CORE
Metadata, citation and similar papers at core.ac.uk
Provided by Northern Michigan University: The Commons

CREATING VIRTUAL FORCE PLATFORMS FOR CUTTING MANEUVERS FROM KINEMATIC DATA BASED ON LSTM NEURAL NETWORKS

Dominik Fohrmann[1], Marion Mundt[2], Sina David[1], Arnd Koeppe[2], Bernd Markert[2], Wolfgang Potthast[1]

Institute of Biomechanics and Orthopaedics, German Sport University Cologne, Cologne, Germany [1]
Institute of General Mechanics, RWTH Aachen University, Aachen, Germany [2]

The precise measurement of ground reaction forces and moments (GRF/M) usually requires stationary equipment and is, therefore, only partly feasible for field measurements. In this work we propose a method to derive GRF/M time series from motion capture marker trajectories for cutting maneuvers (CM) using a long short-term memory (LSTM) neural network. We used a dataset containing 637 CM motion files from 70 participants and trained two-layer LSTM neural networks to predict the GRF/M signals of two force platforms. A five-fold cross-validation resulted in correlation coefficients ranging from 0.870 to 0.977 and normalized root mean square errors from 3.51 to 9.99% between predicted and measured GRF/M. In future, this method can be used not only to simplify lab measurements but also to allow for determining biomechanical parameters during real-world situations.

KEYWORDS: ground reaction forces, artificial intelligence, change of direction

INTRODUCTION: Sports biomechanics studies investigating kinematic and kinetic aspects of specific motions such as maximum effort changes of direction are usually conducted in controlled laboratory environments. Differences in motion patterns can be very subtle between and within subjects (David et al., 2018; Sheu et al., 2015). Therefore, high precision laboratory measurement equipment is necessary to reveal these differences. A widely applied standard method for biomechanical analyses is a stationary setup of a set of infrared cameras and one or more force platforms embedded in the ground (David et al., 2018; Johnson et al., 2018).
However, the external validity of sports biomechanical studies like those of field sports conducted under controlled lab conditions is usually inferior compared to those conducted in the field (Knudson, 2009) albeit neglecting opponents, noise, tactics, fatigue, etc. Therefore, there is an ongoing trend to make precise biomechanical analyses in the field possible (Johnson, Mian, et al., 2019; Verheul et al., 2020) overcoming the aforementioned limitations. For investigations in field sports, which take place in complex multivariate environments, the shift from the lab to the field could allow for studies closer to real match scenarios. This will enable researchers to gain new insights, especially on possible causes for injuries, which in turn can lead to new implications for sport practitioners.
To promote the ongoing trend to shift biomechanical measurements from the lab to the field, fully-connected feedforward artificial neural networks have been successfully applied to predict biomechanical parameters which cannot be measured directly (Ancillao et al., 2018; Mundt et al., 2019a; Wouda et al., 2018). These networks have the disadvantage that they need time normalized data and the entire time sequence needs to be unrolled, which results in large networks (Mundt et al., 2019a).
Johnson et al. successfully used a simple partial least squares (PLS) algorithm (2018) and convolutional neural networks (2019) to predict the ground reaction forces and moments (GRF/M) during fast cutting maneuvers based on marker trajectories with an accuracy of $r > 0.9$. Additionally, long short-term memory (LSTM) networks have been investigated in biomechanical applications recently (Choi et al., 2019; Hu et al., 2018; Mundt et al., 2020b). Since LSTM networks retain the time sequence, the networks can be held small, which saves system resources, requires less computational power and, thereby, can be beneficial for certain applications. Both Mundt et al. (2020b) and Choi et al. (2019), time normalized the data

used as inputs to the LSTM network, hence, information contained in the time domain was reduced. Both studies compared the performance of an LSTM and a fully-connected network with different results: while Choi et al. (2019) achieved a higher accuracy using LSTMs, Mundt et al. (2020b) achieved lower accuracy.
To further investigate the performance of LSTMs in biomechanics, the purpose of the present work was to predict the GRF/M of 90° cutting maneuvers based on marker trajectories using an LSTM network and to directly add the predicted parameters to the c3d files. This enables the use of the predicted parameters for inverse dynamics simulations.

METHODS: A previously published dataset consisting of 637 90-degree cutting maneuver trials of 70 healthy participants containing both execution and depart contact was used for this study. It encompassed a heterogeneous population of participants (David et al., 2017, 2018). During pre-processing, force plate and marker signals were down sampled to a common frequency of 200Hz. Four different approach- and depart-direction combinations were present. Therefore, marker trajectories and force plate signals were transformed to be uniform. Complete trials lasting from 20 frames before the approach contact to the end of the depart contact were used as input data to the neural network without any time normalization.
Subsequently, the dataset was randomly and subject-wise split into training, validation and test subsets. From the 70 participants, 10% have been held back for testing. The data of the remaining participants were, in a first step, used to determine the model architecture. Other studies which have utilized LSTM-based neural networks for biomechanical data reported architectures consisting of two hidden LSTM layers with 64-512 nodes per layer (Choi et al., 2019; Hu et al., 2018). A grid search was performed over two stacked layers on the remaining 90% (75% training, 15% validation) of the subject data over 100 epochs. It revealed an optimum layer size to be 200 each for our data set. The other hyperparameters, i.e. learning rate, batch size and keep probability for the drop-out have been determined exploratorily. After choosing the optimum model architecture, a five-fold cross-validation has been conducted on 90% of the subject data to evaluate the model performance. Each model was trained over 1000 epochs, whereby overfitting has been prevented by stopping the training process if the loss of the validation began to increase. We used three-dimensional coordinates of 28 markers of the lower body as input features. In previous work it could be shown that adding markers of the upper body does not improve prediction accuracy (Mundt et al., 2019a). Output features were the three-dimensional forces and moments of the two force plates. This resulted in 28x3 = 84 input features and 2x6 = 12 output features.

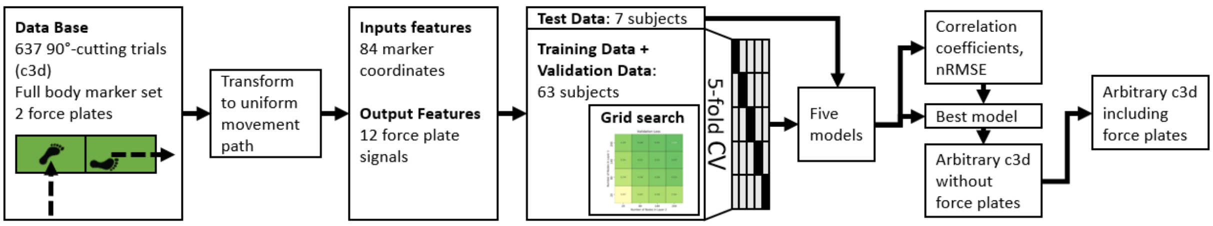

Figure 1: Schematic of the workflow

We calculated the normalized root mean square error (nRMSE) relative to the feature's range as well as the correlation coefficients for each fold. Both metrics were calculated for the approach and depart contact separately. After predicting the GRF/M, the data is added to the .c3d file containing the marker data for further processing, e.g. inverse dynamics simulations. The outline of the workflow is displayed in Figure 1.

RESULTS: For all trials, the approach contact was performed on the first force plate (FP1). The mean correlation coefficients of predicted and measured ground reaction forces over the five folds were 0.907, 0.887 and 0.904 for the anterior-posterior (AP), medio-lateral (ML) and vertical (V) axis respectively. The nRMSE was 9.99%, 8.41% and 9.91%. The predictions of

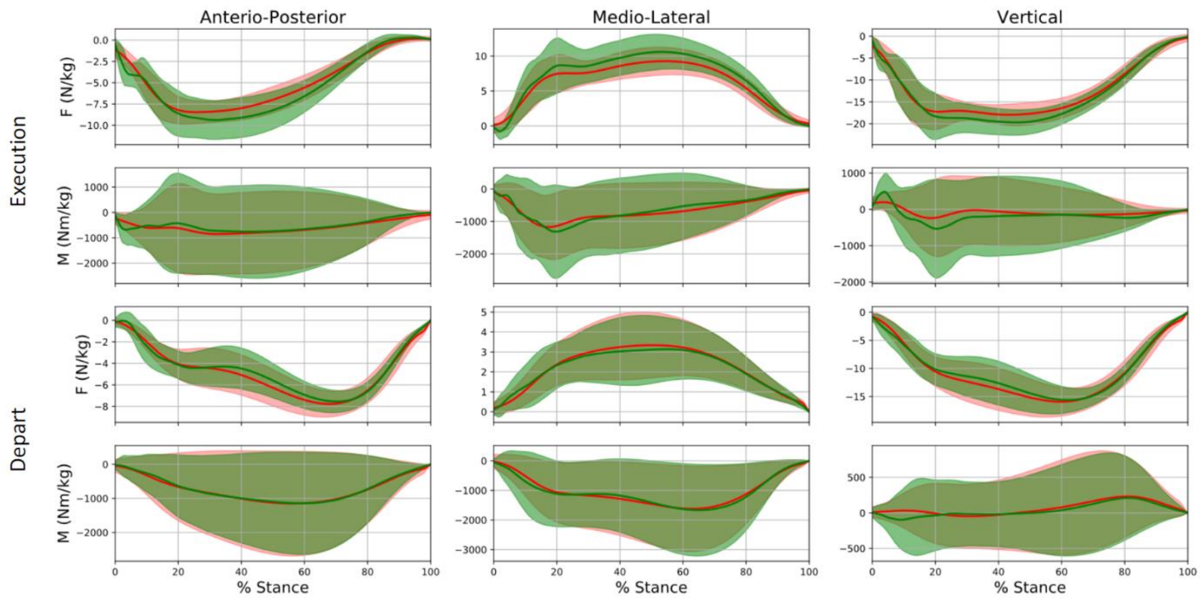

Figure 2: Test-Set output of cross-validation #3. green: ground truth, red: predicted values of n=64 trials. Lines are mean, shaded areas are mean ± one standard deviation

the ground reaction moments around these axes achieved a correlation coefficient of 0.934, 0.888 and 0.870 and an average nRMSE of 4.88%, 5.57% and 6.90%.
The depart contact was performed on the second force plate (FP2). Over the five models, the mean correlation coefficients and nRMSE values between predictions and measurements were 0.916, 0.883 and 0.943 as well as 8.66%, 7.44%, and 8.20% respectively for the GRF. The comparison of the model's predictions and the measured GRM resulted in correlation coefficients of 0.977, 0.945 and 0.942, and nRMSE of 3.51%, 5.52% and 4.59%.
The mean and standard deviation of the measured and predicted values for the execution and depart contact are displayed in Figure 2.

DISCUSSION: The aim of this study was to predict the GRF/M of a complete 90° change of direction using an LSTM network. The approach contact is mainly characterized by braking and rotation towards the depart direction while the depart contact is mainly characterized by propulsion and only little rotation. Overall, very good agreement (r > 0.870) between the measured and predicted values could be achieved, although both contacts evaluated show very different motion patterns. The predictions of the values of the depart contact (r = 0.934) resulted in higher accuracies than those of the execution contact (r = 0.898). There are different possible reasons for that: the GRF/M of the depart contact show less variance in the motion between subjects, which might make this task easier predictable. This hypothesis is supported by the higher accuracy found in those motion directions showing less variance. Another possible explanation can be found in the LSTM cells. The first frames of each sample contain the approach contact, while the last frames contain the depart contact. Hence, the LSTM has much more previous information present for the depart than for the approach contact.
Johnson et al. (2019; 2018) evaluated the prediction of the GRF/M using different machine learning algorithms for the approach contact. They achieved higher accuracies than in this study using a convolutional neural network and a comparable accuracy using an PLS algorithm. However, they did not investigate the combination of the approach and depart contact. We found that the combination of both contacts reduced the prediction performance for a fully-connected feedforward network compared with the accuracy when using specific networks for each task (Mundt et al., 2020b). In this study we also achieved higher accuracies for the prediction of the GRF only than in the present study. In this work, we aimed to explore the potential of a generic approach, i.e. predicting the whole time series of GRF/Ms. However, a more task-specific approach, e.g. training on peak values only, could possibly result in higher accuracy. The approach proposed here is the first one without performing any time

normalization on the data and reduction to the stance phase before training. Additionally, steps executed with the right and left leg were analyzed. Thereby, the applicability of this approach for the user can be considered higher compared with previous methods.
At the moment, the proposed method is still limited to a camera-based setup. However, we could show that the use of (simulated) inertial sensor data can be successfully used to predict the joint angles and joint moments during gait and cutting maneuvers (Mundt et al. 2019b; 2020a; 2020b). This indicates that similar results to those presented can potentially be achieved with a more mobile measurement setup. Wouda et al. (2018) investigated the use of inertial sensors for the determination of the sagittal knee joint angles and the vertical GRF during straight running. They could achieve very good correlations. For this reason, it can be expected that the findings of these previous studies and those of the proposed study can be combined to further improve in-field motion analysis.
In future work, the use of inertial data as inputs should be investigated to further improve the feasibility of this approach for in-field analyses. Thereby, the understanding of biomechanical parameters during real world situations can be strongly improved.

CONCLUSION: The proposed method showed its feasibility in predicting the GRF/M during maximum effort cutting maneuvers without extensive pre-processing of the data. No division of the complete trial into approach and execution task is necessary as well as time normalization could be avoided. With this approach, laboratory-based setups can be simplified by avoiding the use of force plates that restrict the athlete's execution of the task.

REFERENCES:

Ancillao, A., Tedesco, S., Barton, J., & O'Flynn, B. (2018). Indirect Measurement of Ground Reaction Forces and Moments by Means of Wearable Inertial Sensors: A Systematic Review. *Sensors (Basel, Switzerland)*, *18*(8).
Choi, A., Jung, H., & Mun, J. H. (2019). Single Inertial Sensor-Based Neural Networks to Estimate COM-COP Inclination Angle During Walking. *Sensors (Basel, Switzerland)*, *19*(13).
David, S., Komnik, I., Peters, M., Funken, J., & Potthast, W. (2017). Identification and risk estimation of movement strategies during cutting maneuvers. *Journal of Science and Medicine in Sport*, *20*(12), 1075–1080.
David, S., Mundt, M., Komnik, I., & Potthast, W. (2018). Understanding cutting maneuvers—The mechanical consequence of preparatory strategies and foot strike pattern. *Human Movement Science*, *62*, 202–210.
Hu, B., Dixon, P. C., Jacobs, J. V., Dennerlein, J. T., & Schiffman, J. M. (2018). Machine learning algorithms based on signals from a single wearable inertial sensor can detect surface- and age-related differences in walking. *Journal of Biomechanics*, *71*, 37–42.
Johnson, W. R., Alderson, J., Lloyd, D., & Mian, A. (2019). Predicting Athlete Ground Reaction Forces and Moments from Spatio-Temporal Driven CNN Models. *IEEE Transactions on Biomedical Engineering*, *66*(3), 689–694.
Johnson, W. R., Mian, A., Donnelly, C. J., Lloyd, D., & Alderson, J. (2018). Predicting athlete ground reaction forces and moments from motion capture. *Medical & Biological Engineering & Computing*, *56*(10), 1781–1792.
Johnson, W. R., Mian, A., Robinson, M. A., Verheul, J., Lloyd, D. G., & Alderson, J. A. (2019). Multidimensional ground reaction forces and moments from wearable sensor accelerations via deep learning. *ArXiv:1903.07221 [Cs]*. http://arxiv.org/abs/1903.07221
Knudson, D. (2009). Significant and meaningful effects in sports biomechanics research. *Sports Biomechanics*, *8*(1), 96–104.
Mundt, M., David, S., Koeppe, A., Bamer, F., Markert, B. & Potthast, W. (2019a). Intelligent prediction of kinetic parameters during cutting manoeuvres. *Medical & Biological Engineering & Computing*, *57*(8), 1833–1841.
Mundt, M., David, S., Koeppe, A., Bamer, F., Potthast, W., & Markert, B. (2019b). *JOINT ANGLE ESTIMATION DURING FAST CUTTING MANOEUVRES USING ARTIFICIAL NEURAL NETWORKS*. ISBS Proceedings Archive, 37(1), 101.
Mundt, M., Koeppe, A., David, S., Witter, T., Bamer, F., Potthast, W., & Markert, B. (2020a). *Estimation of Gait Mechanics Based on Simulated and Measured IMU Data Using an Artificial Neural Network*. Frontiers in Bioengineering and Biotechnology, 8, 41.
Mundt, M., Thomsen, W., Witter, T., Koeppe, A., David, S., Bamer, F., Potthast, W., & Markert, B. (2020b). Prediction of lower limb joint angles and moments during gait using artificial neural networks. *Medical & Biological Engineering & Computing*, *58*(1), 211–225.
Sheu, C. L., Gray, A. M., Brown, D., & Smith, B. A. (2015). Sex Differences in Knee Flexion Angle During a Rapid Change of Direction While Running. *Orthopaedic Journal of Sports Medicine*, *3*(12), 2325967115617932.
Verheul, J., Nedergaard, N. J., Vanrenterghem, J., & Robinson, M. A. (2020). Measuring biomechanical loads in team sports – from lab to field. *Science and Medicine in Football*, *0*(0), 1–7.
Wouda, F. J., Giuberti, M., Bellusci, G., Maartens, E., Reenalda, J., van Beijnum, B.-J. F., & Veltink, P. H. (2018). Estimation of Vertical Ground Reaction Forces and Sagittal Knee Kinematics During Running Using Three Inertial Sensors. *Frontiers in Physiology*, *9*, 218.