Prediction of lower limb joint moments during walking based on 3D hip, knee and ankle angles

Bernd J. Stetter[1], Sonja Kuklok[1], Hannah Steingrebe[1], Stefan Sell[1,2], Thorsten Stein[1]

[1] Institute of Sports and Sports Science, Karlsruhe Institute of Technology, Germany;

[2] Joint Center Black Forest, Clinic Neuenbuerg, Germany

Introduction

Research on joint loading is important for understanding risk factors and developing interventions to prevent or treat gait-related injuries and conditions such as hip osteoarthritis (HOA) (Bulat et al., 2019; Egloff et al., 2012). Investigations in this field have traditionally been performed in laboratories using motion capture and force plate measurements as well as biomechanical modeling. A major shortcoming of laboratory-based analyses is that they cannot be included into a patients' habitual environment. While joint kinematics (i. e. joint angles) can also be measured outside the laboratory using inertial sensors (Seel et al., 2014), the analysis of kinetic quantities (e. g. joint moments) mainly relies on stationary measurement equipement. More recently, machine learning algorithms such as artificial neural networks (ANN) have shown to be an effective tool to predict joint kinetics based on kinematic gait measurements (Dinovitzer et al., 2023; Mundt et al., 2020; Stetter et al., 2020). The quality of the input data used to construct an ANN influences the accuracy of joint moment predictions (Halilaj et al., 2018). However, especially the composition of the input dataset has received relatively little attention so far. Therefore, the purpose of this study was to compare the ANN-based prediction accuracy of 3D hip, knee, and ankle moments for three different lower limb joint angle input datasets. Each dataset consisted of walking data either exclusively from (1) HOA patients or (2) healthy adults or (3) of a combination of both groups.

Methods

This study used data recorded for a study investigating effects of hip bracing on gait biomechanics (Steingrebe et al., 2022). Data from 19 participants with mild to moderate unilateral HOA (64.1 ± 8.4 years, 70.8 ± 11.5 kg, 170.7 ± 6.8 cm) as well as from 19 matched healthy controls (62.9 ± 9.4 years, 74.4 ± 13.0 kg, 171.0 ± 9.4 cm) were considered in this analysis. The available 3D hip, knee and ankle angles and external moments were calculated using the traditional inverse kinematic and dynamic approaches based on motion capture (Vicon Motion Systems, 200 Hz) and force plate measurements (AMTI, 1000 Hz) using the multi-body model ALASKA Dynamicus. Joint angles and moments were time normalized to the stance phase (100 time points) beginning with the heel strike on the force plate until the toe off of the same foot. Joint moments were additionally normalized to bodyweight. Three different datasets with input (i. e. joint angles) and output (i. e. joint moments) data were build for training and evaluation of ANNs based on three walking trials of each participant. A first dataset combined data of 19 HOA patients (19 participants x 3 trials = 57), a second dataset combined data of 19 healthy controls (19 participants x 3 trials = 57) and a third dataset combined data of 10 randomly selected HOA patients and 9 randomly selected healthy controls (10 HOA participants x 3 trials + 9 control participants x 3 trials = 57). An individual ANN that maps the joint angles to the joint moment time series was built for each of the three datasets (ANN-HOA, ANN-healthy, ANN-mixed). The ANNs contained two hidden layers of 40 and 30 neurons inspired by previous studies (Dinovitzer et al., 2023; Stetter et al., 2020). Evaluation of the ANNs was done using a leave-one-subject-out cross-validation. For each model the similarity between the ANN predicted continuous outcomes (flexion extension moment (flex. M.), add- abduction moment (add. M.), internal external rotation moment (rot. M.)) and the inverse dynamics calculated data were assessed using Pearson's correlation coefficient (r) and relative root mean squared error (rRMSE). rRMSE was calculated by dividing the root mean squared error with the range of each individual joint moment time series (difference between maximum and minimum values) (Giarmatzis et al., 2020).

Results

The prediction accuracy of 3D hip, knee, and ankle moments for three different ANNs are shown in Table 1. Across all joints and dimensions, the r values for the ANN-HOA, ANN-healthy, and ANN-mixed model ranged between 0.82 and 0.99, 0.87 and 0.99, and 0.40 and 0.95, respectively. The ANN-predicted moments yielded rRMSEs that ranged from 8.26 to 25.86 (ANN-HOA model), 8.96 to 29.34 (ANN-healthy model), and 23.02 to 60.10 (ANN-mixed model) for the different joints and dimensions.

Model	Joint	r, flex. M.	rRMSE [%], flex. M.	r, add. M.	rRMSE [%], add. M.	r, rot. M.	rRMSE [%], rot. M.
ANN-HOA	Hip	0.98 (0.41)	10.40 (6.36)	0.98 (0.46)	8.27 (4.94)	0.94 (0.40)	12.92 (7.64)
	Knee	0.97 (0.47)	10.61 (8.84)	0.95 (0.52)	17.44 (16.44)	0.95 (0.47)	25.86 (52.75)
	Ankle	0.99 (0.48)	8.26 (5.74)	0.82 (0.45)	25.49 (12.21)	0.98 (0.44)	12.84 (17.27)
ANN-healthy	Hip	0.98 (0.44)	9.60 (8.21)	0.97 (0.53)	9.51 (6.53)	0.96 (0.51)	12.61 (7.77)
	Knee	0.98 (0.49)	9.94 (6.37)	0.93 (0.59)	21.72 (22.91)	0.90 (0.59)	29.34 (39.19)
	Ankle	0.99 (0.47)	8.96 (8.54)	0.87 (0.43)	27.55 (22.95)	0.97 (0.28)	11.30 (4.45)
ANN-mixed	Hip	0.88 (0.50)	33.57 (19.78)	0.87 (0.46)	26.55 (15.14)	0.85 (0.60)	24.37 (10.59)
	Knee	0.87 (0.53)	24.59 (12.67)	0.71 (0.57)	43.99 (26.87)	0.77 (0.62)	54.32 (56.94)
	Ankle	0.95 (0.56)	23.02 (16.06)	0.40 (0.54)	60.10 (29.56)	0.92 (0.47)	25.13 (18.52)

Table 1: Accuracy of the predicted continuous joint moments using different input datasets. Values are presented as mean and standard deviations (sd).

Discussion

The results showed a similar agreement between the 3D ANN-predicted outcomes and the inverse dynamics-calculated data for the ANN-HOA model and ANN-healthy model. Reduced prediction accuracy ($r < 0.71$, rRMSE > 43.99) was observed for the ANN-mixed model, primarily for the knee and ankle add. M. as well as the knee rot. M. in comparison to the other two models ($r > 0.82$, rRMSE < 29.34). Previous studies focussing on joint moment estimation presented comparable prediction accuracies for healthy persons as well as for mixed datasets including healthy and impaired persons (i. e. after knee replacement) as received for the ANN-HOA and ANN-healthy model (Dinovitzer et al., 2023; Mundt et al., 2020). A potential reason for the higher estimation accuracy of the models built based on walking data exclusively from HOA patients or healthy adults is a reduced variance in the corresponding 3D joint angles and moments. The mixed dataset combines diverse gait patterns from the HOA patients and healthy adults (Steingrebe et al., 2022), which may result in a reduced ability to systematically map the joint angles to the joint moment. Overall, the estimation accuracies in the minor motion planes (i. e. add. M. and rot. M.) should be interpreted with caution, as these planes are known to be more error-prone (Mundt et al., 2020; Stetter et al., 2020).

Conclusion

This study presents the possibility for ANN-based lower limb joint moment predictions based on kinematic variables and demonstrates the impotance of the composition of the input dataset for model building. The findings have high practical implications and suggest that lower limb joint moment prediction models should be built with data from the targeted population. In future work, it should be investigated if these results persist when alternative and/or more complex ANN architectures or different movements are used.

References

[1] Bulat, M., Can, N. K., Arslan, Y. Z., & Herzog, W. (2019). Musculoskeletal simulation tools for understanding mechanisms of lower-limb sports injuries. Current Sports Medicine Reports, 18(6), 210–216.

[2] Dinovitzer, H., Shushtari, M., & Arami, A. (2023). Accurate Real-Time Joint Torque Estimation for Dynamic Prediction of Human Locomotion. IEEE Transactions on Biomedical Engineering.

[3] Egloff, C., Hügle, T., & Valderrabano, V. (2012). Biomechanics and pathomechanisms of osteoarthritis. Swiss Medical Weekly, 142(2930), w13583.

[4] Giarmatzis, G., Zacharaki, E. I., & Moustakas, K. (2020). Real-time prediction of joint forces by motion capture and machine learning. Sensors, 20(23), 6933.

[5] Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J. L., Hastie, T. J., & Delp, S. L. (2018). Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities. Journal of Biomechanics, 81, 1–11.

[6] Steingrebe, H., Stetter, B. J., Sell, S., & Stein, T. (2022). Effects of hip bracing on gait biomechanics, pain and function in subjects with mild to moderate hip osteoarthritis. Frontiers in Bioengineering and Biotechnology, 10, 888775.

[7] Stetter, B. J., Krafft, F. C., Ringhof, S., Stein, T., & Sell, S. (2020). A machine learning and wearable sensor based approach to estimate external knee flexion and adduction moments during various locomotion tasks. Frontiers in Bioengineering and Biotechnology, 8, 9.

[8] Mundt, M., Koeppe, A., David, S., Bamer, F., Potthast, W., & Markert, B. (2020). Prediction of ground reaction force and joint moments based on optical motion capture data during gait. Medical Engineering & Physics, 86, 29–34.

[9] Seel, T., Raisch, J., & Schauer, T. (2014). IMU-based joint angle measurement for gait analysis. Sensors, 14(4), 6891–6909.