PREDICTION OF JOINT KINETICS BASED ON JOINT KINEMATICS USING NEURAL NETWORKS

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The high cost and low portability of measurement systems as well as time-consuming inverse dynamic calculations are a major limitation to motion analysis. Therefore, this study investigates predictions of joint kinetics based on kinematic data using an artificial neural network (ANN) approach. For this purpose, 3D lower limb joint angles and moments of twelve healthy subjects were calculated using inverse dynamics. Kinematic and anthropometric data was used as input parameter to train, validate and test a long short-term memory recurrent ANN to predict joint moments. The ANN predicts joint moments for subjects whose motion patterns are known to the ANN accurately. Although the prediction accuracy for unknown subjects was lower, this study proved the capability of ANNs to predict joint moments based on kinematic and anthropometric data.

KEYWORDS: gait analysis, 3D joint moments, artificial intelligence.

INTRODUCTION: During the last years, researchers aim to make gait analysis more practical for clinical applications by increasing the flexibility and usability of different systems (Shahabpoor and Pavic, 2017). Inertial measurement unit (IMU)-based systems offer the possibility to measure kinematic parameters easily without the necessity of long preparation. But these systems are limited to the extraction of the IMUs raw data, segment's orientations in space and joint angles (Mundt et al., 2017). To use commercial or open-source software for inverse dynamics calculations, marker trajectories gathered by optoelectronic systems as well as ground reaction forces (GRFs) gathered by force plates or instrumented shoes are necessary. Therefore, IMU data cannot be used as input parameter for this software.
Different approaches based on artificial intelligence exist to support gait analysis (Caldas, 2017), but hardly any of them is used to determine joint kinetics. Favre et al. (2012) used a feed-forward multi-layer perceptron neural network to predict the knee adduction moment based on GRFs, centre of mass velocity and displacement, stance duration, percentage of time in stance phase, and knee joint axis during gait. Aljaaf et al. (2016) evaluated four different machine learning approaches for their performance on predicting knee adduction moments during gait based on joint angles only. Ardestani et al. (2014) compared the performance of a feed-forward neural network and a wavelet neural network in predicting 3D joint moments based on GRFs and electromyography (EMG) data inputs. Karatsidis et al. (2016) used optical and IMU data and compared the results in predicting GRFs analytically to those of a force plate. They achieved comparable results for both measuring systems, but higher root mean square error (RMSE) values than ANN applications. They did not determine joint kinetics based on the calculated GRFs.
Therefore, this study aims to predict 3D lower limb joint kinetics based on joint angles received from an optoelectronic motion capture system and anthropometric data using a recurrent ANN based on long short-term memory.

METHODS: 12 healthy subjects (7 male, 5 female, age = 26.9 ± 2.3 years, mass = 70.8 ± 13.2 kg, height = 171.9 ± 10.2 cm) participated in this study approved by the Ethics Committee of the German Sport University after giving written consent. Anthropometric parameters were measured before each subject performed level walking tasks at five different speeds for ten times. The motion was captured by ten infrared cameras (VICON™, Oxford, UK, 100 Hz) with 28 reflective markers placed on bony landmarks. Kinetic data was collected by one force plate (Kistler Instrumente AG, Winterthur, Switzerland, 1000 Hz). 3D joint angles and moments of the lower extremities were calculated using an anatomic-landmark-scaled Lower-Body-Model (Lund et al., 2015) from the AnyBody Modeling System™ (Version 6.0, AnyBody Technology, Aalborg, Denmark).

A long short-term memory (LSTM)-based recurrent ANN with three consecutive cells of 512 units each (Koeppe et al., 2017) was trained using the joint angles and joint moments calculated by Anybody software as well as the gait velocity and the anthropometric data height, weight, foot length, shank length and thigh length. Each step of the data set was normalised in time to a sequence length of 100 frames, representing a gait cycle lasting from one initial contact to the next. For the training process, 70 % of the shuffled data from 11 out of 12 subjects was used. The validation was performed using 15 % of the shuffled data set. The process of testing was conducted double-staged. First, the remaining 15 % of the aforementioned data set was used. Second, the data of the twelfth subject was evaluated. The first data set consisted of a total amount of 185 steps from eleven subjects at five gait velocities ranging from 0.8 m/s to 2.0 m/s. A number of 131 steps was used for training, 27 for validation and 27 for testing. The test data set of the twelfth subject contained 29 steps. The neural network was trained on chunks of increasing sequence lengths from 20 to the full 100 of the time-variant data. The batch size was adjusted between 50 and 500 samples and the learning rate was decreased using exponential decay and scheduled adjustment to stabilise the training process. During online preprocessing, the data was normalised using moving mean and variance across all processed batches to ensure equal convergence behaviour of all features. An additional fully-connected feed-forward layer of 512 units with rectifier activation before the first LSTM cell was used to project the data into a favourable dimensional representation. In the online postprocessing step after the neural network, the data features were rescaled back to their original scale.

To compare the results, the NRMSE, the RMSE normalised by the range of joint moments predicted by the NN, is calculated. Additionally, the Pearson correlation coefficient between the calculated and predicted joint moments is determined.

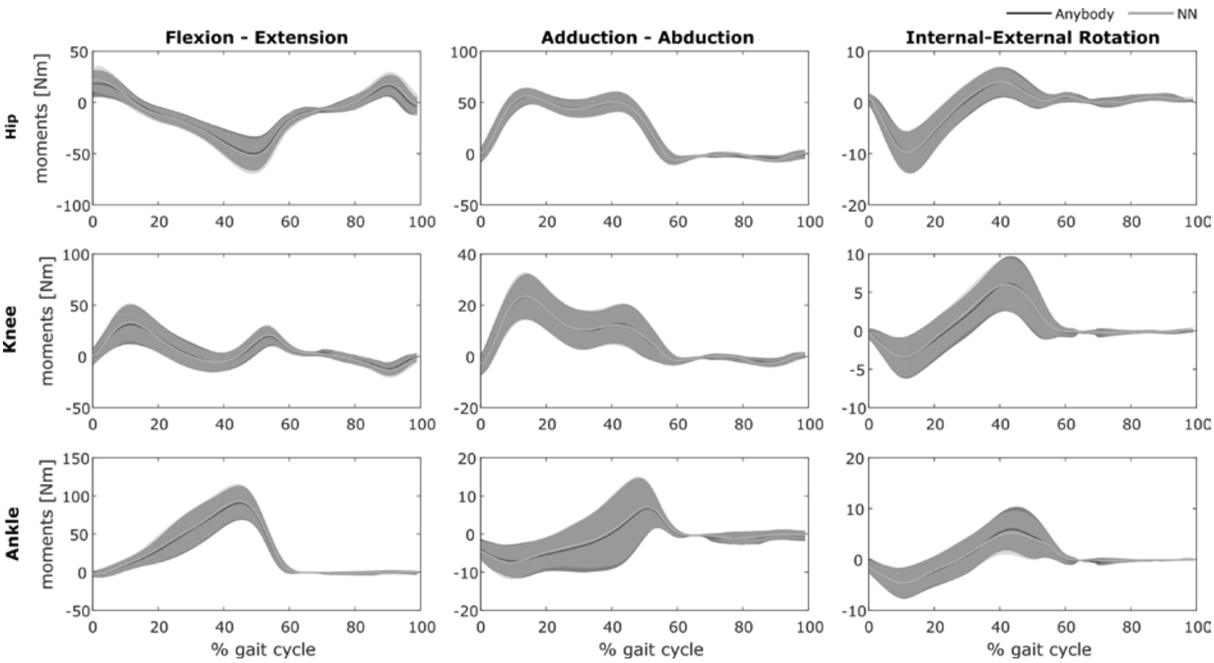

Figure 1: Mean and standard deviation of the moments calculated by the AnyBody Modeling System™ and predicted by the Neural Network for the first data set containing steps from 11 out of 12 subjects.

RESULTS: Mean and standard deviation of the first data set for 3D moments of hip, knee and ankle are displayed in Figure 1. The NRMSE between the mean moment progressions

of the calculated and predicted model is 2.08 % for hip flexion, 0.77 % for hip adduction, 1.08 % for hip rotation, 2.02 % for knee flexion, 0.77 % for knee adduction, 1.86 % for knee rotation, 1.43 % for ankle flexion, 2.68 % for ankle adduction and 2.38 % for ankle rotation. The mean NRMSE over all moments and joints is 1.67 %. The Pearson correlation coefficient for all joints and moments is $\rho > 0.997$ ($\alpha = 0.05$).
Figure 2 displays mean and standard deviation of the 3D moments of hip, knee and ankle for the twelfth subject. The NRMSE between the mean moment progressions is 18.15 % for hip flexion, 8.03 % for hip adduction, 6.47 % for hip rotation, 13.50 % for knee flexion, 14.96 % for knee adduction, 10.69 % for knee rotation, 6.41 % for ankle flexion, 15.15 % for ankle adduction and 11.35 % for ankle rotation. The overall NRMSE is 11.63 %. The Pearson correlation coefficient is $\rho = 0.97$ for hip flexion, $\rho = 0.99$ for hip adduction, $\rho = 0.98$ for hip rotation, $\rho = 0.93$ for knee flexion, $\rho = 0.95$ for knee adduction, $\rho = 0.97$ for knee rotation, $\rho = 0.98$ for ankle flexion, $\rho = 0.92$ for ankle adduction and $\rho = 0.97$ for ankle rotation ($\alpha = 0.05$).

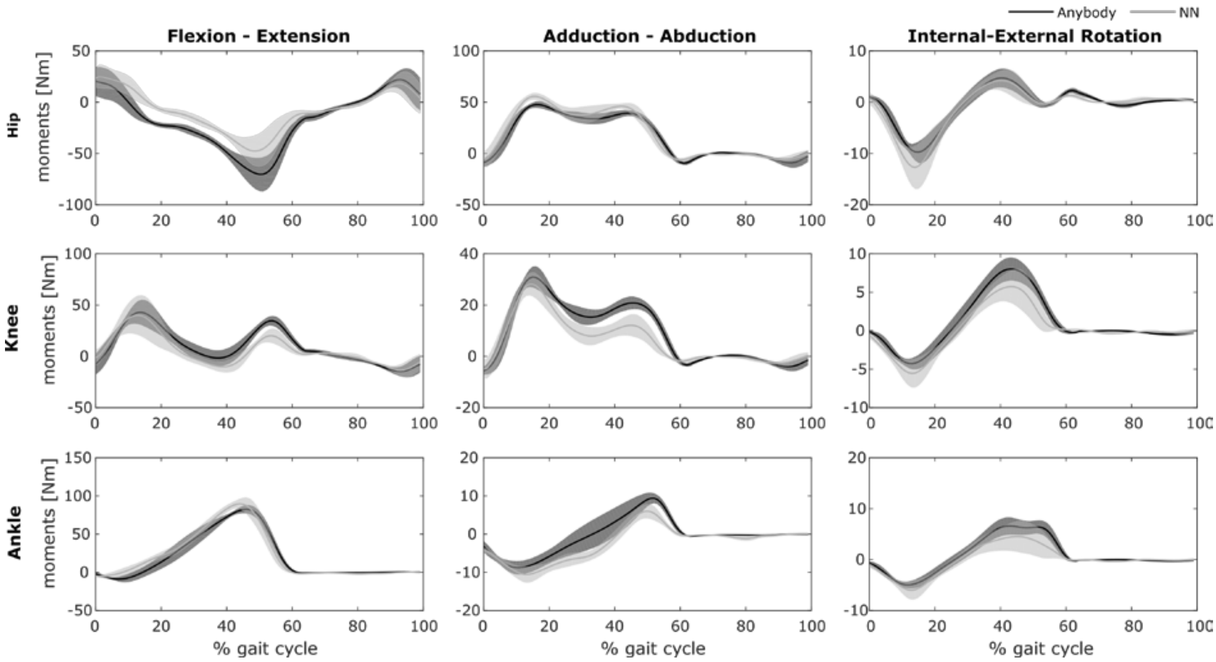

Figure 2: Mean and standard deviation of the moments calculated by the AnyBody Modeling System™ and predicted by the Neural Network for the unknown subjects.

DISCUSSION: The results of the first data set showed an outstanding conformity concerning the calculated and predicted joint moments. This can be explained by the fact that partial steps used for testing come from the same subjects as used for training. Presumed that the subjects did not change their typical motion patterns among the different trials, the NN learned their specific motion. These results demonstrate the possibility to predict joint moments from joint angles and anthropometric data for subjects that were used for training the NN. Thereby, it is possible to increase the amount of steps whose joint kinetics can be analysed. Additionally, it offers the opportunity to perform one gait analysis in the laboratory using force plates to generate training data for the NN and to perform another analysis, e.g. using an IMU-based measurement system, afterwards, presupposed that the motion patterns do not change.
Regarding the second data set, which comes from a subject completely unknown to the NN, the overall NRMSE increased almost by seven times compared to the first data set. However, the Pearson correlation coefficient proved a strong correlation between both moment progressions being $\rho > 0.9$ for all joints and moments. The results' accuracy is comparable to those achieved by Ardestani et al. (2014) using a feed forward NN with EMG and force plate data as input and slightly worse than the accuracy using a wavelet NN.

Unfortunately, the results for the NRMSE can only be compared with caution, because the data normalisation is not depicted.
In another study, Ardestani et al. (2015) proved the high sensitivity of joint kinetics to joint kinematics. This suggests the possibility to predict joint kinetics based on joint kinematics. In future studies, the prediction accuracy might be improved by either using further training data or different input parameters to expand the prediction of the NN to unknown subjects. The small amount of steps and the homogeneity of subjects that were available for training in this study might have led to an underestimation of the possibilities of the NN. Using more sophisticated preprocessing steps to enlarge and randomise the available data should even improve the results (Ardestani et al., 2015).

CONCLUSION: This study evaluates the possibilities of NNs to predict joint kinetics based on kinematic data. Although there are limitations due to the small data set, the results indicate the possibilities of NN applications in gait analysis. Once trained, the NN is capable of predicting joint kinetics with a high accuracy for the subjects used for training. This is a valuable tool because it can replace time consuming inverse dynamics calculations and allows for gait analyses with less equipment, time and effort. By broadening the training data, the accurate prediction of joint moments for subjects not used for the training process should be possible. Due to the promising results, further research in this direction is intended.

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