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Democratizing Clinical Movement Analysis: Assessing the Versatility of MoJoXlab with Open-protocol Inertial Sensors

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Abstract

This study evaluated the versatility of the MoJoXlab in conducting clinical movement analysis using inertial sensors from various manufacturers, including low-cost, non-proprietary, and open-protocol wearable options. Data were collected from 15 healthy participants who performed a range of clinically relevant activities and exercises using two sets of sensors. Dynamic time warping analysis of the sensor signals suggested that the collected dataset could be used for further algorithm development. The findings demonstrate that the current iteration of MoJoXlab can perform movement analysis using quaternions from sensors of any manufacturer. However, the accuracy of the resulting joint angles is not yet suitable for clinical applications across all sensor types, and only Xsens and NGIMU sensors are currently supported. This study also explored the potential for reducing the number of sensors required by MoJoXlab, which currently uses seven sensors to calculate joint angles for three joints (hip, knee and ankle) on both sides of the body. The creation of a comprehensive databank for lower limb movement analysis algorithms was an additional outcome of this work. Further research and development are necessary to expand MoJoXlab's support for multiple sensor manufacturers and improve the accuracy of joint angle calculations for clinical applications.

Keywords: clinical movement analysis; inertial sensors; MoJoXlab; wearable sensors; low-cost sensors; open-protocol sensors; quaternion-based analysis; joint angle calculation; databank for movement analysis; reducing sensor count; clinically relevant activities; dynamic time warping;

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1. Introduction

Movement analysis plays a crucial role in various clinical applications, particularly in the field of rehabilitation. Wearable inertial sensors have emerged as a promising technology for enabling quantitative assessment of human movement, offering advantages such as portability and the ability to capture data in real-world environments. However, the widespread adoption of movement analysis systems in clinical practice has been hindered by several challenges, including the reliance on proprietary hardware and software solutions, which can be expensive and limit interoperability [1,2]. In this context, the development of MoJoXlab [3,4], a software platform for movement analysis, has aimed to address these limitations by supporting the integration of inertial sensors from multiple manufacturers. While previous studies have validated MoJoXlab's performance using proprietary sensors from Xsens MVN [3,4]. There is a need to evaluate its versatility in accommodating sensors from other manufacturers, particularly those employing open protocols and more cost-effective solutions.

This paper investigates the feasibility of using MoJoXlab in conjunction with open-protocol wearable inertial sensors from NGIMU (X-IO Technologies) for conducting clinical movement analysis in lower limb rehabilitation. By comparing the sensor data obtained from NGIMU and the previously validated Xsens sensors, this study aims to assess the potential for optimizing the use of movement analysis software and wearable sensors in clinical practice. It is worth noting that each sensor manufacturer has distinct software for data collection and output file formats [5]. In addition, NGIMU sensors are relatively more affordable than Xsens's and other proprietary sensor manufacturers' offerings. They have also been previously leveraged in movement analysis research [6–10].

Prior research comparing inertial sensors has used either goniometer-based measurements [11] or simulation-based techniques [12] or compared sensors with established motion capture systems [13]. MoJoXlab was previously validated using Xsens's sensors in conjunction with Xsens's commercial software [3] and, consequently, with a VICON-based optical motion capture system [13]. Specifically, this paper compares NGIMU sensors with the previously validated MoJoXlab software [4].

This study collected data from 15 healthy participants who performed various lower-limb activities relevant to clinical applications while wearing two sensor sets. The activities were selected based on input from three senior clinicians. Both sensor systems captured data for the same activities, but due to using different software for data collection, the resulting time series signals were out of sync, resulting in a lag between them and unequal signal lengths. In contrast to prior work [3], where data was captured using a single software package (Xsens's MVN), the issue of data synchrony, lag, or unequal lengths was absent. As such, a different method for comparing similarities is more appropriate. The dynamic time warping (DTW) method is used for this purpose, as cross-correlation and root mean square error methods are unsuitable in this context. DTW has been employed in movement analysis applications and can provide a similarity metric even when signals are out of sync or have varying lengths [11,14].

Prior work [3] demonstrated how MoJoXlab calculated joint angles for three clinically relevant activities: walking, squatting and jumping. In this paper, MoJoXlab is deployed to conduct movement analysis of additional activities, including knee exercises while seated and supine. The data collected in this study adds to a repository of movement analysis databank [15] that employs two distinct sensor systems for nine different clinically relevant activities. This databank [15] can be leveraged for several purposes, such as advancing the development of MoJoXlab, creating algorithms for lower limb movement analysis, supporting activity recognition tasks, and training machine learning models.

2. Methods

2.1. Research participants

This study received ethical approval from The Open University Human Research Ethics Committee (HREC/2019/3237/Bennasar), and written informed consent was obtained from all participants before their participation. A total of 15 healthy participants were recruited using convenience sampling according to the following criteria: aged between 18 and 60 years without any active lower limb disability or injury. The participant demographics are summarized in Table 1.

Table 1. Participant demographics of healthy individuals including sample size, mean age with standard deviation, gender ratio, mean body height with standard deviation, and mean foot size with standard deviation.

Sample	Age	Male/Female	Height	Foot Size
N = 15	44yrs ± 13	M:F = 7:8	171.5cm ± 9.6	27.8cm ± 3.5

2.2. Data collection

Data collection was conducted in the Pervasive Lab at The Open University campus. Each participant performed nine clinically relevant activities and exercises (described in Table 2) while simultaneously wearing two sets of wearable inertial sensors: seven MTw2 sensors from Xsens Technologies and seven NGIMU sensors from X-IO Technologies.

Table 2. Activities and exercises

Activity	Description
Basic Activities	
Walking	Walking on a straight line without carrying any objects.
Sitting and relaxing	Sitting on a chair and relaxing without engaging in any activity, maintaining an upright posture with support from the chair’s backrest.
Standing	Standing stationary without any leg movement.
Lying down (supine position)	Lying down flat on the back in a supine position on a hospital bed without any movement.
Jumping	Standing on both feet, slightly bending the knees, and then jumping upwards and landing on the same spot.
Squatting	Starting from a standing position, bending the knees and moving down as far as possible.
Exercises	
Seated active knee extension/flexion	While sitting on a chair, extend and flex the left leg to make it parallel to the ground and then return it to the original position. Repeat the same process for the right leg.
Seated assisted knee extension/flexion	While sitting on a chair, place the left leg over the right leg, and then extend and flex the left leg to make it parallel to the ground while resting it on the right leg. Repeat the same process for the right leg.
Heel Slide	While lying down in a supine position flat on the back, bend the knees slowly to slide the heels towards the buttocks.

As illustrated in Figure 1, the sensors were attached to the feet, calves, thighs, pelvis, and sacrum using adjustable straps and adhesive tape. The sensors were placed according to Xsens's protocol [13]. The same individual placed the sensors on all participants following a consistent protocol to ensure data consistency and quality.

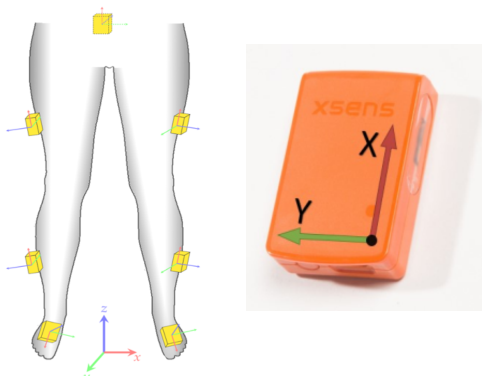

Fig. 1. Locations of sensors for lower limb body and sensor axes.

Two commercially available sensor systems were used in this study: the low-cost, open-protocol NGIMU sensors (X-IO Technologies) and the proprietary Xsens MTw2 sensors (Xsens Technologies). The NGIMU sensors have an open protocol and freely available data capture software, making them suitable for integration into custom software like MoJoXlab. In contrast, the Xsens sensors require proprietary software for data acquisition and lack the ability to generate joint angles directly. Kinematic data were collected at a sampling frequency of 50 Hz using the respective software for each sensor system: Xsens MT Manager for Xsens sensors and NGIMU Open-Source Software for NGIMU sensors. The collected data were exported as CSV files for further processing.

2.3. Data pre-processing and joint angle calculation

Custom Python scripts were developed to pre-process the collected data. Subsequently, MoJoXlab was used to calculate joint angles for the hip, knee, and ankle joints in the sagittal, frontal, and transverse planes (except for the ankle joint, which was limited to the sagittal and frontal planes) for each activity and exercise using the data from both sensor systems. The MoJoXlab algorithm for joint angle calculation has been published before [16]. A static calibration dataset was collected during the standing activity, where participants maintained a standard standing posture, as described in a previous study [3]. This calibration dataset was used by MoJoXlab to compute joint angles from the raw inertial sensor data.

2.4. Data analysis and validation

The joint angles generated by MoJoXlab for the two sensor systems were compared and validated using DTW. DTW is a distance measure that can assess the similarity between two time series signals, even when they have different lengths or are out of sync [14]. Custom Python scripts were employed to visualize the joint angle waveforms, calculate the DTW distance between the waveforms, and plot graphs corresponding to the calculated distance. Two metrics derived from the DTW values were used for comparison: Normalized Dynamic Time Warping (NDTW) and a DTW Similarity Metric. NDTW calculates the minimum distance required to align two time series, accounting for differences in their time scales by computing the sum of squared differences between corresponding points [17]. This distance is then divided by the length of the optimal warping path to obtain a normalized distance value representing the similarity between the two time series.

$$NDTW = DTW \,/\, (\textit{length of optimal warping path}) \tag{1}$$

The DTW Similarity Metric is a normalized measure ranging from 0 to 1, where higher values indicate greater similarity between the two time series [18]. It is calculated by subtracting the ratio of the DTW distance and the maximum possible distance based on the time series length and sample values from 1.

$$\textit{DTW Similarity Metric} = 1 - \frac{DTW}{(\textit{max value of time series})} * (\textit{length of optimal warping path}) \tag{2}$$

These metrics were used to assess the similarity between the joint angles calculated by MoJoXlab for the two sensor systems, providing insights into the performance and versatility of the software in accommodating different sensor data.

3. Results

The results are presented in two parts: a comparison of the raw quaternion signals obtained from the Xsens and NGIMU sensor systems, followed by a comparison of the joint angles calculated by MoJoXlab using data from these two sensor systems.

3.1. Comparison of Raw Quaternion Signals

The similarity between the raw quaternion signals acquired from the two sensor systems was evaluated using NDTW and a DTW similarity metric. Figure 2 (a) displays the distribution of mean sorted NDTW values across all sensor positions and participants, with most mean values being below 0.001. Figure 2 (b) shows the corresponding DTW similarity metric values, with all mean values exceeding 0.8, indicating high similarity between the quaternion signals. To further investigate the similarities, the NDTW values were sorted by sensor position, as shown in Figure 2 (c). The distribution of mean NDTW values for each sensor position was generally below 0.001, suggesting high similarity across positions. Figure 2 (d) presents the DTW similarity metric values sorted by sensor position, with all mean values greater than 0.8, reinforcing the high similarity observed across positions.

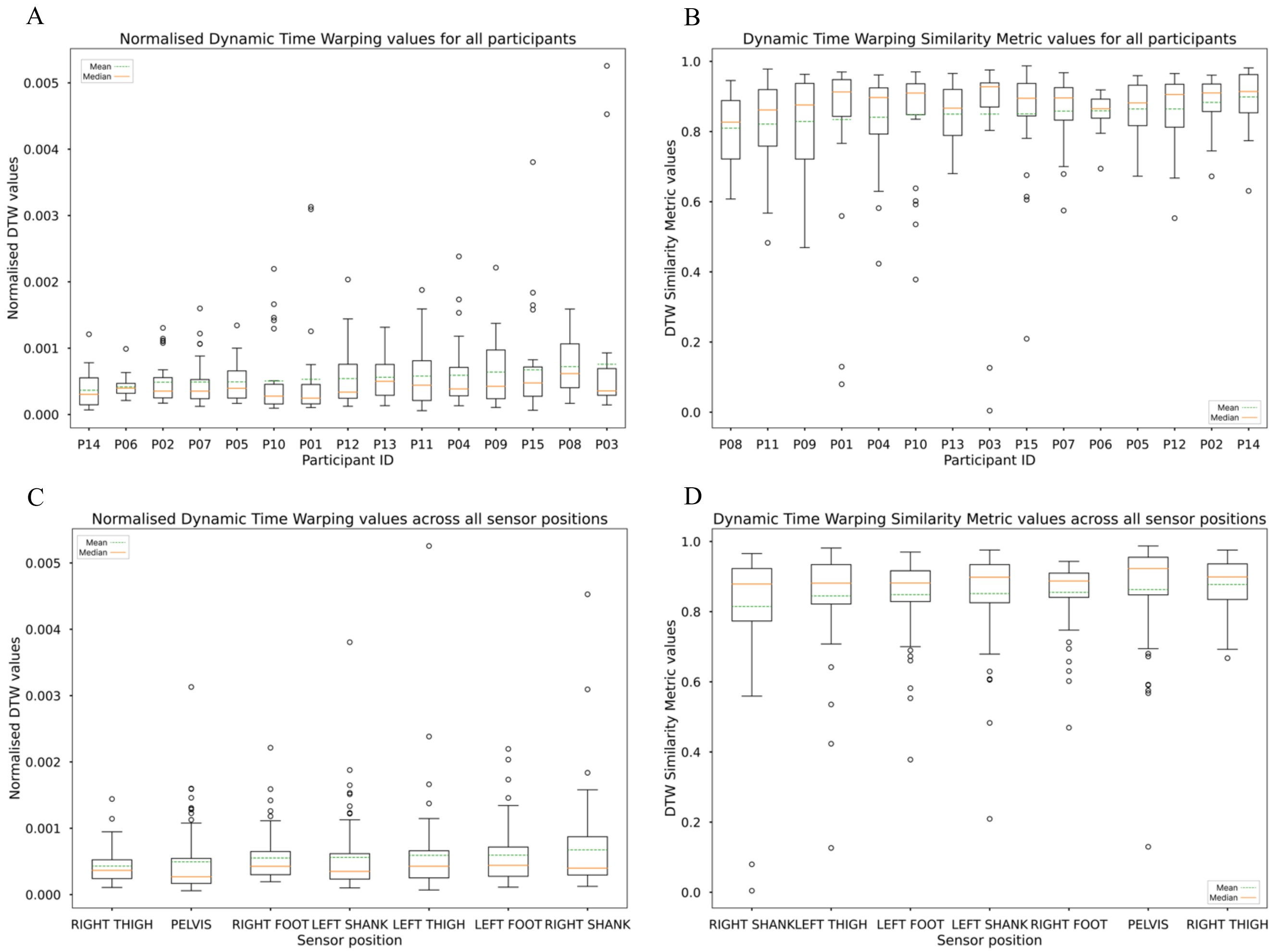

Fig. 2. Comparison of raw quaternion signals between Xsens and NGIMU sensors; (a) Boxplot of mean sorted normalized dynamic time warping values across all sensor positions and participants. The green dotted line denotes each participant's mean values, while the orange solid line represents the median values. (b) Boxplot of mean sorted dynamic time warping similarity metric values across all sensor positions and participants. The green dotted line denotes each participant's mean values, while the orange solid line represents the median values. (c) Boxplot of mean sorted normalized dynamic time warping values for each sensor position. The green dotted line denotes each participant's mean values, while the orange solid line represents the median values. (d) Boxplot of mean sorted dynamic time warping similarity metric values for each sensor position. The green dotted line denotes each participant's mean values, while the orange solid line represents the median values.

Visual inspection of the raw quaternion signals for a representative participant (Figure 3) supported the quantitative results. The signals exhibited similar patterns between the two sensor systems, although vertical offsets and lags were observed in some cases. Overall, the analysis of the raw quaternion signals indicated a high degree of similarity between the Xsens and NGIMU sensor systems.

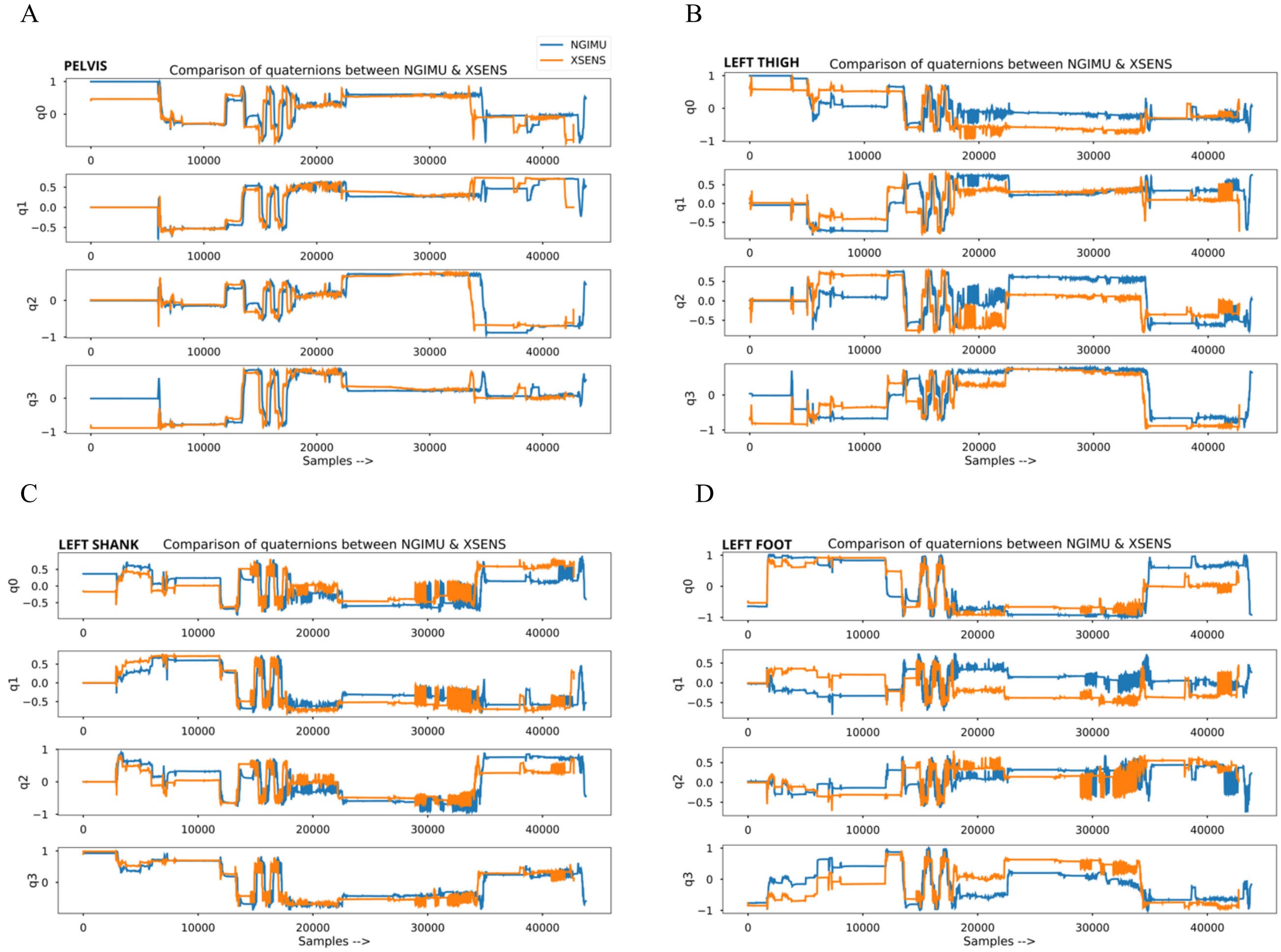

Fig. 3. Comparison of raw quaternion signals (q0, q1, q2, q3) between Xsens and NGIMU sensors for a representative participant. (a) Pelvis joint; (b) Left thigh joint; (c) Left shank joint; (d) Left foot joint

3.2. Comparison of Joint Angles

The joint angles calculated by MoJoXlab using data from the two sensor systems were compared to evaluate the software's performance in accommodating different sensor data. The DTW similarity metric values for the raw quaternion signals (0.85) and the joint angles (0.84), demonstrating nearly identical values, thereby validating the similarity between the quaternion signals and the calculated joint angles. Figure 4 (a) displays the distribution of mean sorted NDTW values for joint angles across the hip, knee, and ankle joints. The mean and median NDTW values ranged from 0.3 to 0.6, indicating moderate similarity. Figure 4 (b) shows the corresponding DTW similarity metric values, ranging from 0.8 to 0.9, suggesting high similarity. To further analyze the joint angle similarities, Figure 4 (c) presents the mean sorted NDTW values across all joints, planes, and sides, sorted by mean values. Figure 4 (d) displays the corresponding DTW similarity metric values. The results indicated higher accuracy for the ankle joints compared to the hip and knee joints. Additionally, the left side demonstrated more similarity than the right, and the sagittal and frontal planes exhibited higher similarity than the transverse planes.

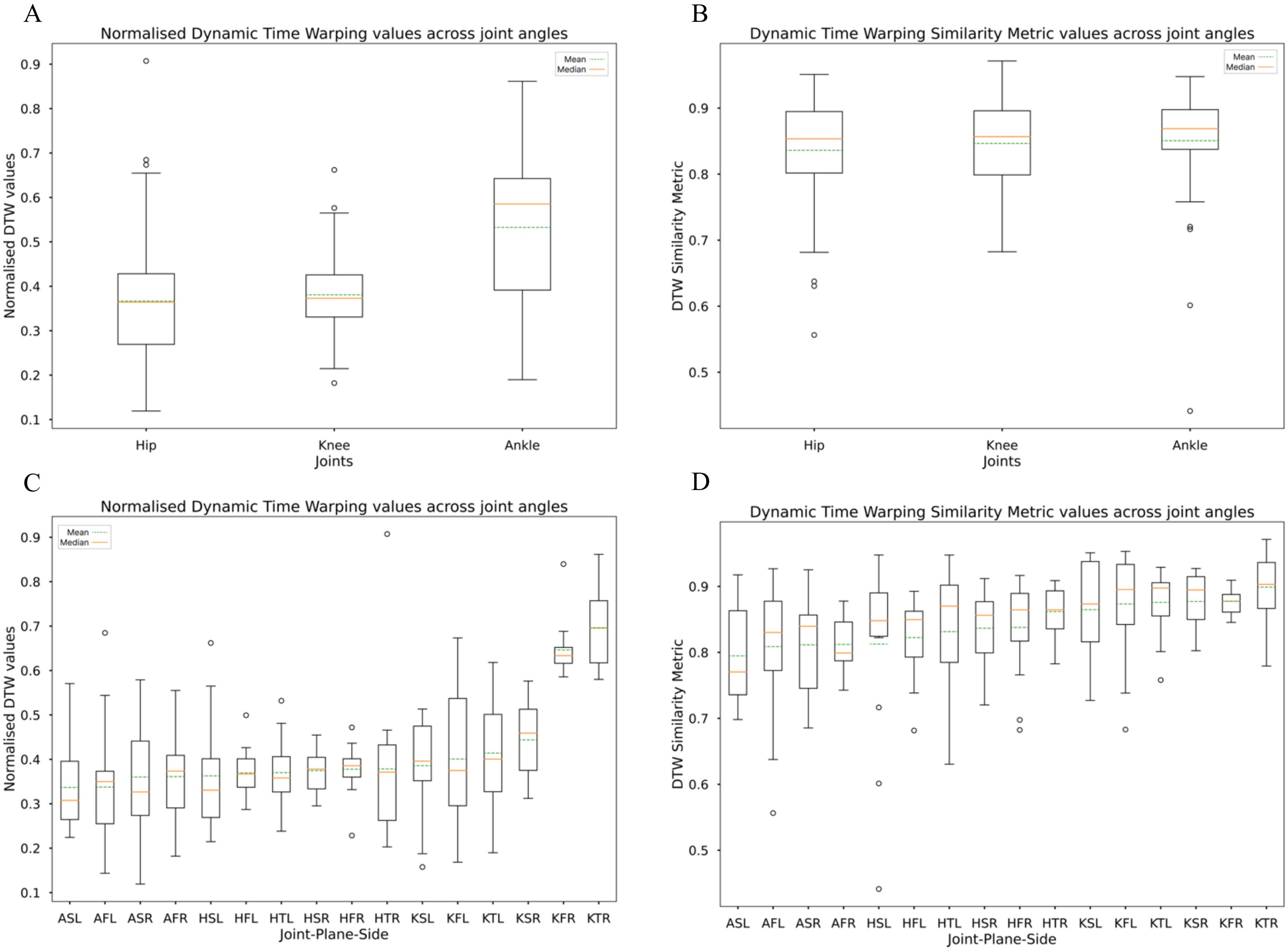

Fig. 4. Comparison of joint angles calculated by MoJoXlab using Xsens and NGIMU sensor data. (a) Boxplot of mean sorted normalized dynamic time warping values across hip, knee, and ankle joints. Mean values are denoted by the green dotted line, while median values are represented by the orange solid line. (b) Boxplot of mean sorted dynamic time warping similarity metric values across hip, knee, and ankle joints. Mean values are denoted by the green dotted line, while median values are represented by the orange solid line. (c) Normalized dynamic time warping values sorted by mean values across all joints, planes, and sides. Joints are identified as A (ankle), H (hip), K (knee); planes as S (sagittal), F (frontal), T (transverse); and sides as L (left), R (right). (d) Dynamic time warping similarity metric values sorted by mean values across all joints, planes, and sides. Joints are identified as A (ankle), H (hip), K (knee); planes as S (sagittal), F (frontal), T (transverse); and sides as L (left), R (right).

Visual inspection of the joint angle waveforms for a representative participant (Figure 5) revealed that the signals followed similar patterns between the two sensor systems for certain portions of the activities. However, vertical offsets and lags were also observed, consistent with the quantitative similarity metrics.

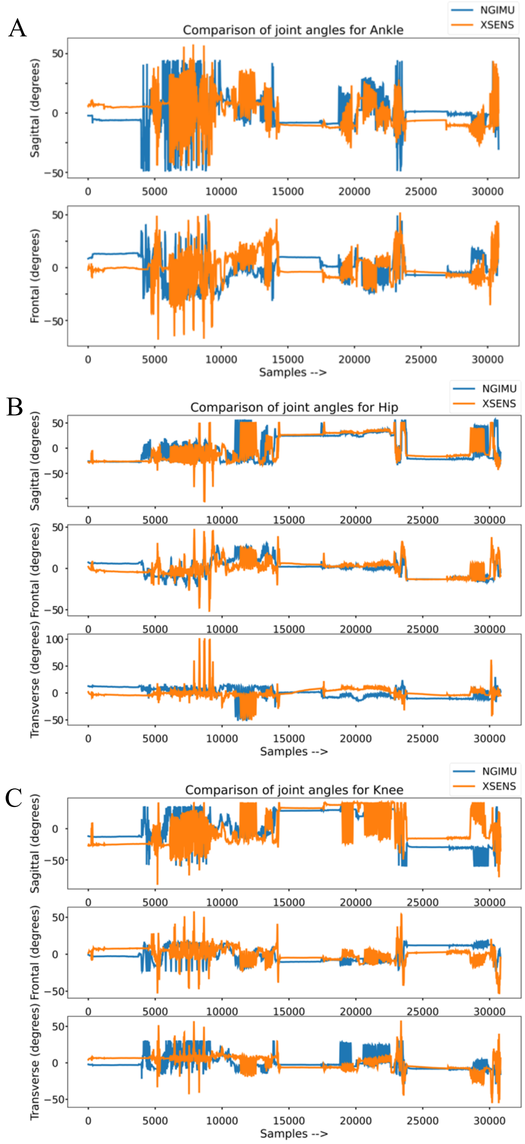

Fig. 5. Joint angle waveforms calculated by MoJoXlab for a representative participant using Xsens and NGIMU sensor data. (a) Ankle joint angles in the sagittal and frontal planes for the left side. (b) Hip joint angles in the sagittal, frontal, and transverse planes for the left side. (c) Knee joint angles in the sagittal, frontal, and transverse planes for the left side.

In summary, the results demonstrated that MoJoXlab could generate accurate joint angles from the NGIMU wearable inertial sensors, although further improvements to the algorithm are necessary to better support these sensors. The comparable raw quaternion signals suggest that the calculated joint angles should also be similar, but the observed differences highlight the need for algorithm modifications to account for factors such as vertical offsets and differences in signal timing between different sensor systems.

4. Discussion

MoJoXlab has been previously validated against XSENS MVN Software [3] that was also validated across Vicon's optical motion capture system [13]. Therefore, MoJoXlab can be potentially used in clinical applications but warrants further clinical validation. MoJoXlab currently supports XSENS and NGIMU sensors only, further research is required to support other sensor systems. The present study aimed to compare the raw quaternion signals and joint angles calculated from two different sensor systems, Xsens and NGIMU, to investigate the interchangeability of these systems in measuring joint angles during human movement. The results from comparing raw quaternion signals and joint angles showed a high similarity between the two sensor systems. This suggests that the Xsens and NGIMU systems can be used interchangeably to measure joint angles during human movement. However, the vertical offset between the two sensors remains, which may be due to differences in sensor placement or the sensor's measurement properties. This finding is consistent with previous studies that have reported sensor placement as a critical factor affecting the accuracy and reliability of the sensor data [19]. To minimise the effect of sensor placement on sensor data, future studies should investigate the optimal sensor placement for each sensor system and provide guidelines for sensor placement in different applications. Additionally, future studies should investigate the cause of the vertical offset between the two sensors and explore ways to minimise it, such as through sensor calibration or algorithm modification. The use of DTW similarity metric values proved useful in comparing sensor data in the present study. This finding is consistent with previous studies that have used dynamic time warping to compare different sensor systems [14,20]. DTW allows for comparing time series data with different lengths and temporal alignments, making it a suitable method for comparing sensor data collected from different sensor systems.

The present study's findings have important implications for developing movement analysis software that supports multiple sensor manufacturers. The development of non-proprietary wearable inertial sensor-based movement analysis software such as OpenSense [21] and OpenSenseRT [22] is an important step towards providing clinicians with accessible and cost-effective tools for movement analysis. However, these systems are currently limited in their ability to support multiple sensor systems, and further investigation is required to identify specific requirements for each sensor manufacturer.

The current study has several limitations that warrant attention when interpreting the findings. Although the study compared joint angles generated by the two sensor systems for various movements, it did not compare the results of specific activities such as walking, jumping, or squatting. Furthermore, the study only examined joint angles and did not compare other movement parameters such as range of motion, speed, stride length, or gait symmetry. Therefore, future research should explore the similarity of other movement parameters to determine MoJoXlab's reliability in analysing various aspects of human movement. Moreover, the current study did not investigate the effect of sensor placement on the observed vertical offset between the two sensor systems. Further research is needed to identify this offset's cause and devise strategies to reduce it. Additionally, the study only included healthy participants performing predetermined movements.

Lastly, the current study employed dynamic time warping similarity metric values as the sole measure to compare sensor data. While this metric is useful for measuring the similarity between two signals, it does not provide information on the absolute accuracy of the joint angle measurements. Therefore, future research should examine the accuracy of MoJoXlab's joint angle measurements by comparing them with gold standard methods such as motion capture systems.

5. Conclusion

This study demonstrated that MoJoXlab's algorithm applies to various sensor manufacturers, including low-cost, non-proprietary, open-protocol wearable inertial sensors. This study also expanded on MoJoXlab's capabilities for conducting clinical movement analysis for various activities and exercises while creating a databank for developing lower limb movement analysis algorithms. Data were collected from 15 healthy participants who performed various clinically relevant activities and exercises using two sets of sensors [15]. The dynamic time warping analysis showed relatively low values, and the signals appeared similar visually, suggesting that the data can be used for algorithm development. This dataset can serve as a basis for further development of MoJoXlab to reduce the number of sensors required. Currently, MoJoXlab uses seven sensors to calculate joint angles for three joints on both sides of the body. However, if the clinician is interested in fewer joints, using a smaller number of sensors would save time, resources, and money. In conclusion, the study finds that the current iteration of MoJoXlab can conduct movement analysis using quaternions from sensors of any manufacturer. However, the accuracy of the resulting joint angles is not yet appropriate for clinical applications from all sensor manufacturers, and currently, only Xsens and NGIMU sensors are supported. Additional research and development are necessary to support multiple sensor manufacturers.

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