

## Vision-based approach for long-term mobility monitoring: Single case study following total hip replacement

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**Abstract**—This article presents a single case study on the feasibility of using a low-cost and portable vision-based system (a Microsoft Kinect sensor) to monitor changes in movement patterns before and after a total hip replacement surgery. The primary subject was an older male adult with total hip replacement who performed two different functional tasks: walking and sit-to-stand. The tasks were recorded with a Kinect multiple times, starting from 1 d before the surgery until 9 wk after the surgery. An automated algorithm has been developed to extract the important spatiotemporal characteristics from the video recorded functional tasks (walking and sit-to-stand). Statistical analysis was then performed by Tryon *C* statistic to study changes in spatiotemporal characteristics between different stages before and after the surgery. The statistical analysis indicated significant difference and slight improvement between all measures from the presurgery to each postsurgery date. The study confirmed that the Kinect sensor and an automated algorithm have the potential to be integrated into a patient's home to monitor changes in mobility during the recovery period.

**Key words:** balance, feasibility study, long-term monitoring, markerless vision-based system, Microsoft Kinect sensor, mobility, naturalistic follow-up, rehabilitation, sit-to-stand, spatiotemporal kinematics, total hip replacement, walking.

### INTRODUCTION

Due to an aging global population, balance disorders are becoming more prevalent. These disorders can result

from normal changes associated with aging or from more acute events such as a stroke or musculoskeletal injuries (e.g., hip fractures or orthopedic surgeries). To cut health-care costs, it is common to discharge older adults early after such events and attempt to make rehabilitation more home-based. However, rehabilitation at home may have risks. For instance, a majority of these groups of older adults experience long-term balance disorders, which result in a high incident of falls and mobility deficits [1–2].

There is little detailed information about balance and mobility issues that this population faces once discharged from the hospital because of limited availability of rehabilitation services. One solution would be finding specialists (i.e., clinicians or physical therapists) willing to

**Abbreviations:** 3D = three-dimensional, AVHE = angular velocity of hip extension, AVHF = angular velocity of hip flexion, CARE = NSERC CREATE Academic Rehabilitation Engineering, CoM = center of mass, HCoM = horizontal velocity of center of mass, NSERC CREATE = Natural Sciences and Engineering Research Council of Canada Collaborative Research and Training Experience, STS = sit-to-stand, THR = total hip replacement, VCoM = vertical velocity of center of mass.

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travel to clients' homes in order to monitor their motor progress after early discharge from a hospital or a rehabilitation facility. But this strategy is costly [3]. Therefore, for cost reduction, most clinicians have to rely on self-reports from clients and intermittent follow-up assessments to assist them with the long-term rehabilitation and assessment. However, balance outcome measures derived from self-reports often do not conform to clinical assessments [4]. Moreover, follow-up assessments made in the clinic or gait laboratory cannot reflect long-term changes in mobility functionalities since balance failures often take place in homes, where standardized assessment cannot be directly applied [5]. In addition, tasks performed in the gait laboratory or clinics do not always simulate normal daily activities of older adults because people may feel more distracted at home than in the laboratory.

A gait laboratory typically uses different tools, including force platform, pressure-sensing walkway, and three-dimensional (3D) motion analysis to evaluate the biomechanics of gait [6–7]. However, despite their high precision, these laboratory tools are less appropriate for home use because of their high cost and elaborate setup requirements.

Monitoring the functional change during the recovery period at home helps clinicians better understand balance failures and better target effective rehabilitation treatments [8]. These facts motivate the assessment of mobility and balance in an older adult's own home through monitoring functional mobility parameters. This case study aimed to fill a gap in the current understanding of mobility and balance failures at home. Recent technological advances in motion sensing and in computer vision algorithms have opened new possibilities for long-term home monitoring and automatically computing objective measures of mobility and balance.

Although there is a growing demand for comprehensive, cost-effective, long-term mobility monitoring at home, there are not enough investigations on the use of such technologies as a means to deliver rehabilitation services at home. Consequently, there is a need for feasibility studies to address a series of questions regarding the demand and preliminary implementation of such technologies to provide effective home rehabilitation for individuals after discharge from the hospital. The purpose of this study was therefore to investigate the use of a vision-based motion capture system to provide long-term rehabilitation monitoring at home. To this end, we studied the technical feasibility of capturing mobility measures in the home and

inferring the kinematics of functional activity recorded over time via an affordable vision-based system. A naturalistic follow-up of one participant recovering from a total hip replacement (THR) surgery is presented in this study.

To meet the objectives of this feasibility study, we deployed a Microsoft Kinect sensor (Redmond, Washington) in the home of a THR participant and aimed to automatically analyze performance of two functional activities—walking and sit-to-stand (STS)—to determine whether we can capture the balance and mobility parameters in the home, developed custom-made automated algorithms to determine whether we can infer the kinematics of functional activity recorded over time, and carried out statistical analysis on the measured kinematics to determine whether we can recognize balance and mobility changes throughout rehabilitation recovery at home. In the end, the feasibility questions regarding the demand and implementation—both the key area of focus for feasibility studies [9]—were addressed by this study.

The single case study is a valuable research approach to investigate scientific practice [10]. The case study conducted here was targeted to provide a useful, powerful, and practical methodology for defining basic principles on testing this type of system (specifically, a Microsoft Kinect sensor and custom-developed automated algorithms) in analyzing balance. This approach has been used within the clinical, technical, and social studies and introduced as a robust approach to define basic principles [11–12].

The major contribution of this case study is the quantitative analysis of changes in mobility using a vision-based system over several weeks in the home. The functional activities evaluated included walking and STS. While the study focused on THR surgery, results may extend to the analysis of balance in the home for other target populations, e.g., people with neurological movement disorders or poststroke patients.

## PREVIOUS WORK

Several studies have developed gait assessment tools using wearable sensors, including accelerometers and gyroscopes (e.g., Najafi et al. [13]). Although such systems are small and portable, they suffer from limitations, including short battery life, trouble capturing information about the environment and context of activities, and sensitivity to sensor placement. e.g., foot versus ankle. In addition, they

require the person having to remember to wear the device to capture real-world data, which is not practical.

Over the past decade, vision-based human gait analysis has been a thriving area of research. Markerless motion capture systems (e.g., using a simple webcam) offer an opportunity to reconstruct kinematic features comparable to gait laboratory tools and motion sensors [14]. Computer vision approaches have also been employed in video-based systems to assist older adults to age-in-place [15–16]. These systems do not require the placement of additional sensors or markers on or around the person's body. However, they sometimes require a controlled environment and complicated algorithms in order to track people, find their body parts, and analyze their behavior.

Depth sensors such as the Kinect offer several advantages over webcams, including the capacity to work in low light or dark environments and also simplified silhouette extraction and human tracking. By processing captured depth information, the Kinect provides real-time tracking of people within its field of view. It also fits a skeletal model to each person to track his or her major body parts (head, shoulders, elbows, hands, etc.) in real time, i.e., 30 frames per second.

The accuracy of using the Kinect for joint estimation in comparison with 3D motion capture systems, webcams, and wearable sensor has been evaluated by several research groups [17–18]. Their results confirmed the good accuracy of the Kinect to be used for motion tracking applications. However, the majority of previous studies that used the Kinect for quantitative walking and balance evaluation were either limited to preliminary trials with nondisabled subjects or focused only on measuring the gait parameters in a clinical or laboratory setting [19–20].

By contrast, our study explored the understanding of changes in walking and STS over an extended period of time to investigate the integration of assessment and rehabilitation programs in the home. The methodology used in this study was developed based on analysis of data taken from a real patient following early discharge from the hospital.

To the best of our knowledge, the only published study to date that has employed the Kinect for gait monitoring in the homes of real patients or older adults is the work of Stone and Skubic [21–22], in which the depth sensing (and not the skeletal tracking) capabilities of the sensor were used in the analysis of spatiotemporal gait parameters and the Timed “Up and Go” test. More recently, the viability of using the Kinect to evaluate the static foot posture has also been successfully studied [23].

Our study differed from the previous works in two ways: (1) we took advantage of the real-time skeletal tracking information, and (2) we quantitatively evaluated how the recovery period could be monitored by extracting kinematic features from the skeletal data and investigating how those features correspond with balance.

## METHODS

### Study Description

#### *Participant*

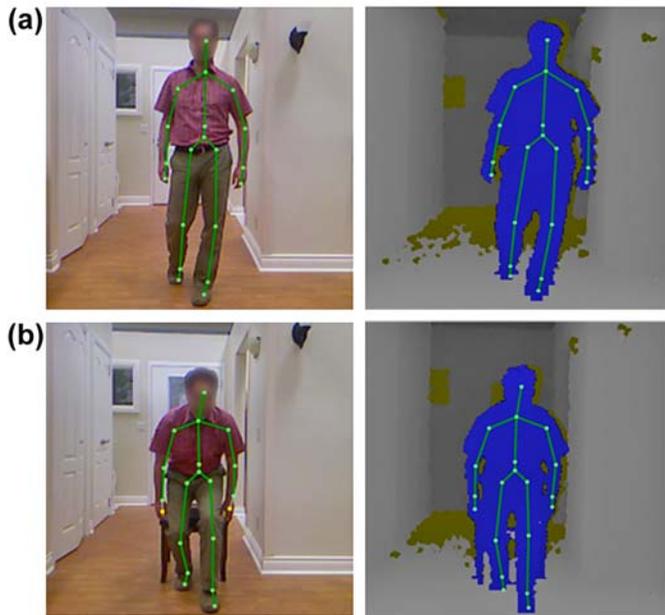
Our participant was a 64 yr old male with THR surgery on his right side (height 193 cm, weight 63 kg). He was discharged from the hospital 2 d after the surgery and received postsurgery physical therapy at home. We began the research study at 1 d before the surgery and resumed it subsequently 1 wk after the surgery as soon as minimum recovery had taken place, continuing until 9 wk after the surgery [24]. The study was deemed as research exempt by the University Health Network-Research Ethics Board review.

#### *Measuring Device*

The system included a Microsoft Kinect sensor, connected to a laptop, which captured walking (**Figure 1(a)**) and STS sequences (**Figure 1(b)**). The accuracy and feasibility of using the Kinect for mobility assessment and rehabilitation in comparison with 3D motion capture (VICON; Centennial, Colorado) and webcam have been studied by different research groups. One of the foremost validation studies has been carried out by Dutta [17]. Based on these findings, as compared with a VICON system, the Kinect sensor was able to estimate the 3D relative positions of markers with root mean square errors (standard deviation) of less than 0.005 m in the  $x$ ,  $y$ , and  $z$  directions.

A skeletal tracking application based on the Microsoft Software Development Kit was developed and used to detect, track, and record the human pose and motion for postanalysis [25].\* The application tracked and recorded the 3D locations, i.e., the  $x$ ,  $y$ , and  $z$  coordinate relative to the depth sensor, of 20 body joints (**Figure 1**). The program also recorded depth and color video streams for visual postanalysis. All recorded skeletal information and

\*Our software tool for saving Kinect streams is available for free download at <https://kinectstreamsaver.codeplex.com/>.



**Figure 1.** Sample video frames from (a) walking and (b) sit-to-stand sequences taken from nondisabled male adult.

video frames were time stamped. This enabled us to follow the displacement of each 3D joint location over time in order to extract primary kinematic features to understand changes in mobility parameters.

### Protocol

Walking and STS are the two important functional tasks usually considered to reveal balance failures and abnormalities [8,26–27]. The THR recovery period is generally fast, and patients typically resume normal light activities of daily living within 3 to 4 wk after surgery [28]. This means that gait and balance improve rapidly over a few weeks, making the population ideal for a case study concerning the monitoring of changes in mobility parameters.

### Data Collection

Data collection from the THR participant began 1 d before the surgery (baseline) and continued over multiple points in time after the surgery, specifically 1 d before, 1 wk after, 2 wk after, 4 wk after, 6 wk after, 7 wk after, and 9 wk after the surgery. During each recording session, the participant was asked to (1) walk and (2) perform an STS action in front of the sensor. Recording sessions were carried out at two different locations depending on the func-

tionality level of the participant with THR, i.e., whether the THR participant was able to leave his home and come to the Homelab. The two locations included (1) the THR participant's home for the first two postsurgery sessions of recording and (2) the HomeLab in the iDAPT facility at the Toronto Rehabilitation Institute [29] during the presurgery session and the remaining postsurgery sessions.

For the walking task, we followed the protocols used at the Balance Mobility and Falls Clinic at the Toronto Rehabilitation Institute to measure gait conditions [30]. At the clinic, the walking task is done on a pressure sensitive mat (GAITRite System, CIR Systems; Clifton, New Jersey), which is 5.25 m long and 0.88 m wide. However, in our study, the gait parameters were measured via tracks of body skeleton and the participant was not asked to walk along the mat. The beginning and end of each walking test sequence were selected to be at 0.2 m and 5.5 m away from the sensor, respectively, and marked on the floor. In order to capture enough steps for each set of walking, the participant was asked to complete nine sequences of walks between the beginning and end points toward the Kinect sensor at his preferred speed. This resulted in recording a total of 63 walking sequences, during both pre- and postsurgery phases. The average number of steps collected and analyzed per session was 27 (3 steps at each sequence of walk). For each session, spatiotemporal measures of gait have been calculated. For the STS task, the participant was instructed to rise from a wooden, armless chair at a comfortable rising speed. During each session of postsurgery recording, seat cushions had to be used to adjust the height of the chair in order for the subject to perform the task of STS more comfortably after the surgery. The subject completed 9 STS sequences at each session, resulting in 63 STS sequences in total. The chair was located at 2 m away from the sensor so the entire STS motion could be recorded for postprocessing.

Since we were interested in naturalistically following the participant during his rehabilitation with poststroke motor recovery, we avoided interfering with his recovery in terms of using assistive devices: crutches and cane for walking and cushions for STS. So, for all sessions, the subject wore his own shoes and also used crutches for 1 wk and a cane for the following 2 wk after the surgery. Moreover, during each session of postsurgery recording, seat cushions had to be used to adjust the height of the chair in order for the subject to perform the task of STS more comfortably after the surgery.

## Data Analysis

### Preprocessing

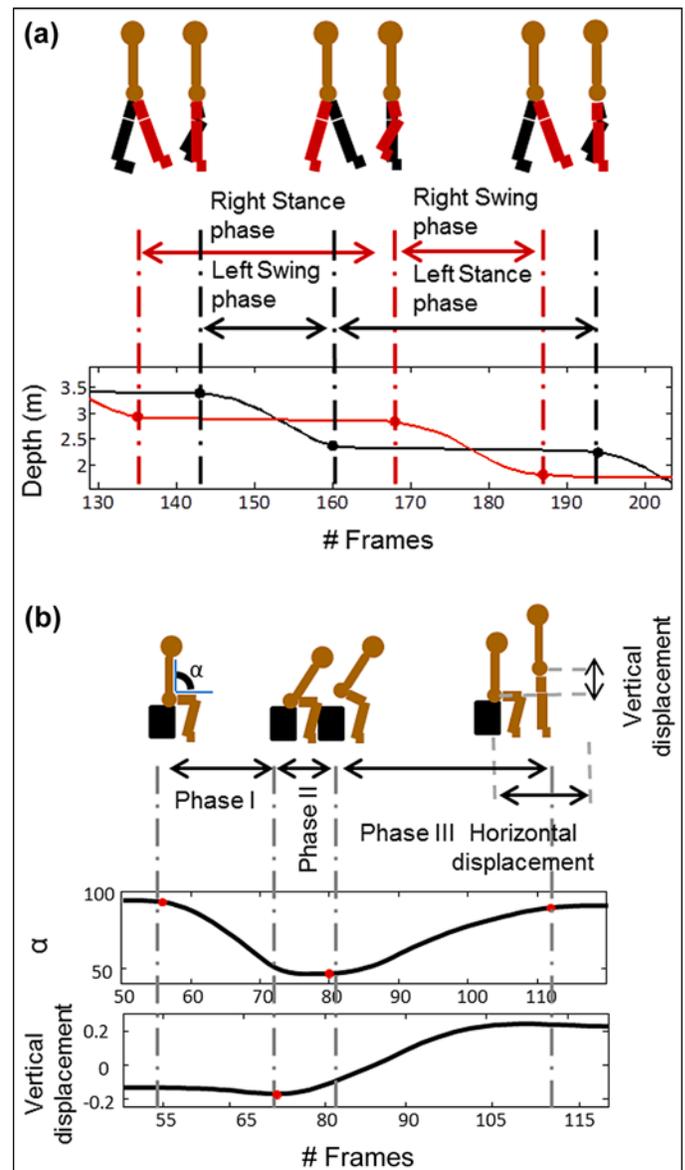
As a first step, the center of mass (CoM) was computed as the average 3D location of the hip, shoulders, and spine joints at each frame [31]. The frames in the beginning and at the end of each test sequence were excluded if the computed CoM was beyond the practical viewing range of the Kinect (0.8–4 m). This process cleaned up the data by discarding potentially erroneous skeletal tracking information recorded when the subject was outside the working range of the sensor.

The skeletal information (i.e., the  $x$ ,  $y$ , and  $z$  values of each joint at each frame) is provided in the coordinate frame of the sensor. Analyzing the data in this coordinate frame was dependent on the placement of the sensor (position and orientation) relative to the room and also relative to the seating position and walking direction of the subject. It was therefore necessary to perform a preprocessing step to express the joint information in world coordinates, independent of the mounting position and orientation of the sensor and its relative placement with respect to the subject.

Similar to Parra-Dominguez et al. [32], a  $3 \times 3$  rotation matrix and a  $3 \times 1$  translation vector were formed and applied to transform sensor coordinates to world coordinates. Under the transformed world coordinates, the  $y$ -axis is aligned with the room vertical pointing upward; the subject's walking direction is along the  $z$ -axis; and the  $x$ -axis, which defines the left and right direction, is computed as a cross product of the  $y$ - and  $z$ -axes to form a right-handed frame. The transformation also ensures that the floor is height  $y = 0$  m.

### Feature Extraction

Several movement features were computed by processing the recorded 3D skeletal motion sequences. The analysis of walking balance typically involves the partitioning of a temporal sequence into subsequence stance and swing phases, as shown in **Figure 2(a)**. Here, the stance and swing phases were identified automatically from the inspection of lower-limb 3D joint motions (specifically the ankle joint) along the  $z$ -axis (depth). Consequently, basic spatiotemporal gait parameters including the step length, stance time, and cadence were automatically measured from these two phases.



**Figure 2.** (a) Walking is divided into two phases: swing and stance. (b) Sit-to-stand is divided into three phases: phase I as hip flexion, phase II as transfer phase, and phase III as hip extension (angle  $\alpha$  is defined as angle between line segment connecting hip to center of shoulders and horizontal plane).

Processing algorithms were developed in MATLAB (MathWorks; Natick, Massachusetts) to detect the walking phases (stance and swing phases) automatically. During walking, when a foot is in a stance phase, its location should not be changing. By calculating the numerical derivative of the ankle joint trajectory along the  $z$ -coordinate (via

a Gaussian derivative filter,  $n = 2$ ,  $\sigma = 2$ ), we could detect whether a foot was in a swing phase (i.e., the location of the foot was changing) or if it was in a stance phase (**Figure 2(a)**). This binary classification method used a sliding window (with a step size of three frames) to identify the beginning and ending of each phase. The start of each phase was estimated if the second-order derivative of the sliding window was above a threshold. The threshold was set based on the inspection of the distribution of second-order derivative of data.

The STS task was characterized based on the model offered by Schenkman et al. [33]. In this model, an STS sequence is divided into three phases, as shown in **Figure 2(b)**. The initial phase, titled hip flexion, begins with hip flexion and ends at the beginning of lift off from the chair. The second phase, titled transfer phase, begins with the lift off from the chair and ends at the beginning of hip extension. The final phase, titled hip extension, begins with hip extension and ends by full extension to the standing position. We estimated the basic kinematic parameters from STS based on the inspection of 3D joint motions of the shoulders and hips along the  $x$ -,  $y$ -, and  $z$ -axes. In **Figure 2(b)**, the angle  $\alpha$  is defined as the angle between the line segment connecting the hip to the center of shoulders and the horizontal plane.

The same binary classification algorithm was used to automatically identify the three phases of STS, i.e., hip flexion, transfer phase, and hip extension. Similar to processing the walking phases, a sliding window (with a step size of three frames) was used to identify the beginning and ending of each phase of STS from the angle  $\alpha$  trajectories and the CoM displacement. Various spatiotemporal measures were computed automatically by processing recorded joint trajectories, the angle  $\alpha$ , and the CoM displacement over the STS phases. These measures included the angular displacement and the angular velocity of the hip flexion and extension phases and the vertical and horizontal displacement and velocity of CoM.

As explained earlier, the chair height varied across different weeks because the subject used cushions in some sessions. Accordingly, measures extracted from the STS sequences (e.g., trunk flexion and extension angular velocities and the CoM vertical and horizontal displacements) were all influenced by the varying height of the chair. Rather than analyzing displacement values, which were highly affected by chair height, we analyzed velocities, which were mostly unaffected by chair height. Consequently, velocity measures from sessions with different

chair heights could be compared with monitor recovery trend.

### Statistical Analysis

A combination of visual and statistical analysis was used to compare changes in walking and STS characteristics between different stages ranging from 1 d before to 9 wk after surgery. Since visual inspection alone might result in inconsistent and unreliable interpretation of time-series data [34], the  $C$  statistic method was utilized for quantitatively evaluating the presence of significant changes ( $p < 0.01$ ) in walking and STS parameters across the seven time groups. The Tryon  $C$  statistic is a simple method of time-series analysis used with small and serially dependent data sets [35]. The  $C$  statistic is a robust statistical approach if the data points at each time group are shown to be stable [34–35].

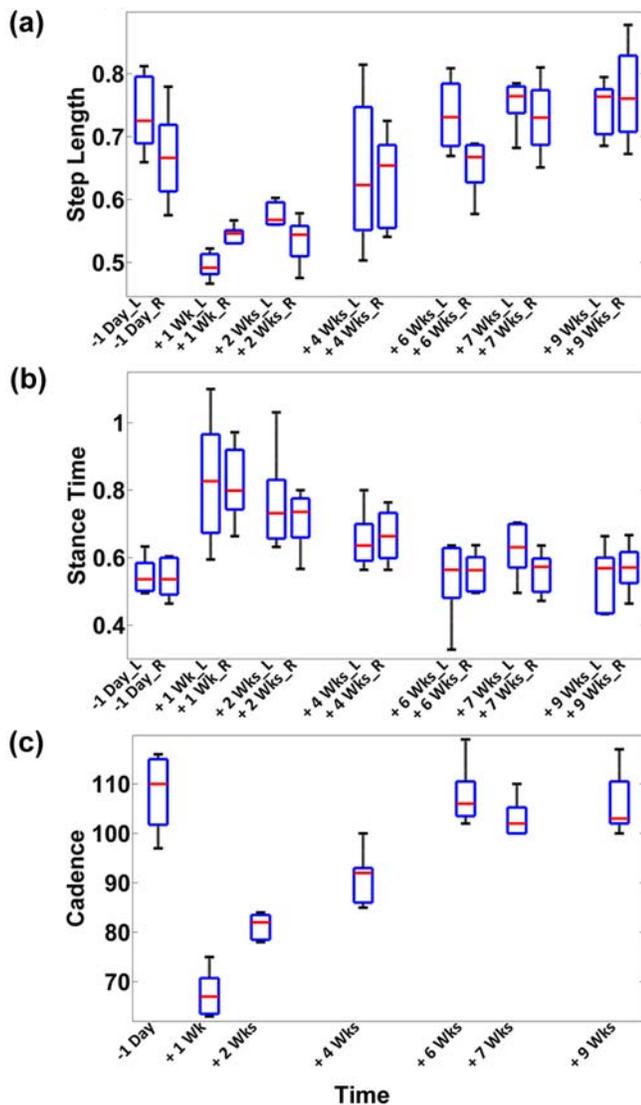
## RESULTS

### Differences in Walking Task

The changes in the step length, stance time for each leg, and cadence for all sessions are all illustrated in **Figure 3(a)–(c)** in the form of a box plot. On each box, the central mark denotes the median value, the box denotes values within the 25 to 75 percentile, and the whiskers extend to the most extreme data considered inliers.

Using the  $C$  statistic, no significant trend was found ( $0 < Z$  statistic  $< 1$ ,  $p > 0.1$ ) on the spatiotemporal gait measures collected separately at each pre- to postsurgery sessions. However, the  $C$  statistic computed on ensemble data points taken from all seven time groups from presurgery to all postsurgery sessions together indicated the presence of significant differences between the gait measures across time specifically for right step length ( $p < 0.001$ ,  $Z$  statistic = 4.4), left step length ( $p < 0.001$ ,  $Z$  statistic = 5.5), left stance time ( $p < 0.004$ ,  $Z$  statistic = 2.69), and cadence ( $p < 0.001$ ,  $Z$  statistic = 5.05).

**Table 1** presents the results of  $C$  statistic analysis applied on gait measures for 1 wk after surgery plus every other pre- to postsurgery sessions to determine which time groups depart from the 1 wk after surgery time group. For the step length measured on the left leg, four time groups—1 d before, 6 wk after, 7 wk after, and 9 wk after the surgery—were significantly different from 1 wk after surgery ( $Z$  statistic  $> 2.33$ ,  $p < 0.01$ ). For the right step length, however, no significant difference was found between 1 d



**Figure 3.**

Changes in (a) step length, (b) stance time, and (c) cadence for all sessions from 1 d before surgery to 9 wk after surgery. *C* statistic method was used for evaluating presence of significant changes ( $p < 0.01$ ) in walking parameters across seven time groups. *Z* statistic is ratio of each value of *C* statistic to its standard error. For significance at  $p < 0.01$ , *Z* statistic must be  $>2.33$  for sample size of 90 (13 samples at each time group) for walking. Results indicated presence of significant differences between gait measures across time as follows: right step length ( $p < 0.001$ , *Z* statistic = 4.4), left step length ( $p < 0.001$ , *Z* statistic = 5.5), left stance time ( $p < 0.004$ , *Z* statistic = 2.69), and cadence ( $p < 0.001$ , *Z* statistic = 5.05). There is no significant difference between measures of stance time on right side. Note, – and + denote pre- and postsurgery data points (e.g., +1 wk R denotes 1 wk after surgery for right leg). L = left, R = right.

**Table 1.**

Statistical analysis results of *C* statistic computed on walking for one 1 wk postsurgery plus every other pre- (–) to postsurgery (+) session to determine which time groups depart from 1 wk after surgery. Difference is significant at 0.01 level. According to this procedure, significant difference between pairs can be determined if *Z* statistic is  $>2.33$  for sample size of 26 (13 samples at each time group).

Measure	Time Group II	<i>Z</i> Statistic*	<i>p</i> -Value
Step Length			
	R		
	+7 wk	3.01	<0.002
	+9 wk	3.24	<0.001
L			
	–1 d	3.55	<0.001
	+6 wk	3.27	<0.001
	+7 wk	3.54	<0.001
	+9 wk	3.38	<0.001
Stance Time (L)			
	–1 d	2.42	<0.008
	+4 wk	2.7	<0.004
	+6 wk	2.33	<0.01
	+7 wk	3.37	<0.001
	+9 wk	2.83	<0.003
Cadence			
	–1 d	2.81	<0.003
	+4 wk	3.03	<0.002
	+6 wk	3.01	<0.002
	+7 wk	3.02	<0.002
	+9 wk	2.78	<0.003

\**Z* statistic values calculated for between Time Group I (+1 wk) and Time Group II.

L = left, R = right.

before and 1 wk after surgery (*Z* statistic = 2.12,  $p > 0.01$ ). As the results present, step length measures worsened from 1 d before the surgery to 1 wk after the surgery. Moreover, no significant difference was observed between 1 wk and 2 wk after the surgery (*Z* statistic  $< 0$ ,  $p > 0.01$ ). Starting from 2 to 4 wk following the surgery, considerable improvement was obtained. And finally, gradual recovery (but not statistically significant) occurred from 4 wk to 9 wk after surgery. In brief, the highest variation was observed between the 1 wk and 9 wk after the surgery for both legs (right and left), which indicates the substantial improvement obtained within this period.

For the left stance time, the test showed that five time groups (1 d before and 4, 5, 6, and 9 wk after the surgery) had means pointedly different from 1 wk after surgery (*Z* statistic  $> 2.33$ ,  $p < 0.01$ ). Similar to left stance time, the same statistical difference between time groups can be observed for the cadence measures. So, unlike the step

length, the difference between 1 and 4 wk after surgery was significant in stance time and cadence measures.

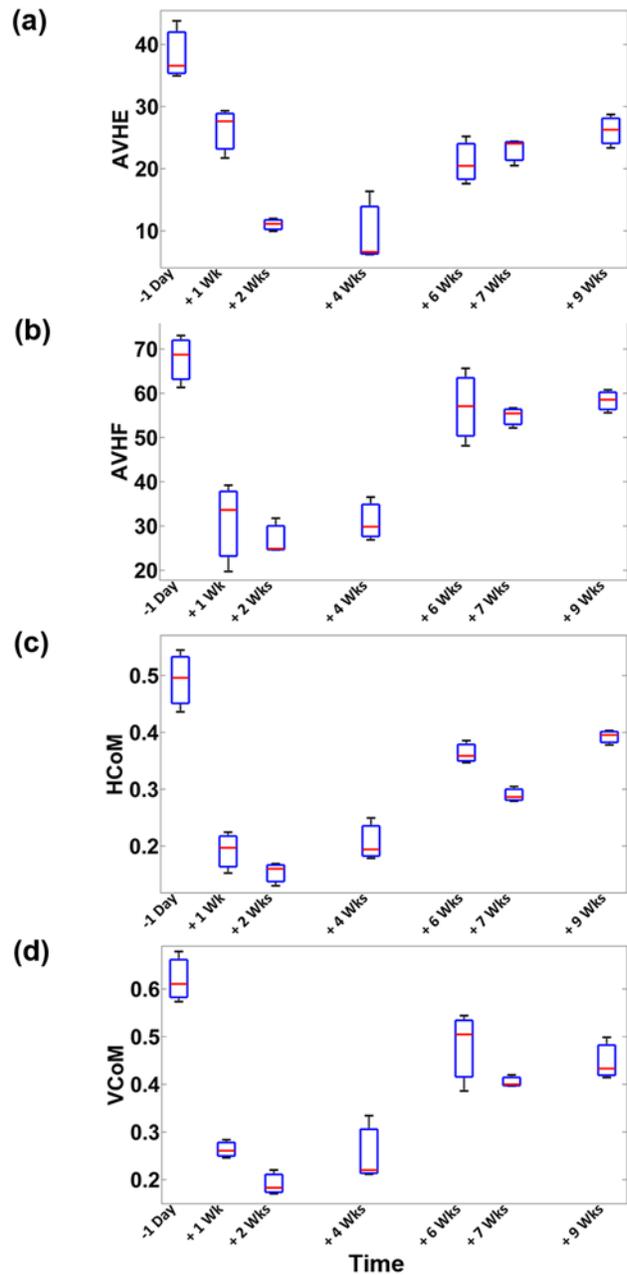
### Differences in Sit-to-Stand Task

Changes in the angular velocity of hip flexion (AVHF), angular velocity of hip extension (AVHE), vertical velocity of CoM (VCoM), and horizontal velocity of CoM (HCoM) for all time groups are shown in **Figures 4(a), (b), (c), and (d)**, respectively. Similar to gait measures, no significant trend has been found ( $0 < Z \text{ statistic} < 1, p > 0.1$ ) on the STS measures collected separately at each pre- to postsurgery sessions. As expected, the *C* statistics computed on ensemble STS velocities from all sessions revealed significant differences for AVHF ( $p < 0.002$ ,  $Z \text{ statistic} = 2.99$ ), AVHE ( $p < 0.003$ ,  $Z \text{ statistic} = 2.76$ ), VCoM ( $p < 0.006$ ,  $Z \text{ statistic} = 3.2$ ), and HCoM ( $p < 0.001$ ,  $Z \text{ statistic} = 3.14$ ) between measures across seven time groups from presurgery to all postsurgery sessions.

**Table 2** lists the most statistical differences observed between 2 wk after surgery and every other time groups for AVHF, HCoM, and VCoM and 4 wk after surgery and every other time groups for AVHE. Based on the results, all velocity measures during STS, except the AVHE, were significantly smaller for 1 and 2 wk after the surgery than 6 wk after the surgery. And so, the four time groups of 1 d before, 6, 7, and 9 wk after surgery had velocity measures significantly different from 2 wk after surgery ( $Z \text{ statistic} > 2.25, p < 0.01$ ). The AVHE, by contrast, did not differ significantly from 1 d before to 1 wk after the surgery ( $Z \text{ statistic} = 1.8, p > 0.01$ ). Furthermore, there was still significant difference between 4 and 6 wk after the surgery ( $Z \text{ statistic} = 2.42, p < 0.008$ ), which was contrary to the pattern of changes observed for all walking parameters throughout this period. That is, while the recovery of walking plateaued after about 4 wk, the STS recovery seemed to extend to a longer length of time and continued to week six. The first important result given by this study was that a substantial improvement in walking and STS occurred following the surgery.

## DISCUSSION

The demand for a home-based, cost-effective, quantitative, and continuous assessment of balance is growing in order to better understand changes in movement pattern and balance. This single case study represents the first attempt to investigate the feasibility of using an affordable



**Figure 4.**

Changes in **(a)** angular velocity of hip extension (AVHE), **(b)** angular velocity of hip flexion (AVHF), **(c)** horizontal velocity of center of mass (HCoM), and **(d)** vertical velocity of center of mass (VCoM) for all sessions from 1 d before surgery to 9 wk after surgery. For significance at  $p < 0.01$ ,  $Z \text{ statistic}$  must be  $>2.33$  for sample size of 63 (9 samples at each time group) for sit-to-stand (STS). Results indicated presence of significant differences between STS measures across time as follows: AVHF ( $p < 0.002$ ,  $Z \text{ statistic} = 2.99$ ), AVHE ( $p < 0.003$ ,  $Z \text{ statistic} = 2.76$ ), VCoM ( $p < 0.006$ ,  $Z \text{ statistic} = 3.2$ ), and HCoM ( $p < 0.001$ ,  $Z \text{ statistic} = 3.14$ ). Note, – and + denote pre- and post surgery data points.

**Table 2.**

Statistical analysis results of *C* statistic computed on sit-to-stand velocities for 2 wk postsurgery and every other time groups for angular velocity of hip flexion (AVHF), horizontal velocity of center of mass (HCoM), and velocity of center of mass (VCoM) and 4 wk postsurgery and every other time groups for angular velocity of hip extension (AVHE). Difference is significant at 0.01 level. According to this procedure, significant difference between pairs can be determined if *Z* statistic is  $>2.25$  for sample size of 18 (9 samples at each time group). – and + denote pre- and postsurgery data points.

Measure	Time Group I	Time Group II	Z Statistic	p-Value
AVHF	+2 wk	–1 d	3.58	<0.001
		+6 wk	3.54	<0.001
		+7 wk	3.78	<0.001
		+9 wk	3.71	<0.001
AVHE	+4 wk	–1 d	3.2	<0.001
		+1 wk	2.58	<0.005
		+6 wk	2.42	<0.008
		+7 wk	2.34	<0.01
VCoM	+2 wk	+9 wk	2.75	<0.003
		–1 d	4.01	<0.001
		+6 wk	3.04	<0.002
		+7 wk	3.82	<0.001
HCoM	+2 wk	+9 wk	3.38	<0.001
		–1 d	3.69	<0.001
		+6 wk	3.74	<0.001
		+7 wk	3.48	<0.001
		+9 wk	3.82	<0.001

vision-based motion capture tool (Microsoft Kinect) to investigate long-term changes in mobility and balance following early discharge from the hospital.

The results of this realistic follow-up study provide evidence that, at least in the case of one individual with THR, it is feasible to study and monitor long-term changes in mobility through an innovative, affordable, markerless motion capture system.

Case studies have been used as a successful and rigorous method in several research areas [10]. It has been proposed that single case approaches are probably the best research tools for evaluating research methods in rehabilitation [36]. As such, we expect that our results will extend across additional similar users.

Overall, the system and the algorithms to automatically analyze collected data provided reliable accuracy for studying significant mobility changes through walking and STS. Experimental analysis revealed postsurgery improvement in function following the surgery. In brief, the mea-

sured spatiotemporal gait parameters all worsened in comparison with presurgery values after the surgery and mostly started to improve 1 to 4 wk following the surgery. Subsequently, they all remained stable, as seen between the 6 and 9 wk points after the surgery. Moreover, we could not observe any significant difference between the left and the right spatiotemporal gait measures during the study period. This is in agreement with previous studies [37–38]. The only asymmetrical feature was the difference between the patterns of change in the step length and stance time measured on the right side (the operated side) compared with those measured on the left side. As the patient underwent the THR on his right side, the right step length and stance time measures did not change substantially from the presurgery baseline to any postsurgery time points. The left side step length and stance time, on the contrary, altered significantly from pre- to postsurgery time points, but with a slower improvement rate than the other spatiotemporal gait measures.

The analysis on STS data indicated that all velocity measures were worse in the earlier stages, i.e., from 1 to 4 wk after surgery. All velocity measures deteriorated from 1 d before to 2 wk after the surgery, and they did not improve significantly across the early stages postsurgery (up to 4 wk after surgery). Starting from 4 wk after surgery, these measures improved faster until 6 wk after surgery and then did not improve significantly over the 6 to 9 wk after surgery. For the vertical and horizontal velocities, a small decrease was observed from 6 to 7 wk after surgery, but the difference was not statistically significant.

In order to examine the reliability of results given by the developed vision-based motion capture tool, we met one more time with our one participant after the completion of the study. During the meeting, he was asked to visually review the graphs shown in **Figures 3** and **4**. Following his review, he provided his own personal experience during rehabilitation recovery at home. The verbal interpretation report given by the participant was then compared with the statistical analysis shown in **Tables 1** and **2**. His inputs not only were in line with our statistical outcomes but also in some cases explained the results that were difficult to interpret without understanding the participant's thoughts. For instance, in response to the question of why the STS velocity measures deteriorated from 1 to 2 wk after surgery (while they were all expected to improve), the participant explained that during the STS task he felt more pain at week two than week one because he was taking less analgesic at week two.

## Limitations of Study

While this case study examined a novel approach to assess balance in the home, there are a number of limitations that could be addressed in future work. Further work is required, for instance, to examine the generalizability of the study for various subject populations since the statistical analysis and findings here are limited since this was a single case study. This case study lacked adequate support for conclusions concerning other subjects' population and environment; e.g., other participants with balance problems might be different from our participant in terms of mobility recovery, gait patterns, and baseline. In addition, all data here were collected only in two separate locations (HomeLab and the participant's home) and, as a result, the variability in lighting conditions and furniture arrangements (potential sources of partial occlusion) was limited in our recording sessions. Hence, in general, the findings and statistical analysis are limited to the studied participant and location. However, it is important to note that the methodologies provided by this case study are not highly affected by these limitations. That is, Kinect-based tracking of body joints and the subsequent computation of significant kinematic features can be applied to any subject and any environment. Another potential limitation is comparing walking and STS with and without assistive devices across recorded postsurgery sessions. Naturalistic follow-up without any interference during rehabilitation recovery has both advantages and disadvantages that might affect the comparison results. But it should be noted that it would not affect the major conclusion of this study, which is accepting the feasibility of monitoring rehabilitation recovery through an affordable vision-based approach.

## CONCLUSIONS

Toward the goal of this single case feasible study, the Kinect sensor was set up in a THR participant's home to track changes in kinematic measures through analysis of functional tasks including walking and STS. Study recording started from 1 d before surgery (baseline) to 9 wk after surgery. Following utilizing the Kinect sensor, an automated algorithm was designed to compute spatiotemporal kinematic measures from the tasks recorded by the Kinect sensor. In this regard, spatiotemporal gait measures, including step length, stance time, and cadence, were automatically extracted from a walking task. Other spatiotemporal

measures, including AVHF and extension along with VCoM and HCoM, were extracted from the STS task.

In conclusion, monitoring balance and mobility during rehabilitation recovery at home appears to be feasible following early discharge from the hospital. This single case study is the first of its kind and has a significant potential value to researchers and clinicians in the field. It will give them an opportunity to build studies on using affordable, markerless motion capture systems, replacing the current expensive 3D motion capture systems, pressure sensing walkways, and wearable sensors to investigate long-term changes in balance and mobility following acute events such as stroke, brain injuries, and orthopedic surgeries. Developing such a tool is novel because it would require little or no effort from the individuals using it in a home environment compared with existing wearable sensors. For clinicians in particular, it will help them understand recovery and balance failures taking place at home. More importantly, this study provided reasonable outcomes that evaluated the proof of concept regarding using a single Kinect sensor for gait and movement analysis. Having the state-of-the-art practical methodologies as a means of investigation for balance and mobility changes, future work will include recruiting more participants, recording more functional tasks, and collecting data for longer follow-up periods.

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### Author Contributions

*Acquisition of data:* E. Dolatabadi.

*Analysis and interpretation of data:* E. Dolatabadi, B. Taati, A. Mihailidis.

*Drafting of manuscript:* E. Dolatabadi.

*Critical revision of manuscript for important intellectual content:*

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