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Unlocking Gait Analysis Beyond the Gait Lab: High-Fidelity Replication of Knee Kinematics Using Inertial Motion Units and a Convolutional Neural Network

Stefano A. Bini, MD[a, *], Nicholas Gillian, PhD [b], Thomas A. Peterson, PhD[a, c], Richard B. Souza, PhD, PT[a, d], Brooke Schultz, MS, ACE-CPT[a], Wojciech Mormul, MS [d], Marek K. Cichoń, MS [d], Agnieszka Barbara Szczotka, MS [d], Ivan Poupyrev, PhD[d]

[a] *Department of Orthopaedic Surgery, University of California San Francisco, San Francisco, CA, USA*
[b] *Google Advanced Technology & Projects (ATAP) Invention Studio, Palo Alto, CA, USA*
[c] *Bakar Computational Health Sciences Institute, University of California San Francisco, San Francisco, CA, USA*
[d] *Department of Physical Therapy and Rehabilitation Science, University of California San Francisco, San Francisco, CA, USA*

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ABSTRACT

Background: Gait analysis using three-dimensional motion capture systems (3D motion capture) provides a combination of kinematic and kinetic measurements for quantifying and characterizing the motion and loads, respectively, of lower extremity joints during human movement. However, their high cost and limited accessibility impact their utility. Wearable inertial motion sensors offer a cost-effective alternative to measure simple temporospatial variables, but more complex kinematic variables require machine learning interfaces. We hypothesize that kinematic measures about the knee collected using motion capture can be replicated by coupling raw data collected from inertial measurement units (IMUs) to machine learning algorithms.

Methods: Data from 40 healthy participants performing fixed walking, stair climbing, and sit-to-stand tasks were collected using both 3D motion capture and IMUs. Sequence to sequence convolutional neural networks were trained to map IMU data to three motion capture kinematic outputs: right knee angle, right knee angular velocity, and right hip angle. Model performance was assessed using mean absolute error.

Results: The convolutional neural network models exhibited high accuracy in replicating motion capture-derived kinematic variables. Mean absolute error values for right knee angle ranged from 4.30 ± 1.55 to 5.79 ± 2.93 degrees, for right knee angular velocity from 7.82 ± 3.01 to 22.16 ± 9.52 degrees per second, and for right hip angle from 4.82 ± 2.29 to 8.63 ± 4.73 degrees. Task-specific variations in accuracy were observed.

Conclusions: The findings highlight the potential of leveraging raw data from wearable inertial sensors and machine learning algorithms to reproduce gait lab-quality kinematic data outside the laboratory settings for the study of knee function following joint injury, surgery, or the progression of joint disease.

Introduction

In recent years, the utilization of commercial-grade wearable sensors to measure human gait has become increasingly common [1-4]. However, these devices typically provide limited information, focusing on spatiotemporal gait features such as step count and walking speeds. In clinical research, specialized "gait lab" facilities are used to assess and evaluate a person's walking pattern to help diagnose and understand abnormalities or imbalances. Such in-person facilities use three-dimensional motion capture technology (3D motion capture) and static force plates, allowing for the measurement of complex kinematic and kinetic outputs along with spatiotemporal data. Today, 3D motion capture serves as the gold standard in clinical research of human motion and plays a crucial

* Corresponding author. Department of Orthopaedics, University of California San Francisco, 500 Parnassus Avenue, MU 323-W, San Francisco, CA 94143.
E-mail address: stefano.bini@ucsf.edu

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role in evaluating the relative benefits of different clinical management strategies [5,6], particularly in conditions such as arthritis [7,8] ligament injury [9], and postsurgical recovery [10]

While gait analysis data could be useful in the clinical management of many different disorders affecting movement [11,12], accessing a gait lab to obtain 3D motion capture is too complicated and time-consuming for day-to-day clinical care. Two to 3 hours of data collection might only yield a few minutes of useful data. Moreover, gait labs are expensive to set up and maintain, few in number, and require the patient to be present alongside highly specialized technicians. Therefore, to apply gait analysis to patients in their home or work environment, there is a need to develop technology that can capture well-established kinematic metrics like those obtained in a gait lab without expensive technical equipment and in-person clinical visits. Some progress has been made in this regard [10,13,14] with respect to the capture of quantitative motion data such as temporospatial data.

However, for more complex kinematic and kinetic metrics, advanced machine learning tools have the greatest potential to directly replicate complex 3D motion capture outputs with a high degree of accuracy using raw data from inertial measurement units (IMUs) [4,15-20]. Further, they can do so over a prolonged period and outside of a laboratory environment. Thus, the aim of this project is to test our hypothesis: outputs from the gait lab that are known to be useful in the measurement of hip and knee function during injury recovery and disease progression can be accurately replicated via machine learning on the raw data from inertial motion sensors.

Material and methods

Data collection and preprocessing

Forty healthy individuals [28 females, age range 19-33] were recruited to participate in this study (IRB#: 17-23,339) and were evaluated at the University of California San Francisco Human Performance Center. Restrictions on the participant's height and weight were in place since these are known to affect gait. Male participants were within 168-184 cm tall and had a mass within 66-96 kg. Female participants were within 152-170.5 cm tall and had a mass within 49-75 kg. Kinematic data were collected in a gait lab consisting of a 9-camera Vicon Motion Capture system and processed in Visual3D using a 6 degrees of freedom model and the functional hip joint center. Simultaneously, data were captured using a total of 6 Jacquard [21] inertial sensors attached to the body in various combinations at the following anatomic locations: left and right thighs, left and right foot, and left and right shank.

To create a 1:1 mapping of the gait lab data to that from the sensors, a 7th sensor was secured to a wooden rod, which also included 3 motion capture markers. The rod was able to swing in an arc of 180 degrees and was fixed to a goniometer. At the start of the data capture session, all 7 sensors were secured to the wooden rod. To identify the starting timepoint for synchronization of the IMUs to the 9-camera Vicon Motion Capture system, the rod was then taken through a back-and-forth arc pattern 5 consecutive times, paused for 2-4 seconds, and the motion repeated. Six sensors would next be removed from the rod and placed on the patient for the motion capture data collection. Upon the completion of the data collection, the six sensors were returned to the same location on the rod, and the swing patterns were repeated (5 swings-pause-5 swings) to identify the timepoint for the ending timepoint. The identical start and end movements were used to align the 7 sensors and account for any drift and/or delays in starting or stopping the data collection using the application. After data were collected, a quality filter was applied to filter examples with no movement by removing examples with labels smaller than 10% of the maximum label value computed on the entire dataset.

IMUs were attached to the body the same way traditional motion capture markers are secured. Thigh and shank were secured with toupee tape (double-sided tape) to the underwrap of the leg, flush to the marker cluster. Both IMU and cluster were wrapped in Coban to secure them to the segment. Wrist and pelvis IMUs were secured with toupee tape directly to the skin. The wrists had an outer wrap of Coban as well. Pelvis was taped on top using transpore tape (surgical tape) since we could not wrap it. Foot IMUs were slotted into the insoles with a designated pocket for the device.

Motion capture benchmarks

Participants were asked to complete three tasks selected to reflect common activities of daily living and align with the Osteoarthritis Research Society International's functional testing recommendations. The first task was to walk 4 meters across level ground at a self-selected purposeful walking speed, then climb up a 4-step staircase. This was repeated a handful of times until each participant successfully completed 10 trials with ±5% of walking speed variability. For half (5) of the completed tasks, the first step was taken with the right foot, and for 5, the first step was taken with the left foot. The second task was to walk 4 meters across level ground at a fixed walking speed of 1.35 m/s (±5%). This was repeated as many times as necessary to capture 10 trials. The third task was the completion of the 5-repetition sit-to-stand functional assessment. The participant was asked to transition from a seated position to an upright standing position and then return to a seated position five times as fast as possible. The seat was an 18" armless

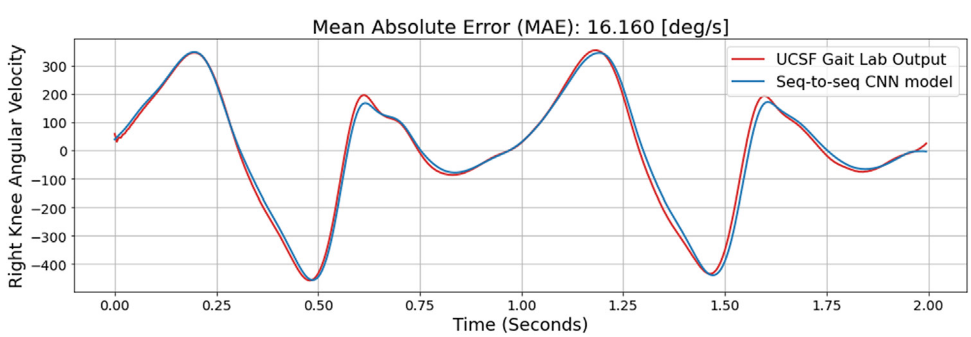

Figure 1. Example comparison of the gait lab ground truth data (red) to the predictions from the CNN model (blue) trained with inertial sensor data for the fixed walk task. The right knee angular velocity predictions (y-axis) over time (x-axis) have a 16.160 deg/s mean absolute error (MAE).

Table 1
Mean absolute error (MAE) results for all variables for stairs up, fixed walk, and sit-to-stand tasks and an average score for “all tasks” combined.

Variable	All	Stairs up	Fixed walk	Sit to stand
Right knee angle [deg]	5.32 ± 2.26	5.57 ± 1.63	4.30 ± 1.55	5.79 ± 2.93
Right knee angular velocity [deg/s]	14.70 ± 9.22	22.16 ± 9.52	16.80 ± 6.22	7.82 ± 3.01
Right hip angle [deg]	6.70 ± 3.82	5.66 ± 2.62	4.82 ± 2.29	8.63 ± 4.73

Each row in the table represents the output variable of interest; the columns represent the task being measured.

box. Time to completion was recorded. This was repeated for a total of 3 successful trials.

Model training

The kinematic outputs of interest derived from the Vicon Motion Capture system (knee angle, hip angle, and knee angular velocity) were replicated by using inertial sensor data as the input for the machine learning model. Specifically, we trained sequence to sequence convolutional neural networks (CNNs) to directly map the time series data captured with the inertial sensors to a time series of the motion capture output variable of interest (eg, knee angular velocity). For training the CNN architecture, we split the data into three groups: the training data set with 16 users, the validation set with 7 users, and the test set with 17 users. We ensured that there were no overlapping users between sets. Data were further transformed into fixed-length sequences by sliding window, with window size set to 400 samples (2-second window) and step size set to 200 samples (1-second step). The CNN architecture was further designed using a grid search over the number of layers, the number of filters, and kernel sizes for each layer on the training and validation sets. Specifically, we used three 1-D CNN layers with 32, 64, and 1 filter each, and kernel sizes 30, 26, and 18, respectively, for knee angular velocity; 32, 64, and 1 filter each, and kernel sizes 15, 13, and 9, respectively, for knee angle; and 32, 64, and 1 filter each, and kernel sizes 30, 26, and 18 for hip angle. We used a stride equal to 1 for all 3. During training, we applied L2 kernel regularization with weight 0.001. The loss function was mean absolute error (MAE), and optimization was performed with a root mean squared propagation (RMSprop) learning rate set to 0.001 and batch size set to 8 for 200 epochs for knee angular velocity, 16 for 300 epochs for knee angle, and 16 for 100 epochs for hip angle. We validated the model after each epoch to check for possible overfitting on the validation set in each case.

Statistical analysis

The current angular position of the knee and hip as well as the knee angular velocity was calculated from 3D motion capture data and was used as the ground truth for measuring the performance of the model. The performance of the CNN model for predicting these three kinematic variables was measured in mean absolute error (MAE) of degrees per second (deg/s) for knee angular velocity and in degrees (deg) for knee angle and hip angle. An example of the output is depicted in Figure 1. In this example, the motion capture output for right knee angular velocity for 1 volunteer performing the fixed walk task in the gait lab is depicted in red (y-axis) over time (x-axis), while the CNN output prediction is depicted in blue (y-axis) over time (x-axis).

Results

The performance of the CNN model for each task and output variable is outlined in Table 1. For capturing the angular degree of the right knee, the MAE values were found to be 5.57 ± 1.63 for stairs up, 4.30 ± 1.55 for fixed walk, and 5.79 ± 2.93 for sit-to-stand. For the right knee angular velocity (deg/s), the MAE results were 22.16 ± 9.52 for stairs up, 16.80 ± 6.22 for fixed walk, and 7.82 ± 3.01 for sit-to-stand. As for "right hip angle (deg)," the MAE values were 5.66 ± 2.62 for stairs up, 4.82 ± 2.29 for fixed walk, and 8.63 ± 4.73 for sit-to-stand.

While the assessment of knee/hip degree and knee angular velocity were all highly accurate, the results demonstrate variations in accuracy across different tasks. For example, for knee angle, overall performance yielded an MAE of 5.32 ± 2.26 degrees (Fig. 2), but the results show that the fixed walk task has a slightly lower error than the stair climb and sit-to-stand tasks. Similarly, for hip angle (Fig. 3), the overall MAE was 6.70 ± 3.82 degrees, but the fixed walk and stairs-up tasks have a slightly lower error than the sit-to-

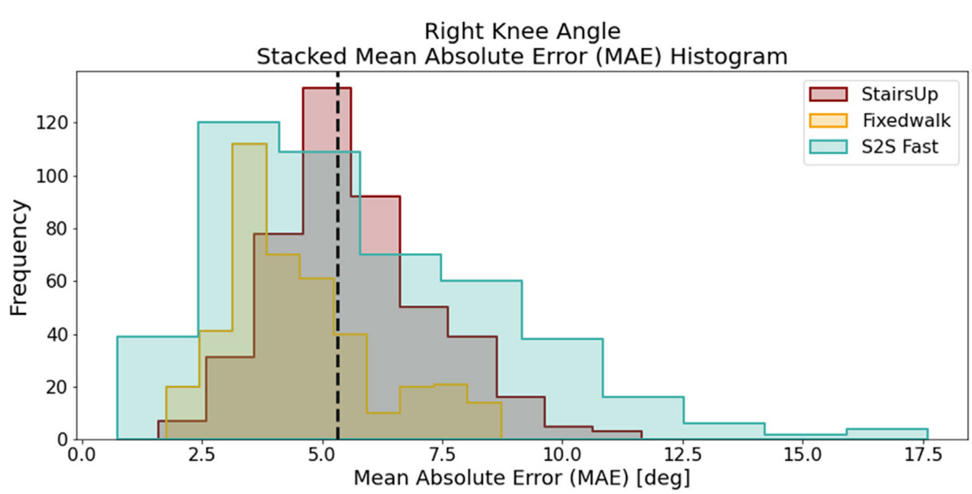

Figure 2. A histogram of mean absolute error (MAE) for reproducing right knee angle for each task. The dotted line shows the overall mean MAE across all tasks. These results show that the fixed walk task has a slightly lower error than the stair climb and sit-to-stand tasks.

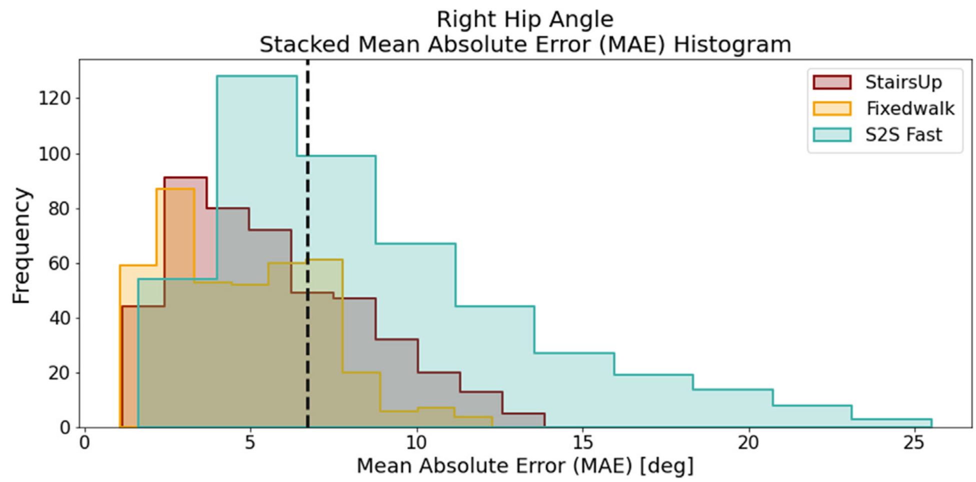

Figure 3. A histogram of mean absolute error (MAE) for reproducing right hip angle for each task. The dotted line shows the overall mean MAE across all tasks. These results show that the fixed walk and stairs up task has a slightly lower error than the sit to stand.

stand. A different pattern was seen for knee angular velocity where the overall MAE was 14.70 ± 9.22 deg/s but the sit-to-stand task had a slightly lower error than the stair climb and fixed walk tasks, although the performance is still satisfactory (Fig. 4).

Discussion

We explored the potential of coupling inexpensive wearable sensors with embedded inertial measurement units with advanced machine learning algorithms to replicate 3D motion capture measurements typically obtained through gait labs. Our results demonstrated that CNNs trained on raw data from IMU-based sensors accurately reproduce kinematic 3D motion capture-derived variables related to knee and hip motion.

The findings of this study are in concordance with prior publications [18,22,23] but present generally higher correlations with ground truth, possibly due to our use of a more recent CNN. The evolution of CNNs and the AI space in general suggests that further optimization is certain to come and that the accuracy of the output will become increasingly indistinguishable from ground truth. The MAE values for knee angle, knee angular velocity, and hip angle were within acceptable ranges for different tasks such as fixed walk, stair climbing, and sit-to-stand. While variations in accuracy were observed across tasks, overall performance was satisfactory, with the fixed walk task showing slightly lower error compared to the other tasks for knee angle and hip angle measurements.

Gait lab analysis using 3D motion capture is considered the gold standard for assessing lower extremity kinematics, variables that provide valuable insights into the qualitative details of joint motion and biomechanics not readily discernible with more quantitative temporospatial metrics like step-related data. Kinematic variables are particularly relevant in the assessment of implant design or surgical technique. However, obtaining kinematic motion capture data in a gait lab are often impractical due to the need for in-person clinical settings and the associated costs. This study, alongside the pioneering studies now being published, highlights the potential benefits of coupling wearable inertial sensors and machine learning algorithms for capturing gait lab quality kinematic data in the wild [19,23-25]. The ability to capture such information outside of the laboratory setting opens new possibilities for long-term kinematic monitoring and to do so in much larger numbers of patients than heretofore possible. Data sets of this nature will enable researchers

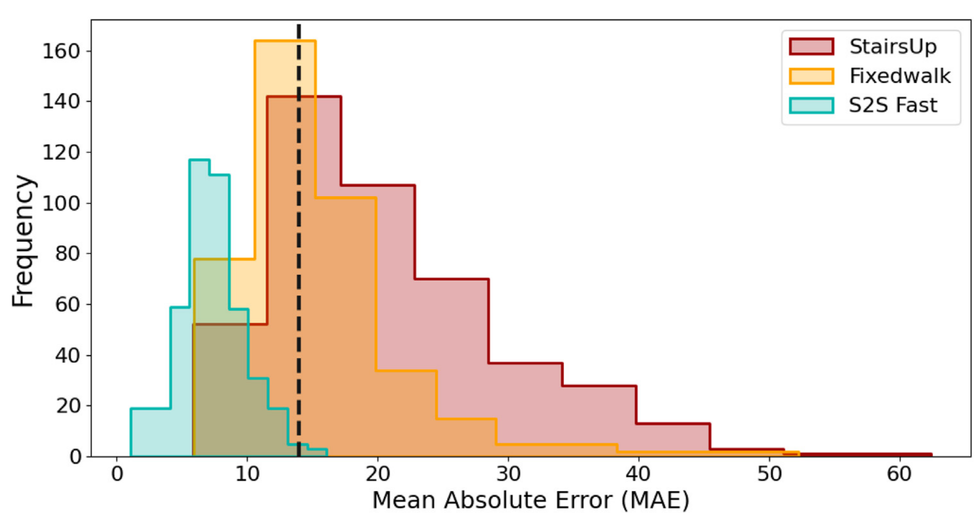

Figure 4. Histograms of the frequency of mean absolute error (MAE) for reproducing right knee angular velocity for each task. The dotted line shows the overall mean MAE across all tasks. These results show that the sit-to-stand task has a slightly lower error than the stair climb and fixed walk tasks, although the performance is still satisfactory.

to truly understand the progression of functional outcomes following knee surgery, trauma, or disease progression in different contexts and patients. Such granular understanding is likely to help us to better define treatment phenotypes or personalize treatment, prognosis, and even implant design.

The pilot study has several important limitations. The sample size was relatively small, with only 40 patients' data available for analysis. However, we found that the data were sufficient to train an accurate model with decreasing improvement of the model with the last 10 patients. Further research on varied populations and patients in recovery is recommended to validate the findings and enhance the generalizability of the results across subjects with different parameters. Additionally, the optimal position and number of sensors necessary to replicate kinematic knee variables need to be studied, as does the ability of CNNs using inertial motion sensor data to replicate kinetic outputs. Lastly, the accuracy of IMU sensors as well as motion capture data, relative to true skeletal kinematics, has been questioned. It has further been shown that small variations in sensor placement can affect output. While this is true, our aim was to test whether machine learning can be coupled to raw data from IMUs to accurately replicate kinematic variables collected using motion capture techniques, not test the accuracy of the latter.

Conclusions

This pilot study demonstrates the feasibility and accuracy of using wearable inertial sensors and advanced machine learning algorithms to replicate complex kinematic measures typically obtained through 3D motion capture analysis in a gait lab. The potential of this approach for capturing kinematic data outside of laboratory settings holds promise for advancing personalized patient care and gaining valuable insights into the real-world impacts of musculoskeletal diseases and clinical interventions used to manage them. Further research and development are needed to refine the algorithms, leverage more advanced techniques such as self-supervised training to enhance the model's accuracy in more complex tasks, expand the range of replicated measures, and validate the approach in larger cohorts.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT 3.5 to help summarize the abstract to 250 words and inform the selection of optimal keywords. It was not used in other sections. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Conflicts of interest

S. A. Bini receives royalties from Stryker; has stock options in Archetype.ai, siramedical.com, and StartupHealth.com; receives research support from Google; receives royalties/financial support from Elsevier; is an editorial board member of Arthroplasty Today, Journal of Arthroplasty, Journal of Bone and Joint Surgery; and is a board/committee member of Personalized Arthroplasty Society. A. B. Szczotka is a paid consultant of Google. W. Mormul is a paid consultant of Mobica Limited and Cognizant Technology Solutions Corporation. N. Gillian is a paid employee and has stock options in Google LLC and Archetype AI Inc. All other authors declare no potential conflicts of interest.

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CRediT authorship contribution statement

Stefano A. Bini: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Thomas A. Peterson:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Richard B. Souza:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Formal analysis, Data curation, Conceptualization. **Brooke Schultz:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis. **Ivan Poupyrev:** Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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