PREDICTING NET JOINT MOMENTS DURING A HANG-POWER CLEAN FROM GROUND REACTION FORCES WITH A NEURAL NETWORK

Kristof Kipp[1] and Matthew D. Giordanelli[1]

[1]Department of Physical Therapy, Marquette University, Milwaukee, WI, USA

The purpose of this study was to develop a deployable neural network (NN) to predict hip, knee, and ankle Net Joint Moments (NJM) from Ground Reaction Force (GRF) data during the hang-power clean. Thirteen male lacrosse players performed the hang-power clean exercise at 70% of their one-repetition maximum while GRF and 3-D motion data were acquired. An inverse dynamics procedure was used to calculate hip, knee, and ankle NJM. Center-of-mass velocity, position, and power were calculated from the GRF data and used as inputs to a NN that predicted hip, knee, and ankle NJM. Predicted NJM from the trained NN exhibited moderate root mean squared errors, but produced large percentage differences between predicted and calculated peak NJM when tested on new data, which likely resulted from overfitting during open loop training or insufficient closed loop training.

KEYWORDS: biomechanics, machine learning, weightlifting, sports.

INTRODUCTION: Weightlifting exercises and their derivatives, such as the hang-power clean (HPC), are commonly used within strength and conditioning programs to increase jump performance (Hackett et al., 2016). Although research has characterized barbell-lifter system velocity, force, and power of these exercises (e.g., Comfort, Allen, & Graham-Smith, 2011; Kawamori et al., 2005), relatively few studies have investigated joint-level mechanics (Kipp et al., 2018). However, knowledge about the net joint moments (NJM) that are produced by the muscles about the three primary lower extremity joints would greatly facilitate the design of resistance programs, because weightlifting exercises and their derivatives could be implemented with greater specificity and efficiency.

To calculate NJM, researchers collect whole-body kinematic, ground reaction force (GRF), and anthropometric data and use them as inputs to inverse dynamics procedures (Winter, 2005). Unfortunately, the gathering and processing of these biomechanical data is very resource intensive, relies on expensive equipment, and can be very obstructive to the athlete. Neural networks (NN) may provide a solution because they can be used to model complex relationships between biomechanical inputs and outputs (Schollhorn, 2004). For example, Liu et al. (2009) used NN to predict lower extremity NJM during countermovement and squat jumps from GRF data, such as vertical GRF, centre-of-mass velocity, and centre-of-mass position.

The purpose of this study was to develop and train a NN to predict hip, knee, and ankle joint NJM from GRF data during the HPC. The ultimate goal of this research is to develop deployable NN models that can be used by sports scientists and practitioners to analyze joint-level mechanics of weightlifting exercises and derivatives during field testing, without the need for expensive equipment, large computational resources, and obtrusive data collection procedures for athletes.

METHODS: Thirteen male, NCAA DI lacrosse players (Mean±SD; age: 20.1±1.2 years; height: 1.78±0.07 m; body mass: 80.4±8.1 kg; 1-RM HPC: 100.4±8.1 kg) were recruited for this study. All subjects were familiar with the HPC, and were tested during their off-season training. The study was approved by the local University's IRB, and all subjects provided written informed consent before the beginning of any data collection.

Players performed a general warm-up that consisted of calisthenics and different types of vertical jumps. They then proceeded to a specific warm-up that consisted of two submaximal (30% & 50% 1-RM HPC) sets of the HPC. Players performed one work set of three repetitions at 70% of HPC 1-RM, which was based on results from 1-RM testing performed a week prior to the current study. All sets were performed as cluster sets with 20 seconds of rest between the repetitions within each set.

A 12-camera motion capture system recorded the kinematic data of reflective markers that were attached to various anatomical landmarks of each lifter's feet, shanks, thighs, and pelvis at 100 Hz (Kipp et al., 2018). Two force plates were used to collect GRF data at 1,000 Hz. A standard biomechanical model (Plug-in Gait) was then used to calculate hip, knee, and ankle joint biomechanics. GRF data were also used to calculate centre-of-mass (COM) velocity, position, and power (Figure 1). Time-series data for the right leg were extracted and time-normalized to 100% of the pull-phase, which was defined as the period from beginning of the countermovement to when the GRF fell below 10 N. Three-trial ensemble averages were created for all biomechanical variables.

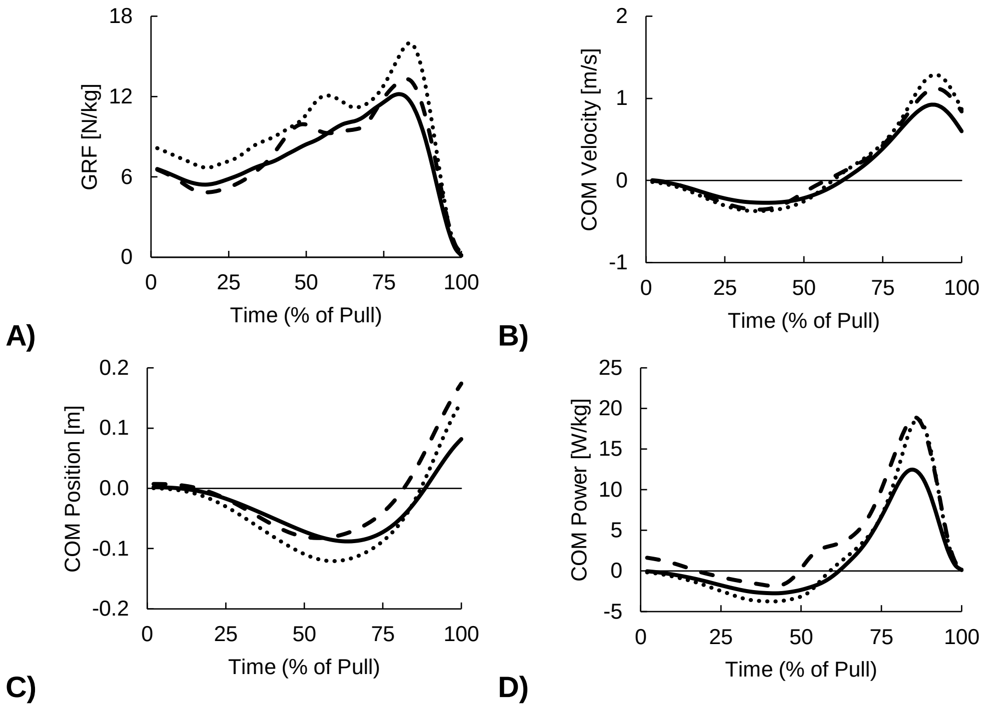

Figure 1: Ensemble average ground reaction forces [N/kg] (A), centre-of-mass (COM) velocities [m/s] (B), centre-of-mass positions [m] (C) centre-of-mass powers [W/kg] (D) during the Hang-power Clean. Input data for the open (n=5) and closed (n=5) loop neural networks are shown in solid and dashed lines, respectively. Ensemble average test data (n=3) are shown in dotted lines.

All GRF and COM data served as inputs to a NN to predict the NJM time-series data. The NN consisted of a nonlinear autoregressive network with exogenous inputs, and had a 4-node input level, a 20 neuron hidden level, and a 3-node output level. The NN was trained with Bayesian Regularization back-propagated error correction and had a feedback-delay of 1:2. The NN was trained in an open loop format with data from five participants, the NN was then further trained in a closed loop format from five additional participants. The final closed loop, deployable NN was then tested on three remaining 'test' participants (Figure 1). The performance of the open and closed loop NN were evaluated based on their root mean square errors (RMSE). In addition, the performance of the closed loop NN was also evaluated based on visual inspection of the predicted output data in relation to the actual, calculated output data. Lastly, the percent difference between inverse-dynamics calculated and NN predicted peak hip, knee, and ankle NJM were calculated to provide a pragmatic interpretation of the NN performance.

RESULTS: The final RMSE for open and closed loop training of the NN were 0.90 and 0.89 [N·m/kg], respectively. The subsequent testing the NN produced joint-level RMSE of 0.58±0.50, 0.91±0.77, and 0.71±0.44 [N·m/kg] for the hip, knee, and ankle, respectively (Figure 2).

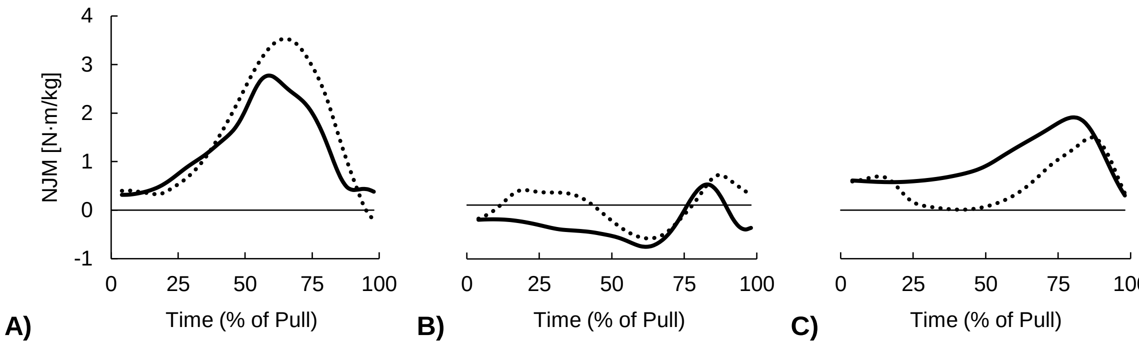

Figure 2: Hip (A), Knee (B), and Ankle (C) Net Joint Moments (NJM [N·m/kg]) during the Hang-Power Clean. Inverse-dynamics calculated NJM are shown in solid lines and Neural-Network predicted NJM are shown in dotted lines. Values in the positive y-direction indicate extension/plantar-flexion NJM.

The percentage difference between the predicted and actual NJM are presented in Table 1.

Table 1: Inverse dynamics calculated (Actual) and neural network predicted (Predicted) peak average±SD net joint moments (NJM) for the three test cases.

NJM	Actual	Predicted	% Difference
Hip	2.89±1.41	3.61±0.05	25%
Knee	0.39±1.02	0.58±0.03	46%
Ankle	1.92±0.90	1.50±0.11	-22%

DISCUSSION: The purpose of this study was to develop and train a NN to predict hip, knee, and ankle joint NJM from GRF data during the HPC. The goal of this research is to develop a deployable NN that can be used in combination with GRF data acquired from portable force plates during field testing to predict joint-level mechanics of weightlifting exercises and their derivatives.

Evaluation of NN is typically based on the RMSE obtained during training and testing of each model. The NN was initially trained in an open loop format, where past time-steps of the actual inverse dynamics calculated data were used, and in a closed loop format, where data from past time-steps of the NN predicted based output data were used. The RMSE for open and closed loop training were 0.90 and 0.89 [N·m/kg], respectively, which indicates that the NN performed equally well under both formats. The lack of difference may indicate either poor training in open loop format or the relatively quick convergence and lack of improvement in closed loop training. Given that the hidden-layer consisted of 20 neurons, the NN may have overfitted the data at the expense of generalizability.

The joint-level RMSE for the NN predicted NJM were 0.58, 0.91, and 0.71 [N·m/kg] for the hip, knee, and ankle joints, respectively. Liu et al. (2009) reported RMSE in the range of 0.12 to 0.28 in their NN prediction of lower extremity NJM during squat and countermovement jumps. Considering the similarities between jumping and weightlifting movements (Garhammer & Gregor, 1992), the findings of Liu et al. (2009) provide a reasonable comparison and indicates that the prediction ability of the current NN is worse than what is found in the literature.

Evaluation of NN are also sometimes based on visual inspection of the predicted output data in relation to the actual, calculated output data. The percent difference between inverse-dynamics calculated and NN predicted peak hip, knee, and ankle NJM ranged between 22 and 46%, which are quite large and indicate that the NN is not suitable to predict peak joint kinetics.

CONCLUSION: The NN that was developed and tested for the current study did not adequately model the associations between GRF parameters and NJM during the HPC. To improve the performance of the NN and facilitate its deployment, future research may need to refine the training parameters (e.g., feedback-delays and/or number of hidden neurons) and partitioning of the open and closed loop training data.

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