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Wearable sensor performance for clinical motion tracking of the lumbar spine

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Abstract— **Inertial measurement units (IMUs) have potential to be integrated into clinical assessments of movement-related disorders of the spine. This study evaluated 2 Mbientlab MetaMotionR IMUs relative to Vicon motion capture equipment in tracking 3D spine motion during 35 cycles of constrained repetitive spine flexion-extension (FE) in 10 participants. Root-mean-square error (RMSE) was low in all anatomical planes (RMSE ≤ 2.43°). Pearson's correlation coefficient was strong in the FE and lateral bend (LB) planes (R ≥ 0.746), and weak-to-moderate in the axial twist (AT) plane (0.343 ≤ R ≤ 0.679). Additionally, there was very strong correlation between range of motion measurements in the FE plane ($ICC_{2,1}$ = 0.99), and a wide range from weak to strong in the LB and AT planes (0.239 ≤ $ICC_{2,1}$ ≤ 0.980). This study reveals that the IMUs perform well in tracking motion in the primary movement plane, and can be used for planar assessments of movement quality.**

Keywords— **Wearables, motion tracking, low back pain.**

I. Introduction

Low back pain (LBP) is one of the leading causes of disability worldwide, affecting approximately 80% of people at some point in their lives [1]. Despite the high prevalence of LBP, symptoms and severity vary greatly between patients, making diagnosis and treatment difficult and often unreliable. Researchers and clinicians are moving toward the assessment of spine movement quality and control to better understand and identify dysfunction for better guidance of treatment planning; however, visual appraisal performed by healthcare providers can be unreliable [2–4]. Thus, there is a need for an objective means to be able to measure spine motion and movement characteristics in clinical settings.

Inertial measurement units (IMUs) specifically are being recognized as a portable and cost-effective alternative to conventional gold-standard motion analysis systems (i.e., video-based optical motion capture equipment), and have the potential to be introduced into clinical settings [5]. However, lack of confidence regarding sensor accuracy and reliability is limiting the integration of IMU-based assessments into routine clinical practice [6–8]. Some commercial versions are being used in clinics to provide feedback on measures such as postural range of motion (ROM; viMOVE, © 2017 DorsaVi Ltd); however, this does not provide insight into one`s functional movement quality and motor control strategies.

Previous work has shown that the Mbientlab MetaMotionR IMUs (Mbientlab Inc., San Francisco, USA) perform well at tracking repetitive, planar sinusoidal motion on a controlled robotic platform relative to Vicon (Vicon Motion Systems Ltd., Oxford, UK) [9]. Correlation between instruments was very strong in the primary axis of rotation and one non-primary axis; however, there was weak-to-moderate correlation between systems in the last non-primary axis, and this axis changed depending on the direction of the motion [9]. There was little-to-no motion in both non-primary axes in the previous study, and despite the weaker correlation, absolute errors were still small (root-mean-square error (RMSE) ≤ 1.40°). The previous study was performed to highlight error inherent in the IMU itself by eliminating sources of error that may arise when assessing performance in humans (e.g., skin motion artefacts). It was speculated that uncertainties in the sensor fusion process, signal noise, and trigonometric calculation incongruencies were all factors contributing to the weak-to-moderate correlation in the non-primary axis. Building upon the positive results from the previous study, the aim of the current study is to validate the MetaMotionR IMUs on the lumbar spine of human participants, during motion that is commonly used to assess movement quality. In order to achieve validity for clinical motion tracking, absolute error must be less than 2°. Error between 2° and 5° is also accepted, but may require additional interpretation [10].

II. Methodology

A. Equipment and Experimental Setup

In this study, 2 MetaMotionR IMUs (~$80USD; equipped with an accelerometer, gyroscope, magnetometer, and onboard sensor fusion) were adhered to two rigid plates in the configuration shown in Figure 1, with 4 passive reflective markers in each of the 4 corners. Rigid plates were firmly attached to the participant superficial to the T_{10}-T_{12} spinous processes, and over the sacrum (S_2) using a palpation technique (Figure 1). Data were collected at 100 Hz from the Mbientlab MetaBase mobile application and a 10-camera passive optical motion capture system (Vicon Vantage V5 cameras; 5 megapixels).

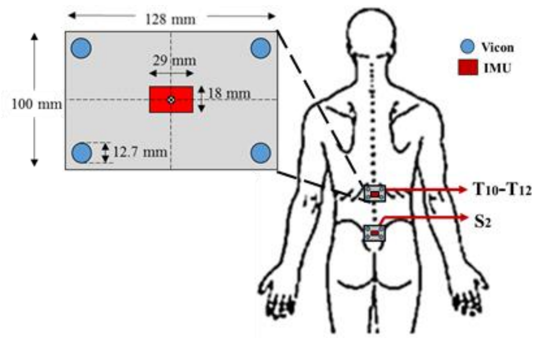


Fig. 1 Sensor configuration and placement.

B. Participants and Movement Protocol

Ten participants with no history of LBP within the last 6 months were recruited via posters and word-of-mouth. Prior to participation, informed consent was obtained. All procedures followed were in accordance with the ethical standards of the University of Ottawa research ethics board and the Declaration of Helinski. Participants were constrained at the hip and asked to perform 35 cycles of repetitive spine flexion-extension (FE; a movement protocol that permits assessments of movement quality). Participants were instructed to touch 2 targets with hands outstretched. Each target was in line with the sagittal midline to minimize movement in lateral bend (LB) and axial twist (AT) planes, with one located at shoulder height and at arms' length away, and the other located at knee height, and positioned 50 cm anterior to the knee as shown in Figure 2 [11,12]. This task was performed in synchrony with a metronome at 30 beats/minute (i.e., 15 cycles/minute and 4 seconds/cycle).

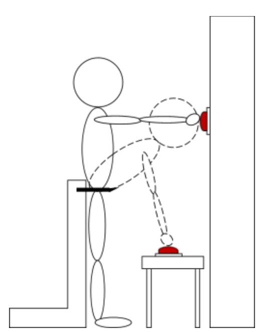


Fig. 2 Flexion-extension task.

C. Data Processing and Analysis

IMU performance was evaluated using fused Euler orientation data to enhance interpretation of results. A right-handed coordinate system was generated for the Vicon rigid-body marker clusters and Euler angles were extracted using an FE-LB-AT rotation sequence. It is common practice to exclude the first 5 cycles of motion to ensure steady-state motion when assessing human movement quality [13,14]; therefore, to ensure consistency of analyses, the last 30 cycles were analyzed. Data from Vicon and MetaMotionR IMUs were synchronized using the first peak maximum value in the FE data and low-pass filtered with a zero-phase Butterworth filter (effective 4th order with a cutoff frequency of 3 Hz) to filter out unwanted signal noise [15]. Gyroscopic drift was removed from the IMUs by subtracting a least-squares line of best-fit from the data. Relative motion between IMUs was calculated using an FE-LB-AT rotation sequence.

D. Statistical Analysis

Bland-Altman plots were used to evaluate level of agreement between instruments, and intraclass correlation coefficients ($ICC_{2,1}$) were applied to determine correlation of cycle-to-cycle ROM. Tests for normality revealed normal distribution in most cases; in cases where data were not normally distributed, data were transformed by taking the inverse of the data to achieve normality. RMSE was used to quantify overall error, and Pearson's correlation coefficient (R) was used to assess correlation between Vicon and MetaMotionR IMUs throughout the entire duration of the task. R-values above 0.7 can be regarded as a strong positive correlation, with 1.0 being perfect correlation. Values between 0.3 and 0.7 represent weak to moderate positive correlation [16].

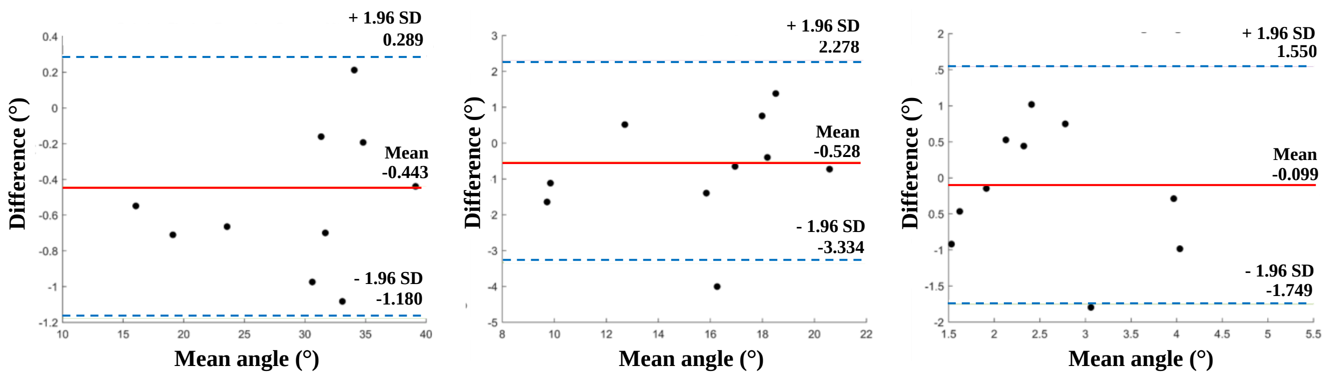
III. Results

Table 1 Participant Specifications. (SD: standard deviation).

Demographic	Mean (SD)
Sex	5 Make / 5 Female
Age	25.6 (2.8)
Height (cm)	174.2 (8.4)

In general, strong relationships for motion tracking were found in both the FE and LB planes, whereas results in the AT plane demonstrated weaker relationships (Table 2). RMSE $\leq$ 2.43° for the T_{10}-T_{12} IMU. Similar trends were found for the S_2 IMU; however, overall RMSE was lower than the T_{10}-T_{12} IMU (RMSE $\leq$ 1.03°) as the thorax has an overall larger ROM during an FE task than the pelvis.

Intraclass correlation ($ICC_{2,1}$) analyses demonstrated excellent results when comparing mean cycle-to-cycle FE ROM (Table 3). Weaker relationships were found in LB and AT planes ($0.239 \leq ICC_{2,1}^{LB} \leq 0.980$; $0.356 \leq ICC_{2,1}^{AT} \leq 0.745$).-ROM differences between systems were within 2 SDs of error, with one outlier observed in LB and AT plots (Figure 3).



(a) (b) (c)

Fig. 1 Bland-Altman analysis for relative range of motion measurements between IMUs and Vicon. (a) Flexion-extension. (b) Lateral bend. (c) Axial twist.

Table 2 Root-mean-square error and Pearson's correlation coefficient for individual and relative motion of IMUs and Vicon. (FE: flexion-extension; LB: lateral bend; AT: axial twist; R: Pearson's correlation coefficient).

	Direction	RMSE (°)	R
T_{10}-T_{12}	FE	1.75	0.998
	LB	0.89	0.978
	AT	2.43	0.343
S_2	FE	0.89	0.987
	LB	0.33	0.889
	AT	1.03	0.547
Relative	FE	1.60	0.995
	LB	1.63	0.746
	AT	0.83	0.679

Table 3 Mean (SD) cycle-to-cycle range of motion and intraclass correlation for individual and relative motion of IMUs and Vicon. (ICC: intraclass correlation coefficient; FE: flexion-extension; LB: lateral bend; AT: axial twist; SD: standard deviation; ROM: range of motion).

	ROM (°)			
	Direction	**IMU**	**Vicon**	**$ICC_{2,1}$**
T_{10}-T_{12}	FE (°)	37.8 (5.5)	37.2 (5.7)	0.999
	LB (°)	2.5 (1.2)	2.5 (1.1)	0.980
	AT (°)	3.7 (2.2)	2.7 (1.1)	0.356
S_2	FE (°)	9.2 (3.4)	9.1 (3.3)	0.999
	LB (°)	1.1 (0.4)	1.1 (0.5)	0.770
	AT (°)	2.3 (1.1)	1.1 (0.9)	0.745
Relative	FE (°)	29.6 (7.3)	29.1 (7.4)	0.999
	LB (°)	3.0 (1.4)	2.2 (0.9)	0.239
	AT (°)	2.2 (0.8)	2.0 (0.8)	0.559

IV. Discussion

Previous work has shown that the IMUs also perform well in tracking motion in controlled environment during motion that simulated spine FE, LB, and AT [9]. While this study previous was performed to highlight limitations that were inherent in the IMU and sensor fusion process, the present study was conducted to provide a more realistic validation scenario with respect to clinical motion tracking of the spine.

Similar to the previous study, low measurement error was found in all axes. Strong correlation was observed in the primary axis (FE) and one non-primary axis (LB), and similar to the previous study, there was weak-to-moderate correlation between system measurements in one non-primary axis (AT). In both cases, this likely has something to do with the fusion algorithms used for the MetaMotionR IMUs. Because the on-board sensor fusion process utilized by Mbientlab is unknown, the process becomes somewhat of a "black box", whereas the inputs and outputs are known (i.e., raw sensor data and Euler orientations, respectively); however, the corrective computational fusion algorithms used to get from point A to B are unknown. Because motion in the non-primary axes was supposed to be minimized (and in the current study, did not exceed 2°), the weak correlation in the one non-primary axis could essentially be signal noise [17], in which case weak correlation is to be expected. Future work will explore these relationships by considering signal-to-noise ratio.

The current study has additional factors that likely influence off-axis motion tracking (e.g., skin-motion artefacts, intrinsic neuromuscular perturbations). In addition, rigid plate and/or IMU local coordinate systems were intended to line up with the local anatomical coordinate system to accurately capture motion of the specified anatomical region. Therefore, misalignment of the rigid plate and/or IMU can introduce potential measurement error as a result of trigonometric calculation incongruity when estimating absolute orientation [18].

Even with substandard motion tracking in the AT plane, it is likely that this has little influence on the calculation of common movement quality measures (e.g., local dynamic stability, variability, and coordination). Generally, these measures are assessed using solely planar motion (i.e., FE, LB, and AT); therefore, the Mbientlab MetaMotionR IMUs can likely be used for planar clinical motion tracking and assessment of movement quality. Local dynamic stability is also commonly calculated using the sum-of-squares of the planar movement data, in which case poor non-primary motion tracking would highly affect this; however, due to the low magnitude of the off-axis movements, it is likely that the large-magnitude primary axis movement will outweigh any poor off-axis contributions. Future studies will assess the effect of these results on measurement of specific outcomes measures used to assess spine movement quality.

V. Conclusion

Mbientlab MetaMotionR IMUs have acceptable performance in tracking spine FE and can accurately and reliably measure ROM in FE and LB planes. Future studies will explore multidirectional spine movement to understand the relationship between magnitude of motion and the percentage of error, as well as the effect of these errors on the calculation of movement quality features. Custom fusion of accelerometer, gyroscope, and magnetometer data will be implemented to match post-processing to that of Vicon. Overall, this work provides a foundation of understanding for motion tracking using Mbientlab MetaMotionR IMUs, and a framework to further optimize performance of IMUs for clinical motion tracking and measurement of spine movement quality.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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