Short communication

Validity of a novel method to measure vertical oscillation during running using a depth camera

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ABSTRACT

Recent advancements in low-cost depth cameras may provide a clinically accessible alternative to conventional three-dimensional (3D) multi-camera motion capture systems for gait analysis. However, there remains a lack of information on the validity of clinically relevant running gait parameters such as vertical oscillation (VO). The purpose of this study was to assess the validity of measures of VO during running gait using raw depth data, in comparison to a 3D multi-camera motion capture system. Sixteen healthy adults ran on a treadmill at a standard speed of 2.7 m/s. The VO of their running gait was simultaneously collected from raw depth data (Microsoft Kinect v2) and 3D marker data (Vicon multi-camera motion capture system). The agreement between the VO measures obtained from the two systems was assessed using a Bland-Altman plot with 95% limits of agreement (LOA), a Pearson's correlation coefficient (r), and a Lin's concordance correlation coefficient (r_c). The depth data from the Kinect v2 demonstrated excellent results across all measures of validity (r = 0.97; r_c = 0.97; 95% LOA = −8.0 mm – 8.7 mm), with an average absolute error and percent error of 3.7 (2.1) mm and 4.0 (2.0)%, respectively. The findings of this study have demonstrated the ability of a low cost depth camera and a novel tracking method to accurately measure VO in running gait.

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1. Introduction

Three-dimensional (3D) gait analyses can provide an objective and clinically valuable assessment of spatiotemporal, kinematic, and kinetic parameters of human motion (Cimolin and Galli, 2014; Wren et al., 2011). These data can be important in the diagnosis, treatment, and tracking of various musculoskeletal and gait disorders (Kobsar et al., 2015; McArdle et al., 2017). Moreover, 3D gait analyses can be useful for assessing injury risk (Milner et al., 2006; Noehren et al., 2007), training status (Clermont et al., 2017; Schmitz et al., 2014), and rehabilitation (Marcolin et al., 2015) in runners. Unfortunately, conventional multi-camera, 3D gait analysis systems are expensive and often time consuming, which makes them impractical, or simply inaccessible, to most clinicians.

In contrast to these limitations, recent advancements in low-cost depth camera technology may provide a clinically accessible

alternative to conventional 3D gait analysis systems. Specifically, depth cameras are more affordable (less than $200), do not require the placement of retroreflective makers, and rely on simple calibration procedures. Research has shown that while lower limb joint angular kinematics (e.g., sagittal plane hip, knee, and ankle angular excursions) from these cameras have poor to moderate validity (Eltoukhy et al., 2017; Mentiplay et al., 2015), spatiotemporal parameters (e.g., step length, step time, etc.) display moderate to excellent validity (Dolatabadi et al., 2016; Eltoukhy et al., 2017; Mentiplay et al., 2015). Similar to the validity of spatiotemporal parameters, measures of vertical pelvis motion have been found to display moderate to excellent validity (Eltoukhy et al., 2017; Mentiplay et al., 2015). Therefore, assessing pelvis kinematics may provide a viable clinical application for depth cameras.

The vertical oscillation (VO) of the pelvis segment for a runner has been shown to be important for running economy and performance, with a lower VO related to reduced mechanical energy cost as the body performs work against gravity (Folland et al., 2017; Halvorsen et al., 2012). Therefore, a lower VO has been suggested to be beneficial for runners (Cavanagh et al., 1977). In addition,

research has demonstrated that this is a modifiable biomechanical parameter as verbal cues or changes in step rate can reduce VO by approximately 20 mm (Heiderscheit et al., 2011; Messier and Cirillo, 1989). However, no study has investigated whether these measures, based on depth data, are valid during running gait. Moreover, any previous assessments of VO during walking (Eltoukhy et al., 2017; Mentiplay et al., 2015) have only utilized a proprietary skeletal model tracking techniques (i.e., Microsoft Kinect Software Development Kit; SDK). In order to make the assessment of VO clinical viable using a depth camera, research needs to develop new methods to that can utilize raw depth data in a system-agnostic manner.

Therefore, the aim of this study was to assess the validity of measures of VO during running gait using raw depth data, in comparison to a 3D multi-camera motion capture system. Based on previous research in walking (Eltoukhy et al., 2017; Mentiplay et al., 2015), we hypothesized that VO measures obtained from the depth camera would be consistent with those from the gold-standard 3D system (relative consistency > 0.80; absolute validity > 0.70; 95% limits of agreement (LOA) $\leq$ 10 mm).

2. Methods

2.1. Participants

Sixteen healthy, injury free adults (9 female, age: 29 ± 9 years; height: 169.6 ± 8.3 cm; mass: 65.4 ± 11.5 kg) were recruited for this study based on a sample size calculation (n = 15; $\rho_0 = 0.3$; $\rho_1 = 0.8$; $\alpha = 0.05$; $\beta = 0.2$). The study was approved by the Conjoint Health Research Ethics Board at the University of Calgary. All participants provided informed consent prior to testing.

2.2. Procedures

Participants were fitted with a pelvic marker cluster over the sacrum to track the vertical position of the pelvis using a 7-camera Vicon motion capture system (Vicon Motion System, Oxford, UK). Following a short warmup, one minute of data (200 Hz with 10 Hz low-pass 2nd order recursive Butterworth filter of marker trajectories) were collected as participants ran on treadmill (Bertec, Columbus, OH, USA) at a 2.7 m/s. Raw depth data (30 Hz) were simultaneously collected during the first 12 s of this

one minute trial using a Kinect v2 depth camera (Microsoft Corporation, Redmond, WA) placed 2 m posterior to the runner. A total of 12 s was recorded as a trade-off between the file size (e.g., ≈20 MB per second) and number of strides recorded (i.e., ≈20 strides). In addition to the dynamic trial, an empty scene and static scene were recorded by the Kinect v2 to allow for camera frame calibration during processing.

2.3. Kinect processing

The Kinect v2 was connected to a laptop running the Kinect SDK software required to collect raw depth data, but all raw data underwent custom processing, external to the Kinect SDK. The tracking of the vertical displacement of the pelvis/torso was accomplished with through two steps: (i) point cloud preprocessing, (ii) torso tracking using an Iterative Closest Point (ICP) algorithm. These steps are visualized in Figs. 1 and 2, respectively, with additional detail below and in a Supplementary File.

First, the raw depth image from the Kinect v2 underwent pre-processing to remove the background and create a point cloud of the runner. Previous research has detailed similar methods for this preprocessing (Han et al., 2013), but our detailed preprocessing steps are described in a Supplementary File. Briefly, the raw depth data were collected as a 512 × 424 pixel depth image (Fig. 1: left) and orthographically projected using camera intrinsics provided by Microsoft (Fig. 1: middle), before the runner's point cloud was isolated, denoised, and downsampled (Fig. 1: right).

Second, the vertical displacement of the runner's torso was tracked using an ICP algorithm. To our knowledge, the application of an ICP algorithm to gait analysis is novel, however, it has been previously demonstrated as an effective method for object tracking and facial recognition using depth data (Besl and McKay, 1992; Cook et al., 2004; Simon et al., 1994). The ICP algorithm is a point cloud registration algorithm that matches (i.e., 3D rotation and translation) one point cloud to another, with the goal of minimizing the distance of data points within each point cloud (Besl and McKay, 1992; Cook et al., 2004; Simon et al., 1994). While there are numerous variations of the ICP algorithm, the Wilm and Kjer's (Wilm and Kjer, 2012) ICP function for MATLAB (The MathWorks Inc., Natick, MA) was used for the purposes of this study.

The ICP algorithm was used iteratively to measure the VO of a runner from one frame to the following frame of data. To do so, a
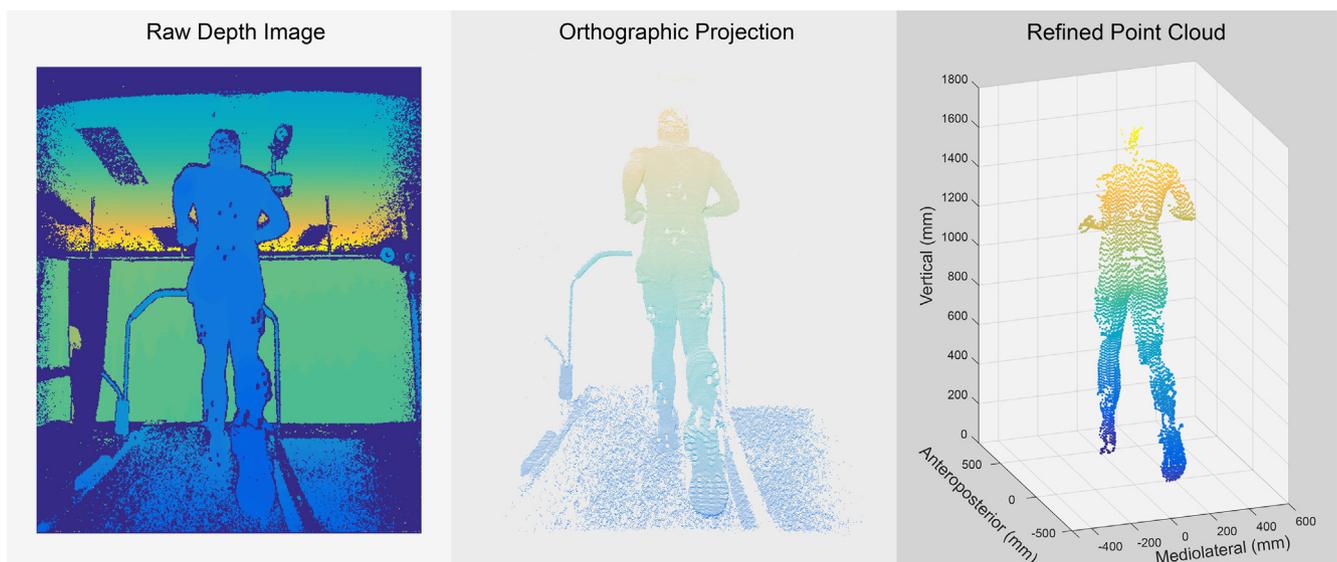

Fig. 1. Preprocessing steps demonstrated for a single frame from raw depth image (left) to orthographic projection (middle) to refined point cloud (right).
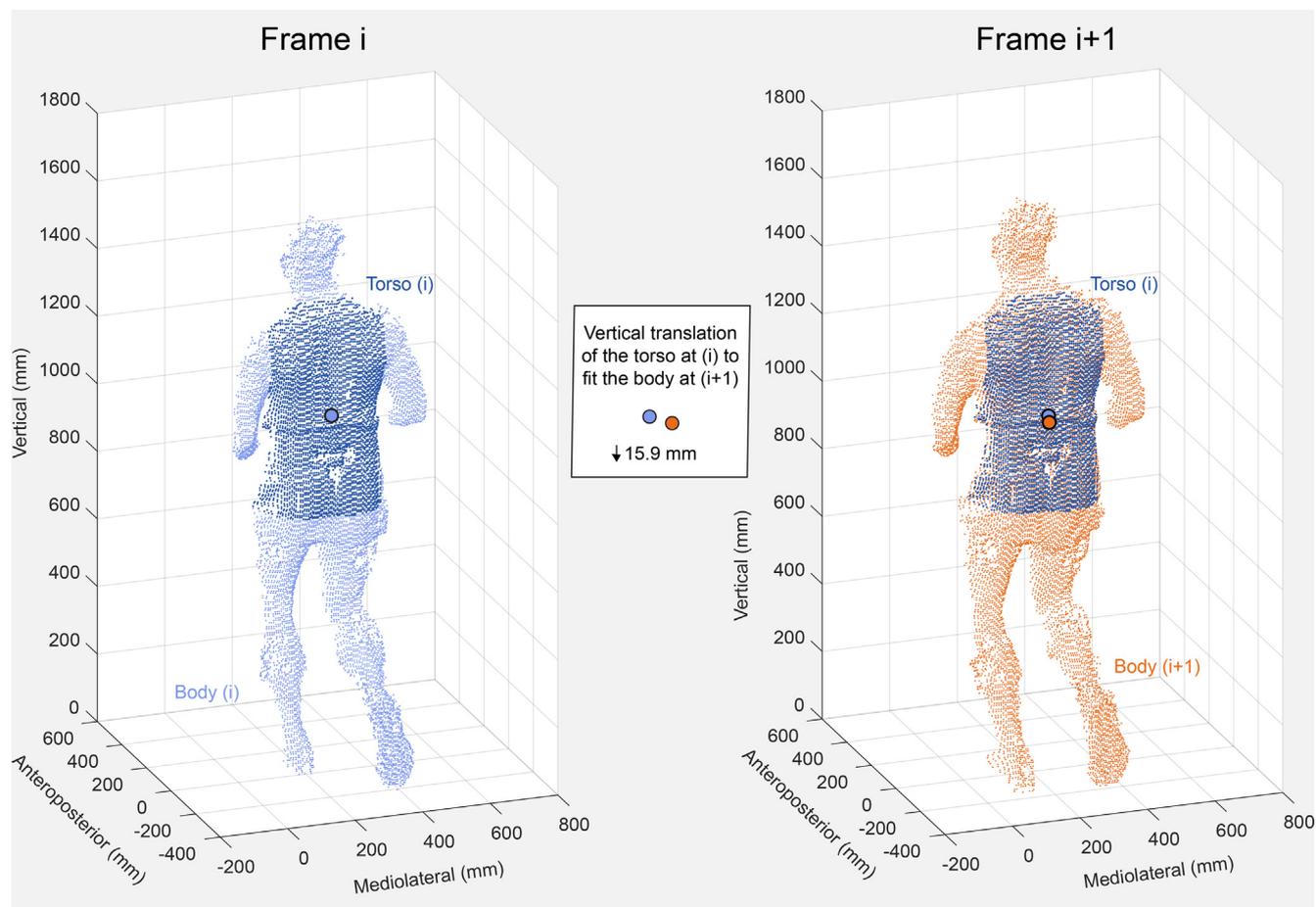
Fig. 2. Representative example of the torso tracking method using an Iterative Closest Point algorithm over two frames (frame i and frame i + 1).

rough selection of the torso was obtained based on the height of the point cloud and anthropometric tables. Fig. 2 (left) highlights the selection of this torso-specific point cloud in a single frame (e.g., frame i) which is then aligned with the following frame of data (e.g., frame i + 1) using the ICP algorithm (Fig. 2: right). The vertical translation that occur in this matching process defines the change in vertical displacement of the runner's torso over a single frame of data. Therefore, the vertical displacement trace of the runner was computed as the cumulative sum of this change score over the 12 s of depth data.

2.4. Vertical oscillation

The outcome variable under investigation was the VO of a runner's pelvis/torso. The VO measure was calculated from each of the Vicon and Kinect vertical displacement traces as the maximum vertical displacement minus the minimum vertical displacement occurring over each step. The average VO over the first 12 s of Vicon data was compared to the average VO of the 12 s of Kinect data collected simultaneously.

2.5. Statistical analysis

The agreement between the VO obtained from the two systems was assessed using a Bland-Altman plot with 95% limits of agreement (LOA; mean difference of methods ± 1.96SD; Bland and Altman 1986). Additionally, a Pearson's correlation coefficient (r) and a Lin's concordance correlation coefficient (r_c) with 95% confidence intervals (CIs) were computed between the two systems for

comparison with previous literature (Eltoukhy et al., 2017; Mentiplay et al., 2015). The r_c values were conservatively interpreted as poor ($r_c < 0.90$), moderate ($0.90 < r_c < 0.95$), excellent ($0.95 < r_c < 0.99$), and nearly perfect ($r_c > 0.99$; McBride et al., 2005).

3. Results

Individual demographics and results are presented Table 1. Mean ± SD values for the VO obtained from each system are also presented in Table 1, with accompanying error measures. The depth data from the Kinect v2 demonstrated excellent results across all measures of validity (r = 0.97 with 95% CI = 0.90–0.99; r_c = 0.97 with 95% CI = 0.90–0.99), with an average absolute difference and percent error of 3.7 (2.1) mm and 4.0 (2.0)%, respectively. Individual results are shown in the Bland-Altman plot presented in Fig. 3. The VO measures from the Kinect v2 demonstrated almost no bias (0.3 mm), with a 95% LOA of −8.0 mm to + 8.7 mm.

4. Discussion

The aim of this study was to assess the validity of VO measures during running using a depth camera and a novel processing technique. Overall, the Kinect v2 depth camera demonstrated excellent agreement with the gold standard Vicon system. In fact, the agreement observed for both relative consistency (r = 0.97) and absolute agreement (r_c = 0.97) were well above the hypothesized values (r > 0.80; r_c > 0.70) and previous results from walking and the Kinect-specific skeletal model tracking software (Eltoukhy et al.,

Table 1
Individual results for vertical oscillation (VO) across the two systems.

Subject	Demographics				Kinect v2 VO		Vicon VO		Error	
#	Sex	Height (cm)*	Mass (kg)*	Age (yrs)	Mean (mm)	SD (mm)	Mean (mm)	SD (mm)	Absolute (mm)*	Percent (%)
01	F	165	59.0	22	94.3	11.0	95.2	9.5	0.9	0.9
02	F	170	54.4	19	78.6	6.1	79.4	6.0	0.8	1.0
03	F	152	45.8	50	77.5	6.9	75.1	6.1	2.3	3.2
04	M	175	62.0	24	70.8	7.9	67.6	4.8	3.2	4.7
05	F	162	67.8	20	102.1	8.4	104.2	6.4	2.2	2.0
06	M	180	78.5	33	109.5	8.2	101.2	8.2	8.4	8.2
07	M	175	74.8	31	87.8	5.6	82.9	4.0	4.9	5.9
08	F	171	67.1	27	106.4	6.5	103.0	6.1	3.4	3.3
09	M	175	59.0	25	100.6	7.4	94.8	5.1	5.7	6.1
10	M	183	86.2	23	107.4	6.7	113.2	7.2	5.8	5.1
11	F	168	69.9	49	83.7	10.4	87.7	4.0	4.0	4.6
12	F	165	54.4	31	82.4	5.5	87.5	6.1	5.1	5.8
13	M	180	81.7	30	81.2	10.1	78.2	10.2	3.1	3.8
14	F	163	54.4	20	78.1	5.0	77.0	4.3	1.0	1.4
15	F	160	56.7	27	67.2	5.5	70.0	5.2	2.9	4.0
16	M	169	75.0	30	124.0	8.9	128.7	7.9	4.7	3.7
Average ± SD	9F/7M	169.6 ± 8.3	65.4 ± 11.5	28.8 ± 9.2	90.7 ± 16.1	7.5 ± 1.9	90.4 ± 16.7	6.3 ± 1.9	3.7 ± 2.1	4.0 ± 2.0

* Significant correlation of subject height ($r = 0.58$; $p = 0.02$) and mass ($r = 0.56$; $p = 0.03$) with absolute difference.
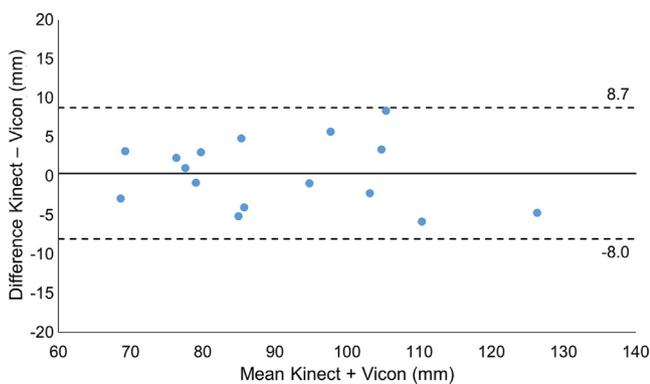

Fig. 3. Bland-Altman plot of vertical oscillation (VO) for agreement between the Kinect v2 and Vicon motion capture system.

2017; Mentiplay et al., 2015). Further, these data demonstrated 95% LOAs that were within our *a priori* goal of ± 10 mm, suggesting the ability to measure clinically relevant changes in VO (Heiderscheit et al., 2011). Therefore, this study is the first of its kind to demonstrate the utility of raw depth data, in combination with the novel ICP method, for the clinical assessment of VO during treadmill running.

In addition to the validity and clinical relevance of the results, the current method provides a system-agnostic solution that is important for the continued use of depth camera-based clinical gait analysis. This point is critical, as technology evolves quickly, and Kinect-specific skeletal model tracking software, and all analyses directly derived from it, will eventually be superseded. With this in mind, the current method utilized an ICP algorithm that can be applied to any raw point cloud data obtained from a depth camera (Besl and McKay, 1992; Cook et al., 2004; Simon et al., 1994). Further, unlike other forms of computer vison, this method does not require large sets of data to train the algorithm, making it easily adaptable to different depth cameras and gait analysis problems. For example, the ICP tracking method used in the current study is a flexible tool that can be applied over the entire body or various segments of the body within a single gait trial, across multiple gait trials, or between subjects.

As this is a first step in developing a system-independent VO tracking method for raw depth data, the current study has a number of limitations. First, all runners ran at speeds of 2.7 m/s. While running at faster or slower speeds may influence these results,

given the low frequency characteristics of the VO signal, we feel that this is unlikely. Nevertheless, there is a need to test the current method on a larger cohort of runners at a variety gait speeds. Second, the depth camera was located at the rear of the treadmill as this provides the most obstruction free view of a runner on most treadmills. However, it is unclear how these results may change if the depth camera is placed in laterally or in front of the runner. Regardless, the treadmill console and side bars would obstruct the camera's view of the runner, which would introduce error. Third, a significant correlation was observed for subject height and mass with absolute VO difference. This indicated that larger subjects had greater error overall, however the error was not systematic. Future research may seek to improve these current findings by addressing the impact of subject size. Also, given the large amount of data recorded and processed at each frame, the current state of the method cannot provide results in real time. In general, we found post-processing of the 12 s trials to take approximately 4–5 min. Therefore, future work may look to implement methods to improve this processing time, working towards a real time application. For example, introducing methods similar to Benson et al. (2018) could serve to significantly reduce computational load and provide an opportunity to perform real-time data processing.

Lastly, VO was the only outcome measure examined in the current study. While this was a successful demonstration of the validity of raw depth data, there remain numerous clinically-relevant biomechanical variables that may be derived from these data related to lower limb asymmetry (Auvinet et al., 2017, 2015), trunk lean (Clark et al., 2013), or pelvic rotation, to name a few. Future research that seeks to apply the current method towards such measures may continue to improve the clinical utility of this device. Nevertheless, the current findings present a significant first step in developing a novel and clinically accessible method for gait assessments in runners.

Acknowledgements

Conflict of Interest Statement

The authors declare that they do not have a conflict of interest with this work.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2019.01.006.

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