

Evaluating the use of machine learning in the assessment of joint angle using a single inertial sensor

Rob Argent^{1,2,3} , Sean Drummond¹, Alexandria Remus^{1,3}, Martin O'Reilly^{1,3} and Brian Caulfield^{1,3} 

Abstract

Introduction: Joint angle measurement is an important objective marker in rehabilitation. Inertial measurement units may provide an accurate and reliable method of joint angle assessment. The objective of this study was to assess whether a single sensor with the application of machine learning algorithms could accurately measure hip and knee joint angle, and investigate the effect of inertial measurement unit orientation algorithms and person-specific variables on accuracy.

Methods: Fourteen healthy participants completed eight rehabilitation exercises with kinematic data captured by a 3D motion capture system, used as the reference standard, and a wearable inertial measurement unit. Joint angle was calculated from the single inertial measurement unit using four machine learning models, and was compared to the reference standard to evaluate accuracy.

Results: Average root-mean-squared error for the best performing algorithms across all exercises was 4.81° ($SD = 1.89$). The use of an inertial measurement unit orientation algorithm as a pre-processing step improved accuracy; however, the addition of person-specific variables increased error with average RMSE 4.99° ($SD = 1.83^\circ$).

Conclusions: Hip and knee joint angle can be measured with a good degree of accuracy from a single inertial measurement unit using machine learning. This offers the ability to monitor and record dynamic joint angle with a single sensor outside of the clinic.

Keywords

Joint angle, wearable sensor, range of motion, inertial measurement unit, biomechanics, machine learning, neural networks

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Introduction

The assessment of joint angle is a commonly used clinical measurement tool in rehabilitation medicine and serves as a key objective marker in monitoring treatment effectiveness, patient progress, and is often used to guide treatment interventions.¹ For example, after orthopaedic surgery such as total knee replacement, the restoration of joint range of motion is an essential rehabilitation focus and is achieved through targeted exercise programmes which commence immediately in the hospital setting and continue on in the home environment for numerous weeks. A reduced range of motion post-operatively can have significant impact on functional activities of daily life including walking and rising from sitting, and in more intensive pursuits

such as cycling.^{2,3} As increasing numbers of healthcare providers move towards value-based care, the use of objective outcome measures, such as joint angle, holds even greater importance and as such, the use of

¹Insight Centre for Data Analytics, University College Dublin, Dublin, Ireland

²Beacon Hospital, Dublin, Ireland

³School of Public Health, Physiotherapy and Sport Science, University College Dublin, Dublin, Ireland

Corresponding author:

Rob Argent, Insight Centre for Data Analytics, O'Brien Science Centre (East), University College Dublin, Belfield, Dublin 4, Ireland.
Email: rob.argent@insight-centre.org



valid and reliable methods to assess joint angle is imperative.

The current norm in clinical practice is to measure joint angle in a single plane at an isolated joint with a universal goniometer. These are inexpensive and portable and are considered easy to use.⁴ However, post-operative joint angle assessment with a universal goniometer can only be captured with a trained examiner when the patient attends clinic appointments.⁴ These measurements are often taken several weeks apart, at a single time-point, with a static posture, and do not necessarily provide the data to inform judgement on the overall trend of progress, with measures potentially being affected by short-term pain or swelling.¹ Whilst this method is more accurate than visual estimate,^{5,6} the use of the universal goniometer is subject to high levels of variance in inter and intra-tester reliability.^{7,8}

In an effort to offer a more robust method of measurement, the use of smartphone applications and inertial measurement unit (IMU) systems to measure joint angle has been investigated.^{9–14} Both tools harness data analytics to obtain clinical measurements in an attempt to remove human error. Whilst smartphone applications still require an examiner and static posture to operate, wearable IMU systems have the potential to offer a continuous method of assessment of joint angle remotely during home-exercises, without the need for an examiner or a maintained static posture. Measures of joint angle derived from IMU systems have the potential to be built into biofeedback devices designed to support the patient in their rehabilitation programme away from the clinic.^{15–16}

Current methods of joint angle assessment with IMUs typically require multiple sensors with one IMU per limb segment.^{11,13,14,17–19} At present, it is common to use an orientation algorithm, such as the Madgwick filter,²⁰ Kalman filter,²¹ or complementary filter²² to compute the IMU orientation of each individual sensor.^{17,18,23,24} In the interest of usability and cost, minimising the number of sensors required is preferred; however, there is a lack of research outlining predictive algorithms, or joint angle estimation with a single IMU.²⁵ A recent study was the first to investigate joint angle measurement with a single IMU.²⁶ The authors represented joint angle as a Fourier series and optimised a cost function structured using kinematic data, with a mean error of 3.2° across four exercises. However, their method required the input of a number of additional variables including limb segment length data for each participant.

A potential alternative method of joint angle measurement with data from a single IMU is to use machine learning (ML) algorithms. ML algorithms are used widely to find patterns in data and build models to

make predictions. This can be done with discrete data, known as classification, or regression, where the prediction output is continuous data, such as joint angle.²⁷ Supervised learning is one of the two categories of ML algorithms and involves learning a model which best maps input features to labelled outputs. There are wide-varieties of supervised learning algorithms including models such as linear regression, polynomial regression, decision trees, and random forest regression.^{28–30} As such, supervised ML regression algorithms may offer the ability to measure continuous joint angle during rehabilitation exercises captured by IMUs.

To date, the use of ML to assess continuous joint angle captured by IMUs has not been heavily studied. Therefore, the aim of this study was to explore if it is possible to accurately measure joint angle with a single IMU and ML algorithms. This was done by exploring three fundamental questions; (1) which is the best performing ML algorithm to predict joint angle from a single IMU, (2) whether the input of additional anthropometric variables improves the accuracy of such an assessment method, and (3) whether an IMU orientation algorithm is required in addition to ML algorithms to provide this joint angle.

Methods

Participants

A sample of 14 participants (6 female and 8 male, age = 28 ± 3 years, height = 172 ± 9.5 cm, weight = 75 ± 13 kg, BMI 25 ± 4) were recruited from the University. Subjects were eligible to participate in this study if they were over 18 years of age and were capable of performing the eight rehabilitation exercises. Exclusion criteria included: (1) diagnosed neurological conditions and (2) lower limb musculoskeletal injury in the past six months. Ethical approval was obtained from the University Human Research Ethics Committee. All subjects provided written informed consent prior to participation.

Rehabilitation exercises

Each participant performed eight lower limb exercises routinely prescribed in the early-stages following orthopaedic surgery under instruction and supervision of a Chartered Physiotherapist. The exercises ranged from lying, sitting and standing positions and were specifically chosen to correspond with standard exercises following total hip and knee replacement surgery.^{31,32} The heel slide, straight leg raise, inner range quadriceps, and seated active knee extension for the knee utilising an IMU on the shin, with supine hip abduction, standing hip flexion, standing hip abduction, and standing hip

Table 1. Rehabilitation exercises including the joint angle measured for each exercise with relevant IMU.

| Exercise | Description of exercise | Joint angle measured | IMU placement |
|------------------------------|--|----------------------|---------------|
| Heel slide | In supine lying, the exercise is performed by flexing the hip and knee to slide the foot closer to the ipsi-lateral hip. | Knee flexion | Shin |
| Supine hip abduction | In supine lying, the exercise is performed by abducting the hip, sliding the foot away and then back towards the midline. | Hip abduction | Thigh |
| Straight leg raise | In supine lying, the exercise is performed by flexing the hip, lifting the leg off the supporting surface while keeping the knee in full extension. | Hip flexion | Shin |
| Inner range quadriceps | In supine lying, a roll is placed under the knee to be exercised. The exercise is performed by contracting the quadriceps muscles to bring the knee from a position of slight flexion into full extension. | Knee flexion | Shin |
| Seated active knee extension | In sitting with the upper thigh supported on a chair, the exercise is performed by contracting the quadriceps to bring the knee from a position of flexion into full extension. | Knee flexion | Shin |
| Standing hip flexion | In standing, the exercise is performed by lifting the leg forwards, flexing at the hip and knee. | Hip flexion | Thigh |
| Standing hip abduction | In standing, the exercise is performed by lifting the leg out to the side, whilst maintaining full knee extension. | Hip abduction | Thigh |
| Standing hip extension | In standing, the exercise is performed by lifting the leg backwards out behind the body, whilst maintaining full knee extension. | Hip extension | Thigh |

IMU: inertial measurement unit.

extension for hip rehabilitation, with an IMU placed on the thigh. A detailed description of these exercises can be found in Table 1. Participants were allowed three practice repetitions prior to data collection. All exercises were performed continuously for 60 s. Participants were instructed to vary the joint angle between maximal and sub-maximal repetitions across the set in a self-selected random order.

Data acquisition

A three-dimensional (3D) motion capture system, considered the gold standard tool for dynamic measurement of lower limb joint angle with a low error of measurement,⁷ was used as the reference standard. This CODA motion capture system comprised of a unilateral, right-sided, eight marker set-up, and three motion capture cameras (Charnwood Dynamics, Leicestershire, UK). Two IMUs were used to collect tri-axial accelerometer and gyroscope data from each participant (Shimmer, Dublin, Ireland),³³ and all knee rehabilitation exercises were analysed with data solely from the shin sensor (Figure 1: IMU 2), with the thigh sensor being used for hip joint angle measurement (Figure 1: IMU 1). Additional variables including sex,

age, height, weight, hip-knee length and ankle-knee length were also recorded. These additional metrics were included to account for variances in joint angle between participants attributed to anthropometric variability. Each participant was required to wear a pair of skin tight Lycra shorts or leggings and a light shirt rolled up past the navel in order to obtain an unobstructed view of all testing equipment. The markers and IMUs were then applied by the same Chartered Physiotherapist for all subjects and were positioned as described in Figure 1. The markers and IMUs were fixed to the skin, or Lycra, with double-sided adhesive tape. Synchronous kinematic data acquisition was conducted using three CODA mpx1 units sampling at 100 Hz and the two IMUs, calibrated prior to testing, sampling at 102.4 Hz, with accelerometer and gyroscope ranges configured to $\pm 2G$ and $\pm 500^\circ/s$, respectively, mirroring the configuration of similar research.^{34,35} 3D motion capture data acquisition was performed with a single CODA motion analysis system, while IMU data were captured using the Multi Shimmer Sync Android tablet application (Shimmer, Dublin, Ireland). Both systems recorded 60 s segments of continuous kinematics during eight post-operative rehabilitation exercises. A set of exercises was only

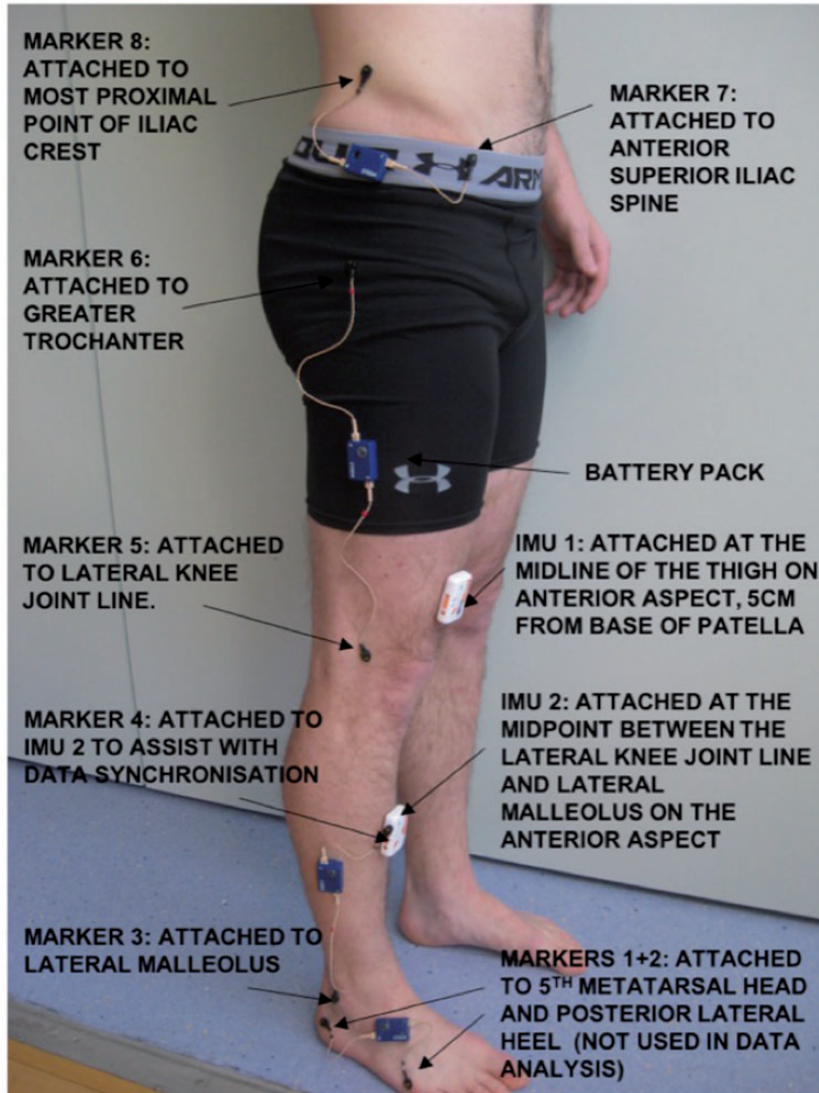


Figure 1. Infra-red markers 1–8 and IMUs 1 and 2 attached with double-sided adhesive tape to anatomical landmarks. Each marker is attached to a battery pack. Only one IMU was used to calculate joint angle, the location dependent on the exercise performed.

repeated when the CODA marker visibility was less than 99% for any of the eight markers.

Data processing

Reference joint angle calculation. The CODA system provided raw data in the form of the X, Y, Z positions of each of the markers over time. These 3D co-ordinates were first reduced to 2D, based on the plane of movement the exercise occurred, in order to derive clinically relevant metrics which are already used in current practice (e.g. heel-slide movement is in the Y-Z plane, supine hip abduction is in the X-Y plane and standing hip abduction is in the X-Z plane). Vectors were created from the two markers on each limb involved in the exercise movement and joint angles were calculated

using equation (1). The method of calculating the joint angle based on vectors from the CODA system is shown in equation (1).

$$\theta = \cos^{-1} \left(\frac{\hat{u} \cdot \hat{v}}{\|\hat{u}\| \cdot \|\hat{v}\|} \right) \quad (1)$$

Synchronisation of the motion capture and IMU systems. Prior to synchronisation, the IMU data were down-sampled to 100 Hz using linear interpolation. To synchronise the systems, the participants were instructed to perform a “kick” before exercise commencement. The kick was performed in a perpendicular plane to the exercise plane, so that the marker’s largest displacement over the duration of the exercise in the

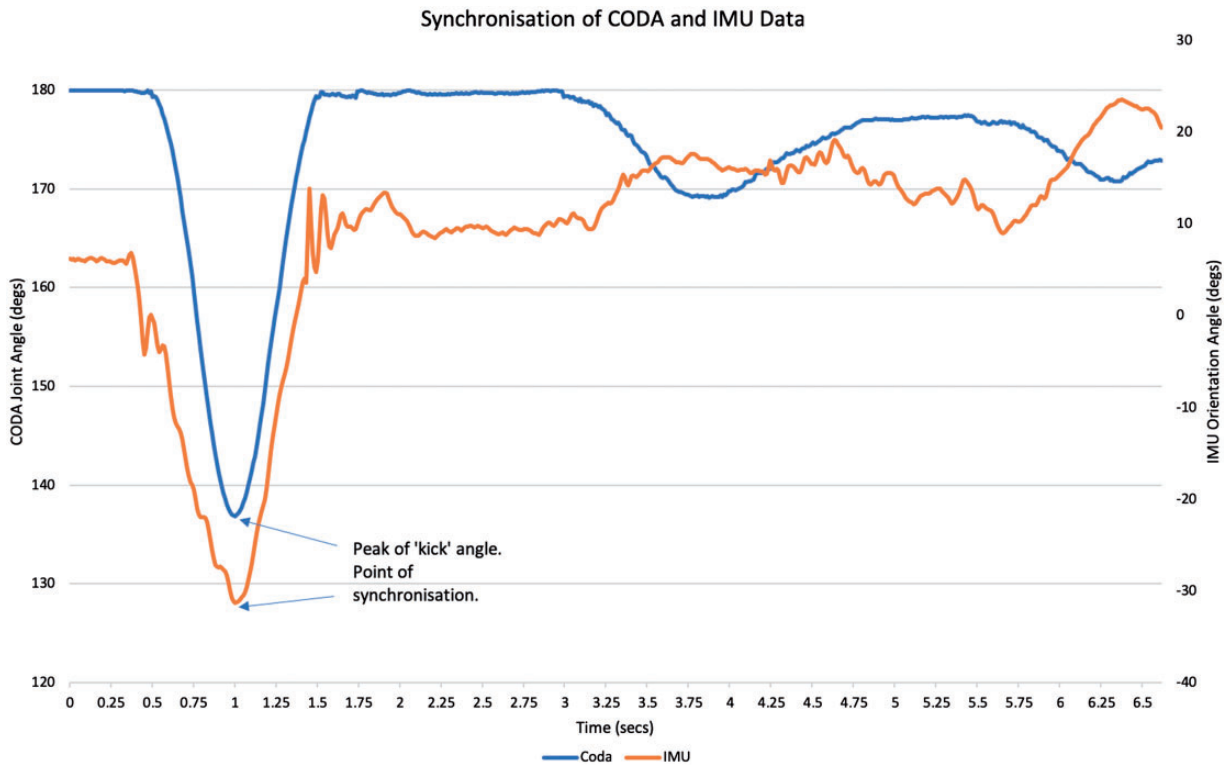


Figure 2. An example of CODA and IMU data synchronised from the peaks of the “kick” angles.

perpendicular plane was during the kick. For the CODA system, the joint angle in the direction of the kick was calculated using equation (1), and for the IMU data the IMU orientation in relation to the global frame was computed by using the Madgwick orientation algorithm.²⁰ These two data sources were then synced on the peaks of the respective kick data (Figure 2).

IMU joint angle calculation. Data from a single IMU were used to measure joint angle as specified in Table 1. Two methods were used to calculate the joint angle from the IMU raw data which are highlighted in Figure 3. Method 1 derived joint angle from the raw IMU data passing through an orientation algorithm which is regularly used in literature pertaining to exercise analysis with IMUs,²⁰ whereas Method 2 modelled joint angle straight from the raw IMU data. Four commonly used ML regression algorithms were modelled on the IMU datasets from each of these methods to estimate joint angle, namely linear regression (LR), polynomial regression (PR), decision tree regression (DT), and random forest regression (RF). This culminated in a total of eight models to estimate joint angle from the IMU data (Figure 3). The additional anthropometric variables of height, weight, age, sex and limb segment length were used as additional features to investigate their influence on accuracy. These additional variables

particular to each participant were included in the models as part of the feature vector for each timepoint.

Hyperparameter tuning. In order to optimise the accuracy of a ML model, a number of parameters that cannot be learned through the ML training process (known as hyperparameters) must be selected before initial training takes place. These hyperparameter values are then adjusted, in this case through manual search, over multiple train and test iterations to identify the optimal model configuration, which is then used for analysis. In this study, L2 penalty coefficient values were explored for the linear regression and polynomial regression, with the polynomial regression model also searching cubic and quadratic features. The decision tree and random forest models searched for the optimal maximum depth value, with estimator values also trialled in the random forest model.

Accuracy analysis. The loss metric for all of the models was mean squared error. The root-mean squared error (RMSE) and the coefficient of determination (R^2) were computed to compare the predicted joint angle from the IMU to the reference 3D-motion capture system across every data point (Figure 4), for each of the four ML models in all eight exercises. Leave-one-subject-out cross validation was used with 14 folds, and the RMSE values stated in the results are the mean

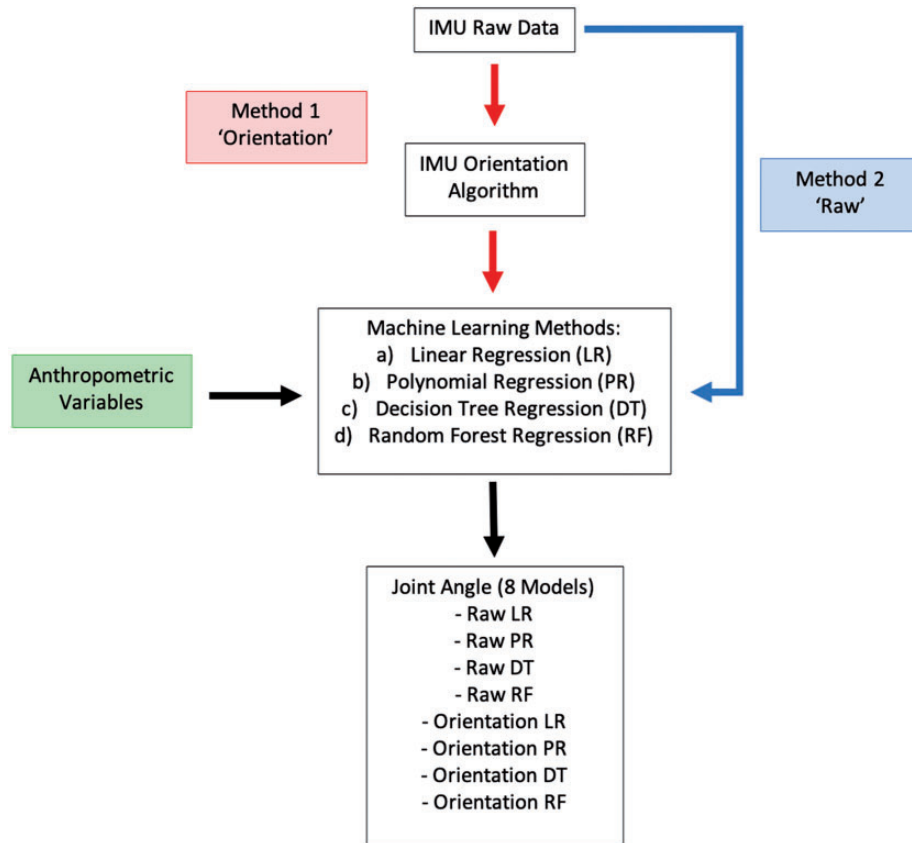


Figure 3. Flowchart illustrating the process of IMU joint angle calculation. The input label for the training of the models is the raw IMU values, with the output being the joint angle derived from the reference standard CODA.

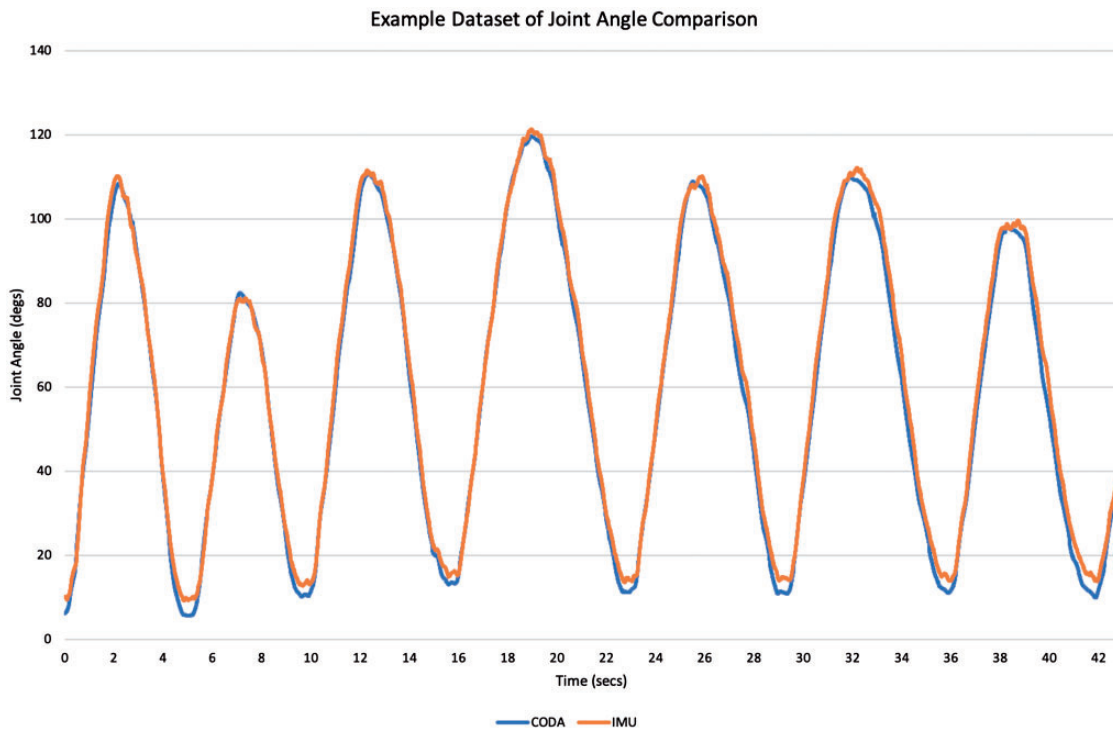


Figure 4. Randomly selected sample of one participant illustrating joint angle comparison between reference standard CODA and IMU. RMSE was calculated across every data point in the exercise set sampled at 100 Hz for each participant.

Table 2. Results showing the best performing algorithm, mean R^2 and mean RMSE for data from both the entire time-series and the maximum and minimum joint angles for each repetition.

| Exercise | Additional variables | Algorithm | Entire data-set | | Maximum and minimum joint angles | |
|------------------------------|-------------------------------|----------------|-----------------|------------------------|----------------------------------|------------------------|
| | | | R^2 | RMSE ($^\circ$) (SD) | R^2 | RMSE ($^\circ$) (SD) |
| Heel slide | Sensor data only | Orientation PR | 0.98 | 5.70 (2.29) | 0.99 | 5.19 (2.21) |
| | Sensor + additional variables | Orientation LR | 0.98 | 5.50 (2.50) | 0.98 | 5.85 (2.42) |
| Inner range quadriceps | Sensor data only | Orientation PR | 0.59 | 3.98 (2.43) | 0.75 | 3.95 (2.14) |
| | Sensor + additional variables | Orientation LR | 0.51 | 4.02 (2.16) | 0.65 | 4.42 (2.24) |
| Straight leg raise | Sensor data only | Raw PR | 0.92 | 3.62 (1.32) | 0.95 | 3.76 (1.17) |
| | Sensor + additional variables | Orientation LR | 0.93 | 3.54 (1.02) | 0.93 | 3.48 (1.60) |
| Seated active knee extension | Sensor data only | Raw RF | 0.96 | 6.08 (1.63) | 0.97 | 6.79 (2.44) |
| | Sensor + additional variables | Raw RF | 0.95 | 6.92 (2.04) | 0.96 | 7.41 (2.68) |
| Supine hip abduction | Sensor data only | Orientation PR | 0.85 | 3.46 (2.16) | 0.92 | 3.54 (1.67) |
| | Sensor + additional variables | Orientation RF | 0.82 | 3.93 (2.11) | 0.90 | 4.08 (1.78) |
| Standing hip abduction | Sensor data only | Orientation LR | 0.86 | 4.16 (2.18) | 0.92 | 4.21 (2.54) |
| | Sensor + additional variables | Orientation PR | 0.88 | 4.34 (1.80) | 0.93 | 4.49 (1.93) |
| Standing hip extension | Sensor data only | Orientation PR | 0.37 | 5.31 (1.40) | 0.54 | 6.58 (1.56) |
| | Sensor + additional variables | Orientation LR | 0.38 | 5.59 (1.09) | 0.51 | 7.06 (1.49) |
| Standing hip flexion | Sensor data only | Raw RF | 0.93 | 6.19 (1.67) | 0.96 | 6.13 (2.19) |
| | Sensor + additional variables | Raw LR | 0.94 | 6.10 (1.89) | 0.96 | 6.64 (2.43) |

RMSE: root-mean-squared error.

RMSE and R^2 of the test data in each of the 14 folds with the standard deviation (SD) provided to show the variance between participants. To maximise clinical application, healthcare professionals are primarily interested in the peak joint angles achieved. Therefore, the same RMSE analysis was also conducted on the isolated maximum and minimum joint angles for each repetition.

Results

Table 2 illustrates the best performing algorithm, average RMSE and R^2 across all participants for each exercise. The average RMSE for the best performing algorithm across all eight exercises was 4.81° ($SD=1.89$), with a maximum value of 6.19° . This increased to 4.99° ($SD=1.83$), with a maximum of 6.92° when participant-specific additional variables were included. There was variance between the best performing algorithm dependent on the exercise being conducted, although the use of the orientation algorithm improved performance on the majority of the tested models (11 out of 16).

For clinical relevance, the mean RMSE and R^2 for the maximum and minimum joint angles of each exercise repetition are also outlined in Table 2. The average RMSE for these joint angles across all eight exercises was 5.02° ($SD=1.99$), with a maximum value of 6.79° ,

resulting in an average increase of 0.21° ($SD=0.54$) from the entire time-series. When participant-specific additional variables were included, the RMSE increased to 5.43° ($SD=2.07$), with a maximum of 7.41° , resulting in an average increase of 0.44° ($SD=0.46$) compared to every data-point.

Discussion

The aim of this study was to investigate whether it is possible to use a single IMU with ML algorithms to accurately measure lower limb joint angles, and which algorithm is most effective in doing so. Furthermore, it explored whether additional anthropometric variables were required to improve the accuracy of such a method, and whether an IMU orientation algorithm was required in addition to the ML methods to provide this joint angle. The results identified low levels of RMSE which suggest that it is possible to measure joint angle with a single IMU with the assistance of a variety of ML algorithms. Additional variables such as sex, age and limb segment lengths reduced the accuracy of this method.

In this study, the best performing ML algorithm with solely the input of sensor data from a single IMU to measure joint angle resulted in an average RMSE of 4.81° using leave-one-subject-out cross validation. These results indicate that the novel approach

described in this paper is comparable to those using two sensor models and a recently published single IMU method. Bakhshi et al.¹¹ used a two-IMU model to assess knee joint ROM with errors ranging from 0.08 to 3.06° across four tasks.¹¹ In this method, validation was performed by a single participant and data down-sampled to 5 Hz. Another two sensor method published by O'Donovan et al.³⁶ measured ankle joint angle with an error range from 0.5 to 4.09° in two subjects.³⁶ Bonnet et al.²⁶ is the only other study in the current literature to use a single sensor method, although this required the input of all anthropometric variables.²⁶ The authors reported an average RMSE of 3.2° across four exercises with their single sensor model. However, it is unclear what validation process was used to calculate these accuracy metrics. Finally, the low RMSE identified in this study is also comparable to those found in functional tasks such as gait.^{13,17,18} Yet these joint angles do not necessarily mirror the standardised joint angle assessment methods that would be familiar to healthcare professionals in clinical practice.

In a clinical setting, it is desirable to minimise any additional input that a user would be required to perform in order to use this method of measurement. Overall, the addition of anthropometric variables to these models does not appear to increase accuracy. This has positive implications for the ease of implementation, as users will not be required to add further information including measuring limb segment length. Although the addition of person-specific variables is not required to improve accuracy, it is apparent that the use of an IMU orientation algorithm is still necessary, with few models evaluated performing better with raw IMU data.

When viewing the randomly selected sample in Figure 4, there is a suggestion that the model may be less accurate at the end of ranges of each exercise repetition. As clinicians are particularly interested in these end ranges, it is important to conduct further accuracy analysis on these points. The results show that there is a small increase in error at the maximum and minimum joint angle, with mean RMSE at 5.02°. However, this is only an average 0.21° increase from the full time-series and does not substantially affect the accuracy of the models, providing the clinician with a convenient method of measurement within five degrees of the gold standard.

Further clinical implications of using such a method of joint angle assessment include negating the need for an examiner to perform measurements, therefore removing any error from inter-tester reliability or incorrect placement of the universal goniometer.^{1,4,37} This method of assessment can also offer real-time dynamic joint angle feedback, compared to current methods of

goniometry requiring a static position. Whilst other proposed methods are also able to complete this, to the best of the authors' knowledge, none have been able to do this with a single IMU without the need for limb segment length features to be inputted.

The sensor placement has also been carefully considered for the target user to position appropriately without assistance. Similar work has used sensors on the distal shank or multiple sensors,^{11,14,17,18,26} whereas this system is designed for all of the hip rehabilitation exercises to work with an IMU placed on the thigh, as currently many users may be prevented from reaching below the knee, particularly after total hip replacement.³⁸ The knee rehabilitation exercises have an IMU located at the midpoint of the shin, ensuring that users are able to place the sensor easily and maintain the same position for all exercises, although in both cases, further 'real-world' validation is required to ensure that IMU placement by untrained patients does not detract from accuracy.

This study is not without its limitations. Results are based on a sample of convenience of young healthy adults in a highly controlled lab-based environment with all placements of markers and IMUs performed by an experienced therapist. Participants were required to wear Lycra shorts and therefore there is the possibility of minor movement from the markers during the exercise. The exercises performed and joint angles measured are relatively early-stage rehabilitation exercises, with motion primarily in a single plane from a standardised starting position, as is usual practice. However, this method may not be applicable to more complex multi-planar functional movements such as in gait or compound lower limb exercises. Finally some data during two exercises were excluded due to technical difficulties, with suspected issues with the marker battery packs leading to unreliable data from the 3D motion capture system.

This work mirrors numerous previous studies that have included RMSE as the loss metric,^{17,19,26,36} which is common in assessing the accuracy of regression tasks. However, there is some debate in the literature regarding the most appropriate indicator of average model performance, and it is suggested that a combination of metrics including RMSE and mean absolute error are required to assess model performance.^{39,40} The use of RMSE does not necessarily provide an indication of whether systematic errors are present in the model, or the precision of the model over a given time period. Therefore, while this study has shown potential for ML methods to measure joint angle, further in-depth evaluation should be carried out on unseen and uncontrolled data in order to determine the validity, reliability (inter- and intra-person) and minimum detectable changes of the proposed model.

These limitations aside, the results from this study suggest future work that can incorporate this novel method of joint angle assessment into an exercise biofeedback system that can be used in the home-setting, providing continuous joint angle measurement with remote monitoring for the clinician. This would also offer clinicians a reliable and dynamic method of assessing joint angle in the clinic which removes any examiner-based error. Additionally, future work should include validating this method in a clinical population with sensor placement performed by the participant, as well as building on the training data used in this study with data from a wider participant demographic. Finally, having shown the potential of this method of joint angle measurement, an interesting field of future work is to compare the accuracy of this single IMU ML model with the traditional multi-IMU approaches discussed in the wider literature.

Conclusions

This study illustrates a novel and effective method of measuring joint angle across numerous exercises using only a single IMU, with a good level of accuracy when compared to the gold standard. This model is designed to maximise ease of clinical implementation as it reduces the need for patient-specific features such as limb segment length, sex and age to be input into the model. This has potential to be built into an exercise biofeedback platform to offer an accurate and dynamic method of joint angle assessment outside of the clinic, without the need for a trained examiner.

Declaration of conflicting interests

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Guarantor

RA.

Contributorship

RA and SD are co-lead authors. RA proposed the concept in liaison with SD and BC. The study was designed by RA and

SD. Recruitment was performed by RA. Data collection was carried out by RA, SD and AR with RA, SD and MOR carrying out data analysis. BC provided supervision throughout. Original draft was prepared by RA, SD and AR with review and editing from MOR and BC. All authors read and approved the final manuscript.

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Research ethics and patient consent


Ethical approval was obtained from the University College Dublin Human Research Ethics Committee – Sciences (HREC-LS). This study was deemed to be exempt from full ethical review (Ref: LS-E-18-76-Argent-Caulfield). All participants provided written informed consent prior to participation.

Data

The datasets generated and/or analysed during the current study are available in the Zenodo research data repository, [www.zenodo.org].

ORCID iD

Rob Argent  <https://orcid.org/0000-0002-3522-9409>

Brian Caulfield  <https://orcid.org/0000-0003-0290-9587>

References

- Gajdosik RL and Bohannon RW. Goniometry emphasizing reliability and validity clinical measurement of range of motion: review of clinical measurement of range of motion review of goniometry emphasizing reliability and validity. *Phys Ther* 1987; 67: 1867–1872.
- Ericson MO, Nisell R and Nemeth G. Joint motions of the lower limb during ergometer cycling. *J Orthop Sports Phys Ther* 1988; 9: 273–278.
- Laubenthal KN, Smidt GL and Kettelkamp DB. A quantitative analysis of knee motion during activities of daily living. *Phys Ther* 1972; 52: 34–43.
- Norkin CC and White DJ. *Measurement of joint motion: a guide to goniometry*. 5th ed. Philadelphia: F A Davis Company, 2016.
- Rothstein JM, Campbell SK, Dominion O, et al. Task force on standards for measurement in physical therapy. Standards for tests and measurements in physical therapy practice. *Phys Ther* 1991; 71: 589–622.
- Watkins M, Riddle D and Lamb R. Reliability of goniometric and visual estimates of knee range of motion obtained in a clinical setting. *Phys Ther* 1991; 71: 90–97.
- Priyaprasarth P and Morris ME. Psychometric properties of measurement tools for quantifying knee joint position and movement: a systematic review. *Knee* 2007; 14: 2–8.
- Lenssen AF, Van Dam EM, Crijns YHF, et al. Reproducibility of goniometric measurement of the

- knee in the in-hospital phase following total knee arthroplasty. *BMC Musculoskelet Disord* 2007; 8: 1–7.
9. Milanese S, Gordon S, Buettner P, et al. Reliability and concurrent validity of knee angle measurement: smart phone app versus universal goniometer used by experienced and novice clinicians. *Man Ther* 2014; 19: 569–574.
 10. Dos Santos RA, Derhon V, Brandalize M, et al. Evaluation of knee range of motion: correlation between measurements using a universal goniometer and a smartphone goniometric application. *J Bodyw Mov Ther* 2017; 21: 699–703.
 11. Bakhshi S, Mahoor MH and Davidson BS. Development of a body joint angle measurement system using IMU sensors. In: *33rd annual international conference on IEEE engineering in medicine and biology society conference*, Boston, MA, USA, 30 August–3 September 2011, pp. 6923–6926. IEEE.
 12. Mourcou Q, Fleury A, Franco C, et al. Performance evaluation of smartphone inertial sensors measurement for range of motion. *Sensors* 2015; 15: 23168–23187.
 13. Seel T, Raisch J and Schauer T. IMU-based joint angle measurement for gait analysis. *Sensors* 2014; 14: 6891–6909.
 14. McGinnis RS, Patel S, Silva I, et al. Skin mounted accelerometer system for measuring knee range of motion. In: *Proceedings of annual international conference on IEEE engineering in medicine and biology society*, Orlando, FL, USA, 16–20 August 2016, pp.5298–5302. IEEE.
 15. Giggins OM, Persson UM and Caulfield B. Biofeedback in rehabilitation. *J Neuroeng Rehabil* 2013; 10: 1.
 16. Argent R, Slevin P, Bevilacqua A, et al. Wearable sensor-based exercise biofeedback for orthopaedic rehabilitation: a mixed methods user evaluation of a prototype system. *Sensors* 2019; 19: 432.
 17. Cooper G, Sheret I, McMillian L, et al. Inertial sensor-based knee flexion/extension angle estimation. *J Biomech* 2009; 42: 2678–2685.
 18. Favre J, Aissaoui R, Jolles BM, et al. Functional calibration procedure for 3D knee joint angle description using inertial sensors. *J Biomech* 2009; 42: 2330–2335.
 19. El-Gohary M and McNames J. Shoulder and elbow joint angle tracking with inertial sensors. *IEEE Trans Biomed Eng* 2012; 59: 2635–2641.
 20. Madgwick SOH, Harrison AJL and Vaidyanathan R. Estimation of IMU and MARG orientation using a gradient descent algorithm. In: *IEEE international conference on rehabilitation robotics*, Zurich, Switzerland, 29 June–1 July 2011, pp.1–7. IEEE.
 21. Bishop G and Welch G. *An introduction to the Kalman filter*. Chapel Hill, Chapel Hill, NC, USA: University of North Carolina, 2001.
 22. Lai Y-C, Jan S-S and Hsiao F-B. Development of a low-cost attitude and heading reference system using a three-axis rotating platform. *Sensors* 2010; 10: 2472–2491.
 23. El-Gohary M and McNames J. Human joint angle estimation with inertial sensors and validation with a robot arm. *IEEE Trans Biomed Eng* 2015; 62: 1759–1767.
 24. Teruyama Y and Watanabe T. A basic study on variable-gain Kalman filter based on angle error calculated from acceleration signals for lower limb angle measurement with inertial sensors. In: *Proceedings of annual international conference on IEEE engineering in medicine and biology society*, Osaka, Japan, 3–7 July 2013, pp.3423–3426. IEEE.
 25. O'Reilly M, Caulfield B, Ward T, et al. Wearable inertial sensor systems for lower limb exercise detection and evaluation: a systematic review. *Sport Med* 2018; 48: 1221–1246.
 26. Bonnet V, Joukov V, Kulić D, et al. Monitoring of hip and knee joint angles using a single inertial measurement unit during lower-limb rehabilitation. *IEEE Sens J* 2016; 16: 1557–1564.
 27. Tack C. Artificial intelligence and machine learning | applications in musculoskeletal physiotherapy. *Musculoskelet Sci Pract* 2019; 39: 164–169.
 28. Neter J, Kutner MH, Nachtsheim CJ, et al. *Applied linear statistical models*. Chicago: Irwin Chicago, 1996.
 29. Rokach L and Maimon O. *Data mining with decision trees: theory and applications*. 2nd ed. River Edge, NJ, USA: World Scientific Publishing Co., Inc., 2014.
 30. Bishop CM. *Pattern recognition and machine learning*. Berlin: Springer, 2006.
 31. American Academy of Orthopaedic Surgeons. Total Knee Replacement Exercise Guide, <http://orthoinfo.aaos.org/topic.cfm?topic=a00301> (2017, accessed 24 May 2018).
 32. American Academy of Orthopaedic Surgeons. Total Hip Replacement Exercise Guide, <https://orthoinfo.aaos.org/en/recovery/total-hip-replacement-exercise-guide/> (2017, accessed 24 May 2018).
 33. Burns A, Greene BR, McGrath MJ, et al. SHIMMERTM – a wireless sensor platform for noninvasive biomedical research. *IEEE Sens J* 2010; 10: 1527–1534.
 34. Bevilacqua A, Huang B, Argent R, et al. Automatic classification of knee rehabilitation exercises using a single inertial sensor: a case study. In: *IEEE 15th international conference on wearable and implantable body sensor networks (BSN)*, Las Vegas, NV, USA, 4–7 March 2018, pp.21–24. Piscataway, NJ: IEEE.
 35. Giggins O, Kelly D and Caulfield B. Evaluating rehabilitation exercise performance using a single inertial measurement unit. In: *7th international conference on pervasive computing technologies for healthcare and workshops*, Venice, Italy, 5–8 May 2013, pp.49–56. Piscataway, NJ: IEEE.
 36. O'Donovan KJ, Kamnik R, O'Keefe DT, et al. An inertial and magnetic sensor based technique for joint angle measurement. *J Biomech* 2007; 40: 2604–2611.
 37. Brosseau L, Balmer S, Tousignant M, et al. Intra- and intertester reliability and criterion validity of the parallelogram and universal goniometers for measuring maximum active knee flexion and extension of patients with knee restrictions. *Arch Phys Med Rehabil* 2001; 82: 396–402.
 38. Mandel RT, Bruce G, Moss R, et al. Hip precautions after primary total hip arthroplasty: 'it's what we've always done'. *Physiotherapy* 2017; 103: e24.
 39. Willmott CJ and Matsuura K. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim Res* 2005; 30: 79–82.
 40. Chai T and Draxler RR. Root mean square error (RMSE) or mean absolute error (MAE)? Arguments against avoiding RMSE in the literature. *Geosci Model Dev* 2014; 7: 1247–1250.