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IMU positioning affects range of motion measurement during squat motion analysis

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A R T I C L E I N F O

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A B S T R A C T

Inertial Measurement Units (IMUs) provides embedded and accessible (financially and technically speaking) motion analysis for sports or clinical applications (rehabilitation, therapy…). Despite being advertised for it ease of use, the very nature of IMU sensor makes it prone to errors which are usually corrected through calibration processes thus adding extra complexity for the users. The main goal of this study is to estimate the effect of sensor positioning on the thigh for a simple assessment of squat motion range of motion (ROM) as could be done in a pragmatic clinical approach (i.e., without prior calibration). Kinematics, squat counts and timing of three IMU sensors along the thigh were recorded during squat motion and compared to an optoelectronic reference system. Results showed concordance coefficients of the IMU system over 0.944 without the need for calibration with a preference for placement on the distal part of the segment regarding kinematics data.

1. Introduction

Applications of Inertial Measurement Units (IMUs) in various fields like sports or rehabilitation have been a growing field for more than a decade. Amongst the numerous new applications of this technology, the NOMADe project (https://nomadeproject.eu/) aimed at facilitating the acquisition of quantitative motion information for the completion of clinical assessment and patients rehabilitation follow-up (Cappelle et al., 2020). The first clinical focus of this project was on low back pain (LBP), one of most common reasons people see a doctor or miss work days according to the U.S. National Institutes of Health.

Previous works (Burns et al., 2019) established the main focus for LBP clinical therapy was hip joint strengthening (91 % of interventions). For this purpose, 83 % of interventions used the double leg squat as a muscle strengthening exercise. Double squat analysis is considerably documented in the scientific literature with development related to squat detection algorithms or (Stevens et al., 2018), or IMU validation when compared to opto-electronic motion capture (OMC) system (Horenstein et al., 2019). In this scenario, IMUs are indeed very interesting for the clinicians who will save a previous time with automated task-evaluation and tracking (Cook et al., 2014; Pereira et al., 2019). However the IMU system is designed to be used by clinicians (e.g. physiotherapist, occupational therapist…) who are not trained in motion capture procedures which is known to lead to wrong usage and erroneous data (Loup-Escande and Loup, 2021).

To the best of our knowledge, despite recent works on upper-limb sensor placement (Höglund et al., 2021), there is no standardized procedure from motion capture experts committees related to sensor positioning on the body (Kobsar et al., 2020; Poitras et al., 2019). However it is known to greatly alter the final results in motion capture, both for OMC (Della Croce et al., 2005) or IMUs (Guichard et al., 2021). To counter bad sensor positioning, several studies proposed a calibration procedure of the IMU system based on static poses (Palermo et al., 2014; Vargas-Valencia et al., 2016) or through functional calibration related to the motion of interest (Horenstein et al., 2019). The drawback of such approach lies in an increase of trials number which goes against the argument of time saving when using IMUs and adds to the risk of users demotivation. Usage constraints (like supplementary acquisition) can decrease the acceptance and final usage of this systems by the clinicians (Loup-Escande and Loup, 2021). Hence the novelty of this article is to evaluate the impact of a pragmatic approach without additional calibration steps on the IMU system accuracy.

Quantifying leg motion with a single IMU, without calibration procedures, would have a high clinical value since it could be done at the physiotherapist office. The main goal was thus to assess how an IMU's positioning on the thigh affected the number of squats, timing, and knee range of motion.

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● Marker

▪ IMU

Number	Localisation
1 & 2	Right & Left Crest
3 & 4	Right & Left Anterior Superior Iliac Spine
5	Right Trochanter
6	Right Femur
7 & 8	Lateral & Medial Condyle Right Femur
9	Right Leg
10 & 11	Lateral & Medial Malleolus Right Leg
12 & 13	Left & Right Posterior Superior Iliac Spine

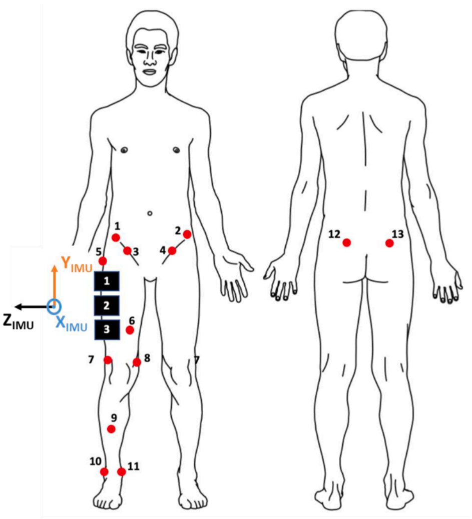

Fig. 1. IMUs and marker placement.

2. Materials and methods

2.1. Participants

Fifteen healthy subjects (3F/12M) from the LAMIH UMR CNRS 8201 voluntarily participated in this study. Mean and standard deviation characteristics were for age 31.7 years (±10.5), body mass 73.6 kg (±15.9) and height 1.74 m (±0.079). Inclusion criteria was the absence of any neuro-musculoskeletal disorder for the past 6 months. The study was approved by the Lille University's ethics committee (reference number: 2021-523-S97).

2.2. Material

The IMU system is based on a Data Capturing Unit (DCU) receiving the measured data of up to four wireless IMUs (MPU6050 sensor, 3-axis gyroscope and accelerometer, Dramco KUL, Ghent, Belgium). Advanced details and validation of the IMU system are provided in previous work (Blandeau et al., 2022; Hubaut et al., 2022). For each participant 13 spherical retro-reflective markers were placed over anatomical landmarks of the pelvis and right lower limb (see Fig. 1). The IMU system was validated against an OMC reference system composed of 13 VICON-MX infrared cameras (Vicon © Motion Systems Ltd UK) with a 100 Hz sampling frequency.

Three IMU sensors were placed on the lateral face of the right thigh, with the Y axis aligned between the lateral femoral condyle and the trochanter pointing up and the Z axis perpendicular to the thigh pointing outward. A first IMU was fixed at the middle point between the great trochanter and the femur's lateral condyle and the other two IMUs were placed respectively 2 cm above and below the first one on this same axis. IMU output was the orientation quaternion, angular velocity vector and acceleration vector at a sampling frequency of 50 Hz.

2.3. Protocol

Participants completed 3 squatting trials each lasting 10 s. During each trial, they were asked to execute as many squats as possible with arms kept horizontal and maintaining a straight back. A squat was considered completed when reaching an estimated 90° knee flexion angle. Each participant had the opportunity to train before the trials. A 30-second rest was given between each trial.

2.4. Signal processing

Optoelectronic data were resampled at 50 Hz for comparison with the IMU data. Both OMC, and IMU signals were filtered using a fourth order Butterworth low-pass filter with a cut-off frequency of respectively 6 Hz, and 20 Hz (Blandeau et al., 2022). Data synchronization between IMU and OMC was carried out using a cross correlation algorithm using the linear acceleration from IMUs and clusters position from the OMC.

2.5. Parameters computation

Hip and knee joint centres from the markers applied on the thigh and pelvis were deduced using regression equations (Dumas et al., 2007). Rotation matrix of the thigh segment was deduced from theses points then transformed into thigh angles using a ZYX mobile sequence (Dumas et al., 2012). The rotation matrix of each IMU is computed from the quaternion vector (Dumas et al., 2004), followed by the same angle mobile sequence. In this article the main flexion motion of squatting is obtained as the rotation around the mediolateral axis of the thigh (in the assumption that a limited pelvic anteversion occurs during squatting), and will be compared between OMC and IMU system. The first value of the flexion angle signal was subtracted from the corresponding OMC and IMU time series to define the neutral position.

A squat detection algorithm was created based on the works of (Stevens et al., 2018) for OMC system. Squat counts (number of maxima) and timing (time occurrence of maxima) were automatically detected from the thigh inclination angle using the MATLAB R2020b function *findpeaks* (The Mathworks Inc, Natick, MA.) with a minimum peak prominence threshold at 30 % of the flexion angle amplitude measured during acquisition. The prominence threshold avoids the detection of local maxima due to sensor trembling or soft tissue wobbling (Guichard et al., 2021).

2.6. Statistical analysis

Mean and standard deviation of flexion angle errors from the 3 IMUs were computed. Lin's Concordance Coefficient (LCC) (Lin, 1989) was also used to quantify the agreement between flexion angle computed from each IMU sensor and the reference data.

All statistical analyses were performed using MATLAB software. The squat counts and timing per acquisition were compared between the OMC and the IMU system using the Friedman test. Flexion angle error was computed between the OMC system and all 3 IMUs. Each squat was defined between two consecutive maxima of angle flexion. Because not

Table 1
Parameter comparison between IMU sensors and reference motion capture system. All values are averaged between acquisitions with standard deviation in parentheses.

Parameter	Details	IMU 1	IMU 2	IMU 3
Squat count	Error	0 (0.0)	0 (0.0)	0 (0.0)
Squat timing	Error (s)	−0.01 (0.03)	0.00 (0.03)	0.00 (0.04)
Flexion orientation angle	Error (°)	6.2 (8.8)	2.5 (6.8)	2.2 (6.7)
	Lin's CC	0.944 (0.043)	0.971 (0.039)	0.969 (0.033)

all squats have the same duration, the flexion angle error during a squat was time normalized to 100 data points using MATLAB function *interp1*. Using smooth normalized flexion angle errors vector allowed to use the Statistical Parameter Mapping (SPM) methodology (Pataky, 2010) to test for the IMU placement impact on flexion angle error through a one-way repeated measures ANOVA with an α = 0.01 (spm1d package v.1.0.5, https://www.spm1d.org, (Pataky, 2012)). The null-hypothesis was: the mean within-subject flexion angle ROM error across IMU positioning is zero (i.e., flexion angle error between OMC and IMU is not impacted by the position of the IMU sensor). Post-hoc analysis within subjects was performed to study potential effects of IMU positioning using paired *t*-test with a multiple comparison correction.

3. Results

A total of 471 squats were recorded with an average of 10.4 squats per trial. Results for the parameters comparison between the 3 IMUs are presented on Table 1. Based on the squat detection algorithm, the amount of squat detected by all IMUs across subjects is in perfect agreement with the reference system and mean squat timing error is under 10 ms. The ROM computed with the OMC and the 3 IMUs is presented in Fig. 2 maximum flexion is reached at 0 and 100 % of the cycle.

Regarding flexion angle analysis, Lin's concordance coefficient shows a *very good* to *excellent* concordance between IMU sensor and OMC system. Moreover, mean and standard deviation of flexion angle error appears to be more important for IMU 1 than for the other

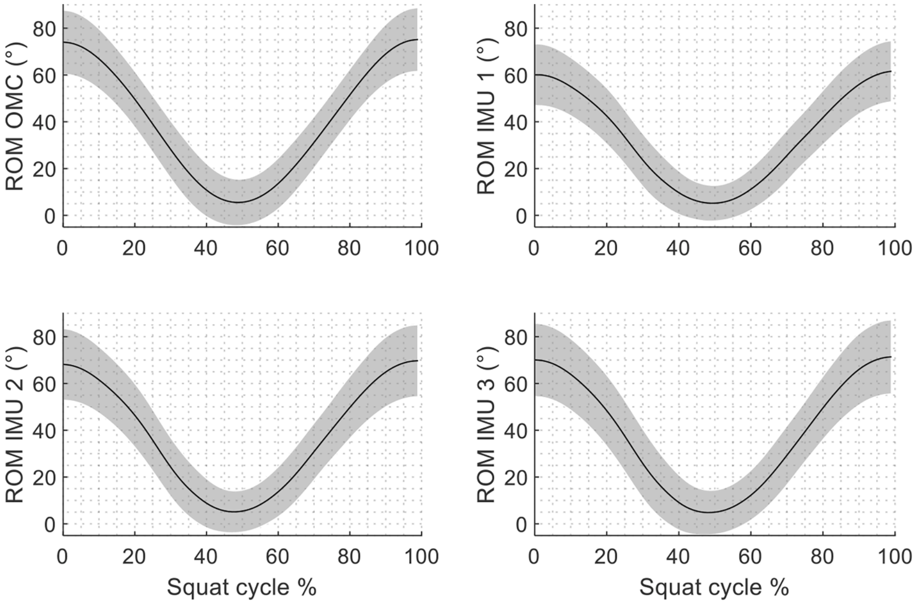

Fig. 2. Mean ROM (black line) ± one standard deviation for the 4 motion capture sensors.

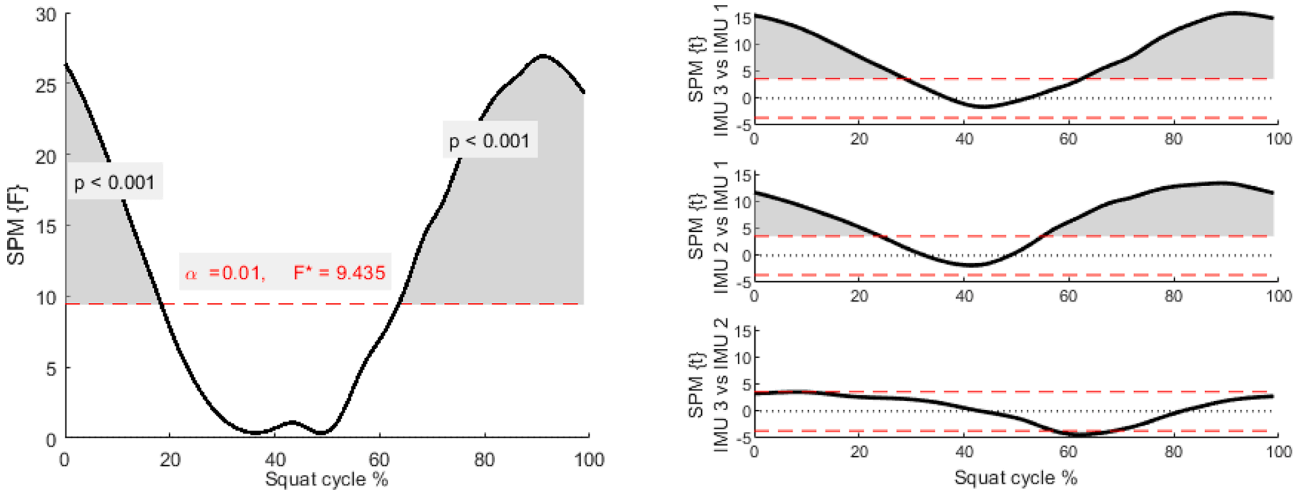

Fig. 3. SPM results over squat cycle. Left: Repeated Measures ANOVA inferences. Right: post-hoc analysis paired *t*-test inference.

positions.

Fig. 3 displays the results of the repeated measurement ANOVA and the post-hoc analysis using SPM methodology over the squat cycles. There was a significant difference in angle error between the three sensors positioning from 0 to ~20 % and from ~65 % to 100 % of the squat cycle. Identically smooth random 1D data would produce two clusters of this breadth with a probability of $p < 0.001$ each, hence we consider these results significant.

Post-hoc paired *t*-test showed a strong effect of IMU 1 versus IMU 2 ($p < 0.001$) and IMU 3 ($p < 0.001$) over the same squat cycle region and a smaller yet significant effect of IMU 2 against IMU 3 ($p < 0.001$). Hence, we can refute the null-hypothesis and affirm that in this pragmatic approach, IMU positioning has an impact on squat angle ROM.

4. Discussions

The main goal of this paper was to assess the impact of IMU positioning on the thigh for squat motion analysis when compared to a reference motion capture system. A limitation is that the angle studied here is not an anatomical joint angle, it represents a fast to obtain, quantitative motion feature which is compatible with the clinical reasoning. This pragmatic approach is directly intended to clinicians and medical practitioners who could benefit from the quantified embedded motion capture allowed by IMUs without having to rely on complex acquisition procedure (e.g., extra acquisition for posing) or signal processing.

Data from more than 400 hundred squats across 15 healthy subjects showed no impact on the IMU positioning when looking at simple parameters like squat count and squat timing. This result is encouraging because those parameters are often studied (O'Reilly et al., 2018) despite the absence of standardization for IMU placement.

On the other hand, the SPM analysis pointed-out that longitudinal positioning had a significant impact on flexion angle ROM error during squatting at the beginning and end of the motion. Computing the ROM excludes the potential error source of sensor orientation which would have resulted in a constant value of flexion angle error and could be explained by artefact motions of soft tissues like muscle or fat tissue along the thigh (Guichard et al., 2021). Flexion angle is often found in current literature to validate the use of IMUs (Dahl et al., 2020; Horenstein et al., 2019) and also in the clinical approach for squat motion analysis (Teufl et al., 2019). Knowing of this inherent sensitivity regarding squat motion and sensor positioning is capital for comparing the various scientific contributions to this topic. Using the SPM methodology instead of a classical ANOVA allows to assess significant difference between IMUs placements while keeping the dimensional continuity of the signal. Moreover, it is possible to pinpoint the significative difference location during the squat motion, which is aligned with the clinicians reasonings and interests. Keeping a dimensionless approach would reduce the continuous squat ROM to a single value, resulting in an incomplete description of our signal and increasing the risk of false positive results (Pataky et al., 2016).

In summary, this paper presented the effect of IMU positioning on the thigh for squat motion analysis without previous calibration as a clinical practitioner with no motion capture expertise could realize. It appears that flexion angle ROM is significantly impacted with a lesser angle error when positioning the IMU at the center or distal position of the thigh. It could be recommended to place a single IMU distally because of the soft-tissue segment's distribution (de Leva, 1996) and deformation (Buchman-Pearle and Acker, 2021) around the studied joint. Classical squat analysis like counting and timing is not impacted by sensor position. Future works should be dedicated to standardizing IMU positioning to improve the motion capture system robustness and comparison between studies.

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Ethical approval

The study was approved by the Ethics Committee of Lille University (protocol code 2021-523-S97 and date of approval 15/09/2021).

CRediT authorship contribution statement

Mathias Blandeau: Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Romain Guichard:** Methodology, Validation, Formal analysis, Investigation, Resources, Writing – review & editing. **Rémy Hubaut:** Validation, Formal analysis, Investigation, Writing – review & editing. **Sébastien Leteneur:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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