Exploring the Use of Consumer Grade Technology for Kinematic Assessment of the Upper Limb Following a Stroke

by:

Johnathan Quoc Trung Tran

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Science
in
Kinesiology

Waterloo, Ontario, Canada, 2014

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

Upper limb deficits post stroke affect up to 60% of stroke survivors. The assessment of motor deficits post stroke is important for identifying rehabilitation goals and assessing treatment efficacy. Current clinical tools used to assess motor impairment utilize clinical observation to describe the performance of diagnostic motor tasks. There are some concerns regarding the ability of these scales to fully describe the quality of performance, and detect small but important changes which reflect motor recovery. Kinematic analysis has been increasingly suggested to augment clinical assessment; however, current kinematic tools are not well suited to the time and financial constraints of a clinical environment. The objective of this thesis was to investigate the feasibility of utilizing low-cost, depth sensing technology (Kinect sensor) to augment the current upper limb stroke assessment. Study one characterizes the accuracy of the Kinect sensor, and defines optimal markers and conditions for data collection. Results revealed sufficient ability to quantify metrics for the hand, and the trunk. Study two explored the feasibility of clinical use for the Kinect sensor, specifically its ability to distinguish kinematic performance between the affected and less-affected limbs within an individual, and differences in the affected limb between individuals. Results from study 2 indicated that the Kinect is able to identify interlimb differences and correlations with upper limb impairment scores for some kinematic metrics. Findings from this thesis suggest a potential use for the Kinect in a clinical environment for the purposes of upper limb stroke assessment; however, there are many factors and limitations which need to be considered prior to its use.

Acknowledgements

This work would not have been possible without the assistance and guidance of many individuals. Firstly, I would like to express my appreciation and gratitude to my supervisor, Dr. William McIlroy. Thank you for your wisdom, guidance, and especially your encouragement and support; it was paramount in getting this far in the academic journey. Thank you to my committee members Dr. Eric Roy and Dr. Dana Kulić, for providing your expertise and advice. To Robyn Ibey, Sherry Thompson, and Cynthia Danells, thanks for your clinical insights and feedback. I would also like to extend my thanks to Zhenning Li, for your technical assistance during the early stages of this project. Thank you to all my lab mates; your encouragement and support helped me get by the roadblocks along the journey. Thank you to Hannah Jantzi, Anton Trinh and Madison Martin for always offering a ride to the collection sites.

To my family, thank you for your love and support. And finally, thank you to Catherine Hobbis, who stuck by and supported me even when I went a little crazy.

Okay, maybe a lot crazy.

Table of Contents

List of Figures

List of Tables

1.0 Introduction

Physical impairment of the upper limb is common following a stroke, affecting 30-60% of all stroke cases (Nakayama, Jorgensen, Raaschou, & Olsen, 1994; Wade, Langton-Hewer, Wood, Skilbeck, & Ismail, 1983). These impairments often result in a decrease in functional use of the arm, independence (Likhi, Jidesh, Kanagaraj, & George, 2013), and quality of life for stroke survivors (Ones, Yilmaz, Cetinkaya, & Caglar, 2005). The identification of upper limb impairments and deficits following a stroke is therefore important specifically for setting rehabilitation goals and informing the efficacy of rehabilitation interventions. Current impairment assessment tools such as the Fugl Meyer, and Chedoke McMaster Stroke Assessment scales are valid and reliable measures commonly used for post-stroke assessment (Baker, Cano, & Playford, 2011; Gladstone, Danells, & Black, 2002). These impairment scales require individuals to perform a progression of motor tasks which enables the assessment of the challenges to the control of limb movement. The scales however are administered and scored using clinical observation and may lack sufficient sensitivity to identify small but important changes in motor performance during complex multi-joint movements

Kinematic analysis has provided insight into the motor control challenges of the upper limb following a stroke revealing, among other things, deficits in the transport speed and coordination of limbs when performing complex multi-joint movements. (Cirstea, Mitnitski, Feldman, & Levin, 2003; Michaelsen, Luta, Roby-Brami, & Levin, 2001; Roby-Brami et al., 2003; Subramanian, Yamanaka, Chilingaryan, & Levin, 2010). In addition, individuals post-stroke often utilize compensatory strategies such as shoulder elevation and/or increased trunk displacement to assist limb transport during reaching which can be detected using kinematic analysis (Levin, Kleim, & Wolf, 2009; Levin, Michaelsen, Cirstea, & Roby-Brami, 2002; Michaelsen et al., 2001).

The quantification of these deficits has been shown to be highly correlated with stroke severity and may be more sensitive than current clinical measures to changes which occur during the recovery process (Subramanian, Yamanaka, et al., 2010). In spite of growing evidence and support for the potential use of kinematic analysis in clinical assessment there are very few tools which would likely be used clinically. Laboratory grade kinematic analysis systems often require the use of external markers and the use of multiple cameras, requiring considerable setup time. In addition, the cost associated with these systems is not financially feasible for clinical use.

Advancement in computer vision and sensor technology is providing an affordable alternative for kinematic analysis. One example of this technology is the Microsoft Kinect sensor; a low-cost, infrared-based capture system capable of identifying and tracking 20 anatomical landmarks without the use of external markers. While the technology has the potential to be clinically useful, there remain many fundamental questions regarding the accuracy and suitability of the Kinect device for the purposes of upper limb stroke assessment. Studies have shown high correlation of Kinect marker displacement and gold standard kinematic systems (Clark et al., 2012; Galna et al., 2014), demonstrating the validity of Kinect data during standing postural tasks. Evidence also suggests that the Kinect can sufficiently capture and quantify some aspects of upper limb kinematics, such as work reach arc during a seated range-of-motion task (Kurillo et al., 2012). In addition, preliminary evidence suggests that measurements from the Kinect can be used to identify differences in clinical populations (Galna et al., 2014; Lowes et al., 2013). However, previous studies have not investigated the quality of kinematic data using tasks specifically for upper limb assessment , focusing more so on lower limb kinematics for the assessment of balance (Clark et al., 2012; Galna et al., 2014), nor have they considered clinically relevant factors such as the effect of task-related objects for upper limb assessment tasks.

Thus, there is still a need to investigate the kinematic metrics available from the Kinect and to investigate if clinically relevant movements can be sufficiently captured by the Kinect, and whether this performance is maintained with a clinical population. The objectives of this thesis are twofold. The first objective is to identify the displacement error of the Kinect as compared to a gold standard kinematics system and clinically relevant sources of errors during reaching movements in healthy adults. The second objective is to evaluate the feasibility of using the Kinect in a clinical setting to assess upper limb kinematics of individuals with stroke. There will be a specific focus of determining the ability of the Kinect sensor to differentiate performance between affected and non-affected limbs within an individual, and differences between individuals with varying degrees of post-stroke impairment. This information will help to determine the feasibility of using the Kinect in a clinical setting and can be used to guide best practices for potential clinical use.

2.0 Background

2.1 Stroke epidemiology

Stroke has a large impact on the lives of many Canadians. There are approximately 315,000 Canadians are living with the effects of stroke (Public Health Association of Canada, 2011) with over 50,000 new cases of stroke reported each year (Hakim, Silver, & Hodgson, 1998). It is the third leading cause of death in Canada, attributed to over 14,000 deaths in 2012. The direct and indirect costs associated with treating stroke totals more than $3.6 billion annually (Public Health Association of Canada, 2009). In addition to financial costs, the effects of stroke have a direct cost of quality of life of survivors. Post-stroke impairments are variable depending on lesion location and severity, and can result in a multitude of motor impairments. Upper limb impairments occur in 30-60% of all stroke cases (Nakayama et al., 1994; Wade et al., 1983) and often affect the functional use of the upper limb (Ones et al., 2005), limiting the ability to perform activities of daily living and thus reducing one's ability to live independently. Upper limb recovery is a highly desired rehabilitation goal among individuals with stroke (Bohannon, Andrews, & Smith, 1988), therefore it is important to assess motor deficits post stroke to identify rehabilitation goals, evaluate treatment efficacy, and to monitor recovery over time.

2.2 Upper Limb Assessment Following a Stroke

Many clinical assessment tools are available and used to assess upper limb impairment and activity following a stroke. Of the available clinical tools, the following assessments are most often used within rehabilitation literature: 1) Fugl-Meyer Stroke Assessment, 2) Chedoke-McMaster Stroke Assessment and 3) Wolf Motor Function test.

Fugl Meyer Assessment (FMA)

The FMA is a 226- point multi-item scale developed for the evaluation of recovery following stroke. The scale assesses the upper and lower limbs independently, and is divided into 5 main components consisting of motor function, sensory function, balance, joint range-of-motion, and joint pain. Evaluation of motor performance is done using an ordinal 3 point scale (0-2). Due to the availability of more specialized metrics, the predominant use of the FMA has resided in the motor function component (Gladstone et al., 2002), and thus, is regarded as an impairment scale. With respect to the upper limb motor component, the selection of assessment tasks was based on the observations of stroke recovery by Twitchell (1951), who described a distinctive pattern of motor restoration after stroke. Initially, there is restoration of reflexes, however they appear more hyperactive. Subsequently, there is an increase in muscle tone with the potential for the development of spasticity. Voluntary movement follows, but initially appears in two distinct stereotyped synergies; the flexor, and extensor synergy. The flexor synergy is denoted by scapular retraction and elevation, shoulder abduction and external rotation, elbow flexion, forearm supination, wrist and finger flexion. Conversely, the extensor synergy appears as shoulder adduction and internal rotation with extension of elbow, wrist, and finger flexion. Motor recovery further progresses with volitional movement independent of the aforementioned synergies. Additional recovery continues with reduction of muscle weakness, and hyperreflexia (Twitchell, 1951).

Chedoke McMaster Stroke Assessment (CMSA) -

The CMSA is another popular clinical impairment measure used more commonly in Canada. The CMSA impairment inventory is a 42 point scale which evaluates 6 areas (shoulder pain, postural control, arm, hand, leg, foot) each area is evaluated with the 7 stage scale. The CMSA demonstrates high inter-rater reliability, and is highly correlated with other impairment scales such as the FMA (Gowland et al., 1993).

Similar to the FMA, the CMSA is also based on the recovery progression as described by Twitchell (1951). However unlike the FMA, the CMSA retains and extends the motor staging system as described by Brunnstrom (1966). This system describes six discrete stages of motor recovery and the features/signs associated with each stage. This staging system is reported to be advantageous as it allows for the classification of individuals with stroke into subgroups with homogenous features, allowing for treatment decisions specific to each subgroup (Gowland et al., 1993; Gowland, 1990)

Wolf Motor Function Test (WMFT)

In addition to impairment scales, many activity scales exist which evaluate the ability of the upper limb to perform functional tasks. One popular clinical activity scale is the Wolf Motor Function Test. The current version of the WFMT consists of 17 tasks arranged in increasing complexity, and proximal to distal control. Examples of the tasks used for this evaluation include the 'forearm to table' task (proximal control), and the 'flip a card' task (distal control). In addition to functional tasks, the WMFT also includes tasks which probe the strength of the upper limb. Evaluation of functional tasks for the WMFT includes completion time and an 'ability' score. The ability score is a 6 point ordinal scale (0-5) which categorizes the performance quality of task performed. Movement quality characteristics such as the alignment of the head and trunk during task performance, amount of trunk movement, or smoothness and coordination of the moving limb determine the ability score. With regards to strength tasks, the amount of weight or force produced is recorded. The WMFT is shown to be a valid, and reliable clinical measure (Nijland et al., 2010; Wolf et al., 2001)

Limitations of Fugl-Meyer, CMSA and WMFT

These measures are commonly used to provide a general index of impairment and dysfunction; however scoring of the assessment(s) is dependent on clinical observation. While there is sufficient sensitivity to detect presence of features such as dysmetria, tremor and significant restrictions in range of motion or slowing, there is a limit to the ability of current clinical scales to quantify the magnitude of the impairment or dysfunction. In addition, some assessment scales may exhibit a ceiling effect due to a restricted scoring scale, and thus may be less responsive to those with milder impairments or for those whom have recovered to a high level of functioning (Gladstone et al., 2002). Impairment and functional scale scores are also often composite in nature and often do not identify the specific deficiencies of motor performance.

2.3 Kinematic Analysis of the Upper Limb

Reaching movements are required for most human-object interactions, and thus, reaching movements have been often studied. Kinematic studies have revealed common spatial and temporal properties of upper limb reaching movements in healthy adults. Reach-to-touch movements are linear about the hand, despite angular movement at the elbow and shoulder being composed of complex joint angle combinations (Morasso, 1981). The relation of shoulder and elbow angles demonstrates a high level of coordination between these joints during a reach. Temporal analysis demonstrates the simultaneous nature of upper limb joint motion (Morasso, 1981). This is also evidenced by linear relationships when comparing shoulder and elbow angle-angle plots (Lacquaniti & Soechting, 1982; Levin, 1996). Reaching movements also show a distinct characteristic temporal-velocity profile; a stereotypical single-peak endpoint velocity profile is exhibited during a reach-to-touch task (Morasso, 1981). Involvement of the trunk to assist in reaching is also well defined in a healthy population and does not occur with targets placed within distances of 80% arm length (Mark et al., 1997).

2.4 Reaching in stroke

In individuals with stroke, stereotyped single-peak wrist velocity profile deviates depending on stroke severity (Kamper, McKenna-Cole, Kahn, & Reinkensmeyer, 2002). Analysis of end-point velocity displays an increase in the number of velocity peaks, representing increased segmentation and decreased smoothness in the reaching movement (Cirstea & Levin, 2000; Kamper et al., 2002). Individuals with milder impairments display a more stereotypical single-peak pattern of end-point velocity (Cirstea & Levin, 2000; Kamper et al., 2002). Joints of the upper limb no longer display a synchronized and coordinated motion, but rather exhibit a segmented, independent pattern of activation, as evidenced by joint angle-angle plots (Cirstea & Levin, 2000). Stroke patients also typically display decreased joint range of motion (Levin et al., 2002; Roby-Brami, Fuchs, Mokhtari, & Bussel, 1997) and speed of movement (Cirstea & Levin, 2000; Cirstea et al., 2003; Roby-Brami et al., 1997), as a result, individuals with motor impairments often utilize a number of compensatory strategies to assist in achieving an intended goal. With respect to reaching, compensatory behavior often appears as the increased use of trunk flexion to assist in limb transport. In comparison to healthy individuals, the reach-distance threshold at which the trunk is involved during reaching is lower (Cirstea & Levin, 2000; Mark et al., 1997). The magnitude of compensatory behaviours such as trunk displacement is highly correlated with impairment scales (Subramanian, Yamanaka, et al., 2010). Kinematic analysis of tasks such as reaching can identify the presence of such compensatory behaviours, and thus provides insight into whether changes in performance are due to compensatory behaviours or recovery of motor patterns. This is important as the prolonged use of upper limb compensatory behaviours, in some cases can impede the recovery of joint and may lead to further complications such as contractures, and atrophy of surrounding musculature (Levin et al., 2009).

As a result it is important to not only capture whether an individual is able to perform a task, but also how an individual performs a task (e.g. with, or without compensatory behaviours). Such information can be used to disentangle motor recovery from compensation and thus better inform rehabilitation progress and potentially provide insight into the specific control problems that may be limiting function. Kinematic analysis may be a useful tool to quantify movement quality as well as compensations and thus provide a sensitive metric which can be used to augment clinical assessments.

Limitations of Kinematic measurement

Although metrics such as movement speed, and smoothness of the upper limb during functional tasks has been suggested as a more sensitive metric of movement deficits, kinematic analysis cannot identify the source of these deficits (e.g. whether decreased limb velocity is a result of spasticity or a deficit of strength). In addition, current kinematic measures and subsequent data-analysis techniques are not yet standardized, and can vary in complexity. There also remains insufficient information of the key kinematic metrics that might guide clinical decision making. These factors, in combination with costs of analysis systems and setup time, contribute to the obstacles faced with implementing kinematics as part of standard clinical assessment.

2.5 Overview of Kinematic Capture Systems

There are different research tools available to quantify 3D kinematics. The main classes of techniques include: 1) optoelectric, 2) magnetic, and 3) inertial. The gold standard is generally regarded to be optoelectric systems, which measure the spatial characteristics of objects from images from different types of imaging sensors. There are two main categories of optoelectric systems based on marker properties; active and passive marker systems. Both operate on the principle of photogrammetry; in which the internal, (e.g. focal length, lens distortion coefficients) and external (i.e. Spatial location) parameters of a set of cameras, and the pixels for each set of images which correspond to a common scene target allows for the calculation of 3D coordinates (Greaves, 1995). One of the challenges of optical tracking systems is solving the correspondence problem, which refers to the task of finding a set of pixels from two or images which correspond to the same physical location in a given scene (Faugeras, 1993). The correspondence problem is attenuated by the use of external markers in current optoelectric kinematic systems.

Passive Marker Systems

Passive marker systems such as Vicon ™ (UK), Motion Analysis ™ are multi-camera systems equipped with an illuminating source of infrared light. The projected infrared light is used in conjunction with retro reflective markers, which when illuminated, appears with uniform color and intensity. This property eases image feature extraction (i.e. pixel intensity, and colour) and assists in finding correspondences for given a scene target between multiple image sensors (Pedotti & Ferrigno, 1995). The advantage of passive marker systems is the wireless nature of the markers, allowing for more freedom of movement for human subjects.

Active Marker Systems Active marker systems such the Optotrak (NDI, Waterloo) system utilize infrared-emitting diodes, which are captured by their respective imaging sensor. The collection environment is such that the infrared-emitting diode is an exclusive source of infrared light, and thus correspondences for the marker between infrared sensors is obtainable, allowing for the calculation of 3D coordinates.

Though these systems are used extensively in human motion research, the associated costs of these systems and the required setup time prohibit their use in clinical settings. Furthermore, due to the fact that the spatial relationship between multiple image sensors needs to be known, once the system is calibrated, it is difficult to relocate the system, making these systems relatively difficult to move about in clinical space. Due to these factors, there has been interest in utilizing markerless kinematic systems for the purposes of human motion tracking. The task of markerless human pose tracking has been greatly advanced by the developments in depth cameras.

2.6 New technology for Kinematic analysis

Advances in depth camera technology have led to developments of low-cost sensor systems which are capable of kinematic data acquisition. One such system is the Kinect sensor, which is an active-light depth camera unit which comes equipped with an infrared projector, infrared sensor, and RGB sensor. The Kinect is unique in that it is the first consumer grade depth camera bundled with a robust human pose recognition algorithm. This pose-recognition algorithm is capable of estimating 20 anatomical landmarks. This algorithm relies on data from a single depth map image calculated form the Kinect sensor. This image is refined to the foreground image, by performing a background subtraction. The remaining image is the depth-silhouette of an individual.

The foreground pixels are then assessed using a trained, randomized, forest tree approach which labels each pixel with an anatomical landmark. After the anatomical labeling of the depth image, a 20-point general model of the human skeleton is fitted to the labeled depth image. The model provides some constraints and limitations on the coordinates of the limbs. The resulting coordinates obtained from the pose estimation algorithm are the optimized coordinates between the 20 point skeletal model and the labeled depth-silhouette (Shotton et al., 2013)

There is considerable interest in using technologies such as the Kinect in a clinical setting as the markerless nature of these systems greatly decreases the needed setup time and is therefore easier for application in a clinical setting. In addition, due the small size of the device, the system can be fitted into a clinical setting where space is often limited. However, there are several factors which prevent immediate application of this device into a clinical setting, including accuracy of the device, and sensitivity of the device to detect changes in a clinical population.

Obdrzalek et al. (2013) evaluated the accuracy of the Kinect's pose-estimation algorithm compared to ground-truth /gold standard skeletal model generating system (PhaseSpace, USA), which utilizes anatomical landmarks (located by external markers) to generate the model. Participants performed a series of whole-body movement tasks and the coordinates of corresponding markers in each system were compared. Results indicated that across all Kinect markers, there was an average absolute positional error of 10cm when performing whole body movements. Relative kinematic measures such as marker displacement for the trunk and lower limb have been investigated initially for the purposes of assessing standing balance, and results show high correlation in comparison to an optical motion analysis system (Clark et al. 2012).

There have been no studies that have specifically explored the capacity of the Kinect to reveal kinematic details of upper limb reaching movements that could be used to assess recovery after stroke. In addition, previous studies focused on whole body activity and lower limbs, and were not challenged by the potential interference associated with objects as would be required for assessing some functional upper limb movements (e.g. reach to point, reach to grasp).

2.7 Rationale and Hypotheses:

Despite growing evidence for kinematic analysis as a more sensitive metric of recovery, there are very few tools available to clinicians which can be implemented in a clinical setting. Consumer-grade depth cameras such as the Kinect sensor provide an affordable, alternative means of kinematic data acquisition which may better meet the needs of a clinical setting. Many studies have evaluated the accuracy of Kinect measures for standing balance (Clark et al. 2012) and gross whole body movement (Obdrzalek et al. 2013), but no studies to date have evaluated the relative kinematic measures from the Kinect for task conditions specifically relevant for upper limb stroke assessment. Furthermore, the aforementioned studies utilized healthy controls as subjects, and there are no publications to date which speak to the kinematic performance of the Kinect sensor and the pose-estimation algorithm in clinical populations with upper limb impairments.

The overall goal of this thesis was to evaluate the accuracy of the Kinect for tasks relevant to upper limb stroke assessment and to determine the feasibility of implementing the Kinect into a clinical setting. This thesis is focused around two specific studies. Study 1 characterizes the measurement properties of the Kinect system in healthy adults for specific upper limb tasks/movements. Study 2 will explore the feasibility of utilizing the Kinect sensor as part of an upper limb assessment for individuals with stroke.

Specific Objectives:

Study 1: This study focused specifically on characterizing Kinect displacement error for upper limb stroke assessment and identifying factors contributing to kinematic error. Specifically there were three objectives for study one: 1) evaluating the effect of sensor view angle on displacement error, 2) determining the effect of external objects on the accuracy of upper limb markers, and 3) characterizing upper limb marker error and identifying optimal markers for upper limb assessment. It was hypothesized that by altering the view angle of the Kinect such that the side profile of the reaching arm was visible to the Kinect would reduce displacement error. In addition we hypothesized that interacting with hand objects such as grasping and lifting external objects would interfere with Kinect tracking and result in increased displacement errors for the upper limb.

Study 2: The focus of this study was on the feasibility of implementing the Kinect into a clinical setting. Specifically, this study examined the ability of the Kinect to distinguish performance differences between the affected and less-affected limbs within an individual, and affected limbs between individuals with stroke. Two upper limb motor tasks were used to evaluate kinematic performance: a reach-to-touch task and circle-drawing task performed in the transverse plane. It was hypothesized that the Kinect will be able to sufficiently distinguish differences in performance between the affected and less affected limb within an individual, and this will be denoted by an increased hand displacement, peak velocity, and decreased trunk compensation when these tasks are performed by the less affected limb.

Results from this thesis provide evidence for the potential suitability of using consumer-grade technologies such as the Kinect sensor to augment current clinical stroke assessment protocols. Results would also set out possible guidelines and identify viable tasks suitable for the device for an upper limb assessment. Further, this work could directly contribute the guidance and development of assessment and rehabilitative computer programs which utilize the Kinect sensor.

3.0 Study 1: Evaluation of the Kinect for Measurement of Upper Limb Movement

3.1 Introduction

There are over 50,000 new cases of stroke in Canada each year (PHAC, 2009). The upper limb (UL) is often affected after stroke, affecting approximately 30-60% of the stroke population (Nakayama et al., 1994; Wade et al., 1983). Those suffering from upper limb disability experience a multitude of motor control impairments ranging from spasticity, hemiparesis (O'Dwyer, Ada, & Neilson, 1996) and abnormal muscle activation patterns (Dewald, Pope, Given, Buchanan, & Rymer, 1995). These impairments can influence functional use of the arm as measured by activity inventories such as the Functional Independence Measure (Heinemann, Linacre, Wright, Hamilton, & Granger, 1993). In turn altered arm function can influence participation, quality of life and result in decreased independence in stroke survivors (Laurent et al., 2011; Ones et al., 2005)

The assessment of motor control impairments following a stroke is important for creating targeted rehabilitation programs and monitoring recovery progression. Current clinical assessment tools for the upper limb consist of impairment inventories (e.g. Chedoke McMaster Stroke Assessment (CMSA) (Gowland et al., 1993), Fugl Meyer (Gladstone et al., 2002) or functional ability inventories (e.g. Wolf Motor Function test (Wolf et al., 2001), Functional Independence measure (Ottenbacher, Hsu, Granger, & Fiedler, 1996). These inventories require patients to perform a progression of motor tasks; categorizing patients into different levels of impairment. Assessment of each task considers the quality of the movement and includes kinematic characteristics such as speed, coordination of limbs, or the use of compensatory strategies.

These assessments are often performed by clinical observation and may lack sensitivity to capture small but important changes in quality of movement. Kinematic analysis of upper limb movements such as reaching is a more revealing method of assessing post-stroke impairment and recovery. Following a stroke, patients often show slower hand transport times, (Cirstea & Levin, 2000; Cirstea et al., 2003; Roby-Brami et al., 1997) and increased segmentation in hand velocity profiles; indicating poor control and coordination in the arm musculature (Cirstea & Levin, 2000; Cirstea et al., 2003; Levin et al., 2002). Patients also show a decrease in elbow extension during reaching (Levin et al., 2002; Roby-Brami et al., 1997), as well as increased use of compensatory trunk strategies (Cirstea & Levin, 2000; Roby-Brami et al., 2003). Upper limb kinematic measures are also shown to be correlated with clinical impairment scales (Subramanian, Yamanaka, et al., 2010). In spite of the potential benefits of kinematic analysis there has been little incorporation of such measurements into clinical assessment. This is likely due to financial and time barriers, as current motion capture systems are expensive, and require considerable setup time.

Novel technology such as the Microsoft Kinect (Redman, WA, USA) may present a potential solution to these problems. The Kinect sensor is an affordable device capable of markerless human-pose measurement. The device utilizes an infrared projector sensor to create depth maps of a scene. A human pose recognition algorithm analyzes the depth map, identifies a human silhouette, and subsequently performs a foreground isolation. Each pixel is then further analyzed by a trained decision forest which categorizes each pixel as an anatomical landmark, yielding a labeled silhouette. A 20 point skeletal model is then fitted to the labeled silhouette and an optimization of the labeled silhouette and skeletal model is then performed to yield the final coordinates of each landmark (Shotton et al., 2013; Taylor, Shotton, Sharp, & Fitzgibbon, 2012).

The Kinect is a small and lightweight sensor, and could provide clinicians an affordable and mobile system capable of kinematic data acquisition in clinical or community settings. The suitability of this technology for clinical use remains unknown. There remain two important steps: 1) identifying the validity of kinematic measures and the factors which affect its accuracy and 2) determining the suitability of the Kinect to measure movement after stroke. There have been some initial studies looking at the accuracy of the Kinect sensor. For example, previous work involving the Kinect has explored the measurement error of the depth camera with respect to static objects (Dutta, 2012), position accuracy of Kinect-joint locations during various full-body movements (Obdrzáleket al., 2012) and joint displacement errors during standing balance(Clark et al., 2012). Dutta (2012) recorded the coordinates of a simple static rectangular object using a Kinect and gold standard motion capture system (Vicon, Oxford, UK). Root mean square error values were computed and results indicated a small error between the two systems depending on object depth from the Kinect and proximity to the Kinect's field of view boundaries. Locations further away from the sensor and near the capture boundaries increased the error of the Kinect system. Kinect coordinates were obtained directly from depth images and were not processed with the pose-estimation algorithm, thus these results cannot be directly translated to the tracking ability of the Kinect. Obdrzalek et al. (2012) explored the positional accuracy of the estimated Kinect virtual-markers compared to another marker based kinematic capture system (PhaseSpace, CA, USA). The comparison system utilized active infrared markers positioned on anatomical landmarks, which were used to estimate a 3D skeletal model of the participant. The marker position of the control skeletal model was assumed to be accurate and compared to the position of Kinect virtual-markers. Results indicated an inter-joint difference in accuracy with a high positional error average of 10cm across all virtual-markers. Finally, Clark et al. (2012) investigated the use of the Kinect more specifically for assessing postural control. Forward and lateral reaching with the upper limb was also explored, but an incomplete upper limb data set was reported. Results indicated a high intra-class correlation to a Vicon motion system.

In spite of the potential usefulness of this new technology the utility of the Kinect measures for assessing upper limb movement remains unknown. Initial validation studies noted above have revealed some limitations in positional accuracy but have not fully explored the accuracy of relative motion metrics such as displacement. Furthermore, unexplored factors such as the grasp configuration of the hand, body orientation relative to the sensor and even the presence of task related objects may affect kinematic accuracy and are important to consider for the purposes of clinical assessment.

The focus of this study is to identify the accuracy of the Kinect for describing upper limb movement and relevant factors which may affect its accuracy. There are three main objectives for this study. (1) Characterize the accuracy, and identify optimal Kinect markers for motion tracking for clinically relevant upper limb tasks. (2) Determine the influence of human-object manipulations during a reaching task on kinematic accuracy. (3) Determine the influence of body orientation relative to the Kinect sensor on kinematic accuracy.

Accuracy will be determined by comparing kinematic measures between the Kinect and a gold standard kinematic system. Results from this work, specifically the displacement error and the influence of matters such as external objects and spatial relationships between individuals and Kinect sensor, will be used to optimize clinical application in future studies.

3.2 Methods

3.2.1 Participants

Seven healthy young adults were recruited for this study. Participants were informed of experimental procedures, and provided written consent in accordance with the study protocol approved by the ethics committee of the University of Waterloo. Participants had no prior upper limb impairments that would interfere with the physical demands of the experiment.

3.2.2 Task conditions

A full listing of task conditions can be found in Table 1. To characterize accuracy and identify optimal Kinect markers, we selected range-of-motion (ROM) tasks for the shoulder (flexion, extension, transverse adduction) and elbow (flexion, extension) joints. Reaching tasks were also evaluated, for which participants performed a reach-to-touch to targets located at 75%, and 120% arm length (shoulder-plane, mid-torso height). The latter distance elicits trunk motion during the reach to grasp motion and was used to identify optimal proxy measures for trunk movement. To evaluate the effect of human-object manipulations, reaching targets were modified to include a small and large object. A third condition requiring individuals to grasp the large object was also used. The large object was a cylinder with the dimensions: height 15.7 cm, diameter: 8.9 cm. The effect of body position with respect to the Kinect sensor was evaluated by using three body positions for a reaching task: frontal, proximal and distal. In the frontal position, the subject was facing the sensor such that the subject’s frontal plane was parallel to the medial-lateral plane of the Kinect sensor. The proximal condition consisted of a 45 degree rotational shift in seating position such that the reaching arm was closer to the sensor. The reverse was done for the distal condition.

Participants were seated on a backless-wooden chair (width: 53 cm, depth: 51 cm, height: 43 cm). Starting positions were standardized for each task condition: wrist was in neutral position (0° flexion, 0° ulnar deviation) and the hand held in a closed fist.

Researchers verbally cued the participants to begin each trial. Participants were instructed to perform each task at a comfortable self-selected pace. For the reaching trials, participants were instructed to accurately reach towards the presented target. Participants returned to their starting position following each trial. A closed fist was kept during all task conditions except in the reach-to-grasp condition, which required the participant to open their hand and grasp an object. Prior to each task condition, participants performed a synchronization movement consisting of rapid elbow flexion and extension cycles performed in the sagittal plane. This event was then used to temporally align the data streams between the Kinect and Polhemus systems (Section 3.2.5).

3.2.3 Data Collection Setup

Kinematic data was simultaneously acquired with a Polhemus Liberty HST-2400 tracking system (Colchester VT, USA) and a Microsoft Kinect sensor (Redmond WA, USA). Polhemus data was collected with a sampling frequency of 120 Hz. Kinect data was collected on an Intel I5-670 3.4GHz machine with 4 GB RAM running Windows 7 using custom C# software written with the Microsoft Kinect SDK (v1.5). The sampling rate of the Kinect was a variable 30Hz.

The Polhemus reference cube was positioned posterior and contralateral to the dominant limb. Polhemus markers were attached to C7, styloid, lateral epicondyle, and acromion of the dominant limb. The Kinect sensor was placed 2m from the base of the chair, at a height of 0.85 m measured from the floor to lens of the sensor.

3.2.4 Alignment of Kinect and Polhemus systems:

Spatial alignment of the two systems was achieved by recording the 3D coordinates of the corners for a rectangular calibration object. Coordinates were recorded in Polhemus space using a digital stylus. In Kinect space, depth images were taken of the calibration object and coordinates were manually extracted using custom software. Colour representation of the depth image was programmatically modified to assist the digitization process; pixels with a depth between of 0.8 to 1.5 m were coloured white, pixels outside of this range were coloured black. This created a high-contrast scene in which the calibration object was isolated in white pixels (Figure 3.1).

The calibration object was positioned at different depths and heights relative to the sensor and was rotated to multiple orientations. A list of points was created containing the Kinect and corresponding Polhemus points. A homogenous transformation matrix was created between the Kinect and Polhemus coordinate system via single value decomposition and least squares estimation using a custom MATLAB program. Upon establishing the transformation matrix, the Kinect dataset was transformed into Polhemus coordinate space.

3.2.5 Signal Processing and Feature extraction:

Due to the non-uniform sampling rate of the Kinect sensor, data was interpolated and resampled to 20 Hz. Polhemus data was also down sampled to 20 Hz prior to analysis. Polhemus and Kinect data were low-pass filtered at 5 Hz using a second order Butterworth filter. Temporal synchronization was obtained by aligning the data sets of both systems to the synchronization event. Individual trials were isolated from the continuous data set by using the initial and peak wrist position from the Polhemus system as event-markers. Kinect virtual-markers were compared to the corresponding control markers located at standard anatomical locations.

Due to virtual-markers outnumbering control markers, Kinect virtual-markers were compared to the closest available control marker. Table 2 highlights the specific pairings between from Kinect virtual markers and their corresponding control markers.

3.2.6 Dependent Measures

Displacement was calculated for each marker location for both systems from the initial and final marker positions for each movement trial. Elbow angle was determined by the vectors formed by the elbow-hand and elbow-shoulder markers. Angular displacement of the elbow was calculated as the difference in elbow angle at two instances during the movement trial. Three intervals of the movement trial were observed for angular displacement: start- end, start-middle, and middle-end (Figure 3.2).

Displacement error was calculated as the displacement difference between the Kinect and Polhemus systems. Similarly angular displacement error was the difference in angular displacement reported by the Kinect and Polhemus systems. Temporal resolution was investigated by measuring the peak to peak time intervals of the calibration movement performed by participants prior to each task. This time interval was measured for each system and the temporal error, taken as the peak-peak difference between systems, was subsequently analyzed.

3.2.7 Statistical Analyses

In order to compare the effect of body orientation and effect of object interaction on displacement error, two separate two-way ANOVAS (factors: joint, task) were used. For angular displacement error, two separate two-way ANOVAS (factors: task, interval) were used to assess the effect of 1) body orientation and 2) object interaction. Post-hoc tests were used to determine differences in the presence of significant main effects. Statistical significance was determined with a significance level of $p \leq 0.05$.

3.3 Results

Characterization

Displacement error for ROM task conditions is summarized in Table 3.3. Under optimal task conditions, displacement error for the Kinect hand marker was 1.0 ± 4.0 cm across participants. Variability of displacement error between participants was high, however, within participant variability, as determined by the average standard deviation for participants across trials, was lower. Displacement errors of Kinect markers were significantly greater than 0 for all task conditions ($p < 0.05$). Displacement error was variable across upper limb Kinect markers, and was particularly high for the Kinect wrist, with errors up to 15.0 cm. This performance difference between Kinect hand and wrist markers can also be seen in trajectory profiles; the hand marker produces a smooth trajectory profile which is consistent with the control ulnar-styloid marker (Figure 3.3b), while the wrist marker produces a trajectory which is inconsistent and variable (Figure 3.3c). Trunk motion was evaluated using the Kinect sternum and head marker. The Kinect head marker had a lower displacement error relative to the sternum marker, however the within subject variability of the sternum marker was lower than that of the Kinect head (Table 3.3).

Influence of External Reaching Object

Marker Displacement Error

The details of the effect of external reaching object on marker displacement error are summarized in Figure 3.6. Two-way ANOVA revealed a main effect for joint ($F_{(5, 30)} = 28.70$, $p < .001$) and, task ($F_{(2, 7)} = 5.78$, $p=0.0330$) as well as a significant interaction between joint and task ($F_{(10,35)} = 5.96$, $p<.0001$). Specifically there was an increase in displacement error for the Kinect hand in the Touch-large condition relative to the Touch-small condition.

Error further increased in the Grasp-large condition, however only the Grasp-large condition was significantly different from Touch-small ($t_{(11)} = 4.79$ $p<0.01$).

There was also an increase in displacement error for the Kinect wrist in the Touch-large and Grasp-Large conditions, but this change was not statistically significant.

Elbow Angular Displacement Error:

Figure 3.7 details the effect of external objects on elbow angular displacement error. There was no significant main effect for task ($F_{(2, 7)}$ =0.32, p =0.73), or interval ($F_{(2, 12)}$ = 1.55, p = 0.2527). In addition there was no significant interaction effect between task and interval ($F_{(4, 14)}$ = 0.85, p = 0.51).

Influence of Body Orientation Relative to Kinect Sensor

Marker Displacement Error

Figure 3.4 highlights the effect of body orientation on marker displacement error. Two-way ANOVA (body-orientation, joint) revealed a significant main effect for joint ($F_{(5, 30)}$ = 43.81, p<0.0001) and a significant interaction effect between virtual-marker and body orientation ($F_{(10, 45)}$ = 2.71 p=0.0108) for marker displacement difference. No main effect of body orientation ($F_{(2, 9)}$ = 1.67, p =0.2421) was found. Wrist and shoulder virtual-marker error significantly decreased in the proximal body orientation when compared to the frontal orientation (Wrist: $t_{(9)}$ = -2.28, p = 0.0485; shoulder: ($t_{(9)}$ = 2.63, p= 0.0272). In the proximal camera location there was a decrease in the standard deviation across individuals in the hand marker when compared to the frontal camera position; however displacement errors in the two conditions were not statistically different.

Elbow Angular Displacement Error

A summary of the results is displayed in Figure 3.5. There was no significant main effect for task condition ($F_{(2, 9)} = 2.61$, $p=0.12$) or trial interval ($F_{(2, 12)} = 1.48$, $p = 0.26$). In addition, no significant interaction effect was found ($p=0.14$). Despite lack of statistical significance there was a subjective increase in elbow angular displacement error in the touch-large condition when compared to the touch-no object condition.

Temporal Resolution:

Figure 3.8 details the temporal error between the Kinect and the gold standard system. Peak to peak time interval differences between the Kinect and control system indicate good temporal resolution for the Kinect sensor. Mean temporal error was reported to be 1.0 ± 1.8ms across individuals. This value was not significantly different from 0 ($p = 1.862$).

3.4 Discussion

The purpose of this study was to determine optimal Kinect markers for tracking and identify factors which may affect the kinematic performance of the Kinect system.

Kinect Marker Performance

Displacement error is variable depending on the Kinect marker; errors can be less than 2cm for some markers such as the Kinect hand, but can exceed 10cm for others such as the wrist, and elbow. Large errors in Kinect markers such as the elbow and shoulder, limit the ability to calculate joint angles, which were shown to be large. Variability of displacement errors was also large across individuals; this result may be attributed to inconsistencies in the pose-recognition algorithm to accurately track anatomical locations of individuals. Previous work has identified variation in the estimated locations of Kinect markers, with positional differences of up to 10cm (Obdrzálek et al., 2012). Such differences in marker position may contribute to the large variability seen the displacement errors across individuals of this study.

Effect of External Objects

The presence of task-related objects greatly increased the displacement error for the Kinect hand, and wrist. Hand displacement errors increased when participants interacted with the large reach object. This error is most likely due to the system's inability to differentiate between the individual's hand, and object. It is possible that the depth-image pixels belonging to the object are incorrectly labeled as belonging to the hand, resulting in a miscalculation of the 3D location of virtual-markers, as proposals are based on the local mode of the labeled depth pixels (Shotton et al., 2013). In addition to object interactions, movements such as opening and closing the hand can affect depth representation of the hand and thus affect the reported position of the virtual hand and wrist markers. This was qualitatively observed as the wrist and hand virtual-markers moved when participants opened and closed their hands.

Although the intricacies of the pose-estimation algorithm of the Kinect have not been fully revealed, literature suggests a hybrid discriminative and generative approach for pose-estimation (Taylor et al., 2012). This suggests that some Kinect-marker positions are estimations based on the skeletal model (generative), while others markers may be more data driven in their tracking (discriminative). Due to the single view depth images afforded by the Kinect, some virtual markers may be more occluded than others during certain movements, and are more likely to be estimated. Thus, joint estimations for Kinect markers such as the wrist, elbow, and shoulder may be more generative in nature, which would explain their larger displacement errors, and variable trajectory profiles. Variability in markers such as the Kinect-elbow would directly affect calculations of elbow angle, which would explain the large error and variability seen in elbow angle metrics.

Potential Clinical Utility

This study has identified the Kinect hand and sternum markers as good indices of upper limb endpoint and trunk kinematics respectively. The Kinect hand has the lowest displacement error when it is not interacting with external objects, and when its hand configuration is kept consistent. With regards to trunk tracking, although the Kinect head marker had a lower displacement error, the sternum marker was a more consistent marker, as evidenced by lower within-subject variability. In addition, the head marker would be susceptible further increases in variability due to additional head movement. It remains to be seen if these Kinect markers can produce a clinically useful metric, however the clinical research of Cirstea and colleagues certainly suggests a potential. Cirstea et al. (2003) characterized the kinematic reaching properties of stroke patients and have identified differences between healthy, mild, and severe subgroups based on the Fugl Meyer impairment inventory Differences in trunk displacement between subgroups were reported to be 4 cm and 10 cm respectively.

With regards to the amount of elbow extension, differences of 16 degrees and 14 degrees were reported between subgroups respectively. There is a potential clinical use for the Kinect considering the displacement error of the Kinect virtual markers is within the threshold of these clinical differences. However due to errors of angular displacement exceeding the limits of clinical thresholds, the Kinect may not be a sufficient tool to measure differences in elbow ROM.

Usage Considerations

Findings from the current study have important implications if the Kinect is to be used in clinical settings. Collection areas should be uncluttered, minimizing objects around the participant. If the participant is seated during a collection, then chairs/seats should be without armrests and/or overly large backrests. Movements should be simple and designed to minimize self-occlusion, and maintain the same hand configuration throughout the movement. If reaching targets are to be used, then the target should be small and mounted or suspended in a manner to minimize occlusion of other limbs. Positioning of therapists is another point of consideration, for seated upper limb motions, therapists can be positioned out of the Kinect scene while an individual is performing a task. However task conditions which require the presence of a therapist to prevent falls may result in tracking issues if the position of the therapist occludes the tracked individual. In addition, choice of clothing may affect the kinematic data produced by the Kinect. To our knowledge, there is no literature describing the effect of clothing on kinematic data quality, and studies using the Kinect have only performed collections with minimal or form-fitting clothing (Clark et al., 2012; Obdrzálek et al., 2012). One can only assume based on the observed effects of foreign objects in this study, that overly large and ill-fitting clothing could potentially increase tracking error.

Though we did not test the lower limb, it is plausible that such estimations occur for the lower limb as well. A potential improvement to this system would be to provide the system with anthropometric measures of limb segments; this would allow more accurate modeling of Kinect markers which are prone to occlusion.

3.5 Conclusion

Measurements from the Kinect may augment current clinical assessments for the upper limb by providing information regarding trunk and endpoint motion. The kinematic accuracy of the Kinect is joint dependent and can be affected by the presence of foreign objects. Thus, clinical applications should be designed with these limitations in mind. It should be noted that this technology is still evolving and future iterations of the sensor and tracking algorithms may greatly improve the kinematic performance.

3.6 Tables and Figures

Table 3.1. Description of the range-of-motion (ROM) and reaching tasks performed. 15 trials were performed for each task. Reaching tasks were performed in the sagittal plane unless noted otherwise. Proximal and distal reaching arm position required the participants to rotate their torso in seat 45 degrees to left/right to facilitate reaching arm position.

Category	Tasks (n=14)	Starting position	Object	# Trials
Shoulder ROM	Forward Flexion	Shoulder: 0° extension, 0° abduction.	N/A	15
	Backward Extension			
	Shoulder Elevation			
	Transverse flexion	Shoulder: 0° flexion, 90° abduction.		
Elbow ROM	Frontal plane: flexion/extension of elbow	Shoulder: 0° extension, 0° abduction. Elbow full extension.	N/A	15
	Sagittal plane: flexion/extension of elbow	Shoulder: 0° extension, 90° abduction. Elbow full extension.		
Reach-to-touch	To target at 75% and 120% arm length	Shoulder: 0° extension, 0° abduction. Elbow 90° flexion.	Small	15
	To target located in contralateral space		Large	
	Reaching arm position to sensor: proximal/distal			
Reach-to-grasp	To object at 75% arm length		Large	15

Table 3.2. Kinect markers and corresponding control marker used for kinematic analysis.

Kinect Marker	Polhemus Marker
Hand	Wrist
Wrist	Wrist
Elbow	Elbow
Shoulder	Shoulder
Sternum	C7
Head	C7

Table 3.3. Comparison of displacement measures (Mean ± standard deviation) for ROM tasks between Kinect and Polhemus systems. Virtual marker indicates the anatomical landmark provided by the Kinect system. All values are averaged across individuals (n=7).

Task	Location	Kinect Displacement(cm)	Polhemus Displacement(cm)	∆Displacement (cm)	Within-subject Variability[4] (cm)
Shld Extension[1]					
	Hand	86.94±6.18	87.21±8.85	-2.56±0.77	0.91±0.16
	Wrist	76.80±7.20	87.21±8.85	-10.76±3.13	1.76±0.42
	Elbow	42.41±4.31	47.21±4.84	-4.80±1.44	1.5±1
Shld Flexion[1]					
	Hand	69.46±10.35	64.42±10.03	4.12±1.90	2.45±2.18
	Wrist	61.41±9.20	64.42±10.03	-2.81±1.39	2.16±0.97
	Elbow	33.33±5.93	37.06±5.33	-3.72±1.71	1.55±0.92
Shld Flexion[3]					
	Hand	94.60±1.95	96.45±1.87	-1.08±4.05	1.19±0.49
	Wrist	85.96±4.82	96.45±1.87	-14.76±2.91	1.62±0.37
	Elbow	46.04±3.76	52.73±5.41	-6.69±4.50	1.43±0.48
Elbow Flexion[1]					
	Hand	55.79±5.17	53.73±6.15	2.01±2.25	0.94±0.22
	Wrist	44.46±3.73	53.73±6.15	-9.27±3.58	1.33±0.68
	Elbow	7.91±2.64	6.35±3.22	1.57±1.23	1.12±0.47
Elbow Flexion[2]					
	Hand	46.39±5.54	50.06±6.26	-3.67±2.27	1.71±0.33
	Wrist	34.63±4.71	50.06±6.26	-15.29±2.79	1.75±0.5
	Elbow	3.37±2.13	3.50±1.56	-0.13±1.17	0.79±0.29
Touch. Far[1]					
	Head	29.74±4.88	28.35±4.40	1.39±1.36	1.13±0.76
	Sternum	25.17±4.58	28.35±4.40	-3.17±0.59	0.39±0.09
	Shoulder	27.40±3.03	31.27±2.83	-3.87±0.86	0.58±0.21
S. Shrug[1]					
	Shoulder	3.66±1.01	8.42±2.07	-4.76±1.15	0.44±0.16

1. Sagittal plane. 2. Frontal plane. 3. Transverse plane. 4. Within-subject variability shown as (AVGSTDEV (for all individuals, across all trials) ± STDEV)

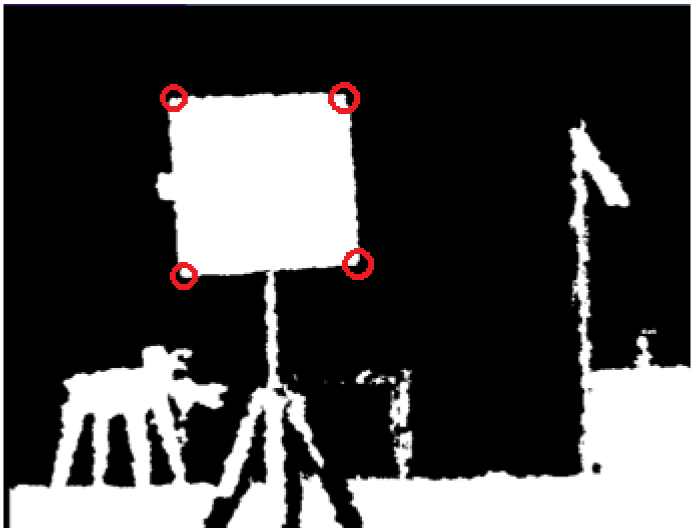


Figure 3.1. Kinect depth image of calibration scene. 3D-coordinates of the corners of the rectangular object (circled) were manually using the Microsoft Kinect SDK and used to transform Kinect coordinate system into the control coordinate system.

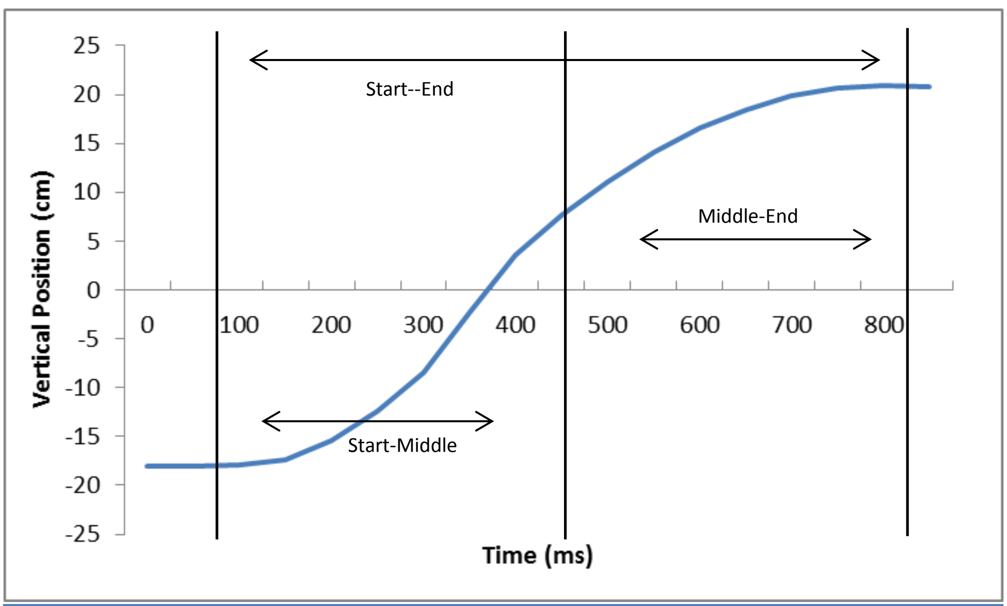


Figure 3.2. Representative trial from one subject during elbow flexion in the frontal plane. Depicted above is the vertical position of the Kinect virtual hand marker and the time intervals used for analysis. Start, middle and end of this trial are located at 100ms, 450ms and 800ms respectively.

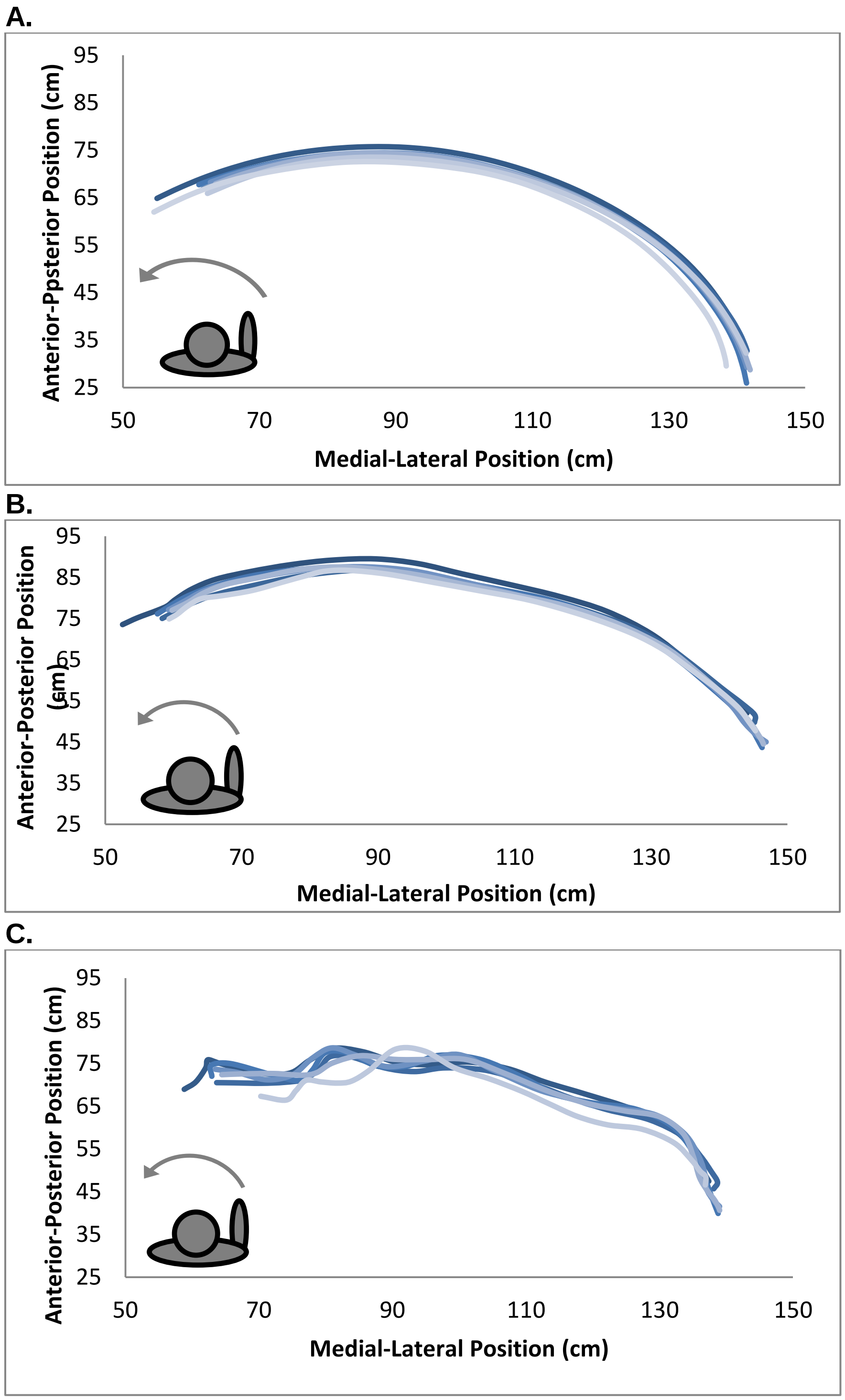


Figure 3.3. Representative data comparing the transverse plane trajectories during the transeverse shoulder flexion task for a single participant. Each trace represents a single trial. Panel A: Trajectory of control system ulnar-styloid marker. Panel B: Trajectory of Kinect hand virtual marker. Panel C: Trajectory of Kinect wrist virtual marker.

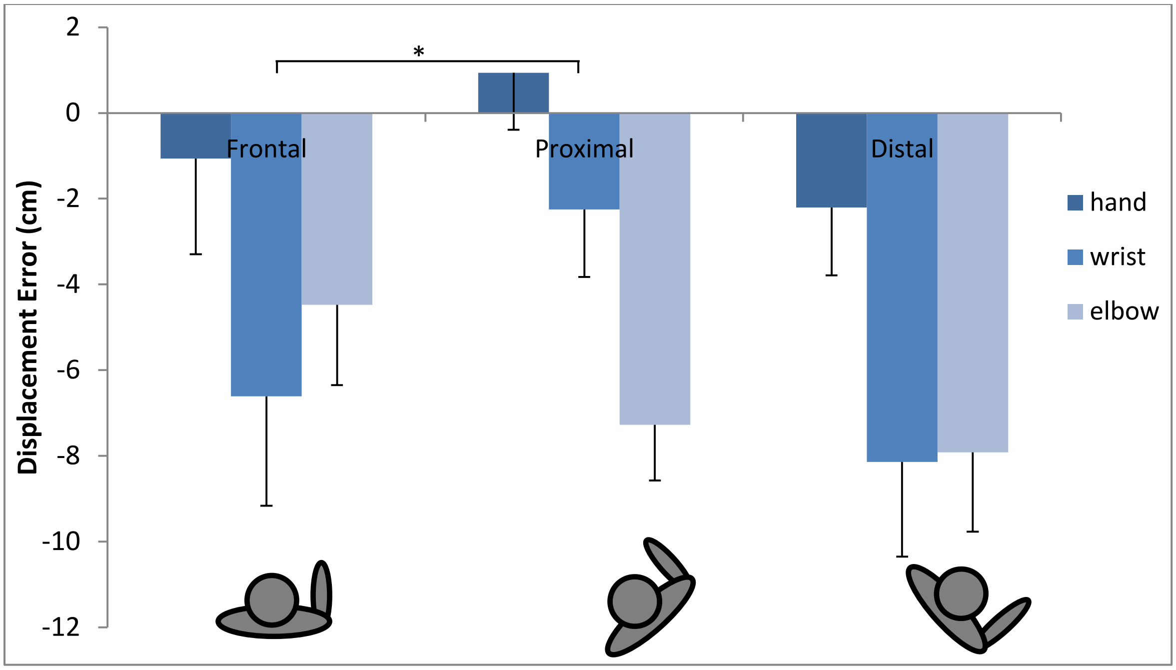


Figure 3.4 Interaction effect of camera location for marker displacement error. Plotted are the mean values and standard deviation bars of the displacement differences between the Kinect and gold standard system. Each virtual marker is the anatomical landmark as given by the Kinect system. Inset schematic depicts the body orientation assumed by participants for each task condition. Kinect sensor was oriented to project squarely onto the participant in the frontal condition. * denotes significance ($p < 0.05$).

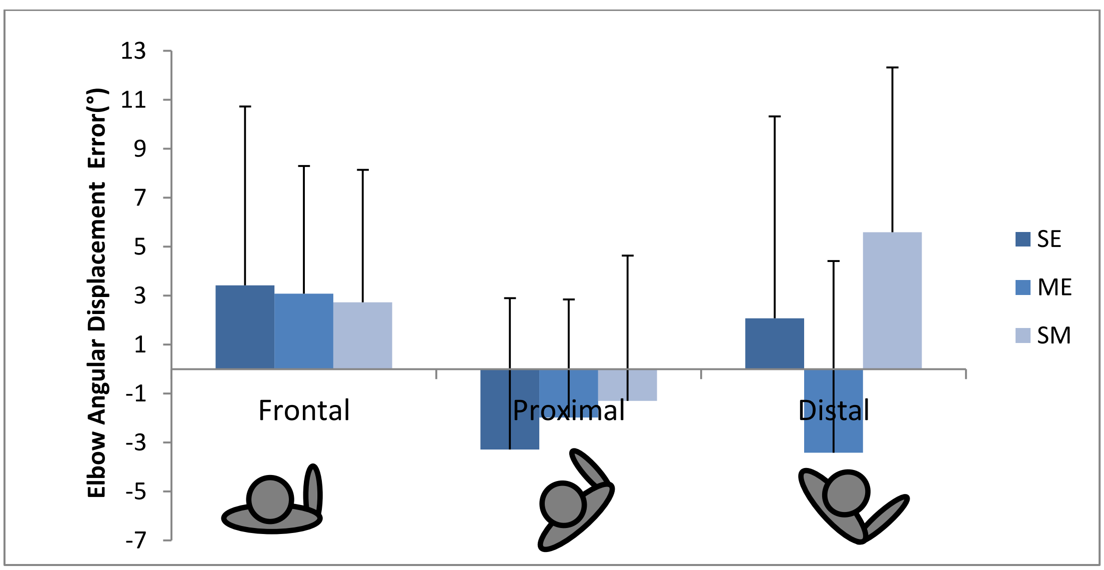


Figure 3.5. Interaction effect of camera location for elbow angular displacement error. Plotted are the mean values and standard deviation bars of the difference in elbow angular displacement between the Kinect and gold standard system. The following denotes time intervals during the trial; SE: start-to-end, ME: Middle-to-end SM: start-to-middle.

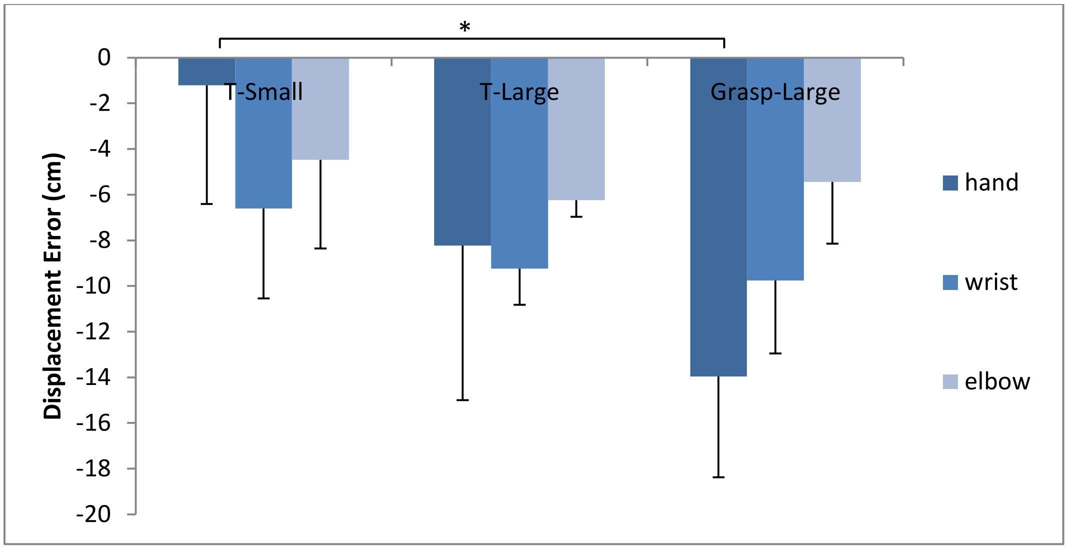


Figure 3.6. Object interaction for marker displacement error. Plotted are the mean values and standard deviation bars of the displacement difference between the Kinect and gold standard systems. Task conditions consist of reach-to-touch a small object (T-Small), reach-to-touch a large object (T-Large), and reach-to-grasp a large object (Grasp-large). All reaches were performed in the sagittal plane. Each anatomical landmark is the virtual marker as given by the Kinect. * denotes significance ($p < 0.05$).

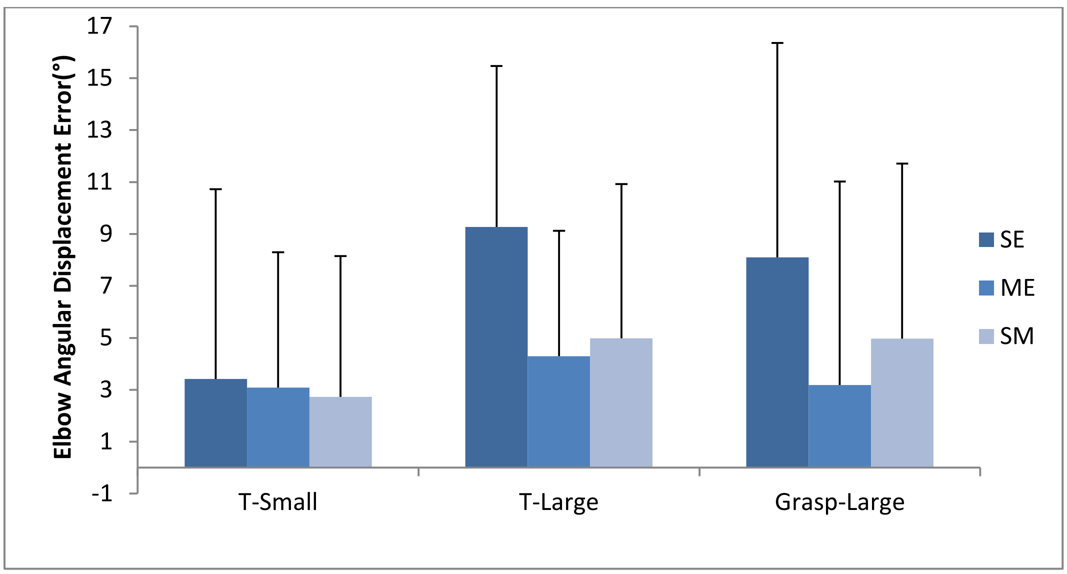


Figure 3.7. Object interaction for ∆ elbow angle displacement. Plotted are the mean values and standard deviation bars of the elbow angular displacement difference between the Kinect and gold standard systems. Task conditions consist of reach-to-touch a small object (T-Small), reach-to-touch a large object (T-Large), and reach-to-grasp a large object (Grasp-large). The following denotes time intervals during the trial; SE: start-to-end, ME: Middle-to-end SM: start-to-middle.

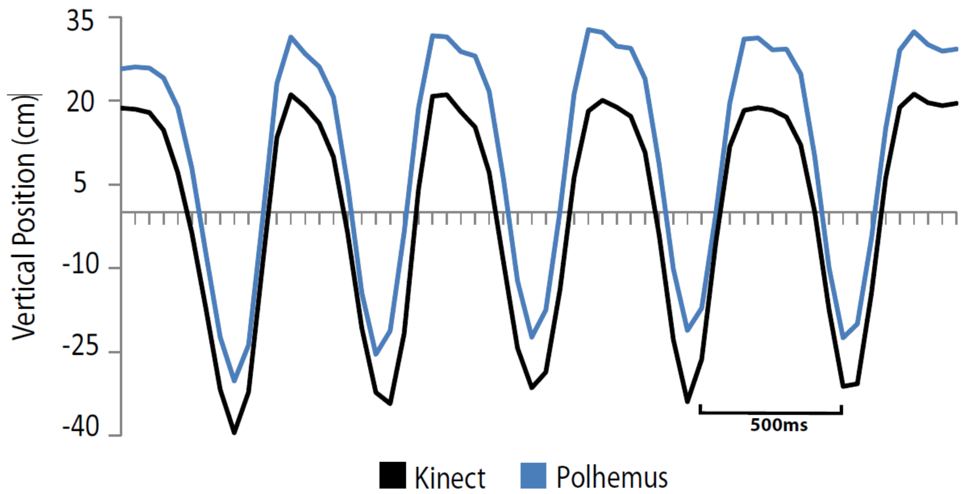


Figure 3.8. Temporal resolution of Kinect compared to the gold standard system. Event shown is the calibration movement consisting of rapid elbow flexion and extension cycles performed prior to each task. The two lines dipcted above are the vertical positions of the Kinect hand virtual marker (blue) and the gold standard ulnar styloid marker (black).

4.0 Study 2: Determining the Feasibility for the Clinical Use of the Kinect System for Upper Limb Stroke Assessment

4.1 Introduction

The assessment of upper limb impairment and disability post stroke is important in identifying rehabilitation goals and efficacy of rehabilitation programs. Current clinical assessment tools for the upper limb consist of impairment inventories (e.g. Chedoke McMaster Stroke Assessment (Gowland et al., 1993), Fugl Meyer (Gladstone et al., 2002)), or functional ability inventories (e.g. Wolf Motor Function test (Wolf et al., 2001), Functional Independence Measure (Ottenbacher et al., 1996)). These assessments require individuals to perform a series of complex multi-joint movements which evaluate the level of impairment or function of a given limb. Spatial characteristics such as speed, coordination of limbs, and magnitude of compensatory strategies are often evaluated. Evaluation of task performance is typically performed by clinical observation, which may not be sufficient to detect and quantify small changes in motor performance.

Kinematic analysis of fundamental upper limb movements such as reaching may be a more sensitive method to evaluate motor deficits (Subramanian, Yamanaka, et al., 2010). Kinematic studies of upper limb reaching in stroke survivors have revealed altered motor performance. Hand transport times are often lower (Cirstea & Levin, 2000; Cirstea et al., 2003; Roby-Brami et al., 1997), and velocity profiles show increased segmentation when compared to healthy controls, indicating deficient control of the upper limb (Cirstea & Levin, 2000; Cirstea et al., 2003; Levin et al., 2002; Roby-Brami et al., 1997). Individuals recovering from stroke also show decreased elbow extension (Levin et al., 2002; Roby-Brami et al., 1997), and increased use of compensatory mechanisms such as increased trunk movement during reaching (Cirstea & Levin, 2000; Cirstea et al., 2003; Levin et al., 2002; Roby-Brami et al., 1997).

Kinematic analysis can provide detailed information regarding the coordination of limbs and the use of compensatory strategies, affording insight into motor control. Such measures have been shown to be correlated with clinical impairment scales (Cirstea & Levin, 2000; Subramanian, Yamanaka, et al., 2010) and may be used to augment clinical assessment. Despite growing support of the benefits of kinematic analysis, there is little implementation within current clinical practice. Conventional kinematic analysis systems remain a non-feasible option for clinical sites as they are cost prohibitive and require extensive setup time.

Advancements in technology have led to the development of low-cost portable sensors which may be able to provide an affordable and feasible means of kinematic capture. The Microsoft Kinect sensor (Redmond, WA, USA) is a small lightweight device which is capable of tracking 20 anatomic landmarks without the use of external markers commonly used in conventional kinematic systems. The Kinect sensor utilizes infrared light to calculate a three-dimensional depth map of the scene in front of the sensor. A pose-estimation algorithm identifies the presence of a human silhouette within the depth map, and performs a foreground-isolation. Each depth pixel from the silhouette is then further classified as a body segment. This classification allows for the fitting of a skeletal model composed of 20 virtual-markers, from which kinematic information can be obtained (Shotton et al., 2013; Taylor et al., 2012). Studies evaluating the accuracy of the locations of the Kinect virtual markers in comparison to other motion capture systems reveal a position error of 10 cm across all Kinect virtual markers (Obdrzálek et al., 2012). However the ability of the Kinect to detect changes in motion is promising for some markers; displacement error was reported to be less than 2 cm for the Kinect hand and Kinect sternum marker when compared to a research grade kinematics system (Tran and McIlroy 2013).

Given the magnitude of the measurement error associated with the Kinect system, there remains some concern regarding the ability of the Kinect to sufficiently identify kinematic differences in a clinical population. Cirstea et al. (2003) compared kinematic differences in compensatory trunk displacement between healthy, mild, and severe stroke populations. Reported differences in trunk displacement between healthy/mild and mild/severe were 4 cm and 10 cm respectively. Considering the displacement error of the Kinect system is less than 4 cm, there is potential for using the Kinect sensor to assess differences in the upper limbs of stroke survivors. Other studies have shown the potential use of the Kinect with clinical populations, including Lowes and colleagues who investigated the clinical use of the Kinect with individuals with muscular dystrophinopathy (Lowes et al., 2013). Participants performed reaching tasks on a tabletop. Results indicated an ability to differentiate patients based on functional reach volume and reach velocity, highlighting the potential of the Kinect for clinical use. However, this study utilized an alternative algorithm to identify and track colored objects placed on the hand. This approach removes the restriction of placing the sensor such that it views the participant in the frontal plane, allowing the sensor to be positioned at better viewing positions to better observe the movement. However, using this approach requires the development of a tracking algorithm which will accurately and robustly track the external markers. In addition, this approach requires the use external markers, adding time to the setup of the system, and limits kinematic information to the number of available markers.

Overall, there is recognition of the potential importance of kinematics captured in clinical settings though there remains a knowledge gap regarding the feasibility of using the Kinect sensor and its markless tracking algorithms for measuring upper limb control after stroke. This study investigated the feasibility of using the Kinect sensor and the pose-estimation algorithms to differentiate motor performance between the affected and less-affected limbs in stroke survivors. In addition, the study also set out to determine if the Kinect could differentiate performance of affected limbs in stroke survivors with varying degrees of impairment.

There are two hypotheses for this study. 1) It was hypothesized that the Kinect would be able to identify performance differences between the affected and less affected limb within an individual. Performance differences will be similar to those reported in the literature, and thus affected limb movements will be marked by increased trunk displacement, and lower hand velocity. 2) In addition, it was hypothesized that the magnitude of hand velocity will decrease, and compensatory trunk displacement will increase as post stroke limb impairment increases as determined across individuals.

4.2 Methods

4.2.1 Participants

A summary of participant characteristics can be found in Table 4.1. Twelve participants (age: 63.5±11.3, M: 6, F: 5) were recruited from at the Sunnybrook Health Sciences Centre (Toronto, ON) and Grand River Hospital (Freeport Site, Kitchener, ON). Inclusion criteria for participation was the presence of unilateral upper limb impairment assessed using the arm component of the Chedoke McMaster Stroke Assessment (CMSA) scale. Participants required a minimum CMSA arm score of 3 and the ability to move both upper extremities with no pain. This threshold of impairment was selected as individuals with lower CMSA scores do not possess the capacity to volitionally move against gravity, and would not be able to perform the experimental tasks.

4.2.2 Experimental setup

Individuals were seated on an armless chair located 2 m from the Kinect sensor. The Kinect sensor was mounted on a tripod at a height of 0.85 m from the ground. Prior to collection the Kinect sensor's pitch orientation was programmatically set to 0 degrees using the internal actuators. Roll orientation was leveled using leveling instrumentation equipped on the tripod.

Reaching targets used in the experiment were suspended from an extended arm mounted on a tripod (Figure 4.1). The reaching target was attached to fine gauge wire and was suspended centrally at mid-torso height in front of the patient. Target distance was located at 80% of the arm length of the patient. In the situation where the participant did not move the affected limb to this distance, the maximal voluntary excursion of the affected limb without threatening balance was used. Suspension of the reaching target minimizes the tracking interference between the Kinect sensor and objects in the Kinect scene (Baak, Müller, Bharaj, Seidel, & Theobalt, 2013; Obdrzálek et al., 2012).

4.2.3 Task Conditions

A standard starting position was assumed prior to each trial. This position consisted of the shoulder positioned in 0° flexion and 0° adduction, and the elbow in 90°flexion. Forearm rotation was kept in neutral position, as was the wrist (0° flexion, 0° ulnar deviation). The hand was held in a closed fist during all task conditions (Figure 4.2), this was done to keep the hand position consistent, and reduce hand tracking errors.

Participants were asked to perform two upper limb tasks: (1) a reach-to-touch and (2) an arm circle-drawing task. The reaching task had two variations. (1a) Reach for a centrally located target at a self-selected speed. The target was located at a distance 80% arm length, mid-torso height, and in front of the sternum. (1b) After removing the original target, reach to the original target location as fast as possible. The circle drawing task required participants to draw large circles in the transverse plane. This task had two variations. (2a) Draw a circle in the clockwise direction. (2b) Draw a circle in the counterclockwise direction. For each task, five trials were attempted, some participants performed fewer trials due to fatigue. During both reaching tasks participants were not given instruction regarding the use of compensatory behaviours.

4.2.4 Data Collection

Kinematic data was acquired with a Microsoft Kinect sensor (Redmond WA, USA). Kinect data was collected on an Intel I5-2430 2.4 GHz laptop with 4 GB RAM running Windows 7. A custom C# program utilizing the Microsoft Kinect SDK (v1.5) was used for data acquisition. The sampling frequency of the Kinect was a non-uniform 30 Hz.

4.2.5 Data Processing

Due to the non-uniform sampling rate of the Kinect sensor, acquired data was spline interpolated to a 20 Hz sampling rate. The kinematic data stream for each virtual marker was then low-pass filtered at 5 Hz using a second-order Butterworth filter.

4.2.6 Feature Extraction

A LabVIEW program was used to identify and segment individual trials from the continuous data set. Both tasks utilized the virtual-hand marker to identify the start and end of each trial. Analysis of the reaching task identified the initial position, and the maximum anterior excursion of the virtual-hand marker as the start and end of each trial respectively. Individual trials of the circle drawing task were identified by graphing the AP and ML coordinates of the virtual-hand marker. Each consecutive frame of data was incrementally plotted, and visual inspection of the movement trace determined the initiation and completion of a circle-drawing repetition.

4.2.7 Dependent Measures

Displacement, travel distance, peak velocity and mean velocity of the hand and sternum were calculated for each trial for all tasks. For the circle drawing task, maximum AP and ML range was additionally calculated for both the hand and sternum markers.

4.2.8 Statistical Analysis

All statistical evaluation was performed with SAS software 9.3 (Cary, NC, USA). A two-factor analysis of variance (LIMB: affected/less-affected, TARGET: target/speeded reaching) was used to analyze kinematic metrics for the reaching task. A two-factor analysis of variance (LIMB: affected/less-affected, DIRECTION: internal/external rotation) was also used to analyze the circle drawing task. Spearman's ranked correlations were performed to compare kinematic metrics of the affected limb and participant limb impairment scores (CMSA arm score). Statistical significance was determined with a significance level of $p \leq 0.05$.

4.3 Results

Differences between affected and less-affected limbs

Reaching

Table 4.2 details the reaching metrics of each participant. Two-way ANOVA revealed a statistically significant main effect of LIMB for sternum mean velocity ($F_{(1, 9)} = 5.72$, $p = 0.04$) and sternum peak velocity ($F_{(1, 9)} = 16.68$, $p = 0.002$). Both sternum velocities increased with affected limb use. Additionally, a significant interaction effect of LIMB*TARGET was found for sternum distance ($F_{(1, 9)} = 8.08$, $p = 0.019$), and sternum displacement ($F_{(1, 9)} = 6.37$, $p = 0.033$). Both sternum metrics increased with affected limb use, however during TARGET condition, use of the affected limb showed the most sternum motion.

With regards to hand movement quality metrics, significant main effects of LIMB ($F_{(1, 9)} = 6.22$, $p = 0.034$) and TARGET ($F_{(1, 9)} = 29.42$, $p < 0.001$) were found for mean hand velocity. Mean hand velocity increased with less-affected limb use and during the NO-TARGET condition. Additionally, a significant interaction effect was identified for peak hand velocity ($F_{(1, 9)} = 5.33$, $p = 0.046$). Post-hoc testing of peak hand velocity revealed a significant difference between affected and less-affected limb in the NO-TARGET condition only.

Circle Drawing

Two-way ANOVA revealed a significant main of effect of LIMB for mean hand velocity ($F_{(1, 10)}$ = 7.09, p = 0.0238). The less-affected limb displayed higher mean velocities than the affected limb. Additional metrics were unable to show group significance. Analysis of each participant revealed a significant main effect of LIMB for AP and ML hand displacement for many participants (6/11, and 7/11 respectively). The trend in these participants suggests that AP and ML ranges decreased when using the affected limb. Additionally, a main effect of LIMB was revealed for mean sternum velocity and sternum AP range for three participants. In these cases, sternum AP range increased with affected limb use. Significant differences of sternum metrics were isolated to more impaired persons.

Relationship between clinical limb impairment and kinematic measures

Reaching

Significant correlations between affected limb kinematic metrics and impairment scores were revealed only in the NO TARGET condition. A statistically significant, positive correlation was identified for peak hand velocity (r= 0.83, p=0.003, n=10), and mean hand velocity (r = 0.8, p=0.005, n=10) (Figure 4.4B). With regards to sternum metrics, a significant, negative correlation was found for sternum distance (r= -0.75, p = 0.01, n=10), and sternum displacement (r= -0.72, p = 0.02, n=10) (Figure 4.3B).

Circle Drawing

Statistically significant correlations were revealed between CMSA arm score and many kinematic metrics. Correlations were consistent in both the internal and external rotation conditions. With respect to hand metrics, significant positive correlations were found for AP hand range (r = 0.85, p<0.001, n=11), ML hand range (r =0.82, p=0.002, n=11), and mean hand velocity (r = 0.81, p= 0.002) (Figure 4.5B, 4.6B).

For sternum metrics, a significant negative correlation was found for peak sternum velocity ($r = 0.62$, $p=0.04$, $n=11$) and mean sternum velocity ($r = 0.65$, $p=0.03$, $n=11$) (Figure 4.7).

4.4 Discussion

The purpose of this study was to investigate the clinical feasibility of using the Kinect sensor and its markerless tracking algorithm to detect kinematic differences in stroke survivors.
Results support the hypotheses regarding the Kinect's ability to identify differences between the affected and less affected limb, as well as the ability to identify correlations between kinematic metrics and levels of limb impairment. However, not all metrics were able to identify differences between affected and less-affected limbs.

Affected vs. Less-affected Limb

For the reaching task, inter-limb differences were observed both for sternum and hand metrics across the group. Results were in agreement with findings in reaching literature, which report increased sternum excursion and slower hand kinematics with affected limb use (Cirstea & Levin, 2000; Finley, Combs, Carnahan, Peacock, & Buskirk, 2012; Subramanian, Yamanaka, et al., 2010). The circle-drawing task was less effective in identifying interlimb differences across the group; however, individual analysis did reveal significant interlimb differences for AP and ML hand range in some individuals. Non-significant group findings may be attributed to the variability seen between subjects in AP and ML hand range. Additionally, some of the more impaired participants produced similar magnitudes of hand movement for both the affected and less affected limb in the reaching task. It is possible that some individuals were matching the magnitude of movement between limbs, despite task instructions explicitly asking to create a circle of maximum size.

Sternum metrics in the circle drawing task were hypothesized to behave similarly to sternum metrics during reaching; displaying an interlimb difference for sternum AP and/or ML movement, and decreased sternum movement with less impaired individuals. However, results were inconsistent across the group, as more impaired and less impaired individuals both displayed large sternum movement during the task, suggesting that the use of trunk motion may not be a consistent compensatory strategy with circle drawing.

Correlation with CMSA score

Kinematic metrics and participant CMSA scores showed strong correlations in both the reaching and circle-drawing tasks. Reaching metrics were only statistically significant for the NO TARGET variation of the reach task. During this task, participants exhibited decreased sternum movement, increased hand velocities, while exhibiting no statistically significant change in hand displacement relative to the TARGET condition. When taken together, these findings suggest that the effect of placing emphasis on the speed of movement may increase reaching performance. This finding is consistent with the findings of Massie and Malcolm who demonstrated similar results when stroke survivors were asked to perform a reaching task with their affected limb at a self-selected speed, and as quickly as possible (Massie & Malcolm, 2012). The significant correlations may have been related to the task demands associated with the speeded condition, resulting in participants selecting a motor strategy which was more revealing of upper limb ability. The utilization of trunk musculature to assist in limb transport is often reported with stroke survivors during volitional reaching (Cirstea & Levin, 2000); however the recruitment of the trunk may not be the most optimal strategy for a speeded reach. Thus a more optimal strategy may have consisted of recruiting musculature capable of faster hand transport; utilizing more shoulder flexion and/or elbow extension torque, and would therefore be more revealing of upper limb function.

4.5 Conclusion

Overall, the results of this study suggest a potential for using the Kinect as a clinical assessment tool for the upper limb after stroke. Kinematic differences were found at the group level between affected and less affected limbs. Additionally, strong correlations were found between affected limb kinematic metrics and CMSA arm scores. However, the kinematic variables which identified differences may be dependent on the task, and its specific instructions. One of the challenges going forward with the clinical implementation of the Kinect device will be establishing a protocol of assessment tasks and task instructions which are suitable for the device and which will best elicit a sensitive metric.

4.6 Tables and Figures

Table 4.1. Demographic data and clinical information of participants.

ID	Age	Gender	Affected Limb	Lesion Area	Bryden Score (Handedness)	CMSA Arm-Score	Last completed CMSA Arm-Stage
1	72	F	R	R. Int. Capsule	-10	**3**	(4): Elbow @ 90 sup./pron.
2	63	M	L	R. Pons	10	**3**	(4): Resisted arm ext. rot.
3	42	M	R	L. Globis Pallidus	6	**3**	(4): Elbow@ 90 pron. /sup.
4	63	F	L	R. Prefrontal	3	**3**	(4): Shld flex. to 90
5	54	M	L	R. Hemisphere	10	**3**	(3): All
6	85	M	R	L. Hemisphere	6	**4**	(5): Shld abd. to 90 with pron.
7	64	F	R	L. Parietal and Basal Ganglia	-7	**5**	(6) : Figure-8
8	65	F	R	Int. Capsule, Thalamus	10	**6**	(7): Arm-scissor, resisted ext. rot.
9	64	M	L	R. Frontal lobe	10	**6**	(6): Figure-8, hand from knee-head x5
10	63	M	L	R. Frontal lobe	10	**6**	(6): Raise arm overhead with sup., Hand from knee-to-head x5.
11	64	F	R	L. Thalamus	-1	**7**	(7): All

Table 4.2. Kinematic metrics for each individual for the reaching task.

		Hand Disp (cm)		Stern Disp. (cm)		Hand Peak Vel. (cm/s)		Hand Mean Vel. (cm/s)		Stern Mean Vel. (cm/s)	
ID		**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**
1	No Target	33.7±1.1	**43.0±2.9**	1.2±0.7	**2.4±0.6**	126.0±34.6	**54.2±11.4**	46.9±14.5	**19.8±8.8**	1.7±0.8	1.1±0.2
	Target	37.2±2.1	**42.7±2.8**	2.7±0.4	**5.0±0.6**	96.2±11.4	**61.2±23.4**	35.2±4.7	**17.4±12.0**	4.0±1.4	4.0±1.6
2	No Target	38.4±5.0	31.2±5.4	1.3±1.1	**2.2±1.6**	167.5±25.4	**71.7±11.9**	89.8±22.5	**32.2±3.8**	3.6±1.2	2.5±1.2
	Target	32.6±8.3	36.2±4.9	3.2±0.8	**6.0±0.8**	97.3±50.2	**55.6±13.2**	24.1±4.7	**16.7±4.2**	3.1±0.4	3.2±0.8
3	No Target	37.3±10.4	32.4±2.9	2.6±0.5	**5.0±1.3**	142.0±12.7	101.1±19.2	71.9±12.1	**51.2±11.9**	4.5±0.6	**7.6±2.3**
	Target	27.0±2.1	42.2±5.2	0.6±0.4	**15.5±2.6**	103.2±21.5	103.8±21.8	48.1±6.3	**43.4±5.1**	1.0±0.6	**13.3±1.8**
4	No Target	39.0±10.6	44.6±5.7	2.1±1.6	2.5±0.7	171.1±43.2	127.9±26.7	84.7±14.2	56.1±6.3	4.0±2.8	4.3±1.3
	Target	36.3±2.2	36.9±4.5	3.7±0.6	2.0±0.9	91.9±7.3	121.2±14.9	44.5±8.0	64.8±15.6	4.4±0.8	3.5±1.3
5	No Target	38.8±2.5	**25.2±2.7**	1.5±0.3	**2.9±1.4**	217.3±24.2	**114.9±23.0**	129.0±16.3	**65.4±6.5**	4.0±1.2	**7.9±4.6**
	Target	46.5±3.2	**25.6±4.0**	0.6±0.3	**4.8±1.7**	168.6±45.0	**73.5±11.1**	98.4±10.8	**37.9±5.4**	1.2±0.6	**5.9±1.4**
6	No Target	41.6±4.1	38.2±3.0	1.4±0.4	**1.5±0.3**	215.7±43.9	182.4±33.2	113.0±20.2	108.2±18.3	3.9±1.6	**5.6±2.0**
	Target	47.0±1.4	38.7±6.8	2.3±0.3	**4.7±0.7**	80.1±12.6	74.0±12.3	28.5±4.4	32.9±6.6	1.5±0.3	**4.0±1.3**
7	No Target	39.6±4.9	38.5±4.5	1.2±0.6	**2.7±1.6**	153.2±8.4	177.3±31.7	83.4±10.8	76.7±11.3	2.7±1.0	**6.8±2.6**
	Target	39.8±1.7	44.2±4.2	1.4±0.4	**6.4±0.8**	79.4±7.4	66.5±23.3	39.3±3.1	33.1±5.0	2.0±0.2	**4.6±0.4**
8	No Target	36.4±3.1	33.7±6.4	2.0±1.2	**0.8±0.8**	183.5±15.0	178.8±8.6	93.7±21.8	89.8±7.8	4.9±3.2	1.9±1.2
	Target	38.8±2.6	38.3±2.5	5.1±1.0	**10.5±1.4**	103.0±14.6	90.7±16.9	56.9±5.4	41.2±3.9	7.2±1.1	11.4±1.8
9	No Target	34.3±4.4	25.0±15.4	0.9±0.4	1.1±0.5	193.1±22.4	173.9±55.6	104.2±15.4	91.4±24.2	2.6±1.0	2.8±1.1
	Target	33.1±1.7	39.5±2.9	1.3±0.3	2.2±0.7**	88.4±4.6	132.4±28.3	55.4±5.0**	69.2±12.6**	2.3±0.5	3.0±0.8
11	No Target	31.8±6.2	**40.7±5.1**	0.6±0.3	**1.1±0.8**	206.2±28.0	203.7±19.7	101.4±21.5	103.7±12.1	1.5±0.5	**2.8±1.8**
	Target	42.4±2.3	**46.0±6.0**	1.0±0.5	**4.8±1.0**	107.8±8.9	104.9±6.4	57.8±10.0	44.3±5.1	1.4±0.9	**5.8±1.2**

Bolded values denote a significant main effect between the affected and less affected limb. P<0.005

Table 4.3. Kinematic metrics for each individual for the circle-drawing task.

		Hand AP Range (cm)		Hand ML Range (cm)		Stern. AP Range (cm)		Stern. ML Range (cm)		Hand Mean Vel. (cm/s)		Stern. Mean Vel. (cm/s)	
ID		**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**	**Less Aff.**	**Aff.**
1	Ext. Rot	30.6±6.6	**26.1±1.8**	47.2±5.8	**34.3±2.8**	0.6±0.2	0.7±0.2	0.5±0.3	0.6±0.3	55.1±4.3	**22.9±4.5**	0.8±0.2	0.5±0.1
	Int. Rot	36.6±4.6	**22.8±2.0**	48.1±5.3	**30.5±4.0**	1.6±0.8	0.8±0.3	1.1±0.7	1.2±0.7	58.4±7.4	**20.5±1.7**	1.7±0.7	0.7±0.3
2	Ext. Rot	37.9±1.5	39.8±2.3	54.1±1.9	**38.4±2.7**	4.5±0.8	3.0±2.0	5.6±0.5	2.7±1.3	89.9±13.9	**29.2±3.7**	12.8±0.8	**2.6±0.7**
	Int. Rot	38.3±6.6	32.7±3.7	51.0±6.9	**35.7±1.4**	6.4±1.4	4.8±2.1	6.4±1.5	4.3±2.5	80.7±4.9	**33.6±5.4**	13.0±2.6	**3.0±1.0**
3	Ext. Rot	47.9±4.1	**33.6±4.5**	52.0±2.0	**49.6±5.3**	3.8±1.3	**6.1±1.6**	3.4±1.2	**5.6±1.8**	131.8±7.0	**79.8±4.5**	10.6±4.0	**12.1±3.1**
	Int. Rot	50.0±11.1	**33.5±4.7**	55.8±10.8	**45.1±5.7**	3.2±2.0	**11.0±4.2**	3.6±1.7	**10.3±4.1**	122.1±6.0	**77.3±7.1**	9.5±3.5	**19.5±6.3**
4	Ext. Rot	43.2±4.9	36.2±5.1	45.4±2.6	48.9±7.6	3.9±0.3	**4.8±1.6**	3.9±0.4	4.1±2.1	118.7±10.0	**94.2±7.5**	9.1±2.2	8.1±1.9
	Int. Rot	40.1±4.3	41.1±2.9	49.4±4.3	47.8±3.5	2.3±1.4	**4.8±1.5**	2.2±0.9	2.9±0.5	105.2±7.1	**93.7±6.4**	4.4±1.6	9.9±3.1
5	Ext. Rot	49.0±6.9	**13.0±1.3**	50.1±3.4	**16.5±1.2**	2.4±0.4	2.0±0.4	2.3±0.4	1.5±0.5	123.3±11.4	**32.3±3.9**	4.2±1.1	**3.2±0.6**
	Int. Rot	41.3±3.6	**13.0±2.7**	44.2±2.8	**12.8±2.0**	3.2±1.7	2.6±0.6	2.0±1.0	2.2±0.2	100.1±7.5	**27.6±7.0**	5.9±1.9	**3.5±1.1**
6	Ext. Rot	30.6±7.0	45.4±4.2	38.3±7.7	47.2±2.8	1.3±0.4	3.6±0.2	1.3±0.4	3.2±0.8	98.6±14.2	116.7±6.8	2.8±1.3	10.3±1.7
	Int. Rot	42.7±7.3	37.1±8.9	39.9±5.7	44.2±3.6	3.4±0.5	2.5±0.5	2.9±0.3	2.2±0.3	116.1±18.4	97.9±11.4	9.0±2.2	6.5±0.8
7	Ext. Rot	65.7±9.1	**58.7±8.3**	69.0±2.6	66.5±5.2	10.9±2.1	14.0±1.2	7.4±2.2	12.0±2.1	102.2±4.9	91.8±11.4	13.2±1.9	17.3±1.6
	Int. Rot	61.9±4.2	**47.7±8.3**	60.2±7.7	58.8±7.7	3.3±1.6	4.1±2.5	2.2±0.9	3.9±2.7	87.5±9.1	76.8±10.8	4.1±2.4	4.4±2.1
8	Ext. Rot	61.1±5.2	**53.9±7.3**	62.8±4.2	**68.9±6.9**	14.9±2.3	15.4±3.1	9.1±3.7	8.0±4.9	137.7±16.8	**111.2±11.9**	27.5±4.0	21.7±2.8
	Int. Rot	70.8±2.6	**47.1±9.1**	76.5±6.5	**53.9±4.2**	19.9±1.8	23.8±2.3	10.0±3.4	9.7±6.5	142.7±6.3	**85.5±5.3**	27.6±3.0	35.0±3.4
9	Ext. Rot	52.3±4.4	46.9±6.9	60.2±3.9	**51.3±4.6**	3.7±1.0	3.3±2.4	2.5±1.2	2.8±2.6	112.1±3.5	133.8±15.7*	5.4±0.6	5.5±2.7
	Int. Rot	52.7±1.0	44.3±5.2	62.6±1.4	**51.5±3.7**	6.1±0.8	4.4±1.5	4.6±1.6	3.6±1.2	120.8±12.8	123.4±9.7	11.0±3.5	7.4±2.4
10	Ext. Rot	50.8±4.5	**61.4±4.1**	64.9±3.6	**81.5±4.7**	6.8±1.5	6.4±1.3	5.6±0.5	5.5±1.1	108.5±7.3	129.2±8.9	12.0±2.3	13.7±4.3
	Int. Rot	46.1±3.8	**64.4±2.0**	66.2±3.9	**78.8±9.2**	6.4±0.9	11.1±1.6	5.0±1.2	10.8±4.7	104.7±31.0	110.3±5.7	12.3±3.2	24.5±7.8
11	Ext. Rot	50.3±5.1	48.7±2.3	55.9±3.0	49.1±2.5	4.1±1.0	5.3±2.0	2.2±0.7	**5.6±2.5**	128.1±8.9	111.8±13.0	7.4±2.4	**14.0±4.5**
	Int. Rot	55.7±7.8	48.4±5.6	54.6±10.3	60.8±3.7	5.7±1.6	8.3±1.0	3.3±0.8	**7.2±1.3**	123.8±10.5	133.4±21.8	10.1±1.7	**20.7±2.3**

Bolded values denotes a significant main effect between the affected and less affected limb $p<0.005$

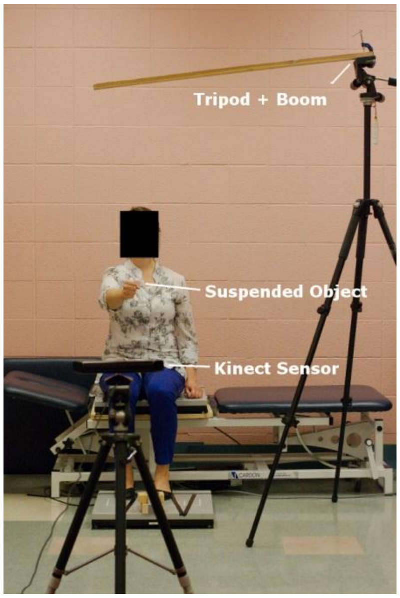
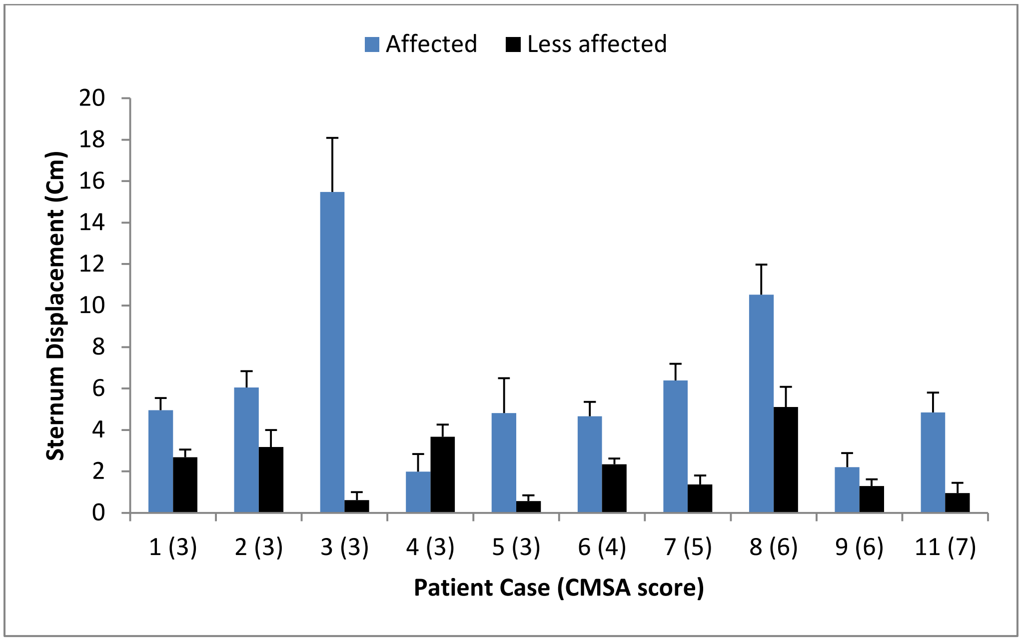


Figure 4.1. Experimental setup for study two. The Kinect sensor is positioned to project on the participant frontally. The tripod and boom setup is used to suspend an object via fine-gauge wire to ensure that there are no external objects occluding the participant from the Kinect sensor.

Figure 4.2. Sagittal view of a participant in the standard starting position. Participants will be asked to start with their shoulder in zero degree flexion and abduction, and the elbow in 90 degree flexion. The hand will be kept in a fist orientation at all times to minimize tracking errors from the Kinect.

A



B

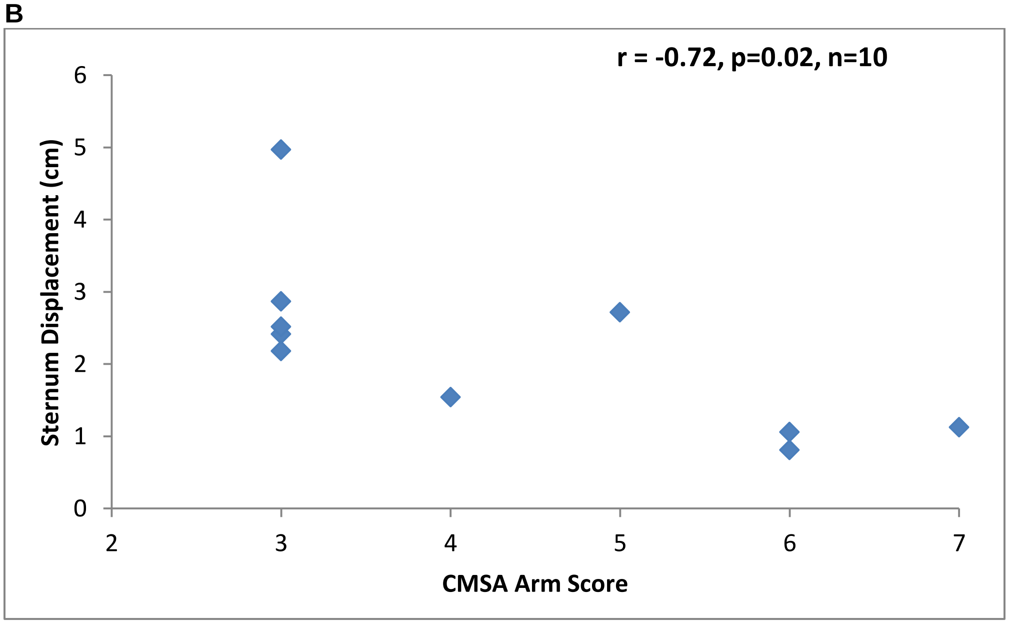
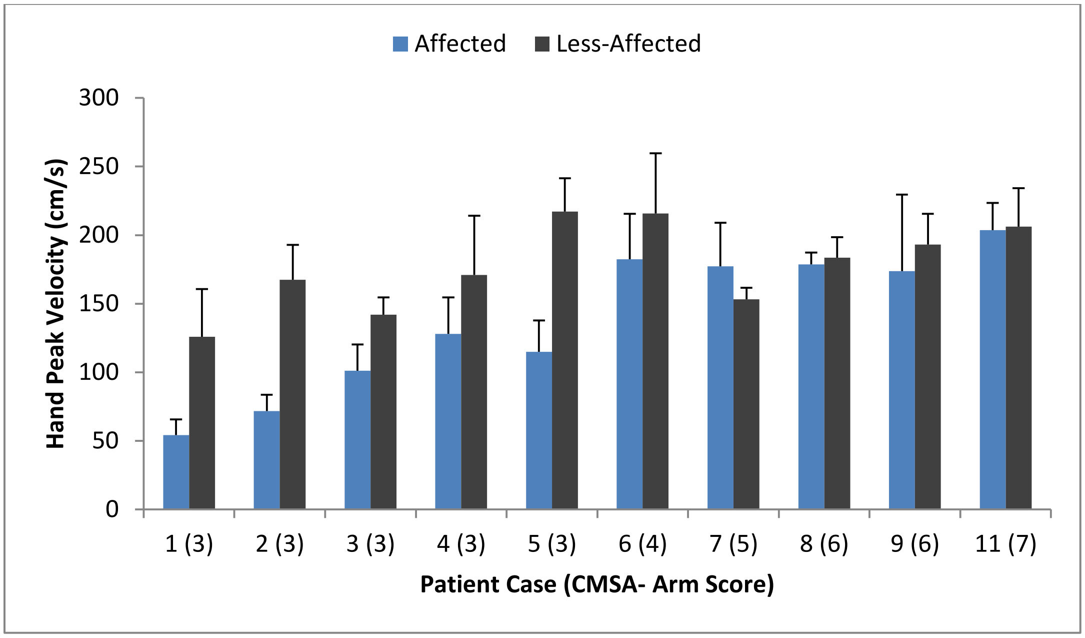


Figure 4.3. Sternum displacement during reaching. Panel A. Mean sternum displacement values for each participant during the TARGET reach condition, each error bar represents 1 standard deviation. **Panel B.** Spearman's ranked correlations between sternum displacement during the NO TARGET condition and patient CMSA arm score.

A



B

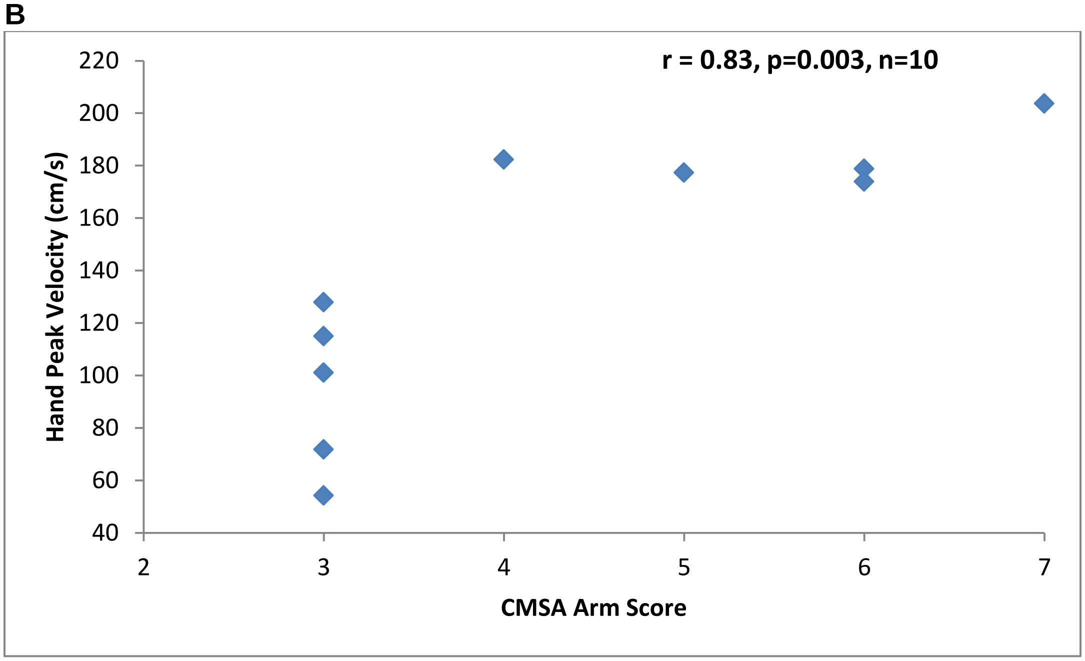
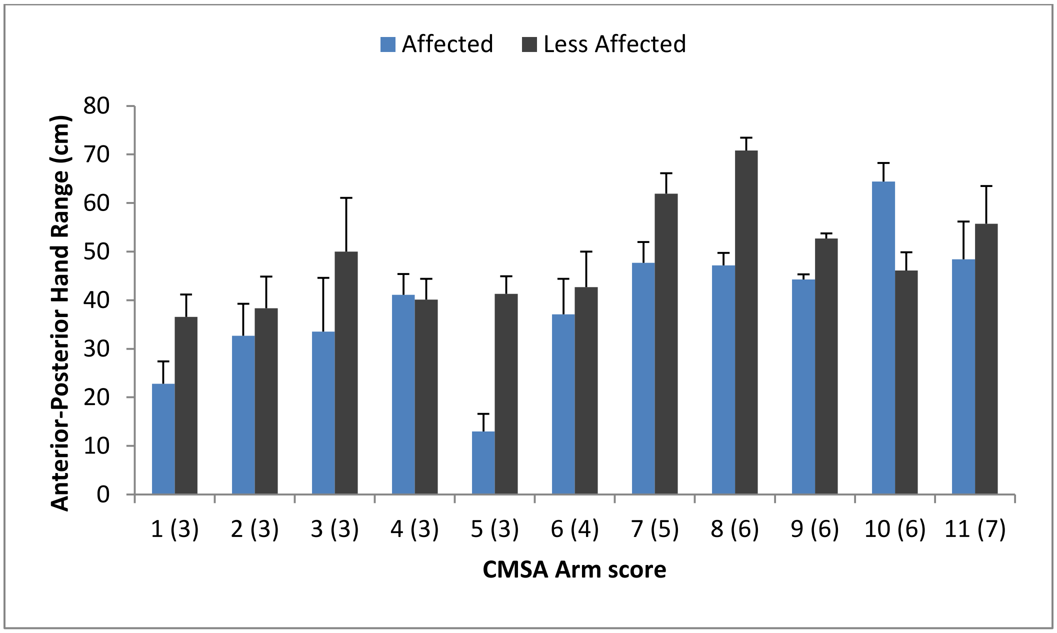


Figure 4.4. Peak hand velocity during speeded reaching. Panel A. Peak hand velocity values for both affected and less affected limbs across all participants. Error bars represent 1 standard deviation. Patient cases are ordered as most to least impaired. **Panel B.** Spearman's ranked correlation values between peak hand velocity and patient CMSA score.

A



B

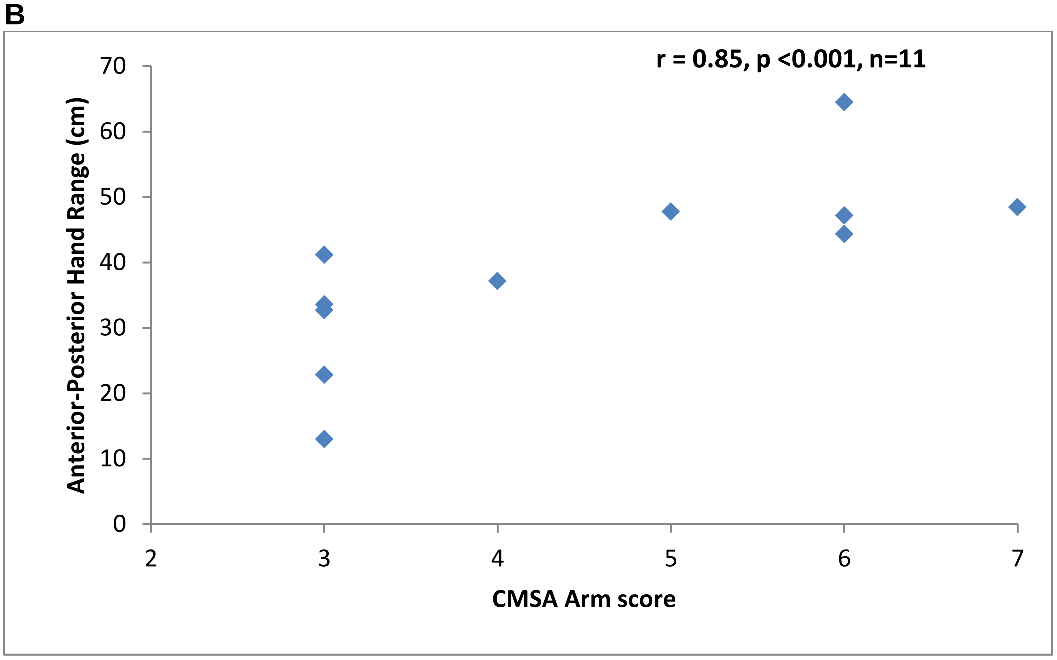
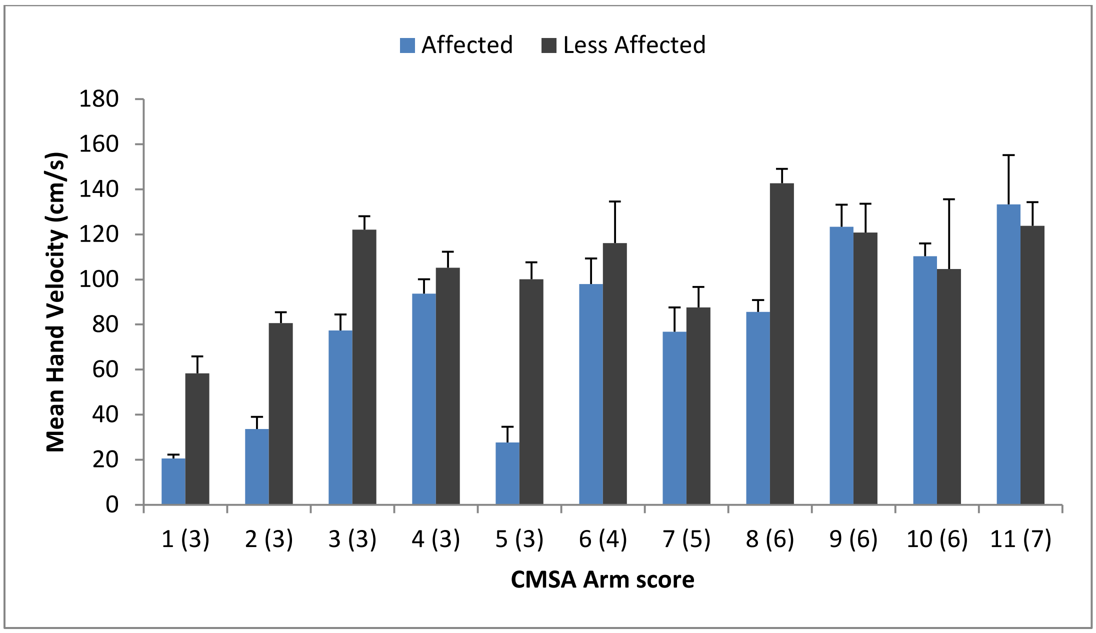


Figure 4.5. AP Hand excursion during internal rotation circle drawing. Panel A. AP hand excursion across all participants, error bars represent 1 standard deviation. **Panel B.** Spearman's ranked correlation values are between affected limb AP hand excursion and patient CMSA score.

A



B

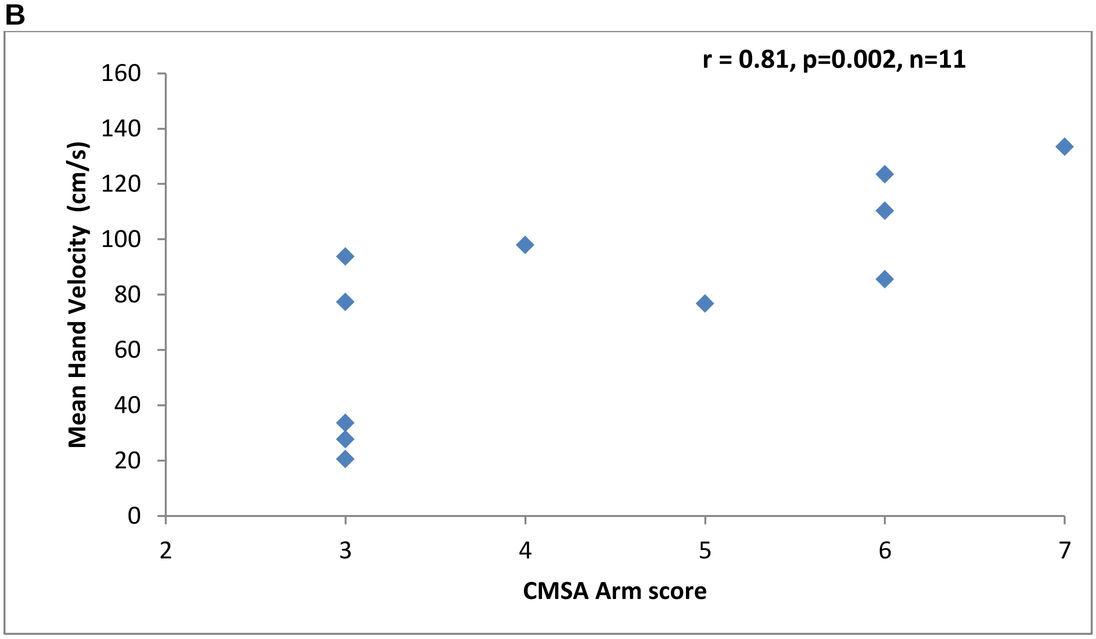


Figure 4.6. Mean Hand velocity during internal rotation circle drawing. Panel A. Mean hand velocity across all participants. Error bars represent 1 standard deviation. **Panel B.** Spearman's ranked correlation values are between Mean hand velocity and patient CMSA score.

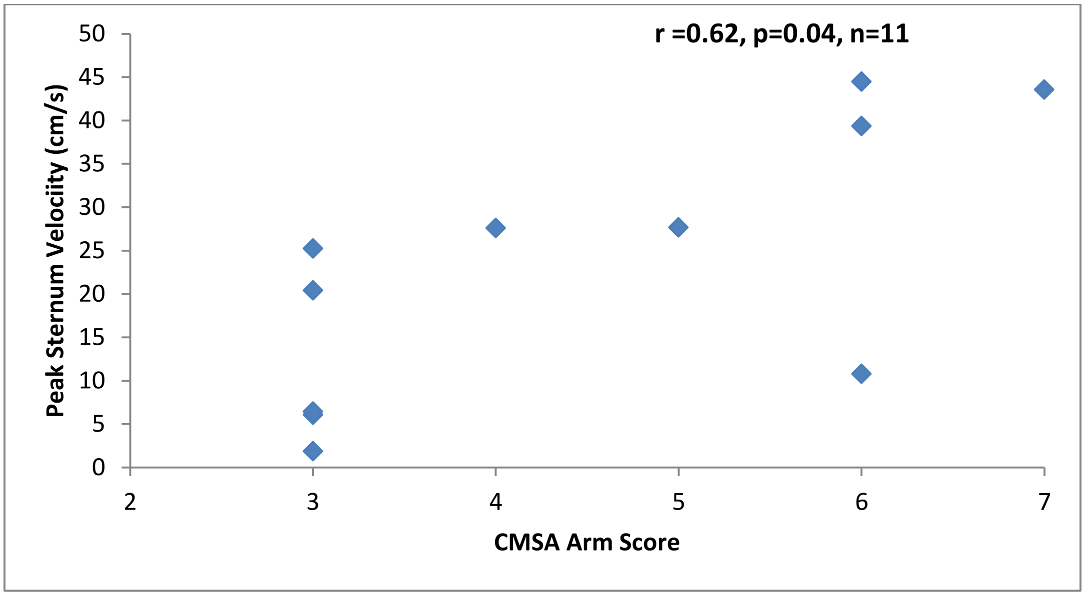


Figure 4.7. Peak sternum velocity during internal rotation circle drawing. Spearman's ranked correlation values are between peak velocity and patient CMSA score.

5.0 General Discussion

The purpose of this thesis was to investigate the potential of using new technology for the assessment of upper limb recovery after stroke. This project specifically focused on using the Microsoft Kinect sensor as a potential clinical tool. The work presented in this thesis shows support for the assessment of the upper limb in stroke survivors. The advantage offered by this system is the unique ability for markerless kinematic data capture. The markerless nature of the system allows for rapid data collection sessions, with no need for additional calibration steps. This is ideal in a clinical setting where time is a limited commodity. There are however, limitations to this system that need to be considered prior to clinical implementation. These limitations and are addressed below.

Influence of Objects

Many different task conditions may be of interest to researchers and clinicians, particularly those involving the manipulation of external objects, as they are often used in functional evaluations (i.e. Wolf motor function test). Previous research has indicated that the presence of external objects and changes in hand configuration (i.e. opening and closing the hand) can negatively affect the accuracy of the kinematic output (Tran and McIlroy 2014). While the newest iteration of this technology (Kinect ONE) is equipped with a higher resolution sensor and has demonstrated the ability to detect changes in hand configuration, the accuracy of this detection has yet to be determined. Furthermore, it is hypothesized that the problem of interfering effects of external objects on hand tracking performance has not been resolved. In addition to direct manipulation of objects by participants, objects which remain in the foreground of the Kinect scene can cause miss-tracking and negatively affect data obtained from the Kinect. Researchers have reported cases of armrests and legs of chairs to cause miss-tracking for upper and lower limb markers in seated participants (Baak et al. 2012).

Therefore, for optimal data collection, it is recommended that the area in which Kinect data is being used is uncluttered. If using a chair, it recommended that the back rest and armrests should not be present

Influence of Lighting

Another point of consideration is sensor exposure to sunlight. Because the Kinect system is an infrared based device, exposure to sunlight can over expose the infrared sensors, impairing the system's ability to detect the projected infrared scatter pattern, and thus its ability to calculate depth. It is recommended that the system be used in a uniformly lit room, away from direct exposure to sunlight.

Day-to Day Testing Consistency

In study 1 we saw variations in performance metrics between subjects, and attributed variations in performance to differences in body anthropometrics and the subsequent Kinect processing. There remain concerns that this variation may also exist within a person on separate collection dates. Although the body anthropometrics of an individual would not change, many of the estimation processes associated with modelling which occurs with markerless tracking are unknown, and may be a source of variation on a day-to-day basis. Another human factor which may affect kinematic performance is clothing. Publications detailing the processes involved with the markerless acquisition of kinematic data suggest that clothing could potentially interfere with the reliability of measures. Shotton et al. describes the performance of the markerless tracking algorithm as being accurate across a variety of individuals, wearing a variety of clothing (Shotton et al. 2012). Accuracy in this context refers to the ability of the algorithm to correctly classify depth pixels as part of the appropriate body segment. It does not refer to the precision of kinematic measurements obtained after processing the classified depth pixels.

Thus we must consider the potential effect of clothing: the system will fit a skeletal model to a silhouette regardless of the type of clothing an individual is wearing. However, clothing can/will alter a silhouette of and individual viewed from the Kinect and thus will affect the coordinates of the calculated joint centers. Therefore, it is recommended that clothing is kept to a minimum, or is form fitting in order to keep the silhouette of an individual consistent with the individual.

*Signal Noise Consideration*s

In using the Kinect system, there are instances when the kinematic data has a large amount of noise. In study 1, this noise was seen particularly in the trajectory profiles of wrist, and elbow virtual markers. Because the kinematic data from the Kinect is derived from singular depth images, it may be susceptible to error due to occlusion. Taylor et al. 2012 described the Kinect's pose-estimation algorithm as a hybrid generative and discriminative approach, allowing the system to calculate coordinates for occluded limb segments. We hypothesized that when limbs were occluded and coordinates were obtained using primarily a generative approach that there was a considerable amount of noise. As a result, our joint locations of interest were primarily of the hand and sternum, which were in full view of the sensor. However, there were still instances during complex task conditions, (such as the arm-circle drawing task), when the movement of limb(s) occluded other markers (i.e. sternum marker), which produced noise in the signal of the occluded marker. This particular effect may be difficult to completely avoid, and careful examination of the task for moments of occlusion may be beneficial.

Other Determinants of Variability Between, and Within Participants

Variability of kinematic metrics was larger in the more impaired individuals of the stroke group. Additional factors which were not assessed in this thesis including state of arousal, fatigue, and motivation may have been variable across participants and may have influenced group variability. These factors are important to consider as they pertain the reliability of testing metrics.

With regards to within-subject variability, additional factors such as the magnitude of inherent noise associated with the Kinect system need to be investigated. Though the presence of system noise was acknowledged, the magnitude of this noise is important to understand to further gauge the potential sensitivity of the Kinect system. Another factor which may have contributed to within-participant variability may have been the presence of potential practice effects which may have occurred during the assessment. Practice effects may be mitigated by allowing practice trials prior to assessment, followed by a resting period to mitigate fatigue.

Potential Improvement:

A potential technique for improving data collection with the Kinect is the use of multiple sensors. This technique would alleviate some of the issues of occlusion which is hypothesized to be a source of variability in the kinematic data. One challenge to this technique is circumventing the interference effects which one sensor has on another. The Kinect sensor utilizes a projected structured light array to calculate depth, and by introducing another sensor to a same scene we also introduce another projected light pattern. The presence of two light patterns interferes with the system's ability to calculate depth and therefore would create areas of missing depth values (Butler, Izadi, & Hilliges, 2012; Maimone & Fuchs, 2012) .

However, by introducing constant motion to one sensor (i.e. 15 Hz oscillation), a motion-blur can be induced onto the moving light pattern relative to the non-moving sensor (Butler et al., 2012; Maimone & Fuchs, 2012). This limits the interfering effect and could be a potential solution for using multiple sensors simultaneously in a common scene. The introduction of a constant oscillation would also require some additional post-processing steps to remove the motion signal in the data stream. Additionally , if this were used as a potential solution, additional action would be required to train an appropriate decision process to analyze depth images from multiple sensors, as previous data used to train the current decision forest tree was done using depth images from a single sensor (Shotton et al. 2012).

Application and future directions

The potential applications of this technology may also extend beyond assessments. Previous gaming technologies (Nintendo Wii) have been used in stroke rehabilitation and have been shown to be effective (Saposnik et al., 2010). Similarly, the Kinect may also be used to augment current rehabilitation and therapy. The advantage of using a system such as the Kinect is that we are able to capture significantly more movement information, and are thus able to better monitor and provide feedback during rehabilitation or training sessions to the participant. The use of feedback may augment the retraining of motor patterns and simultaneously quantify the quality and volume of training. One specific example of this application would be the continuous monitoring of an individual's trunk displacement during an upper limb training task; if trunk displacement exceeds a certain threshold, then we can then present to the individual a signal (auditory/visual feedback) indicating excessive trunk motion. It has been shown that auditory feedback can be used to modify motor patterns (Oscari, Secoli, Avanzini, Rosati, & Reinkensmeyer, 2012) and may be more effective at retraining compensations than a physical restraint system (Subramanian, Massie, Malcolm, & Levin, 2010).

One limitation of this type of feedback provision has been in the lack of feasible equipment necessary to facilitate the training; both in a clinical setting and especially in a home setting. Technologies like the Kinect provide the opportunity to overcome such barriers due to the small size and low cost of the device. In addition to augmented therapy and rehabilitation, such technologies may also facilitate remote assessments and therapy; as data recorded can easily be transferred via remote communication.

6.0 Conclusion

The Kinect is an affordable system which allows markerless kinematic data acquisition. Results from this thesis suggest a potential for the use of the system to assess some aspects of upper limb kinematics. Under ideal conditions the system was shown to measure kinematic measurements of the hand and trunk, and was able to successfully capture and identify kinematic differences in a clinical stroke population. However, there are many factors that affect kinematic data quality as well as limitations to the system. These factors and limitations need to be considered prior to clinical implementation.

References

Baak, A., Müller, M., Bharaj, G., Seidel, H.-P., & Theobalt, C. (2013). A data-driven approach for real-time full body pose reconstruction from a depth camera. In *Consumer Depth Cameras for Computer Vision* (pp. 71–98).

Baker, K., Cano, S. J. C., & Playford, E. D. (2011). Outcome measurement in stroke: a scale selection strategy. *Stroke*, *42*(6), 1787–94.

Bohannon, R., Andrews, A., & Smith, M. (1988). Rehabilitation goals of patients with hemiplegia. *International Journal of Rehabilitation Research*, *11*(2), 181–184.

Brunnstrom, S. (1966). Motor testing procedures in hemiplegia: based on sequential recovery stages. *Physical Therapy*.

Butler, D., Izadi, S., & Hilliges, O. (2012). Shake'n'sense: reducing interference for overlapping structured light depth cameras. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1933–1936.

Cirstea, M., & Levin, M. (2000). Compensatory strategies for reaching in stroke. *Brain*, *123*, 940–53.

Cirstea, M., Mitnitski, A., Feldman, A., & Levin, M. (2003). Interjoint coordination dynamics during reaching in stroke. *Experimental Brain Research*, *151*(3), 289–300.

Clark, R. A., Pua, Y.-H., Fortin, K., Ritchie, C., Webster, K. E., Denehy, L., & Bryant, A. L. (2012). Validity of the Microsoft Kinect for assessment of postural control. *Gait & Posture*, *36*(3), 372–7.

Dewald, J. P. A., Pope, P. S., Given, J. D., Buchanan, T. S., & Rymer, W. Z. (1995). Abnormal muscle coactivation patterns during isometric torque generation at the elbow and shoulder in hemiparetic subjects. *Brain*, *118*, 495–510.

Dutta, T. (2012). Evaluation of the Kinect™ sensor for 3-D kinematic measurement in the workplace. *Applied Ergonomics*, *43*(4), 645–9.

Faugeras, O. (1993). Stereo Vision. In *Three-Dimensional Computer Vision: A Geometric Viewpoint* (pp. 165–240).

Finley, M., Combs, S., Carnahan, K., Peacock, S., & Buskirk, A. Van. (2012). Comparison of "Less Affected Limb" Reaching Kinematics in Individuals with Chronic Stroke and Healthy Age-Matched Controls. *Physical & Occupational Therapy in Geriatrics*, *30*(3), 245–259.

Galna, B., Barry, G., Jackson, D., Mhiripiri, D., Olivier, P., & Rochester, L. (2014). Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease. *Gait & Posture*, *39*(4), 1062–8.

Gladstone, D. J., Danells, C. J., & Black, S. E. (2002). The Fugl-Meyer Assessment of Motor Recovery after Stroke: A Critical Review of Its Measurement Properties. *Neurorehabilitation and Neural Repair*, *16*(3), 232–240.

Gowland, C. (1990). Staging motor impairment after stroke. *Stroke*, *21*(9 Suppl), 19–21.

Gowland, C., Stratford, P., Ward, M., Moreland, J., Torresin, W., Van Hullenaar, S., Plews, N. (1993). Measuring physical impairment and disability with the Chedoke-McMaster Stroke Assessment. *Stroke*, *24*(1), 58–63.

Greaves, J. O. (1995). Instrumentation in Video-Based Three-Dimensional Systems. In P. Allard, I. A. Stokes, & J.-P. Blanchi (Eds.), *Three-Dimensional Analysis of Human Movement* (pp. 41–56).

Hakim, A., Silver, F., & Hodgson, C. (1998). Organized stroke care: A new era in stroke prevention and treatment. *CMAJ*, *159*(6 Suppl).

Heinemann, A., Linacre, J., Wright, B. D., Hamilton, B. B., & Granger, C. (1993). Relationships between impairment and physical disability as measured by the functional independence measure. *Archives of Physical Medicine and Rehabilitation*, *74*(6), 566–573.

Kamper, D. G., McKenna-Cole, A. N., Kahn, L. E., & Reinkensmeyer, D. J. (2002). Alterations in reaching after stroke and their relation to movement direction and impairment severity. *Archives of Physical Medicine and Rehabilitation*, *83*(5), 702–707.

Kurillo, G., Han, J., Obdržálek, Š., Yan, P., Abresch, R. T., Nicorici, A., & Bajcsy, R. (2012). Upper Extremity Reachable Workspace Evaluation with Kinect. In *Medicine meets Virtual Reality 20* (pp. 247–253).

Lacquaniti, F., & Soechting, J. (1982). COORDINATION OF ARM AND WRIST MOTION DURING A REACHING TASK. *The Journal of Neuroscience*, *2*(1982), 399–408.

Laurent, K., De Sèze, M.-P., Delleci, C., Koleck, M., Dehail, P., Orgogozo, J.-M., & Mazaux, J.-M. (2011). Assessment of quality of life in stroke patients with hemiplegia. *Annals of Physical and Rehabilitation Medicine*, *54*(6), 376–90.

Levin, M. (1996). Interjoint coordination during pointing movements is disrupted in spastic hemiparesis. *Brain*, *119*, 281–293.

Levin, M., Kleim, J., & Wolf, S. (2009). What do motor “recovery” and “compensation” mean in patients following stroke? *Neurorehabilitation and Neural Repair*, *23*(4), 313–319.

Levin, M., Michaelsen, S. M., Cirstea, C. M., & Roby-Brami, A. (2002). Use of the trunk for reaching targets placed within and beyond the reach in adult hemiparesis. *Experimental Brain Research*, *143*(2), 171–80.

Likhi, M., Jidesh, V., Kanagaraj, R., & George, J. (2013). Does trunk, arm, or leg control correlate best with overall function in stroke subjects? *Topics in Stroke Rehbilitation*, *20*(1), 62–67.

Lowes, L., Alfano, L., Yetter, B. A., Worthen-Chaudhan, L., Hinchman, W., Savage, J., Mendell, J. R. (2013). Proof of Concept of the Ability of the Kinect to Quantify Upper Extremity Function in Dystrophinopathy. *PLoS Currtents*, *4*(Muscular Dystrophy), 1–13.

Maimone, A., & Fuchs, H. (2012). Reducing interference between multiple structured light depth sensors using motion. *2012 IEEE Virtual Reality (VR)*, (May), 51–54.

Mark, L. S., Nemeth, K., Gardner, D., Dainoff, M. J., Paasche, J., Duffy, M., & Grandt, K. (1997). Postural dynamics and the preferred critical boundary for visually guided reaching. *Journal of Experimental Psychology. Human Perception and Performance*, *23*(5), 1365–79.

Massie, C. L., & Malcolm, M. P. (2012). Instructions emphasizing speed improves hemiparetic arm kinematics during reaching in stroke. *NeuroRehabilitation*, *30*(4), 341–50.

Michaelsen, S. M., Luta, A., Roby-Brami, A., & Levin, M. F. (2001). Effect of Trunk Restraint on the Recovery of Reaching Movements in Hemiparetic Patients. *Stroke*, *32*(8), 1875–1883.

Morasso, P. (1981). Spatial control of arm movements. *Experimental Brain Research*, *42*(2), 223–227.

Nakayama, H., Jorgensen, H., Raaschou, H., & Olsen, T. (1994). Recovery of upper extremity function in stroke patients: the Copenhagen Stroke Study. *Archives of Physical Medicine and Rehabilitation*, *75*(4), 394–398.

Nijland, R., van Wegen, E., Verbunt, J., van Wijk, R., van Kordelaar, J., & Kwakkel, G. (2010). A comparison of two validated tests for upper limb function after stroke: The Wolf Motor Function Test and the Action Research Arm Test. *Journal of Rehabilitation Medicine*, *42*(7), 694–6.

O'Dwyer, N. J., Ada, L., & Neilson, P. D. (1996). Spasticity and muscle contracture following stroke. *Brain : A Journal of Neurology*, *119*((Pt 5)), 1737–49.

Obdrzálek, S., Kurillo, G., Ofli, F., Bajcsy, R., Seto, E., Jimison, H., & Pavel, M. (2012). Accuracy and robustness of Kinect pose estimation in the context of coaching of elderly population. *IEEE Engineering in Medicine and Biology Society. Conference*, *2012*, 1188–93.

Ones, K., Yilmaz, E., Cetinkaya, B., & Caglar, N. (2005). Quality of life for patients poststroke and the factors affecting it. *Journal of Stroke and Cerebrovascular Diseases*, *14*(6), 261–6.

Oscari, F., Secoli, R., Avanzini, F., Rosati, G., & Reinkensmeyer, D. J. (2012). Substituting auditory for visual feedback to adapt to altered dynamic and kinematic environments during reaching. *Experimental Brain Research.*, *221*(1), 33–41.

Ottenbacher, K., Hsu, Y., Granger, C., & Fiedler, R. C. (1996). The reliability of the functional independence measure: a quantitative review. *Archives of Physical Medicine and Rehabilitation*, *77*(December), 1226–1232.

Pedotti, A., & Ferrigno, G. (1995). Optoelectronic-Based Systems. In P. Allard, I. A. Stokes, & J.-P. Blanchi (Eds.), *Three-Dimensional Analysis of Human Movement* (pp. 41–56).

Public Health Agency of Canada. (2009). Tracking Heart Disease and Stroke in Canada - Stroke Highlights 2009.

Public Health Agency of Canada. (2011). Tracking Heart Disease and Stroke in Canada - Stroke Highlights 2011.

Roby-Brami, A., Feydy, A., Combeaud, M., Biryukova, E. V, Bussel, B., & Levin, M. F. (2003). Motor compensation and recovery for reaching in stroke patients. *Acta Neurologica Scandinavica*, *107*(23), 369–81.

Roby-Brami, A., Fuchs, S., Mokhtari, M., & Bussel, B. (1997). Reaching and grasping strategies in hemiparetic patients. *Motor Control*, *1*(2), 72–91.

Saposnik, G., Teasell, R., Mamdani, M., Hall, J., McIlroy, W., Cheung, D., … Bayley, M. (2010). Effectiveness of virtual reality using Wii gaming technology in stroke rehabilitation: a pilot randomized clinical trial and proof of principle. *Stroke; a Journal of Cerebral Circulation*, *41*(7), 1477–84.

Shotton, J., Sharp, T., Kipman, A., Fitzgibbon, A., Finocchio, M., Blake, A., … Moore, R. (2013). Real-time human pose recognition in parts from single depth images. *Communications of the ACM*, *56*(3), 116–124.

Subramanian, S. K., Massie, C. L., Malcolm, M. P., & Levin, M. F. (2010). Does provision of extrinsic feedback result in improved motor learning in the upper limb poststroke? A systematic review of the evidence. *Neurorehabilitation and Neural Repair*, *24*(2), 113–24.

Subramanian, S. K., Yamanaka, J., Chilingaryan, G., & Levin, M. F. (2010). Validity of movement pattern kinematics as measures of arm motor impairment poststroke. *Stroke*, *41*(10), 2303–8.

Taylor, J., Shotton, J., Sharp, T., & Fitzgibbon, A. (2012). The Vitruvian Manifold : Inferring Dense Correspondences for One-Shot Human Pose Estimation Optimization of Model Parameters. *CVPR 2012 Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition*, 103–110.

Tran, J., McIlroy, W.E. (2013). Evaluation of the Kinect for Measurement of Upper Limb Movement. Unpublished manuscript. University of Waterloo, Waterloo, ON.

Twitchell, T. E. (1951). The restoration of motor function following hemiplegia in man. *Brain*, *74*(4), 443–80.

Wade, D. T., Langton-Hewer, R., Wood, V. A., Skilbeck, C. E., & Ismail, H. M. (1983). The hemiplegic arm after stroke: measurement and recovery. *Journal of Neurology, Neurosurgery, and Psychiatry*, *46*(6), 521–4.

Wolf, S., Catlin, P., Ellis, M., Archer, A., Morgan, B., & Piacentino, A. (2001). Assessing Wolf Motor Function Test as Outcome Measure for Research in Patients After Stroke. *Stroke*, *32*(7), 1635–1639.