EFFECTS OF THE APPLICATION OF MARKERLESS MOTION CAPTURE (MMC) TECHNOLOGY FOR PATIENTS WITH STROKE

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Effects of the Application of Markerless Motion Capture (MMC) Technology for Patients with Stroke

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_________________________ (Signed)

__LAM WING TUNG_______ (Name of student)

DEDICATION

I am dedicating this thesis to my maternal grandmother who passed away in a stroke during my PhD study. I hope my research work can contribute to the living qualities of the patients who survive after stroke and their love ones.

I also dedicate this work to my beloved mother who supports me all the way. She has been looking forwards to my PhD graduation and I am proud to present her my thesis which summarizes my research in the past three years.

Last but not the least, this thesis is dedicated to my late father who is no longer with us. I know you have been looking after me continuously somewhere in a peaceful place. I hope to share with you my growth and I am sure that you will continue to guard me in every milestone of my life.

ABSTRACT

Markerless Motion Capture (MMC) technology has been developed to eliminate the need of attaching markers on the human body during motion capturing and analysis. One of the clinical conditions that MMC technology can be applied is in the patients with stroke - a population who usually requires continuous measurement on their motor performance in pre/post rehabilitation intervention. However, there remains questions on the reliability of the MMC technology for clinical application, and the benefits of it in providing clinical measurement for patients with stroke. Therefore, this thesis aimed to examine the application of MMC technology in the patients with stroke.

Our systematic review and meta-analysis on the application of MMC technology in rehabilitation training revealed the potential for MMC systems to be used in telerehabilitation training program. Additionally, the review on the application of MMC systems in clinical measurement revealed that MMC system can analyze the movement kinematics of the disease populations, which suggested that they can serve as an alternative tool to measure the movement kinematic in these populations.

We then conducted a pilot study that investigated the validity and reliability of a customized MMC system developed using iPad Pro with LiDAR scanner for the capturing of movement kinematics. The performance of measuring the active range of motion (AROM) and the angular waveform of the upper-limb-joint angles in functional

tasks on healthy adults using the MMC system was examined. We found that the AROM measurements calculated by the MMC system had consistently smaller values than those measured by the goniometer. An MMC in iPad Pro system might not be able to replace conventional goniometry for clinical ROM measurements, but it is still suggested for use in telerehabilitation for intra-subject measurements because of its good reliability and portability.

We further investigated the application of MMC system in the measurement of both upper and lower limb kinematics in the stroke population, by examining the differences in the upper and lower limb joint angles between patients with stroke with different functional levels and their healthy counterparts in controlled and uncontrolled environments. Machine-learning models were also applied for classification of the functioning levels of the participants with stroke. We found significant differences between the upper limbs of the hemiplegic and non-hemiplegic sides of the stroke participants in most of the tasks. The four selected machine-learning models revealed ≥ 0.85 sensitivity in the stroke upper limb functional level classification.

For the lower limb measurement, significant differences were found between the angle change of the hemiplegic and non-hemiplegic lower limb of the stroke participants in most of the selected task. Our result revealed that MMC system can be used to provide precise data to evaluate the upper and lower limb functional recovery of the patients with stroke. Our study hence supports the feasibility of applying MMC system in mobile device in measuring the upper and lower limb kinematics for evaluation of the limb function of the stroke population. Future directions of research including increasing of the usability of the MMC system using smartphone or tablets in telerehabilitation are suggested.

LIST OF RESEARCH OUTPUTS

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Lam, W. W., Tang, Y. M., & Fong, K. N. (2023). A systematic review of the applications of markerless motion capture (MMC) technology for clinical measurement in rehabilitation. *Journal of NeuroEngineering and Rehabilitation*, *20*(1), 57.

Lam, W. W., & Fong, K. N. (2024). Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System: A Pilot Study. *Archives of Physical Medicine and Rehabilitation*, *105*(4), 673-681.

Journal publication under review

Lam, W. W., & Fong, K. N. (under review). Upper limb kinematic measurement using markerless motion capturing (MMC) in stroke survivors: A cross-sectional experimental study. *Journal of NeuroEngineering and Rehabilitation*

Lam, W. W., & Fong, K. N. (under review). Lower extremity kinematic measurement using markerless motion capturing (MMC) in persons with a stroke: A cross-sectional experimental study. *Archive of physical medicine and rehabilitation*

<u>Journal publications during PhD study period (not arising from this thesis)</u>

Toh, F. M., **Lam, W. W.**, Gonzalez, P. C., & Fong, K. N. (2024). 'Smart reminder': A feasibility pilot study on the effects of a wearable device treatment on the hemiplegic upper limb in persons with stroke. *Journal of Telemedicine and Telecare*, 1357633X231222297.

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Bronze award of the China College Students' 'Internet+ 'Innovation and Entrepreneurship Competition 2022.

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1st runner up of the Three Minute Thesis (3MT) Competition in the Faculty of Health and Social Sciences of the Hong Kong Polytechnic University 2024.

Champion award and **people's choice award** of the Three Minute Thesis (3MT) Competition of the Hong Kong Polytechnic University 2024.

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TABLE OF CONTENTS

AND META-ANALYSIS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

10MT	10-m Walking Test
AROM	Active Range of Motion
ATP	Angles in the Target Positions
BBA	Brunel Balance Assessment
BBS	Berg Balance Scale
BBT	Box and Blocks Test
BDI-FS	Beck's Depression Inventory Fast screening tool
BI	Barthel Index
BPBI	Brachial Plexus Birth Injury
BRS	Brainstorm stage of recovery
CEQ	Credibility/Expectancy Questionnaire
CHAQ	Childhood Health Assessment Questionnaire
CMC	Coefficient of Multiple Correlation
CNNs	Convolutional Neural Networks
CNS	Central Nervous System
COMP	Canadian Occupational Performance Measure
CP	Cerebral Palsy
CSI	Composite Spasticity Index
CSQ-8	Client Satisfaction Questionnaire
DextQ-24	Dexterity Questionnaire 24
DHI	Duruoz Hand Index
DT	Decision Tree
EQ-VAS	EuroQol visual analogue scale
FIM	Functional Independence Measure
FMA	Fugl-Meyer Assessment
FMA-LE	Fugl Meyer Assessment: Motor Function of the Lower Extremity
FMA-UE	Fugl-Meyer Assessment for Upper Extremity
fMRI	Functional magnetic resonance imaging
FRT	Functional Reach Test
FSS	Fatigue Severity Scale
FTHUE	Functional Test for the Hemiplegic Upper Extremity
GPT	Grooved Pegboard Test

GS	Grip Strength
HOA	Hand Opening accuracy
HOR	Hand Opening Range
HRA	Hand Roll Accuracy
HRR	Hand Roll Range
ICC	Intraclass correlation coefficient
iMCR	interactive Motion Capture-based Rehabilitation
IMI	Intrinsic Motivation Inventory
JIA	Juvenile Idiopathic Arthritis
JTHFT	Jebsen-Taylor Hand Function Test
LG	Logistic Regression
LiDAR	Light Detection and Ranging
LMC	Leap Motion Controller
LMCBT	Leap Motion Controller-Based Training
LRT	Lateral Reach Test
MAL	Motor Activity Log
MAS	Modified Ashworth Scale
MD	Mean Difference
MFAC	Modified Functional Ambulation Classification
MHQ	Michigan Hand Questionnaire
MMAS	Modified Motor Assessment Scale
MMC	Markerless Motion Capture
MMDT	Minnesota Manual Dexterity Test
MMT	Manual Muscle Test
mRS	Modified Rankin Scale
MS	Multiple Sclerosis
MSIS-29	Multiple Sclerosis Impact Scale
NB	Naive Baye classifier
NDT	Neurodevelopmental Therapy
NHPT	Nine Hole Peg Test
NRS	Numeric Rating Scale
OT	Occupational Therapy
PD	Parkinson’s Disease
PedsQL	Pediatric Quality of Life Inventory
POMA	Tinetti Performance-Oriented Mobility Assessment
POMA-B	Performance-Oriented Mobility Assessment Balance subscale

POMA-G	Performance- Oriented Mobility Assessment Gait subscale
PPT	Purdue Pegboard Test
PRPS	Pittsburgh Rehabilitation Participation Scale
PS	Pinch Strength
PT	Physical Therapy
RCT	Randomized Controlled Trial
RGB	Red-Green-Blue
RMSE	Root Mean Squared Error
ROM	Range of Motion
RPE	Borg Perceived Level of Exertion scale
RPS	Reaching Performance Scale
RPSS	Reaching Performance Scale for Stroke
SBS	Sitting Balance Scale
SEQ	Suitability Evaluation Questionnaire
SF12	MCS Short-Form 12 Health Survey Mental Component Score
SF12 PCS	Short-Form 12 Health Survey Physical Component Score
SFQ	Short Feedback Questionnaire
SIS	Stroke Impact Scale
SLB	Single Leg Balance test
ST	The Step Test
SUS	System Usability Scale
SVM	Support Vector Machine
TBS	Tinetti Balance Scale
TUG	Timed Up and Go test
UEFMA	Upper Extremity Fugl-Meyer Assessment
VAS	Visual Analogue Scale
VGBT	Video game-based therapy
VR	Virtual Reality
WMFT	Wolf Motor Function Test
WPA	Wrist Pitch Accuracy
WPR	Wrist Pitch Range

CHAPTER 1

INTRODUCTION

Chapter 1

Introduction

In this first chapter, we present an outline of our research studies on the application of markerless motion capture technology in the rehabilitation of patients with stroke as well as methods of application. This chapter consists of three sections. The first section is a general overview of markerless motion capture technology; the second section provides background information on stroke, a description of motor impairment in patients with stroke, and the rationales of applying markerless motion capture technology in the assessment and treatment of patients with stroke. The third section is an outline of the purpose of our studies and the structure of this thesis.

1.1 BACKGROUND OF MARKERLESS MOTION CAPTURE (MMC) TECHNOLOGY

Markerless motion capture (MMC) is a technique for human body kinematics estimation that does not require markers or fixtures placed on the body (Mündermann et al., 2006). It hence allows for greater freedom of movement and more natural performance during motion capturing. It uses computer vision algorithms and machine learning techniques to track and analyze human movement. Commonly used MMC approaches include silhouette-based methods, optical flow algorithms, and pose estimation algorithms (Salisu et al., 2023).

1.1.1 Silhouette-based methods

In silhouette-based methods, the outline of a moving person is extracted from a video. The key algorithms involved in such methods include background subtraction, in which the image of the human subject is separated from the background of the video; silhouette extraction, in which the moving human subject is extracted from the background; and pose estimation, in which the postures of the subject are estimated (Bottino & Laurentini, 2001). By analyzing changes in a subject's silhouette at different times, the joint coordinates and hence the movement of the subject can be identified (Chaaraoui et al., 2013). This technology has been applied in human action recognition and used in fields such as sports analysis and animation productions (Correa et al., 2005).

1.1.2 Optical flow algorithms

Optical flow algorithms analyze the pattern of pixels in consecutive video frames and estimate the motion of a human object. Based on the presumption that there is a single motion in each pixel, the algorithms analyze the changes in pixel intensities to infer motion information (Ranjan et al., 2018). One of the commonly used methods for optical flow calculation is the Lucas-Kanade method. It tracks the displacement of small patches of pixels in an image over time and estimates the flow field (Ranjan et al., 2018). This method requires obtaining key points for identification of pixels for the tracking of motion. The Shi-Tomasi corner detection technique, which detects the corner of objects, is one of the approaches for obtaining key points (Kaur et al., 2022). It can be applied in real-time gesture recognition systems (Danafar & Gheissari, 2007).

1.1.3 The pose estimation algorithm

The pose estimation algorithm uses computer vision to identify the human pose. It predicts and tracks a human object's location and orientation (Dhore et al., 2022). There are two types of pose estimation algorithm, namely 2D pose estimation algorithms and 3D pose estimation algorithms. 2D pose estimation algorithms perform the estimation of body joints coordinates from 2D videos. The body joints' coordinates are presented as 2D points. Convolutional neural networks (CNN) is one of the approaches to detect body joint points (Aloysius & Geetha, 2017). 3D pose estimation algorithms estimate 3D positions of human joints. They usually require the use of views or depth information from multiple cameras to detect the 3D human pose (Desmarais et al., 2021). Typically-used 3D pose estimation algorithms include graph convolutional network (GCN), which constructs a graph structure to connect body joints (Zhang et al., 2019). Examples of the application of pose estimation algorithms include augmented reality applications and human activity recognition systems applications (Guleryuz & Kaeser-Chen, 2018).

1.1.4 Application of MMC technology

With advances in technology, the development of MMC technology has overcome the limitations on the restraint of movement caused by the attachment of body markers on subjects and the time-consuming preparation process of traditional marker-based motion capture systems (Wade et al., 2022). Previous studies have been done to investigate the validity and reliability of some MMC systems, including Kinect, leap motion controller (LMC), and video from RGB cameras (Huber et al., 2015; Ramos Jr. et al., 2021; Smeragliuolo et al., 2016). The findings showed that MMC technology generally appears to be equivalent to marker-based motion capture in application, but the joint center locations and joint angles still varied among systems and the body parts being focused on. Despite the uncertainty about the accuracy of MMC technology, its advantage of allowing the capture of more lifelike human motion in a natural environment has been emphasized (Wade et al., 2022). Scientists have identified the potential of using MMC technology in capturing the kinematics of human movement in research and clinical practice. As suggested by Mündermann et al. (2008), MMC technology can be used in the rehabilitation field since the precise kinematic information that it can provide might be beneficial to therapists in understanding the motor deficits of patients. The application of MMC technology in the rehabilitation area can be divided into two aspects: 1) for rehabilitation training and 2) for rehabilitation measurement. The use of the MMC approach in rehabilitation training refers to its use in providing real time feedback to patients to guide or correct their movement during the rehabilitation exercise (Lam & Fong, 2022), while the utilization of MMC technology in rehabilitation measurements refers to the identification and measurement of movement kinematics in a clinical population (Lam et al., 2023). Despite the belief that MMC technology can contribute objective and precise movement analysis during rehabilitation, the actual application of MMC technology, such as the parameters that it captures and the clinical population that it could be applied on, is still under investigation. Two systematic reviews have hence been done by the authors of this thesis, which will be further described in section 3 of this chapter.

1.2 GENERAL INTRODUCTION OF STROKE

1.2.1 Background of stroke

Stroke is a disease that is triggered when the blood supply to the brain is interrupted or reduced, leading to an impairment of brain function (Boehme et al., 2017). It can be classified into two main types: ischemic stroke and hemorrhagic stroke. Ischemic stroke refers to the blockage of blood flow in the blood vessels supplying the brain, while hemorrhagic stroke is a condition wherein the blood vessels in the brain have ruptured or leaked, causing a bleeding in the brain area (Andersen et al., 2009; Chen et al., 2010). Presently, one in four adults will suffer stroke in their lifetime, with this number increasing 50% over the last 17 years (Feigin et al., 2022). The overall incidence rate of stroke is around 2–25 per 1,000 population and it is estimated that there will be about 101 million stroke patients globally by the year 2023 (Xu et al., 2023). Stroke is one of the leading causes of disability and one of the three most common causes of hospital admission in Hong Kong (Woo et al., 2014). The incidence of stroke in Hong Kong is no different from that in other developed countries (Feigin et al., 2021). In Hong Kong, stroke was the fourth most common cause of death in 2012 (Yu et al., 2012). A survey conducted by the Census and Statistics Department reported that the number of people who had a stroke increased by 52% over the last 10 years from 37,800 in 2009/10 to 57,500 in 2018/19 (Feigin et al., 2021). Stroke induces physical and cognitive disabilities, most of which are irreversible. Among them, motor impairment, including hemiparesis, incoordination, and spasticity are the most common conditions. According to research done by Mayo et al. (1999), 78% of patients with stroke had not reached age-specific norms for upper extremity function and 68% of them still demonstrated slow physical mobility after 3 months of stroke onset. Since motor impairments in both the upper and lower extremity greatly affect the completion of activities of daily living (ADL), seriously compromise the quality of life of patients with stroke, and impose a large socioeconomic burden on families and society, long-term rehabilitation of motor function has therefore become one of the major challenges in stroke recovery (O'Dell et al., 2009).

According to Hendricks et al. (2002), the recovery of motor function is the most rapid during the first month post-stroke, slowing down during subsequent months, and plateauing by 6 months post-stroke. Another study substantiated the fact that motor impairment, including balance and lower limb ability, strongly accounts for functional recovery in the rehabilitation of patients with stroke staying in hospital (Fong, Chan, & Au, 2001). However, Cauraugh & Summers (2005) also observed that patients with stroke still experience a significant degree of motor functional improvement after intensive training even after 6 months post-stroke. Researchers suggest that intensive motor training in stroke patients with mild to moderate impairment facilitates motor gains, which is associated with a shift in the laterality of activation in the sensorimotor cortex in the brain (Richards et al., 2008). Evidence shows that there is a shift of brain activity towards more normal functional movement in rehabilitation-induced motor recovery in hemiparetic patients with stroke over time following intensive training (Richards et al., 2008). It is hence suggested that comparing the movement of the hemiplegic limbs with that of the non-hemiplegic side would be beneficial for understanding stroke patients' motor recovery (Kim et al., 2016). Since the motor function of patients with stroke might change gradually across time due to the plasticity of the nervous system (Pin-Barre & Laurin, 2015), the motor conditions of patients with stroke might change during different stages of stroke recovery. The prescription of rehabilitation tasks or training should also be modified or changed according to patients' motor recovery progress (Ivey et al., 2006). As the motor regain of patients with stroke depends on a number of factors, including type of stroke, training intensity, patients' impairment severity, and the overall health and age of patients, it can vary greatly from person to person (Kwakkel et al., 2004). Therefore, it is very important for therapists to provide continuous and regular monitoring of the motor conditions of patients with stroke so as to develop a training protocol with optimal parameters in the type of training tasks and training regime according to the patients' recovery progress.

1.2.2 Rationales of applying markerless motion capture (MMC) technology on patients with stroke

The traditional monitoring of motor recovery of patients with stroke heavily depends on eyeball assessment and manual assessments conducted by the therapists (Poole & Whitney, 2001). Such approach requires frequent attendance by patients at the rehabilitation setting or regular visits to the patients' living environment by the therapists. A persistent complaint is that neither the intensity of stroke survivors' attendance at rehabilitation clinics nor the frequency of home visits by therapists were sufficient to meet the motor rehabilitation needs of patients with stroke (Dewey et al., 2007). This issue is caused by multiple factors, such as limited access to healthcare services of some stroke patients, inadequate medical capacity, and geographical constraints (Dewey et al., 2007). These problems have as yet remained unsolved, which significantly hinders the motor recovery prognosis of patients with stroke (Assylbek et al., 2024). Due to the outbreak of Covid-19 in 2019, many of the visits to rehabilitation settings and home visits for rehabilitation services were suspended (Burns et al., 2022). The problem of insufficient rehabilitation progress monitoring of patients with stroke became more severe and hence raised concerns in society (Ostrowska et al., 2021). The importance of remote monitoring and telerehabilitation has therefore been heavily emphasized. MMC technology can capture movement kinematics without the requirement of performing motion capture in the standard laboratory environment; hence, MMC technology could be a potential approach for the remote monitoring of stroke patients' movement and telerehabilitation for motor regain progress tracking. Remote or home-based training enhances stroke rehabilitation by providing precise data for long-term progress monitoring, which enables therapists to assess the effectiveness of home-training programs and therefore the motor recovery progress of patients with stroke (Hellsten et al., 2021). Other than using MMC technology as a measurement, Hellsten et al. (2021) proposed that MMC technology can also be applied to training programs, since it might provide real-time feedback to patients to help them correct their posture or movement patterns. Due to the current advantages of MMC technology in providing objective and precise data for motor activities, Almasi et al. (2022) suggested MMC technology has the potential to identify motor impairment and monitor the motor recovery of patients with stroke along their rehabilitation process. Moro et al. (2020) applied MMC technology in measuring the gait of patients with stroke, while Evett et al. (2011) and Levin et al. (2012) combined the use of MMC technology with virtual reality (VR) in rehabilitation training programs. Although they all reported that the use of MMC technology is effective in measuring the movement of patients with stroke, the application of MMC technology in stroke rehabilitation is still in its preliminary stages due to the complexity of algorithms, challenges in achieving individual variations, cost and accessibility constraints, and the need for further validation and clinical evidence (Hellsten et al., 2021). Eichler et al. (2018) found significant correlation between the movement kinematics of patients with stroke captured by MMC systems and stroke motor assessment scores, but how the movement data can reflect stroke motor impairment severity is still inconclusive. Further research is warranted to explore an accurate prediction of prognostic stroke recovery that can maximize the rehabilitation outcomes of patients and minimize their disabilities and caregivers' burden, as well as optimize rehabilitation efficacy. We hypothesize that the kinematic data from MMC systems can reflect the motor function or motor recovery progress of stroke populations.

1.3 PURPOSE OF THE STUDIES IN THIS THESIS AND STRUCTURE OF THE THESIS

Since the actual application of MMC technology for rehabilitation in the disease population is still uncertain, in this thesis we developed a home-based MMC system and elucidate the purpose of using this MMC system in rehabilitation; we conducted systematic reviews on the application of MMC technology in rehabilitation training and rehabilitation measurement, respectively, to explore the current trend in the rehabilitation field of using MMC technology. Chapter 2 of this thesis presents a systematic review and meta-analysis of the application of MMC technology in rehabilitation training programs. The focus is on the disease population that MMC technology is being applied on, the MMC systems that are being used, the format of rehabilitation with MMC technology, and the effect of using MMC systems in rehabilitation programs (Lam & Fong, 2022). Chapter 3 contains the systematic review of the application of MMC systems for clinical measurement in rehabilitation. In this chapter, we describe the clinical population, the types of MMC systems used for measurement, and the kinematic parameters being measured (Lam et al., 2023). In our study, a tailor-made MMC system developed using an iPad Pro with a LiDAR scanner was used to capture movement kinematics. Chapter 4 is a description of the pilot study that we conducted to investigate the validity and reliability of our MMC system in capturing the upper extremity kinematics of healthy adults. The focus of the main study was on the investigation of the application of our MMC system in kinematic measurement for patients with stroke. The content of the main study is divided into two chapters: Chapter 5 is the study of the measurement of the upper extremity using our MMC system, whereas Chapter 6 is a description of the MMC measurement of the lower extremity in patients with stroke. The aim of the main study was to investigate: 1) the kinematic differences between the hemiplegic and non-hemiplegic side of stroke patients with different functioning levels, as well as their healthy counterparts; 2) the relationship between movement kinematics and manual motor assessments; and 3) the effects of using machine learning models in the classification of the motor function of patients with stroke. Machine learning classification models were applied to train the kinematic data to examine their effect in differentiating the functional impairment level of patients with stroke. Chapter 7 is the summary and conclusion of this thesis.

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CHAPTER 2

THE APPLICATION OF MARKERLESS MOTION CAPTURE (MMC) TECHNOLOGY IN REHABILITATION PROGRAM: A SYSTEMATIC REVIEW AND META-ANALYSIS

Chapter 2

The application of Markerless Motion Capture (MMC) technology in rehabilitation program: A systematic review and meta-analysis

ABSTRACT

This chapter is a review that explores the effects of markerless motion capture technology-based rehabilitation programs targeting clinical populations and identifies the types of MMC systems used. A systematic search was conducted in the PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE databases. All eligible studies—single-group or controlled trial studies investigating the effectiveness of MMC technology-based rehabilitation programs—were selected. Single-group studies were qualitatively described; only controlled trial studies were included in the meta-analysis. Effects regarding the application of MMC technology for different types of patients and training body parts are summarized. Five single-group studies and 18 controlled trial studies were included. All studies applied MMC technology as a form of virtual reality training to provide rehabilitation programs. Most of the studies were conducted in regard to upper extremity training in stroke populations. Our meta-analysis revealed that there is no significant difference in the upper limb rehabilitation effects between

VR training and control interventions. There is potential to apply MMC technology as an alternative way of providing rehabilitation to increase patients' motivation and adherence. Future studies on the design of training programs and MMC systems in home settings, which are affordable and accessible for patients, are warranted. (This review is registered in PROSPERO, registration ID: CRD42022298189).

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S.I. : NEW TRENDS ON IMMERSIVE HEALTHCARE

The application of markerless motion capture (MMC) technology in rehabilitation programs: a systematic review and meta-analysis

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Abstract
This review explores the effects of markerless motion capture technology-based rehabilitation programs targeting clinical populations and identifies the types of MMC systems used. A systematic search was conducted in the PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE databases. All eligible studies—single-group or controlled trial studies investigating the effectiveness of MMC technology-based rehabilitation programs—were selected. Single-group studies were qualitatively described; only controlled trial studies were included in the meta-analysis. Effects regarding the application of MMC technology for different types of patients and training body parts are summarized. Five single-group studies and 18 controlled trial studies were included. All studies applied MMC technology as a form of virtual reality training to provide rehabilitation programs. Most of the studies were conducted in regard to upper extremity training in stroke populations. Our meta-analysis revealed that there is no significant difference in the upper limb rehabilitation effects between VR training and control interventions. There is potential to apply MMC technology as an alternative way of providing rehabilitation to increase patients' motivation and adherence. Future studies on the design of training programs and MMC systems in home settings, which are affordable and accessible for patients, are warranted. (This review is registered in PROSPERO, registration ID: CRD42022298189).

Keywords Markerless motion capture · Virtual reality · Rehabilitation · Stroke · Upper extremity

2.1 BACKGROUND

Intensive and repetitive exercise significantly improves motor function recovery in neurological rehabilitation and after stroke. (Carr & Shepherd, 2010) In order to increase the exercise intensity, patients should be self-motivated and actively engaged in rehabilitation training. To promote functional recovery, there is also a significant need for regular and continuous rehabilitation training at home after inpatient hospital discharge.

However, patients have reported that they are hindered from engaging in home exercise programs due to unclear feedback about their positions, the quality and quantity of their movements, and the level of intensity (Burridge et al., 2017). Without supervision from therapists, patients are often doubtful about their rehabilitation progress and whether they are moving correctly (Hughes et al., 2017). The absence of instant feedback during repetitive movements during home exercise programs further reduces patients' motivation of actively participating, which might in turn reduce their adherence to the home rehabilitation exercise program (Alsinglawi et al., 2018).

Remote rehabilitation is a safe and effective alternative to typical rehabilitation programs in clinics (Tan, 2020). Tsekleves et al. (2016) investigated the use of a remote Nintendo Wii program that offers virtual reality-based upper-limb stroke rehabilitation, and found that participants benefited from better wrist control and greater functional improvement. Recent research findings suggest that remote stroke rehabilitation programs have significant effects on limb function recovery after stroke (Sarfo et al., 2018). However, most remote stroke rehabilitation programs require input from therapists in terms of supervising and monitoring the quality of the patients' movements (Paneroni et al., 2015). Patients are not able to acquire instant feedback with which to regulate their actions and movements without monitoring from therapists (Hughes et al., 2020).

There are new methods that rely on the motion tracking and analysis of patients' movements during exercise. Wearable devices with sensors are one of the proposed ways to conduct unsupervised stroke rehabilitation (Maceira-Elvira et al., 2019). Wearable sensors located on specific body parts allow movement tracking for the users as well as enabling analysis of their movement quality and quantity (Lee et al., 2018). Using wearable sensors to detect the movement of patients during rehabilitation exercises reduces the human effort that would be required to continuously observe the patients (Bonato, 2005). However, the use of wearable sensors usually requires setup and multiple forms of calibration in the early stages, and so patients may not find these sensors to be user-friendly.

With the advance of technology in the past 10 years, markerless motion capture (MMC) technology has been used in rehabilitation programs (Mündermann et al., 2006). MMC technology does not require the placement of any markers on a person's body, and the capturing and analysis of the subject's movements are based on visual hull reconstruction (Mündermann et al., 2006). MMC and analysis technology is becoming common and studies have begun to investigate its application in the rehabilitation field. Pastor et al. (Pastor et al., 2012) tried applying the MMC system Kinect in the form of

VR training with a patient with stroke in 2012. There are also small-scale case series (Capo et al., 2014; Ding et al., 2018; Palacios-Navarro et al., 2015; Pompeu et al., 2014; Shiri et al., 2012) that have applied MMC and engaged patients in rehabilitation in a VR training context. Previous research has indicated the potential of MMC technology in rehabilitation exercises (Knippenberg et al., 2017); however, the effects of its application have been inconsistent. Both Rodríguez-Hernández et al. (2021) and Wang et al. (2017) applied MMC technology and provided training programs in a VR game format for patients with stroke. They reported a significant improvement in the upper limb function in the VR training group compared with the conventional therapy group (Rodríguez-Hernández et al., 2021; Wang et al., 2017). Afsar et al. (2018) and Sin and Lee (2013) found that patients who received the MMC technology-based rehabilitation program showed significantly greater improvements than the groups receiving conventional therapy. However, Saposnik et al. (2016) proposed that the use of VR training supported by the MMC system does not generate a better effect than receiving intensive rehabilitation in the form of recreational activities. Cannell et al. (2018) further reflected that patients receiving VR training with Kinect did not improve more significantly than the conventional therapy group.

The inconsistent findings from the literature generate a research gap regarding the uncertain effects of MMC technology-based rehabilitation programs compared to conventional therapy. A systematic review (Knippenberg et al., 2017) of the use of the MMC system in rehabilitation programs in 2017 concluded that MMC technology was still not common in rehabilitation; however, most of the studies included by Knippenberg et al. (2017) were small-scale case studies or featured single-group designs, which made it difficult to draw conclusions. Therefore, the aims of this systematic review are to explore the effects of MMC technology-based rehabilitation programs targeting the clinical population, including patients' feedback regarding the technology, and to identify the types of MMC systems used in rehabilitation training and the format in which they appeared.

2.2 METHODS

2.2.1 Search Strategy

A systematic computerized literature search was conducted by one of the authors (WTL) in PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE. The keywords used for the searches in each database include Markerless Motion Capture OR Motion Capture OR Motion Capture Technology OR Markerless Motion Capture Technology AND Rehabilitation OR Rehabilitation program OR Training Program OR Treatment.

The author also conducted a manual search using Google Scholar with the same keywords, and screened the reference lists of the previous systematic reviews. The years of publication were not limited and the last search took place on 20 January 2022.

2.2.2 Inclusion Criteria

Studies were included if they: 1) are either controlled studies or single-group studies; 2) applied MMC technology in a rehabilitation program; 3) aimed to evaluate the effects of the application of an MMC system in rehabilitation training on patients' functional recovery; 4) had at least one assessment outcome related to clinical effects conducted before and after the intervention; and 5) were published in English.

2.2.3 Exclusion Criteria

Studies were excluded if they: 1) involved healthy subjects only; 2) focused on evaluating the users' experiences only; 3) applied MMC technology in clinical evaluations only; 4) did not report any outcomes; 5) involved other robotic training, such as the use of exoskeletons, robotic walkers, or haptic devices; or 6) were systematic reviews.

2.2.4 Data Extraction

The general characteristics and results of the studies were recorded, including the names of the authors, the year of publication, study design, sample size, patient types, format of the interventions, type of MMC system used, and components of the training program. Information regarding the clinical effects and clients' feedback were extracted. The initial mean scores and standard deviations (SDs) of the assessment outcomes after the rehabilitation programs were extracted from the clinical effects reported in the controlled studies. We recorded the mean change in scores calculated from the pre- and post-experiment outcome measures and calculated standard errors (SEs) for meta-analysis. The researchers contacted the article authors to request extra information if the data provided in the articles were insufficient to be used for data pooling. Meta-analysis was only performed on the controlled studies.

2.2.5 Methodological Quality Assessment

The methodological quality of the controlled studies was assessed by independent reviewers (WTL) using the Physiotherapy Evidence Database (PEDro) rating scale (Moseley et al., 2002). Disagreements between the two reviewers during the methodological quality assessment of the studies were reconciled via consensus or arbitration by a third reviewer (KNKF). The PEDro scale has 11 items, including the risk of bias in terms of randomization, allocation concealment, baseline measurement, blinding, dropout rate, intention to treat, and data reporting in statistical comparisons. One mark is scored for each item if the criterion is met. The total score is calculated by summation of the scores from the 11 items. Studies with a PEDro score of 9–10 are considered to be of "excellent" quality, 6–8 of "good" quality, 4–5 of "fair" quality, and below 4 of "poor" quality (Teasell et al., 2003).

2.2.6 Data Synthesis

Randomized controlled studies that focused on the upper extremity rehabilitation of patients with stroke were identified and included in a further meta-analysis to determine the effects of the use of MMC technology in the rehabilitation of the upper limb in the stroke population.

In this meta-analysis, we used the mean change scores (post-pre) and the standard errors (SEs) to pool the results. The post-intervention outcomes were used. Most of the mean change scores were calculated from the pre- and post-assessment scores provided in the studies, while the SEs were calculated according to the suggestions in Cohen's handbook (Higgins, 2011).

Among the randomized controlled studies, the most commonly used outcome measurement for upper limb function is the Box and Block Test (BBT). One study used the Fugl-Meyer Assessment (FMA) (Afsar et al., 2018) as the primary outcome measure, in which they did not include the BBT as the outcome measurement. One of the included studies used the Wolf Motor Function Test (WMFT) (Wang et al., 2017) to measure hand motor function. One study that used Manual Muscle Testing (MMT) (Lee, 2013) as the major outcome measurement to determine the recovery of hand muscle strength has been excluded from this meta-analysis due to the difference in the nature of assessments compared with the three other scales. We combined the outcomes of the BBT, FMA, and WMFT in our meta-analysis by transforming the mean changes and SEs into a standardized mean difference expressed as Hedges' g, with 95% confidence intervals (CI) as the pooled effect size. Heterogeneity across the included studies was confirmed by checking the Higgins I^2 statistic. If the I^2 statistic was below 50%, a fixed-effects model was used for data pooling. If the I^2 statistic was above 50%, a random effects model was used. Publication bias was checked through a meta-analysis or subgroup analysis including five or more studies, using Egger's linear regression test to quantify the asymmetry of the funnel plots generated. Procedures related to data pooling and checking of publication bias were conducted using the Comprehensive Meta-Analysis 3.0 software (Englewood, NJ, USA).

We also summarized the feedback from the patients' responses to the use of MMC technology in rehabilitation, as reported in the included studies. Qualitative description was applied to the single-group studies.

2.3 RESULTS

2.3.1 Literature Search and Study Characteristics

A total of 1,213 articles were identified and 67 of them were selected for full-text reading. After excluding 44 articles according to the inclusion and exclusion criteria, 23 studies were included in the final review (Figure 2.1). Among the included studies, 18 of them are controlled studies (Afsar et al., 2018; Avcil et al., 2021; Cannell et al., 2018; Dabholkar & Shah, 2020; Lee, 2013; Levin et al., 2012; Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Tarakci et al., 2020; Waliño-Paniagua et al., 2019; Wang et al., 2017), while five of them are single-group studies (Jonsdottir et al., 2019; Knippenberg et al., 2021; Qiu et al., 2020; Tarakci et al., 2016; Vanbellingen et al., 2017). A total of 15 out of the 18 controlled studies applied MMC technology in upper extremity rehabilitation and used upper limb motor function as the outcome measurement. A total of 10 out of those 15 studies involved adults with neurological diseases. Among them, eight studies focused on patients with stroke and two studies focused on patients with multiple sclerosis (MS) and Parkinson's disease (PD). These 10 studies were included in our meta-analysis. The remaining eight controlled-trial studies focused on the training of balance with patients with various neurological diseases or the training of hand dexterity with patients with hand functional deficits, which could not be pooled together for effect size analysis. All of the five single-group studies applied MMC technology in upper limb rehabilitation.

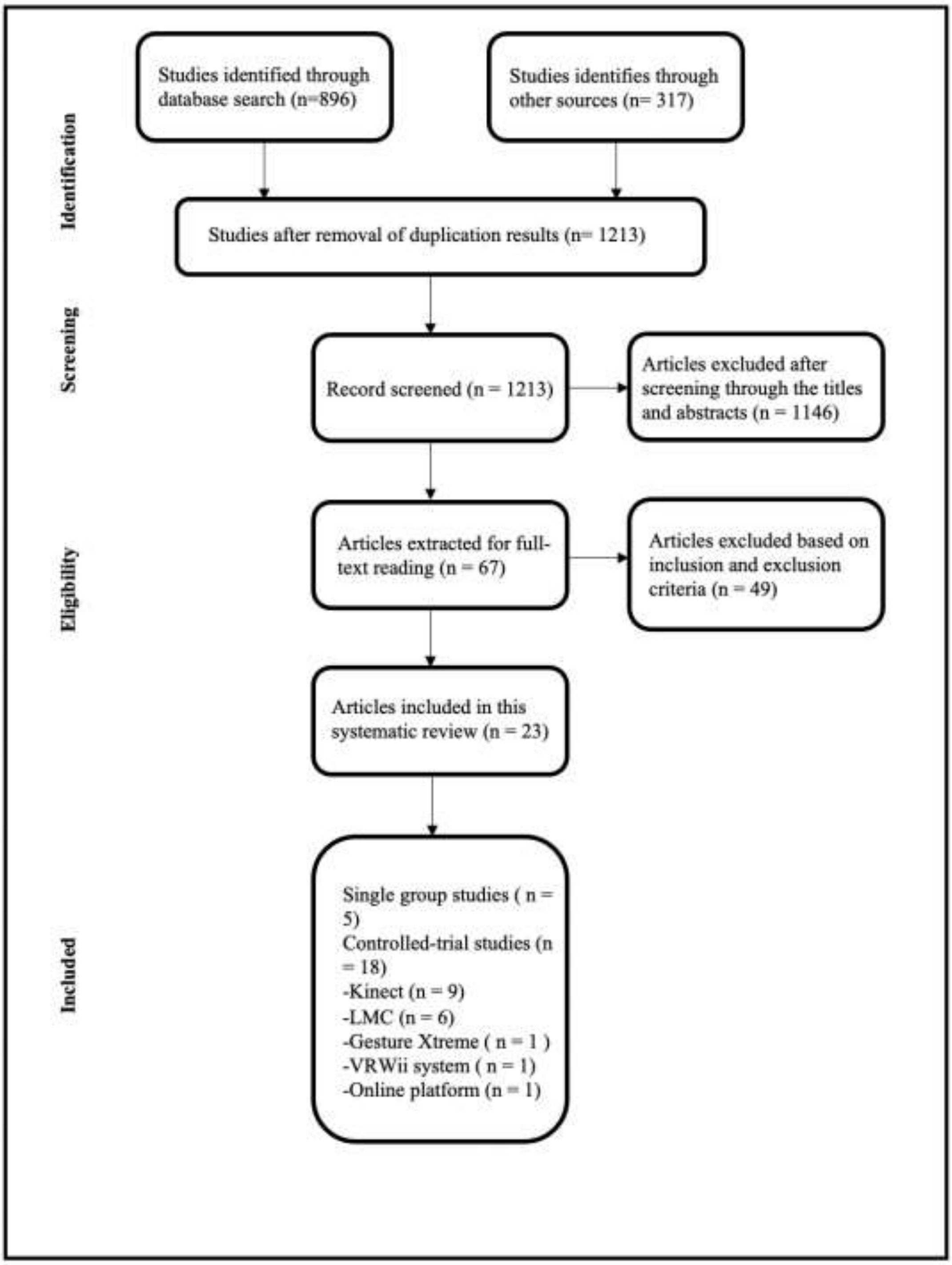

Figure. 2.1 Flow chart of study selection

2.3.2 Single-Group Studies

The summary in Table 2.1 presents the characteristics of the five single-group studies.

Two of them provided training programs to the stroke population using the LMC system. Qiu et al. (2020) reported a functional improvement in the subjects' upper extremity by an increase of the group's average. The Upper Extremity Fugl-Meyer Assessment (UEFMA) score after training, according to Vanbellingen et al. (2017), detected no significant change in the UEFMA score but significant improvement was noticed in hand dexterity using the Nine Hole Peg Test. Tarakci et al. (2016) claimed a significant improvement was found in hand grip strength and range of motion (ROM) after the MMC treatment program in patients with juvenile idiopathic arthritis (JIA). Both Knippenberg et al. (2021) and Jonsdottir et al. (2019) used Kinect as the MMC system and studied patients with central nervous system (CNS) diseases and patients with multiple sclerosis (MS). The two studies used different outcome measures and both concluded that improvements were found in the upper limb function of the patients.

Table 2.1 Characteristics of the single-group studies

Study	Subject Types (n)	Age (years)[a]	Type of MCS	Format	Frequency	Outcome Measurements	Main Results
Tarakci et al. (2016)	JIA (18)	12.22±3.30	LMC	Video game	Three sessions a week (8 weeks)	ROM, GS, CHAQ, NRS, PedsQL	Significant statistical differences were found between pre- and post-treatment in regard to all outcomes
Vanbellingen et al. (2017)	Stroke (13)	68.2±17.5	LMC	Video game	Three sessions a week (3 weeks)	SUS, PRPS, interview form, NHPT, DextQ-24, GS, FM-UE	Significant improvements were found in hand dexterity and GS; no changes were found in FM-UE
Jonsdottir et al. (2019)	MS (18)	56.1±10.5	Microsoft Kinect	VR game	3–5 sessions a week (12 sessions)	NHPT, BBT, SF12 MCS, SF-12 PCS, EQ-VAS, BDI-FS	Improvements were found in dexterity and arm function bilaterally; only the improvement in the treated arm was statistically significant
Qiu et al. (2020)	Chronic stroke (15)	56.67±11.8	LMC	Video game	25–168 mins a week (12 weeks)	UEFMA, HOR, HOA, WPR, WPA, HRR, HRA	Improvements were found in UEFMA and the six measurements of hand kinematics
Knippenberg et al. (2021)	CNS diseases (17)	57.2±16.3	Microsoft Kinect	Exercise	Three sessions a week (6 weeks)	IMI, SUS, CEQ, COMP, WMFT	Upper limb functional ability improved significantly over time on the WMFT

[a]Data are reported as means (SD).

JIA: Juvenile Idiopathic Arthritis, LMC: Leap Motion Controller, ROM: Range of Motion, GS: Grip Strength, CHAQ: Childhood Health Assessment Questionnaire, NRS: Numeric Rating Scale, PedsQL: Pediatric Quality of Life Inventory, SUS: Self-Reported System Usability, PRPS: Pittsburgh Rehabilitation Participation Scale, NHPT: Nine Hole Peg Test, DextQ-24: Dexterity Questionnaire 24, FM-UE: Fugl-Meyer Assessment for Upper Extremity, MS: Multiple Sclerosis, VR: virtual reality, BBT: Box and Blocks Test, SF12: MCS Short-Form 12 Health Survey Mental Component Score, SF12 PCS: Short-Form 12 Health Survey Physical Component Score, EQ-VAS: EuroQol visual analogue scale, BDI-FS: Beck's Depression Inventory Fast screening tool, UEFMA: Upper Extremity Fugl-Meyer Assessment, HOR: Hand Opening Range, HOA: Hand Opening accuracy, WPR: Wrist Pitch Range, WPA: Wrist Pitch Accuracy, HRR: Hand Roll Range, HRA: Hand Roll Accuracy, CNS: Central Nervous System, IMI: Intrinsic Motivation Inventory, SUS: System Usability Scale, CEQ: Credibility/Expectancy Questionnaire, COMP: Canadian Occupational Performance Measure, WMFT: Wolf Motor Function Test.

2.3.3 Controlled-Trial Studies

Target Population

There are a total of 18 studies included in this review, with a total of 675 subjects (339 patients in experimental groups; 336 patients in control groups) (Table 2.2). A total of 15 out of the 18 studies applied the MMC system in rehabilitation for adults with neurological diseases (Afsar et al., 2018; Cannell et al., 2018; Cuesta-Gómez et al., 2020; Fernández-González et al., 2019; Lee, 2013; Levin et al., 2012; Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Waliño-Paniagua et al., 2019; Wang et al., 2017), including 11 studies targeting the stroke population (n = 453) (Afsar et al., 2018; Cannell et al., 2018; Lee, 2013; Levin et al., 2012; Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Wang et al., 2017), three studies focusing on patients with MS (Cuesta-Gómez et al., 2020; Lozano-Quilis et al., 2014; Waliño-Paniagua et al., 2019), and one study focusing on patients with PD (Fernández-González et al., 2019). Two studies focused on children and adolescents with physical disabilities, including CP, juvenile idiopathic arthritis (JIA), and brachial plexus birth injury (BPBI) (Avcil et al., 2021; Tarakci et al., 2020). One study reported data from adults suffering from wrist and hand stiffness with non-specified diagnoses (Dabholkar & Shah, 2020). The methodological quality of the 18 controlled studies was evaluated using the PEDro items (Table 2.3).

Table 2.2 Characteristics of the controlled-trial studies

Study	Design	Subject Types	*n* (E/C)	Age	Type of MCS	Format	Experimental Group	Control Group	Outcome Measurements
Levin et al. (2012)	RCT	Stroke (chronic)	12 (6/6)	E: 58.1±14.6 C: 59.8±15.1	Gesture Xtreme	VR game	A total of nine sessions of 45 minutes of VR training (3 weeks)	A total of nine sessions of 45 minutes of OT rehab (3 weeks)	FMA-UE, CSI, RPSS, BBT, WMFT, MAL
Lee et al. (2013)	RCT	Stroke (chronic)	14 (7/7)	E: 71.71±9.14 C: 76.43±5.80	Microsoft Kinect (Xbox)	Video game	Three sessions of 60 minutes of Xbox games a week (6 weeks)	Three sessions of 30 minutes of OT rehab a week (6 weeks)	MMT, MAS, FIM
Sin and Lee (2013)	RCT	Stroke (chronic)	35 (18/17)	E: 71.78±9.42 C: 75.59±5.55	Microsoft Kinect (Xbox)	VR game	Three sessions of 30 minutes of VR training + 30 minutes of OT rehab a week (6 weeks)	Three sessions of 30 minutes of OT rehab a week (6 weeks)	FMA, ROM, AROM, BBT
Lozano-Quilis et al. (2014)	RCT	MS	11 (6/5)	E: 48.33±10.82 C: 40.60±9.24	Microsoft Kinect	VR exercise	One session of 45 minutes of PT rehab + 15 minutes of VR training a week (10 weeks)	One session of 60 minutes of PT rehab a week (10 weeks)	BBS, TBS, SLB, 10MT, TUG, SEQ
Lloréns, Gil-Gómez, et al. (2015)	RCT	Stroke (chronic)	20 (10/10)	E: 58.3±11.6 C: 55.0±11.6	Microsoft Kinect	VR exercise	Five sessions of 30 minutes of PT rehab + 30 minutes of VR training a week (4 weeks)	Five sessions of 60 minutes of PT rehab a week (4 weeks)	BBS, POMA, BBA, 10MT, SFQ

Lloréns, Noé, et al. (2015)	RCT	Stroke (chronic)	30 (15/15)	E: 55.47±9.63 C: 55.60±7.29	Microsoft Kinect	VR exercise	Three sessions of 45 minutes of VR training a week in a home setting (20 sessions)	Three sessions of 45 minutes of VR training a week in a clinical setting (20 sessions)	BBS, POMA-B, POMA-G, BBA, SUS, IMI
Saposnik et al. (2016)	RCT	Stroke (subacute)	141 (71/70)	E: 62±13 C: 62±12	Nintendo Wii gaming system (VRWii)	VR game	Ten sessions of 60 minutes of VR training (2 weeks)	Ten sessions of 60 minutes of recreational activity (2 weeks)	WMFT, BBT, SIS, FIM, BI, mRS, GS, RPS, RPE
Wang et al. (2017)	RCT	Stroke (subacute)	26 (13/13)	E: 55.3±8.4 C: 53.4±7.6	LMC	VR game	Five sessions of 45 minutes of PT & OT rehab a week + five sessions of 45 minutes of VR training a week (4 weeks)	Five sessions of 45 minutes of PT & OT rehab a week (4 weeks)	WMFT, fMRI
Afsar et al. (2018)	RCT	Stroke (subacute)	35 (19/16)	E: 69.42±8.55 C: 63.44±15.73	Microsoft Kinect (Xbox 360)	VR game	Five sessions of 60 minutes of rehab program a week + 30 minutes of VR training/sessions (4 weeks)	Five sessions of 60 minutes of rehab program a week (4 weeks)	FMA-UE, BRS, BBT, FIM
Cannell et al. (2018)	RCT	Stroke (subacute)	79 (39/40)	E: 72.8±10.4 C: 74.8±11.9	Microsoft Kinect	Game-based activities	Five sessions of PT rehab + 5 hours of iMCR intervention a week (between eight and 40 sessions)	Five sessions of PT rehab + 5 hours of rehab exercise a week (between eight and 40 sessions)	FRT, MMAS, BBT, SBS, LRT, ST, TUG

Fernández-González et al. (2019)	RCT	PD	23 (12/11)	E: 65.77±7.67 C: 67.36±12.12	LMC	Video game	Two sessions of 30 minutes of serious games a week (6 weeks)	Two sessions of 30 minutes of PT rehab a week (6 weeks)	BBT, PPT, CSQ-8, GS
Waliño-Paniagua et al. (2019)	RCT	MS	16 (8/8)	E: 46.75±9.31 C: 46.13±9.49	Online platform	VR game	Two sessions of 30 minutes of OT rehab + two sessions of 20 minutes of VR training a week (10 weeks)	Two sessions of 30 minutes of OT rehab a week (10 weeks)	PPT, JTHFT, GPT
Cuesta-Gómez et al. (2020)	RCT	MS	30 (16/14)	E: 49.86±2.46 C: 42.66±3.14	LMC	VR game	Two sessions of 45 minutes of PT rehab + 15-min VR training a week (10 weeks)	Two sessions of 60 minutes of PT rehab a week (10 weeks)	GS, BBT, PPT, NHPT, FSS, MSIS-29, CSQ-8
Dabholkar et al. (2020)	NRS	Patients with wrist and hand stiffness	50 (25/25)	E: 48.8 (SD not provided) C: 47.9 (SD not provided)	LMC	VR game	Two sessions of 15–20 minutes of PT rehab + 10–15 minutes of VR training a week (4 weeks)	Three sessions of 25 minutes of PT rehab a week (4 weeks)	VAS, ROM of wrist and hand, GS, PPT, MHQ
Norouzi-Gheidari et al. (2020)	RCT	Stroke (subacute/chronic)	18 (9/9)	E: 42.2±9.5 C: 57.6±10.5	Microsoft Kinect	VR game	Regular OT/PT rehab + three sessions of 30 minutes of VR training a week (4 weeks)	Regular OT/PT rehab (4 weeks)	FMA-UE, BBT, SIS, MAL
Tarakci et al. (2020)	RCT	CP + JIA + BPBI	CP: 30 (15/15)	E(CP): 10.93±4.09	LMC	Video game	Three sessions of 60 minutes of	Three sessions of 60 minutes of	DHI, JTHFT, NHPT, CHAQ, GS, PS

			JIA: 43 (18/25) BPBI: 19 (9/10)	C(CP): 11.06 ±3.23 E(JIA): 12.22±3.29 C(JIA): 13.16±3.35 E(BPBI): 8.22±2.58 C(BPBI): 8.30±2.21			LMCBT a week (8 weeks)	conventional rehab program a week (8 weeks)	
Rodríguez-Hernández et al. (2021)	RCT	Stroke (subacute)	43 (23/20)	E: 62.6±13.5 C: 63.6±12.2	Microsoft Kinect	VR exergames	Five sessions of 50 minutes of PT rehab + 50 minutes of OT rehab + 50 minutes of VR training a week (3 weeks)	5 sessions of 75 minutes of PT rehab + 75 minutes of OT rehab/week (3 weeks)	FMA-UE, MAS, SIS
Avcil et al. (2021)]	RCT	CP	30 (15/15)	E: 10.93±4.09 C: 11.07±3.24	LMC	Video game	Three sessions of 60 minutes of VGBT a week (3 weeks)	Three sessions of 60 minutes of NDT-based rehab a week (3 weeks)	MMDT, GS, PS, CHAQ, DHI

[a]Data are reported as means (SD).

RCT: *Randomized Controlled Trial,* VR: Virtual Reality, OT: Occupational Therapy, FMA-UE: Fugl-Meyer Assessment for Upper Extremity*,* CSI: Composite Spasticity Index, RPSS: Reaching Performance Scale for Stroke*,* BBT: Box and Block test, WMFT: Wolf Motor Function Test, MAL: Motor Activity Log, MMT: Manual Muscle Test, MAS: Modified Ashworth Scale, FIM: Functional Independence Measure*,* FMA: Fugl-Meyer Assessment, ROM: Range of Motion, AROM: Active Range of Motion, *PT: Physical Therapy,* BBS: Berg Balance Scale, TBS: Tinetti Balance Scale, SLB: Single Leg Balance test, 10MT: 10-m Walking Test, TUG: Timed Up and Go test, SEQ: Suitability Evaluation Questionnaire, POMA: Tinetti Performance-Oriented Mobility Assessment, BBA: Brunel Balance Assessment, SFQ: Short Feedback Questionnaire, POMA-B: Performance-Oriented Mobility Assessment Balance subscale, POMA-G: Performance-Oriented Mobility Assessment Gait subscale, SUS: System Usability Scale, IMI: Intrinsic Motivation Inventory, SIS: Stroke Impact Scale, BI: Barthel Index, mRS: Modified Rankin Scale, GS: Grip Strength, RPS: Reaching Performance Scale, RPE: Borg Perceived Level of Exertion scale, LMC: Leap Motion Controller, fMRI: Functional magnetic resonance imaging, BRS: Brunnstrom stage of recovery, iMCR: interactive Motion Capture-based Rehabilitation, FRT: Functional

Reach Test, MMAS: Modified Motor Assessment Scale, SBS: *Sitting Balance* Scale, LRT: Lateral Reach Test, ST: The Step Test, PD: Parkinson's Disease, PPT: Purdue Pegboard Test, CSQ-8: Client Satisfaction Questionnaire, MS: Multiple Sclerosis, JTHFT: Jebsen-Taylor Hand Function Test, GPT: Grooved Pegboard Test, NHPT: Nine Hole Peg Test, FSS: Fatigue Severity Scale, MSIS-29: Multiple Sclerosis Impact Scale, NRS: *non-randomized controlled study, VAS:* Visual Analogue Scale, MHQ: Michigan Hand Questionnaire, CP: Cerebral Palsy, JIA: Juvenile Idiopathic Arthritis, BPBI: Brachial Plexus Birth Injury, LMCBT: Leap Motion Controller-Based Training, DHI: Duruoz Hand Index, CHAQ: Childhood Health Assessment Questionnaire, PS: pinch strength, VGBT: video game-based therapy, NDT: neurodevelopmental therapy, MMDT: Minnesota Manual Dexterity Test.

Table 2.3 PEDro scores of the controlled-trial studies

Authors	PEDro Items											Total
	1	2	3	4	5	6	7	8	9	10	11	
Levin et al. (2012)	1	1		1			1	1				5
Lee et al. (2013)	1	1	1	1					1	1	1	7
Sin and Lee (2013)	1	1	1	1			1	1		1	1	8
Lozano-Quilis et al. (2014)	1	1	1	1				1		1	1	7
Lloréns, Gil-Gómez, et al. (2015)	1	1	1	1			1	1		1	1	8
Lloréns, Noé, et al. et al. (2015)	1	1	1	1			1	1		1	1	8
Saposnik et al. (2016)	1	1		1			1	1	1	1	1	8
Wang et al. (2017)	1	1	1	1				1	1	1	1	8
Afsar et al. (2018)	1	1	1	1			1	1		1	1	8
Cannell et al. (2018)	1	1	1	1	1		1	1	1	1	1	10
Fernández-González et al. (2019)	1	1		1				1		1	1	6
Waliño-Paniagua et al. (2019)	1	1		1			1			1	1	6
Cuesta-Gómez et al. (2020)	1	1	1	1			1	1		1	1	8
Dabholkar et al. (2020)	1			1				1	1	1	1	6
Norouzi-Gheidari et al. (2020)	1	1	1	1			1	1		1	1	8
Tarakci et al. (2020)	1	1	1	1			1	1		1	1	8
Rodríguez-Hernández et al. (2021)	1	1		1				1		1	1	6
Avcil et al. (2021)	1	1	1	1				1		1	1	7

1 = eligibility criteria; 2 = random allocation; 3 = concealed allocation; 4 = baseline comparability; 5 = blind subjects; 6 = blind therapists; 7 = blind assessors; 8 = adequate follow-up; 9 = intention-to-treat analysis; 10 = between-group comparisons; 11 = point estimates and variability.

2.3.4 Training Content and Format

Most of the studies (15 out of 18) conducted rehabilitation programs by training the upper extremity (Afsar et al., 2018; Avcil et al., 2021; Cannell et al., 2018; Cuesta-Gómez et al., 2020; Dabholkar & Shah, 2020; Fernández-González et al., 2019; Lee, 2013; Levin et al., 2012; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Tarakci et al., 2020; Waliño-Paniagua et al., 2019; Wang et al., 2017), while the remaining three studies conducted balance training programs using the MMC system (Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014). Among the 15 studies that trained the upper extremity, two of them mainly focused on examining the improvement in hand dexterity (Tarakci et al., 2020; Waliño-Paniagua et al., 2019) and one used manual muscle testing as an outcome measure to determine the effects of using an MMC system in the training of hand muscle strength (Lee, 2013). A total of 15 studies (Afsar et al., 2018; Avcil et al., 2021; Cannell et al., 2018; Cuesta-Gómez et al., 2020; Dabholkar & Shah, 2020; Fernández-González et al., 2019; Lee, 2013; Levin et al., 2012; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Tarakci et al., 2020; Waliño-Paniagua et al., 2019; Wang et al., 2017) used MMC systems in the form of a video or VR game, while three of them (Lloréns, Gil-

Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014) provided training programs using MMC systems in the form of VR exercises.

2.3.5 Type of MMC System

The most frequently used MMC system in the studies was the Kinect system developed by Microsoft in 2010 (out of production since 2017). Nine studies applied the Kinect system in the form of VR games or VR exercises in rehabilitation programs (Afsar et al., 2018; Cannell et al., 2018; Lee, 2013; Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Sin & Lee, 2013). Microsoft Kinect is a kind of MMC system that uses depth-sensing technology to detect and capture human movement with infrared sensors (Zhang, 2012). Instant feedback can be provided to users about their gestures and movement patterns through the system.

The Leap Motion Controller (LMC) was adopted by six studies (Avcil et al., 2021; Cuesta-Gómez et al., 2020; Dabholkar & Shah, 2020; Fernández-González et al., 2019; Tarakci et al., 2020; Wang et al., 2017) and was the second most commonly used MMC system. The LMC captures motion performed within a small observation area with its monochromatic cameras and infrared LEDs (Lu et al., 2016). It is commonly used to track hand and finger movements when users interact with digital content.

Other MMC systems used include the Gesture Xtreme, the Nintendo Wii gaming system (VRWii), and a free online platform, which were adopted by the remaining three studies (Levin et al., 2012; Saposnik et al., 2016; Waliño-Paniagua et al., 2019). Gesture Xtreme is a VR gaming system that allows users to immerse themselves in virtual worlds and interact with virtual environments (Kizony et al., 2003). Instant feedback is generally obtained from how the users interact with the virtual context. The motion tracking of the VRWii depends on the recognition of positions by its 3D accelerometer, which translates motion into gesture recognition (Lee, 2008). The free online website adopted by Waliño-Paniagua et al. (2019) is cited as motiongamingconsole.com; it provides online VR games.

2.3.6 Training Effects of the Application of MMC Technology in Upper Limb Rehabilitation in Adults with Stroke

A total of 389 adults with stroke across eight studies were included in this meta-analysis (Afsar et al., 2018; Cannell et al., 2018; Cuesta-Gómez et al., 2020; Fernández-

González et al., 2019; Levin et al., 2012; Norouzi-Gheidari et al., 2020; Rodríguez-Hernández et al., 2021; Saposnik et al., 2016; Sin & Lee, 2013; Wang et al., 2017). The PEDro scores for all of the controlled-trial studies ranged from 5–10, with an average score of 7.33 $\pm$ 1.33 (Table 2.3). The eight selected studies in the meta-analyses ranged from 5–10. No serious adverse effects as a result of the MMC technology-based training programs were noted in any of the studies. The pooled results show that applying an MMC system in upper limb rehabilitation for patients with stroke is not significantly more effective than a control intervention regarding upper extremity functional improvement in adults with stroke (Hedges' g = 0.351; 95% CI = -0.195 – 0.896; I^2= 84.001; P = 0.208; random effects model) (Figure 2.2). A funnel plot after trim and fill showed that the effect size shifted to the left (Figure S2.1) and Egger's test suggested that there is no evidence of publication bias ($\beta = 3.918$; standard error = 2.087; P = 0.110).

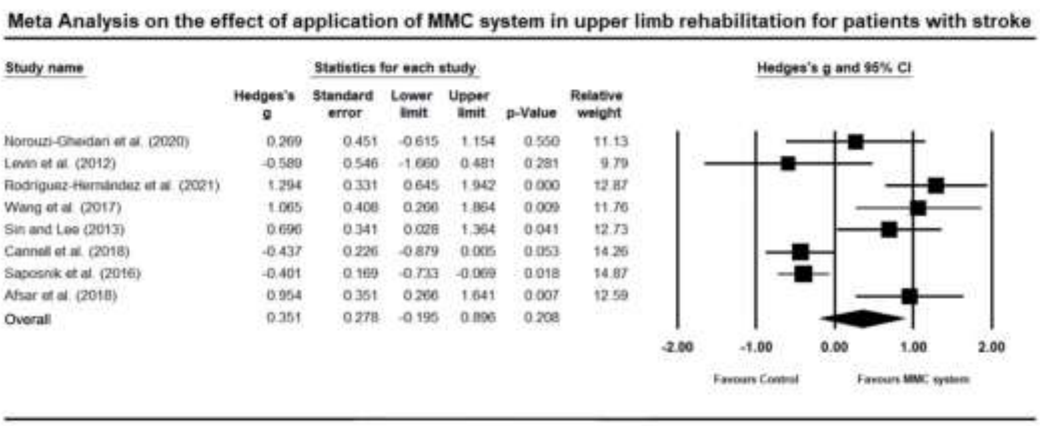

Fig. 2.2 Effects of application of MMC system and control intervention on upper extremity rehabilitation for adults with stroke. The hedges' g was converted by the

mean change in scores and standard error (SE) of both MMC system group and control groups in the 8 included studies. Results were pooled and the overall effect of the using MMC system in rehabilitation program was computed as hedges' g with 95% confidence interval. The results indicated that rehabilitation using MMC system has no significant difference in effect of improving upper extremity function when compared with control intervention (Hedges' g = 0.351; 95% CI = -0.195 – 0.895; I^2= 84.001; P = 0.208; random effect model) Funnel plot after trim and fill showed that effect size shifted to the left (Figure S2.1) and Egger's test suggested that there is no evidence of publication bias ($\beta =$ 3.918; standard error = 2.087; P = 0.110)

2.3.7 Effects of Training via MMC Systems in Adults with Other Diseases

Fernández-González et al. (2019), Cuesta-Gómez et al. (2020), and Dabholkar et al. (2020) conducted their studies using LMC as the MMC system in rehabilitation programs with patients with PD, MS, and wrist and hand stiffness, respectively. All three studies reported a significant improvement in Pegboard Test (PPT) scores compared with the control groups. Waliño-Paniagua et al. (2019), who used a free online website as the MMC platform, reported no significant difference in the improvement of the hand dexterity of their subjects with MS in the VR training group when compared with the control group.

2.3.8 Effects of Training Muscle Strength

The only study that investigated the effect of using MMC technology in regard to training muscle strength was conducted by Lee et al. (2013). The improvements in muscle strength among patients with stroke in the MMC system training group were not significantly different from those of the patients in the control group, who received conventional occupational therapy.

2.3.9 Effects of Balance Training in Adults

Three studies applied MMC technology using the Kinect system to provide balance rehabilitation programs (Lloréns, Gil-Gómez, et al., 2015; Lloréns, Noé, et al., 2015; Lozano-Quilis et al., 2014). The target populations were adults with stroke and MS, respectively. Lloréns et al. (2015) reported a significant improvement in the patients with stroke who underwent rehabilitation using the Kinect system, measured by the Berg Balance Scale, when compared with the control group. His team further studied the effects of balance training via Kinect in home settings and in clinical settings (Lloréns, Noé, et al., 2015). They found that patients who received VR training at home and those who underwent VR training in the clinical setting did not show significant differences in their balance ability, as measured by the BBS. Lozano-Quilis et al. (2014) conducted a balance rehabilitation program with subjects with MS and discovered a significant group-by-time interaction in the BBS scores of the VR group.

2.3.10 Effects of Applying MMC in Rehabilitation Programs for Children and Adolescents

Two studies (Avcil et al., 2021; Tarakci et al., 2020) reported findings from applying LMC in upper limb rehabilitation for children and adolescents. Avcil et al. (2021) focused on patients with CP, while Tarakci et al. (2020) included CP, JIA, and BPBI populations. One study reported a significant improvement in the manual dexterity of the more affected side, compared to NDT-based treatment (Tarakci et al, 2020), while another study reported no significant difference in hand function and grip strength between the experimental group and the control group, which received conventional rehabilitation (Avcil et al., 2021).

2.3.11 Patients' Acceptance

Both CSQ-8 scores reported by Fernández-González et al. (2019) and Cuesta-Gómez et al. (2020) reflected the high degree of satisfaction in the LMC training group. Patients were generally reported to be motivated and enjoying themselves when training with the MMC system.

2.4 DISCUSSION

2.4.1 Effects of the Application of MMC Technology in Rehabilitation Training Programs

Our meta-analysis revealed no significant difference in the upper limb training effects between the use of MMC technology and the use of conventional therapy among patients with stroke. The effects of using MMC systems in balance training with MS and stroke populations were found to be more significant than conventional therapy. The studies using MMC systems in rehabilitation programs for other types of neurological diseases and for children were too limited to draw conclusions regarding their effectiveness.

We investigated the features of MMC technology to deduce its comparable effectiveness with conventional therapy in the stroke population. First, the MMC system can generate instant feedback for users through its real-time movement detection and analysis technology. Users can correct their movements or adjust their gestures based on real-time feedback during the training to improve the training efficacy. Although MMC systems are able to capture and analyze patients' real-time movements (Liang & Miao, 2015), they do not support the detection of force exerted by the patients in each task. Hence, the training effect of hand muscle strength using an MMC system might not be superior to similar training using conventional therapy, as reflected by the only study (Lee, 2013) that investigated muscle strength. Second, applying MMC technology in training in the form of VR games allows patients to interact with virtual contexts, which provides more dynamic training elements. This advantage appears to be more obvious in the training of balance. As balance performance depends on reactions toward stimuli from the environment (Hess & Woollacott, 2005), the simulation of environmental factors that threaten stability might help to improve balance. The VR platform enables the simulation of environmental stimuli and obstacles, which promotes the acquisition of motor strategies for patients reacting to the changing environmental stimuli (Cho et al., 2014). Patients could gain more competence in maintaining stability despite threatening stimuli through training in virtual contexts. VR might hence result in more significant improvements in balance, as measured by Lloréns, Gil-Gómez, et al. (2015) and Lozano-Quilis et al. (2014). Providing rehabilitation programs in the form of VR games is also a way to increase the enjoyment that can be derived from the training, as reflected by patients' feedback, which might enhance their adherence to and motivation to complete the training. By providing real-time feedback and enabling patients to be trained in a VR platform, the use of MMC technology can be considered as a low-cost and efficient form of training.

Despite the fact that the use of MMC technology can be a low-cost and useful way of capturing and evaluating the performance of patients, there are several drawbacks to the MMC technology used in rehabilitation. First, the requirement of using a specific camera, such as an infrared camera or a depth camera, reduces the accessibility of the large-scale use of motion capture technology in rehabilitation. The cost of the current MMC devices was affordable for hospitals and clinics, but might not be for patients looking to purchase one in order to conduct VR rehabilitation in home settings. A concern raised by (Saposnik et al., 2016) is that a significant group of the stroke population have low incomes and so likely have limited access to technologies such as VR for rehabilitation. Their findings reveal that an MMC system should be accessible and affordable for patients so they can benefit from VR training. Second, older generations may have less knowledge about how to set up and calibrate MMC systems, which constitute a new technology (Gramstad et al., 2013). They might not be competent in participating in VR training programs at home, due to the knowledge and skills needed to set up and calibrate the system. Further, task-specific and client-oriented VR training programs are required to precisely analyze body parts when MMC technology is used in rehabilitation. Current VR exercises or serious games especially designed for patients with particular types of diseases are limited (Kharrazi et al., 2012). The content of VR games and exercises might not provide patients with the right challenge. Most VR exercises and games only reflect patients' performance through game scores (Mubin et al., 2020) and therapists might not be able to evaluate the actual functional improvement of the patients with this alone. The motion analysis system of MMC gaming technology cannot be adopted to extract clinical data in order to deduce patients' degree of recovery.

The selection of a suitable MMC system for training specific targeted body functions is also important. As the current meta-analysis focuses on the upper limb rehabilitation of patients with stroke, the major outcome measurement is the BBT score. The BBT is an assessment that measures unilateral gross manual dexterity (Desrosiers et al., 1994). To complete the BBT, patients are required to transfer as many blocks as possible from one compartment to another in 60 seconds. Gross manual dexterity, including being able to accurately pick up the blocks and the ability to lift up the arm, is required to complete the assessment. It is important to note that the LMC mainly tracks fine hand movement and patients who have trained with the LMC should have adequate ability to control their hand gestures, so they can engage in VR training supported by the LMC (Lu et al., 2016). As Kinect mainly performs gross motor tracking, hand manual dexterity might not be included as an element of the training games that it supports (Seo et al., 2019). Patients trained with the LMC might be more aware of their gross manual dexterity, while patients trained with the Kinect system might be more aware of their gross movement. The different features of the LMC and Kinect might result in different areas of recovery in regard to the upper extremity, which cannot be fully reflected by only investigating the change in BBT scores after treatment. Hence, it is important for therapists to select suitable types of MMC systems according to the targeted training body functions.

2.4.2 Development Trends in MMC Technology in Rehabilitation

Being relatively low cost, easy to install, its user-friendly controlling system, and multiple gaming contexts, Kinect is often chosen as the most frequently used MMC system in rehabilitation programs (Mousavi Hondori & Khademi, 2014). It has been 10 years since Kinect was first adopted as an MMC system to provide rehabilitation programs. Kinect enables the capture of real-time whole body gross movements, although it is less sensitive in tracking fine hand movements. Although Kinect has been adopted as an MMC system in rehabilitation training, it has been out of production since 2017 and was no longer supported by the Xbox Series X, as announced by Microsoft (*This Is Why Microsoft Kinect Was A Complete Failure*, 2021). Future rehabilitation programs that intend to use MMC technology might have to consider using other kinds of MMC systems or platforms. The LMC was launched to the market in 2012 and its real-time tracking of hand motions induced its adoption in the rehabilitation of fine motor movements (Pereira et al., 2020). de Los Reyes-Guzmán et al. (2021) considered the LMC to be a low-cost and effective way of tracking the hand gestures of patients. Besides the current VR games developed by the Leap Control Company, the LMC also supports self-developed VR games; tasks for rehabilitation programs using the LMC can be created specifically for hand training purposes. Although the most frequently used MMC system included in this systematic review is Kinect, the use of the LMC is becoming more frequent in studies published in the past five years. Gesture Xtreme and the Nintendo VRWii are less frequently adopted in rehabilitation programs. This may be due to their marketing as gaming platforms, with games that are not designed with appropriate levels of challenge for patients with disabilities. As MMC systems are developed mainly for healthy populations and their commercial purposes mostly concern entertainment, the use of VR games in rehabilitation has been confined to a small group of the population (Lee et al., 2016). In recent years, studies have tended to develop their own platforms and training tasks, rather than directly using built-in VR games available in the market. This trend suggests that there is more awareness concerning the necessity of constructing client-centered and task-oriented VR training programs with MMC technology to meet patients' functional levels (Knippenberg et al., 2017). Low-cost MMC devices and their software development kits lower the threshold for the design and development of rehabilitation exercise programs and serious games in virtual contexts for patients with different needs and functional levels.

2.4.3 Suggestions for the Future Use and Development of MMC Technology in Rehabilitation

This paper reveals that it might be feasible to provide MMC technology-based rehabilitation programs such as VR training games and exercises to patients as an alternative treatment option. The use of MMC technology-based rehabilitation programs instead of conventional therapy can reduce the workforce required to closely monitor and supervise patients during training. With the instant feedback provided by the MMC system, patients can adjust and regulate their movement patterns, which allows them to perform training exercises in a more self-oriented way. VR training can be prescribed as a home program, enabling patients to be continuously motivated to complete the training at home; therapists could remotely monitor their rehabilitation progress through the analyses generated by the MMC system. Given that MMC systems can capture and analyze gestures in real time, they could be used as a tool to measure the range of motion (ROM) of patients. Both therapists and patients might then be able to visualize the physical restoration of the ROM in the affected body parts during or immediately after the VR training. As the current hardware required for MMC systems is largely not accessible or affordable for patients, we suggest that further research and development are needed in regard to the generalization of a MMC system that does not require a specific camera. An MMC system using a mobile device could be a solution to further enhance the generalizability of MMC technology in regard to its application in the rehabilitation field, as this would not require further purchases or the setting up of new hardware devices by patients. Motion tracking algorithms are being developed to enable the tracking of body movements via the Light Detecting And Ranging (LIDAR) camera installed in certain kinds of mobile phones and tablets, which could be further investigated as a solution to this generalizability limitation (Pusztai & Hajder, 2017).

Further research also needs to be conducted into the design and development of different VR exercises and serious games in MMC systems that best suit the needs of patients with different types of diseases. Interpretations of patients' game scores or data extracted from MMC systems should be further researched in regard to their correlation with the functional recovery of the patients.

2.5 CONCLUSION

Most of the selected studies investigated the effects of MMC technology in the training of the upper extremity of the stroke population. Our meta-analysis revealed that there is no significant difference in the effects of upper limb rehabilitation between MMC technology training groups and control intervention groups. The use of MMC systems in rehabilitation training is, however, enjoyable, and enables patients to stay motivated in regard to their training. There is potential to apply MMC technology in home programs for rehabilitation, which could increase patients' adherence to the programs and hence the intensity of their training at home. Future studies need to consider the design of MMC technology-based training programs and the generalization of the use of MMC systems in home settings, to ensure they are affordable and accessible for all patients.

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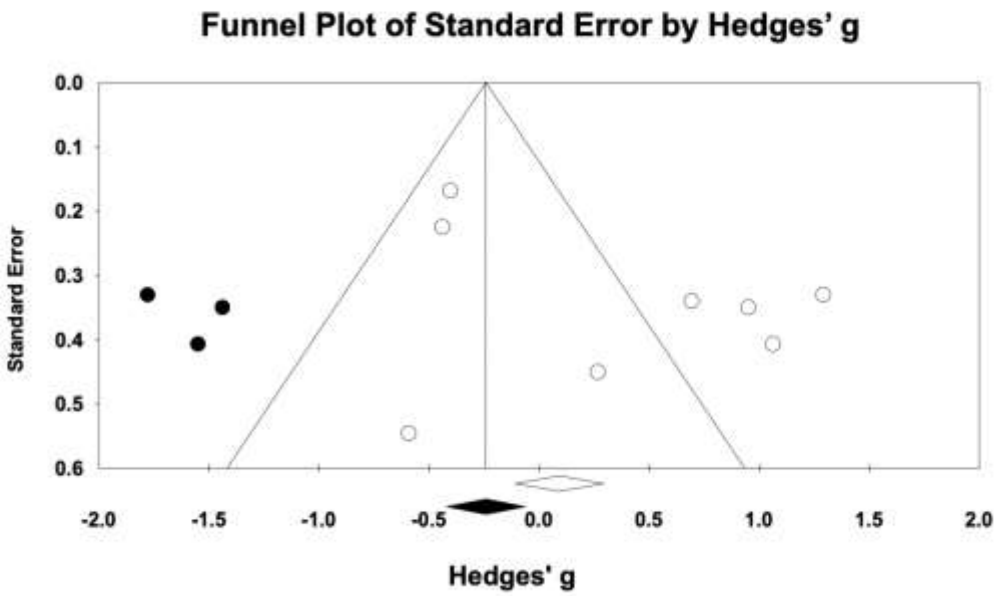
2.7 APPENDIX



Note:

White circle Papers that reported the effect of MMC training is significantly more effective than control intervention

Black circle Papers that reported the effect of MMC training has no significant difference with the control intervention

Figure S2.1 Funnel Plot of standard error by Hedges' g in studies comparing the effects of using the MMC system in upper limb rehabilitation with the effects of conventional therapy in the stroke population; the effect size would shift to the left if the apparent bias were to be removed

CHAPTER 3

A SYSTEMATIC REVIEW OF THE APPLICATION OF MARKERLESS MOTION CAPTURE (MMC) TECHNOLOGY FOR CLINICAL MEASUREMENT IN REHABILITATION

Chapter 3

A systematic review of the application of markerless motion capture (MMC) technology for clinical measurement in rehabilitation

ABSTRACT

This chapter is a systematic review that investigate the current utilization of Markerless Motion Capture (MMC) as a clinical measurement tool — identification and measurement of movement kinematics in a clinical population in rehabilitation. In this review we put a minor focus on the method's engineering components and sought primarily to determine its application for clinical measurement. A systematic computerized literature search was conducted in PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE. The search keywords used in each database were "Markerless Motion Capture OR Motion Capture OR Motion Capture Technology OR Markerless Motion Capture Technology OR Computer Vision OR Video-based OR Pose Estimation AND Assessment OR Clinical Assessment OR Clinical Measurement OR Assess." Only peer-reviewed articles that applied MMC technology for clinical measurement were included. A total of 65 studies were included. The MMC systems used for measurement were most frequently used to identify symptoms or to detect differences in movement patterns between disease populations and their healthy

counterparts. Patients with Parkinson’s disease (PD) who demonstrated obvious and well-defined physical signs were the largest patient group to which MMC assessment had been applied. This review revealed that MMC technology has the potential to be used as an assessment tool as well as to assist in the detection and identification of symptoms, which might further contribute to the use of an artificial intelligence method for early screening for diseases. Further studies are warranted to develop and integrate MMC system in a platform that can be user-friendly and accurately analyzed by clinicians to extend the use of MMC technology in the disease populations.

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REVIEW **Open Access**

A systematic review of the applications of markerless motion capture (MMC) technology for clinical measurement in rehabilitation

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Abstract

Background Markerless motion capture (MMC) technology has been developed to avoid the need for body marker placement during motion tracking and analysis of human movement. Although researchers have long proposed the use of MMC technology in clinical measurement—identification and measurement of movement kinematics in a clinical population, its actual application is still in its preliminary stages. The benefits of MMC technology are also inconclusive with regard to its use in assessing patients' conditions. In this review we put a minor focus on the method's engineering components and sought primarily to determine the current application of MMC as a clinical measurement tool in rehabilitation.

Methods A systematic computerized literature search was conducted in PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE. The search keywords used in each database were "Markerless Motion Capture OR Motion Capture OR Motion Capture Technology OR Markerless Motion Capture Technology OR Computer Vision OR Video-based OR Pose Estimation AND Assessment OR Clinical Assessment OR Clinical Measurement OR Assess." Only peer-reviewed articles that applied MMC technology for clinical measurement were included. The last search took place on March 6, 2023. Details regarding the application of MMC technology for different types of patients and body parts, as well as the assessment results, were summarized.

Results A total of 65 studies were included. The MMC systems used for measurement were most frequently used to identify symptoms or to detect differences in movement patterns between disease populations and their healthy counterparts. Patients with Parkinson's disease (PD) who demonstrated obvious and well-defined physical signs were the largest patient group to which MMC assessment had been applied. Microsoft Kinect was the most frequently used MMC system, although there was a recent trend of motion analysis using video captured with a smartphone camera.

Conclusions This review explored the current uses of MMC technology for clinical measurement. MMC technology has the potential to be used as an assessment tool as well as to assist in the detection and identification of symptoms, which might further contribute to the use of an artificial intelligence method for early screening for diseases. Further studies are warranted to develop and integrate MMC system in a platform that can be user-friendly and accurately analyzed by clinicians to extend the use of MMC technology in the disease populations.

3.1 INTRODUCTION

Markerless motion capture (MMC) technology has been developed to avoid the need for marker placement during tracking and analyzing human movement (Corazza et al., 2010). By elimination of the time-consuming marker placement procedure, motion capturing experiment can be performed in a more convenient way (Rahul, 2018) . With the removal of constraints from body markers on movement, the development of MMC technology allows the capture of a more lifelike human motion in the environment, in a more natural way, and with the feature that it uses more portable and low-cost sensors compared to marker-based multi-camera systems (Scott et al., 2022), MMC in turn creates the potential of additional applications.

Previous studies have been conducted to compare the accuracy of MMC and body-marker-based analysis systems (Knippenberg et al., 2017). Bonnechere and colleagues (2014) compared the measuring accuracy of full body scanning by Microsoft Kinect 3D scanner software versus that of a high-resolution stereophotogrammetric system, which is a marker-based system in the healthy population. They concluded that Kinect is a reliable markerless tool that is suitable for use as a fast estimator of morphology. Schmitz and colleagues (2013) validated the accuracy of Kinect in measuring knee joint angle of a jig by comparing its measurement using a digital inclinometer that acted as a ground-truth, and they reported that the performance of the Kinect system was satisfactory in terms of knee flexion and abduction. The accuracy of using a smartphone as a measurement system for joint angle has been reviewed by Mourcou and colleagues (2015), who concluded that smartphone applications are reliable for clinical measurements of joint position and range of motion (ROM).

Earlier in 2006, Mündermann and colleagues (2006) described several methods of MMC video processing modules including background separation, visual hull which is an object's 3D shape formed by intersecting silhouettes from multiple views, and iterative closest point methods, etc., and pointed out that MMC has the potential to achieve a level of accuracy that facilitates the biomechanics research of normal and pathological human movement. Together with the reliable performance of MMC technology in the measurement of joint angle and body movement as reflected by Schmitz, et al. (2013) and Mourcou, et al. (2015), it is suggested that the MMC system can be further applied to the rehabilitation field to measure patients' motor function. However, the actual application of MMC technology for clinical measurement in rehabilitation is still at a preliminary stage. Most of the extant studies have focused on calibration of the MMC system or on validating the MMC system only on healthy persons. Applied research on the actual use of MMC technology in measurements in patient groups has been very diverse: Vivar and the teams (2019) applied MMC technology in people with Parkinson's disease (PD) to detect and classify their tremor level, while Gritsenko and colleagues (2015) used Kinect as the MMC system to measure the shoulder ROM for women breast cancer patients after surgery. Instead of applying MMC technology in adults, Chin and colleagues (2017) assessed the level of proprioceptive ability in children with cerebral palsy by using Kinect as the MMC system to measure the arm position of both healthy children and children with unilateral spastic cerebral palsy (USCP). These researchers found significant differences between the proprioceptive ability of the typically developing children and the children with USCP, as measured by Kinect, thus suggesting that MMC technology has the potential to be useful as a clinical measurement tool for proprioception.

Despite these trials, however, studies on the applications of MMC technology in clinical evaluation are still preliminary and limited in number, and it remains inconclusive how MMC technology can benefit therapists, patients, or the healthcare system, in terms of measuring patients' conditions. Review studies have been conducted on the use of MMC technology in rehabilitation training, but not in regard to its use in clinical measurement including application of MMC technology in clinical assessment and detection of kinematic parameters that assist in disease diagnosis (Knippenberg et al., 2017). Mousavi Hondori and Khademi (2014) reviewed the clinical impact of Kinect in rehabilitation, but their study did not cover other types of MMC technology. Therefore, to investigate the current uses of MMC technology as an assessment tool in the healthcare field, in this review we put less focus on the engineering components and attempted primarily to determine the current evidence for using MMC as a measurement tool, in order to further explore the potential benefits of MMC technology in rehabilitation evaluations. In this paper, we define clinical measurement as identification and measurement of movement kinematics in a clinical population (Sakkos et al., 2021), while MMC technology include systems and methods that capture and analysis movements without the need of marker placement, including video-based analysis. This systematic review further investigated: 1) the types of patients to whom MMC technology has been applied; 2) the contents of the MMC measurements; 3) the types of MMC systems used; and 4) the efficacy of these MMC systems as measurement tools.

3.2 METHODS

3.2.1 Search strategy

A systematic computerized literature search was conducted by one of the authors (WTL) in PubMed, Medline, CINAHL, CENTRAL, EMBASE, and IEEE. Only peer-reviewed articles were included. The search keywords used in each database were "Markerless Motion Capture OR Motion Capture OR Motion Capture Technology OR Markerless Motion Capture Technology OR Computer Vision OR Video-based OR Pose Estimation AND Assessment OR Clinical Assessment OR Clinical Measurement OR Assess." A manual search was also conducted that included searching Google Scholar using the same keywords, and the reference lists of the previous systematic reviews were also screened. The published data were not limited, and the last search took place on March 6, 2023.

3.2.2 Inclusion criteria

Studies were included if they met certain inclusion criteria. Specifically, the studies had to: 1) be peer-reviewed; 2) apply MMC technology for measurement; 3) involve subjects with symptomatic conditions; 4) have any quantitative study design except systematic reviews; 5) include at least one assessment item for clinical evaluation; and 6) be published in English.

3.2.3 Exclusion criteria

Studies were excluded if they met any one of the following exclusion criteria: 1) studying only healthy persons; 2) focusing only on calibration of the MMC system; 3) applying MMC technology only in rehabilitation training; or 4) not reporting results of an assessment evaluation.

3.2.4 Data extraction

The information we assessed included: 1) the types of MMC systems used in the studies; 2) the conditions of the participants that underwent the measurement, such as diagnoses or disabilities; and 3) the contents of the measurements conducted. The interpretations of the studies' results were extracted and are presented in a summary table (Table 3.1). The contents of the measurement included the body functions or body parts that were measured, and the context in which the assessment was conducted.

Table 3.1 Details of the selected studies

Study	Patient types	Sample size (n)	MMC system	Measurement items	Content of measurement	Context of measurement	Primary results	Results interpretation
Cho et al., 2009	PD	Patients with PD (7); healthy controls (7)	Sony HDR-HC3 camcorder	Gait pattern	Recognition of PD gait by algorithm combining PCA with LDA	Laboratory	The proposed system can identify healthy adults and patients with PD by their gaits with high reliability	Video-based analysis helps in discriminating the gait patterns of PD patients and healthy adults
Adde et al., 2010	CP	Infants with high risk of CP (30)	Digital video camera	Quantity of motion, velocity and acceleration of the centroid of motion	Comparison of quantity of motion and centroid of motion in infants who developed into CP with those who did not develop into CP	Hospital	Quantity of motion mean, median, and standard deviation were significantly higher in the group of infants who did not develop CP than in the group who did develop CP	Quantitative variables related to the variability of the center of infant movement and to the amount of motion predicted later CP in young infants with high sensitivity and specificity
Bahat, Weiss, & Laufer, 2010	Chronic neck pain	Patients with chronic neck pain (25); asymptomatic participants (42)	Customized VR assessment system	Cervical ROM (flexion, extension, rotation, and lateral flexion)	Comparison of cervical movement in patients with chronic neck pain, versus in healthy controls	Laboratory	Significant group differences for 3 of the kinematic measures: V_{peak}, $V_{mean,}$ and number of velocity peaks	"Goal-directed fast cervical movements performed by patients with chronic neck pain were characterized by lower velocity and decreased smoothness compared with asymptomatic participants" (Bahat, Weiss, & Laufer, 2010, p.1888)
Chen et al., 2011	PD	Patients with PD (12); healthy adults (12)	CCD video camera	Gait parameters including gait cycle time, stride length, walking velocity, and cadence	Quantification of gait parameters	Structured environment	KPCA-based method achieved a classification accuracy of 80.51% in identifying different gaits	Kinematic data extracted from video might allow clinicians to obtain the quantitative gait parameters and assess the progression of PD
Khan et al., 2013	PD	Patients diagnosed with advanced PD	Video recordings,	Index-finger motion in finger tapping,	SVM classification to categorize the	Medical facility	The proposed CV-based SVM scheme	The ML framework offers good classification performance in

		(13); healthy controls (6)	analyzed by CV algorithm	features including speed, amplitude, rhythm, and fatigue in tapping were computed	patient group between UPDRS-FT symptom severity levels, and to discriminate between PD patients and healthy controls		discriminated between control and patient group with an average of 94.5% accuracy	distinguishing symptom severity levels based on clinical ratings, as well as in identifying PD patients and the healthy controls
Lowes et al., 2013	Dystrophinopathy	Patients with dystrophinopathy (5); healthy controls (5)	Kinect	Upper extremity functional reaching volume, velocity, and rate of fatigue	Validity and Reliability of the MMC system in capturing upper extremity functional reaching volume, movement velocity, and rate of UE fatigue in individuals with dystrophinopathy	Laboratory	Preliminary test-retest reliability of the MMC method for 2 sequential trials was excellent for functional reaching volume	“The newly available gaming technology has potential to be used to create a low-cost, accessible, and functional upper extremity outcome measure for use with children and adults with dystrophinopathy” (Lowes et al., 2013, p.9)
O’Keefe et al., 2013	FXS	Males with FXS (13); healthy controls (7)	BioStage^{TM}	Motion parameters (frequency and total traveled distance) of body segments during 30 s of story listening while standing in the observation space	Comparison between groups, MMC system results were compared with scores on video-capture methodology and behavioral rating scales	Laboratory	Arm and foot travel distances were significantly greater in the FXS group compared with the controls	“Motion parameters obtained from the markerless system can quantify increased movement in subjects with FXS relative to controls” (O’Keefe et al., 2013, p.830)
Olesh et al., 2014	Stroke	Patients with stroke (9)	Kinect	10 movements of the upper extremity	Quantitative scores derived from motion capture were compared to qualitative clinical scores produced by trained human raters	Laboratory	Strong linear relationship was found between qualitative scores and quantitative scores derived from both standard and low-cost motion capture system	“The low-cost motion capture combined with an automated scoring algorithm is a feasible method to assess objectively upper-arm impairment post stroke” (Olesh et al., 2014, p.6)

Gritsenko et al., 2015	Breast cancer	Women with mastectomy (4) or lumpectomy (16) for breast cancer	Kinect	Active and passive shoulder motions	Regression coefficients for active movements were used to identify participants with clinically significant shoulder ROM limitation	Laboratory	Participants had good ROM in the shoulder ipsilateral to the breast surgery at the time of testing. Three participants showed clinically significant shoulder motion limitations	Findings support the use of MMC approach as part of an automated screening tool to identify people who have shoulder motion impairment
Lee et al., 2015	AC of shoulder	Healthy volunteers (15); patients with AC (12)	Kinect	Shoulder ROM	Validity of measure shoulder ROM in AC by calculating the agreement of Kinect measurements with measurements obtained using a goniometer, and assessment of its utility for the diagnosis of AC	Laboratory	Measurements of the shoulder ROM using Kinect showed excellent agreement with those taken using a goniometer	"Kinect can be used to measure shoulder ROM and to diagnose AC as an alternative to a goniometer" (Lee et al., 2015, p.11)
Tupa et al., 2015	PD	Patients with PD (18); healthy age-matched individuals (18); students (15)	Kinect	Leg length, normalized average stride length, and gait velocity	A two-layer sigmoidal neural network was used for the classification of gait features (stride length and gait velocity)	Laboratory	Results showed high classification accuracy for the given set of individuals with PD and the age-matched controls	Kinect has potential to be used in the detection of gait disorders and the recognition of PD
Sá et al., 2015	Schizophrenia	Clinically stable outpatients with schizophrenia (13); healthy controls (16)	BioStage^{TM}	Kinematic parameters and motor patterns during a functional task	Comparison of the kinematic parameters and motor patterns of patients with schizophrenia and those of healthy subjects	Laboratory	Patients with schizophrenia displayed a less developed movement pattern during performance of overarm throwing	"The presence of a less mature movement pattern can be an indicator of neuro-immaturity and a marker for atypical neurological development in schizophrenia" (Sá et al., 2015, p.77)

Kim et al., 2016	Stroke	Patients with hemiplegic stroke (41)	Kinect	Upper extremity motion of 13 of 33 items of upper extremity motor FMA	Correlation of the prediction accuracy for each of the 13 items between real FMA scores and scores using Kinect were analyzed	Laboratory	Prediction accuracies ranged from moderate to good in each item. Correlations were high for the summed score for the 13 items between real FMA scores and scores obtained using Kinect	"Kinect can be a valid way to assess upper extremity function, which may be useful in the setting of unsupervised home-based rehabilitation" (Kim et al., 2016, p.1)
Matsenet al., 2016	Variety of diagnoses (cuff disease, instability, arthritis)	Patients with a variety of diagnoses, including cuff disease, instability, arthritis (32); control healthy subjects (10)	Kinect	Shoulder active ROM	Correlation of Kinect shoulder active ROM measurement with SST	Laboratory	The total SST score was strongly correlated with the range of active abduction. The ability to perform each of the individual SST functions was strongly correlated with active motion	"Kinect provides a clinically practical method for objective measurement of active shoulder motion" (Matsenet al., 2016, p.221)
Chin et al., 2017	CP	Children with USCP (31); typically developing children (21)	Kinect v2	Proprioception	Comparison of proprioceptive ability in children with USCP versus that in typically developing children	Laboratory	Children with USCP showed significant impairments in proprioception compared with typically developing children	The use of MMC technology can clearly identify differences in proprioceptive ability between typically developing children and children with UCSP
de Bie et al., 2017	ALS	Patients diagnosed with ALS (10)	Kinect	Upper extremity reachable workspace RSA	Evaluation of longitudinal changes in upper extremity reachable workspace RSA versus the ALSFRS-R, ALSFRS-R upper extremity sub-scale and FVC	Laboratory	RSA measures were able to detect changes in the upper limbs while the ALSFRS-R could not. The RSA measures were also able to detect a declining trend similar to that of FVC	"Kinect-measured RSA can detect declines in upper extremity ability with more granularity than current tools" (de Bie et al., 2017, p.22)
Bakhti et al., 2018	Stroke	Individuals with hemiparetic stroke (19)	Kinect	Movements of 25 predefined body "joints" that	Use of ICC and linear regression analysis to quantify	Laboratory	PANU scores determined by the Kinect were similar to	"The Kinect sensor can accurately and reliably determine the PANU score in

				approximately correspond to the center of the anatomical joint or body part	the degree to which an ultrasound 3D motion capture system motion capture system and Kinect measurements were related		those determined by the ultrasound 3D motion capture system	clinical routine” (Bakhti et al., 2018, p.1)
Bonnechère et al., 2018	Stroke	Healthy young adults (40); elderly adults (22); and patients with chronic stroke (10)	Kinect	Parameters including length, angle, velocity, angular velocity, volume, sphere, and surface of upper limb motion	The different scores and parameters were compared for the three groups	Laboratory	Highly significant differences were found for both the shoulders’ total angle, the velocity for young adults and elderly individuals, and patients with stroke	Results of the evaluation could be useful in monitoring patients’ conditions during rehabilitation, while further studies are needed to select which parameters are the most relevant
Butt et al., 2018	PD	Participants with PD (16); healthy people (12)	LMC	PSUP, OPCL, THFF, and POST	Comparison of parameters between a PD group and control group; Supervised learning methods SVM, LR, and NB for classification of patients with PD and healthy subjects	Laboratory	The best performing classifier was the NB. All the other subset features selected by the other feature selection methods, showed the worst classification performance in all ML classifiers (LR, NB, SVM)	“LMC is not yet able to track motor dysfunction characteristics from all MDS-UPDRS proposed exercises” (Butt et al., 2018, p.19)
Dranca et al., 2018	PD	Patients with PD (30)	Kinect	Gait step, limbs angle, and bent angles related to Parkinson disease	Classification of different PD stages by the features from FoG using classification algorithms	Hospital	The accuracy obtained for a particular case of a Bayesian Network classifier built from a set of 7 relevant features is 93.40%	“Using Kinect is adequate to build an inexpensive and comfortable system that classifies PD into three different stages related to FoG” (Dranca et al., 2018, p.1)
MH. Li et al., 2018	PD	Patients with PD (9)	Consumer grade video camera	416 features including kinematics, frequency distribution	Quantifying the severity of levodopa-induced dyskinesia by video-based features	Laboratory	Features achieved similar or superior performance to the UDysRS for detecting the onset and remission of dyskinesia	“The proposed system provides insight into the potential of computer vision and deep learning for clinical application in PD” (Li et al., 2018, p.1)

				extracted from 14 joint angle positions				
T. Li et al., 2018	PD	Patients with PD after DBS (24)	Ordinary 2D video camera	TUG sub-task segmentation	Frame classification algorithm to classify video frame in sub tasks of TUG test	Semi-controlled environments	Classification accuracies for the sub-tasks 'Walk,' 'Walk-Back,' and 'Sit-Back' are apparently higher than that of the other three sub-tasks	The results support that clinical parameters for the assessment of PD can be automatically acquired from TUG videos
Martinez et al., 2018	PD	Patients with PD (6); healthy subjects (6)	DARI system	BME of 16 different movements	UPDRS-III and BME of 16 different movements in six controls paired by age and sex were compared with those in PD populations with DBS in 'on' and 'off' states	Laboratory	A better performance in the BME was correlated with a lower UPDRS-III score. No statistically significant difference between patients in 'on' and 'off' states of DBS regarding BME	A potential use of the DARI system in PD classification
Pantzar-Castilla et al., 2018	CP	Participants with CP (18)	Kinect 2 for Xbox One	Gait variables (i.e., Knee flexion at initial contact; Maximum knee flexion at loading response; Minimum knee flexion in stance; Maximum knee flexion in swing)	Comparison of 2D MMC and 3D marker-based gait analysis methods for the selected variables	Laboratory	The reliability within 2D Markerless and 3D gait analysis was mostly good to excellent	2D MMC is a convenient tool that could be used to assess the gait in children with CP
Rammer et al., 2018	Pediatric manual wheelchair users	Pediatric manual wheelchair users (30)	Kinect 2.0	Upper extremity kinematics during manual wheelchair propulsion (i.e., joint range of motion and musculotendon excursion)	Kinematic parameters were used to develop and evaluate a markerless wheelchair propulsion	Laboratory	Inter-trial repeatability of spatiotemporal parameters, joint range of motion, and musculotendon excursion were all found to be significant	"A markerless wheelchair propulsion kinematic assessment system is a repeatable measurement tool for pediatric manual wheelchair users" (Rammer et al., 2018, p.10)

					biomechanical assessment system			
Langevin et al., 2019	PD	Patients with PD (127); healthy controls (127)	Webcam	Frequencies of hand movement in hand motor task	Comparison of the differences in the hand motion between the groups with and without PD	Home Setting	PD group had a mean frequency that is lower than the control group in the hand motor tasks	“Online framework that assesses features of PD could be introduced during a clinic visit to initially supplement the tool with personal support” (Langevin et al., 2019, p.19)
Lee et al., 2019	PD	Participants with PD that are receiving benefit from DBS (8)	LMC	PSUP, OPCL, and THFF tasks during ‘on’ and ‘off’ condition, amplitude, frequency, velocity, slope, and variance were extracted from each movement	Correlation of the kinematic features with the overall bradykinesia severity score (average MDS-UPDRS ratings across tasks)	Laboratory	An exhaustive LOSOCV assessment identified PSUP, OPCL, and THFF as the best task combination for predicting overall bradykinesia severity	“Data obtained from the LMC can predict the overall bradykinesia severity in agreement with clinical observations and can provide reliable measurements over time” (Lee et al., 2019, p.6)
Liu et al., 2019	PD	Patients with PD (60)	Camera	Periodic pattern of hand movements in finger tapping, hand clasping and hand pro/supination	Correlation analysis on each feature parameter and clinical assessment scores; Classification of bradykinesia	Semi-controlled environment	Classification accuracy in 360 examination videos is 89.7%	Reliable assessment results on Parkinsonian bradykinesia can be produced from video with minimal device requirement
Sato et al., 2019	PD	Patients with PD (117 in phase I and 2 in phase II); healthy controls (117)	Home video camera	Cadence , gait frequency, gait speed, step length, step width, foot clearance	Estimation of cadence of periodic gait steps from the sequential gait features using the short-time pitch detection approach	Structured environment	Cadence estimation of gait in its coronal plane in the daily clinical setting was successfully conducted in normal gait movies using ST-ACF	2D movies recorded with a home video camera is helpful in identifying an effective gait and calculate its cadence in normal and pathological gaits
Vivar et al., 2019	PD	Patients with PD (20)	LMC	Tremor levels measured during hand extension and pushing the ball action	Classification of tremor level in PD according to the MDS-UPDRS standard	Laboratory	The proposed method classified the patient measurements following MDS-UPDRS in tremor	“It is possible to classify the different levels of tremor in patients with PD using only two statistical features, such as homogeneity and contrast” (Vivar et al., 2019, p.12)

							levels 0, 1, and 2 with high accuracy	
Caruso et al., 2020	ASD	Infants with high risk of ASD (50); infants with low risk of ASD (53)	Video recording	Quantity of motion, centroid of motion, presence of repetitive movements in the motion of limbs	Kinematic parameters related to upper and lower limb movements in infants with low risk and high risk of ASD	Bed	Early developmental trajectories of specific motor parameters were different in high-risk infants later diagnosed with neurodevelopmental diseases from those of infants developing typically	"Computer-based analysis of infants' movements may support and integrate the analysis of motor patterns of infants at risk of neurodevelopmental diseases in research settings" (Caruso et al., 2020, p.12)
Chambers et al., 2020	Neuromotor disease	Infants at risk of neuromotor impairment (19); healthy infants (85)	GoPro cameras, YouTube video	Absolute position and angle, variability of posture, velocity of movement, variability of movement, complexity, left-right symmetry of movement	Extent of kinematic features from infants at risk deviate from the group of healthy infants as reflected by Naïve Gaussian Bayesian Surprise metric	Childcare facility, hospital, natural environment	Infants who are at high risk for impairments deviate considerably from the healthy group	"Markerless tracking promises to improve accessibility to diagnostics, monitor naturalistic movements, and provide a quantitative understanding of infant neuromotor disorders" (Chambers et al., 2020, p.15)
Fujii et al., 2020	Patients with gait disturbance	Patients with gait ataxia (6); control subjects (6)	Kinect 2, migrated to Azure Kinect	Gait parameters (e.g., walking speed and stride length)	Gait comparison between the patient group and the healthy subject group	Laboratory	Significant differences were observed between the patient group and the healthy subject group in terms of the mean value and variation of stride length	"A low-cost noninvasive motion capture device can be used for the objective clinical assessment of patients with stroke and PD who display manifestations of gait and motor deficits" (Fujii et al., 2020, p.213)
Hu et al., 2020	PD	Patients with PD (45)	Video	Gait parameters, motion patterns	Automatic FoG detection by fine-grained human action recognition method	Structured environment	The experimental results demonstrate the superior performance of the proposed method over the state-of-the-art methods	"Anatomic joint graph representation provides clinicians an intuitive interpretation of the detection results by localizing key vertices in a FoG video" (Hu et al., 2020, p.1900)

Krasowicz et al., 2020	CP	Patients with diagnosed ICP (8)	4DBODY system	TMFPI developed based on movement sequences	TMFPI compared with the assessment made according to the GMFM-88 scale	Laboratory	The system provided results agreeable with the clinical indicator GMFM-88 and with clinical observations of a PT	“The conducted assessments indicated that the use of dynamic 3D surface measurements is a promising direction of research and can provide valuable information on patient movement patterns” (Krasowicz et al., 2020, p.18)
Lin et al., 2020	PD	Patients with PD (121)	iPhone 6s Plus	Motor behaviors, including stability, completeness, and self-similarity	Quantification of motor behaviors in patients with PD and bradykinesia recognition by a periodic motion-based network consisting of an autoencoder and fully connected neural network	Laboratory	The proposed periodic motion model delivers the F-score of 0.7778 for bradykinesia recognition	Using single RGB video for bradykinesia recognition is easy and convenient for patients and doctors
Oña et al., 2020	PD	Patients with PD (20)	LMC	Manual dexterity in BBT	Evaluation the validity of VR-BBT to reliably measure the manual dexterity	Laboratory	VR-BBT significantly correlated with the conventional assessment of the BBT	“VR-BBT could be used as a reliable indicator for health improvements in patients with PD” (Oña et al., 2020, p.1)
Pang et al., 2020	PD	Patients with PD; healthy controls (22)	Logitech HD Pro C920 webcams	Hand motion in tap thumb to the finger, creating a fist, pronation and supination of hand and resting state	Measurement of parkinsonian symptomology using automated analysis of hand gestures	Structured environment	Behavior of patients with PD and control subjects can be distinguished by analyzing the detailed motion features of their hands/fingers	Automatic hand movement detection method may help clinicians to identify tremor and bradykinesia in PD
Sabo et al., 2020	Dementia	Older adults with dementia (14)	Kinect	Gait parameters including cadence, average and minimum margin of stability per step, average step width, coefficient of	Correlation and regression of gait features with clinical scores UPDRS and SAS	Hospital	Gait features extracted from both 2D and 3D videos are correlated to UPDRS-gait and SAS-gait scores of parkinsonism severity in gait	“Vision-based systems have the potential to be used as tools for longitudinal monitoring of parkinsonism in residential settings” (Sabo et al., 2020, p.1)

				variation of step width and time, the symmetry index of the step times, number of steps in the walking bout				
Schroeder et al., 2020	CP	High-risk infants (29)	Kinect v1	Infants' general movement	Correlation of expert GMA ratings of standard RGB videos with GMA ratings on SMIL motion videos of the same sequence	Clinical environment	GMA based on computer-generated virtual 3D infant body models closely corresponded to the established gold standard based on conventional RGB videos	SMIL motion video might capture the movement characteristics required for GMA of infants
Williams, Relton et al., 2020	PD	Patients with PD (20); control participants (15)	Smartphone	Bradykinesia assessed by finger tapping	ML models to predict no/slight bradykinesia or mild/moderate/ severe bradykinesia, and presence or absence of Parkinson's diagnosis	Clinical setting	SVM with radial basis function kernels predicted presence of mild/moderate/ severe bradykinesia with good accuracy. NB model predicted the presence of PD with moderate accuracy	The proposed approach supports the detection of bradykinesia without purchasing extra hardware devices
Williams, Zhao et al., 2020	PD	Patients with idiopathic PD (39); healthy controls (30)	Smartphone	Bradykinesia assessed by finger tapping	Correlation of machine learning models with clinical ratings of bradykinesia	Clinical setting	Computer measures correlated well with clinical ratings of bradykinesia	"The research provides a new tool to quantify bradykinesia. It could potentially be used to support diagnosis and monitoring of PD" (Williams, Zhao et al., 2020, p.5)
Zefinetti et al., 2020	SCI patients using a wheelchair	Patients with SCI (60)	Kinect v2	Kinematic data, including humeral elevation, horizontal abduction of humerus, humeral	Correlation between the movements and the patients' assessment	Laboratory	The measurements computed by the proposed system showed a good reliability for analyzing	"The proposed markerless solutions are useful for an adequate evaluation of wheelchair propulsion" (Zefinetti et al., 2020, p.18)

				rotation, elbow flexion, trunk flexion/extension of wheelchair propulsion			the movements of SCI patients' wheelchair propulsion	
Abbas et al., 2021	Schizophrenia	Patients with Schizophrenia (18); healthy controls (9)	Smartphone	Head movement	Comparison of head movement measurements between patients and healthy controls, relationship of head movement to schizophrenia symptom severity	Home setting/ Natural environment	Rate of head movement in participants with schizophrenia and those without differed significantly; head movement was a significant predictor of schizophrenia diagnosis	"Remote, smartphone- based assessments were able to capture meaningful visual behavior for computer vision-based objective measurement of head movement" (Abbas et al., 2021, p.29)
Ardalan et al., 2021	Neurodevelopmental Disorders	Children with 16p11.2 mutation (15); TD children (12)	A single point-and-shoot camera	Gait synchrony, balance parameters	Comparison of gait synchrony and balance in children with 16p11.2 mutation and TD children	Natural environment	Children with 16p11.2 mutation had significantly less whole-body gait synchrony and poorer balance compared to TD children	Remote video analysis approach facilitates the research in motor analysis in children with developmental disorders
Cao et al., 2021	PD	Patients with PD (18); healthy controls (42)	RGB camera	Shuffling step	Detection of shuffling step and severity assessment	Hospital	3D convolution on videos achieves an average shuffling step detection accuracy of 90.8%	Video-based detection method might facilitate more frequent assessment of FoG in a more cost-effective way
Hurley et al., 2021	Patients awaiting TKR who were attending POAC	Patients awaiting unilateral primary TKR (23)	BioStage™	LLM, VVM	Comparison of LLM and VVM performed clinically, radiologically, and using MMA	Laboratory	Discrepancies existed in LLM and VVM when evaluated using clinical, radiological, and MMA modalities	A MMC system alone may not be a suitable method to assess the patients for TKR
Kojovic et al., 2021	ASD	Children with ASD (169); TD children (68)	2D camera	Patterns of atypical postures and movements	Differentiation between children with ASD and TD	Clinical setting	The classification accuracy is 80.9% with the prediction	Remote machine learning-based ASD screening might be possible in the future

					using non-verbal aspects of social interaction by deep neural network		probability positively correlated to the overall level of symptoms of autism in social affect and repetitive and restricted behaviors domain	
Lee et al., 2021	Stroke	Patient with stroke (206)	Smartphone	Swing time asymmetry between paretic and non-paretic lower limbs while walking	Classification of dependence in ambulation by employing a deep model in 3D-CNN	Hospital	The trained 3D-CNN performed with 86.3% accuracy, 87.4% precision	"Monitoring ambulation using videos may facilitate the design of personalized rehabilitation strategies for stroke patients with ambulatory and balance deficits in the community" (Lee et al., 2021, p.9)
Li et al., 2021	PD	Patients with PD (157)	Video	Skeleton sequence from finger-tapping test	Classification of finger tapping performance according to MDS-UPDRS score	Hospital	Fine-grained classification net- work achieved an accuracy of 72.4% and an acceptable accuracy of 98.3%	Vision-based assessment method has potential for remote monitoring of PD patients in the future
Mehdizadeh et al., 2021	Dementia	Individuals admitted to a specialized dementia inpatient unit (54)	Kinect v2	Gait variables, including gait stability, step length, step time variability, step length variability	Changes in quantitative gait measured over a period during a psychogeriatric admission	Laboratory	Results showed that there was deterioration of gait in this cohort of participants, with men exhibiting greater decline in gait stability	"Quantitative gait monitoring in hospital environments may provide opportunities to intervene to prevent adverse events, decelerate mobility decline, and monitor rehabilitation outcomes" (Mehdizadeh et al., 2021, p.1)
Negin et al., 2021	ASD	Children with or without ASD (108)	YouTube video	Spinning, head banging, hand action, arm flapping	Recognition of ASD associated behaviors	Natural environment	HOF descriptor achieves the best results when used with MLP classifier	"An action-recognition-based system can be potentially used to assist clinicians to provide a reliable, accurate, and timely diagnosis of ASD disorder" (Negin et al., 2021, p.145)

Nguyen-Thai et al., 2021	CP	Videos of infants who were at 14-15 weeks post-term age (235)	Smartphone	FM	Predicted the risk of CP by FM	Natural environment	Pose sequences were strong signals that retained motion information of joints and limbs while ignoring irrelevant, distracting visual artifacts	A STAM model can be used to identify infants at risk of cerebral palsy via video-based infant movement assessment
Rupprechter et al., 2021	PD	Patients with PD (729)	Smartphone	Leg ratio difference, vertical angle of the body, horizontal angle of the ankles and wrists, horizontal distance between the heels, speed of the ankles, step frequency	Estimation of severity of gait impairment in Parkinson's disease using a computer vision-based methodology	Hospital and offices	Step frequency point estimates from the Bayesian model were highly correlated with manually labelled step frequencies	"Automated systems for quantifying Parkinsonian gait have great potential to be used in combination with, or the absence of, trained assessors, during assessments in the clinic or at home" (Rupprechter et al., 2021, p.18)
Stricker et al., 2021	PD	Patients with PD (24)	Standard camera	Step length	Reliability of step length measurements from 2D video in patients with stroke; comparison of the step lengths of patients with/without a recent history of falls	Structured environment	Step length measurements from the video demonstrated excellent intra- and inter-rater reliability; patients with PD who had experienced a fall within the previous year demonstrated shorter step lengths	"Quantification of step length from 2D video may offer a feasible method for clinical use" (Stricker et al., 2021, p.252)
Wei et al., 2021	Wheelchair user	Full-time wheelchair users (91)	Kinect	Wheelchair transfer motions including joint angles and positions	ML algorithm for evaluation of the quality of independent wheelchair sitting pivot transfers	Structured environment	Accuracies of the ML classifier were over 71%.	"The results show promise for the objective assessment of the transfer technique using a low cost camera and machine learning classifiers" (Wei et al., 2021, p.1)
Williams et al., 2021	Tremor	Patients with PD (9); patients with essential tremor (5); patient	Smartphone	Hand tremor at rest and in posture	Measurement of hand tremor frequency	Clinical setting	There was less than 0.5 Hz difference between the computer vision and accelerometer	"The study suggests a potential new, contactless point-and-press measure of tremor frequency within standard clinical settings,

		with functional tremor (1)					frequency measurements in 97% of the videos	research studies, or telemedicine” (Williams et al., 2021, p.69)
Wu et al., 2021	PD	Patients with PD (7)	LMC	Hand kinematic in finger tapping hand opening and closing, and hand pronation and supination	Quantification of the motor component of bradykinesia	Laboratory	Average velocity and average amplitude of pronation/supination isolate the bradykinetic feature	“The LMC achieved promising results in evaluating PD patients’ hand and finger bradykinesia” (Wu et al., 2021, p.1)
Ferrer-Mallol et al., 2022	DMD	Patients with DMD (8)	Smartphone	Time, pattern of movement trajectory, smoothness and symmetry of movement	Quantitative measurement of the motor performance of the patients in the functional tasks	Home	Computer vision analysis allowed characterization of movement in an objective manner	“Video technology offers the possibility to perform clinical assessments and capture how patients function at home, causing minimal disruption to their lives” (Ferrer-Mallol et al., 2022, p.16)
Guo et al., 2022	PD	Patients with PD (48); healthy controls (11)	RGB camera	Finger movement in finger tapping test	Classification of PD from finger tapping video	Structured environment	Classification accuracy is of 81.2% on a newly established 3D PD hand dataset of 59 subjects	Novel computer-vision approach could be effective in capturing and evaluating the 3D hand movement in patients with PD
Lonini et al., 2022	Stroke	Patients with stroke (8)	Digital RGB video camera	Gait parameters including cadence, double support time, swing time, stance time, and walking speed	Comparison of gait parameters obtained from clinical system and video-based method for gait analysis	Laboratory	Absolute accuracy and precision for swing, stance, and double support time were within 0.04 ± 0.11 s	“Single camera videos and pose estimation models based on deep networks could be used to quantify clinically relevant gait metrics in individuals poststroke” (Lonini et al., 2022, p.9)
Morinan et al., 2022	PD	Videos from patients with PD (447)	Smartphone	Body kinematics including movement, velocity variation and smoothness	Estimation of ‘arising from chair’ task score in MDS-UPDRS	Clinical setting	Compute-vision based method can accurately quantify PD patients’ ability to perform the arising from chair action	Computer-vision based approach might be used for quality control and reduction of human error by identifying unusual clinician ratings

Vu et al., 2022	CD	Patients with CD (93)	Video recording	Peak power, frequency, and directional dominance of head movement	Quantification of oscillatory and directional aspects of HT	Structured environment	Computer-vision based method of quantification of HT exhibits convergent validity with clinical severity ratings	"Objective methods for quantifying HT can provide a reliable outcome measure for clinical trials" (Vu et al., 2022, p.7)
Morinan et al., 2023	PD	Patients with PD (628)	Consumer-grade hand- held devices	Movements during the bradykinesia examinations including finger tapping, hand movement, pronation-supination, toe tapping, leg agility	Quantification of bradykinesia according to clinician ratings	Clinical setting and laboratory	Classification model estimate of composite bradykinesia had high agreement with the clinician ratings	Computer vision technology can be adopted in the current clinical workflows with smartphones or tablet devices
Song et al., 2023	ASD	Children with ASD (29); TD child (1)	RGB camera	Head and body movement during response to name behavior	Prediction of ASD by response to name behavior	Structured environment	The prediction method is highly consistent with clinical diagnosis	Automatic detection method can help to carry out remote autism screening in the early developmental stage of children

3D-CNN: 3D Convolutional Neural Network, AC: Adhesive Capsulitis, ALS: Amyotrophic Lateral Sclerosis, ALSFRS-R: Revised Amyotrophic Lateral Sclerosis Functional Rating Scale, ASD: Autism Spectrum Disorder, BME: Body Motion Evaluation, CCD: Commercial Digital Charge-coupled Device, CD: cervical dystonia, CP: Cerebral Palsy, CV: Computer Vision, DBS: Deep Brain Stimulation, DMD: Duchenne muscular dystrophy, FM: Fidgety Movement, FMA: Fugl-Meyer Assessment, FoG: Freezing of Gait, FoG: Freezing of gait, SAS: Simpson- Angus Scale, FVC: Forced Vital Capacity, FXS: Fragile X Syndrome, GMA: General Movement Assessment, GMFM-88: Gross Motor Function Measure-88, HOF: Histogram of Optical Flow, HT: Head Tremor, ICC: Intra-Class Correlation Coefficient, ICP: Infantile Cerebral Palsy, KPCA: Kernel-based Principal Component Analysis, LDA: Linear Discriminant Analysis, LLM: Leg Length Measurement, LMC: Leap Motion Controller, LOSOCV: Leave-One-Subject-Out Cross-Validation, LR: Logistic Regression, MDS-UPDRS: Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale, ML: Machine Learning, MLP: Multi-layer Perceptron, MMA: Markerless Motion Analysis, MMC: Markerless Motion Capture, NB: Naïve Bayes, NN: Neural Network, OPCL*:* Hand Opening/Closing, PANU: Proximal Arm Non-Use, PCA: Principal Component Analysis, PD: Parkinson's Disease, PFP: Patellofemoral pain, POAC: Pre-Operative Assessment Clinic, POST: Postural Tremor, PSUP: Forearm Pronation-Supination, PT: Physiotherapist, RGB: Red Green Blue, ROM: Range of Motion, RSA: Relative Surface Area, SCI: Spinal Cord Injured, SDK: Software Development Kit, SMIL: Skinned Multi-Infant Linear Body Model, SST: Simple Shoulder Test, ST-ACF: short-time autocorrelation function, STAM: Spatio-Temporal Attention-Based Model, SVM: Support Vector Machine, TD: Typically Developing, THFF: Thumb Forefinger Tapping, TKR: Total Knee Arthroplasty, TMFPI: Trunk Mobility in the Frontal Plane Index, UDysPS: Unified Dyskinesia Rating Scale, UPDRS: Unified Parkinson's Disease Rating Scale, UPDRS-FT: Unified Parkinson's Disease Rating Scale-Finger Tapping, USCP: Unilateral Spastic Cerebral Palsy, VR: Virtual Reality, VVM: Varus/Valgus Knee Measurements

3.3 RESULTS

3.3.1 Literature search and study characteristics

A total of 4283 articles were identified, 278 of which were selected for full-text reading after removal of duplicates and irrelevancies, according to their abstracts (Figure 3.1). After next excluding 213 articles on the basis of the inclusion and exclusion criteria, 65 studies remained and were included in the final review (Figure 3.1). More than 40% of the studies applied MMC technology to assess a patient population with PD (*n* = 28) (Butt et al., 2018; Cao et al., 2021; Chen et al., 2011; Cho et al., 2009; Dranca et al., 2018; Guo et al., 2022; Hu et al., 2020; Khan et al., 2013; Langevin et al., 2019; Lee et al., 2019; Li et al., 2021; M. H. Li et al., 2018; T. Li et al., 2018; Lin et al., 2020; Liu et al., 2019; Martinez et al., 2018; Morinan et al., 2023; Morinan et al., 2022; Oña et al., 2020; Pang et al., 2020; Rupprechter et al., 2021; Sato et al., 2019; Stricker et al., 2021; Tupa et al., 2015; Vivar et al., 2019; Williams, Relton, et al., 2020; Williams, Zhao, et al., 2020; Wu et al., 2021) . Two other diseases that had commonly been measured by the MMC system were cerebral palsy (CP) (*n* = 6) (Adde et al., 2010; Chin et al., 2017; Krasowicz et al., 2020; Nguyen-Thai et al., 2021; Pantzar-Castilla et al., 2018; Schroeder et al., 2020) and stroke (*n* = 6) (Bakhti et al., 2018; Bonnechère et al., 2018; Kim et al., 2016; Lee et al., 2021; Lonini et al., 2022; Olesh et al., 2014). Four other studies focused on children with autism spectrum disorder (ASD) (*n* = 4) (Caruso et al., 2020; Kojovic et al., 2021; Negin et al., 2021; Song et al., 2023) while there are two studies focused on patients with schizophrenia (*n* = 2) (Abbas et al., 2021; Sá et al., 2015) and patients with dementia (*n* = 2) (Mehdizadeh et al., 2021; Sabo et al., 2020) respectively. The rest of the studies were conducted on various other diseases: Fragile X syndrome (FXS) (O'Keefe et al., 2013), chronic neck pain (Bahat et al., 2010), breast cancer (Gritsenko et al., 2015), spinal cord injury (SCI) (Zefinetti et al., 2020), amyotrophic lateral sclerosis (ALS) (de Bie et al., 2017), adhesive capsulitis of shoulder (AC) (Lee et al., 2015), dystrophinopathy (Lowes et al., 2013) and neuromotor diseases (Chambers et al., 2020) . There were also studies that had been conducted on wheelchair users (n = 2) (Rammer et al., 2018; Wei et al., 2021), people awaiting total knee arthroplasty (TKR) (Hurley et al., 2021), patients with gait disturbance (Fujii et al., 2020), patients with neurodevelopment disorders (NDD) (Ardalan et al., 2021), patients with tremor (Williams et al., 2021), patients with Duchenne muscular dystrophy (DMD) (Ferrer-Mallol et al., 2022), patients with cervical dystonia (CD) (Vu et al., 2022) and patients with a variety of diagnoses (Matsen et al., 2016). Table 3.1 summarizes the 65 selected studies.

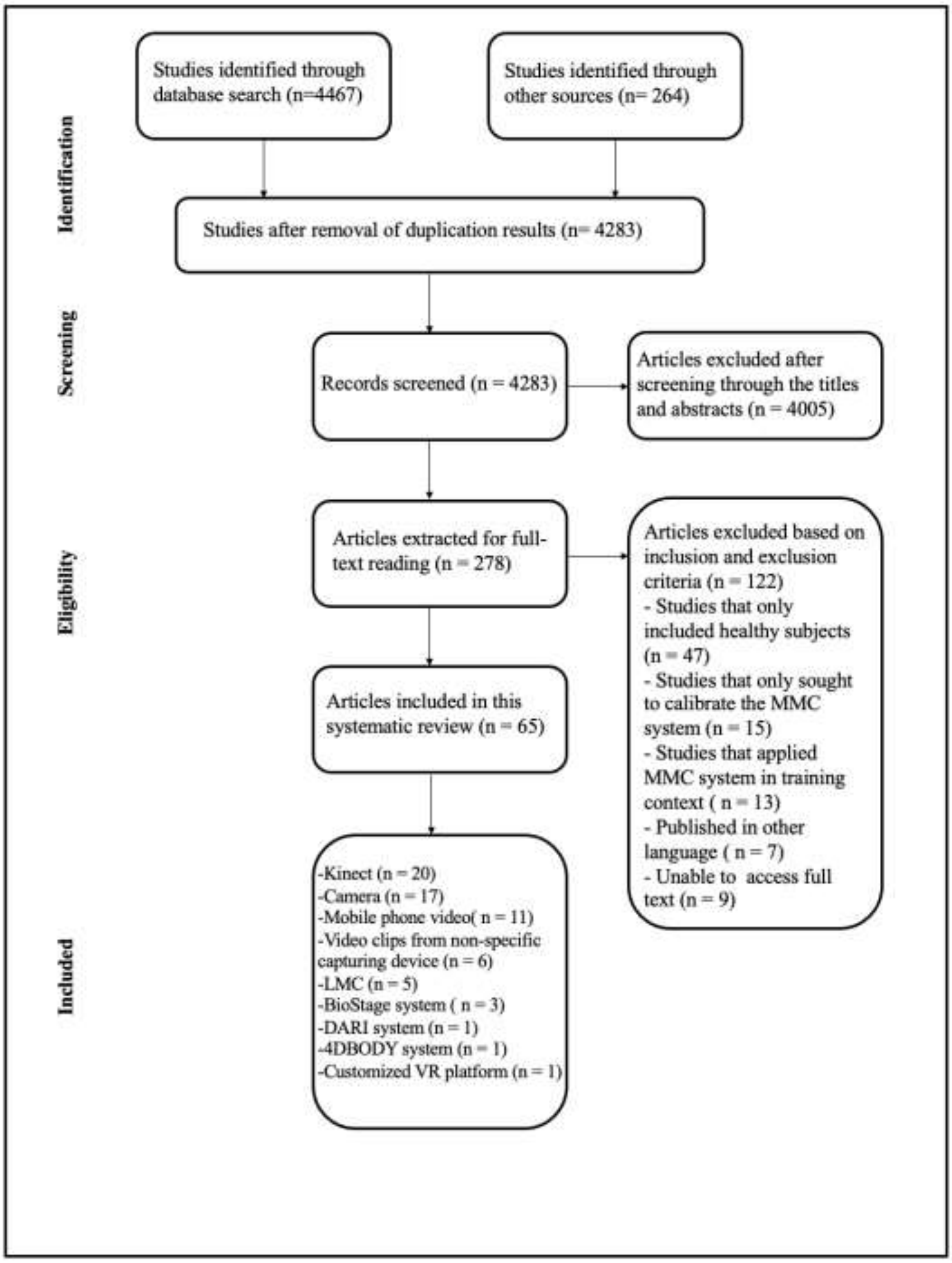

Figure 3.1 Flow chart for selection of the studies for this review

3.3.2 Body function/body part being measured

Of the 28 studies that assessed the PD population by using MMC technology, fourteen measured the hand's motor conditions to classify or to predict the severity of PD (Butt et al., 2018; Guo et al., 2022; Khan et al., 2013; Langevin et al., 2019; Lee et al., 2019; Li et al., 2021; Lin et al., 2020; Liu et al., 2019; Oña et al., 2020; Pang et al., 2020; Vivar et al., 2019; Williams, Relton, et al., 2020; Williams, Zhao, et al., 2020; Wu et al., 2021). These fourteen studies used the PD features of bradykinesia and tremor, as reflected during hand movements such as a finger-tapping exercise, to train machine-learning models to serve as classifiers. Of the remaining fourteen studies, four focused on using whole-body motion to classify PD (M. H. Li et al., 2018; Martinez et al., 2018; Morinan et al., 2023; Morinan et al., 2022), and the other ten measured gait features to detect gait disorder in people with PD (Cao et al., 2021; Chen et al., 2011; Cho et al., 2009; Dranca et al., 2018; Hu et al., 2020; T. Li et al., 2018; Rupprechter et al., 2021; Sato et al., 2019; Stricker et al., 2021; Tupa et al., 2015). The measured body function for the CP population by the MMC system included gait pattern, trunk mobility, general body movement, fidgety movements, and the level of proprioceptive ability (Adde et al., 2010; Chin et al., 2017; Krasowicz et al., 2020; Nguyen-Thai et al., 2021; Pantzar-Castilla et al., 2018; Schroeder et al., 2020). The six studies on stroke survivors applied

MMC technology to measure their upper limb movement, including their motor function, movement velocity, and joint angle (Bakhti et al., 2018; Bonnechère et al., 2018; Kim et al., 2016; Olesh et al., 2014) as well as lower limb movement gait parameters and walking pattern (Lee et al., 2021; Lonini et al., 2022). The studies that worked on the ASD population mainly focused on prediction of diagnosis of ASD by children's behavioral patterns (Caruso et al., 2020; Kojovic et al., 2021; Negin et al., 2021; Song et al., 2023). The measured areas in the studies that applied MMC technology in patients with other types of diseases varied, and the details are listed in the summary table (Table 3.1).

3.3.3 Details of measurement and efficacy

The applications of the MMC systems in measurement were classified into several categories. Sixteen out of the 65 selected studies used MMC technology in symptoms identification in disease populations (Butt et al., 2018; Dranca et al., 2018; Khan et al., 2013; Lee et al., 2021; Lee et al., 2019; M. H. Li et al., 2018; T. Li et al., 2018; Negin et al., 2021; Oña et al., 2020; Rupprechter et al., 2021; Song et al., 2023; Tupa et al., 2015; Vivar et al., 2019; Williams et al., 2021; Williams, Relton, et al., 2020; Wu et al., 2021). Butt and colleagues attempted to distinguish patients with PD from healthy subjects by features of their hand movements, reporting that their Leap Motion

Controller (LMC) system together with the machine-learning models did not provide a reliable measurement for the PD symptoms (Butt et al., 2018). Fifteen studies focused on comparing the movement patterns of the disease populations and a healthy population, with all of them reporting a significant difference in at least one of the measured parameters including gait parameters, hand movement patterns, head movement patterns and general body movements (Abbas et al., 2021; Adde et al., 2010; Ardalan et al., 2021; Bahat et al., 2010; Bonnechère et al., 2018; Caruso et al., 2020; Chambers et al., 2020; Cho et al., 2009; Fujii et al., 2020; Kojovic et al., 2021; Langevin et al., 2019; Martinez et al., 2018; O'Keefe et al., 2013; Pang et al., 2020; Sá et al., 2015). Fifteen studies applied MMC technology to detect and identify movement limitations or specific movement patterns of patients with certain diseases, and significant parameters that indicate movement abnormity including bradykinesia, shuffling gait, abnormal walking pattern, and tremor were identified (Cao et al., 2021; Chen et al., 2011; de Bie et al., 2017; Ferrer-Mallol et al., 2022; Gritsenko et al., 2015; Guo et al., 2022; Hu et al., 2020; Krasowicz et al., 2020; Lin et al., 2020; Lonini et al., 2022; Mehdizadeh et al., 2021; Nguyen-Thai et al., 2021; Sato et al., 2019; Schroeder et al., 2020; Stricker et al., 2021). Two studies used the MMC system to measure range of motion (ROM), and they suggested MMC could be an alternative to the goniometer as a tool for ROM assessment (Lee et al., 2015; Matsen et al., 2016). Three studies used the MMC system as a tool to analyze the wheelchair propulsion skills of wheelchair users (Rammer et al., 2018; Wei et al., 2021; Zefinetti et al., 2020). Ten studies correlated or compared the MMC measurements with clinical assessment scales (Bakhti et al., 2018; Kim et al., 2016; Li et al., 2021; Liu et al., 2019; Lowes et al., 2013; Morinan et al., 2023; Morinan et al., 2022; Olesh et al., 2014; Sabo et al., 2020; Vu et al., 2022). Among the other three studies, one applied MMC technology in a comparison with the optic marker system (Pantzar-Castilla et al., 2018), one used it to measure leg length (Hurley et al., 2021), and one used it as a tool to assess proprioception (Chin et al., 2017). Only one study reported unsatisfactory results, claiming that the use of the MMC system alone to measure leg length was not accurate (Hurley et al., 2021). The details are listed in the summary table (Table 3.1).

3.3.4 Types of MMC systems

Twenty studies used Kinect in their research, thus making Kinect the most popular MMC system used in the selected studies (Bakhti et al., 2018; Bonnechère et al., 2018; Chin et al., 2017; de Bie et al., 2017; Dranca et al., 2018; Fujii et al., 2020; Gritsenko et al., 2015; Kim et al., 2016; Lee et al., 2015; Lowes et al., 2013; Matsen et al., 2016; Mehdizadeh et al., 2021; Olesh et al., 2014; Pantzar-Castilla et al., 2018; Rammer et al., 2018; Sabo et al., 2020; Schroeder et al., 2020; Tupa et al., 2015; Wei et al., 2021; Zefinetti et al., 2020). Sixteen studies used camera including RGB camera, digital video camera, GoPro camera and webcam (Adde et al., 2010; Ardalan et al., 2021; Cao et al., 2021; Chen et al., 2011; Guo et al., 2022; Kojovic et al., 2021; Langevin et al., 2019; Lee et al., 2019; M. H. Li et al., 2018; T. Li et al., 2018; Liu et al., 2019; Lonini et al., 2022; Pang et al., 2020; Sato et al., 2019; Song et al., 2023; Stricker et al., 2021), while twelve studies analyzed patients' movement by using smartphone or mobile tablet videos (Abbas et al., 2021; Ferrer-Mallol et al., 2022; Khan et al., 2013; Lee et al., 2021; Lin et al., 2020; Morinan et al., 2023; Morinan et al., 2022; Nguyen-Thai et al., 2021; Rupprechter et al., 2021; Williams et al., 2021; Williams, Relton, et al., 2020; Williams, Zhao, et al., 2020). Six studies performed the motion analysis from YouTube video or video recordings that captured by nonspecific capturing device (Caruso et al., 2020; Chambers et al., 2020; Hu et al., 2020; Li et al., 2021; Negin et al., 2021; Vu et al., 2022). Five studies used the leap motion controller (LMC), an optical hand-tracking module (Butt et al., 2018; Lee et al., 2019; Oña et al., 2020; Vivar et al., 2019; Wu et al., 2021). The rest of the studies applied the BioStage™ System (Organic Motion Inc., N.Y., USA) (n = 3) (Hurley et al., 2021; O'Keefe et al., 2013; Sá et al., 2015); the DARI Motion platform's motion capture system (n = 1) (Martinez et al., 2018); the 4DBODY System (n = 1) (Krasowicz et al., 2020), and a nonspecific customized motion capture system (n = 1) (Bahat et al., 2010). Table 3.2 describes and compares the characteristics of these seven types of MMC systems in terms of their mechanisms, set-up procedures, relative costs, the body part(s) that can be captured, and the systems' methods of data extraction and analysis.

Table 3.2 Comparison of the MMC Systems

MMC system	Mechanisms	Relative cost	Assessable Body parts	*Portability*	Set-up procedure	Methods of data extraction and analysis
Kinect	Monochrome CMOS sensor and infrared projector measures player's body by transmitting invisible near-infrared light, data are then processed by algorithms	Low	Whole body except fine hand movement	Yes	Simple	Data can be extracted by the Microsoft Kinect algorithm, and offline analysis can be performed using software such as R or MATLAB
Camera	2D images are captured directly by camera	Low	Whole body	Yes	Simple	Data is commonly analyzed by pose estimation algorithm, and kinematic features are extracted from the joint trajectories
LMC	Hand movements captured by two monochromatic IR cameras and three infrared LEDs and a rather "complex math algorithm" are used to process the raw data	Low	Hand and finger movement	Yes	Simple	Data can be obtained from the LMC SDK
BioStage™	3D images captured by high-speed color cameras and data are analyzed by computer vision software	High	Whole body	No	Complicated	The 3D motion data can be analyzed using the Motion Monitor software

Smartphone	Mobile phone camera is used to capture the movement directly	No extra cost needed	Whole body	Yes	Simple	Specific algorithms are required to analyze the video image
DARI Motion system	Uses eight high-speed cameras placed around the subject and a state-of-the-art computer-vision engine to collect whole-body data, including the fastest motions	High	Whole body	No	Complicated	Data analyzed by images captured by eight high-speed cameras using the software provided by the DARI Motion company
4DBODY System	Uses a single-frame structured light illumination method to allow the registration of the shape of body surface with a frequency of up to 120 Hz	High	Whole body	No	Complicated	Data from 4D measurement sequences can be extracted by the FRAMES software package
Customized motion capture system	Two main components: an electromagnetic tracker and an HMD. The tracker sampled motion via two sensors at 60 Hz each.	Not mentioned	Particularly neck and trunk movement	Not mentioned	Not mentioned	Tracking data can be analyzed by MATLAB software

CMOS: Complementary Metal Oxide Semiconductor, HMD: Helmet-mounted Displays, LED: Light-emitting Diode, LMC: Leap Motion Controller, SDK: *Software Development Kit*

3.4 DISCUSSION

Our results revealed that most of the research applications of an MMC system for measurement were with patient groups with physical disabilities, and more than half of the studies assessed the PD and CP populations. A possible reason for this trend could be that both PD and CP have obvious and well-defined physical signs and symptoms and abnormal movements. PD is characterized by the presence of tremor, bradykinesia, and rigidity during movement (Poewe et al., 2017), whereas patients with cerebral palsy demonstrate spasticity, ataxia, rigidity in movement, and the like (Rosenbaum et al., 2006). The characteristic types of movement in these two groups of patients might be especially favorable for detection and analysis by the MMC system because of the significant homogeneity in the patients' movement patterns. Applications of an MMC system for measurement in other kinds of physical disabilities have been limited, and that was the case in this review, but the heterogeneous disease types that were evaluated in the selected studies suggest the possibility of a high variety of generalized uses of MMC technology in assessing different types of patients.

In addition to the use of MMC systems in applications involving physical disabilities that demonstrate observable physical symptoms, it was noteworthy that such systems were also applied in patients with mental illness and NDD, in an attempt to deduce the presence of movement markers for mental disorder and the behavior associated with NDD. Experimental use of MMC technology in patients with mental illness and NDD suggests an entirely new trend for the application of MMC technology in the clinical field. Heretofore, motion tracking has been used in targeted patients with physical disabilities, because the analysis of their movements can provide necessary information and data about their level of impairment, and that in turn can indicate their recovery progress. However, although clinical observations have demonstrated that there is a difference between the movement patterns of patients with mental illness and those of healthy individuals, application of motion capture systems to assess the physical ability of patients with mental illness is still quite limited (Walther et al., 2020). Since traditional marker-based systems for motion analysis are time-consuming to set up given that it requires calibration procedure and attachment of markers on the body, using the traditional motion analysis marker systems might not be cost-effective to study the motion dysfunctions in patients with mental illness whose cognitive functions are predominantly affected. In fact, previous studies on motion detection of patients with mental illness adopted the fuzzy movement method, and precise actions and movement patterns have been less emphasized (Walther et al., 2014). Therefore, the development of MMC technology allows motion capture in a more cost-effective way, and that improvement may facilitate future scientific investigations of movement patterns and motor functions in patients with mental illness. Identifying the risk of NDD by extracting the children's behavioral features with the help of computer-vision technology also proposed a new direction of early screening of NDD (de Belen et al., 2020), in which children's developmental conditions can be closely monitored in their familiar environment without the need of attachment of markers on the infants' body . Similarly, the studies that have applied the MMC system to compare the motion patterns of a disease population and a healthy population provide evidence for the technology's use to identify biomarkers for certain diseases. MMC technology may also contribute to the development and use of big data for future AI screening for diseases, based on body movements. The combination of MMC technology and a machine-learning algorithm in classification of CP in infants by Nguyen-Thai and colleagues (2021) is one of the good examples that demonstrates how MMC technology can help in the preliminary screening of diseases. Compared with screening methods for traditional diseases, which depend heavily on behavioral observations by parents or on subjective self-reported questionnaires (Horwitz et al., 2016), MMC technology, which identifies symptoms via movement detection, could be a more objective method for early screening for diseases, facilitating early identification of a disease and thus improving the prognosis for rehabilitation, as well as providing a tool for evaluation before and after rehabilitation.

In contrast to using MMC technology for symptoms identification or for detection of differences in movement patterns between disease groups and their healthy counterparts, other studies applied MMC technology as a direct clinical measurement tool. Although the use of the MMC system to measure leg length was found to be inaccurate (Hurley et al., 2021), the use of Kinect to measure ROM was found to be reliable (Lee et al., 2015; Matsen et al., 2016). These findings suggest that MMC technology might have the potential to serve as an alternative clinical assessment tool. MMC technology also provides a new approach to assessing functional or cognitive abilities, such as objectively evaluating proprioception, which previously relied heavily on manual evaluations by rehabilitation therapists. However, future studies on the measurement accuracy and the validity of MMC technology as a clinical measurement tool are warranted.

Microsoft Kinect, the most commonly used MMC system in the studies in this review, is a relatively low-cost, commercially available system that captures and analyzes whole-body movement. Kinect enables the capture of real-time whole body gross movements, but it appears to be less sensitive in tracking fine hand movements (Galna et al., 2014). Although many of the studies used Kinect in their MMC measurements, the system has been out of production since 2017 and was no longer supported by the Xbox Series X, as announced by Microsoft (Weinberger, 2018). Future rehabilitation assessors that wish to use MMC technology may have to consider using other kinds of MMC systems, or the newly developed Azure Kinect. Our review also found that the most recent studies adopted the use of camera, smartphone, or video clips from the internet in conjunction with pose estimation algorithms and motion analysis algorithm, which has been rapidly developed in the recent years, to capture images and analyze motion. Human pose estimation method is a way of identifying and classifying human joints position using computer vision, for example, the open-source libraries OpenPose and PoseNet for human pose estimation are widely adopted in motion analysis (Nishani & Çiço, 2017). With the development of human pose estimation database containing various types of movement datasets, accuracy of pose estimation from video clips can be further enhanced by using a large set of training data. This facilitates the use computer vision methods for motion analysis in video clips captured by portable and low-cost camera rather than using specific sensors in the traditional way. The use of machine-learning algorithms allows meaningful information such as kinematic data to be extracted directly from regular videos, thus making the use of MMC technology much easier in motion capturing in a natural environment without the need to buy any extra hardware devices. Human pose estimation technology such as Convolutional Pose Machines (CPM) and convolution neural network (CNN) based methods which allow extraction of human movement information directly from video clips have been repeatedly tested by researchers (Andrade-Ambriz et al., 2022; Qiang et al., 2019) while human pose estimation application on analyzing movement in the disease populations were reported to be useful by the studies in our review (Abbas et al., 2021; Adde et al., 2010; Ardalan et al., 2021; Cao et al., 2021; Caruso et al., 2020; Chambers et al., 2020; Chen et al., 2011; Ferrer-Mallol et al., 2022; Guo et al., 2022; Hu et al., 2020; Khan et al., 2013; Kojovic et al., 2021; Langevin et al., 2019; Lee et al., 2021; Lee et al., 2019; Li et al., 2021; M. H. Li et al., 2018; T. Li et al., 2018; Lin et al., 2020; Liu et al., 2019; Lonini et al., 2022; Morinan et al., 2023; Morinan et al., 2022; Negin et al., 2021; Nguyen-Thai et al., 2021; Pang et al., 2020; Rupprechter et al., 2021; Sato et al., 2019; Song et al., 2023; Stricker et al., 2021; Vu et al., 2022; Williams et al., 2021; Williams, Relton, et al., 2020; Williams, Zhao, et al., 2020). Given that such trajectory extraction method is in rapid evaluation and is becoming more mature for promising identification of posture (Doosti et al., 2020; Luo et al., 2022; Wrench & Balch-Tomes, 2022), using hand-held camera or smartphone as the MMC system would be especially beneficial for understanding the motor performance of individuals in their daily living tasks, hence providing valuable information on levels of impairment and on the constraints that patients might encounter in their activities of daily living in their real-life environment. It is understandable that individuals, particularly young children and older people, might behave differently when they are placed for motion capturing in an unfamiliar laboratory or a simulated environment, thus risking the possibility that the motion analysis might not truly reflect the individuals' actual movement patterns (Tronick et al., 1979). The use of a smartphone camera combined with an algorithm for analysis could provide a solution to that problem and suggests the feasibility of assessing patients' daily movements through an MMC combination of a smartphone and an advanced algorithm. Since it does not require additional hardware for motion capturing, such a system would further broaden MMC technology for measurement and clinical assessment in the field of rehabilitation.

3.4.1 Limitations of the current MMC technology's applications for clinical measurement

Although the use of MMC system in motion capturing is becoming more common in movement measurement and helps us extend the application of MMC technology to clinical use, the technologies used for analyzing movement and distinguishing motor patterns are not yet generalized. Extracting and processing the data from MMC devices video files is still complicated and time-consuming, preventing the approach from being user-friendly for therapists to adopt as a quick clinical measurement tool. Further investigation is needed in order to design and develop a platform or software that can accurately analyze the movement patterns from videos in a more user-friendly and accurately way so as to further extend its application by clinicians. Although most of the studies that we included reported detecting a significant difference between the motor parameters of healthy control groups and those of disease populations, and while the identification of physical symptoms by the MMC system was also reported to be mostly effective, the sample sizes adopted by these studies were too small. A reliable AI tool for disease screening and classification will need to be trained and tested from a large set of data, to provide better specificity and sensitivity. In order to make use of MMC technology-assisted AI screening and early detection of diseases, a larger database that records movement patterns of both the disease population and the healthy population must be developed. Research on the development and selection of a suitable machine-learning or deep-learning model for classification is also needed. Ultimately, a cost-effective and accurate method for early patient screening will help therapists to identify individuals at risk and involve them in further, in-depth assessments, so that subsequent interventions can be made as early as possible. Moreover, it has been suggested that telerehabilitation could incorporate the use of MMC technology as a measurement tool for assessing and monitoring patients' prognosis and recovery, thus offering an objective and precise evaluation of patients' rehabilitation progress.

3.4.2 Limitation of this review

A limitation of this review is the potential overlap among some of the included studies. Several papers may report findings from the same population, which could result in redundancy and impact the overall conclusions. Future research should aim to clarify and differentiate the populations studied to enhance the robustness of the evidence.

3.5 CONCLUSIONS

This review explored the current uses of MMC technology to perform assessments in clinical situations. Most of the studies in the review combined MMC technology and a classification algorithm to perform symptoms identification for disease populations or to detect the differences in movement between disease groups and their healthy counterparts. Findings from these studies revealed a potential use of MMC technology for detecting and identifying disease signs and symptoms. The method might also contribute to early screening by using AI and big data to screen for diseases that lead to physical or mental disabilities. Further studies are warranted to develop and integrate MMC system in a platform that can be user-friendly and accurately analyzed by clinicians to extend the use of MMC technology in clinical measurement.

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CHAPTER 4

VALIDITY AND RELIABILITY OF UPPER LIMB KINEMATIC ASSESSMENT USING A MARKERLESS MOTION CAPTURE (MMC) SYSTEM: A PILOT STUDY

Chapter 4

Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System: A Pilot Study

ABSTRACT

A customized Markeress Motion Capture (MMC) system developed in iPad Pro with a LiDAR scanner was programmed using Xcode. The aim of developing such system is to serve as a portable and user-friendly MMC system for motion capturing which might further enhance the generalizability of MMC technology in the rehabilitation. To investigate the validity and reliability of this MMC system in measuring the kinematic parameters, this pilot study was conducted. In this study, the performance of measuring the active range of motion (AROM) and the angular waveform of the upper-limb-joint angles of healthy adults performing functional tasks by the MMC system was examined. Thirty healthy participants were asked to perform shoulder and elbow actions for the investigator to take AROM measurements, followed by four tasks that simulated daily functioning. Each participant attended two experimental sessions, which were held at least 2 days and at most 14 days apart. A Vicon system and two iPad Pros installed with our MMC system were placed at two different angles to the participants and recorded

their movements concurrently during each task. The AROM and the angular waveform of the upper-limb-joint angles. It is found that the iPad Pro MMC system underestimated the shoulder joint and elbow joint angles in all four simulated functional tasks. The MMC demonstrated good to excellent test-retest reliability for the shoulder joint AROM measurements in all four tasks. Our results showed that the maximal AROM measurements calculated by the MMC system had consistently smaller values than those measured by the goniometer. An MMC in iPad Pro system might not be able to replace conventional goniometry for clinical ROM measurements, but it is still suggested for use in home-based and telerehabilitation training for intra-subject measurements because of its good reliability, low cost, and portability. Further development to improve its performance in motion capture and analysis in disease populations is warranted.

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ORIGINAL RESEARCH

Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System: A Pilot Study

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Abstract

Objective: To investigate the validity and test-retest reliability of a customized markerless motion capture (MMC) system that used iPad Pros with a Light Detection And Ranging scanner at two different viewing angles to measure the active range of motion (AROM) and the angular waveform of the upper-limb-joint angles of healthy adults performing functional tasks.

Design: Participants were asked to perform shoulder and elbow actions for the investigator to take AROM measurements, followed by four tasks that simulated daily functioning. Each participant attended 2 experimental sessions, which were held at least 2 days and at most 14 days apart.

Setting: A Vicon system and 2 iPad Pros installed with our MMC system were placed at 2 different angles to the participants and recorded their movements concurrently during each task.

Participants: Thirty healthy adults (mean age: 28.9, M/F ratio: 40/60).

Interventions: Not applicable.

Main Outcome Measures: The AROM and the angular waveform of the upper-limb-joint angles.

Results: The iPad Pro MMC system underestimated the shoulder joint and elbow joint angles in all four simulated functional tasks. The MMC demonstrated good to excellent test-retest reliability for the shoulder joint AROM measurements in all 4 tasks.

Conclusions: The maximal AROM measurements calculated by the MMC system had consistently smaller values than those measured by the goniometer. An MMC in iPad Pro system might not be able to replace conventional goniometry for clinical ROM measurements, but it is still suggested for use in home-based and telerehabilitation training for intra-subject measurements because of its good reliability, low cost, and portability. Further development to improve its performance in motion capture and analysis in disease populations is warranted.

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4.1 INTRODUCTION

Due to recent advancements in motion analysis technology (Parks et al., 2019), markerless motion capture (MMC) system via a mobile device has recently been used for home-based rehabilitation and telerehabilitation (Finkbiner et al., 2017; Moral-Munoz et al., 2021; Vincent et al., 2022). The system offers the advantage of easy setup for motion capturing (mocap), facilitating measurements of active range of motion (AROM) and motion kinematics. Compared with conventional goniometry and the conventional marker-based mocap technology used in the laboratory, MMC allows users to capture a more objective, lifelike and natural form of human motion in a user-friendly and real-life environment.

However, most of the MMC systems in mobile devices are not specifically designed for clinical measurements and have not undergone validity and reliability testing. For example, smartphone videos have been used to analyze the symptoms of patients with Parkinson's Disease, but those videos were analyzed with sophisticated post-processing, in contrast to an MMC system that could allow motion data to be exported and analyzed directly (Williams, Relton, et al., 2020; Williams, Zhao, et al., 2020). The current use of mobile phone videos for determining patients' physical performance still depends heavily on prolonged post-processing to analyze movement kinematics.

A recently developed system using a Light Detection And Ranging (LiDAR) scanner installed on an iPhone and an iPad (Apple, Inc.) enables the detection of the depth of the environment, which might enhance the detection of human joint positions (Dong & Chen, 2017). The MMC system in mobile devices with a LiDAR scanner has also become more user-friendly for mocap through a software development kit (SDK) supported by the Apple software development platform (Farewik et al., 2022). However, a previous study only compared the motion tracking by an iPad Pro with a LiDAR scanner with a marker-based motion capture system from Vicon, to evaluate the lower limb (Farewik et al., 2022). Only a limited number of studies using the MMC approach have been done for the upper limb, even though that upper limb's accurate measurement is important for predicting the ability to perform activities of daily living (Gates et al., 2016). To date, it is uncertain whether an MMC system in mobile devices with a LiDAR scanner is accurate for measuring upper limb AROM and kinematic movement. Since it is also suggested that the different viewing angles of an MMC system might affect its capturing accuracy – that is, the limbs might be blocked by certain body parts during movement (Sarafianos et al., 2016) – this study investigated the validity and test-retest reliability of a customized MMC system using two iPad Pros with a LiDAR scanner from two different viewing angles for measuring the 1) AROM and 2) angular waveform of the upper limb joint angles during the performance of functional tasks by the healthy participants.

4.2 METHODS

This study adopted a criterion-based and concurrent validity, test-retest reliability design. A marker-based system by Vicon (Oxford Metrics Group, Oxford, UK) was used as the criterion measurement (Albert et al., 2020; Karunarathne et al., 2014; Saggio et al., 2020; Scano et al., 2020), and conventional goniometry was used for the manual AROM measurement of a single joint in a static position to determine concurrent validity.

4.2.1 Angle extractions from our MMC system

The normalized coordinates of the angles were relative to the center of the pelvis and defined as the origin of the ARKit's coordinate system. The adjacent 3D joint coordinates extractions calculated the angles of interest (AOI). Angle θ was calculated by the three joints – shoulder, elbow, and wrist – namely, $A, B, C \in R^3$or associated vectors $\overrightarrow{v_1} = A - B \; and \; \overrightarrow{v_2} = C - B,$ with the formula

$$\theta = \arccos \frac{v_1 \cdot v_2}{||v_1||_2||v_2||_2}$$

4.2.2 Sample Size Consideration

A two-tailed comparison at a type I error rate of 0.05, with 80% power, was assumed. Consideration of the data discard rate and the results of a power analysis based on the statistical parameters using G*Power3.1.9.2 (Faul et al., 2007) yielded a recommended sample size of approximately 30. The effect size was calculated to be 0.71, which is between a medium (0.5) and large effect (0.8) (Fidler & Cumming, 2013).

4.2.3 Participants

Adults from the community were recruited through a poster advertisement. Participants had to be at least 18 years old and without any history of upper limb or spinal disabilities. Informed written consent was obtained from all participants prior to the experiment. Ethical approval was obtained from the Human Subjects Research Ethics Committee of the Hong Kong Polytechnic University (Ref No.: HSEARS20220530001).

4.2.3.1 Inclusion criteria

To be eligible to take part in the study, participants had to 1) be adults aged 18 years old or above, 2) have no history of previous neurological or orthopedic diseases and no congenital disorders of the upper extremities and/or spine, 3) have adequate cognitive ability to understand instructions, and 4) be able to engage in at least a one-hour experimental session.

4.2.3.2 Exclusion criteria

Participants were excluded from participating in the study if they 1) were medically unstable, 2) had previous injuries or medical conditions of their upper extremities or spine that affected their upper limb functions, or 3) were severely allergic to glue or sellotape, both of which were essential for the placement of markers on the body.

4.2.4 Experimental setup

A total of nine Vero cameras were used in the Vicon motion capturing (mocap) system. For the MMC system recording, two iPad Pros were used, each mounted on a 1.5-m tripod stand and placed 1.8 m from the subject – one in front of the subject and the other to the person's side. We assumed that the effect of the iPad Pro mocap would be similar for its position on either the left or right lateral side of the body. The left side has been chosen as the convenient side, so we placed the second iPad Pro on the left lateral side at 35 degrees to the subject.

4.2.5 Equipment

4.2.5.1 Vicon system

The Vicon 3D mocap system with nine infrared high-speed cameras (Vicon, Oxford Metrics Ltd., Oxford, UK) and a sampling frequency of 120 Hz was used as the gold standard. The PlugInGait FullBody model for the upper arm (UPA) and forearm (FRM) was applied in this study, and the Vicon Nexus software (version 2.11) was used for data capture. A total of 23 markers were attached to the anatomical landmark positions on the participants' trunk and arms, according to the UPA and FRM models in the system. For markers attached on the trunk, a magnet was first directly attached to the skin of the landmark position on the participant, and then a reflective marker with magnet was attached on the clothes such that it adhered to the magnet that was stuck on the skin. Therefore, the marker placings on the truck did not move even if the clothes were moving. The marker positions are illustrated in Figure 4.1a and Figure 4.1b.

Figure 4.1a Anatomical landmarks of marker positions (Back View)

Figure 4.1b Anatomical landmarks of marker positions (Front View)

4.2.5.2 MMC system

The MMC system used to perform mocap in this study was developed using Xcode on the basis of the ARKit6 and RealityKit framework supported by an iPad Pro with a LiDAR scanner. The detection of the human body and the joint positions were extracted and realized through computer-vision algorithms using convolutional neural networks (CNNs). A total of 14 3D body-joint positions including the shoulder joints, elbow joints, wrist joints, pelvic joints, knee joints, hip joints, ankle joints, spinal cord segments C7 and T12 and the timestamp of the motion detection were captured by our motion-tracking platform. The capture frequency of the MMC system was set at 30 Hz.

4.2.6 Procedure

All participants were required to remove their jackets before the experiment. The Vicon system with nine infrared high-speed cameras and the MMC system installed on two iPad Pros that were placed at two different angles to the participant (one from the front, or “iPad Frontal”, and one from the lateral left side, or “iPad Lateral”) recorded each participant’s movements simultaneously (Figure 4.2). The experiment consisted of two parts: 1) measurement of the AROM of the participant’s shoulder joint and elbow joint, and 2) measurement of the angular waveform and the shoulder and elbow angles at the targeted position in simulated upper-limb functional tasks. The participants performed each task with their right hand followed by their left hand.

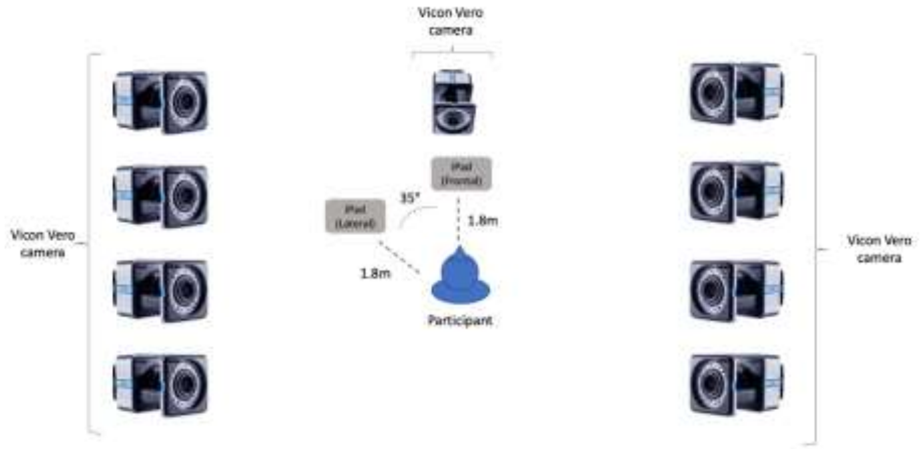

Figure 4.2 Environmental setup for the experiment: A total of nine Vero cameras were used in the motion capturing. Two iPad Pros, each placed on a 1.5-m tripod stand, were used in the MMC recording. One iPad Pro was placed 1.8 m in front of the subject and the other was placed laterally to the subject

In the first part of the experiment, each individual was instructed to perform four static positions: shoulder flexion, shoulder abduction, elbow flexion, and elbow extension. When each participant reached the maximal AROM for each movement of the targeted joint, they were instructed to maintain the position for AROM measurement by a trained occupational therapist.

In the second part, the participants were instructed to perform four sets of upper-limb daily tasks. They were instructed to maintain their positions when the target positions were reached. Task 1 was a hand-to-mouth task that simulated feeding; task 2 was a hand-to-head task that simulated grooming; task 3 was a hand-to-waist task that simulated the action of putting on trousers after toileting; and task 4 involved putting one hand to the contralateral underarm, which is a simulation of cleaning the body. Figure 4.3 illustrates the hand-to-head task.

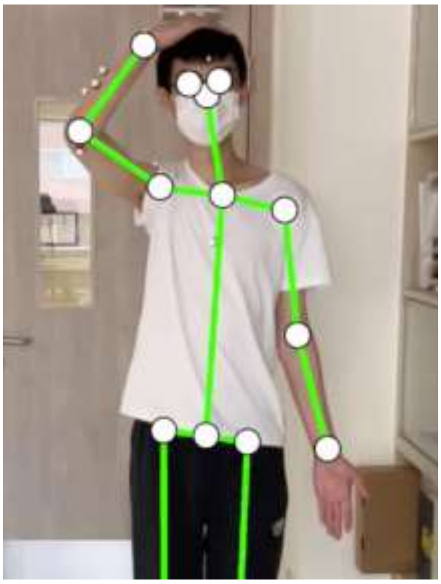

Figure 4.3 Hand-to-head task

Each participant attended two sessions of the experiment for the test-retest reliability evaluation. The second session of the experiment repeated the same procedure that had been done in the first session, and the two sessions were at least 2 days apart but at most 14 days apart. To reduce the intra-subject variability, each participant repeated each task three times. The first trial served as a practice, and the mean values of the second and third trials were used for data analysis.

4.2.7 Data Processing and Analysis

Any mocap data that could not be exported successfully in the Comma-Separated Values (CSV) format from either of the systems were filtered out in the data analysis session. The mocap data in both the iPad MMC and the Vicon systems were filtered and converted to 300Hz by MATLAB R2020a. The angular waveforms between the two systems were synchronized using a cross-correlation-based shift-synchronization technique.

The coefficient of multiple correlation (CMC) and the root-mean-squared error (RMSE) values were used to assess the validity of the angular waveforms generated by our iPad MMC and Vicon systems. CMC value below 0.3 indicates a weak correlation, while CMC value ranges 0.3 to 0.5 indicates a moderate correlation and the value of 0.5 to 0.7 indicates a strong correlation, a CMC value of 0.7 or above indicates a very strong correlation (Lee, 1971). The values of the angles at maximal AROM for the shoulder and elbow joints measured by the iPad (Frontal) and iPad (Lateral) were compared with those from the Vicon system and those from the manual goniometry, using paired *t*-tests with $p \leq 0.05$. The concurrent validity of the iPad MMC in terms of maximal AROM measurement was further analyzed by the Pearson's *r* correlation and the intraclass correlation coefficients (ICC) (2,*k*) (two-way random effects, absolute agreement) among the three approaches. A comparison of the angles when the target position was achieved for the upper limb joints in the simulated tasks was made only between the Vicon and the MMC systems.

The CMC and RMSE values of the waveforms generated by the iPad MMC in the first and second sessions were compared for the evaluation of test-retest reliability. The ICC (two-way mixed-effects, absolute agreement) was used to evaluate the reliability of the MMC system in measuring the maximal AROM of the shoulder and the elbow during the simulated tasks. Values of ICC were referenced to indicate poor, moderate, good, and excellent agreement, respectively (Koo & Li, 2016). All analyses were performed using IBM SPSS 26, and the CMC and RMSE values were generated by MATLAB R2020a.

4.3 RESULTS

Thirty-nine participants were recruited, but one dropped out after the first session. Participants with any data files that failed to be exported were regarded as having missing data and were excluded from the data analysis. After eliminating the participants with missing data, we had a total of 1,440 data sets from 30 participants in the final analysis (Figure 4.4).

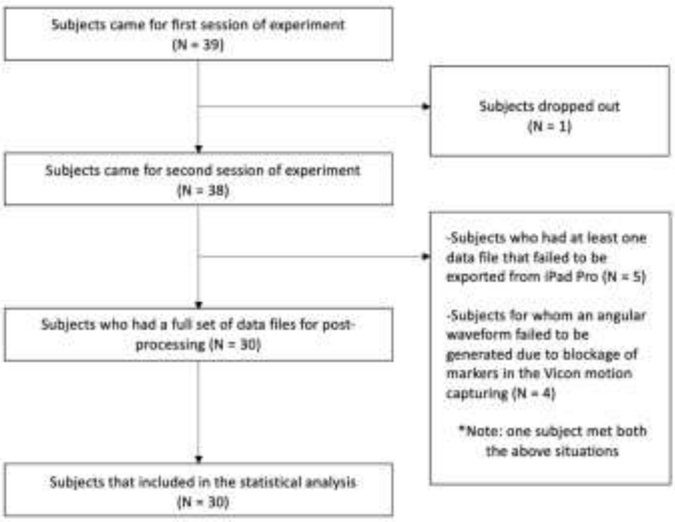

Figure 4.4 Flow chart of the study

The demographics of the participants are shown in Table 4.1.

Table 4.1 Characteristics of the participants

Characteristics: Study Variables	Participants (n = 30)
Age (years)	
Range	18 - 65
Mean (SD)	28.9 (11.8)
18 – 30 years old (%)	76.7
31 – 50 years old (%)	13.3
51 years old or above (%)	10
Gender (%)	
Male	40
Female	60
Height (cm)	
Range	152 - 178
Mean (SD)	165.5 (7.7)
Dominant Hand (%)	
Right	100
Left	0

The mean values of the maximum AROM measurements by the iPad (Frontal), the iPad (Lateral), the Vicon system, and the goniometry are shown in Tables 4.2 and 4.3.

Table 4.2 Validity of the AROM of the selected actions measured by iPad (Frontal)

Action	Mean AROM			Comparison 1 (iPad and Goniometer)				Comparison 2 (iPad and Vicon)			
	iPad (Frontal)	**Goniometer**	**Vicon**	Mean Difference (iPad – G)	P (G, iPad)	r	ICC	Mean Difference (iPad – V)	P (V, iPad)	r	ICC
Right											
Shoulder Flex	154.7 (9.0)	162.6 (9.8)	155.4 (12.9)	-7.9 (9.0)	<0.01	0.55*	0.40*	-0.7 (10.0)	0.69	0.63*	0.59*
Shoulder Abd	162.0 (7.9)	172.7 (8.2)	161.6 (13.4)	-10.7 (4.3)	<0.01	0.86*	0.43*	0.46 (8.8)	0.78	0.78*	0.69*
Elbow Flexion	133.7 (5.4)	147.3 (4.4)	144.2 (10.9)	-13.6 (5.7)	<0.01	0.32	0.03	-10.5 (11.2)	<0.01	0.20	0.06
Elbow Extend	10.7 (8.2)	-5.7 (5.6)	21.2 (9.3)	16.5 (8.9)	<0.01	0.20	0.06	-10.5 (8.1)	<0.01	0.58*	0.34*
Left											
Shoulder Flex	156.8 (10.2)	151.6 (9.4)	157.6 (12.2)	5.2 (7.9)	0.56	-0.24	0.45*	-0.8 (9.5)	0.65	0.65*	0.66*
Shoulder Abd	161.1 (11.8)	173.6 (8.5)	161.5 (12.6)	-12.5 (11.3)	<0.01	0.42*	0.23*	-0.3 (15.0)	0.90	0.25	0.33*
Elbow Flex	131.6 (6.3)	145.3 (4.1)	146.2 (9.2)	-13.7 (5.7)	<0.01	0.47*	0.12*	-14.6 (8.8)	<0.01	0.41*	0.18*
Elbow Extend	13.1 (9.2)	-6.6 (6.3)	22.9 (7.0)	19.7 (10.2)	<0.01	0.17	0.08*	-9.8 (9.8)	<0.01	0.63*	0.28*

Arom: Active range of motion
Note: [#]pair t test, [a]pearson's r correlation, *p<0.05

Table 4.3 Validity of the AROM of the selected actions measured by the iPad (Lateral)

Action	Mean AROM			Comparison 1 (iPad and Goniometer)				Comparison 2 (iPad and Vicon)			
	iPad (Lateral Side)	**Goniometer**	**Vicon**	Mean Difference (iPad – G)	#P (G, iPad)	a r	ICC (2,k)	Mean Difference (iPad – V)	#P (V, iPad)	a r	ICC (2,k)
Right											
Shoulder Flex	152.6 (9.4)	162.6 (9.8)	155.4 (12.9)	-10.1 (5.5)	<0.01	0.83*	0.48*	-2.9 (14.0)	0.27	0.23	0.20
Shoulder Abd	159.9 (8.6)	172.7 (8.2)	161.6 (13.4)	12.8 (5.5)	<0.01	0.78*	0.33*	-1.6 (10.7)	0.41	0.61*	0.55*
Elbow Flex	130.9 (4.4)	147.3 (4.4)	144.2 (10.9)	-16.4 (4.7)	<0.01	0.45*	0.06*	-13.3 (11.1)	<0.01	0.17	0.04
Elbow Extend	10.9 (8.3)	-5.7 (5.6)	21.2 (9.3)	-16.6 (10.2)	<0.01	-0.04	0.01	-10.3 (11.2)	<0.01	0.21	0.12
Left											
Shoulder Flex	154.2 (9.6)	151.6 (9.4)	157.6 (12.2)	2.5 (5.0)	0.78	-0.29	0.52*	-3.5 (12.2)	0.13	0.40*	0.30*
Shoulder Abd	163.3 (7.6)	173.6 (8.5)	161.5 (12.6)	-10.3 (4.5)	<0.01	0.85*	0.40*	1.8 (10.6)	0.36	0.54*	0.50*
Elbow Flex	129.7 (4.6)	145.3 (4.1)	146.2 (9.2)	-15.5 (3.9)	<0.01	0.61*	0.11*	-16.4 (8.5)	<0.01	0.41*	0.12*
Elbow Extend	11.6 (11.6)	-6.6 (6.3)	22.9 (7.0)	18.2 (9.6)	<0.01	0.37*	0.08*	-11.3 (8.3)	<0.01	0.57*	0.28*

AROM: Active range of motion

Note: #pair t test, apearson's r correlation, *p<0.05

Measurements by the iPad MMC on both sides were compared separately with those of the goniometry and the Vicon system (Table 4.2 and 4.3). For the iPad (Frontal), the paired *t*-test results suggested that there was no significant difference between the MMC and the Vicon measurements in terms of the measurement of maximal AROM in all of the shoulder actions, for both the left and right sides (the mean difference [MD] = –0.7° and 0.46° for right shoulder flexion and abduction, respectively; and MD = –0.8 ° and –0.3 ° for left shoulder flexion and abduction, respectively). The measurements of maximal AROM for elbow flexion and extension produced by the two MMC systems, on both sides, were significantly different from those obtained by the Vicon system (Frontal: MD = –10.5° for both the right elbow flexion and the right elbow extension; and MD = –14.6° and –9.8° for left elbow flexion and extension, respectively). All of the measurements using both the iPad (Frontal) and iPad (Lateral) were also significantly different from the measurements obtained by the manual goniometer, except for left shoulder flexion (Frontal: MD = 5.2°; Lateral: MD = 2.5°). The ICC values suggested that there was a poor agreement between the MMC system and the goniometer in all of the measurements, except for the left shoulder flexion measured by the iPad (Lateral) (ICC = 0.52).

Overall, compared with the measurements by the iPad (Lateral), the measurements by the iPad (Frontal) demonstrated a higher CMC value and a lower RMSE value for both the shoulder and elbow joints in the four functional tasks (Table 4.4). Regarding angle measurements, significant differences were found in all of the joint angles at the targeted positions measured by both the MMC and the Vicon systems, except for the measurement of left shoulder abduction/adduction during the hand-to-head task measured by the iPad (Lateral) (MD = 4.1°). The MMC system underestimated both the shoulder and elbow angles during the functional tasks, while the mean difference between the iPad (Frontal) and the Vicon system was generally smaller (the MD ranged from 5.2° to –25.8°) than that between iPad (Lateral) and the Vicon system (MD ranged from 4.1° to –33.3°). A poor-to-moderate agreement was found between the measurements obtained from the iPad (Frontal) and from the Vicon (ICC values between 0.14 and 0.75) systems in all four tasks (Table 4.5).

Table 4.4 Mean coefficient of multiple correlation (CMC) and mean of root mean square error (RMSE) of the angular waveform between the angular waveform of the MMC system and the Vicon system

	iPad (Frontal)		iPad (Lateral)	
Action	CMC (SD)	RMSE (SD)	CMC (SD)	RMSE (SD)
T1 Hand to mouth				
Right				
Shoulder Flex/Extend	0.69 (0.12)	15.82 (6.91)	0.58 (0.17)	21.36 (7.63)
Shoulder Abd/Add	0.72 (0.14)	7.93 (2.70)	0.63 (0.10)	10.05 (2.91)
Elbow Flex/Extend	0.65 (0.17)	21.68 (5.63)	0.66 (0.12)	23.40 (6.72)
Left				
Shoulder Flex/Extend	0.62 (0.12)	17.63 (7.64)	0.65 (0.05)	26.84 (6.21)
Shoulder Abd/Add	0.65 (0.13)	9.20 (2.92)	0.61 (0.07)	9.17 (2.88)
Elbow Flex/Extend	0.69 (0.10)	27.84 (7.76)	0.65 (0.08)	32.20 (8.59)
T2 Hand to head				
Right				
Shoulder Flex/Extend	0.63 (0.11)	19.25 (8.41)	0.54 (0.12)	41.72 (11.31)
Shoulder Abd/Add	0.65 (0.09)	16.42 (6.17)	0.61 (0.06)	23.56 (6.75)
Elbow Flex/Extend	0.48 (0.09)	36.77 (9.47)	0.39 (0.08)	49.68 (16.77)
Left				
Shoulder Flex/Extend	0.69 (0.09)	16.34 (4.22)	0.68 (0.08)	25.92 (6.35)
Shoulder Abd/Add	0.62 (0.10)	10.12 (5.92)	0.63 (0.11)	17.41 (5.56)
Elbow Flex/Extend	0.52 (0.07)	39.84 (9.65)	0.51 (0.08)	38.80 (11.93)

T3 Hand to waist				
Right				
Shoulder Flex/Extend	0.51 (0.07)	18.23 (7.46)	0.48 (0.11)	37.43 (8.64)
Shoulder Abd/Add	0.66 (0.07)	9.81 (3.31)	0.57 (0.10)	18.70 (4.22)
Elbow Flex/Extend	0.50 (0.07)	28.92 (6.36)	0.51 (0.09)	30.92 (7.46)
Left				
Shoulder Flex/Extend	0.50 (0.06)	13.70 (2.74)	0.55 (0.12)	14.28 (2. 32)
Shoulder Abd/Add	0.63 (0.06)	12.13 (3.56)	0.62 (0.07)	16.89 (3.24)
Elbow Flex/Extend	0.49 (0.07)	32.33 (7.82)	0.51 (0.09)	39.66 (6.79)
T4 Hand to contralateral underarm				
Right				
Shoulder Flex/Extend	0.73 (0.10)	14.61 (3.26)	0.70 (0.13)	22.27 (2.73)
Shoulder Abd/Add	0.74 (0.08)	17.14 (5.93)	0.76 (0.08)	15. 78 (3.30)
Elbow Flex/Extend	0.71 (0.10)	11.52 (4.70)	0.71 (0.11)	26.56 (5.61)
Left				
Shoulder Flex/Extend	0.68 (0.10)	16.22 (3.12)	0.66 (0.12)	32.85 (5.58)
Shoulder Abd/Add	0.73 (0.07)	11.23 (2.69)	0.75 (0.06)	14.72 (3.45)
Elbow Flex/Extend	0.74 (0.07)	14.77 (3.98)	0.72 (0.07)	8.97 (2.16)

Table 4.5 Validity of iPad (Frontal) and iPad (Lateral) compared with the Vicon system in four simulated functional tasks in terms of the angle at shoulder flexion, shoulder abduction, and elbow flexion

	Vicon	iPad Pro (Frontal)	Comparison with Vicon				iPad Pro (Lateral)	Comparison with Vicon			
Actions	Mean Angle (SD)	Mean Angle (SD)	Mean Difference (iPad – V)	#P	ar	ICC	Mean Angle (SD)	Mean Difference (iPad – V)	#P	ar	ICC
Task 1. Hand to mouth											
Right											
Shoulder Flex/Extend	49.5 (13.0)	36.0 (14.2)	-13.5	<0.01	0.77*	0.52*	32.4 (14.3)	-17.1	<0.01	0.70*	0.39*
Shoulder Abd/Add	-5.6 (13.8)	-0.4 (10.8)	5.2	<0.01	0.83*	0.74*	1.4 (11.8)	7.0	<0.01	0.62*	0.54*
Elbow Flex/Extend	127.7 (7.9)	121.3 (11.5)	-6.3	<0.01	0.40*	0.32*	117.0 (11.9)	-10.6	<0.01	0.30	0.18
Left											
Shoulder Flex/Extend	50.7 (10.8)	37.4 (11.8)	-13.3	<0.01	0.55*	0.33*	35.7 (12.6)	-15.0	<0.01	0.60*	0.33*
Shoulder Abd/Add	-10.5 (14.7)	-3.7 (12.2)	6.8	<0.01	0.78*	0.69*	-3.2 (11.3)	7.3	<0.01	0.80*	0.68*
Elbow Flex/Extend	128.4 (6.6)	117.3 (6.6)	-11.1	<0.01	0.57*	0.24*	117.5 (8.0)	-10.9	<0.01	0.22	0.10

Task 2. Hand to head										
Right										
Shoulder Flex/Extend	48.6 (14.2)	35.6 (14.5)	-13.0	<0.01	0.79*	0.56*	33.8 (13.7)	-14.8	<0.01	0.75*	0.48*
Shoulder Abd/Add	119.4 (13.3)	112.3 (12.9)	-7.1	<0.01	0.83*	0.73*	108.0 (12.1)	-11.5	<0.01	0.47*	0.35*
Elbow Flex/Extend	121.4 (7.9)	95.6 (8.9)	-25.8	<0.01	0.40*	0.70*	88.1 (7.5)	-33.3	<0.01	0.18	0.02
Left											
Shoulder Flex/Extend	53.1 (15.0)	39.4 (12.6)	-13.7	<0.01	0.47*	0.31*	35.9 (13.6)	-17.2	<0.01	0.37*	0.21*
Shoulder Abd/Add	122.6 (14.3)	128.2 (16.4)	5.6	<0.01	0.80*	0.75*	126.7 (13.4)	4.1	0.05	0.69*	0.67*
Elbow Flex/Extend	119.2 (7.0)	100.5 (5.4)	-18.6	<0.01	0.78*	0.14*	91.5 (7.1)	-27.7	<0.01	0.25	0.03
Task 3. Hand to waist											
Right											
Shoulder Flex/Extend	-19.7 (13.8)	-5.6 (9.8)	14.1	<0.01	0.83*	0.46*	-4.1 (8.1)	15.6	<0.01	0.62*	0.28*
Shoulder Abd/Add	43.0 (9.5)	36.6 (8.7)	-6.4	<0.01	0.75*	0.60*	36.3 (9.2)	-6.7	<0.01	0.72*	0.58*
Elbow Flex/Extend	96.3 (10.1)	79.6 (9.0)	-16.7	<0.01	0.78*	0.31*	77.7 (7.3)	-18.6	<0.01	0.70*	0.21*
Left											
Shoulder Flex/Extend	-12.9 (15.1)	-3.5 (11.1)	9.4	<0.01	0.88*	0.67*	-5.1 (13.0)	7.7	<0.01	0.86*	0.74*
Shoulder Abd/Add	42.5 (8.7)	34.0 (7.5)	-8.5	<0.01	0.58*	0.37*	34.5 (8.3)	-8.0	<0.01	0.60*	0.42*
Elbow Flex/Extend	99.1 (10.1)	79.8 (7.1)	-19.4	<0.01	0.81*	0.22*	78.8 (5.8)	-20.3	<0.01	0.59*	0.13*
Task 4. Hand to contralateral underarm											
Right											

Shoulder Flex/Extend	46.7 (13.4)	34.1 (11.0)	-12.6	<0.01	0.87*	0.56*	33.2 (10.5)	-13.5	<0.01	0.79*	0.47*
Shoulder Abd/Add	-17.8 (15.9)	-3.0 (6.3)	14.8	<0.01	0.64*	0.26*	-3.2 (5.8)	14.6	<0.01	0.72*	0.27*
Elbow Flex/Extend	109.4 (6.6)	104.1 (8.7)	-5.3	<0.01	0.67*	0.53*	100.0 (8.6)	-9.4	<0.01	0.54*	0.30*
Left											
Shoulder Flex/Extend	45.2 (11.7)	30.9 (8.9)	-14.3	<0.01	0.88*	0.44*	28.7 (7.6)	-16.5	<0.01	0.72*	0.28*
Shoulder Abd/Add	-18.5 (9.2)	-10.6 (7.8)	7.9	<0.01	0.89*	0.62*	-7.6 (6.4)	11.0	<0.01	0.67*	0.32*
Elbow Flex/Extend	106.9 (9.3)	100.1 (9.5)	-6.7	<0.01	0.93*	0.74*	101.9 (10.4)	-5.0	<0.01	0.70*	0.62*

NOTE: [#]pair t test, [a]pearson's r correlation, *p<0.05

The CMC and RMSE values of the angular waveforms and the ICC values (two-way mixed-effects, absolute agreement) of the AROM at the targeted positions are shown in Table 4.6.

Table 4.6 Test-retest reliability of iPad (Frontal) and iPad (Lateral) between the two sessions in terms of the CMC, RMSE, and ICC of the joints at the targeted position

Action	iPad (Frontal)			iPad (Lateral)		
	CMC	RMSE	ICC	CMC	RMSE	ICC
Right (AROM)						
Shoulder Flex	NA	NA	0.42*	NA	NA	0.48*
Shoulder Abd	NA	NA	0.55*	NA	NA	0.59*
Elbow Flex	NA	NA	0.02	NA	NA	0.32*
Elbow Extend	NA	NA	0.04	NA	NA	0.11
Left (AROM)						
Shoulder Flex	NA	NA	0.63*	NA	NA	0.80*
Shoulder Abd	NA	NA	0.17	NA	NA	0.50*
Elbow Flex	NA	NA	0.13	NA	NA	0.35*
Elbow Extend	NA	NA	0.23	NA	NA	0.16
T1 Hand to mouth						
Right						
Shoulder Flex/Extend	0.87	12.12	0.95*	0.82	9.67	0.84*
Shoulder Abd/Add	0.91	7.95	0.96*	0.87	11.33	0.87*
Elbow Flex/Extend	0.93	10.34	0.85*	0.76	14.52	0.73*

Left						
Shoulder Flex/Extend	0.92	9.52	0.88*	0.90	10.41	0.81*
Shoulder Abd/Add	0.88	7.28	0.96*	0.89	6.77	0.93*
Elbow Flex/Extend	0.70	14.23	0.56*	0.77	11.79	0.80*
T2 Hand to head						
Right						
Shoulder Flex/Extend	0.89	7.26	0.86*	0.81	8.63	0.86*
Shoulder Abd/Add	0.84	13.25	0.71*	0.73	17.41	0.83*
Elbow Flex/Extend	0.92	8.91	0.80*	0.67	16.20	0.45*
Left						
Shoulder Flex/Extend	0.90	8.36	0.93*	0.92	7.31	0.89*
Shoulder Abd/Add	0.71	17.48	0.78*	0.76	11.26	0.88*
Elbow Flex/Extend	0.56	19.30	0.34*	0.32	23.84	0.45*
T3 Hand to waist						
Right						
Shoulder Flex/Extend	0.82	9.87	0.78*	0.80	9.53	0.83*
Shoulder Abd/Add	0.93	12.31	0.89*	0.85	11.42	0.78*
Elbow Flex/Extend	0.64	15.66	0.80*	0.41	31.78	0.49*
Left						
Shoulder Flex/Extend	0.88	7.83	0.87*	0.89	6.69	0.83*
Shoulder Abd/Add	0.42	12.16	0.57*	0.65	13.23	0.78*
Elbow Flex/Extend	0.60	10.99	0.66*	0.53	15.92	0.62*

T4 Hand to contralateral underarm						
Right						
Shoulder Flex/Extend	0.88	5.74	0.82*	0.88	7.41	0.87*
Shoulder Abd/Add	0.84	5.62	0.87*	0.88	7.86	0.86*
Elbow Flex/Extend	0.49	32.14	0.27	0.81	13.60	0.78*
Left						
Shoulder Flex/Extend	0.80	9.43	0.71*	0.93	6.51	0.84*
Shoulder Abd/Add	0.76	10.20	0.65*	0.64	17.85	0.51*
Elbow Flex/Extend	0.83	9.69	0.72*	0.89	10.52	0.91*

NOTE: $^*P<0.05$

The ICC values for all of the AROM measurements were below 0.5, which indicates poor reliability, except for right shoulder abduction (iPad Frontal: ICC = 0.55; iPad Lateral: ICC = 0.59) and for left shoulder flexion, which demonstrated the highest ICC values in the iPad (Frontal) and the iPad (Lateral) measurements (Frontal: ICC = 0.63; Lateral: ICC = 0.80). Regarding the measurement of joint angles in the four simulated functional tasks, all of the ICC values from the iPad (Frontal) were above 0.7, which indicates good reliability, except for left elbow flexion/extension in tasks 1, 2, and 3 (ICC = 0.34; 0.56; 0.66, respectively), right elbow flexion/extension in task 4 (ICC = 0.27), and left shoulder abduction/adduction in tasks 2 and 4 (ICC = 0.57 and 0.65, respectively). Excellent reliability (ICC > 0.9) was found for right shoulder flexion/extension, right and left shoulder abduction/adduction in task 1, and left shoulder flexion/extension in task 2. Moderate correlation was found in all of the waveforms produced by the iPad (Frontal) (the CMC values ranged between 0.42 and 0.93), except for the right elbow flexion/extension measurement in task 2 and the left elbow flexion/extension measurement in task 3.

4.4 DISCUSSION

Our study shows that the iPad MMC system generally underestimated the shoulder and elbow joint angles. The maximal AROM measurements calculated by the MMC were approximately 10 to 15 degrees lower than those measured by the goniometer. The MMC system was found to have estimated the shoulder AROM better than the elbow AROM. One reason for the significant difference in the measurements of the maximal elbow extension range, which probably was a systematic error, could have been the MMC system's inability to detect elbow joint hyperextension, which usually happened when the participants were instructed to extend their elbows to the maximum range. As elbow joint hyperextension is a minor change in joint position, it might not be detectable by iPad cameras spaced 1.8 m apart, whereas it might be noticed by an assessor who places a goniometer directly on the arm of the subject at a close distance. In addition, we observed that when the participants performed a shoulder flexion or abduction to their maximum range, their clothes were usually tilted upward on the side of the raising arm. The MMC system tended to incorrectly recognize the wrinkled of the clothes as a flexion of the trunk, and that error caused a reduction in the estimated shoulder joint angle because it was calculated in relation to the trunk position. Our results are consistent with those of another study, in which an MMC system experienced the problem of a clothes blockage that tended to lead to a distortion of the image and hence to an inaccurate estimation of posture (Sarafianos et al., 2016).

Our findings revealed that the MMC had underestimated both the shoulder and elbow angles in all four simulated functional tasks when compared with those measured by the Vicon system. The patterns of the angular waveforms between the MMC and the Vicon systems were moderately similar. Although there was a significant measurement difference between the two systems, the mean differences of the angles for the shoulder flexion/extension were consistently kept at 9.4 to 14.1 degrees, and those for the shoulder abduction/adduction held at 5.2 to 14.8 degrees. The moderate-to-strong correlation between the shoulder measurements produced by the MMC and the Vicon systems suggests that the joint-position data acquired by the MMC might have the potential to be further processed and normalized by an algorithm during post-processing to enhance the accuracy of its joint-angle predictions (Desmarais et al., 2021). We found that the tasks that involved less shoulder movement, such as task 1 (the hand-to-mouth task) and task 4 (the hand-to-contralateral-underarm task), generated a greater accuracy for the elbow-joint angle. That greater accuracy might be explained by a relatively steady shoulder-joint position, which would cause fewer disturbances and thus allow a more accurate recognition of the elbow and wrist positions for the angle calculation. Furthermore, task 2 (the hand-to-head task) and task

3 (the hand-to-waist task) might have been prone to inducing a blockage of the waist joint if subjects accidentally put their hand behind their waist or head. A blockage of the waist position would cause errors in the calculation of the elbow joint angle and hence a poorer agreement between the elbow joint angle measurement by the MMC and that obtained by the Vicon in these two tasks.

Placing the iPad on the lateral left side generally did not improve the accuracy of the measurement of the left upper-limb angle for either the AROM measurement or the simulated functional tasks. That inaccuracy may have arisen because our MMC system used the pelvis as the reference point. Capturing the human image from a side view may have produced an incomplete viewing angle of the right iliac crest, resulting in errors in the identification of the torso position and therefore incorrect calculations of the upper-limb-joint angle. The accuracies of the angle measurements for the right upper limb calculated by the iPad (Lateral) also were lower. One possible reason is that the shoulder and elbow joints on the right side were occasionally blocked by clothing, which caused a misidentification of the joint position, likely due to the MMC system having lost its tracking during the movement. This finding and plausible explanation are consistent with the results of another study, in which an iPad MMC system that was developed using ARKit 5 produced better motion capturing when it was placed at the frontal side of the participants (Reimer et al., 2022).

Our MMC system demonstrated good-to-excellent test-retest reliability in detecting the shoulder AROM in all four tasks. The system's lower reliability in detecting the elbow AROM compared with that of the shoulder suggests that the MMC provides greater stability in detecting the shoulder joint position. Our reliability findings imply that the MMC system is able to reproduce the motion data and might be applicable in analyzing motion kinematics and in detecting abnormal or symptomatic movement patterns between healthy and disease populations (Takeda et al., 2021).

4.4.1 Study Limitations

First, as most of our participants were between 18 and 30 years old, the results may not be representative of populations of other age ranges. Furthermore, although the desired data-acquisition procedure required the participants to wear an identical set of tight clothing in the two sessions, the compliance varied. The different sets of clothes that some participants wore might have affected the test-retest reliability of the MMC because the system might have misidentified a wrinkle in the clothes as a body trunk segment. Finally, all of the maximal AROM measurements from both the MMC and the Vicon systems were reported as the largest values that the systems obtained during the actions performed in the maximal AROM measurement sessions, but those maximal AROM angles might not have been taken at the same point in time as those used by the goniometer measurements.

4.5 CONCLUSIONS

Our findings showed that the iPad MMC system, despite its low cost and portable nature, generally underestimated the shoulder and elbow AROM. The angle inconsistency between the measurements obtained by the MMC and the goniometry suggest that the MMC system might not currently be a good replacement for goniometry in clinical use. Nevertheless, the system has satisfactory test-retest reliability in terms of the angular waveforms and joint angles in the simulated functional tasks. Further research on improving the accuracy of MMC systems and investigating their applications for disease populations is warranted.

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CHAPTER 5

UPPER LIMB KINEMATIC MEASUREMENT USING MARKERLESS MOTION CAPTURING (MMC) IN STROKE SURVIVORS: A CROSS-SECTIONAL EXPERIMENTAL STUDY

Chapter 5

Upper limb kinematic measurement using markerless motion capturing (MMC) in stroke survivors: A cross-sectional experimental study

ABSTRACT

Introduction: With advances in technology, markerless motion capture (MMC) technology has emerged as a clinical measurement tool that can be used to assess the physical performance of patients, so as to reduce the time-consuming tasks involved in manual measurements for therapists. This study evaluates: 1) the differences in the upper limb joint angles between stroke survivors with different functional levels and their healthy counterparts in controlled indoor and uncontrolled outdoor environments; and 2) the relationship between the kinematic information obtained by MMC technology through a customized MMC system using an iPad Pro and the scores of manual motor assessments. **Methods:** A customized MMC system developed using an iPad Pro with a LiDAR scanner was designed to capture the movements of the participants. The stroke survivors first underwent three upper limb assessments and then performed seven sets of upper limb tasks with their non-hemiplegic side, followed by their hemiplegic side. The healthy participants performed the same sets of tasks for the motion capturing, with their dominant side followed by their non-dominant side. All of the participants performed tasks in the laboratory first, then repeated them in three randomly selected outdoor areas. The sensitivity and specificity of the selected machine models were calculated in regard to the classification of upper limb motor functional level based on the kinematic data from the MMC system on the iPad Pro. **Results:** Fifty stroke survivors and 49 healthy adults were recruited. Significant differences were found between the upper limbs of the hemiplegic and non-hemiplegic sides of the stroke participants in most of the tasks. Significant positive correlations were found between the results of the manual motor assessments and most of the kinematic parameters. The results of the four selected machine learning models revealed ≥ 0.85 sensitivity in the stroke upper limb functional level classification. **Conclusion:** The MMC system combined with a machine learning classification algorithm can be used to provide precise data with which to evaluate the upper limb functional recovery of stroke survivors. Further studies on the operation of the MMC system by stroke survivors at home during remote therapy is warranted.

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5.1 INTRODUCTION

Stroke survivors often have to go through a long rehabilitation journey lasting months or even years in order to regain motor functions (Hawkins et al., 2017). Their recovery usually requires continuous monitoring from rehabilitation therapists so as to customize tailored exercises that best fit their needs at different stages of motor recovery (Jung, 2017). Traditional practices undertaken by therapists, such as regular functional assessments and the manual measurement of range of motion (ROM), require patients' regular attendance in clinical settings (Poole & Whitney, 2001). With advances in technology, markerless motion capture (MMC) technology has emerged as a clinical measurement tool that can be used to assess the physical performance of patients, so as to reduce time-consuming tasks in manual measurements conducted by therapists (Mündermann et al., 2006). It is suggested that MMC technology can provide a precise measurement of the movement kinematic of stroke survivors, as well as quick screenings of motor performance (Knippenberg et al., 2017). Despite the way in which MMC systems enable the tracking of movement kinematics, it is still unclear how therapists can interpret kinematic data in order to translate the findings into an understanding of the actual motor functions of patients (Lorenz et al., 2024). A previous study has been conducted to capture the kinematic data of stroke survivors and healthy adults when performing tasks, through a stroke-specific performance-based impairment index: the Fugl-Meyer Assessment (FMA). It was found that the movement data from stroke survivors and healthy adults can be successfully classified with a rate of above 90% using machine learning classification models (Eichler et al., 2018). Therefore, the MMC system has the potential to identify symptomatic movement patterns in stroke survivors through artificial intelligence (AI)-assisted detection technology, in order to monitor patients' motor performance and activities of daily living, especially during remote assessments as part of telerehabilitation (Fong & Kwan, 2020). Another study also found that the correlation between the actual FMA scores and the movement data captured by the MMC system in Kinect was high (Kim et al., 2016). Researchers have responded positively to the utilization of MMC systems in remote assessments for patients with stroke in regard to the high quality of kinematic data that they can provide (Metcalf et al., 2013).

Although studies have shown a high correlation between kinematic data generated by MMC systems and actual performance-based impairment indexes, the types of standardized assessment used by these studies are very limited. The generalizability involved in using MMC systems for other motor assessments among stroke survivors is hence still uncertain. There is still inadequate evidence of how kinematic data can help to distinguish between different stroke severity levels and reflect the actual functioning of patients. Moreover, most of the current research on using MMC systems in assessments for stroke patients uses Kinect as the motion tracking device (Da Gama et al., 2015). Kinect is a low-cost and comfortable device in regard to motion capturing but it might not be user-friendly for patients in their home environments, given that it requires the purchase and installation of the hardware device in the patients' home (Lam & Fong, 2022). Researchers have proposed the use of mobile devices as the MMC system in remote rehabilitation assessments, which would not require the patients to buy and calibrate extra hardware sensors for motion capturing (Aoyagi et al., 2022). This further facilitates the accessibility of MMC technology for patients and hence their access to telerehabilitation. However, little research has been carried out to investigate the use of MMC systems in mobile devices for motor assessments among stroke survivors (Lam & Fong, 2023) (Sohn et al., 2019). There is still a large research gap in the application of MMC systems in mobile devices in terms of the evidence and whether they can provide accurate measurements with which to evaluate the motor performance of stroke survivors with different levels of severity. Therefore, this study evaluates: 1) the differences in the upper limb joint angles between stroke survivors with different motor functional levels and their healthy counterparts in both controlled indoor and uncontrolled outdoor environments, measured by a customized MMC system on an iPad Pro; and 2) the relationship between the kinematic information obtained by the

MMC system and the scores of manual motor assessments. This study also investigates the sensitivity and specificity of the classification of upper limb motor functional level using machine learning methods, based on the kinematic data from the MMC system on the mobile device.

5.2 METHODS

5.2.1 Study design

This is a cross-sectional experimental study. Ethical approval was obtained from the Human Subjects Research Ethics Committee of the Hong Kong Polytechnic University (Reference no.: HSEARS20230214010). Prior to participation, all subjects were informed about the objectives and procedures of the study. Subjects who met the inclusion criteria provided informed written consent before taking part in the study. A customized MMC system developed on an iPad Pro with an LiDAR scanner was designed to capture the movement of the participants. The stroke survivors first underwent three upper limb assessments conducted by a registered occupational therapist. After the assessments, the stroke survivors were invited to perform seven sets of upper limb tasks extracted from the stroke-specific upper limb assessments with their non-hemiplegic side first, followed by their hemiplegic side. As the healthy participants would score full marks in all the assessments, they skipped the assessment sessions and directly performed the same sets of tasks for the motion capturing with their dominant side, followed by their non-dominant side. In order to simulate the use of the MMC system in the home setting for telerehabilitation, participants were required to perform the same sets of tasks in both the controlled indoor environment and again in three randomly selected uncontrolled outdoor environments immediately after the indoor experiment.

5.2.2 Sample size calculation

We assumed a two-tailed comparison with a type I error rate at 0.05, with 80% power. A total of 50 stroke survivors and 50 healthy counterparts were thus required. The stroke survivors were stratified according to the lower and higher functioning of their upper limbs' performance using the Functional Test for the Hemiplegic Upper Extremity (FTHUE) (Fong et al., 2004). As a conservative estimation with a discard rate of 15% due to bad data or outliers, according to our previous pilot study (Lam & Fong, 2023), we presumed that 42 subjects in each group would be required for the final data analysis. After conducting power analysis based on the statistical parameters, using the software GPower3.1.9.2, the effect size was calculated as 0.74, which is between medium (0.5) and large (0.8) (Kang, 2021).

5.2.3 Participants

Stroke survivors were recruited from community self-help groups, whereas their healthy counterparts were recruited by means of convenience sampling in the community. To be eligible to take part in the study, participants were included if: 1) they were adults aged 18 years old or above; 2) they had been diagnosed with a hemiplegic stroke; 3) they did not have a history of previous neurological or orthopedic diseases or congenital disorders of the upper or lower extremities or the spine; 4) they possessed adequate cognitive ability to understand instructions; and 5) they were able to engage in a one-hour experimental session. Participants in this study were invited to participate in both the upper and lower limb motion capturing experiment. In this chapter, we focus solely on reporting and discussing the results of the upper limb experiment.

Participants who met the following conditions were excluded: 1) medically unstable; 2) previous injuries or medical conditions over the upper limbs or spine affecting their upper limb functions (for healthy participants); 3) stroke survivors with a functional level of two or below, as measured using the FTHUE.

5.2.4 Measurements

The Fugl-Meyer Assessment (FMA) scale is an index used to assess sensorimotor impairment in individuals who have had a stroke (Kim et al., 2012). It is divided into the upper extremity (FMA-UE) part and the lower extremity (FMA-LE) part, with a maximum score of 66 and 34 points in the FMA-UE and the FMA-LE, respectively. The upper limb sub-scores will be adopted in this study.

The Wolf Motor Function Test (WMFT) is an assessment that quantifies upper extremity (UE) motor ability through timed and functional tasks. It consists of 21 items and each item is rated based on a six-point scale. Patients score zero points if they do not attempt to perform an item with the upper extremity, while five points are given if the movement appears to be normal (Taub et al., 2011).

5.2.5 Equipment

The MMC system

The MMC system used to perform motion analysis in this study was developed using Xcode, with the ARKit6 and RealityKit framework supported by the iPad Pro with an LiDAR scanner. Three iPad Pros were placed in front of, on the left side, and on the right side of each participant, respectively, for the motion capturing process. The detection of the human body and the joint position from the three angles were extracted, integrated and realized through computer-vision algorithm convolutional neural networks (CNNs). A total of 14 3D body joint positions and the timestamp of each motion detection were captured by our motion tracking platform. The capturing frequency of the MMC system was set at 30 Hz. A predefined humanoid model, which is the Unity Humanoid Rig, was applied to estimate the joint position and kinematic structure of the tracked subject (Reimer et al., 2022). The joint coordinates in 2D or 3D for every captured frame were established and delivered by the algorithms. The normalized coordinates were relative to the center of the pelvis and defined as the origin of the ARKit's coordinate system (Reimer et al., 2022). The adjacent 3D joint coordinate extraction calculated the angles of interest (AOI). Angle θ was calculated by the three joints, $A, B, C \in R^3$, or associated vectors $\overrightarrow{v_1} = A - B \; and \; \overrightarrow{v_2} = C - B$ with the formula $\theta = \arccos \frac{v_1 \cdot v_2}{||v_1||_2 ||v_2||_2}$

5.2.6 Experiment setup

Controlled indoor environment

The experiment was conducted at the assistive technology laboratory at the Hong Kong Polytechnic University, where the floor was covered with vinyl to prevent it from being slippery. For the motion capturing session, participants stood in front of a plain wall in the same laboratory. One iPad Pro was placed two meters in front of the participant, and another two iPad Pros were placed at the lateral left and right sides of the participants, respectively.

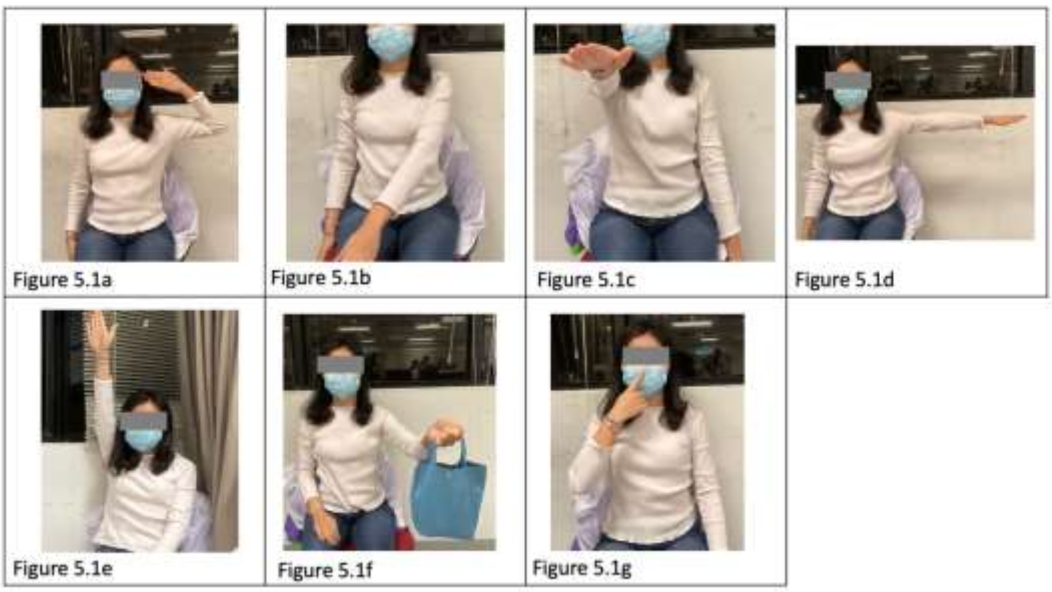
Uncontrolled outdoor environment

Three open areas at the Hong Kong Polytechnic University were chosen as uncontrolled outdoor environments. A 2.5m × 2.5m area was marked. Two 1m × 1m anti-slip mats were placed on both sides of the participants to prevent them from slipping. Three iPad Pros placed on a tripod stand were brought to the locations. The iPad Pro placement was the same as that in the laboratory environment.

5.2.7 Procedures

The experiment was divided into two sessions. The first session was for the upper limb assessment. Stroke survivors who participated in the study were first assessed by the investigator to determine their eligibility. Stroke survivors who satisfied the inclusion criteria were further assessed using the FMA-UE and the WMFT for their upper limb performance.

The motion capturing experiment took place in the second session. Participants were instructed to perform seven sets of upper limb tasks, including: 1) Task 3 in the FMA-UE, bringing the hand to the same side of the ear; 2) Task 4 in the FMA-UE, extending the arm to the opposite knee; 3) Task 6 in the FMA-UE, with shoulder flexion to 90 degrees with the elbow at 0 degree; 4) Task 8 in the FMA-UE, with shoulder abduction 0 degree to 90 degrees with the elbow fully extended and the forearm pronated; 5) Task 9 in the FMA-UE, with shoulder flexion beyond 90 degrees with the elbow at 0 degree and the forearm in the mid position; 6) Task 3D in the FTHUE, holding a pouch; and 7) Task 24 in the FMA-UE, which is a finger-to-nose test. All of the tasks in this session were repeated five times. The stroke survivors were instructed to perform each task with their unaffected side first, followed by their affected side. Figures 5.1a to 5.1g illustrate the desired postures in the seven tasks.



Figures 5.1a to 5.1g Left to right, top to bottom, the desired postures for Task 1 to Task 7

Healthy participants were not required to participate in the upper limb assessment. They were instead instructed to perform the motion capturing session directly. They were asked to perform the tasks with their dominant side first, followed by their non-dominant side.

To simulate their performance in a natural environment, participants were invited to repeat the motion capturing session in the unstructured environment after the capturing session in the laboratory. Participants were randomly assigned to one of the three open areas for the motion capturing, with an identical set of tasks, after their motion capturing session in the laboratory.

5.2.8 Statistical analysis

Kinematic data, including completion time, the angular waveform of the movement, and the angle of the joints when the target position was achieved, were extracted from the MMC system. The first trial in each task served as a practice trial and was not included in the analysis. The averages of the second to the fifth trials in each task were obtained for statistical analysis. Comparisons of the joint angles in the target positions (ATP) were carried out using independent t-tests between 1) the affected side and the unaffected side in the stroke population; and 2) the affected side in the stroke population and the dominant side in their healthy counterparts. Comparisons of the completion times of Task 7 and the ATP of Tasks 1 to 6 were carried out between the affected side in the stroke population with the higher functional level (FTHUE level 5 or above) (Fong et al., 2022), the stroke population with the lower functional level (FTHUE level 4 or below), and the dominant side of the healthy subjects, using an ANOVA with post hoc comparison. Differences in the angular waveforms between the affected hand and the unaffected hand in the stroke population, and the two sides of the healthy subjects were compared using the coefficient of multiple correlation (CMC) and the root mean square error (RMSE). Correlations between the assessment results corresponding to the actions and the completion times for Task 7, the ATP, and the CMC values were evaluated using Pearson's r correlation. Logistic regression (LG), a naive Bayes (NB) classifier, a support vector machine (SVM), and a decision tree (DT) model were used to investigate the trajectory in the predictions of the stroke participants' upper limb assessment results, with kinematic information from the MMC system, including the ATP from all tasks and the differences between the affected and unaffected sides from all tasks. The data set was divided into training and test splits, using five-fold subject-wise stratified cross validation, in which the training set accounted for 80%, and the test set accounted for 20%. All of the statistical tests were performed using IBM SPSS

26, while the CMC and RMSE values were generated by MATLAB R2020a. All of the four machine learning models were run using the Scikit-learn package in Python. The linear support vector machine (SVM) used a linear kernel. l_2 Regularization was implemented logistic regression model.

5.3 RESULTS

Fifty stroke survivors and 49 healthy adults were recruited. The mean age of the stroke survivors and the healthy adults was 58.9 years (SD: 11.7) and 60.2 years (SD: 8.5), respectively. Detailed demographic information regarding the participants is presented in Table 5.1.

Table 5.1 Demographic information of the participants

	Stroke Group	Healthy Group
Mean age	58.9 (11.7)	60.2 (8.5)
Gender ratio (male: female)	32:18	18:31
Functional level (n)		
FTHUE levels 3–4	18	NA
FTHUE levels 5–7	32	NA
Hemiplegic side (n)		
Right	22	NA
left	28	NA
Dominant hand (Pre-onset) (n)		
Right	49	48
Left	1	1

Note: ***FTHUE*** Functional Test for the Hemiplegic Upper Extremity

The shoulder and elbow joint ATP at task completion for Tasks 1 to 6 and the completion times for Task 7 are presented in Table 2. Significant differences were found between the hemiplegic and non-hemiplegic sides of stroke survivors with lower upper limb functioning in all tasks, except in regard to the shoulder angle in Task 1 and Task 2 (MD = -3.0 and -4.1, respectively). There are significant differences between the hemiplegic and non-hemiplegic sides of the stroke survivors with higher upper limb functioning in all tasks except in regard to the shoulder angle in Task 3 and Task 5 (MD = -2.2 and -5.0, respectively). No significant difference was found between the lateral sides of the healthy participants, except in regard to the shoulder and elbow ATP in Task 3 (MD = 11.5 and 4.2, respectively) and in regard to the elbow ATP in Task 6 (MD = 14.8). The hemiplegic sides of the higher functioning and lower functioning stroke survivors in each task were also compared. Significant differences were observed in the shoulder and elbow ATP in all of the tasks except for the shoulder ATP in Task 2 ($p = 0.11$). There are significant differences between the hemiplegic side of the lower functioning stroke survivors and the healthy counterparts in all tasks except the shoulder ATP in Task 1 and Task 2 ($p = 0.827$ and $p = 0.264$, respectively). Significant differences were also observed between the higher functioning stroke participants and the healthy participants in all tasks, except in regard to the shoulder angle in Task 2 and Task 5 (p = 0.282 and 0.229, respectively).

Table 5.2 Shoulder and elbow joint ATP at task completion for Task 1 to 6 and the completion time for Task 7

Task	Stroke (Lower Functioning Group)			Stroke (Higher Functioning Group)			Healthy Group					
	Hemiplegic Side	Non-hemiplegic Side	Mean Difference (Hemiplegic – Non-hemiplegic)	Hemiplegic Side	Non-hemiplegic Side	Mean Difference (Hemiplegic – Non-hemiplegic)	Dominant Side	Non-dominant Side	Mean Difference (Dominant – Non-dominant	*p* [Stroke Low Hemi vs Stroke High Hemi] (95% CI)	*p* [Stroke Low Hemi vs Healthy Dominant] (95% CI)	*p* [Stroke High Hemi vs Healthy Dominant] (95% CI)
Task 1 Bring hand to ear												
ATP Shoulder	75.4 (22.1)	78.4 (17.3)	-3.0 (29.4)	90.6 (21.7)	70.4 (20.5)	20.2 (29.0)*	76.1 (2.4)	77.6 (14.8)	-1.5 (15.4)	0.02* (2.273 – 28.171)	0.827 (-7.028 – 5.640)	< 0.001* (8.323 – 20.734)
ATP Elbow	95.6 (16.6)	46.1 (11.4)	49.5 (20.4)*	53.3 (13.9)	37.4 (10.8)	15.9 (18.9)*	47.4 (10.9)	43.0 (7.2)	4.4 (13.6)	< 0.001* (-51.107 – -33.483)	< 0.001* (41.293 – 55.169)	0.034* (0.451 – 11.422)
Task 2 Hand to opposite knee												
ATP Shoulder	23.0 (9.7)	27.1 (8.8)	-4.1 (11.5)	27.8 (10.5)	20.4 (4.0)	7.4 (11.7)*	25.6 (8.1)	28.2 (9.2)	-2.6 (12.0)	0.11 (-1.172 – -10.942)	0.264 (-7.335 – 2.042)	0.282 (-1.875 – 6.352)
ATP Elbow	126.7 (19.5)	151.4 (11.9)	-24.7 (21.5)*	147.0 (12.9)	153.4 (12.1)	-6.4 (16.0)*	155.8 (13.5)	158.4 (16.1)	-2.6 (21.2)	< 0.001* (11.020 – 29.479)	< 0.001* (-37.538 – -20.675)	0.004* (-14.815 – -2.899)

Task 3 **Shoulder flexion to 90 degrees**												
ATP Shoulder	71.3 (11.5)	109.1 (12.4)	-37.8 (15.9)*	107.0 (18.0)	109.2 (9.4)	-2.2 (20.2)	117.5 (10.4)	106.0 (11.1)	11.5 (14.3)*	< 0.001* (26.206 – 45.165)	< 0.001* (-52.075 – -40.284)	0.001* (-16.788 – -4.200)
ATP Elbow	90.0 (11.2)	158.2 (8.3)	-68.2 (14.6)*	148.6 (13.3)	167.2 (8.1)	-18.6 (15.6)*	164.2 (10.4)	160.0 (8.4)	4.2 (14.1)*	< 0.001* (51.118 – 66.072)	< 0.001* (-80.021 – -68.330)	< 0.001* (-20.845 – -10.315)
Task 4 **Shoulder flexion to 180 degrees**												
ATP Shoulder	94.6 (12.7)	156.8 (9.9)	-62.2 (11.8)*	137.0 (19.6)	166.1 (9.6)	-29.4 (21.5)*	168.6 (12.8)	165.2 (11.2)	3.4 (16.2)	< 0.001* (31.787 – 52.463)	< 0.001* (-81.078 – -67.021)	< 0.001* (-39.076 – -24.773)
ATP Elbow	50.8 (18.1)	166.0 (6.7)	-115.2 (17.3)*	148.2 (17.6)	170.3 (8.2)	-22.0 (21.0)*	166.1 (9.9)	168.7 (8.3)	-2.6 (13.8)	< 0.001* (86.964 – 107.977)	< 0.001* (-122.221 – -108.400)	< 0.001* (-23.915 – -11.765)
Task 5 **Shoulder abduction to 90 degrees**												
ATP Shoulder	73.7 (20.3)	117.8 (14.2)	-44.1 (22.6)*	111.2 (11.7)	116.2 (10.7)	-5.0 (16.1)	115.2 (16.4)	120.1 (19.6)	-4.9 (25.9)	< 0.001* (28.427 – 46.557)	< 0.001* (-51.185 – -31.921)	0.229 (-10.724 – 2.602)
ATP Elbow	79.5 (12.6)	167.8 (7.7)	-88.3 (14.0)	135.5 (23.5)	164.0 (8.1)	-28.5 (24.9)*	166.7 (8.6)	167.1 (7.7)	-0.4 (10.7)	< 0.001* (44.066 – 68.101)	< 0.001* (-92.626 – -81.865)	< 0.001* (-38.468 – -23.856)

Task 6 **Hold a pouch (for 10 seconds)**												
ATP Shoulder	62.6 (19.3)	113.7 (17.1)	-51.2 (23.5)*	97.3 (13.4)	109.0 (17.3)	-11.6 (22.2)*	115.2 (16.3)	123.1 (17.2)	-7.9 (28.0)	< 0.001* (25.439 – 44.080)	< 0.001* (-62.044 – -43.146)	< 0.001* (-24.726 – -10.945)
ATP Elbow	77.0 (10.1)	147.0 (18.8)	-70.0 (20.3)*	131.2 (19.0)	146.6 (19.7)	-15.4 (23.3)*	156.7 (12.7)	141.9 (20.2)	14.8 (23.5)*	< 0.001* (44.537 – 63.960)	< 0.001* (-86.384 – -73.108)	< 0.001* (-32.496 – -18.499)
Task 7 **Finger-to-nose test**												
Completion time	6.5 (2.4)	1.1 (0.2)	5.4 (2.5)*	2.1 (0.8)	1.0 (0.2)	1.1 (0.9)*	1.0 (0.3)	1.1 (0.3)	-0.1 (0.4)	< 0.001* (-5.350 – -3.462)	< 0.001* (4.790 – 6.178)	< 0.001* (0.824 – 1.331)

Note: *$P < 0.05$. ***ATP*** Angles in the Target Positions

The differences in the angular waveform between the two sides of the lower and the higher functioning stroke groups and the healthy participants were calculated using the CMC and the RMSE. The CMC and RMSE values are presented in Table 5.3. The lower functioning stroke survivors generally had lower CMC values in the angular waveform between the two sides (CMC ranging from 0.23 to 0.67) in all of the tasks. The CMC values for the higher functioning stroke survivors ranged from 0.39 (elbow in Task 1) to 0.86 (elbow in Task 4), while the CMC values for the healthy participants ranged from 0.80 to 0.92 in Tasks 1 to 4.

Correlations between the kinematic data and the assessment results, including the FTHUE, UEFMA, and WMFT, are summarized in Table 5.4. Significant correlations were found between the results of the assessments and most of the kinematic parameters. The elbow ATP of the hemiplegic side in Task 6 (hold a pouch task) demonstrated the strongest positive correlation coefficient with the FTHUE-HK, UEFMA, and WMFT ($r = 0.944$, 0.883, and 0.873, respectively). Kinematic data, including the ATP of the hemiplegic side, the ATP difference between the two sides, the CMC and RMSE values from Task 2 (hand to opposite knee) generally show the weakest correlation coefficients with the three assessment scores.

Table 5.3 CMC and RMSE values of the angular waveform comparison between the two sides

Task	Stroke (Lower Functioning Group)		Stroke (Higher Functioning Group)		Healthy Group	
	CMC (SD)	RMSE (SD)	CMC (SD)	RMSE (SD)	CMC (SD)	RMSE (SD)
Task 1 Bring hand to ear						
Shoulder	0.53 (0.08)	22.3 (9.3)	0.68 (0.06)	26.9 (18.6)	0.89 (0.10)	8.2 (5.2)
Elbow	0.31 (0.12)	38.7 (13.8)	0.39 (0.07)	15.2 (6.5)	0.88 (0.07)	10.5 (3.3)
Task 2 Hand to opposite knee						
Shoulder	0.67 (0.09)	12.1 (7.7)	0.65 (0.11)	16.1 (9.3)	0.92 (0.05)	5.8 (2.4)
Elbow	0.38 (0.08)	37.4 (10.0)	0.53 (0.06)	13.8 (5.6)	0.89 (0.08)	9.4 (5.2)
Task 3 Shoulder flexion to 90 degrees						
Shoulder	0.51 (0.06)	28.9 (15.2)	0.78 (0.05)	26.3 (12.3)	0.78 (0.07)	15.7 (8.2)
Elbow	0.29 (0.05)	33.6 (18.4)	0.61 (0.10)	24.2 (15.9)	0.88 (0.11)	11.3 (6.5)
Task 4 Shoulder flexion to 180 degrees						
Shoulder	0.25 (0.11)	41.2 (19.0)	0.62 (0.09)	21.2 (12.7)	0.87 (0.05)	14.4 (7.2)
Elbow	0.27 (0.07)	28.9 (11.4)	0.86 (0.13)	19.9 (9.3)	0.92 (0.03)	11.2 (6.8)

Task 5						
Shoulder abduction to 90 degrees						
Shoulder	0.56 (0.10)	22.7 (13.9)	0.71 (0.11)	14.1 (6.8)	0.88 (0.11)	15.2 (8.6)
Elbow	0.27 (0.08)	35.8 (16.2)	0.53 (0.15)	23.2 (10.0)	0.91 (0.05)	9.1 (5.4)
Task 6						
Hold a pouch (for 10 seconds)						
Shoulder	0.30 (0.09)	33.6 (14.5)	0.67 (0.10)	18.4 (7.9)	0.82 (0.06)	10.4 (7.7)
Elbow	0.46 (0.11)	28.9 (9.2)	0.80 (0.11)	11.2 (5.2)	0.83 (0.09)	8.6 (4.8)
Task 7						
Finger-to-nose test						
Shoulder	0.39 (0.10)	27.8 (12.7)	0.49 (0.13)	20.9 (11.4)	0.83 (0.05)	10.1 (5.3)
Elbow	0.23 (0.06)	43.2 (22.6)	0.44 (0.07)	16.5 (9.7)	0.80 (0.09)	7.8 (4.2)

Note: ***CMC*** Coefficient of Multiple Correlation; ***RMSE*** Root Mean Square Error

Table 5.4 Correlation between the kinematic data and the assessment results of the FTHUE, UEFMA, and WMFT

Task	Stroke (All)					
	ATP Hemiplegic side r	ATP difference (Non-hemi – Hemi)	CMC (Non-hemi – Hemi)	RMSE (Non-hemi – Hemi)	Completion time	Bilateral difference in completion time
Correlation with FTHUE						
Task 1 **Bring hand to ear**						
Shoulder	-0.046	-0.085	0.691*	0.322*	NA	NA
Elbow	-0.631*	0.496*	0.374*	-0.708*	NA	NA
Task 2 **Hand to opposite knee**						
Shoulder	0.273	-0.399*	-0.27	0.258	NA	NA
Elbow	0.398*	-0.313*	0.588*	-0.742*	NA	NA
Task 3 **Shoulder flexion to 90 degrees**						
Shoulder	0.721*	-0.636*	0.809*	-0.159	NA	NA
Elbow	0.778*	-0.732*	0.793*	-0.091	NA	NA

Task 4						
Shoulder flexion to 180 degrees						
Shoulder	0.698*	-0.582*	0.818*	-0.590	NA	NA
Elbow	0.808*	-0.796*	0.778*	-0.358	NA	NA
Task 5						
Shoulder abduction to 90 degrees						
Shoulder	0.684*	-0.666*	0.393*	-0.264	NA	NA
Elbow	0.639*	-0.653*	0.578*	-0.201	NA	NA
Task 6						
Hold a pouch (for 10 seconds)						
Shoulder	0.683*	-0.556*	0.727*	-0.677*	NA	NA
Elbow	0.944*	-0.839*	0.658*	-0.649*	NA	NA
Task 7						
Finger-to-nose test						
Shoulder	NA	NA	0.322*	-0.638*	-0.655*	0.647*
Elbow	NA	NA	0.641*	-0.581*		
Correlation with the FMA-UE						

Task 1						
Bring hand to ear						
Shoulder	-0.054	-0.015	0.622*	0.247	NA	NA
Elbow	-0.603*	0.445*	0.231	-0.606*	NA	NA
Task 2						
Hand to opposite knee						
Shoulder	0.301*	-0.415*	-0.039	0.261	NA	NA
Elbow	0.364*	-0.306*	0.497*	-0.694*	NA	NA
Task 3						
Shoulder flexion to 90 degrees						
Shoulder	0.668*	-0.593*	0.749*	0.307*	NA	NA
Elbow	0.716*	-0.660*	0.755*	0.310*	NA	NA
Task 4						
Shoulder flexion to 180 degrees						
Shoulder	0.694*	-0.607*	0.748*	0.092	NA	NA
Elbow	0.760*	-0.755*	0.675*	0.339*	NA	NA
Task 5						
Shoulder abduction to 90 degrees						
Shoulder	0.672*	-0.663*	0.310*	0.010	NA	NA
Elbow	0.584*	-0.589*	0.515*	0.365*	NA	NA

Task 6						
Hold a pouch (for 10 seconds)						
Shoulder	0.618*	-0.489*	0.695*	0.168	NA	NA
Elbow	0.883*	-0.760*	0.599*	0.124	NA	NA
Task 7						
Finger-to-nose test						
Shoulder	NA	NA	0.269	-0.432*	-0.602*	0.594*
Elbow	NA	NA	0.599*	-0.365*		
Correlation with the WMFT						
Task 1						
Bring hand to ear						
Shoulder	-0.12	-0.027	0.619*	0.262	NA	NA
Elbow	-0.564*	0.461*	0.237	-0.601*	NA	NA
Task 2						
Hand to opposite knee						
Shoulder	0.214	-0.313*	-0.48	0.266	NA	NA
Elbow	0.291*	-0.216	0.504*	-0.730*	NA	NA
Task 3						
Shoulder flexion to 90 degrees						
Shoulder	0.643*	-0.572*	0.741*	-0.091	NA	NA

Elbow	0.716*	-0.683*	0.732*	-0.115	NA	NA
Task 4						
Shoulder flexion to 180 degrees						
Shoulder	0.688*	-0.606*	0.751*	-0.521*	NA	NA
Elbow	0.746*	-0.737*	0.644*	-0.303*	NA	NA
Task 5						
Shoulder abduction to 90 degrees						
Shoulder	0.664*	-0.653*	0.257	-0.184	NA	NA
Elbow	0.562*	-0.562*	0.565*	-0.108	NA	NA
Task 6						
Hold a pouch (for 10 seconds)						
Shoulder	0.605*	-0.494*	0.671*	-0.655*	NA	NA
Elbow	0.873*	-0.728*	0.611*	-0.624*	NA	NA
Task 7						
Finger-to-nose test						
Shoulder	NA	NA	0.239	-0.214		
					-0.611*	0.594*
Elbow	NA	NA	0.605*	-0.618*		

Note: *$p < 0.05$. ***ATP*** Angles in the Target Positions; ***CMC*** Coefficient of Multiple Correlation; ***FMA-UE*** Fugl-Meyer Assessment for the Upper Extremity; ***FTHUE*** Functional Test for the Hemiplegic Upper Extremity; ***RMSE*** Root Mean Square Error; ***WMFT*** Wolf Motor Function Test (WMFT)

Four selected machine learning models, including LG, an SVM, an NB classifier, and a DT model, were trained for lower and higher functioning upper limb classification based on the kinematic information extracted from the MMC system (Table 5.5). The models trained by the ATP of the hemiplegic side in Tasks 1 to 6 and the completion time in Task 7 achieved a sensitivity of $\geq$ 0.85, while the LG model demonstrated the highest levels of sensitivity and specificity (0.94). The models trained by the ATP difference between the hemiplegic and non-hemiplegic sides for task completion in Tasks 1 to 6 and the completion time difference in Task 7 achieved a minimal level of sensitivity of 0.89 using the DT model and a maximal level of sensitivity of 0.97 using the SVM model. The area under the ROC curve (AUC) was $\geq$ 0.86 for all the selected models. Feature importance analysis revealed that the bilateral difference in ATP of the shoulder and elbow in task 3, 4 and 5 as well as the bilateral ATP difference of elbow in task 6 were the most influential factors in predicting upper limb functioning in stroke. These results were consistent across cross-validation folds, with an average accuracy of 86.3% and a standard deviation of 2.7%.

Table 5.5 Classification performance of the machine learning models

ATP			
Model	Sensitivity (95% CI)	Specificity (95% CI)	AUC (95% CI)
LG	94.6% (75.7% - 98.4%)	94.3% (73.2% - 96.2%)	0.94 (0.83 – 0.98)
NB	91.2% (83.2% – 95.1%)	92.8% (69.3% - 93.2%)	0.91 (0.80 – 0.94)
SVM	93.4% (71.3% - 98.1%)	91.0% (69.2% - 93.8%)	0.91 (0.81 – 0.92)
DT	85.2% (65.6% - 88.4%)	87.3% (66.3% - 89.4%)	0.86 (0.73 – 0.90)
ATP difference between the two sides			
Model	Sensitivity (95% CI)	Specificity (95% CI)	
LG	96.3% (80.1% - 98.6%)	96.5% (78.4% - 98.4%)	0.97 (0.83 – 1.00)
NB	94.1% (79.8% - 96.7%)	93.0% (71.4% - 94.3%)	0.93 (0.79 – 0.96)
SVM	97.1% (84.2% - 98.6%)	96.5% (77.3% - 97.9%)	0.97 (0.88 – 1.00)
DT	89.2% (80.0% - 91.2%)	90.8% (67.0% - 93.4%)	0.90 (0.77 – 0.93)

Note: ***ATP*** Angles in the Target Positions; ***NB*** Naive Bayes; ***DT*** Decision Tree; ***LG*** Logistic Regression; ***SVM*** Support Vector Machine

The kinematic data captured by the MMC system in the outdoor environment contained a significant number of noise signals and missing data points, which hindered the formation of a complete angular waveform. More than half of the data had to be discarded due to noise signals. Due to the significant amount of outdoor data being discarded, analysis of the outdoor data could not be performed. Figures 5.2a and 5.2b depict the angular waveform extracted from two of the participants performing two tasks in the outdoor environment, demonstrating the noise signals and missing data points captured by the MMC system in the outdoor area. Figure 5.2c depicts the complete angular waveform of the same participants performing the task in the indoor area.

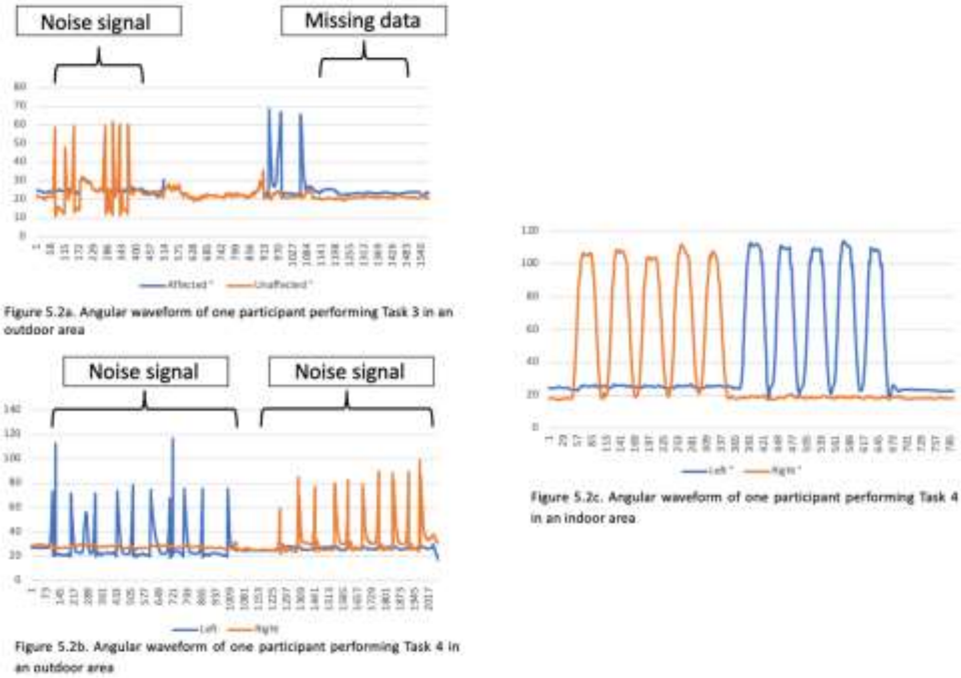


Figure 5.2a. Angular waveform of one participant performing Task 3 in an outdoor area

Figure 5.2b. Angular waveform of one participant performing Task 4 in an outdoor area

Figure 5.2c. Angular waveform of one participant performing Task 4 in an indoor area

Figures 5.2a, 5.2b Angular waveform extracted from two of the participants performing two tasks in the outdoor environment

Figure 5.2c Angular waveform of the same participants performing the task in the indoor area

5.4 DISCUSSION

In this study, we found significant differences in the joint angles at task completion between the hemiplegic side and the non-affected side of the stroke survivors in all of the selected tasks captured by the MMC system, except in regard to the shoulder ATP in the ‘bring hand to the same side of the ear’ task in stroke survivors with lower upper limb functioning. Our findings reveal that the hemiplegic side of the stroke survivors shows a significant limitation in the shoulder and elbow ranges in task completion. This could be a result of limited control, spasticity, or muscle weakness after the stroke. There was no significant difference between the dominant hand and the non-dominant hand of the healthy participants in most of the tasks, except for the shoulder ATP in the ‘shoulder abduction to 90 degrees’ task and the ‘hold a pouch for 10 seconds’ task. This difference could be due to the muscular imbalances between the dominant and non-dominant hand, which is common for healthy individuals (Saul et al., 2015). The CMC and RMSE values from the angular waveforms reveal a larger difference between the hemiplegic side and the non-hemiplegic side in stroke survivors with lower upper limb functioning than those with higher upper limb functioning. This might be due to the greater difficulties in moving experienced by stroke survivors with lower levels of functioning (Luker et al., 2015). Our findings demonstrate that the MMC system in the mobile device is sensitive in detecting the kinematic difference between the affected side and non-affected side of stroke survivors in most of the selected tasks. As the MMC system is sensitive in regard to angle detection, some tasks that require the participants to place their limbs in a specific angle, such as the ‘shoulder abduction to 90 degrees’ task, could be more prone to generating a false positive result; placing the limb at a specific precise angle involves proprioception and joint stability, so as to allow the individuals to consciously and precisely move as well as maintain their joint to and at the desired angle. The bilateral muscular imbalance might induce a significant difference between the joint angle of both sides, even in healthy adults. It is important to be aware that this difference is not due to hemiplegia. Given that there are also significant differences in the dominant and non-dominant hands for healthy participants when performing some tasks, we therefore suggest that tasks are carefully selected or a combination of different tasks are used for motion analysis of the stroke survivors when evaluating their hemiplegic side recovery, especially when comparison with the non-hemiplegic side is warranted.

Significant differences in shoulder and elbow angles were detected between the affected side of the stroke survivors with lower upper limb functioning, stroke survivors with higher functioning, and the healthy participants in the ATP in task completion in all of the selected tasks, except for Task 2, the ‘hand to the opposite knee’ task. The ‘hand to the opposite knee’ task involves minimal shoulder and elbow movement, which hinders the detection of angular differences in the targeted position. Nevertheless, the significant difference detected by the MMC system reflects the way in which the kinematic information provided by the MMC system can differentiate between the movements made by healthy individuals and stroke survivors with high and low upper limb functional ability, which further suggests the potential of the MMC system in detecting symptomatic movement based on the ROM difference.

Although only seven tasks from the standardized upper limb assessment were selected, they are representative of the common functional tasks in standardized upper limb assessments, such as the FTHUE, FMA-UE, and WMFT. In addition, our tracking algorithm only included large joints, in order to test its ability to identify and analyze participants’ gross motor abilities, and so mainly gross movements performed by the shoulder and elbow joint angles were investigated in this study. Future studies could consider tracking more complicated features, such as the contour of the hand, fingertips, and palms, so as to determine the ability of the MMC system to capture and analyze the movement of the wrist and the fine motor ability of stroke survivors.

All of the four selected machine learning models, including LG, an SVM, an NB classifier, and a DT model achieved a sensitivity higher than 0.84 in the stroke functional level classification. Our classification results reveal that the MMC system combined with machine learning methods can satisfactorily classify a stroke patient's upper limb impairment into higher and lower functioning levels. This finding further supports the notion that the MMC system can be used to stratify the motor recovery of the survivors according to their kinematic data from performing the required functional tasks (Zamin et al., 2023). Our AI models were also trained to perform the stroke upper limb impairment classification using the performance difference between the hemiplegic and the non-hemiplegic upper limb. All of the models show a sensitivity above 0.89 and a specificity of at least 0.90, which is considered to be excellent classification performance (Abdullah & Sofyan, 2023). The functional level classification based on the hemiplegic and non-hemiplegic side performance difference generally yielded a higher level of sensitivity than performing the classification simply by considering the performance of the hemiplegic side. One possible explanation for this result is that the performance by the non-hemiplegic hand generally reflects the usual way an individual completes an action when performing a motor task. Therefore, comparisons of the angular differences between the hemiplegic and non-hemiplegic side might reflect to what extent the movement of the hemiplegic limb deviates from the individual's normal motor performance. The smaller the difference between the hemiplegic and the non-hemiplegic side might suggest that the hemiplegic side has recovered better in terms of motor function toward a non-affected state—hence the higher functional level in the classification.

Our findings reveal that the kinematic data captured by the MMC system in the uncontrolled outdoor environment are affected by noise signals, the background of the image, and the condition of the light, which might hinder the demonstration of the joint angle change over time. It was found that the MMC usually lost track of the target participant's joints when a pedestrian passed by in a completely uncontrolled outdoor environment; it misidentified the pedestrian's limbs as the limbs of the target participant. Other than this influence by moving pedestrians, a cluttered background can also confuse the MMC system. Misrecognition of joint position also occurred in the background with green plants; the MMC system occasionally interpreted a tree branch as a human limb. A background consisting of a plain wall would generate a better complete angular waveform during motion capturing. The light in the outdoor environment might also be a contributing factors in the MMC system's joint position recognition (Dubey & Dixit, 2023). The angular waveforms obtained in the evening or with dim light during cloudy weather exhibited more sparsity, with gaps or missing data points at various time points. Insufficient light can make it difficult for the MMC system to capture a clear and detailed image of the human, which leads to a blurry or distorted image that ultimately affects the MMC system's ability to accurately track the participant's motion (Zanfir et al., 2023). This is particularly important for motion capturing during outdoor exercise in remote therapy or telerehabilitation. We suggest that, in future, the MMC system should preferably be placed in front of a plain background with sufficient light and without other moving objects passing by, to ensure better data quality. To further improve the performance of the MMC system in an unstructured environment, the feature extraction function might have to be modified so as to ensure the correct identification and tracking of the relevant body joints. An initial calibration step to establish a reference frame might also help to ensure the accurate measurement and representation of the joint angles.

The overall results of our study are consistent with the previous recommendation by Bonnechère and colleagues (2018) that an MMC system could be utilized to evaluate the upper limb motor performance of stroke survivors. Although it might not be appropriate for motion capturing in outdoor areas with a cluttered background and uncontrollable light levels, the kinematic data captured in a structured indoor environment provides a high level of sensitivity in regard to upper limb function classification. It is imperative to note that although our study employed three iPad Pro devices to capture the kinematic information from multiple angles, stroke survivors have the flexibility to utilize a single iPad Pro or their personal mobile device for motion capturing in a home setting. The use of three iPad Pro devices was solely intended to capture movements from diverse perspectives, while individuals can easily adjust the capturing angle independently when employing a single mobile device. Together with its portable nature, user-friendly setup, and inexpensive features, an MMC system on a mobile device has the potential to be used for the remote monitoring of motor recovery in stroke survivors during telerehabilitation in the home environment (Knippenberg et al., 2017). Moreover, the precise information collected using the MMC system can enable therapists to perform regular quick screening of the patients' functional ability and levels of motor recovery at home without requiring patients to frequently attend a clinic. Even though current studies support the utilization of MMC technology in telerehabilitation, researchers must close the gap between research findings and the real-life implementation of MMC technology in order to promote its actual adoption in remote rehabilitation programs in the future. To facilitate the use of MMC systems for telerehabilitation in the future, designing a user-friendly interface that allows patients to interact with the MMC system, including operating the system and transmitting the data to therapists, is warranted. We also recommend a comprehensive training session for both the patients and the therapists in regard to the MMC system setup and data interpretation, so as to enable them to use the MMC system effectively in telerehabilitation.

5.4.1 Limitations

This study assembles data from 49 healthy adults and 50 stroke survivors. The sample size is considered small for training and testing machine learning models. Second, the ratio of the stroke survivors with higher and lower upper limb functioning was not balanced. Future experiments examining the actual effect of different light levels on the motion tracking quality in MMC systems are still warranted.

5.5 CONCLUSION

This study utilizes an MMC system on a mobile device to detect significant differences in the hemiplegic upper limbs of stroke survivors and healthy adults. The data provided by the MMC system reflects significant kinematic differences between the stroke survivors with lower upper limb functioning and those with higher functioning in all of the selected tasks. Significant correlations were also found between the upper limb motor assessment scores and the kinematic performance of the stroke survivors. The use of an MMC system combined with a machine learning classification algorithm has the potential to provide precise data with which to evaluate the upper limb functional recovery of patients with stroke, particularly during telerehabilitation. It is recommended that MMC system capturing is conducted in front of a plain background with sufficient light in the future. Further studies on the actual operation of MMC systems by patients in home settings are warranted.

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CHAPTER 6

LOWER EXTREMITY KINEMATIC MEASUREMENT USING MARKERLESS MOTION CAPTURING (MMC) IN PERSONS WITH A STROKE: A CROSS-SECTIONAL EXPERIMENTAL STUDY

Chapter 6

Lower extremity kinematic measurement using markerless motion capturing (MMC) in persons with a stroke: A cross-sectional experimental study

ABSTRACT

Motor impairment is a deficit commonly experienced by persons with a stroke. The motor impairment of the lower extremity generally influences the mobility of those persons and hence their quality of life. The aim of this study was to investigate 1) the use of a Markerless Motion Capture (MMC) system in an iPad Pro for the measurement of movement kinematics in persons with a stroke and their healthy counterparts, when doing assessment tasks for the lower extremity, in both a controlled and an uncontrolled environment, and to assess 2) the sensitivity and specificity of machine-learning models in classification of the lower extremity function in persons with stroke, using the kinematics information provided by the MMC system. A customized MMC system developed in an iPad Pro with a LiDAR scanner was designed to capture the movement

of the participants. The recruited persons with a stroke were assessed by the Modified Functional Ambulation Classification (MFAC), the Berg Balance Scale (BBS), and the Fugl Meyer Assessment: Motor Function of the Lower Extremity (FMA-LE). For motion capturing, each participant then performed five selected lower-extremity tasks with their bilateral limbs. Kinematic data captured from the MMC system were extracted and entered into a statistical analysis. Significant differences were found between the angle change of the lower extremities of 1) the hemiplegic and non-hemiplegic sides of the persons with stroke, in most of the selected tasks, and 2) the hemiplegic side of the persons with stroke and the dominant side of the healthy participants. The support vector machine model used the CMC values to classify the lower-extremity functional performance of the persons with stroke into lower-functioning and higher functioning, with very high sensitivity and specificity. Our study supports application of an MMC system in mobile devices for measuring individuals' lower extremity kinematics, to aid evaluations of the lower extremity function of persons with stroke. Further research is warranted to investigate the application of an MMC system in the home setting for telerehabilitation with an increased variety of motor tasks, supported with a user-friendly operational interface.

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6.1 INTRODUCTION

Motor impairment is a deficit commonly experienced by persons with a stroke. The motor impairment of the lower extremity generally influences the mobility of persons with a stroke and hence their quality of life (Bonita & Beaglehole, 1988). Factors such as muscle weakness, spasticity, and changes in muscle tone may contribute to the motor impairment of a hemiparetic lower extremity after stroke (Arene & Hidler, 2009). The residual disabilities caused by lower extremity impairment, such as reduced balance, walking speed, and endurance, in persons with stroke can persist even after several years (Menezes et al., 2017). The most common outcome measure for assessing a lower extremity orthosis-based intervention is gait speed, while the kinematics and functional outcome are comparatively less effectively assessed (Figueiredo et al., 2021). It is suggested that the measurement of lower extremity kinematics should receive significant attention, because it has a high correlation with reduced mobility as well as fall risk in persons with a stroke (Mizuta et al., 2024). The most common method for measuring the lower extremity kinematics of patients with stroke is the use of wearable sensors, instead of using a motion capture system, because the motion capture system is mostly non-portable and can only be operated in a standard structured environment, not in a daily living environment (Figueiredo et al., 2021). However, wearable sensors can cause discomfort in patients and may constrain the person's movements, in which case the data captured by the sensors might not reflect the patient's natural movement (Peters et al., 2021). It has hence been proposed that a markerless motion capture (MMC) system, which eliminates the attachment of any markers or sensors on the skin surface, could be applied in kinematic measurements for capturing a more lifelike movement of patients. Kim and colleagues (2016) and Ozturk and colleagues (2016) investigated the use of an MMC system, Kinect, to measure the motion kinematics of upper limbs only, and not lower extremities, in persons with stroke. Lonini et al. (2022) and Lee et al. (2021) used an RGB camera and smartphone, respectively, for measuring the walking performance of persons with stroke, and both of those studies reported that their use of the MMC system was effective when applied to the patients with stroke. However, those researchers mostly focused on measurements of gait parameters, including the participants' walking speed, cadence, swing time, and stance time. Lower extremity kinematics, which are the core factor affecting gait performance, have not been measured. Hence, this study sought to explore the performance of an MMC system for measuring the lower extremity kinematics in persons with stroke. A customized MMC system in an iPad Pro with a LiDAR scanner was developed for this kinematic measurement. Our MMC system in the iPad Pro served as a portable motion capture device which could have the potential to obtain kinematic measurements in areas other than a controlled laboratory environment. The aim of this study was to investigate: 1) the difference in lower extremity movement kinematics between persons with stroke who had different levels of mobility, and their healthy counterparts, when they were performing assessment tasks in both controlled and uncontrolled environments, as measured by a customized MMC system in an iPad Pro; and 2) the relationship between the kinematic information obtained by the MMC system and the scores from manual motor assessments. This study also investigated the sensitivity and specificity of the classification of lower extremity function in persons with stroke, using machine-learning methods and the kinematic data from the MMC system.

6.2 METHODS

6.2.1 Study design

This was a cross-sectional experimental study. Ethical approval was obtained from the Human Subjects Research Ethics Committee of the Hong Kong Polytechnic University (Reference No.: HSEARS20230214010). Prior to inclusion, all subjects were informed about the objectives and procedures of the study. Subjects who met the inclusion criteria provided informed consent before entering the study. A customized MMC system developed in an iPad Pro with a LiDAR scanner was designed to capture the movements of the participants. The participants with stroke were first assessed with the Modified Functional Ambulation Classification (MFAC) (Park & An, 2016) for their walking ability. Participants who met the inclusion criteria then underwent the Berg Balance Scale (BBS) assessment administered by a trained therapist. After those assessments, the participants were invited to perform five sets of lower extremity tasks that were extracted from the BBS and Fugl Meyer Assessments: Motor Function of the Lower Extremity (FMA-LE) with their non-hemiplegic sides first, followed by their hemiplegic side. Assuming that the healthy participants would score full marks in all of the assessments, the healthy participants skipped the assessment sessions and directly performed the same sets of tasks for the motion capturing with their dominant side followed by their nondominant side. All of the participants repeated each task five times with each limb. To investigate the performance of the MMC system in an uncontrolled environment, after the motion capturing session in the laboratory the participants performed the same sets of tasks again in three randomly selected outdoor areas.

6.2.2 Participants

To be eligible to participate in the study, candidates had to: 1) be adults aged 18 years old or above, 2) have been diagnosed with a hemiplegic stroke, 3) have no history of previous neurological or orthopedic diseases/congenital disorders of the upper, lower extremities and spine, 4) have scored more than 40 points in the Berg Balance Scale (BBS) assessment, 5) have adequate cognitive ability to understand instructions, and 6) be able to engage in at least a one-hour experimental session. Participants in this study were invited to participate in both the upper and lower limb motion capturing experiments. In this chapter, we focus solely on reporting and discussing the results of the upper limb experiment.

Participants were excluded if they met any of the following conditions: 1) they were medically unstable, 2) they had previous injuries or medical conditions of the upper extremities or spine affecting upper limb functions (Healthy participant group), or 3) they had an MFAC score of category II or below.

6.2.3 Assessment

Berg Balance Scale (BBS)

The *Berg Balance Scale* is a 14-item objective measure that assesses static balance and fall risk in adults. Each item is scored in a range of 0 to 4, with 0 indicating the lowest level of function and 4 indicating the highest level of function (Kornetti et al., 2004). It is believed that individuals who score lower than 40 points on the BBS may be at greater risk of falling (Muir et al., 2008).

Fugl-Meyer Assessment (FMA)

The Fugl-Meyer Assessment (FMA) scale is an index used to assess the sensorimotor impairment in individuals who have had a stroke (Kim et al., 2012). The FMA is divided into an upper extremity (FMA-UE) part and a lower extremity (FMA-LE) part, with maximum scores of 66 and 34 points in the FMA-UE and FMA-LE, respectively. The lower extremity subscores were adopted in this study.

6.2.4 Sample size considerations

We assumed a two-tailed comparison with a type I error rate of 0.05, with 80% power. The participants with stroke were stratified according to lower and higher levels of functional ambulation, using the MFAC scale. Participants with a stroke who could walk independently either indoors or outdoors (level 6 or above in the MFAC) were categorized as higher functioning, while persons with a stroke who did not reach an independence level in their ambulation (i.e., had a level 5 or below score on the MFAC) were categorized into the lower-functioning group (Chung, 2018). As a conservative estimation with a discard rate of 15% due to bad data or outliners, according to a previous pilot study, and taking into account a dropout rate of 10%, a sample size of 40 persons with stroke and 40 healthy counterparts was predicted. After we had conducted a power analysis based on statistical parameters and using the software GPower3.1.9.2, the effect size was calculated as 0.70, which is between medium (0.5) and large (0.8) (Fritz et al., 2012).

6.2.5 Equipment

MMC system

The markerless motion capturing system that we used to perform motion analysis in this study was developed using Xcode, on the basis of an ARKit6 and RealityKit framework and supported by an iPad Pro with a LiDAR scanner. For the motion capturing experiment, three iPad Pro machines were placed near each participant—one on the frontal side, one on the lateral left side, and one on the right side of the participant. The detection of the human body and the joint position were extracted and realized through computer-vision algorithms of convolutional neural networks (CNNs). A total of 14 3D body joint positions and the timestamp of the motion detection were captured by our motion tracking platform. The capturing frequency of the MMC system was set at 30 Hz. A predefined humanoid model was applied to estimate the joint position and kinematics structure of the tracked subjects. The joint coordinates in 2D or 3D for every captured frame were established and delivered by the algorithms. The normalized coordinates were relative to the center of the pelvis and defined as the origin of the ARKit's coordinate system (Reimer et al., 2022). The adjacent 3D joint coordinates' extraction calculated the angles of interest (AOIs). Angle θ was calculated by the three joints — $A, B, C \in R^3$ or associated vectors $\overrightarrow{v_1} = A - B \ and \ \overrightarrow{v_2} = C - B$, with the formula $\theta = \arccos\frac{v_1 \cdot v_2}{||v_1||_2 ||v_2||_2}$.

6.2.6 Environmental set-up

Controlled indoor environment (Laboratory)

The experiment was conducted at the assistive technology laboratory in the Hong Kong Polytechnic University, and the laboratory floor was covered with vinyl to prevent slipping. For the motion-capturing sessions, participants stood in front of a plain wall in the same laboratory. One iPad Pro was placed on the frontal side of the participant at a distance of 2 meters, and two additional iPad Pros were placed, one at the participants' lateral left and one at their right side.

Uncontrolled outdoor environment (Campus podium)

Three outdoor spots in the university campus podium were chosen as sites to represent the uncontrolled outdoor environment. A 2.5m × 2.5m area in those spots was marked, then two 1m × 1m anti-slip mats were placed on each side of the participants to prevent slipping. Three iPad Pros were brought to those locations and were placed on tripod stands. The positions of the iPad Pro placements were the same as those used in the laboratory environment.

6.2.7 Procedures

Healthy participants and stroke participants from the community were enrolled into the study by convenience sampling. The experiment was divided into two sessions, the first of which was the assessment session. The participants with stroke were first assessed by the assessor using the MFAC to determine their walking ability. Patients who satisfied the inclusion criteria for the motion capturing were then assessed by the BBS.

The second session was the motion capturing experiment. Participants were instructed to perform five sets of tasks that involved lower extremity muscular control: Task 1 was Task 3.1 in the FMA-LE, knee flexion from a sitting position; Task 2 was Task 4.1 in the FMA-LE, knee flexion to 90 degrees at a standing posture; Task 3 was hip flexion to 90 degrees at a standing posture; Task 4 was Task 8 in the BBS—reaching forward with outstretched arm while standing, and Task 5 was Task 14 in the BBS—standing on a single leg. All of the tasks in this session were repeated five times, and the participants with stroke were instructed to perform each task with their unaffected side first followed by their affected side. Figures 1a through 1e illustrate the desired postures of the five tasks.

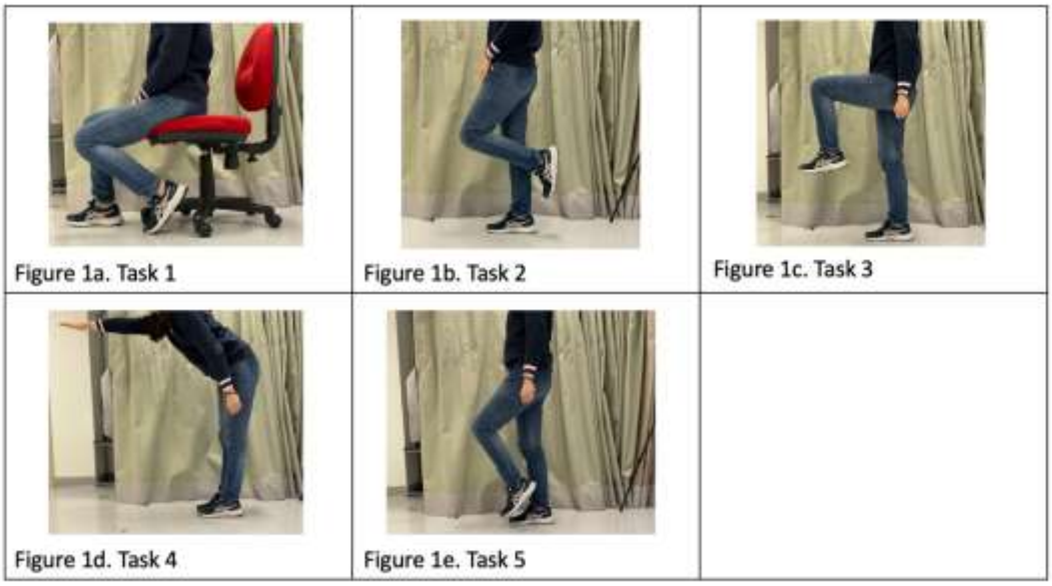

Figure 6.1a to 6.1e (left to right, top down). Illustrations of task 1 through task 5

To test the performance of the MMC system in the natural environment, participants were invited to repeat the motion capturing in the uncontrolled outdoor environment, after they had completed the capturing session in the laboratory. Participants were randomly assigned to one of the three outdoor sites for the motion capturing, and they again performed the identical set of tasks they had done for their motion capturing in the laboratory.

6.2.8 Statistical Analysis

Kinematic data were extracted from the MMC system, including the time of task completion, the angular waveform of the movement, and the angle of the joints when the targeted position was achieved. The first trial of each task served as a practice trial and was not entered into the analysis. The averages of the 2nd – 5th trials of each task were obtained for statistical analysis. Comparisons of the changes in the joints' angles from the initial position to the final position during task completion were made using a *t*-test between 1) the affected side and the unaffected side of the participants with stroke, and 2) the affected side of the stroke participants and the dominant side of the healthy counterparts. Comparisons were made of the time of completion of task 5 and of the angle change of the targeted joint from the initial position to the final position during completion of tasks 1 to 4 for 3) the affected side of the stroke participants with a higher level of functioning (MFAC level 6 or above), the stroke participants with a lower level of functioning (MFAC level 5 or below), and the dominant side of the healthy subjects, using ANOVA with a post hoc test when a significant difference was detected. Differences of the angular waveforms between 1) the affected lower extremity and the unaffected limb of the stroke participants, and the bilateral side of the healthy subjects, were compared using the coefficient of multiple correlation (CMC) and root mean square error (RMSE). Correlations between the assessment results (MFAC, FMA-LE, and BBS) corresponding to the actions and the time of completion for task 5, the angle changes in tasks 1 through 4, the CMC values, and the RMSE values were evaluated using Pearson's *r* correlations. The assessments (MFAC, FMA-LE, and BBS) that showed a significant moderate correlation or above with the kinematic information also then underwent a multiple linear regression analysis with the movement kinematics, which allowed us to quantify the contribution that each kinematic type of data made in the assessment score for the future predictions. A logistic regression (LG) model, Naive Baye classifier (NB) model, support vector machine (SVM) model, and a Decision tree (DT) model were used to investigate the trajectory for the prediction of clinical assessment results for the stroke participants, using the kinematic information from the MMC system, including the 1) angle change of the targeted joint from the joint's initial position to its final position during task completion in all the selected tasks, 2) difference of the angle change between the affected and unaffected side in all selected tasks, and 3) CMC values from all the tasks. All of the descriptive statistics, *t*-test, Pearson's *r* correlations, and regression analyses were performed using IBM SPSS 26 software, while the CMC and RMSE values were generated with MATLAB R2020a. All four of the machine-learning models were performed by using the package Scikit-learn in Python. The linear Support Vector Machine model is SVM using linear kernel. l_2 Regularization was implemented to the Logistic Regression model.

6.3 RESULTS

Fifty persons with a stroke and 49 healthy counterparts were recruited. Among the stroke participants, nine scored below 40 points on the BBS and one failed to complete the whole experimental session due to fatigue, so those individuals were excluded from the motion-capturing experiment. Hence, data from 40 persons with stroke and 49 healthy adults were entered into the final analysis. The mean ages of the stroke group and the healthy adult group were 58.1 years (SD: 12.3) and 60.2 years (SD: 8.5), respectively. Demographic data of the participants are given in Table 6.1.

Table 6.1 Demographic description of the participants

Descriptors	Stroke Group	Healthy Group
Mean Age (years)	57.7 (12.5)	60.2 (8.5)
Gender ratio (males:females)	62.5:37.5	18:31
MFAC (n)		
FTHUE levels 3-5	8	NA
FTHUE levels 6-7	32	NA
Hemiplegic side (n)		
Right	19	NA
left	21	NA
Dominant side (Pre-onset) (n)		
Right	38	48
Left	1	1
FMA-LE Score (Mean)	23.0 (7.2)	NA
BBS Score (Mean)	48.4 (3.7)	NA

Note: **BBS:** *Berg Balance Scale*, **FMA-LE:** *Fugl Meyer Assessment: Motor Function of the Lower Extremity*, **MFAC:** *Modified Functional Ambulation Classification*

The joint angle changes from the initial positions before performing the tasks to the final positions that the participants maintained are presented in Table 6.2. Significant differences in the angle changes of the targeted joint were found between the hemiplegic and non-hemiplegic side of the stroke participants with lower functioning, in all tasks except the change in trunk flexion angle in task 4 (MD = -0.2, SD = 15.7, p = 0.97). Significant differences in the changes of joint angles were found between the hemiplegic and non-hemiplegic side of the stroke participants with higher functioning in all tasks except task 3 (MD = -0.8, SD = 14.4, p = 0.75) and task 4 (MD = -3.7, SD = 14.7, p = 0.17). No significant difference was found in the changes of angles between the dominant and nondominant sides of the healthy participants. Comparisons of the joint angle changes between the hemiplegic side of the two groups of stroke participants and the dominant side of the healthy participants were also conducted. Significant differences were found in the angle changes of the hip and knee joints between the stroke participants with lower functioning and the healthy adults, in all tasks (mean difference, or MD scores ranged from 24.3 in task 4 to 43.9 in task 2, $p<0.05$ in all tasks). The joint angle changes between the stroke participants with higher functioning and the healthy participants were also significantly different in all tasks except in task 3 (MD = 5.0, SD = 12.3, p = 0.36). The joint angle changes on the hemiplegic side of the stroke participants with lower functioning were also significantly different from those of the stroke participants with higher functioning, in all tasks except in task 1 (MD = 9.8, SD = 6.7, $p = 0.10$).

Table 6.2 Joint/body angle changes from the initial joint position before performing the tasks to the final joint positions that the participants maintained at task completion

Task	Changes in joint angle (Initial angle of the targeted joint – final angle of the targeted joint)											
	Stroke (Lower-functioning group)			Stroke (Higher-functioning group)			Healthy Group					
	Hemiplegic Side	Non-hemiplegic Side	Mean Difference (Hemiplegic – Non-hemiplegic)	Hemiplegic Side	Non-hemiplegic Side	MD (Hemiplegic – Non-hemiplegic)	Dominant Side	Non-dominant Side	MD (Dominant – Non-dominant	MD (Stroke low Hemi vs. Stroke high Hemi)	MD (Stroke low Hemi vs. Healthy Dominant)	MD (Stroke high Hemi vs. Healthy Dominant)
Task 1 **Knee flexion at sitting position**												
Change in knee angle	26.4 (11.7)	61.5 (9.7)	-35.2 (15.5)*	36.1 (18.0)	52.7 (18.6)	-16.5 (25.1)*	52.7 (18.0)	55.6 (17.0)	-2.9 (18.1)	9.8 (6.7)	26.4 (16.6)*	16.6 (4.1)*
Task 2 **Knee flexion to 90 degrees in standing position**												
Change in knee angle	48.5 (13.8)	96.3 (7.3)	-47.7 (18.4)*	79.4 (12.0)	99.8 (9.0)	-20.3 (15.9)*	92.5 (10.7)	93.4 (10.7)	-0.9 (14.2)	30.9 (4.9)*	43.9 (5.1)*	13.0 (9.6)*
Task 3 **Hip flexion to 90 degrees in standing position**												
Change in hip angle	38.0 (14.2)	65.6 (7.2)	-27.6 (14.8)*	67.6 (11.0)	68.4 (9.2)	-0.8 (14.4)	72.6 (9.8)	70.5 (10.2)	2.1 (15.6)	29.5 (4.6)*	34.5 (14.0)*	5.0 (12.3)

Task 4												
Reaching forward												
Change in trunk flexion angle	14.9 (13.6)	15.2 (11.2)	-0.2 (15.7)	27.4 (10.7)	31.0 (9.5)	-3.7 (14.7)	39.2 (12.1)	35.6 (10.1)	3.6 (17.1)	12.4 (14.5)*	24.3 (4.7)*	11.9 (2.6)*
Task 5												
Single leg stand												
Time (s)	3.9 (1.4)	17.8 (8.5)	-14.0 (9.3)*	15.9 (16.4)	27.6 (16.5)	-11.7 (11.7)*	42.5 (17.5)	42.2 (19.4)	0.3 (8.9)	12.0 (5.8)	38.1 (9.6)*	26.1 (3.9)*

Footnote: * *P*<0.05

MD: *Mean Difference*

The angular waveforms of each task between the two sides of the participants were compared using CMC and RMSE values (Table 6.3). The CMC values of the stroke participants with lower functioning fell between 0.36 in the knee angle of task 2, and 0.57 in the trunk angle of task 4, while the CMC values of the stroke participants with high functioning were in the range of 0.58 (knee angle in task 5) to 0.78 (knee angle in task 2). The CMC values of the healthy participants had a minimum value of 0.61 (knee angle in task 5) and a maximum value of 0.87 (knee angle in task 1).

Table 6.3 CMC and RMSE values of the angular waveforms of the stroke participants in the lower functioning group, the higher functioning group, and the healthy group

Task	Stroke (Lower-functioning group)		Stroke (Higher-functioning group)		Healthy	
	CMC (SD)	RMSE (SD)	CMC (SD)	RMSE (SD)	CMC (SD)	RMSE (SD)
Task 1 **Knee flexion at sitting position**						
knee	0.48 (0.06)	33.3 (3.00)	0.72 (0.06)	23.32 (7.03)	0.87 (0.04)	10.50 (2.19)
Task 2 **Knee flexion to 90 degrees at standing position**						
knee	0.36 (0.10)	38.1 (14.22)	0.78 (0.05)	22.10 (16.7)	0.84 (0.06)	12.80 (11.95)
Task 3 **Hip flexion to 90 degrees at standing position**						
Hip	0.54 (0.07)	24.67 (6.23)	0.76 (0.08)	18.20 (5.07)	0.81 (0.05)	12.51 (2.73)
Task 4 **Reaching forward**						
Trunk	0.57 (0.05)	24.16 (9.50)	0.77 (0.06)	17.61 (15.7)	0.81 (0.10)	11.79 (12.73)

Task 5						
Single leg stand						
Hip	0.39 (0.14)	34.63 (24.51)	0.59 (0.07)	26.33 (24.43)	0.71 (0.05)	19.96 (25.37)
Knee	0.43 (0.09)	29.10 (5.11)	0.58 (0.15)	27.39 (15.17)	0.61 (0.10)	23.65 (26.22)

Note: **CMC:** *Coefficient of multiple correlations*, **RMS:** *Root mean square error*

The correlations between the kinematic information and the selected assessments are presented in Table 6.4. The CMC values of all tasks generally show a significant, strong correlation with the MFAC scores (ranging from 0.613 in task 3 to 0.768 in task 1), except for the knee CMC values in task 5 (CMC = 0.302). Significant moderate correlations were also found between the FMA-LE scores and the CMC values of all tasks (the CMC values ranged from 0.483 in the hip angles of task 5 to 0.556 in task 4), with the exception of the knee angle in task 5. Weak to moderate correlations were found between the BBS scores and the CMC values of all tasks (ranging from 0.302 to 0.509), except for the knee angle in task 5. The joint angle changes in all tasks generally demonstrated a weak to moderate correlation with the MFAC and FMA-LE scores but not with the BBS score.

Table 6.4 Correlations between the movement kinematics and the assessment scores

Correlations with the MFAC scores						
Task	Stroke (All)					
	Angle change (Hemi initial angle – Hemi final angle)	Angle difference (Non-hemi final – Hemi final)	CMC (Non-hemi – Hemi)	RMSE (Non-hemi – Hemi)	Duration (Hemi)	Difference in duration (Non-hemi – Hemi)
Task 1 Knee flexion in sitting position						
Knee	0.260	0.504*	0.763*	-0.411*	NA	NA
Task 2 Knee flexion to 90 degrees in standing position						
Knee	0.475*	0.594*	0.738*	-0.536*	NA	NA
Task 3 Hip flexion to 90 degrees in standing position						
Hip	0.611*	0.426*	0.613*	-0.414*	NA	NA
Task 4 Reaching forward						
Trunk	0.161	0.006	0.714*	-0.279	NA	NA
Task 5 Single leg stand						
Hip	NA	NA	0.723*	-0.528*	0.416*	-0.172
Knee	NA	NA	0.302	-0.009		
Correlations with the FMA-LE levels						
Task 1 Knee flexion in sitting position						
Knee	0.355*	0.476*	0.500*	-0.406*	NA	NA
Task 2 Knee flexion to 90 degrees in standing position						
Knee	0.465*	0.445*	0.511*	-0.281	NA	NA
Task 3 Hip flexion to 90 degrees in standing position						
Hip	0.361*	0.333*	0.555*	-0.251	NA	NA
Task 4 Reaching forward						
Trunk	0.102	0.087	0.556*	-0.091	NA	NA

Task 5 Single leg stand						
Hip	NA	NA	0.483*	-0.342*	0.363*	0.036
Knee	NA	NA	0.092	0.007		
Correlations with the BBS scores						
Task 1 Knee flexion in sitting position						
Knee	0.156	0.388*	0.509*	-0.162	NA	NA
Task 2 Knee flexion to 90 degrees in standing position						
Knee	0.253	0.290	0.370*	-0.124	NA	NA
Task 3 Hip flexion to 90 degrees in standing position						
Hip	0.260	0.236	0.374*	-0.093	NA	NA
Task 4 Reaching forward						
Trunk	0.117	0.050	0.302	-0.176	NA	NA
Task 5 Single leg stand						
Hip	NA	NA	0.397*	-0.373*	0.191	0.060
Knee	NA	NA	0.043	0.115		

Footnote: *P<0.05

BBS: *Berg Balance Scale,* **CMC:** *Coefficient of multiple correlation*, **FMA-LE:** *Fugl Meyer Assessment: Motor Function of the Lower Extremity*, **MFAC:** *Modified Functional Ambulation Classification,* **RMS:** *Root mean square error*

A multiple linear regression analysis was conducted with the MFAC levels as the outcome, and the joint angle changes, joint angle differences between the bilateral side, task completion durations (task 5), and CMC and RMSE values as the independent variables (Table 6.5). The regression model explained 80.2% of the selected variation in the MFAC levels, thus indicating a strong relationship between the kinematics and the functional ambulation classification. The values of the coefficients of multiple correlations demonstrated the highest values among the covariates (the coefficients ranged from 0.058, $p = 0.974$ for the CMC values in task 3, to 4.393, $p = 0.016$ in task 4).

Table 6.5 Multiple linear regression analysis of the MFAC as the outcome (Adjusted $R^2 = 0.803$)

Covariate	Coefficient (SE)	β	t	p
(Constant)	3.167 (7.069)		0.448	0.659
Angle change (Hemi initial – Hemi final)				
Task 1	-0.001 (0.009)	-0.013	0.099	0.922
Task 2	-0.013 (0.018)	-0.200	-0.731	0.472
Task 3	-0.20 (0.018)	-0.283	-1.107	0.280
Task 4	0.12 (0.16)	-0.113	0.716	0.482
Angle difference (Non-hemi final – Hemi final)				
Task 1	-0.009 (0.008)	-0.129	-1.061	0.300
Task 2	0.012 (0.011)	0.207	1.123	0.274
Task 3	0.014 (0.017)	0.188	0.810	0.426
Task 4	-0.019 (0.018)	-0.159	-1.020	0.319
CMC (Non-hemi – Hemi)				
Task 1	3.043 (1.678)	0.296	1.813	0.084
Task 2	-0.078 (1.370)	-0.012	-0.057	0.955
Task 3	0.058 (1.751)	0.006	0.033	0.974
Task 4	4.393 (1.685)	0.375	2.607	0.016*
Task 5 (Hip)	1.179 (1.343)	0.116	0.878	0.390
Task 5 (Knee)	-1.153 (0.719)	-0.125	-1.603	0.123
RMSE (Non-hemi – Hemi)				
Task 1	0.029 (0.024)	0.166	1.195	0.245
Task 2	-0.030 (0.028)	-0.217	-1.071	0.296
Task 3	-0.025 (0.020)	-0.113	-1.246	0.226
Task 4	-0.009 (0.016)	-0.051	-0.566	0.577

Task 5 (Hip)	0.018 (0.027)	0.089	0.695	0.495
Task 5 (Knee)	-0.002 (0.019)	-0.010	-0.118	0.907
Duration (Hemi)				
Task 5	0.007 (0.009)	0.083	0.834	0.413
Time difference in duration (Non hemi – Hemi)				
Task 5	0.010 (0.010)	0.086	1.053	0.304

Adjusted $R^2 = 0.803$

Footnote: *P<0.05

Note**: CMC:** *Coefficient of multiple correlation,* **MFAC:** *Modified Functional Ambulation Classification,* **RMS:** *Root mean square error*

Data from four repetitions of five tasks from 89 subjects, making a total of 1,780 sets of data, were entered our machine-learning analysis. The data set was divided into training and test splits, using five-fold subject-wise stratified cross validation (Tougui et al., 2021). Four machine-learning models were trained to perform the lower extremity ambulation functional level classification, using the joint angle change of the hemiplegic side, the final angle position difference between the hemiplegic and non-hemiplegic side, and the CMC values (Table 6.6). The sensitivity of the models trained by the angle change showed a maximum sensitivity of 0.75 by the SVM model and a minimum sensitivity of 0.61 by the DT model. The highest sensitivity and specificity were generated by the SVM model, using the CMC values for the classification (sensitivity = 0.85; specificity = 0.82).

Table 6.6 Machine-learning classification for lower extremity ambulation functioning, according to kinematics information

By angle change (Hemi initial angle – Hemi final angle)		
Model	Sensitivity	Specificity
LG	0.64	0.61
NB	0.62	0.65
SVM	0.75	0.73
DT	0.61	0.59
By final angle position, difference between hemi and non-hemi		
Model	Sensitivity	Specificity
LG	0.71	0.71
NB	0.69	0.68
SVM	0.78	0.75

DT	0.69	0.66
By CMC		
Model	Sensitivity	Specificity
LG	0.83	0.80
NB	0.72	0.70
SVM	0.85	0.82
DT	0.77	0.71

Note: **CMC:** *Coefficient of multiple correlation,* **DT:** *Decision Tree,* **LG:** *Logistic Regression,* **NB:** *Naive Bayes classifiers,* **SVM:** *Support Vector Machine*

A total of 41% of the data captured in the outdoor environment were discarded because of noise signals and missing data. Statistical analyses for the outdoor data were not performed, due to insufficient power.

6.4 DISCUSSION

We found a significant difference between the bilateral sides in the persons with stroke, but not in the healthy participants, in terms of the joint angle changes from the initial position to the final position for task completions. The angle change from a joint's initial position to its final position during each task can be interpreted as a reflection of the joint's active range of motion (AROM) for completing the study's lower extremity tasks. The knee flexion and hip flexion AROMs in the healthy adults when performing our selected task were 0 to 93.4 degrees and 0 to 72.6 degrees, respectively, while the bilateral differences were no more than 3 degrees. Those findings are reflected against a significant limitation of the active ranges of motion for the knee flexion and the hip flexion in the hemiplegic lower extremity of the stroke participants, compared with their AROMs for their non-hemiplegic side, and such limitations in AROMs were also detectable by the MMC system. The limitations of the active range of motion on the stroke participants' hemiplegic side could be the result of stroke-induced muscle weakness, rigidity, or spasticity (O'dwyer et al., 1996). Hence, it is apparent that the MMC system in mobile devices is quite sensitive enough for detecting movement limitations in persons with a stroke who have reduced motor ability due to hemiplegia.

We also found that there was a noticeable difference (the mean difference, or MD, ranged between 5.0 degrees and 43.9 degrees) in the knee and hip AROMs between the hemiplegic side of the stroke participants and the dominant side of the healthy adults. This finding is consistent with the suggestions by other researchers that persons with stroke are prone to a reduction in their active range of motion, which in turn could affect their gait and balance (Beebe & Lang, 2009). We also found that the knee and hip AROMs of the hemiplegic side during the tasks done in a standing position were significantly different between the stroke participants with lower functioning and those with higher functioning, with a mean difference of 9.8 to 30.9 degrees in their knee flexion and 29.5 degrees in their hip flexion angle in our selected tasks. In contrast, no significant AROM difference was detected between the unaffected side of the stroke participants with the two different functioning levels and the corresponding side of the healthy counterparts. This finding suggests that the non-hemiplegic lower extremity of the persons with stroke might not exhibit a significant functional difference compared with the lower extremity of healthy adults. Our results therefore might imply that the AROM data obtained through the MMC system could effectively reflect the disparity in functioning of the hemiplegic lower extremity between the stroke participants with lower levels of functionality and those with higher levels of functionality. Our results provide evidence that an MMC system in mobile devices is sensitive enough to detect the reduction in active range of motion experienced by persons with stroke. Thus, the MMC system might be able to serve as an effective alternative for quick AROM assessment in such patients.

Our comparisons of the angular waveforms for performing the tasks by the left and right sides of the participants were represented by the CMC and RMSE values. The stroke participants with lower functioning demonstrated the lowest CMC values and the greatest RMSE values. In addition to the limitations in their active range of motion for task completion, which is a common deficit after stroke, persons with stroke may tend to use compensatory movements to perform required actions (Chen et al., 2003), such as using hip abduction or hip rotation actions instead of hip flexion in task 3. Clinical observations by therapists are typically employed to identify those compensatory movements, which are challenging to quantify objectively (Duncan et al., 1994). However, our study has revealed that an MMC system can effectively capture these compensatory movements, and the movements are reflected in the angular waveforms. It may be that the stroke participants with higher functioning had comparatively less motor deficit, so they adopted fewer compensatory movements and consequently, there was a higher degree of similarity in terms of the angular waveforms between the hemiplegic and non-hemiplegic sides in the higher functioning group. We also observed that although the healthy adults demonstrated high CMC values in most of the tasks, the CMC values of the knee in task 5 were lower than those in the other tasks. Task 5 was a single-leg stand task, while the CMC values here represented the comparison of angular waveforms of the raised leg. Healthy individuals might also experience leg shaking or leg dropping of their raised leg during task 5. Due to a muscle imbalance between the bilateral sides, which is common in healthy adults (Hill et al., 2023), and the disequilibrium that increases with age (Hobeika, 1999), healthy individuals might also generate a rather different angular waveform between their bilateral legs during the single-leg stand task. In that light, comparisons of the bilateral differences of only a single task, and particularly of the single-leg stand task, which commonly produces bilateral difference even in healthy adults, might not adequately reflect the lower extremity function of an individual. Therefore, we suggest that the angular waveform generated by the MMC system should be carefully interpreted, and an evaluation of the kinematics from a combination of motion capture tasks might be necessary for an accurate determination of the lower extremity movements of persons with stroke.

The strongest correlation was found between the MFAC levels and the CMC values of our selected tasks, while a moderate correlation was found between the FMA-LE scores and the CMC values. Instead of the joint angle changes, which reflect active range of motion, the CMC values, which reflect the comparison of the overall difference in the movement pattern between the hemiplegic limb and the non-hemiplegic limb, showed a better correlation with the assessment scores. In our multiple regression analyses, the CMC values, instead of the AROM, showed a greater magnitude of the effect to the MFAC scale. Despite the limitations in range of motion, the lower extremity deficits in the persons with stroke might also be represented in the form of resistance in movement, action tremor, or an increase in compensatory movement (Handley et al., 2009). These forms of lower extremity deficits can be demonstrated by the comparison of the overall angular patterns of movement captured by the MMC, but they cannot be judged only by the form of the AROM. The MFAC is an index of disability, and it reflects the person's overall ambulation independence (Lim et al., 2019), while the FMA-LE scores reflect the person's overall lower extremity performance. Thus, both measures show a significant correlation with the movement pattern differences between the bilateral sides, as captured by the MMC system. The MMC technology therefore demonstrates the advantage of being able to reflect and analyze the individual's movement patterns, in contrast to the traditional manual measurement of range of motion, which can only measure the joint angle at one particular point in time. Although the BBS is a scale that measures the person's ability to balance, which involves a combination of elements such as muscle coordination, the vestibular system, and psychological factors (Tyson et al., 2006), it might not show a strong correlation with solely the lower extremity tasks that we selected.

Our four machine-learning models showed the best performance in classification of the lower extremity ambulation functioning by using the CMC values, which may offer greater sensitivity in the classification of lower extremity functional performance compared with AROM values. Because a comparison of joint angle changes reflects only the difference in the AROM between the bilateral sides, a comparison of the overall movement patterns of the hemiplegic and the non-hemiplegic sides provides more comprehensive information for classifying the subjects' lower extremity ambulation function. The SVM model demonstrated the best performance for classification, with a sensitivity of 0.85 or greater. Our results therefore support the notion that an MMC, in combination with machine-learning methods, can be adopted for lower extremity functional evaluation and can achieve a very satisfactory sensitivity (Moro et al., 2020). This result recommends the future adoption of using the kinematic data captured by an MMC system during a few sets of motion-capturing tasks for classification or quick prediction of lower extremity function in persons with stroke. Such a system might therefore facilitate lower extremity motor recovery screening in persons with stroke, which could allow therapists to understand more precisely the motor conditions of those patients while they are undergoing a rehabilitation program, especially during remote rehabilitation, in which progress in motoring is not sufficient to meet their rehabilitation needs. Because the traditional manual assessment for evaluating lower extremity functioning in persons with stroke involved a large set of assessment tasks for determining their functioning abilities, the MMC system may offer a viable alternative for assessing lower extremity motor function because of its convenient ability to provide kinematic data. Indeed, particularly the CMC values can be used as a predictive marker with high sensitivity for categorizing a stroke patient's functional level as higher or lower, with patients only needing to perform a limited set of tasks.

The quality of data captured by the MMC system in the outdoor environment was comparatively lower than that in the indoor environment. A possible explanation is that the outdoor environments comprised a clustered background with pedestrians passing by, and the MMC system tended to misidentify the moving limbs of the pedestrians and the tree branches as the limbs of the targeted subjects. The MMC system also lost its tracking when the light intensity in the outdoor environment was low, because it failed to recognize the body segment of the subjects from a dim image. Knowing that the MMC system might capture a significant amount of noise signals in a completely unstructured environment, which in turn would affect further motion analysis, we conclude that the utilization of the MMC system in the outdoor setting is not preferred. We recommend that the MMC be used indoors, in front of a plain wall background, and with sufficient light intensity. In addition, a pre-assessment training session for users of the MMC system may be essential, to familiarize them with the appropriate MMC data capturing procedures, such as the environmental setting and system operations.

Our study supports the notion that an MMC system can be used for measuring patients' lower extremity kinematics to evaluate the lower extremity function of persons with stroke, in the indoor environment, and its utilization for clinical measurement may even be further generalizable to other disease populations. To facilitate transferring to healthcare professionals the technology that uses portable MMC systems for remote clinical measurements and for telerehabilitation, the development of a user-friendly interface design for such a system, including an algorithm for the interpretation of the kinematic data, is warranted.

6.4.1 Limitations

This study had certain limitations. First, the study's sample size was small for training and testing the effects of using MMC kinematic data for lower extremity function classification in machine-learning models. Second, the lower extremity functional level of the stroke participants was not in a balanced ratio—the stroke participants with higher functioning and those with lower functioning were not in equal proportion. In addition, only five tasks were selected, in order to conduct a preliminary investigation of the kinematic measurements by using the MMC system in mobile devices. In the future, studies may wish to include a greater variety of motor tasks for kinematic analyses.

6.5 CONCLUSIONS

This study examined the use of a customized markerless motion-capturing system for measuring and evaluating lower extremity kinematics. We found significant differences in the joint angle changes between the hemiplegic and non-hemiplegic sides of stroke participants performing specific tasks, as well as between stroke participants and healthy participants. The stroke participants also demonstrated lower CMC values in terms of angular waveform comparisons between bilateral limbs. Our SVM model used CMC values to classify the lower extremity functional performance of the stroke participants into lower-level functioning and higher-level functioning individuals, and in that regard it achieved very high sensitivity and specificity. Our study's findings support use of an MMC system in mobile devices to assess lower extremity function in persons with stroke. Further research is now warranted to explore such a system's application in home-based telerehabilitation, with a user-friendly interface and a wider range of motor tasks.

6.6 REFERENCES

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CHAPTER 7

CONCLUSION

Chapter 7

Conclusion

ABSTRACT

This chapter concludes the studies that we have conducted in this thesis, "The application of markerless motion capture (MMC) in patients with stroke," and we propose future directions for the application of MMC in rehabilitation.

In this chapter, we summarize and highlight the key findings of the research studies in this thesis. Implications for clinical use of MMC technology, limitations of the thesis, and recommendations for future research are discussed.

This thesis revealed that the development and application of markerless motion capture (MMC) technology using a mobile device is useful in terms of sensitivity in measuring the upper and lower limb kinematics of patients with stroke (Chapter 5 and Chapter 6). The findings reveal that the functioning ability of patients with stroke can be classified by machine learning models with satisfactory accuracy in terms of sensitivity and specificity using the kinematic data captured by our MMC system using an iPad Pro. Our systematic review shows that MMC technology can reliably measure the kinematic movement of patients with stroke (Chapter 2). It is suggested that MMC technology is reliable, accurate, and valid for clinical measurement, and hence has potential to be utilized in telerehabilitation. Besides the investigation on the reliability and validity of the MMC system we used, in this thesis we suggest that in future, researchers should work further on exploring the potential and enhancing the generalizability of MMC technology for telerehabilitation in the home setting.

One of the factors that affects the generalizability of MMC technology in telerehabilitation its usability. The current application of MMC technology for clinical measurement in patients with stroke was mostly conducted in structured laboratory or clinical settings, and the operation of the MMC system was mostly handled by researchers. While the concept of telerehabilitation emphasizes independence in conducting rehabilitation programs in the home setting, the MMC system should allow patient interaction in order to enable them to capture their performance, receive feedback from the system, and transmit the captured data to healthcare professionals for further interpretation. To facilitate the self-operation of an MMC system by patients, we suggest the design of a user-friendly interface. The interface should be clear and easy to understand, which would make it intuitive to interact with. As patients with stroke might suffer from different degrees of motor or cognitive deficits, the user interface of the MMC system should be customized to minimize the cognitive load on the users and ensure that they can access and use the system effectively. Future study on the user interface design for telerehabilitation MMC systems is warranted to facilitate convenient use. To facilitate interoperability in telerehabilitation, future development should be focused on ensuring the MMC system can be integrated with wearables and smart home health technologies in the home.

Another gap to be addressed is the analysis and evaluation of the kinematic data. Most of the current research relies on the use of algorithms or processors in external software for kinematic data analysis. The data post-processing and analysis generally requires a long processing time that does not favor MMC's adoption in telerehabilitation. If an MMC system cannot generate an immediate motion analysis result report, users might lose motivation to use it continuously at home since the system cannot provide them with immediate feedback for exercise performance evaluation. Over and above, it being an accurate tracking system, future development of an MMC system that enables quick processing and analysis of kinematic data would be valuable for the adoption of the MMC system in telerehabilitation programs, allowing therapists to customize and adapt training according to users' impairments.

As our study revealed that the use of MMC systems in an unstructured outdoor environment frequently leads to poor kinematic data quality, we suggest that instructions on the preparation of the environment—such as removal of unnecessary items and avoiding that others enter the capturing areas—have to be given to users before they utilize the MMC system for motion capture. Enhancement of image extraction and segmentation of data is also necessary to filter and remove unwanted artifacts in order to enhance the reliability and accuracy of the data and hence facilitate the use of the MMC system in different environments.

The current application of the MMC system in our study primarily focused on capturing the movement of the upper and lower limbs independently. Since daily activities often involve the use of both upper and lower limbs, we recommend that future task selection for motion capture should emphasize tasks that require the combination of both limbs. This approach would provide a more accurate reflection and analysis of motor performance in diseases populations during their functional activities in daily life.

Last but not least, the systematic reviews and meta-analysis done in this thesis suggest that MMC technology has the potential for application in the case of patients with stroke as an assessment tool to assist in the monitoring of their progress in motor recovery, as well as in telerehabilitation programs to continuously record and evaluate their home training exercise performance.

In conclusion, our study revealed that our customized MMC system using an iPad Pro is innovative and original, and can be used in home-based treatment and telerehabilitation for intra-subject measurements because of its good reliability, low cost, and portability. Our application of the customized MMC system using an iPad Pro also revealed that MMC technology is sensitive in detecting the bilateral difference in both upper and lower extremity measurement. We found that the background in an unstructured outdoor environment could lead to a significant amount of noise and missing data. Nevertheless, machine learning models are able to classify the functioning level of patients with stroke into higher and lower functioning groups using the kinematic data captured by the MMC system. We therefore suggest that the MMC system using smartphone or tablets combined with a machine learning algorithm has the potential to be used in future for motor performance measurement of patients with stroke, particularly for telerehabilitation. Further development is warranted to improve its capturing quality in unstructured environments as well as to facilitate its efficiency in data post-processing and analysis. Further study might shed light on the design of a user-friendly MMC system interface in order to increase its generalizability and interoperability for rehabilitation in future.

APPENDICES

Appendix 1. Chinese Consent form for the pilot study on the Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System

香港理工大學康復治療科學系

科研知情同意書

科研題目

基於平板電腦的無標記式動作捕捉系統於上肢關節活動幅度測量的效度及信度研究

科研機構

香港理工大學康復治療科學系

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林潁彤女士(香港理工大學康復治療科學系博士研究生)

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您現被邀請參加此研究計劃。這項研究已獲香港理工大學康復治療科學系部門科研委員會批准。在您決定之前，重要的是您要了解為什麼要進行此研究計劃及它將涉及的內容。請仔細閱讀以下信息，若有需要您亦可與他人討論。請您經過慎重考慮後才決定您是否願意參加。

科研目的

無標記式動作捕捉系統能減省進行動作追蹤時的準備工序並有利於捕捉及分析用家最自然的動態。有文獻建議無標記式動作捕捉系統可於康復治療上加以應用，用以監測復康人士的康復進度及活動能力。基於平板電腦的無標記式動作捕捉系統是一種新發展的動作捕捉技術，其簡易的設定程序和介面或有利於此技術於康復訓練及評估上廣泛應用。目前關於平板電腦上的無標記式動作捕捉系統於動作測量的準確度及可信度之研究並不常見，而其應用於復康人士上肢活動幅度測量的研究則更為缺乏。此研究專案目的為探討基於平板電腦的無標記式動作捕捉系統於測量健康人士及中風人士的上肢活動幅度之有效度及可信度。

科研程序

本研究將有共計 15 名無病徵人士及 15 名患有腦中風的患者參與。每位參與者會於一週內進行共兩輪實驗環節，兩個環節的間距大概為三天。兩環節的實驗內容均為一致，此舉為驗證無標記式動作捕捉系統的再測信度。

在兩個實驗環節中，研究人員會於受試者身上貼上反光標記，受試者需依照研究人員指示擺出四個姿勢供動作捕捉系統紀錄，而研究人員會以測角儀分別量度其肩膊及手肘的關節活動幅度量度。其後研究員會指示受試者進行四組上肢動作，光學動作捕捉系統及基於平板電腦的無標記式動作捕捉系統會同時紀錄受試者的每一組動作。

兩節實驗所收集到的上肢活動數據將加以分析及對比。

對參與人士和社會的益處

此研究的結果將提升基於平板電腦的無標記式動作捕捉系統的程式及有助檢視此系統於中風復康者上肢活動評估的可信性及有效性。

潛在危險性

零風險

資料保密

有需要的話，每個研究參加者都有權利獲得其個人的數據以及公開報告的研究結果。

根據香港法律（特別是「個人資料（私隱）條例」，第 486 章），您有權對您個人資料進行保密，如在本項研究中或與本項研究有關的個人資料的收集、保管、保留、管理、控制、使用（分析或比較）、在香港內外轉讓、不披露、消除和/或任何方式處理。如有任何問題，您可以諮詢個人資料私隱專員公署或致電到其辦公室（電話號碼：2827 2827），以適當監管或監督您個人資料保護，以便您能完全認識和瞭解確保遵守法律保護隱私資料的意義。

同意參與該項研究，您明確作出以下授權:

- 為了監督該項研究，授權主要研究者及其研究團隊和研究倫理委員會根據本項研究和本知情同意書規定的方式獲得、使用並保留您的個人資料。

- 為了檢查和核實研究資料的完整性、評估研究協定與相關要求的一致性，授權相關的政府機構（如香港衛生署、醫院管理局）可獲得您個人資料。

自願參加

您參加這項研究計劃完全是自願。您可以選擇不參加或可以在任何時候停止參與這研究計劃，而不會對您現在及日後所接受的的醫療進行任何更改或失去。

新信息

假如出現有關這研究的任何新資訊，而這些資訊會影響您繼續參與研究的決定，則會及時告知您。在研究期間，假如出現研究程序更改或會影響您健康或參與研究的意願的重要結果，您將獲得通知。您可能需要簽署新的知情同意書，以表示您已獲知會有關這研究的新資訊。

科研之退出與終止

您可自由決定是否參加本研究；研究過程中也可隨時撤銷同意，退出研究，不需任何理由，且不會引起任何不愉快或影響日後的研究參與。研究負責人亦可能於必要時中止該研究之進行。如果沒有提出特別要求銷毀退出前所收集的數據，我們將會繼續使用。參加者會被給予足夠的時間去考慮是否參與這項研究。

費用及補償

完成本次研究可獲一百元超市禮券作為報酬。

科研結果

科研結果可能會在醫學期刊上或在醫學會議上發表。可識別您身份的資料不會出現於任何與此項研究相關的公開發表報告。

聯絡人

如果需要進一步資訊，您可致電聯絡此專案負責人林穎彤博士研究生(Winnie) 9683 或香港理工大學康復治療科學系方乃權教授 27666716。若您本人對此研究人員有任何投訴，可以聯繫鍾小姐（香港理工大學康復治療科學系部門科研委員會秘書），電話：27664329。

您參與此研究課題需要您本人簽署並保管一份同意書副本。

科研知情同意書

科研題目

基於平板電腦的無標記式動作捕捉系統於上肢關節活動幅度測量及分析的效度及信度研究

1. 我確定我已細閱及明白上述科研資料書的具體情況。
2. 我同意將此科研中收集的數據用於有關的研究。我允許將此科研中的數據用於出版文獻。我了解，我的身份將獲得保密處理。任何共享和發布的數據都將完全匿名，因此我不會被識別。我亦允許香港理工大學康復治療科學系部門科研委員會及有關法定機構在合適的條例及法例容許下及在不侵犯我的私隱情況中，直接翻查我的研究數據以核實有關的臨床研究資料。
3. 我明白我的參與是自願的，我並可以隨時自由退出而不需任何理由，我現在及日後所接受的醫療護理或合法權利不受到影響。
4. 我明白參加此研究課題的潛在危險性以及本人的資料將會保密及不會洩露給與此研究無關的人員。
5. 我同意參與以上科研計劃。

6. 我明白我會獲得此同意書副本一份。

參加者姓名	參加者簽署	日期
見證人姓名 （若適用）	見證人簽署	日期
取得同意書研究員姓名	簽署	日期

Appendix 2. Chinese Consent form for the study on the upper and lower extremity kinematic measurement using markerless motion capturing (MMC) in persons with a stroke: A cross-sectional experimental study

香港理工大學康復治療科學系

科研知情同意書

科研題目

基於無標記式動作捕捉系統於中風康復者及健康人士的動作測量及分析

科研機構

香港理工大學康復治療科學系

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方乃權教授 (香港理工大學康復治療科學系教授)

您現被邀請參加此研究計劃。這項研究已獲香港理工大學康復治療科學系部門科研委員會批准。在您決定之前，重要的是您要了解為什麼要進行此研究計劃及它將涉及的內容。請仔細閱讀以下信息，若有需要您亦可與他人討論。請您經過慎重考慮後才決定您是否願意參加。

科研目的

無標記式動作捕捉系統能減省進行動作追蹤時的準備工序並有利於捕捉及分析用家最自然的動態。有文獻建議無標記式動作捕捉系統可加以應用於康復治療，用以監測復康人士的康復進度及活動能力。基於平板電腦的無標記式動作捕捉系統是一種新發展的動作捕捉技術，其簡易的設定程序和介面或有利於此技術於康復訓練及評估上廣泛應用。目前關於平板電腦上的無標記式動作捕捉系統於動作測量的準確度及可信度之研究並不常見，而其應用於復康人士活動幅度測量的研究則更為缺乏。此研究專案目的為探討無標記式動作捕捉系統於測量健康人士及中風康復者的運動動作，以及其運動數據對判斷中風人士的肢體功能的有效度。

科研程序

本研究將招募及篩選共計 50 名健康成年人士及 50 名中風康復者參與。每位中風康復者會於一天內進行上下肢功能評估及兩節肢體運動捕捉實驗；而健康人士則毋需進行肢體功能評估，只會參與兩節肢體運動捕捉實驗。第一節肢體運動捕捉實驗會於理工大學實驗室內進行，而於第二節肢體運動捕捉實驗中，參與者將被隨機分派到理工大學平台或理工大學 Z 座平台花園，進行第二次肢體運動量度。兩次肢體運動捕捉實驗內容均為一致並且將於同一天內進行，此舉為驗證無標記式動作捕捉系統在實驗室及開放環境下的測量表現。

在肢體功能評估環節中，研究人員將以評估量表分別衡量中風康復者上下肢的功能級別，符合資格的參與者會再進行兩套上肢功能評估及/或兩套下肢功能評估，繼而再進入肢體運動捕捉實驗環節。

在兩節肢體運動捕捉實驗中，參與者須依照研究人員指示作出七組上肢動作及/或四組下肢動作，每組動作重複五次，放置在參與者身前及兩側的基於平板電腦的無標記式動作捕捉系統會同步紀錄受試者的每一組動作。

肢體功能評估需時大概四十五分鐘，而兩節肢體運動捕捉實驗則各大約耗時二十分鐘。故中風康復者約需總共九十五分鐘完成整個實驗，而健康人士則需約四十

分鐘完成整個實驗。以上實驗所收集到的數據將加以分析及對比。而被試者在完成實驗後將獲得 100 元超市代金券作為交通津貼。

對參與人士和社會的益處

此研究的結果將有助檢視基於平板電腦的無標記式動作捕捉系統將來應用於中風復康者肢體活動評估的有效性及可能性，亦可為日後基於平板電腦的家用遙距復康監測系統提供研究數據支持。

潛在危險性

在下肢動作運動捕捉實驗中，參與者在進行單腳站立、單腳屈膝、踢腿及身體前傾動作時或有失去平衡及跌倒的風險。因此只有於柏格氏平衡量表中取得 45 分或以上的參與者方會被邀請進行下肢動作捕捉實驗，以確保參與下肢動作捕捉實驗者不具備高失去平衡的風險。

研究將會在鋪有乙烯基地板的實驗室以及鋪有防滑地墊的戶外空間進行，以防參與者在進行下肢動作期間滑倒。研究人員會在動作捕捉實驗期間為參與者提供現

場監察，中風康復者在必要時亦可以拐杖輔助平衡，以減低參與者在實驗期間跌倒或受傷的風險。而研究負責人亦已為所有參與者購買保險。

資料保密

有需要的話，每個研究參加者都有權利獲得其個人的數據以及公開報告的研究結果。

根據香港法律（特別是「個人資料（私隱）條例」，第 486 章），您有權對您個人資料進行保密，如在本項研究中或與本項研究有關的個人資料的收集、保管、保留、管理、控制、使用（分析或比較）、在香港內外轉讓、不披露、消除和/或任何方式處理。如有任何問題，您可以諮詢個人資料私隱專員公署或致電到其辦公室（電話號碼：2827 2827），以適當監管或監督您個人資料保護，以便您能完全認識和瞭解確保遵守法律保護隱私資料的意義。

同意參與該項研究，您明確作出以下授權:

- 為了監督該項研究，授權主要研究者及其研究團隊和研究倫理委員會根據本項研究和本知情同意書規定的方式獲得、使用並保留您的個人資料。

自願參加

您參加這項研究計劃完全是自願。您可以選擇不參加或可以在任何時候停止參與這研究計劃，而不會對您現在及日後所接受的的醫療進行任何更改或失去。

新信息

假如出現有關這研究的任何新資訊，而這些資訊會影響您繼續參與研究的決定，則會及時告知您。在研究期間，假如出現研究程序更改或會影響您健康或參與研究的意願的重要結果，您將獲得通知。您可能需要簽署新的知情同意書，以表示您已獲知會有關這研究的新資訊。

科研之退出與終止

您可自由決定是否參加本研究；研究過程中也可隨時撤銷同意，退出研究，不需任何理由，且不會引起任何不愉快或影響日後的研究參與。研究負責人亦可能於必要時中止該研究之進行。如果沒有提出特別要求銷毀退出前所收集的數據，我們將會繼續使用。參加者會被給予足夠的時間去考慮是否參與這項研究。

費用及補償

完成本次研究可獲一百元超市禮券作為報酬。

科研結果

科研結果可能會在醫學期刊上或在醫學會議上發表。可識別您身份的資料不會出現於任何與此項研究相關的公開發表報告。

聯絡人

如果需要進一步資訊，您可致電聯絡此專案負責人林潁彤博士研究生(Winnie) 9683 或香港理工大學康復治療科學系方乃權教授 27666716。若您本人對此研究人員有任何投訴，可以聯繫鍾小姐（香港理工大學康復治療科學系部門科研委員會秘書），電話：27664329。

您參與此研究課題需要您本人簽署並保管一份同意書副本。

科研知情同意書

科研題目

基於無標記式動作捕捉系統於中風康復者及健康人士的動作測量及分析

7. 我確定我已細閱及明白上述科研資料書的具體情況。
8. 我同意將此科研中收集的數據用於有關的研究。我允許將此科研中的數據用於出版文獻。我了解，我的身份將獲得保密處理。任何共享和發布的數據都將完全匿名，因此我不會被識別。我亦允許香港理工大學康復治療科學系部門科研委員會及有關法定機構在合適的條例及法例容許下及在不侵犯我的私隱情況中，直接翻查我的研究數據以核實有關的臨床研究資料。
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10. 我明白參加此研究課題的潛在危險性以及本人的資料將會保密及不會洩露給與此研究無關的人員。
11. 我同意參與以上科研計劃。
12. 我明白我會獲得此同意書副本一份。

參加者姓名	參加者簽署	日期
見證人姓名 （若適用）	見證人簽署	日期
取得同意書研究員姓名	簽署	日期

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Expected presentation date	Aug 2024

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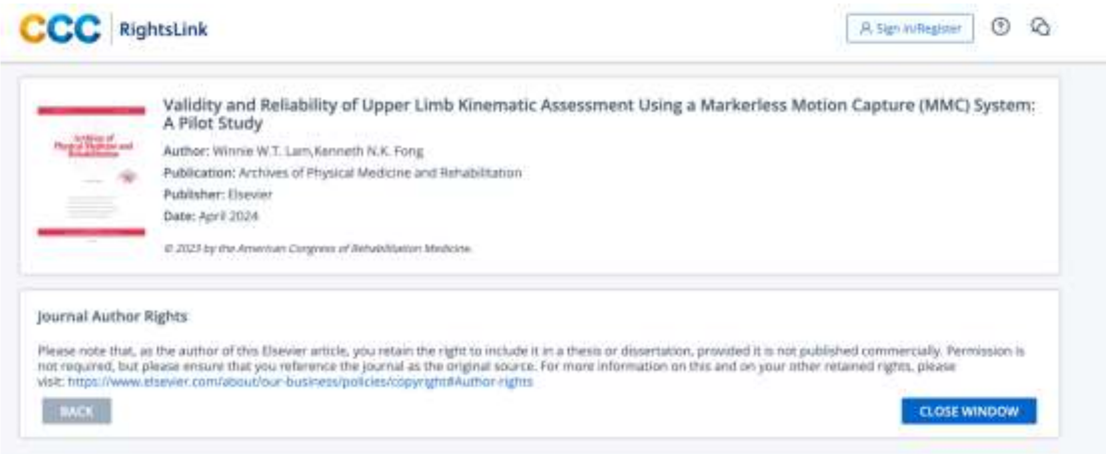
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Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System: A Pilot Study

Author: Winnie W.T. Lam,Kenneth N.K. Fong

Publication: Archives of Physical Medicine and Rehabilitation

Publisher: Elsevier

Date: April 2024

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Appendix 6. Ethical approval memo for the pilot study on the Validity and Reliability of Upper Limb Kinematic Assessment Using a Markerless Motion Capture (MMC) System

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

To	Fong Nai Kuen (Department of Rehabilitation Sciences)		
From	Pang Marco Yiu Chung, Chair, PolyU Institutional Review Board		
Email	marco.pang@	Date	11-Jul-2022

Application for Ethical Review for Teaching/Research Involving Human Subjects

I write to inform you that approval has been given to your application for human subjects ethics review of the following project for a period from 13-Jun-2022 to 13-Sep-2022:

Project Title:	Validity and reliability of upper limb kinematic assessment using Markerless Motion Capture (MMC) system: A pilot study
Department:	Department of Rehabilitation Sciences
Principal Investigator:	Fong Nai Kuen
Project Start Date:	13-Jun-2022
Project type:	Human subjects (clinical)
Review type:	Expedited Review
Reference Number:	HSEARS20220530001

You will be held responsible for the ethical approval granted for the project and the ethical conduct of the personnel involved in the project. In case the Co-PI, if any, has also obtained ethical approval for the project, the Co-PI will also assume the responsibility in respect of the ethical approval (in relation to the areas of expertise of respective Co-PI in accordance with the stipulations given by the approving authority).

You are responsible for informing the PolyU Institutional Review Board in advance of any changes in the proposal or procedures which may affect the validity of this ethical approval.

Pang Marco Yiu Chung

Chair

PolyU Institutional Review Board

Appendix 7. Ethical approval memo for the study on the upper and lower extremity kinematic measurement using markerless motion capturing (MMC) in persons with a stroke: A cross-sectional experimental study

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

To	Fong Nai Kuen (Department of Rehabilitation Sciences)		
From	Pang Marco Yiu Chung, Chair, PolyU Institutional Review Board		
Email	marco.pang@	Date	27-Apr-2023

Application for Ethical Review for Teaching/Research Involving Human Subjects

I write to inform you that approval has been given to your application for human subjects ethics review of the following project for a period from 13-Mar-2023 to 31-Dec-2023:

Project Title:	Markerless Motion Capture (MMC) technology for movement measurement on patients with stroke
Department:	Department of Rehabilitation Sciences
Principal Investigator:	Fong Nai Kuen
Project Start Date:	13-Mar-2023
Project type:	Human subjects (clinical)
Review type:	Expedited Review
Reference Number:	HSEARS20230214010

You will be held responsible for the ethical approval granted for the project and the ethical conduct of the personnel involved in the project. In case the Co-PI, if any, has also obtained ethical approval for the project, the Co-PI will also assume the responsibility in respect of the ethical approval (in relation to the areas of expertise of respective Co-PI in accordance with the stipulations given by the approving authority).

You are responsible for informing the PolyU Institutional Review Board in advance of any changes in the proposal or procedures which may affect the validity of this ethical approval.

Pang Marco Yiu Chung

Chair

PolyU Institutional Review Board