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Developing a Method for Quantifying Hip Joint Angles and Moments during Walking Using Neural Networks and Wearables

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ABSTRACT
Quantifying hip angles/moments during gait is critical for improving hip pathology diagnostic and treatment methods. Recent work has validated approaches combining wearables with artificial neural networks (ANNs) for cheaper, portable hip joint angle/moment computation. This study developed a Wearable-ANN approach for calculating hip joint angles/moments during walking in the sagittal/frontal planes with data from 17 healthy subjects, leveraging one shin-mounted inertial measurement unit (IMU) and a force-measuring insole for data capture. Compared to the benchmark approach, a two hidden layer ANN (n=5 nodes per layer) achieved an average rRMSE=15% and R^2=0.85 across outputs, subjects and training rounds.

Keywords: *Hip Joint, Wearable, Neural Networks, Inertial Measurement Units, Instrumented Insoles*

1. INTRODUCTION

Over 2.5M Americans currently live with a total hip replacement (THR), improving mobility and reducing pain despite advanced osteoarthritis (Kremers et al., 2014). Improving THR designs and post-op rehabilitation plans requires quantifying hip kinematics (i.e. joint angles) and kinetics (i.e. joint moments) during common activities, such as gait (Heller et al., 2001; Kassi et al., 2005; Kirkwood et al., 1999). For instance, hip kinematics and kinetics during gait can be combined with finite element modeling during *in-silico* simulations of THR device failure (Haynes et al., 1997; Nunn et al., 1989; Szivek et al., 2000). Further, these metrics can identify characteristics of pathologic gait to develop postoperative rehabilitation programs, such as abductor strengthening to prevent Trendelenburg gait in patients following THR (Hamacher et al., 2012). Despite this, current methods for quantifying hip kinematics and kinetics during gait are limited.

Gold-standards for quantifying these measures rely on expensive, non-portable tools, which often require specialized laboratory setups. Optical motion capture (MOCAP) records limb motion, and requires expensive, light-sensitive cameras that limit the capture space to small, indoor settings. Furthermore, MOCAP setup is time-consuming and complex, requiring adhering retroreflective markers to subject anatomy and camera calibration to track 3D marker position. Force plates measure ground reaction forces (GRFs), but plates must be embedded in treadmills or walkways to capture successive gait cycles. Attempting to reduce costs and complexity, most studies have used one force plate, capturing one gait cycle per trial (Costigan et al., 2002; Eng; Winter, 1995). For the gold standard, MOCAP/Force data captured almost exclusively in laboratories are inputted into biomechanical modeling software (e.g. OpenSim, Visual3D, etc.) for kinematic/kinetic computation.

In contrast, wearable sensors, like inertial measurement units (IMUs) and force-measuring insoles, represent portable, accessible (i.e. inexpensive, easy setup/calibration) alternatives to MOCAP and force plates (Renner et al., 2019; Robert-Lachaine et al., 2017). IMUs are small, electromechanical devices that measure inertial data (i.e. segmental linear acceleration, angular velocity, etc.). Force-measuring insoles placed inside shoes measure vertical GRFs. IMUs and force-measuring insoles easily capture limb motion and vertical GRFs for repeated gait cycles in and outside laboratory environments. Since wearables capture data in their local coordinate frame, precise fixation and coordinate transformations are required to build subject-specific models necessary for inverse kinematics (IK) and dynamics (ID). Other investigators have successfully applied wearables to traditional modeling for joint moment computation, but the approaches were time-consuming and required many IMUs (Dorschky et al., 2019; Konrath et al., 2019; van den Noort et al., 2013).

Replacing traditional biomechanical modeling with machine learning (ML) may reduce computation time and wearable quantity (Gurchiek et al., 2019). Biomechanists have begun combining wearables with artificial neural networks (ANN) estimating complex, nonlinear relationships between segment kinematics/GRFs (inputs) and joint kinematics/kinetics (outputs) (Halilaj et al., 2018). ANNs emulate biological neurons via computational ‘nodes’ which transform weighted input sums with nonlinear activation functions. Algorithm training consists of optimizing ANN weights and biases via data with known joint kinematics/kinetics. Once trained, ANNs faithfully model complex biomechanical systems with higher accuracy than traditional physics-based modeling (Halilaj et al., 2018; Schollhorn, 2004).

Thus far, most work combining wearables and ANNs to compute lower body kinematics/kinetics has used subject-specific training and testing (i.e. new training data per subject) (Gurchiek et al., 2019). This has greatly prevented translation and adoption. Two recent studies represent the breadth of existing work attempting to establish generalized approaches (i.e. pooled training data to predict new subjects). Mundt et al. used a complex approach (4000-6000 nodes/hidden layer, 5 IMUs) to compute 3D lower body joint angles/moments during walking (Mundt et al., 2020a). They achieved average root mean squared error (RMSE) $<4.8°$ for hip angles and average relative RMSE (rRMSE, relative to the average of predicted and ground truth moment ranges * 100%) $<13\%$ for hip moments. In contrast, Lim et al. proposed a simpler approach (20 hidden nodes, 1 waist-mounted IMU) computing hip joint sagittal angles and moments during walking (RMSE=3.14±1.49°, rRMSE=10.74±1.26% for angles/moments, respectively) (Lim et al., 2020). Accordingly, an opportunity exists to develop a simple solution (i.e. few wearables, ANN with few hidden nodes), like Lim et al., that computes outputs in more than one motion plane, like Mundt et al. As such, this study sought to develop a solution using two wearables and an ANN with <50 hidden nodes to compute biplanar hip kinematics/kinetics during walking. These measures were selected due to their importance studying pathologic gait (Kolk et al., 2014).

Like similar studies, this study used healthy subjects as a first step developing this novel method (Gurchiek et al., 2019; Lim et al., 2020; Mundt et al., 2020a). Specifically, this study developed a Wearable-ANN method computing sagittal/frontal hip joint angles and moments using a shank-mounted IMU and force-measuring insole on the dominant lower extremity as inputs into a simple ANN (1-2 hidden layers, 10 hidden nodes total) (Figure 1: Bottom). Many studies computing gait kinematics/kinetics with few wearables use shank-mounted IMUs because the anteromedial tibia's rigidity facilitates inter-subject consistency reducing soft-tissue noise (Bishop and Li, 2010; Li et al., 2021). Further, shank-mounted IMUs capture a larger range of translational and rotational movement than waist or thigh mounted IMUs which likely facilitates improved ML algorithm prediction capabilities. Moreover, this information is likely critical for computing kinematics/kinetics in the frontal plane, a key goal herein. The developed Wearable-ANN approach was compared to a benchmark approach, using MOCAP and force-measuring insoles for data capture and OpenSim for biomechanical modeling (Figure 1: Top). Force-measuring insoles were used in place of force plates to capture successive gait cycles, without specialized equipment. The study would consider the Wearable-ANN approach successful if it achieved average rRMSE across subjects less than 13%, the average rRMSE achieved by Mundt et al.

2. METHODS

2.1 Data Capture

Broadly, data capture consisted of measuring subject anthropometrics (height, weight), affixing and calibrating sensors (Figure 2), and recording data (MOCAP trajectories, force-insole vertical GRF, 3D IMU acceleration/angular velocity/magnetic field) while subjects performed treadmill walking. 17 healthy subjects (10M; 26.8±6.4years; 1.74±0.08m; 81.6±19.5kg) enrolled from the local university following Institutional Review Board approval. Inclusion criteria consisted of age≥18 years, no musculoskeletal/neuromuscular impairments impacting lower extremities, no terminal illness resulting in death within one year, clinical full hip extension≥10° and flexion≥100°, and complete participation in the study (Svenningsen et al., 1989).

Three sensing modalities were used: 1) MOCAP, 2) force-measuring insoles, and 3) IMUs. Subjects were fitted with a modified lower body Helen Hayes retroreflective MOCAP marker set (Figure 2A) (Collins et al., 2009; Kadaba et al., 1990). Six S250e cameras (OptiTrack Motive Body 1.10, NaturalPoint, Inc., Corvallis, OR) were calibrated per manufacturer's instructions. Subjects donned an IMU (APDM v1 Emeralds, APDM Inc.; Portland, OR; f_s=128Hz) via a silicone backed Velcro strap on the dominant anteromedial shank (Figure 2B, Waterloo Footedness

Questionnaire, 13 right-footed) (Elias et al., 1998). IMUs were calibrated per manufacturer's instructions and continuously logged data during walking trials for offline processing. Finally, subjects donned force-measuring insoles ('Loadsols') measuring vertical ('normal to device surface') GRFs (Novel Electronics, St. Paul, MN, USA; f_s=100Hz; Figure 2C). Loadsols were validated against a force-instrumented treadmill (Bertec Split Belt Instrumented Treadmill, f_s=1000Hz) during treadmill walking (0.9m/s; 3x30sec; 3 healthy subjects). Crossplots indicated insole and treadmill-measured vertical GRF were highly correlated (>0.98) with average absolute error of 30N (average across subjects, trials, and right/left feet). Further, many studies have validated the accuracy and precision of Loadsols for several activities (Bessone et al., 2019a, 2019b; Burns et al., 2019; Peebles et al., 2018; Renner et al., 2019; Seiberl et al., 2018; Strutzenberger et al., 2018). Loadsol data were streamed via Bluetooth to an iPad and stored for offline processing (Apple, Cupertino, CA, USA).

Once fitted with all sensoring modalities, subjects completed 10s of standing for OpenSim model scaling and three, 30s treadmill walking trials at a moderate pace (0.9m/s; gait cycles/subject/trial: 22.18±1.70) (Mundt et al., 2020b; Pizzolato et al., 2017; Stoquart et al., 2008).

2.2 Data Pre-Processing

2.2.1 Overview

Data pre-processing prepared 1) MOCAP and force-insole data for biomechanical modeling and inverse dynamics and 2) IMU and force-insole data for ANN development and training. For each subject, the trial with the fewest MOCAP marker trajectory gaps was selected for final analyses. Custom MATLAB scripts were used to filter and synchronize raw data across sensing modalities (Figure 3) before separating data for modeling and ANN development.

2.2.2 MATLAB Pre-Processing

MOCAP data were edited using Optitrack Motive to interpolate trajectory gaps and filter data (low-pass Butterworth, f_{cutoff}=6Hz) before import to MATLAB. Loadsol and IMU data were filtered (low-pass Butterworth, f_{cutoff}=10Hz) and Loadsol resampled (100 to 128Hz) in MATLAB to attain consistent sampling frequency across sensors for synchronization and time normalization (i.e. convert time to gait cycle percent; heel strike=0%) (Lim et al., 2020; Renner et al., 2019). IMU trials were separated using manufacturer supplied buttons attached to a second IMU held by the researcher during capture, creating 'Start' and 'End' time-marks ('IMU marker truths'). IMU angular velocity was copied: one synchronized IMU and Loadsol data as well as time normalization, and one for ANN training. Leveraging prior work identifying heel strike from shank angular velocity, gait analysis IMU data were filtered (2.3Hz instead of 10Hz) and rotated via transformation matrix and goniometrically measured offset angle (angle between actual IMU position and purely lateral position; 121.3±6.6°) (Coley et al., 2005; Yang et al., 2013).

2.2.3 Temporal Synchronization (Figure 3)

Gait-based synchronization across sensors was then completed. The first heel strike (T_{HS}) was identified for all sensors, data were shifted (arrows) to align at MOCAP T_{HS}, and files truncated ensuring trials contained all data types for their entirety. For MOCAP, T_{HS} occurred when heel anteroposterior velocity passed through zero (Figure 3, top) (Zeni et al., 2008). Loadsol T_{HS} occurred when positively sloped data exceeded 20N (Figure 3, middle) (O'Connor et al., 2007; Zeni et al., 2008). Toe off occurred when negatively sloped Loadsol data fell below 20N. Loadsol heel strikes and toe offs determined gait percentages (stance %: 66.0±2.7%). IMU T_{HS} was the first local shank angular velocity minima about the mediolateral axis during stance (Figure 3, bottom) (Bergmann et al., 2010; Coley et al., 2005; Yang et al., 2013).

2.2.4 OpenSim Workflow

This study used OpenSim, an opensource biomechanical modeling software, to calculate benchmark method hip angles and moments using MOCAP and Loadsol data (Delp et al., 2007; Seth and Delp, 2018). Hullfish et al. demonstrated the validity of using MOCAP and Loadsol data as OpenSim inputs when computing joint moments (e.g. sagittal ankle moments) compared to force plates with average RMSE of 1.0% weight * height across subjects (e.g. height=1.7m, weight=70kg, average RMSE=1.7m*70kg*0.01=1.19) (Hullfish and Baxter, 2020). Settings for Scaling, IK, and ID were derived from OpenSim Tutorial 3 (National Center for Simulation in Rehabilitation Research, 2020a). First, standing trial data and the scaling tool fit the generic gait2392 model to each subject. Model height was manually scaled because no upper body MOCAP markers were present (National Center for Simulation in Rehabilitation Research, 2020b). The OpenSim IK tool then applied MOCAP trajectory inputs to the scaled model computing joint angles (National Center for Simulation in Rehabilitation Research, 2020c). Weighting prioritized minimizing error at bony landmarks. Next, Loadsol vertical GRFs applied to the talus (MOCAP ankle marker midpoint) and IK-computed angles were inputted to the ID tool, which computed net joint moments (National Center for Simulation in Rehabilitation Research, 2020d). OpenSim-computed angles/moments were inputted into MATLAB for time-normalization to gait cycle percentage. Finally, data were ensemble averaged across cycles and subjects using the gait percentage vector.

2.2.5 ANN Workflow

The Wearable-ANN approach was subject-general (i.e. training data pooled across subjects to predict results for new 'test' subject), maximizing convenience and transferibility of the approach. As such, leave-one-out cross-validation (LOO-CV) was used for training a shallow (<3 hidden layers) feed forward ANN. LOO-CV consists of pooling all but one subject's input data for training, leaving one subject's data for validation. Each ANN training round consisted of 17 iterations to allow all subjects to act as the validation set. ANN inputs included activity duration, dominant foot vertical GRF, and shank IMU data. The IMU represents 13 time series inputs (3D acceleration, angular velocity, and magnetic field + 4D orientation quaternion=13 variables) with 3840 observations each (30sec trial * 128Hz sampling frequency). ANN outputs were time series sagittal and frontal plane hip angles/moments.

Similar studies were utilized to select transfer functions and hidden layer quantity (Lim et al., 2020; Mundt et al., 2020a; Stetter et al., 2020). Hyperbolic tangent functions were used for hidden layers because they offer greater sensitivity to input variability and larger working range than sigmoid functions (Baughman and Liu, 1995; Lim et al., 2020; Stetter et al., 2020; Wouda et al., 2018). A linear function was used for the output layer. Larger ANNs have greater capability modeling complex relationships, but are prone to longer computation times and overfitting data (Basheer and Hajmeer, 2000). Prior work (<20 subjects, <150 nodes) informed ANN design iteration that considered hidden layer size with the total hidden node quantity varied between 5 and 100 to identify the lowest average rRMSE across training iterations and rounds (17 subjects each as training set * 10 ANN training rounds = 170 iterations per ANN size). (Lim et al., 2020; Stetter et al., 2020) This approach facilitated optimization to a 2-hidden layer ANN with 5 hidden nodes/layer, using all inputs.

ANN inputs were normalized (range = -1,1; **mapminmax** in MATLAB), initialized using Nguyen and Widrow function (**initnw** in MATLAB), and trained using Levenberg-Marquardt algorithm (**trainlm** in MATLAB). Repeated training allowed each subject to function as validation data. Performance metrics were averaged from the 170 separately trained/tested ANN iterations (Lim et al., 2020; Mundt et al., 2020a; Stetter et al., 2020). **Initnw** filled weights/biases with initial values and **trainlm** completed backpropagation/optimization until the gradient stopped decreasing for >6 epochs (i.e. training passes).

To evaluate overall ANN performance, determination coefficients (R^2) and rRMSE were computed comparing benchmark to ANN results. As an example, if RMSE=0.75Nm and result range=2.5Nm(benchmark) and 3Nm(ANN-computed), then rRMSE=0.75/(average of 2.5+3)*100%=14%. Performance metrics were averaged across 17 LOO-CVs and 10 training rounds. To investigate ANN performance by subject, violin plots were constructed. The violin shape was calculated via probability distribution curves, using the dataset's kernel density estimation without removing statistical outliers. Paired t-tests with alpha set to 0.05 were used to compare average angles/moments between approaches at approximate heel strike(0%), mid-stance(30%), toe off(60%), and mid-swing(80%).

3. RESULTS

3.1 Benchmark Approach

Ensemble averaged hip angles (Figure 4A, top) and moments (Figure 4A, bottom) are displayed alongside ±1SD (shaded). Overall, the benchmark's angle and moment curvature (i.e. peak width, timing) was similar to literature, but smoother and with larger peak moments (Costigan et al., 2002; Eng; Winter, 1995). Peak extension/flexion moments occurred at ~20%/~50% of gait cycle, respectively, consistent with prior work (Eng; Winter, 1995; Hunt et al., 2013; Pizzolato et al., 2017). In the frontal plane, the benchmark yielded the expected double abduction peaks during stance.

3.2 Wearable-ANN Approach

Benchmark and Wearable-ANN angle and moment curves were consistent (Figure 4A; Flexion max moments= 2.28±0.34Nm(Benchmark,), 1.68±0.35Nm(Wearable-ANN); Abduction max moments: 1.73±0.21Nm(Benchmark), 1.54±0.13Nm Nm(Wearable-ANN)). rRMSE ranged from 11.2-20.8% and R^2 from 0.79-0.93 (Table 2). Adduction moment prediction was most successful (R^2=0.93, rRMSE=11.7%). Adduction angle prediction was most challenging (R^2=0.79, rRMSE=20.8%). Similar to results found by Mundt et al. and Lim et al., Wearable-ANN peaks were slightly smaller than benchmarks for all metrics. Wearable-ANN angles had smaller standard deviation than the benchmark's (Lim et al., 2020; Mundt et al., 2020a). Although statistically significant differences were noted between approaches at some points in the gait cycle, the deltas between means were small at most points (e.g. Δ=0.18Nm/kg(flexion moment), Δ=0.05Nm/kg(adduction moment) at heel strike) (Figure 4B).

Violin plots (Figure 5) demonstrate Wearable-ANN performance and intersubject variability. Each dot represents average subject performance as validation across rounds. White dots and grey bars are the median and interquartile range, respectively. Wearable-ANN predicted sagittal outputs well for most subjects (i.e. wide, short violins near R^2=0.90 for angles/moments). Adduction moment prediction was most successful across subjects ($0.8<R^2<0.99$). Correlation between benchmark and ANN-computed adduction angles varied more ($0.5<R^2<0.95$).

4. DISCUSSION

4.1 Benchmark Approach

Benchmark results matched the curvature of previous studies (Costigan et al., 2002; Eng; Winter, 1995; Heller et al., 2001; Hunt et al., 2013; Pizzolato et al., 2017; Stoquart et al., 2008). However, peak moments were greater than anticipated. Notably, prior studies report a wide range of moments, likely due to variable quantity (e.g. MOCAP marker set used, method for determining joint center of model, etc.) from data capture to final moment computation (Camomilla et al., 2017). For instance, Hunt et al. report a peak extension moment of 0.58±0.60 Nm/kg whereas Eng and Winter report one twice as large, at 1.3±0.35 Nm/kg (Eng; Winter, 1995; Hunt et al., 2013).

Benchmark peak moments may be overestimated herein due to holding the CoP at the talus, which increased the vertical GRF lever arm several centimeters during stance (Figure 6). Prior work found CoP shifted 1cm anterior increases extension moments 8%, 1cm posterior increases flexion moments 16%, and 3cm lateral increases double-peak abduction moments 20% (Kim et al., 2007; McCaw and DeVita, 1995; Tekscan, 2020). Accordingly, the benchmark could be improved by modeling CoP more faithfully. Chiu et al. reported gait CoP trajectory by gait cycle and foot length percentage, which could estimate CoP without directly measuring it (Chiu et al., 2013). Hullfish et al. proposed subtracting a constant offset (Hullfish and Baxter, 2020), and still others calculated CoP from pressure-sensing insoles (Forner Cordero et al., 2004; Jönsson et al., 2019; Jung et al., 2014). Ultimately, the aforementioned benchmark approaches should be compared to results from optical MOCAP and 3D force plates to determine which provides the most accurate gold-standard for studies seeking lower cost, more convenient data capture. Overall, our benchmark results reflected literature results, providing an adequate ground truth for initial development of the proposed approach.

4.2 Wearable-ANN Approach

The Wearable-ANN approach (2 hidden layers, 5 nodes/layer) achieved an average R^2=0.85 and rRMSE=14.9% across outputs, slightly higher than our initial goal of <13% (i.e. less than Mundt et al.) (Mundt et al., 2020a). However, neither a 1.9% greater average rRMSE nor statistically significant, but small differences between approaches at specific points in the cycle are likely clinically relevant (e.g. -0.04Nm/kg v. -0.09Nm/kg heel strike adduction moment would be clinically interpreted as 0Nm/kg). Broadly, ML models fill knowledge gaps where biological processes are too complex to physically model and/or investigate directly (Viceconti et al., 2005). Therefore, the model's value should be assessed not only with respect to its accuracy compared to gold-standards, but also in light of its potential to improve patient health while minimizing risk. Using this Wearable-ANN approach to compute hip kinematics/kinetics illuminates hip biomechanics during gait along dimensions not previously possible (i.e. successive gait cycles, outside of laboratory, etc.). While Wearable-ANN approaches are recent developments in biomechanics, they represent exciting steps towards better characterizing joint loading, which could be invaluable to THR failure analysis and pathologic gait diagnoses/retraining.

Ideally, well-established biomechanical modeling methods could guide ANN design for estimating joint biomechanics, making ANNs easier to understand and explain. However, establishing meaningful connections between physics-based and ANN-based computations is challenging, especially for subject-general approaches. Lim et al. developed linked-segment models guiding their design, but ultimately used trial-and-error to determine optimal hidden node quantity (Lim et al., 2020). Rather than reconciling traditional biomechanical modeling with ANN design, researchers may find it more worthwhile to focus on capturing training data that encompasses the variability expected in test datasets. The results herein indicate shallow ANNs are successfully trainable (average R^2=0.85, rRMSE=14.9%) with small datasets (<600 gait cycles).

Poor performance of an ANN computing joint kinematics/kinetics indicates training data failed to encompass validation set patterns. Adduction angle, the most poorly predicted output, exhibited greater variability than other outputs. The Wearable-ANN approach resulted in a much narrower standard deviation than the benchmark, suggesting the ANN had difficulty reconciling variable frontal kinematics. In contrast, the Wearable-ANN computed frontal plane moments successfully (R^2=0.90) with similar variability to the benchmark. ANN performance may be improved using data augmentation techniques (e.g. scaling, rotation etc.) to induce additional training data variability (Mundt et al., 2020a; Rashid and Louis, 2019), designing ANNs for specific subject categories (e.g. age range, gender, pathology) (Saeb et al., 2017), and optimizing sensor types/quantities/placement. Finally, the approach should be extended to predict bilateral metrics.

4.3 Limitations

This work is an exciting first step in developing a simple approach to computing hip angles/moments from wearables. Its novelty induces certain limitations, including a lack of comparison against the highest gold standard (e.g. optical MOCAP and 3D force plates), and higher error than expected (rRMSE=14.9%>13%). These limitations represent opportunities for future work. Further, there are opportunities to characterize the success of the approach in more diverse subjects/environments.

4.4 Significance

This study developed a more accessible, portable approach to quantifying hip joint angles/moments using wearables and ML. The Wearable-ANN approach herein demonstrates the capability of simple ANNs with small training data sets for calculating joint angles/moments that match biomechanical modeling. More specifically, the approach represents a portable alternative to traditional data capture computing hip metrics in seconds with two wearables. The portability and convenience could make long-term, at-home patient studies possible. The approach's speed (<5s for ANN prediction of 30s input data) could make real-time gait retraining possible (Pizzolato et al., 2017; Tate and Milner, 2010). Ultimately, the approach has the potential to impact millions of patients with athroplasties and other gait pathologies.

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