THE INFLUENCE OF FILTER PARAMETERS ON THE PREDICTION ACCURACY OF THE GROUND REACTION FORCE AND JOINT MOMENTS

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Athletes' movement biomechanics are of high interest to predict injury risk, especially in maximum effort cutting manoeuvres. However, using a standard optical measurement set-up with cameras and force plates influences the athlete's performance. Therefore, alternative methods, e.g. Neural Networks, have been used to predict kinetic parameters based on easier to measure kinematic parameters. A previous study has evoked the question, whether the filtering processes of the input and output parameters used for training a feedforward neural network affect the prediction accuracy. To answer this question, four different filter combinations have been used during the pre-processing of joint angles, ground reaction force and joint moments of fast cutting manoeuvres, which were used to train a feedforward neural network. The results revealed a dependency.

KEYWORDS: neural networks, pre-processing, cutting manoeuvres, motion kinetics

INTRODUCTION: The analysis of motion is of high interest to increase the understanding of movement strategies and decrease injury risk, especially during high-risk movements such as cutting manoeuvres (David, Komnik, Peters, Funken, & Potthast, 2017; David, Mundt, Komnik, & Potthast, 2018). Therefore, the analysis of in-field motion becomes more and more relevant to be able to consider internal and external factors occurring in game situations (Elliott & Alderson, 2007). Until today, most research is conducted using laboratory setups consisting of cameras to determine motion kinematics and force plates to determine motion kinetics. Different machine learning approaches have already shown their feasibility for applications in fast changes of directions. Johnson et al. tested different algorithms to overcome the necessity of force plates (Johnson, Donnelly, Mian, & Alderson, 2017; Johnson, Member, Alderson, Lloyd, & Mian, 2019; Johnson, Mian, Donnelly, Lloyd, & Alderson, 2018), while Richter et al. used machine learning to classify different movement strategies during a fast cutting manoeuvre (Richter, King, Falvey, & Franklyn-Miller, 2018). All studies revealed very good correlations. Recently, we tested the prediction accuracy of full body marker trajectories, lower body marker trajectories and joint angles to predict the ground reaction force and joint moments of the lower body with the help of a feedforward neural network (ZITAT UNPUBLISHED MANUSCRIPT). Thereby, the question on whether filtering processes of the input and output data used for such applications influences the results arose, since the joint angles, which are based on filtered and optimised marker trajectories, showed a slightly higher prediction accuracy regarding the joint moments than the unfiltered marker trajectories.

Therefore, this study compares the prediction accuracy of a neural network based on data that was preprocessed using different filter parameters. We hypothesise that smaller cut-off frequencies improve the ability of the neural network to map the inputs and outputs and, thereby, the prediction accuracy increases. All data was filtered using a 4^{th} order low-pass Butterworth filter with the following cut-off frequencies (kinematic data – kinetic data): 10-10, 10-50, 50-50 (Bezodis, Salo, & Trewartha, 2013; Kristianslund, Krosshaug, & Van den Bogert, 2012), 20-20 (David et al., 2017; Vanrenterghem, Venables, Pataky, & Robinson, 2012).

METHODS: The dataset used for training the feed-forward neural network contained 900 execution and depart contacts of 64 subjects (mass 65.32±15.69 kg, height 1.72±0.14 m) that were normalised to 100% stance phase (David et al., 2017, 2018). The study was approved by the Ethics Committee of the German Sport University and all participants gave written consent.
Fourteen infrared cameras (200 Hz, VICONTM, Oxford, UK) and two force plates (1000 Hz, Kistler Instrumente AG, Winterthur, Switzerland) recorded the marker trajectories and ground reaction force. All marker trajectories and force plate data were filtered using a 4th order low-pass Butterworth filter with cut-off frequencies of (kinematic data – kinetic data) 10-10, 10-50, 50-50 and 20-20 Hz, respectively prior to calculating the joint angles and joint moments using the anatomic-landmark-scaled Lower-Body-Model (Lund, Andersen, de Zee, & Rasmussen, 2015)(AnyBody™ Modeling System, Version 6.0, Aalborg, Denmark). The ground reaction force was normalised to the mass of the participant, the joint moments to body height and mass and time was normalised to the stance phase.
For the machine learning approach the data was split randomly in training, validation and test set. Thereby, it was ensured that no data of any subject was part in more than one subset of data. For cross-validation, five different dataset splits were tested. The neural network was implemented using Python Tensorflow. The analysis of the results was undertaken using MATLAB (Release 2018a, The MathWorks, Inc., Natick, Massachusetts, United States). To analyse the prediction accuracy, Pearson's correlation coefficient was calculated for each filter. Based on the mean correlation coefficient, a repeated measures ANOVA was calculated to assess whether different cut-off frequencies affect the prediction. In case of significant differences, a post-hoc t-test with Bonferroni correction was calculated.

RESULTS: The repeated measures ANOVA indicated significant differences between the different filters ($p<0.05$) for the correlation coefficients of the GRF and joint moments. The post-hoc t-test ($p<0.01$) revealed significant differences in all directions of the GRF between all filter combinations besides Filter 10-50 and 50-50 for all directions and Filter 50-50 and 20-20 in the medio-lateral direction only. The prediction of the joint moments is influenced by the filter parameters in most joints and motion planes. The sagittal plane is always affected by the cut-off frequency, while there are some filter combinations showing no difference in the frontal and transverse plane. Filters 10-10 and 20-20 show the least differences. All filters show differences compared to Filter 50-50 in all joints and motion planes (see Table 1).

Table 1: Results of the post-hoc t-test. Green indicates trials where no significant differences were found in the data, while grey indicates significant differences ($p < 0.0125$).

	hip			knee			ankle			GRF		
	sag	front	trans	sag	front	trans	sag	front	trans	ant-post	med-lat	vert
10-10 vs. 10-50												
10-10 vs. 50-50												
10-10 vs. 20-20												
10-50 vs. 50-50												
10-50 vs. 20-20												
50-50 vs. 20-20												

The prediction accuracy for the GRF is very similar for all filter used (Filter 10-10: r = 0.957, Filter 10-50: r = 0.928, Filter 50-50: r = 0. 0.935, Filter 20-20: r = 0.944). The mean correlation coefficient is larger than 0.8 in the medio-lateral direction and larger than 0.9 for the anterior-posterior and vertical direction. For the joint moments, the filter parameters affect the prediction accuracy, showing the highest prediction accuracy for Filter 20-20 and the lowest for Filter 50-50 (Filter 10-10: r = 0.846, Filter 10-50: r = 0.822, Filter 50-50: r = 0.556, Filter 20-20: r = 0.858). Additionally, the standard deviation is higher in Filter 50-50 than in the other filters, indicating a larger number of outliers (see Figure 1).

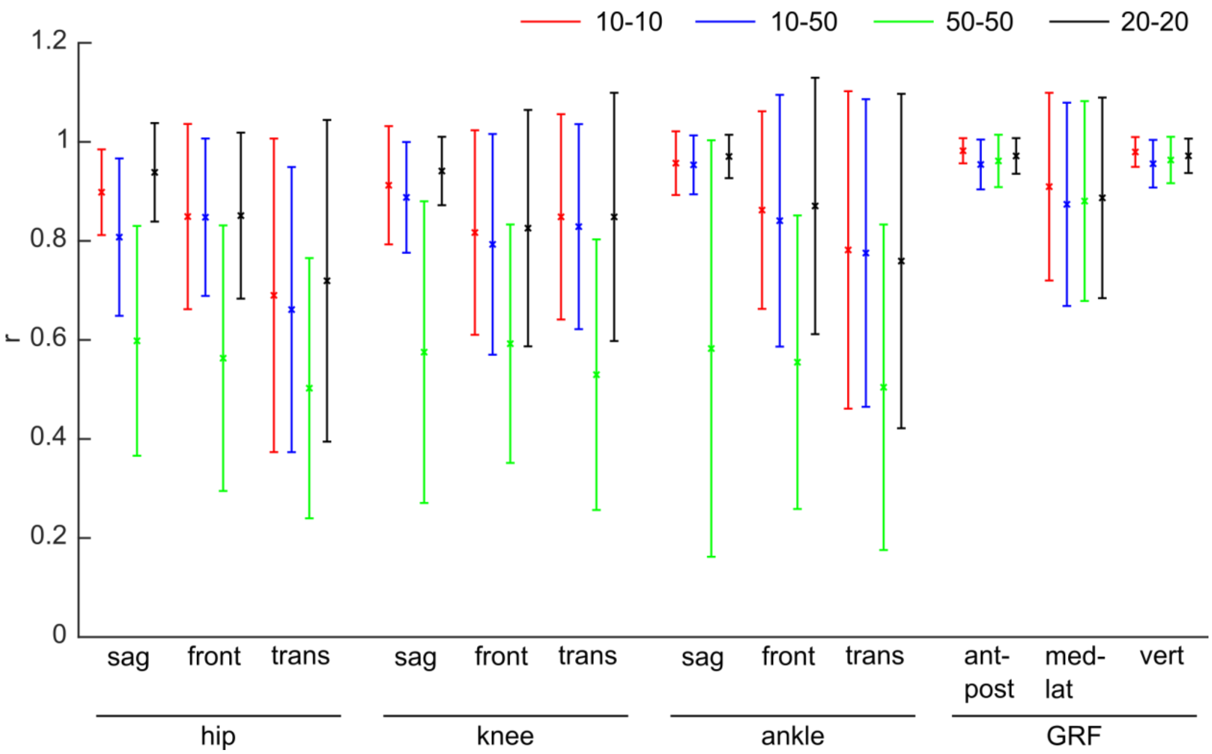

Figure 1: Error bars of the correlation coefficient of the joint moment and GRF prediction based on the different filter parameters.

DISCUSSION: This study aimed to analyse whether there is a difference in the prediction performance of a feedforward neural network dependent on the filtering processes performed on the input and output data. The hypothesis that the cut-off frequency influences the ability of the neural network to map the inputs and outputs could be statistically proven. The highest prediction accuracy could be achieved using the Filter 20-20 for joint moments, and Filter 10-10 for the ground reaction force. Anyway, the ground reaction force prediction was less affected by the filtering process than the joint moment prediction. These results indicate, that the filtering process of the kinematic data is of higher relevance to the prediction accuracy than the filtering of the force data.

Our results support the findings of previous studies, where higher fluctuations in joint moment curves could be observed, especially with increasing cut-off frequency difference between kinematic and kinetic data (Bezodis et al., 2013; Kristianslund et al., 2012). Especially in those planes with less motion, this effect causes high discrepancies in the prediction accuracy of the neural network between the different filters. Large fluctuation in the moment are hard to learn for the model compared to smooth data without sudden spikes.

The dataset used in this study is large compared to many other biomechanical studies, but for a machine learning application, the size still needs to be considered as a limitation (Halilaj et al., 2018). We tried to overcome this limitation using five different dataset splits to cover dependencies based on the data in the test set. We could observe differences in the prediction accuracy based on the dataset split, which indicates the need of more data. Especially in tasks like fast cutting manoeuvres, which are executed based on different movement strategies (David et al., 2018), a large dataset is advantageous for reliable predictions. Probably the prediction accuracy for all filter would improve using more data for the training process. Nevertheless, our results clearly show the importance of data preprocessing and standardisation for machine learning applications.

CONCLUSION: The results of this study indicate the necessity of standardised filtering processes during the preprocessing of data that is used for machine learning applications. Based on the processing steps undertaken, the prediction results differ significantly. Hence, the performance of different machine learning algorithms can only be evaluated based on the same dataset that was similarly preprocessed.

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