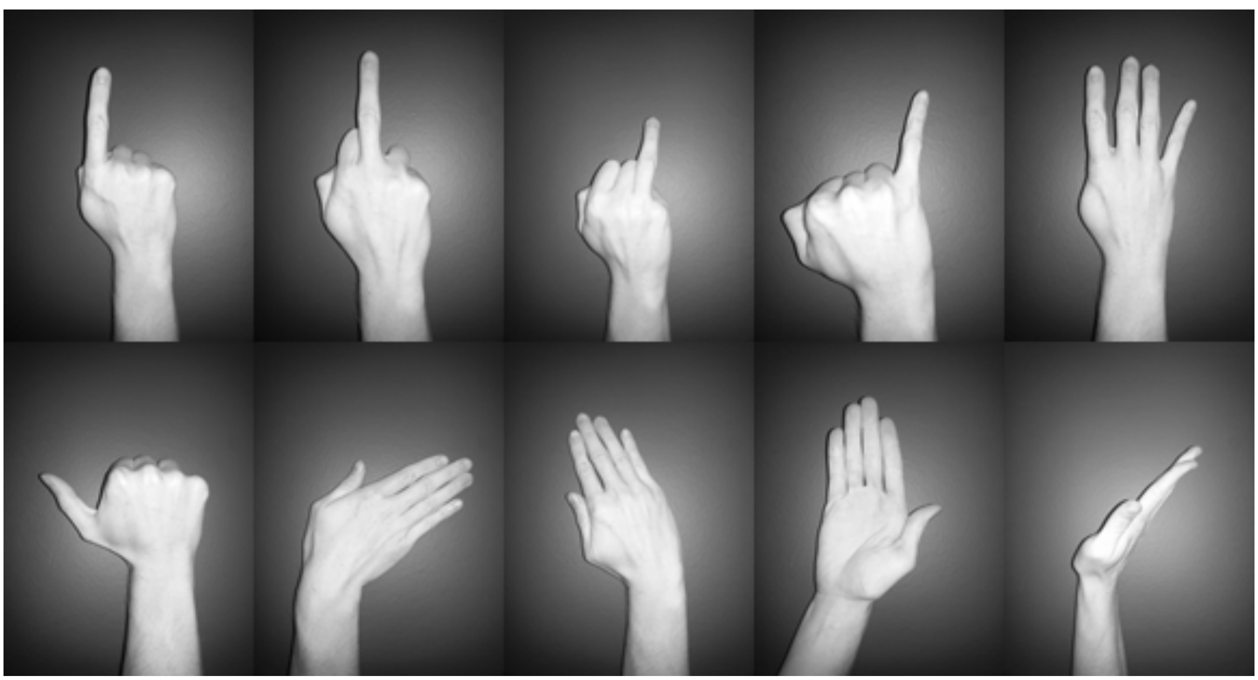

Figure 6.2 Gesture library for the prototype. from top left corner to bottom right: extension of the index finger, extension of the middle finger, extension of the ring finger, extension of the pinky finger, extension of four fingers, extension of the thumb, ulnar deviation, radial deviation, supination of the forearm, extension of the wrist.

The training data for the various classification procedures was gathered by having student volunteers perform the gestures in a controlled environment. A visualization tool was developed using the Unity Game Engine [19] and the Leap Motion API. UI tools were placed in the top left corner to allow the administrator of the data collection to easier start and stop data collection and save the data. Also, the volunteer can see a visualization their hand on the screen to allow the administrator and the volunteer to verify that the gesture is seen correctly by the Leap Motion Controller. Figure 6.3 shows this UI Design.

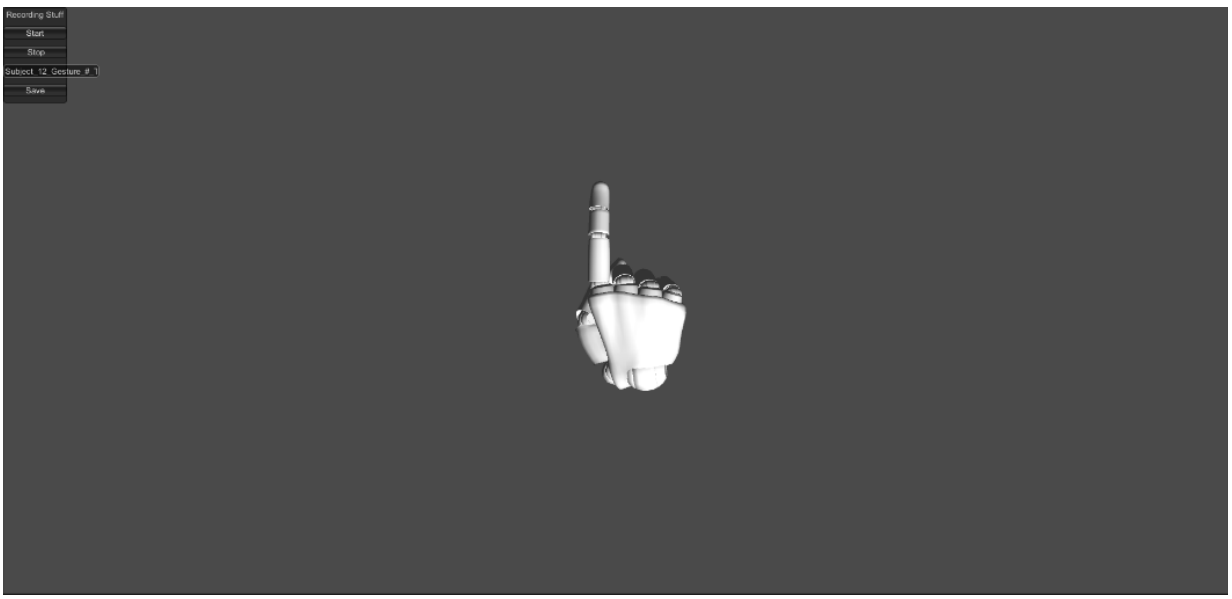

Figure 6.3 View of the data collection program of extension of the index finger

The volunteer was given photos of the gestures before data collection begun so they could know what they had to do. The volunteer then placed their right hand above the Leap Motion controller and made the first gesture. When it was shown correctly on the screen, the administrator collected approximately 5 s of data at a sample rate of 50 Hz and saved it. The volunteer then made the second gesture, and was recorded the same way. This task was repeated till all gestures were recorded, and the whole process was repeated two more times. We did not record all the data points produced by the Leap Motion control. Instead, we only recorded the features that were useful to determine the gesture. These included what fingers were extended, the direction of the forearm and the hand, the normal vector of the palm, and joint angles of the wrist and knuckles.

6.7 Analysis

We used three different methods of classification: Decision Tree, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). First, we had to determine what features are used to classify which gestures. For example, only the Supination of the Forearm gesture has the palm's normal vector in the positive Y direction. This feature can then be ignored for all other gestures in this gesture library. A full list of the features that were used to classify each gesture is shown in Table 6.1.

Table 6.1 List of features used to identify each gesture

Gesture Name	Features Used
Extension of the Index Finger	Extension values of the 5 fingers, angles of the metacarpophalangeal (MP), proximal interphalangeal (PIP), and distal interphalangeal (DIP) joints of the index finger
Extension of the Middle Finger	Extension values of the 5 fingers, angles of the MP, PIP, and DIP joints of the middle finger
Extension of the Ring Finger	Extension values of the 5 fingers, angles of the MP, PIP, and DIP joints of the ring finger
Extension of the Pinky Finger	Extension values of the 5 fingers, angles of the MP, PIP, and DIP joints of the pinky finger
Extension of Four Fingers	Extension values of the 5 fingers, angles of the MP, PIP, and DIP joints of the four fingers
Extension of the Thumb	Extension values of the 5 fingers, angles of the MP and interphalangeal (IP) joints of the Thumb
Unlar Deviation	Direction of Forearm and Hand, angle of the wrist joint
Radial Deviation	Direction of Forearm and Hand, angle of the wrist joint
Supination of the Forearm	Palm's normal vector
Extension of the Wrist	Direction of Forearm and Hand, angle of the wrist joint

We made ten different decision trees to classify the ten different gestures. The reason for this was based on game play. During gameplay, we can assume what gesture someone is supposed to make by where they are in the game, since they would only make certain gestures at certain points. With this assumption, we can classify the gesture with a decision tree with fewer levels than a single tree that would classify all gestures at once. One of the decision trees is shown in Fig. 6.4. The tolerances for the joint angles and directional vectors were determined by looking at the training data to verify that a majority of the training data would be classified correctly, and to allow some error from any potential input from a game.

The KNN analysis was developed using the built in Matlab functions. The number of neighbors chosen was 294 as it still yielded a very low error. No other parameters were changed. This approach only used one model to classify gestures, unlike the decision tree approach mentioned above. We only used one model, because KNN can easily handle multiple classes without consuming too much time. This approach also was the only one to use all features collected to classify the gesture.

Lastly, we used 10 SVMs also developed using the built in Matlab functions using the Gaussian Radial Basis Function as the kernel function. We made 10 different SVMs for the same reason as mentioned with the decision trees. The feature vector for each SVM comes from the Table 6.1.

Table 6.2 shows a comparison between the 3 different methods. The method used to verify the classification models developed was resubstitution. Each model had the data samples that were supposed to match the model resubstituted back into the model to give the results below. As shown, KNN yielded the best results. Most of the decision tree models were above 90 %, and further modification on the tolerances for the middle, ring, and pinky finger extensions would help fix this.

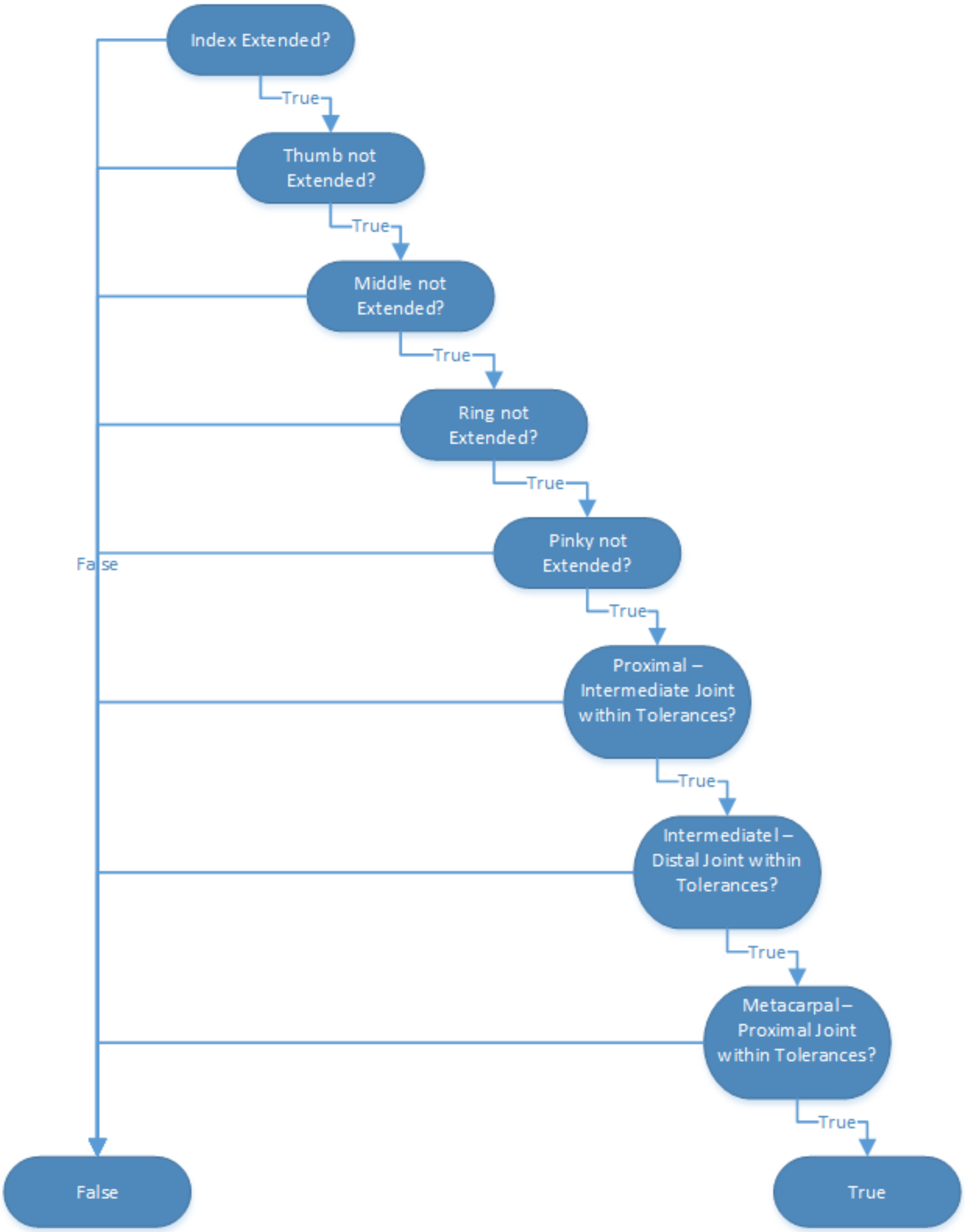

Figure 6.4 Decision tree for extension of the index finger

Table 6.2 Classification results using resubstitution of training data

	Decision Tree		KNN		SVM	
	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Extension of the Index Finger	93.96%	6.04%	100%	0%	100%	0%
Extension of the Middle Finger	76.96%	23.04%	100%	0%	100%	0%
Extension of the Ring Finger	82.57%	17.43%	100%	0%	100%	0%
Extension of the Pinky Finger	89.09%	10.91%	100%	0%	100%	0%
Extension of Four Fingers	97.24%	2.76%	99.51%	0.49%	99.68%	0.32%
Extension of the Thumb	100%	0%	100%	0%	100%	0%
Unlar Deviation	96.7%	3.3%	100%	0%	99.91%	0.09%
Radial Deviation	99.91%	0.09%	99.88%	0.12%	99.86%	0.14%
Supination of the Forearm	100%	0%	100%	0%	100%	0%
Extension of the Wrist	93.32%	6.68%	100%	0%	97.9%	2.1%

6.8 Game

For the game prototype development, we once again used the Unity Game Engine and the Leap Motion API. The game consists of two phases. The first is a fifteen second rest period. The player is not required to do anything during this phase. A picture of the next gesture is shown so that the player can prepare. During the second phase, the player is to match a gesture that is shown on the screen. Both a picture of the gesture and a visualization of the hand as seen from the Leap Motion are shown to players, so that they can see what they are doing with respect to real life and the Leap Motion itself. When the gesture is matched, the top left corner turns green, and red when it is not matched. The score increments by one for every second the gesture is held. A screen capture of this game is shown in Fig. 6.5. This is supposed to help strengthen the hand. We used the decision tree models for this game due to the lack of open source classification software readily available for Unity. The recognition of gestures did not seem to be affected by using decision trees in terms of response and recognizing most gestures. Certain gestures, however, did require more exact positioning than was expected by the authors.

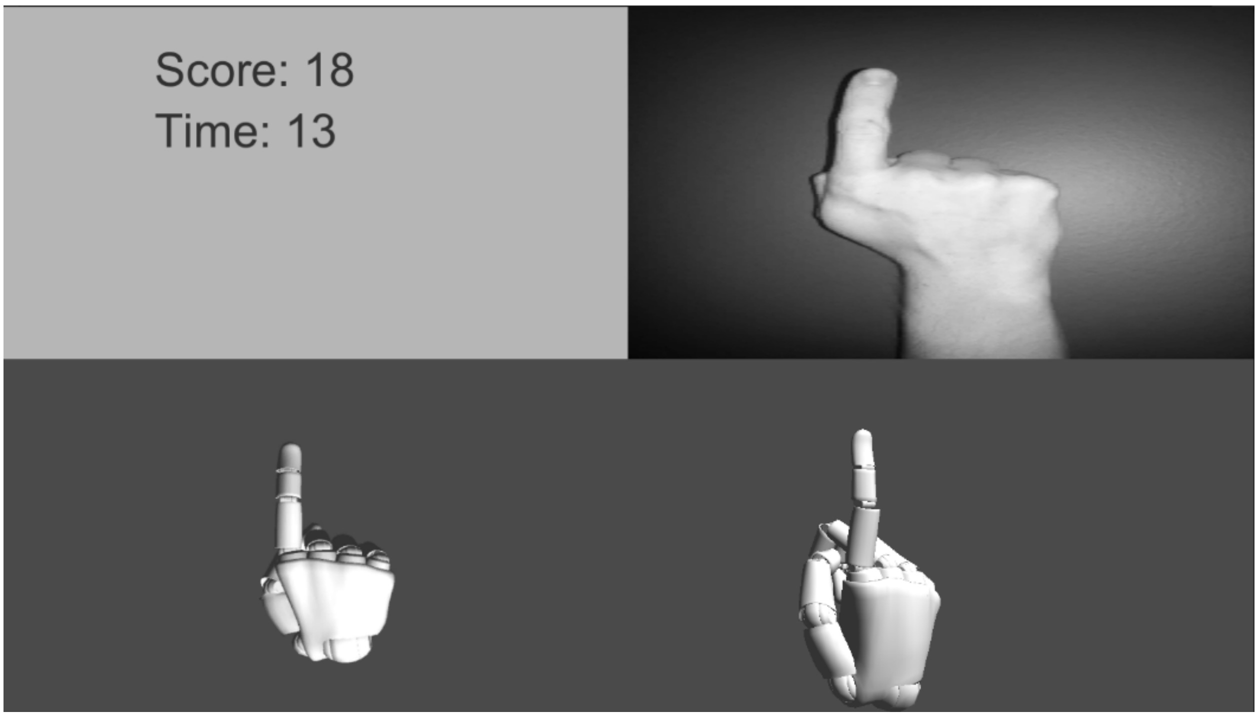

Figure 6.5 Screen capture of the unity leap motion game

Student volunteers played the game then filled out a three question survey afterwards. All but question was on a Likert Scale of 1–5 with 5 being the most positive and 1 being the most negative. The mean of the responses to the question “I feel the overall control interface is easy to use” was 3.67, but the mean of the responses to “I feel that with practice, I could become proficient in using the control interface” was 4.83. This shows that people feel that playing the game more would lead them to a higher score, which would then improve range of motion. The mean of the responses to the question “The tasks presented on the screen are easy to understand” was 4.33. The only comment from the volunteers that one of the pictures was rotated from the Leap Motion model, which caused some confusion.

A video of one of the authors playing the game was made and sent out 2 area hospitals to be evaluated by physical and occupational pediatric therapists. This prototype got mixed reviews. The mean of “The Leap Motion appears easy to use” and “I feel that I could become proficient in using the Leap Motion” was 3.78, while the mean of “The tasks on the screen are easy to understand” was a 4. When asked about an improved version of the prototype, the most interesting response was to “I feel patients would be motivated to use an improved version of this prototype” which had a mean of 2.87. The comments provided by theses therapists said that the game needs to be more engaging, fun, and interactive to help hold a patient’s attention.

6.9 Conclusion

In this paper, we have presented an analysis of classification techniques on data gathered from the Leap Motion controller. Decision trees provided over 90% accuracy for the majority of gestures, but KNN and SVM provided much more accurate results. This is believed to be due to the tolerances chosen for the joint angles of the decision tree now allowing for a wide enough variance to properly classify certain gestures. Further adjustment of the tolerances should yield better classification results.

A game prototype also was presented. The reviews of the student volunteers playing this prototype said that the interface was easy to use and could easily become proficient in using it. Therapists viewing a demo of the game also had positive feedback in terms of using the Leap Motion controller and the way tasks were presented to the user. Therapists did comment on the engagement level of the game, saying that patients might not feel motivated to use the current or improved version of this prototype, saying that the game needs to have more features to keep the patient's attention so that they feel motivated to use the system. Based on the feedback from the student volunteers and the therapists, there is enough evidence to develop a new version of the game which incorporate other gestures and data modalities, as well as a more engaging interface.

6.10 Future Work

The next phase of this prototype is to expand on the gesture library. Adding gestures will increase the number of features to be viewed to distinguish gestures from each other. Gestures added could be either static or dynamic. This would then mean that more analysis of various gesture recognition algorithms would be needed to determine the best use for dynamic gestures using the Leap Motion.

Also, a therapist user interface will be added. This will allow therapists to view any important data gathered during gameplay sessions. This will also enable the potential for telerehabilitation, since the therapist can then view the data from sessions the patient does at home. This interface will also allow the therapist to control the exercises, such as the order of the gestures and the difficulty of the exercises, or how accurate the gesture has to be.

Lastly, a more engaging game will be developed. The current game is very basic, and therapists have commented on it. A more engaging game might help therapists feel that the patient would feel motivated to play this game, especially in pediatrics.

6.11 Acknowledgements

Acknowledgements. Special thanks to the students of the Heracleia Human Centered Computing Laboratory who volunteered to play the game and provide feedback. This work has been partially supported by the following NSF grants: CNS: 1338118, CNS: 1035913, and IIS: 1041637.

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CHAPTER 7

COMPARING OBJECTIVE AND SUBJECTIVE METRICS BETWEEN PHYSICAL AND VIRTUAL TASKS

7.1 Introduction

This is the first chapter of the Box and Blocks section of this dissertation. This section will focus on the Box and Blocks Test, an assessment used in Occupational Therapy. This chapter focuses on a computerized version of the Box and Blocks Test using the Leap Motion. The game is presented and used in a user study. The user study reveals information of how people felt about the computerized, or virtual, version compared to a physical one, as well as their performance between the two different versions. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, designed virtual version, assisted in building the physical version, ran participants, performed analysis, wrote paper
- Caleb Gentry: Built the physical version, wrote physical version of the paper
- James LePage: Assisted in study design, performed analysis, assisted in writing related works, background, and results, edited paper
- Fillia Makedon: Assisted in study design, edited paper.

COMPARING OBJECTIVE AND SUBJECTIVE METRICS BETWEEN PHYSICAL AND VIRTUAL TASKS[6]

Shawn N. Gieser, Caleb Gentry, James LePage, and Fillia Makedon. 2016. Comparing Objective and Subjective Metrics Between Physical and Virtual Tasks. In Stephanie Lackey and Robert Shumaker (eds.) *Virtual Augmented and Mixed Reality* (VAMR ’16). Lecture Notes in Computer Science, vol. 9740. Springer, Cham. DOI: https://dx.doi.org/10.1007/978-3-319-39907-2_1

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7.2 Abstract

Virtual Reality (VR) is becoming a tool that is more often used in various types of activities, including rehabilitation. However, studies using VR rehabilitation mainly focus on comparing the performances of participants, but not their opinions. In this paper, we present a virtual version of the Box and Blocks Test. We also present the results of a pilot study where participants completed a physical version of the Box and Blocks Test and the virtual version, comparing their scores and opinions. We also compare how the participants viewed the passage of time while performing both versions as a way to see how engaged they were during the task.

Keywords: Box and blocks test, Leap Motion, Upper extremity rehabilitation, Gamification, Virtual Reality, Time Perception

7.3 Introduction

The onset of low-cost, off-the-shelf sensing equipment, such as the Leap Motion [1], have made Virtual Reality (VR) more easily accessible to everyone. It has also expanded the use of VR and virtual environments into many different fields, such as driving simulations, cooking, vocational training, and rehabilitation [2–5]. When VR is used in rehabilitation, exercise programs can provide more interesting and engaging tasks, causing patients to perform better and recover quicker than traditional rehabilitation [6]. Research has shown that therapists would use certain types of VR technology in a home environment without their presence, creating a form of tele-rehabilitation [5].

However, with this advent of VR rehabilitation, would people want to perform a VR version of exercises and tasks, or would they rather do the traditional physical version Also, other questions can be asked too, such as which version do people find more fun, more frustrating, or which would they rather do again? This paper aims to answer these questions by presenting a virtual version of an Occupational Therapy assessment task called the Box and Blocks Test using the Leap Motion. This virtual version was then compared to the tangible and traditional physical version by having participants perform both tasks and recording their performance. We will also compare how participants perceive the passage of time to see which version they were more engaged by. Lastly, we will compare their subjective opinions of the participants to see which version they prefer and why, as well as their overall opinions of the technology being developed.

7.4 Background

The Box and Blocks Test is an assessment used in Occupational Therapy used to evaluate gross manual dexterity [7]. This is done by having a participant sit in front of a box with a partition in the middle, and having them move blocks from one side to the other. The goal is to move as many blocks as the participant can in a one minute time period. Blocks can only be moved one at a time. The test is at first uses only the participant’s dominant or non-affected (for people with disabilities) hand, moving blocks from the same side as the dominant hand to the other. The participant get a point for each block they move over. Carrying multiple blocks over at once only counts as one point. If the hand does not completely cross the partition (i.e. the block is thrown over), that block is not counted towards the score. If a block bounces out of the box and lands on the table or the floor, that block is still counted and the participant does not have to pick it up. After one minute has passed, the blocks are counted and the test is reset to be repeated with the person's non-dominant or affected hand.

The assessment of activity engagement can be done by simply asking participants to what degree they enjoyed the activity; however this can create expectation demand which bias the participants' self-reports. To avoid these demand characteristics, more indirect means of assessing engagement is required. A relatively simple way of indirectly assessing engagement is through the assessment of perceived time while per- forming a task.

Characterized by the idiom "time flies when you are having fun," research has shown that being exposed to engaging positive activities or stimuli results in individuals underestimate the amount of time that has passed, while individuals tend to overestimate time passing when under negative conditions [8–10]. In practical terms, being exposed to positive stimuli such as pictures of desserts or pleasurable tactile stimulation [11] result in an underestimation of exposure time. Factors such as pain [12] and fear [13] have been associated with an overestimations of the time passed.

7.5 Related Work

Using VR has been shown to have many strengths when applying it to rehabilitation, as it provides stimulus control, consistency, and real-time performance feedback. VR also allows the adaptation to a patient's abilities, and the ability to distract and motivate a patient [14]. In fact, VR can be used for patients of all ages, helping adults regain the ability to perform activities of daily living [15] to children with Cerebral Palsy to improve motor performance [16]. The Leap Motion has been evaluated for game based therapy. Clinicians and therapists have shown positive feedback when viewing the Leap Motion’s use for therapy [17], and that it has the potential to be used in a home environment with younger users [5].

The Box and Blocks Test has been used in many stages of studies that involves VR rehabilitation, such as evaluation of VR tasks or even being the task performed. The performance of people performing VR tasks and games created is correlated to the scores of that same person performing the Box and Blocks Test [15]. The scores from the Box and Blocks Test are also used as inclusion and exclusion from studies that involve VR games as well [18]. There have been versions of the Box and Blocks Test created in a virtual environment using both a Wii and a Kinect [19, 20]. However, these two studies only showed the performance between the different versions, and did not consider the opinions of the participants performing the task.

Not surprising, video and computer games have also demonstrated distortions in perceived time passing while engaged. For example, when time performing the activities were the same, the perceived time playing a video game was shorter than reading on a computer [21]. Additionally, in a comparison of expert and novice gamers, expert gamers perceived time as passing more quickly than novices after 30 and 60 min of play. While initially novice gamers perceived time as going slower while they were learning the game after 90 min they had similar time experiences as experts as their experience increased [22].

7.6 Experimental Setup and Procedure

For this experiment, we had participants perform two different versions of the Box and Blocks Test. The first version was a traditional version that could be touched. The second version was a virtual version done on a computer, lacking any tactile feedback.

All participants participating in this pilot study were from a healthy general student population. The rest of this section will describe the two different versions followed by the experimental procedure.

7.6.1 Physical Version

The physical version used in the study was 3D printed. The goal with the physical version of the test was simply to recreate the size and shape of the original test. The box has a partition dividing it in half with all of the blocks on one side, where the subject was asked to move all blocks from one side of the partition to the other in one minute [7]. The goal was to see their ability to reach and grab the blocks, and quickly move them over the partition to drop them into the other side. The physical setup used for this experiment is shown below in Fig. 7.1 Left. The box and blocks were designed using SolidWorks CAD software, and printed using Makerbot Replicator 2 and Polyprinter 229 3D printers. The reason for this design was centered around some physical goals for the equipment.

Figure 7.1 (Left) Physical version that was 3D printed. (Right) Virtual version that was created in Unity using the Leap Motion.

Firstly, it was desired that the physical version be mobile, and easy transport to the different subjects in the test. Thus, it was decided that rather than making the box and blocks out of wood, which would be heavy, plastic puzzle pieces would be light, and easy to place into a box for easy transportation. Additionally, if any piece of the box broke, a repair would be easy, requiring only that the broken part be reprinted and then the experiment could easily continue. Thus, this design was more mobile and robust, allowing the experiment to be performed accurately on a continuous basis. In order to accomplish this, the parts needed to be designed using dovetails for a “puzzle-piece” fitting process. This allowed the parts to be easily printed, easy to assemble, and easy to transport.

7.6.2 Virtual Version

A virtual version of the Box and Blocks test was developed using the Unity Game Engine [23], which can be seen in Fig. 7.1 Right. All components were developed to be a scale model of the physical version in comparison to the size of a virtual hand. This allowed the virtual version to be an accurate recreation of the physical version and would require participants to perform the exact same actions to complete the Box and Blocks Test. This virtual environment was displayed on a computer monitor.

A Leap Motion was used to capture the motion of the hand. Grabbing the blocks in the virtual world is done in a similar fashion to that of the physical version. When a participant’s fingers were near a block and then brought their fingers close together in a pinching fashion, a block was bound to the participant’s thumb on their virtual hand. When they moved their fingers apart, the block would be released from the thumb and fall from the hand. This prevented multiple blocks to be picked up at once. The physics model for the hand was turned off to make it easier for the participant to move their virtual hand and pick up blocks without causing other blocks to fly around the environment. The score was automatically tracked and increased each time a block was placed in or fell into the other side of the box.

For gameplay, timers were implemented for the fifteen second practice and the sixty second full sessions that turn off sensor input upon completion. During the full session, the data from the Leap Motion is recorded so that it can be analyzed later and turned into a report for therapists. These data points include, but not limited to, the wrist position, palm position, fingertip positions, and joint angles.

7.6.3 Experimental Procedure

Twelve participants took part in this pilot study. After obtaining consent, the participants were given a survey asking the following questions:

- Demographic questions, such as age, gender, and ethnicity
- Have you had any experience playing video games? Significant/Some/No Experience
- Have you had any experience with virtual reality? Significant/Some/No Experience

Then, the concept of the Box and Blocks Test was described to the participants. Afterwards, the participants performed both the physical and virtual versions in one minute and five minute formats. The order of the tasks were complete were balanced in order to not show any bias towards a certain version. The order of tasks can been seen in Table 7.1.

Both the one minute physical and virtual versions were similar to the original procedure [24], with the physical being exact, and the virtual having minor modifications. The one minute tasks consisted of an optional practice period followed by the actual test. The practice period for the physical version followed the standard rules of fifteen seconds. The virtual version's practice period did not have a time limit, but lasted until the participants had a firm understanding of how to pick up blocks in the virtual world. After the practice period, the participants than performed the Box and Blocks Test with both hands with both versions. The participants' score was recorded after each one-minute tasks.

Table 7.1 Order of tasks completed by participants

Participant Number	**Task 1**	**Task 2**	**Task 3**	**Task 4**
1, 5, 9	Physical One-Minute	Virtual One-Minute	Physical Five-Minute	Virtual Five-Minute
2, 6, 10	Virtual One-Minute	Physical One-Minute	Physical Five-Minute	Virtual Five-Minute
3, 7, 11	Physical One-Minute	Virtual One-Minute	Virtual Five-Minute	Physical Five-Minute
4, 8, 12	Virtual One-Minute	Physical One-Minute	Virtual Five-Minute	Physical Five-Minute

After the one-minute tasks, the participants were given another survey to see what their opinions were of the two different versions. The questions can be seen in Table 7.5 in Sect. 7.7, along with the results of the survey.

Once the survey was completed, the participants were then asked to do a five minute version of both the virtual and the physical tasks. If they ran out of blocks on one side of the box, the participants started moving blocks back to the other side without changing hands. The participants were not told when five minutes were over, but were told to stop whenever they felt five minutes have passed. All other rules of the one minute version still applied to the five minute version. The five minute tasks were performed with both hands. The scores and the elapsed time since the start of the task till the participants stopped were recorded.

A short video explaining the procedure and technology used can be seen here: https://youtu.be/ej5ZQBTGDWU.

7.7 Analysis and Discussion

Below, in Table 7.2 is the demographic information of the student population that participated in this study. The rest of this section will detail the rest of the results obtained.

Table 7.2 Demographic information of student participants

Population Characteristics	**Number of participants**	**Percentage**
Male	9	75%
Age		
18 – 24	6	50%
25 – 34	4	33%
35 – 44	2	17%
Ethnic or racial minority	3	25%
Bacherlors Degree or Higher	6	50%
Right Handed	10	83%

7.7.1 Experience with Video Games and VR

Experience with video games and virtual reality was assessed on a three point self-report measure: No Experience, Some Experience, and Significant Experience. Though this was a very crude evaluation tool, it does allow students to easily classify their experience.

As shown in Table 7.3, there was a fair amount of variability in the response of the students with only one student reporting “Significant Experience” with virtual reality.

To improve the interpretability of the results, scores were coded: No Experi- ence = 0, Some Experience = 1, and Significant Experience = 2. The two scales were summed. Students were then split into two groups, Low Experience (scores of 0 or 1, N = 5) and High Experience (scores greater than 1, N = 7).

Table 7.3 Participants experience with video games and virtual reality

Level of Experience	Number of Participants	Percentage
Video Game Experience		
No Experience	3	25%
Some Experience	3	25%
Significant Experience	6	50%
Virtual Reality Experience		
No Experience	5	42%
Some Experience	6	50%
Significant Experience	1	8%

7.7.2 Comparison of Scores on Physical and VR Tasks

As expected, students scored higher, in the physical task compared to the virtual task, as seen in Table 7.4. At the one minute mark using the dominant hand, students physically moved 53.6 (sd = 7.1) blocks compare to 19.3 (sd = 5.0) moved through the computer interface. The results on the non-dominant had were very similar with 55.7 (sd = 6.7) moved in the physical task and 19.5 (s.d = 5.1) moved in the computer task. Paired comparisons between modalities were significantly different ($p < .001$).

Table 7.4 Number of blocks moved by each participant

Participant Number	Physical		Virtual	
	Right	Left	Right	Left
1	44	48	26	21
2	55	57	24	25
3	58	50	27	28
4	49	46	21	17
5	62	61	16	24
6	56	69	20	21
7	58	52	12	12
8	60	55	13	14
9	63	60	20	13
10	45	46	20	18
11	45	51	21	15
12	59	62	15	24

Overall the it appeared that experience with video games and VR was associated superior ability to perform the computer task as the level of video game/VR experience was positively correlated with total blocks moved in the computer task, $r = .834$, but not in the physical task, $r = .101$. Contrary to expectations, the association between the total moved with both hands was insignificant $p > .5$.

7.7.3 Time Perception

Students, when asked to stop when they perceived five minutes had passed, spent approximately the same amount of time on the each modality. Total time spent of both dominant and non-dominant hands were 545 s (sd = 204) for the physical task and 536 (sd = 227) for the computer task, $p > .5$.

When the analysis was done between Low and High Experience students, there was a significant difference in the time spent performing the computer task. Those with High Experience performed the task for 427 s (sd = 169) compared to the Low Experience students who performed the task for 689 s (sd = 223), 2 min more.

7.7.4 Student's Subjective Experiences

The subjective experiences of the students were evaluated. Table 7.5 presents the questions asked and the preferences of the students. As can be seen, the physical task was viewed as easier and less frustrating by the majority of students. Of note, the majority of students felt that technologies like the one used here should be developed to improve rehabilitation and would recommend this type of system to a family member.

One interesting finding was that the subjective ratings appear, in part, related to the amount of experience the student had in video games/VR. In the item "Which version was more fun?" zero (0 %) of students in with Low Experience felt the virtual task was more ‘fun’; this is significantly lower than the High Experience students where four (57 %) reported the virtual task was more fun, X2(2, N = 7) = 8.6; p = .004).

Table 7.5 Subjective comparison of physical and virtual based tasks

	Physical		**Computer**		**No Preference**	
	N	**%**	**N**	**%**	**N**	**%**
Which version was more fun?	6	50%	4	33	2	17%
Which version was more frustrating?	0	0%	10	83%	2	17%
Which version was stressful?	3	25%	6	50%	3	3%
Which version makes you more tired or worn out?	5	42%	5	42%	2	17%
Which version required more work?	2	17%	9	75%	1	8%
Which version would you rather do again?	7	58%	3	25%	2	17%
Ratings on 1-10 with 10 being the highest					**Average**	**SD**
How useful do you think the technology would be in assisting in rehabilitation?					7.1	2.1
If you were asked to use this type of technology for rehabilitation at home, how likely would you use it?					7.2	2.1
How strongly do you feel these types of technologies should be developed?					9.4	0.9
Would you recommend a friend of family member to use this technology in their rehabilitation?					**N**	**%**
Yes					9	75%
No					0	0%
No Preference					3	25%

There were two common comments that were received by the participants about why the virtual version was harder and more frustrating. The first was that it was very difficult to grab the blocks at times in the virtual version. The second was that it was sometimes hard to perceive where the fingers were and what block you would be picking up.

7.8 Conclusions

In this paper, we have presented a virtual version of the Box and Blocks Test. We compared the scores and opinions of student volunteers who performed both the physical and virtual versions of the test. We showed that the amount of experience with video games and VR was positively correlated with their performance of the virtual task. We also compared their time perception during the two different tasks, showing that students with less video game and VR experience perceive time going slower than students with more experience. Lastly we showed that students, even though they found the virtual version more frustrating, would rather do that version again instead of the physical version. Also students with more VR experience found the virtual activity more fun than students with less experience.

7.9 Future Work

Future plans for this work include conducting a clinical versions of this study to get the opinions of patients who are actually undergoing therapy and whether they would want to use VR technologies or not. The target populations for future studies could include patients who are post-stroke, have significant hand pain due to arthritis, or children with cerebral palsy. Besides just gathering their opinions of the technology and comparing the performances between the two versions, we would also be comparing their pain levels between the two versions to see if patients feel less pain performing the virtual version.

We also plan to develop analysis tools to process the data obtained by Leap Motion during the one and five minute sessions. The data and results will be presented in a user interface designed for therapists. We will meet with therapists and discuss the data that is collected and how to visualize the data in a way that is useful to them.

Lastly, we will improve the ability for the person to interact with the virtual environment, mainly the ability to grasp blocks. There are two possible solutions being considered. The first is to improve how the game interprets the pinching motion of the hand while picking up the blocks. The second is to either change sensors or include other sensors to get a more accurate reading of the hand, fingers, and joints.

7.10 Acknowledgements

The authors wish to acknowledge the work of Benjamin Chebaa for assisting in the creation of the surveys, Raith Hamzah for developing the background elements to the virtual environment, and to Rebekah Roskens for editing the video. Also, we would like to thank the Dallas VA Research Corporation for providing partial support for this study. This work was also partially supported by the following NSF grants: 1041637, 1035913, 1338118 and 1439645. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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CHAPTER 8

COMPUTERIZED BOX AND BLOCKS IN A CLINICAL SETTING

8.1 Introduction

This is second chapter in the Box and Blocks section of this dissertation. This chapter uses the same set up as chapter 7, but this time done in a clinical setting using patients who are experiencing hand pain. The goal of this work is to see if a computerized version would lessen a patient's level of perceived pain when performing the task when compared to pain levels when performing the physical version. We are also looking to see if patients would prefer to use the virtual version over the physical version. Analysis of the data obtained from the Leap Motion is presented to look at the speed of the hand to detect fatigue. The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, designed virtual version, assisted in building the physical version, ran participants, performed analysis, wrote related works, methods, procedure, Assisted in results and discussion
- James LePage: Assisted in study design, performed analysis, wrote results and discussion, assisted in related works, methods, procedure,
- Fillia Makedon: Assisted in study design, edited paper.

COMPARING OBJECTIVE AND SUBJECTIVE METRICS

BETWEEN PHYSICAL AND VIRTUAL TASKS[7]

Shawn N. Gieser, James LePage, and Fillia Makedon. 2017. To Be Submitted

[7] To be submitted

8.2 Introduction

Computer applications in rehabilitation have been used many times in research. Multiple frameworks and system architectures have been proposed for integrating computers and sensors into rehabilitation. [1] presents an architecture for fusing the different types of data collected during rehabilitation exercises. This framework proposes the use of a Microsoft Kinect, microcontroller, accelerometer, gyroscope, temperature sensor, and capacitive touch sensor. They also present an ontology to represent the contextual information obtained from an ambient assisted living environment. [2] shows a software architecture where a therapist can assign tasks to a patient remotely so that the patient can perform these exercises at home in front of a Microsoft Kinect. The results from these exercises are then sent back to the patient and the therapist. The patient sees immediate feedback from the system so he or she can perform exercises correctly. The therapist see a more comprehensive report so that changes may be made to the exercise regime based on patient performance and rate of recovery. This architecture is the basis for a future tele-rehabilitation system, which can aid in the rehabilitation of patients without them having to frequently visit or live in a rehabilitation center. Mobile devices can also be used in rehabilitation. [3] and [4] both present architectures using mobile devices. These papers show how a mobile device can be used as input to a computer or gaming device so it can be displayed on a monitor. Some architectures, however, require the application to be used only on the phone, while the data is sent to a cloud server so a therapist can look at the results [5].

One of the greatest advantages using computers in rehabilitation brings is gamification. Gamification is turning tasks into game-like activities to increase engagement and performance when performing those tasks. Therapists and patients do like many aspects that games bring to rehabilitation, such as adjustability, increased attention, increased enjoyability, and that less negative feelings are felt by patients [6]. The Microsoft Kinect is a common tool used for the gamification of rehabilitation tasks. One of the most common games performing normal exercises [2]. The Kinect grabs the position of the joints from a subject's body and calculates the joints' angles while the subject performs the exercises. The system can then tell the subject how accurately they performed the exercises, how many repetitions they have done, or how to improve for their next session. Regular games using the Kinect have also been used in rehabilitation. [7] presents a patient who improved playing sports games. This however was a single patient, not multiple patients. When used in patients with chronic, acute, or subacute stoke, Kinect games have increased patients Fugl-Meyer Assessment (FMA) and modified Barthel index (MBI) scores, even if just slightly [6]. Kinects have also been used to detect emotions based on facial expression. The patient's current emotional state can then be used to adjust level difficulty to best match this state [8].

Gamification, however, is not just limited to the treatment of motor impairments. Virtual Reality (VR) can be used to immerse the user inside a game that represents a therapeutic task. [9] shows that virtual reality can be used to treat patients with spatial neglect by having patients "touch" certain virtual objects around them. VR has also been used to help older women with Mixed Urinary Incontinence. This approach uses a dance game that cues patients to perform certain dance moves and pelvic floor muscle contractions. This form of intervention not only improved testing results, but also had a high satisfaction rate among patients. Additionally, over half the patients in this study reported a perceived improvement of 75% or greater [10]. The use of virtual reality has also shown improvement in areas of cognitive function, visual perception, balance, lower limb strength, and depression [11].

Other approaches track a patient's hand, wrist, or fingers for game based rehabilitation. Inertial Measurement Units (IMUs) typically contain an accelerometer, gyroscope, and magnetometer. These can be used to track the motion of a user's hand while performing certain gestures or exercises. This motion can then be used as input for many different types of rehabilitation games [12]. Infrared (IR) light has been used to track fingers for rehabilitation games. IR lights were placed on the ends of patients' fingers, which were tracked by IR cameras. The position of these lights served as input for games. This method, combined with using games, showed greater improvement in patients in almost all areas being assessed in [13]. Gloves can be a good way to get a representation of a patient's hand during rehabilitation exercises. This can let the computer application capture a more precise representation of a hand, detecting extension and flexion of various joints. This also provides more accurate timing for how long certain exercises are performed and much time between repetitions is taken [14].

The Leap Motion provides some advantages to using gloves. The Leap Motion is more affordable than most gloves. The Leap Motion is also more durable since it is not susceptible to wear like gloves are [15]. An additional advantage is that the Leap Motion provides additional information than that of most glove systems, such as hand, finger, and joint positions and what direction a user's hand is facing or finger is pointing. This allows for the development of various types of games with many different goals [16, 17].

Mobile devices, such as phones and tablets, have been used in rehabilitation exercise as well. [5] present a mobile rehabilitation program that uses sensors that track movement. These sensors then send data to the phone to give live feedback during the exercises, as well as information about the user's improvement over time. Gamification has also been done using mobile devices as well. Some of these games contain very simple gamification concepts that do not necessarily make a full game played on the device. Some games present tasks to users that need to be done in the real world. The users then check in when the task is completed to earn points, achievements, medals, and earn spots on a leaderboard. This method, when used in patients with heart conditions, was well received by patients and like the game-like aspects of performing everyday tasks. Patients felt these tasks had value outside the game in that it would help them return to everyday life [18]. Full rehabilitation games on mobile devices usually take advantage of the on-board accelerometer to track movement. This allows for more targeted rehabilitation by forcing a patient to perform exercises that increase their range of motion [4]. Mobile games do not just work on motor skills, but also cognitive skills as well. Games have been shown to aid in the development of attention, reaction, and memory skills. Users saw these types of games as a potential rehabilitation tool [3]

[19] presents a virtual version of the Box and Blocks Test using a Microsoft Kinect. This paper shows there is a strong correlation between the scores of the virtual and real Box and Blocks Tests. Our study differs in several ways. We use a Leap Motion to track the user's hand instead of a Kinect. We are comparing the scores of the physical and virtual versions, but we are also looking at the user's level of engagement

and pain levels between the two versions as well. Lastly, we will be looking at estimating fatigue based upon times when a block is transferred.

The current study has three aims. The first is to determine if the virtual hand task using the Leap Motion is an adequate index of performance by comparing results to the physical task. Second is to determine veterans' preferences and opinions about the virtual version modality. The third is to assess the level of engagement in the task experienced by veterans

8.3 Methods

The procedure received approval from the Veteran Affairs North Texas Health Care System Institutional Review Board (IRB) (Reference number 15-049) and was acknowledged by The University of Texas at Arlington's IRB (Reference number 2015-0889).

8.3.1 Participants

24 subjects were recruited. Twelve were Veterans who were experiencing upper extremity pain or limitations. One veteran's responses created a significant outlier and this veteran's information was not included. The inclusion criteria for veterans was 18 years of age or older, currently experiencing hand pain from any etiology, and enough range of motion in the hand to complete basic tasks. Twelve students without hand pain were also recruited as a non-clinical control group.

8.3.2 Materials

The box and blocks test chosen as it is used in several other studies to validate the usefulness of virtual reality based rehabilitation [20]. The physical version, as seen in Figure 8.1, is a 3D printed replica of the one presented in [21]. This 3D printed version was used for a few reasons. The first was that it is lightweight, making it easier to transport as each piece was only filled 10%. Secondly was that the box has a puzzle piece design, allowing easy assembly and disassembly making it portable. Lastly, if a piece was lost or damaged, a replacement could be easily reproduced at little cost instead of having to buy a new set.

Figure 8.1. Physical Version of the Box and Blocks Test.

The virtual version, seen in 8.2 is a scale model developed in Unity [22]. The virtual version is displayed on a computer monitor. A Leap Motion was used to track the motion of the patient's hand and for input for the virtual version [23]. By using the Leap Motion, a patient completing the virtual version would have to perform the same motions as the physical. Picking up blocks can be accomplished by making a pinching motion as if picking up a real block. The virtual environment allowed for several conveniences, such as only forcing a patient to only pick up one block at a time, automatic score keeping, automatic time keeping, making sure the patient's hand completely crossed the partition before releasing the block in order to count towards the score, and making resetting the test much faster.

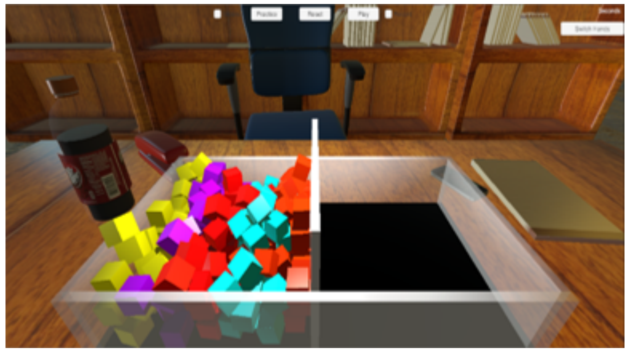

Figure 8.2 Virtual Version of the Box and Blocks Test

8.3.3 Procedures

After obtaining consent, patients were asked to complete a short survey. The questions asked can be seen in Table 8.1.

Table 8.1 Survey questions given before the experimental procedure.

Question	Answer Options		
Have you had any experience playing video games?	Significant Experience	Some Experience	No Experience
Have you had any experience with virtual reality?	Significant Experience	Some Experience	No Experience
What is the usual level of pain you experience when doing your daily activities?	Scale 1 (no pain) to 10 (worst pain you ever felt)		
What is the usual level of pain when your hands are not involved with something, such as watching TV?	Scale 1 (no pain) to 10 (worst pain you ever felt)		
What activities cause the most hand pain?	Open Ended		
How much does pain affect your daily life?	Scale 1 to 10		
Are you left or right handed?	Left	Right	
What is your gender?			
What is your age?			
What is your ethnicity?			
What is the highest degree of level you school that you have completed?			
What is your marital status?			
What is your employment status?			

Prior to beginning the tasks, an optional practice period was used before the patient completed each task. The practice period for the physical version was for fifteen seconds, as it was in the original procedure. The virtual version's practice period was not time based. Instead, the practice period lasted until the patient acknowledged that they had a clear understanding of how to grasp blocks and move them in the virtual environment.

8.3.4 Phase One

Each version was done with both hands, one after the other. After each hand, the score was recorded. The patient's perceived pain level, on a scale of 1 to 10, was also recorded. The test was then reset.

We alternated the order in which the patients completed the two versions in order to balance the study and eliminate bias. Below is a list of the order of tasks completed during phase one.

- Practice period – first version – non-affected hand
- First version – non-affected hand
- Record score and pain level
- Reset
- Practice period – first version – affected hand
- First Version – affected hand
- Record score and pain level
- Switch versions
- Practice period – second version – non-affected hand
- Second version – non-affected hand

- Record score and pain level
- Reset
- Practice period – second version – affected hand
- Second Version – affected hand
- Record score and pain level

After completing the first phase, the patient then completed a survey about which version they preferred. The questions asked can be seen in Table 8.2.

8.3.5 Phase two

Phase two was implemented to determine which of the two versions was found to be more engaging. Similar to the statement “time flies when you are having fun,” we anticipated time would be perceived as passing faster in situations which were engaging or perceived generally more positive. Each patient performed the same virtual and physical versions again, but this time stopped when they felt five minutes had passed. We judged level of engagement by how long they performed the task, i.e. performing the task longer before stopping at the perceived 5 minute mark would indicate a higher level of engagement. After they performed each version, the score, pain level, and time they performed the task were recorded. The order of the versions that the patient performed was alternated in order to balance this phase as well. Below is a list of the order of tasks completed in phase two.

- Practice period (if needed) – first version- non-affected hand
- First version – non-affected hand
- Record score, pain level, and time elapsed
- Reset

- Practice period (if needed) – first version- affected hand
- First version – affected hand
- Record score, pain level, and time elapsed
- Switch versions
- Practice period (if needed) – second version- non-affected hand
- Second version – non-affected hand
- Record score, pain level, and time elapsed
- Reset
- Practice period (if needed) – second version- affected hand
- Second version – affected hand
- Record score, pain level, and time elapsed

8.4 Results

Data collected was analyzed with SPSS v22 [24]

To determine if the virtual task was an adequate estimate of physical ability, the performance on hands were combined and Pearson Moment correlations were performed on total blocks moved. Significant positive associations were identified between the physical and virtual tasks, with correlations between hands fell between .56 and .76; $p < .005$.

8.4.1 Overall performance

Scores and times were combined across hands. Figure 8.3 presents the overall performance on the tasks. Overall students performed better on both the physical and virtual tasks. On the physical task, students successfully moved 43% more blocks. The difference was greater for the virtual task where students successfully moved 2.7 times the number of blocks than the veterans.

Table 8.2. Survey questions given after Phase One

Question	Answer Options		
Which version was more fun?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which version was easier?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which version was more frustrating?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which version was more stressful?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which version made you more tired/worn out?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which version did you feel required more work?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
Which would you rather do again?	Physical Version	Virtual Version	No Preference
Why?	Open Ended		
How useful do you think the technology would be in assisting Veterans with rehabilitation?	Scale 1 (Not useful at all) to 10 (Very useful)		
If you were asked to use this type of technology for rehabilitation at home, how likely would you use it?	Scale 1 (Not likely at all) to 10 (Very likely)		
How strongly do you feel the VA should be developing these types of technologies?	Scale 1 (Not at all) to 10 (Very much)		
What are your overall thoughts or additional comments about the technology?	Open Ended		
Would you recommend other Veterans to use this technology in their rehabilitation?	Yes	No	No Preference

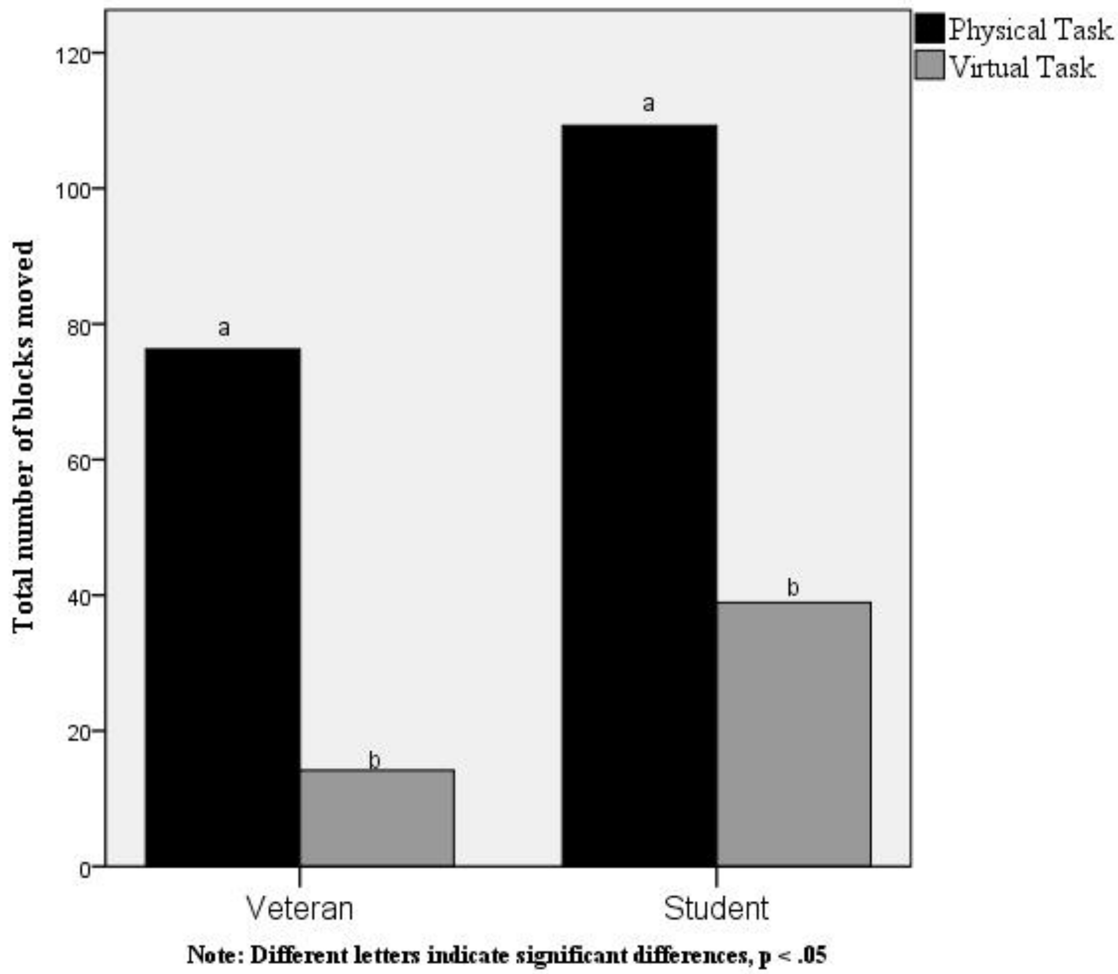

Figure 8.3 Average total number of blocks moved on one minute task

8.4.2 Perceptions of the task

Veteran responses to the technology were encouraging. As can be seen in Table 8.3, Veterans uniformly found the physical task easier and the virtual task more frustrating. However, more than half of the veterans found the virtual task was more fun or had no preference and more than half stated they either would prefer to do the virtual task again or had no preference. This finding is very important as 8 of 11 veterans felt more “worn out” after the virtual task and 9 of 11 found the task required more work.

In relation to whether they supported the development of tasks such as this for veteran care, the veterans were asked to rate on a one to ten scale, ten being higher, how strongly they felt the VA should be developing these types of technology. The average rating was 9.0 (s.d. 1.8) with 9 of 11 veterans giving a rating of 8 or above. When asked how useful the veterans thought this specific technology would be in helping veterans, the average score was 7.5 (s.d. 2.6). When asked how likely they would be to use the technology at home, the average score was 6.9 (s.d. 3.6). All veterans, 11 of 11, reported they would recommend the technology to other veterans.

Table 8.3. Veterans Opinions of the Tasks

Veterans' Opinions of the Tasks	Physical	Virtual	No Preference
Which Version Was Easier	11	0	0
Which Version Was More Frustrating	0	11	0
Which Version Would You Rather Do Again	5	5	1
Which Version Made You Feel More Worn Out	1	8	2
Scale of one (lowest) to ten (highest)			
How useful do you think the technology would be in assisting veterans' rehabilitation?	7.5 (2.6)		
How likely would you be to use this technology for rehabilitation at home?	6.9 (3.6)		
How strongly do you feel the VA should be developing virtual technologies?	9.0 (1.8)		

Numbers in parentheses are standard deviations

8.4.3 Engagement

Generalized Linear Models with Repeated Measures was performed to evaluate the interaction between patient status and the modality of the box and blocks test. On the 5 minute trail of the physical task, both veterans and students stopped the trail at approximately the same time (see Figure 8.4). However, compared to students, during the virtual trial Veterans worked on the task significantly longer than students before stopping at what they perceived to be five minutes. Overall, there was a significant interaction between veteran patient status and modality, $F(1,21) = 19.5$; $p < .001$. Additionally, paired t-tests were performed on the veteran data between the time spent the physical and virtual tasks. Veterans spent significantly longer on the virtual task than they did on the physical task, $t(10) = 5.3$, $p < .001$.

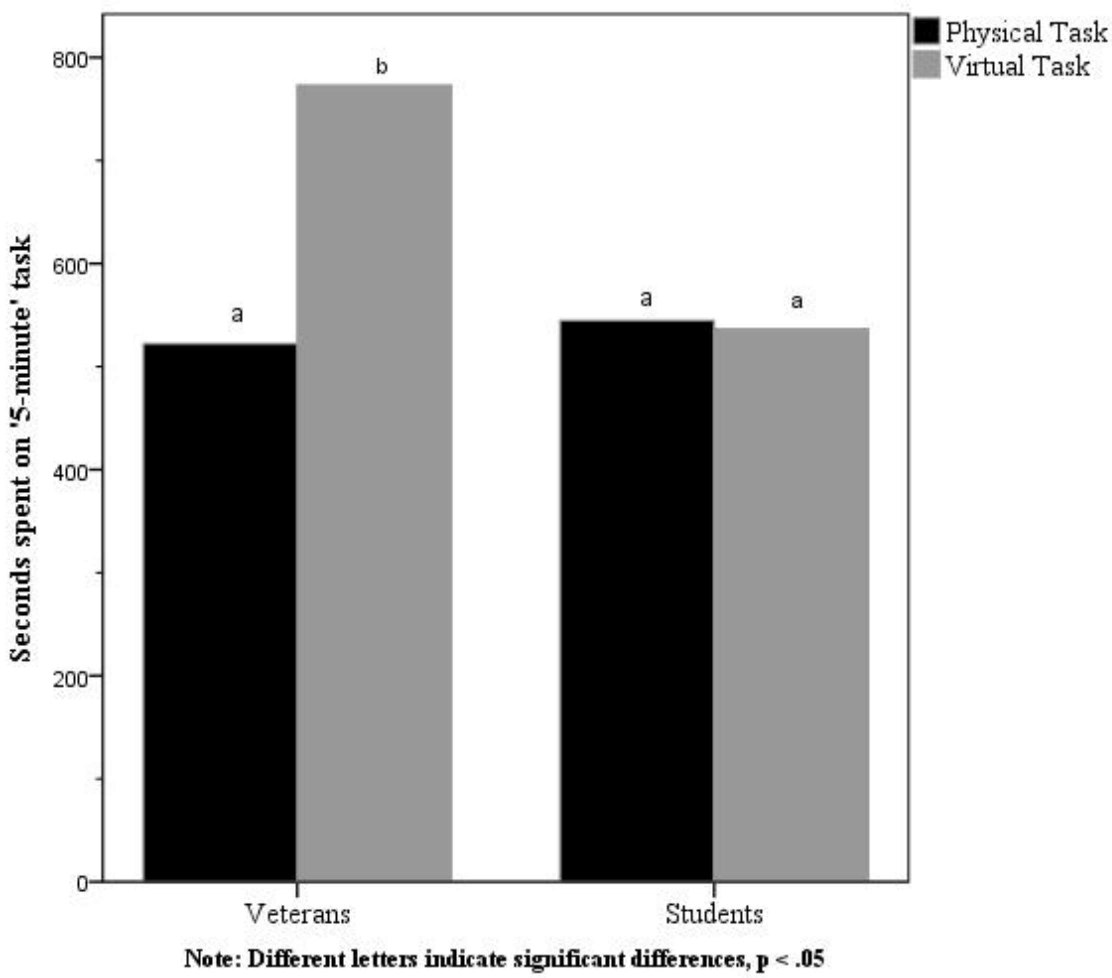

Figure 8.4 Average seconds spent on 'five-minute' tasks

It was important to clarify if the results were due to familiarity with video games and virtual reality. Participants rated their experience with both video games and virtual reality on a zero to two scale. These were combined to obtain a score of 0 to 4. After controlling for familiarity Veterans continued to be demonstrated longer periods of engagement, $F(1,20) = 15.2$, $p < .001$.

8.4.4 Pain and time performance

Overall, there were no significant differences between veterans' pain scores between the physical and virtual tasks. However, not surprisingly, veterans experienced higher levels of pain when performing the longer five minute task, compared to the one minute task. With the veteran subjects, no significant correlations were found between level of pain and time spent performing the task on the five minute trials. Only one correlation, the correlation between resting pain and the time spent performing the physical task was above .3, specifically -.359. All other correlation coefficients were below .15.

8.5 Discussion

This study focused on the acceptability of the use of technology by a veteran population with upper extremity pain. The study obtained qualitative and quantitative data about the veterans' experiences and assessed their level of engagement. The findings of this study highlight several very encouraging findings.

First, there was a strong correlation between total blocks moved when comparing the physical version to the virtual version. This shows that our virtual version could be a good substitute for the physical version in the assessment of patients.

The second broad finding is that, in a veteran population, veterans are supportive of the use of this technology. Though veterans find the use of the technology more frustrating and experienced increased fatigue, the veterans felt the technology would be useful and would recommend its use to others. Additionally, they were strongly supportive of further development of the technology to be used in rehabilitation.

Third, veteran patients with upper extremity pain, demonstrated a higher level of engagement in in the virtual task than the physical task. This was based on their longer time they spent engaging the task. Two aspects are important. The first is that this finding was independent of their self-reported history with virtual reality and video games. The second is that the Veteran population with upper extremity pain, more fully engaged the virtual task than the student comparison group.

Overall, the findings are very encouraging for the acceptability of the use of technology in rehabilitation with a veteran population. There are however, several limitations that must be addressed. The first is the reliance on the participants' self-report of their history of video-games and virtual reality. Due to age and phase of life differences, it is conceivable that the veterans and students do not have similar opinions of what is a significant amount of experience. Though one of the strengths of the study is the indirect assessment of engagement through the use of the 5-minute trial, it is possible that the veterans spent more time, in part, due to wanting to be more successful, in short focusing more on their performance, letting their internal clock go past 5-minutes on purpose to improve their 'score'.

There are a number of obvious directions for future studies related to patient engagement. Most important, is that it is still to be determined if the use of these technologies would improve overall functioning or decrease long-term pain scores. Additionally, would the more immersive environment of a 3d virtual experience increase the engagement and if so what would be the cost/benefits of the improved, yet costlier technology.

One additional area of study would be in the further evaluation of the engagement effect both within a session, i.e. does engagement decrease the longer a person is doing the task within a session, and across sessions, i.e. does engagement decrease over multiple sessions. The exploration of the change in engagement could lead to improved engagement methods. For example, as the technology can detect minute second to second changes in performance, could the system have natural stop points to avoid the patient becoming too fatigued, reducing the enjoyment of the task. Assessment tasks could be built into the system, similar to the 5-minute task used here, which could detect changes in engagement in the environment. This could trigger changes in the game to re-engage the patient in the task to keep motivation and engagement high. These changes could be precipitated by a therapist decision or could be automated within the system.

Finally, this could be extended to do remote assessment of patients. This would be useful for patients who live far away from a hospital or clinic. Patients will be able to still be able to do any prescribed exercises or assessments related to our system without having to deal with the stress of traveling or scheduling meetings. This will allow patients to do these exercises in the comfort of their own home. We can use the remote assessment to get veterans' opinions of this system when used in a home environment. With the system in a new location, technical issues may arise that effect the veterans' perception of or engagement with the system. Opinions of therapists can be collected to evaluate the program from their perspective as well. This way, we can develop a system that will fit the needs of both veterans and therapists.

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CHAPTER 9

COMPARING IMMERSION LEVEL'S IMPACT ON INTERACTION FIDELITY AND ANALYSIS OF BOX AND BLOCKS DATA

9.1 Introduction

This is the third and final chapter of the Box and Blocks Test section of this dissertation. This chapter will address two key points. The first will be comparing how different levels of immersion in a gamified task effects task performance. A user study was done where participants performed a physical version of the Box and Blocks test followed by two virtual versions. They are both updated versions of the version presented in chapters 7 and 8. The first version is displayed on a monitor with the Leap Motion on the table, just like in chapters 7 and 8. The second is displayed inside a virtual reality head mounted display (HMD) with the Leap Motion mounted to the front of it. These different levels of immersion should affect performance, with the HMD version predicted to yield better results than the monitor. We also show that a higher level of immersion makes the task more similar to that of the physical version. This will be done by correlating the scores of the two virtual versions to that of physical, as well as surveys gathering user opinion.

The second point will be on how the data obtained from the game (score, activity in the game, etc.) and the Leap Motion can be used to better assess the user. Techniques will be presented on how to analyze hand data (how fast the user is opening or closing their hand), arm data (how fast the user is moving their arm back and forth, is the user hitting the wall), and other results that may prove beneficial to a therapist.

The contributions of each of the authors is as follows:

- Shawn Gieser: Designed study, assisted in the design of the upgraded virtual version, ran participants, performed analysis, Wrote Related Works, Experimental Setup, Results, Discussion, and Motion Anaylsis
- Cheryl Abellanoza: Assisted in survey design, performed analysis, Wrote Results.
- Joseph Tompkins: Designed the upgraded virtual version, wrote description for upgraded virtual version.
- James LePage: Assisted in survey design, assisted in analysis
- Fillia Makedon: Assisted in study design, edited paper.

COMPARING IMMERSION LEVEL'S IMPACT ON INTERACTION FIDELITY AND ANALYSIS OF BOX AND BLOCKS DATA [8]

Shawn N. Gieser, Cheryl Abellanoza, Joseph Tompkins, James LePage, and Fillia Makedon. 2017. To Be Submitted

[8] To be submitted

9.2 Experimental Setup

9.2.1 Virtual Versions

There were two virtual versions of the Box and Blocks test developed. These are the desktop version and head-mounted display (HMD) version. Both versions were developed in tandem using the Unity3D game engine [1]. Measurements of the box and blocks from the physical Box and Blocks test [2] were used to accurately model the virtual box and blocks for the virtual environment.

Both versions utilized the Leap Motion hardware to capture participant hand and finger motion. Leap Motion's Orion software update [3] provides significant improvements to the motion capture technology observed in [4]. These improvements were expected to ease some of the difficulty participants experienced when using an older version of the Leap Motion software.

The Box and Blocks software uses a position vector between the thumb and index finger to determine if a block is within grabbing distance. If a block is within grabbing distance, this is indicated to the participant by "highlighting" the block. Virtual blocks are grabbed through making a natural grabbing motion, specifically by bringing the fingers near to – or touching – the thumb. Only one block is able to be grabbed at a time. Once the fingers and thumb are within a predetermined threshold distance, the block is grabbed and bound to the virtual hand's movement in the VE. Similar to grabbing, participants are able to release the block by moving apart their fingers and thumb. If a block touches the virtual box divider while being "held", the participant will be made to drop the block. This is counted toward the participant's error count. When a block is brought over the divider while being held, this is automatically counted toward the participant’s score. Blocks in the VE are not able to be “thrown” and the virtual hands pass through the objects in the VE without interaction.

Test administrators are able to toggle between demonstration and recording modes at the start of the software. In addition, just as in the case of the physical Box and Blocks test, the dominant hand of the participant can be specified so that it is the first hand that is tested by toggling between left- and right-dominance. When in recording mode, the software will record Leap Motion data as well as game play data. Just a portion of the Leap Motion data features recorded include position, velocity, and rotation vectors of the palm, fingers, and joints accompanied by timestamps. Game play data features include block events such as timestamps for when a block is scored, hits the divider, grabbed, and dropped.

The same virtual environment is used in both versions. It is meant to resemble a small office environment, with a chair, desk, clock, bookshelf, and a few other assorted items. The clock is the only other object in the VE of significance other than the box and blocks. It is used to display the elapsed time once the test begins. A clock was chosen for this interface for the reason that it translates well into an HMD virtual environment, where traditional HUD interfaces are often disorienting to the user.

9.2.2 Desktop Version

For the desktop version, participants view the virtual environment on a computer monitor. The motion tracker is placed face up on the table between the participant and the monitor. From a seated position, they are able to reach over the motion tracker and see their hand in the virtual environment. The Box and Blocks software adjusts the positioning of the virtual hand at the start of each portion of the test to insure the participant is able to reach the corners of the box in the VE without physically moving their hands outside of the range of the motion tracker.

9.2.3 Head Mounted Display Version

For the HMD version, the HTC Vive system was used. The motion tracker was mounted to the front of the HMD. A chair is placed in the physical room such that is approximately where the virtual chair will appear to be located in the VE. Participants are instructed to sit in the chair before placing on headset.

9.2.4 Procedure

This procedure was approved by the Institutional Review Board at The University of Texas at Arlington, reference number 2017-0323.

Study participants first completed a pre-activity survey. This survey is to collect demographic data, as well as information about the participant's ability to play video games, VR games, and past exposure to PT and OT. Table 9.1 lists the non-demographic questions and answer options for the pre-activity survey.

Table 9.1. Non-Demographic Questions on Pre-Activity Survey

Question	**Answer Options**
Please rate how much you play video games?	Scale from 1 to 10
Please rate how good you feel you are at playing video games?	Scale from 1 to 10
Please rate how often you play VR games?	Scale from 1 to 10
Please rate how good you feel you are at playing VR games?	Scale from 1 to 10
Have you had any PT or OT in the past?	Yes or No
If you had any PT or OT in the past, how long ago was it?	Open ended
If you had any PT or OT in the past, what was it for?	Open ended
Have you ever performed the Box and Blocks Test before?	Yes or No
If yes, what was the Box and Blocks Test used for?	Open Ended
Did you find the Box and Blocks Test useful for its intended purpose?	Yes or No

After completing the pre-activity survey, participants completed the Box and Blocks test three times. Participants first completed a physical version of the test. This physical version and procedure for this version is the same as it was presented in [4]. This version was performed first in order for participants to establish an understanding of the real version before trying any of the virtual versions.

The Desktop and HMD versions were performed second and third. The order of these two different versions were alternated in order to eliminate bias based on order of completion. Each version was demonstrated to the participant before letting he or she try it. Each participant was given an optional period to practice each version until they felt comfortable performing the task. After this practice period, the participant performed the task, following the same procedure for the virtual version mentioned in [4].

During the test, the number of blocks moved and errors were recorded. Also, the practice time was recorded to see how long it takes the participants to become accustomed to the environment. Also, on the virtual versions, data from the Leap Motion was collected to be used for motion analysis.

After completing the virtual versions, the participants took a post-activity survey to collect their opinions of the virtual versions compared the physical version. Table 9.2 shows the questions along with the answer choices for each question. Each question listed was followed with an open ended question asking them to explain their answer.

9.3 Survey Analysis

Table 9.3 shows the demographic information for the participants in this study.

Table 9.2. Post-Activity Survey Questions

Question	Answer Choices
Which version was the easiest?	Physical/Monitor/Headset (Ranking 1–3)
Which version was the most frustrating?	Physical/Monitor/Headset (Ranking 1–3)
Which version required the most physical work?	Physical/Monitor/Headset (Ranking 1–3)
Which version required the most mental work?	Physical/Monitor/Headset (Ranking 1–3)
Which version would you rather do again?	Physical/Monitor/Headset (Ranking 1–3)
Which one of the two computer versions felt more like the physical task	Monitor, Headset, About the same
Would you recommend either of these computer versions to anyone you know that is undergoing rehabilitation?	Yes, No, No Preference
Which of the two versions would you recommend?	Monitor, Headset, About the same
Any other comments or remarks?	Open Ended

Table 9.3 Demographic Information of Participants

Population Characteristics	Number of Participants	Percentage
Gender		
Male	9	75%
Female	3	25%
Age		
18 – 24	9	75%
25+	3	25%
Bachelor’s Degree or Higher	11	92%
Right-handed	10	83%

9.3.1 Video Game and Virtual Reality Experience

Participants reported their experience with video games and with virtual reality. They rated their play rate and skill for each type of experience using a 10-point Likert scale. To aid interpretation, play rate scores and skill scores were summed and coded: Low Experience, and High Experience. Table 9.4 displays this information.

9.3.2 Comparison of Performance on Physical vs. Monitor vs. VR tasks

Table 9.5 shows the scores of the participants for the different versions.

9.3.2.1 Accuracy

A one-way within subjects Analysis of Covariance (ANCOVA) was run to examine participant performance. No significant differences were found across task types overall, but significant differences were found when including handedness as a covariate, $F(5,50) = 2.61$, $p < .036$, partial eta-squared = .21. Specifically, participants had the worst performance during the right-handed trials of the monitor task. Participants performed best for both right- and left-handed trials of the physical tasks, followed by both right- and left-handed trials of the VR tasks. Additionally, VR task performance correlated more strongly with the physical version of the task (Pearson's $r = .68$, $p = .014$, r-squared = .46) than with the monitor version of the task (Pearson's $r = .62$, $p = .03$, r-squared = .38).

Table 9.4 Participants Experience with Video Games and Virtual Reality

Level of Experience	**Number of Participants**	**Percentage**
Video Game Experience		
No Experience	0	0
Some Experience	3	25%
Significant Experience	9	75%
Virtual Reality Experience		
No Experience	10	83.33%
Some Experience	1	8.33%
Significant Experience	1	8.33%

9.3.2.2 Error

A one-way within subjects Analysis of Covariance (ANCOVA) was also run to examine how errors differed based on the three versions of the task. No significant differences were found, regardless of handedness.

9.3.2.3 Subject Experience of Participants

Table 9.5 Participants' scores while performing the different versions

Subject Number	Scores (both hands combined)		
	Physical	Monitor	VR
1	102	22	49
2	107	48	80
3	116	64	107
4	110	64	88
5	131	86	129
6	111	35	90
7	138	57	142
8	102	56	103
9	116	50	94
10	114	61	66
11	99	68	79
12	121	20	64

One-way within subjects Analyses of Variance (ANOVA) were run to examine participants' ratings of the three versions of the tasks. Significant differences were found, and a breakdown of participants' responses can be found in Table 9.6.

Table 9.6 Participants' ratings of the monitor vs. VR. Physical versions of the Box and Blocks task

	Monitor		VR		Physical		No Preference	
	n	%	n	%	n	%	n	%
Which version was the easiest?	0	0%	1	8.33$	11	91.67%	-	-
Which Version was the most frustrating?	12	100%	0	0%	0	0%	-	-
Which required the most physical work?	6	50%	2	16.67%	4	33.33%	-	-
Which required the most mental work?	10	83.33%	1	8.33%	1	8.33%	-	-
Which would you rather play again?	0	0%	12	100%	0	0%	-	-
Which felt more like the physical version of the task?	2	16.67%	10	83.33%	-	-	-	-
Which version would you recommend to others?	0	0%	11	91.67	-	-	1	8.33%

Participants found the physical version to be easiest, followed by the VR version, then the monitor version ($F(2,22) = 133.00$, $p < .001$, partial eta-squared = .92). Participants found the monitor version to be the most frustrating, followed by the VR version, then the physical version ($F(2,22) = 62.77$, $p < .001$, partial eta-squared = .85). There was no significant difference in the reported amount of physical work that the tasks required, but the monitor version was reported by participants to require the most mental effort ($F(2,22) = 17.99$, $p < .001$, partial eta-squared = .62).

Interestingly, participants rated the VR task as the task they would be more likely to want to complete again ($F(2,22) = 133.00$, $p < .001$, partial eta-squared = .92). The majority of participants ($n = 10$) rated the VR task as feeling more like the physical task. All participants noted that they would recommend the VR version for future use in rehab settings. Finally, there was a marginally significant correlation between self-reported video game skill and scores on the monitor version of the task ($r = .55$, $p = .06$).

9.4 Analysis of Game and Motion Data

This section will discuss areas of interest when looking at the motion data obtained from the Leap Motion and the game.

9.4.1 Scoring Rate

The rate at which a person scores can show many different things. If a person takes the same amount of time to score, that is the time between one block is dropped on the other side to when the next block is dropped, then this could show the person can perform the task consistently. If there is a consistent long time between scores, that could mean the person is struggling or in pain, but is still completing the task.

If a time between scores slowly increases over time, then this could be indicative of a person who is experience fatigue during the task. The fatigue could be caused by just normal use of the arm, or be caused by increasing pain in the arm or hand. The goal of a person performing the task would be to improve the time between scores over time, therefor building up strength in the arm, regaining motion in the arm, or show that the arm is recovering from injury.

If there is a random one-time spike in the time between two scores, then this indicates a “struggle point” for the person performing the test. This may be caused by a spike in pain, an issue with the software and the leap motion recognition, or could be caused by the patient being distracted by something outside the game. The cause for these “struggle points” should be investigated and potentially fixed.

9.4.2 Errors

This version of the game records two types of errors. The first is if the person hits the middle wall of the while attempting to transfer the block over. This type of error is called a “wall hit.” A wall hit shows that a person is not lifting their arm up high enough to get the block over the wall. If this type of error happens frequently, then this could show issues with the person’s shoulder.

The second type of error is a “drop.” This is when a person drops a block on the wrong without transferring it over, and when it’s not caused by a wall hit. A drop shows that a person is having issues holding the pinching position needed to hold the block. If this type of error happens frequently, then this could represent issues with the the person’s hand.

9.4.3 Fingers Used for Picking up Blocks

The fingers that are used to pick up a block can tell us about how a patient uses their hand. This can be determined by looking at which finger, or fingers, are close to the thumb. If common fingers to perform the task are used, such as the pointer, middle, or both, then this could remember normal motion. If someone is using other fingers to perform the task, then this could mean that there is some issue with the person wanting to use the pointer and/or middle finger.

A therapist can also have a patient perform the task using certain fingers to pick up the blocks. This can help a patient recover different functions of their hand. The same principle as above applies that if they are not using the proper fingers for the task, then the patient could be avoiding using those fingers.

9.4.4 Joint Angles

How much a person bends their joints can show a lot about the range of motion in their hand. The angle of the joint can be determined with the following formula:

$$\theta = 180 - \cos^{-1}\frac{\vec{a} \cdot \vec{b}}{\| \vec{a} \| \| \vec{b} \|}$$

where a and b are the directional vectors that the 2 bones on either side of the joint are pointing. These vectors are obtained from the Leap Motion data that was recorded during gameplay.

9.5 References

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CHAPTER 10

CONCLUSION

In this dissertation, I have presented a potential use for a VR based Box and Blocks Test to be used for intervention and assessment during rehabilitation. This VR Box and Blocks Test can be used potentially in a clinical or home environment. I have also shown various ways to validate equipment and visualize data collected for use in a rehabilitation setting. I have also presented other uses for gamification in developing rehabilitation games. Finding show that virtual systems generate interest from both the general populous and a targeted user group. Future work and studies are necessary to refine the work presented in this dissertation so that it can be used effectively in a clinical environment.

10.1 Future Work

Future studies are needed to assess the efficacy of VR in rehabilitation. These studies would be long term studies, and would heavily involve many different roles of health professionals. These studies would compare VR based therapies to that of traditional therapies. Patients using VR therapies would have their rate of recovery compared to that of patients using traditional interventions and techniques. This would require a suite of customizable VR therapies to be created for patients at different stages of recovery. Health professionals would have to be trained to use the software and how to interpret the results. Opinions of both health professionals and patients would need to be collected to see how effective users perceive the system and its likelihood to be used a reliable alternative to traditional therapies.

Once the system is proven useful, then a tele-rehabilitation system can be built around the existing games. Patients can perform exercises and play games either at home or a local clinic. The data collected would then be sent to a server where a therapist or doctor can view any results to monitor progress and provide feedback to paitents. This would allow health professionals in increase their patient load without increasing the amount of work required. This would also allow patients to recover with less trips to the doctor's office, allowing the patient to have more time and less stress to focus on recovery.

Lastly, psychological tests can be incorporated into the treatments as well. Patients who have survived traumatic brain injuries suffer not only from physical impairments, but also cognitive. Incorporating cognitive assessments into rehabilitation tests can allow cognitive therapists to view data received from VR interventions. Patients could perform one exercise, or play one game, and benefit from both physical and cognitive rehabilitation at the same time. This would save time during recovery and allow for an increased rate of recovery.

APPENDIX

List of Publications

[1] **Shawn N. Gieser**, Varun Kanal, and Fillia Makedon. 2017. Evaluation of a Low Cost EMG Sensor as a Modaility for use in Virtual Reality. In Stephanie Lackey and Jessie Chen (eds.) Virtual Augmented and Mixed Reality (VAMR ’17). Lecture Notes in Computer Science, vol. 10280. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-57987-0_8

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