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# Predicting Net Joint Moments During a Weightlifting Exercise with a Neural Network Model

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## Abstract

The purpose of this study was to develop and train a Neural Network (NN) that uses barbell mass and motions to predict hip, knee, and ankle Net Joint Moments (NJM) during a weightlifting exercise. Seven weightlifters performed two cleans at 85% of their competition maximum while ground reaction forces and 3-D motion data were recorded. An inverse dynamics procedure was used to calculate hip, knee, and ankle NJM. Vertical and horizontal barbell motion data were extracted and, along with barbell mass, used as inputs to a NN. The NN was then trained to model the association between the mass and kinematics of the barbell and the calculated NJM for six weightlifters, the data from the remaining weightlifter was then used to test the performance of the NN – this was repeated 7 times with a k-fold cross-validation procedure to assess the NN accuracy. Joint-specific predictions of NJM produced coefficients of determination ($r^2$) that ranged from 0.79 to 0.95, and the percent difference between NN-predicted and inverse dynamics calculated peak NJM ranged between 5% and 16%. The NN was thus able to predict the spatiotemporal patterns and discrete peaks of the three NJM with reasonable accuracy, which suggests that it is feasible to predict lower extremity NJM from the mass and kinematics of the barbell. Future work is needed to determine whether combining a NN model with low cost technology (e.g., digital video and free digitising software) can also be used to predict NJM of weightlifters during field-testing situations, such as practice and competition, with comparable accuracy.

## Keywords

Biomechanics; Machine learning; Neural network; Sports

## 1. Introduction

Sport biomechanists and coaches analyse Net Joint Moments (NJM) during sport tasks because they provide useful information about neuromuscular control strategies during those tasks (Bartlett, 2007). To calculate NJM, researchers and practitioners collect whole-body kinematic, ground reaction force (GRF), and anthropometric data, and use them as inputs to inverse dynamics procedures that yield NJM (Winter, 2009). The problems that biomechanists and coaches face are that the gathering and processing of the necessary biomechanical data is resource intensive, relies on expensive equipment, and can be obstructive to athletes.

A possible solution would be to use Neural Networks (NN) to predict NJM from other data that can be more easily collected by biomechanists and practitioners (Schöllhorn, 2004). For example, Hahn and O'Keefe (2008) developed a NJM estimation model that could be used in clinical settings with minimal equipment and technical support. They used NN models to predict NJM during gait from kinematic inputs, and their results indicated that demographic and joint kinematic data in combination with simplified NN models could predict hip, knee, and ankle NJM during normal walking with acceptable accuracy (i.e., coefficients of determinations between 0.90 and 0.95). Liu et al. (2009)developed a NN model that used ground reaction force (GRF) data to predict NJM during squat and countermovement jumps, and showed that lower extremity NJM could be accurately predicted (correlation coefficients between 0.96 and 0.99) from various parameters derived from GRF data (e.g., centre-of-mass position and velocity).

NJM play a crucial role in the sport of weightlifting (Bartonietz, 1996, Baumann et al., 1988). Not only do they provide insight into an athlete’s individual technique, but they also offer information about the performance capacity of individual weightlifters (Enoka, 1988, Garhammer, 1981, Kipp et al., 2012a). The spatiotemporal patterns of the NJM can reflect different technical styles between weightlifters (Garhammer, 1981), whereas peak NJM offer insight into the neuromuscular demands required to exert maximal efforts during maximal effort lifts (Baumann et al., 1988, Kipp et al., 2012b). Collectively, these results highlight the importance of NJM in relation to weightlifting performance.

Even though knowledge about NJM appears to be crucial, the major obstacles that preclude their widespread use in the sport setting relate back to problems associated with the cost of the necessary equipment and the obstructiveness to athletes. One way to overcome these obstacles would be to use NN models to predict NJM from simpler, and more easily collected biomechanical data. Given that barbell mass and motion data can be easily acquired with simple methods and inexpensive equipment (Dæhlin et al., 2017, Garhammer and Newton, 2013), the development and validation of NN models would be a tremendous benefit to sports biomechanists and coaches because these models would allow them to predict NJM of weightlifters without the need for expensive equipment or obstructive instrumentation of athletes. The purpose of this study was to therefore develop and train a NN that uses barbell mass and motions to predict hip, knee, and ankle NJM during an Olympic weightlifting exercise (i.e., the clean).

# 2. Methods

## 2.1. Subjects

Seven weightlifters (body-mass: 106.0 ± 13.2 kg; 1-Repetition Maximum (1-RM): 126.4 ± 22.9 kg) were recruited for this study. All subjects provided written informed consent approved by the University's Institutional Review Board.

## 2.2. Data collection procedures

Sixteen reflective markers were attached to anatomical landmarks of each lifter's feet, shanks, thighs, and pelvis (Kipp et al., 2011). In addition, a strip of reflective tape was wrapped around the long axis of the barbell at its mid-point. Each weightlifter performed a warm-up with several repetitions and sets at lighter loads, and then performed two repetitions at 85% of their most recent 1RM of the clean exercise. The 3-D positions of all markers were recorded with a 6-camera motion capture system (VICON 460, ViconMX, Los Angeles, CA, USA) at 250 Hz. GRF were collected at 1250 Hz from two force plates (Kistler model 9281A, Kistler Instrument Corp, Amherst, NY, USA) that were built into a wooden 2.4 m × 2.4 m weightlifting platform.

## 2.3. Data processing procedures

The kinematic and kinetic data were filtered at 6 Hz and 25 Hz, respectively. Lower extremity biomechanics were calculated with a rigid-link segment model that included a foot, shank, thigh, and pelvis segment (Kipp et al., 2011). A typical 3-D inverse dynamics procedure was used to calculate the internal NJM at the hip, knee, and ankle joints (Winter, 2009). Sagittal-plane NJM were normalised to each lifter's body-mass and height (i.e., N m $kg^{-1}$ $m^{-1}$), and are presented such that hip and knee extension as well as plantarflexion NJM are positive. NJM time-series data from the right leg were time-normalised to 100% of the pull phase, which was defined as period from when the barbell left the platform to when the GRF fell below 10 Newton's (Fig. 1). The horizontal and vertical positions of the barbell were also extracted during that same phase. The direction convention for barbell motion was such that the negative and positive directions indicated barbell motion towards and away from the lifter, respectively. Only data from the 85% 1-RM set were used as part of the NN analysis.

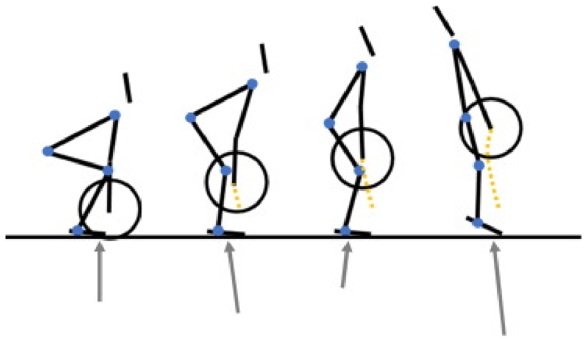

Fig. 1. Depiction of pull-phase time period for the clean, and the biomechanical data that must be obtained for inverse dynamics procedures i.e., kinematic data of the body (blue dots) as well as ground reaction forces (grey vector lines). The motion path of the barbell is shown in yellow dotted lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## 2.4. Neural network analysis

The NN developed for this study consisted of a nonlinear autoregressive network with external inputs (NARX: Fig. 2), and was developed with the Neural Network Toolbox in MATLAB R2015a (The Mathworks, Inc, Natick, MA, USA). The horizontal and vertical position time-series data as well as the mass of the barbell served as inputs and the three NJM time-series served as outputs; the NN thus had three variables (i.e., nodes) in both its input and output layer. The hidden layer had 10 neurons, which were connected to each input and output node. The weights and biases of the NN were trained with Levenberg-Marquardt back-propagated error correction, and the input and feedback delayswere both set to 1:2. A division of 70/15/15 was used for the respective training/validation/testing of the data within the NN.

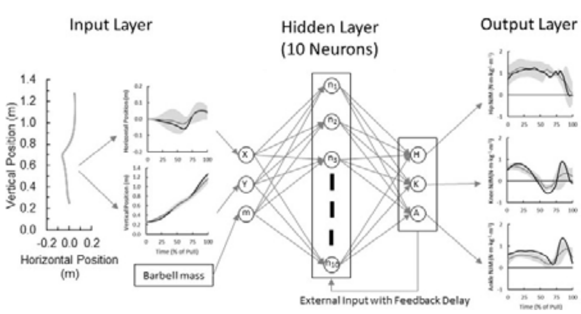


Fig. 2. Neural Network architecture. Note: The time-series figures under the input level (i.e., barbell positions) and output level (i.e., hip, knee, and ankle net joint moments) show the ensemble average (Mean ± SD) of training cases (grey lines and error bars) that were used to train one of the k-fold cross-validation networks, and the single test case (black lines) that was used to test the performance of the respective neural network.

A k-fold cross-validation procedure was used to assess the accuracy of the NN. The 7-fold cross-validation involved training the NN with data from six weightlifters (i.e., the training cases), and then testing with data from the one remaining weightlifter (i.e., the test case). The NN performance was evaluated based on the Root Mean Squared Error (RMSE) and the coefficient of determination ($r^2$) between the NN-predicted output data and the actual inverse dynamics calculated data for each of the three NJM of the test case for each fold of the cross-validation procedure. Visual inspection of the NN-predicted output and the percent difference (%Diff) between NN-predicted and inverse dynamics calculated peak NJM data were used to provide a pragmatic interpretation of the NN performance (Liu et al., 2009). The averages and standard deviations from the 7-fold cross-validation procedures were calculated for the RMSE, $r^2$, and %Diff.

## 3. Results

The overall RMSE for the training and testing of the NN were 0.0022 ± 0.0008 and 0.26 ± 0.11 N m kg$^{-1}$ m$^{-1}$, respectively. The RMSE for the prediction of individual NJM were 0.148 ± 0.183 for the hip, 0.057 ± 0.044 for the knee, and 0.017 ± 0.009 N m kg$^{-1}$ m$^{-1}$for the ankle joint (Fig. 3). The coefficients of determination for the prediction of individual NJM ranged from 0.79 to 0.95, and the percent difference between NN-predicted and inverse dynamics calculated peak NJM ranged from 5% to 16% (Table 1).

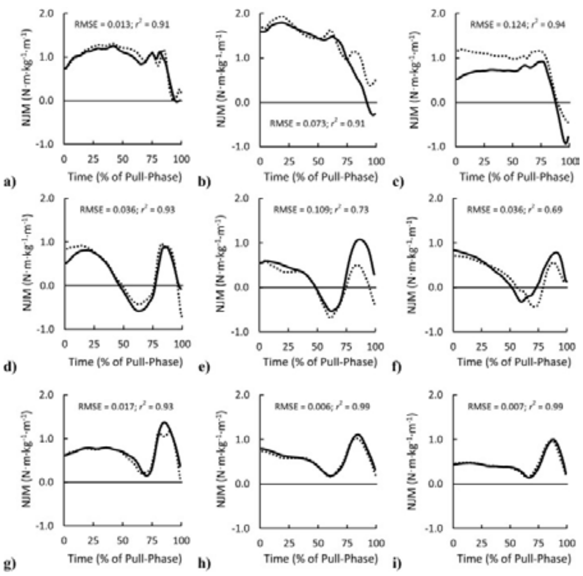


Fig. 3. Inverse dynamics calculated (solid line) and Neural Network predicted (dotted line) Net Joint Moment (NJM: N m kg$^{-1}$ m$^{-1}$) data for the hip (a–c), knee (d–f), and ankle (g–i) joints during the pull-phase of the clean for three different (one per column) weightlifters. Note: The positive y-axis direction indicates hip and knee extension as well as plantarflexion NJM.

Table 1. Mean ± SD of the peak Net Joint Moments (NJM [N m kg$^{-1}$ m$^{-1}$]) as calculated with inverse dynamics procedures (Calculated) and predicted with the Neural Network (Predicted), the coefficient of determination ($r^2$) between the two quantities, and the percent difference (%Diff) between the two quantities.

| NJM | Calculated | Predicted | $r^2$ | %Diff |
|---|---|---|---|---|
| Hip | 1.37 ± 0.36 | 1.47 ± 0.26 | 0.80 ± 0.18 | 6 ± 15 |
| Knee | 0.88 ± 0.13 | 0.77 ± 0.30 | 0.79 ± 0.13 | −16 ± 21 |
| Ankle | 1.14 ± 0.15 | 1.12 ± 0.14 | 0.95 ± 0.03 | −5 ± 6 |

## 4. Discussion

The purpose of this study was to develop and train a NN model to predict hip, knee, and ankle NJM from vertical and horizontal motions and mass of a barbell during an Olympic weightlifting exercise. The low training and testing RMSE suggest that the NN effectively modeled the relationship between the mass and kinematics of the barbell and the lower extremity NJM during the clean. The accuracy of the joint-specific NJM predictions from the trained NN model were comparable to other results reported in the literature. For example, Liu et al. (2009) reported RMSE between 0.122 and 0.280 and correlation coefficients (*r*) between 0.95 and 0.99 in their NN estimation of hip, knee, and ankle NJM during squat jumps and countermovement jumps. Given the similarities between jumping and weightlifting movements (Garhammer and Gregor, 1992), the RMSE and $r^2$values for our NN-based NJM predictions of thus compare well to findings of Liu et al. (2009). The prediction accuracy of our NN model is also similar to that of Hahn and O'Keefe (2008) who used NN models to predict NJM during gait, their results indicated that demographic and joint kinematic data could predict hip, knee, and ankle NJM during normal walking with $r^2$values between 0.90 and 0.95.

We found that the absolute percent difference in discrete peak NJM between the NN-predicted and actual inverse dynamics calculated data ranged between 5 and 16%. The NN model often over-predicted the peak NJM data for the hip (e.g., Fig. 3c), but under-predicted the NJM for the knee (e.g., Fig. 3e). It is somewhat difficult to establish whether these differences are of practical importance because of the paucity of NJM analyses in the weightlifting literature. Baumann et al. (1988) reported NJM for athletes who competed at the 1985 world championships in weightlifting. From their data, one can estimate that the differences in hip NJM between a gold-medal weightlifter and one of the bottom ten weightlifters was approximately 14%. Furthermore, data from a series of world record lifts by a single lifter suggests that the hip NJM increased by 7.6% between lifts at 135 kg and 140 kg, and by another 7.6% between the lifts of 140 kg and 143 kg. While these differences may appear low compared to the present prediction errors, one should note that the pattern of the NJM time-series are sometimes purported to be of greater practical significance than their actual magnitude because temporal aspects also relate to weightlifting performance and technique (Baumann et al., 1988, Enoka, 1988, Garhammer, 1981, Kipp et al., 2012b). The percent difference in discrete peak NJM should therefore be interpreted along with the high $r^2$ values (0.79–0.90) for each of the NJM.

The NN was trained and tested with data from seven college-level weightlifters. Although the performance level of these weightlifters was below that reported in the literature for elite national and international weightlifters (Garhammer, 1980, Garhammer, 1985), barbell mass was an input to the NN to account for differences in performance level. Further, the participants in the current study exhibited barbell trajectoriesand NJM time-series that were similar to data from weightlifters who competed at higher levels (Baumann et al., 1988, Garhammer, 1981, Stone et al., 1998). Given the purported importance of the temporal structure and patterning of the NJM time-series, the qualitative similarity in NJM time-series data is encouraging because it may indicate that the prediction accuracy could indeed be fairly robust and that the NN could generalize well to other populations of weightlifters. Nonetheless, it remains to be determined how the NN would perform with input data from other populations, the generalisability of the NN therefore needs to be further investigated.

The practical implications of our findings are relevant to sports biomechanists and coaches as they suggest that it may be possible to predict NJM during weightlifting practices or competitions with a NN model and information about the mass and bar path of the barbell. While digital video cameras, and free digitizing equipment (e.g. Kinovea), make it easy to track barbell kinematics the effect of lower technical specifications of these cameras needs to be determined. Another issue concerns the accessibility of NN models for coaches, which could be addressed through the use of MATLAB’s Application Compiler to implement the NN code into Microsoft Excel.

This study showed that it is possible to predict NJM with a NN and the motions and mass of the barbell as weightlifters perform the clean exercise. Given that the barbell kinematic data can be easily recorded and processed with low-cost motion analysis solutions (Dæhlin et al., 2017, Garhammer and Newton, 2013), future work should try to determine whether combining a NN models with such technology can accurately predict NJM during of weightlifting exercises without the need for expensive equipment or obstructive instrumentation.

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