NEURAL NETWORK PREDICTION OF BARBELL KINEMATICS FROM JOINT KINETICS IN WEIGHTLIFTING

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The purpose of this study was to develop and train neural networks (NN) to predict barbell motion and velocity from hip, knee, and ankle joint torques during a weightlifting exercise. Seven weightlifters performed two repetitions of the clean exercise at 85% of maximum while reaction forces and 3-D motion data of the lifter and barbell were acquired. An inverse dynamics procedure was then used to calculate torques at the hip, knee, and ankle joints. The joint torque time-series data were used as inputs to two seperate NN to predict 1) the horizontal and vertical barbell trajectories and 2) the vertical barbell velocities. Both NN demonstrated low mean square errors and good agreement with experimental data, which suggests NN could be used to inform weightlifters and their coaches about the relationships between joint kinetics and barbell kinematics.

KEY WORDS: biomechanics, machine learning, sport, technique, clean.

INTRODUCTION: Sports biomechanists often analyse and process barbell kinematic data in an effort to provide weightlifters and their coaches with important biomechanical information about weightlifting technique (Baumann et al., 1988; Gourgoulis et al., 2000; Hakkinen, Kauhanen & Komi, 1984). The analysed kinematic data typically relates to the trajectories and velocities of the barbell during the different pull phases of either the snatch or the clean, because these variables are thought to be important for a successful lift attempt. More specifically, barbell trajectories are often characterized by the discrete backward and forward displacements during the first and second pull, respectively, and together provide a simplified overview of the barbell's motion (Garhammer 1985; Isaka, Okada & Funato, 1996). In addition, the vertical velocity of the barbell is also considered to be of major importance, because an optimal vertical velocity profile is needed for a weightlifter to lift maximal loads (Bartonietz, 1996; Bottcher & Deutscher, 1999; Kipp & Harris, 2015).

To a lesser extent, sports biomechanists also examine joint kinetics during weightlifting exercises (Baumann et al., 1988; Kipp et al., 2012). Joint torques, however, provide insightful information about the neuromuscular and motor control mechanisms during human movement (Winter, 2005). While joint torques obviously contribute to the movement of the human body, not much is known about how they relate to motion or speed of the barbell during weightlifting. To date, only one study has investigated similar relationships, but with a focus on joint and barbell power (Kipp et al. 2013). However, given that the kinematics of the barbell are an integral part of weightlifting technique, it would appear to be very important to study the relationships between muscle-generated joint torques and barbell displacements and velocities.

Neural networks have been widely used to analyse relationships between complex inputs and outputs in a number of biomechanical studies (Hahn & O'Keefe, 2008; Liu et al., 2009). For example, Liu et al. (2009) demonstrated that a neural network could adequately predict the non-linear relationships between lower extremity joint torques and ground reaction force parameters. Particular benefits of neural network models are that they can account for non-linear relationships between large numbers of data inputs and/or outputs and that they exhibit high predictive accuracy over other techniques. Given that neural network analyses would seem ideal to investigate the relationship between joint torques and barbell kinematics in weightlifting, the purpose of this study was to develop and train two neural networks to predict barbell motion and velocity from hip, knee, and ankle joint torques during a weightlifting exercise.

METHODS: Seven US collegiate-level weightlifters (Body-mass: 106.0±13.2 kg; Competition maximum clean (1-RM): 126.4±22.9 kg) provided written informed consent approved by the local University's IRB. Each lifter performed a warm-up that included lifting light loads up to 50% of his 1-RM. After the warm-up, each lifter performed 2-3 repetitions at 65%, 75%, and 85% of 1-RM with approximately 2-3 minutes rest between each set.

Kinematic and kinetic data were collected during each set. Kinematic data were collected with a 6-camera Vicon motion capture system at 250 Hz. Kinematic data of the barbell were recorded from a strip of reflective tape that was wrapped around the long axis at the mid-point of the barbell. Kinematic data of the lifter were recorded from reflective markers that were attached to various anatomical landmarks (Kipp, Harris & Sabick, 2011). Kinetic data were collected at 1,250 Hz from two Kistler force plates that were built into an 2.4 m x 2.4 m weightlifting platform.

Kinematic and kinetic data were filtered with 4^{th}-order Butterworh filters at 6 Hz and 25 Hz, respectively. Horizontal and vertical barbell positions were extracted. The vertical barbell position was differentiated once to derive vertical barbell velocity. Lower extremity biomechanics were calculated based on a four rigid-link model that included a foot, shank, thigh, and pelvis segment. A standard inverse dynamics procedure, which combined kinematic and kinetic data with anthropometric data, was used to calculate the net internal joint torques of the hip, knee, and ankle joints (Winter, 2005). Time-series data from the right leg, and in the sagittal-plane, were then extracted for analysis. All data were time-normalized to 100% of the lift phase (i.e., time from when the the barbell left the platform to the time the vertical ground reaction force fell below 10 Newtons).

The joint torque time-series data were then used as inputs to two seperate neural networks to predict the 1) horizontal and vertical barbell trajectories (NN1) and 2) vertical barbell velocity (NN2). Both networks consisted of nonlinear autoregressive networks with exogenous inputs. Both networks had a 3-layer input level and a 10-layer hidden level. The output levels of NN1 and NN2 had 2 layers and 1 layer, respectively. Both networks were trained with Levenberg-Marquardt back-propagated error correction and had a feedback-delay of 1:2. The networks were developed and trained on data from the six randomly chosen weightlifters. The network was then tested on the one remaining weightlifter. The performance of each network was evaluated based on the mean square error (MSE) and inspection of the predicted output data in relation to the actual output data. In addition, the percentage difference between selected discrete variables were calculated to provide a pragmatic interpretation of the networks' performances. These variables included peak backward, forward, and vertical barbell displacements and peak vertical velocity.

RESULTS: The MSE for the training of NN1 was 5.51×10^{-6}, and the MSE for the training of NN2 was 2.36×10^{-1}. The MSE between the predicted and actual barbell trajectory data for the randomly chosen test subject was 5.56×10^{-2}, and the MSE between the predicted and actual barbell velocity data for the randomly chosen test subject was 1.99.

The actual barbell kinematic data from the test case and the predicted barbell kinematic data from the two neural networks are presented in Table 1, along with the percentage difference between the predicted and actual peak displacement and velocity data.

Table 1
Barbell kinematic data from the test case (Actual) and the neural network (Predicted)

Kinematic Data	Actual	Predicted	% Difference
Backard Displacement (m)	-0.06	-0.06	0.01%
Forward Displacement (m)	0.05	0.05	0.03%
Vertical Displacement (m)	1.27	1.26	0.01%
Peak Vertical Velocity (m/s)	2.01	1.90	5.68%

The predicted network outputs in relation to the actual barbell trajectories are presented in Figure 1A. The predicted network outputs in relation to the actual barbell trajectories presented in Figure 1B.

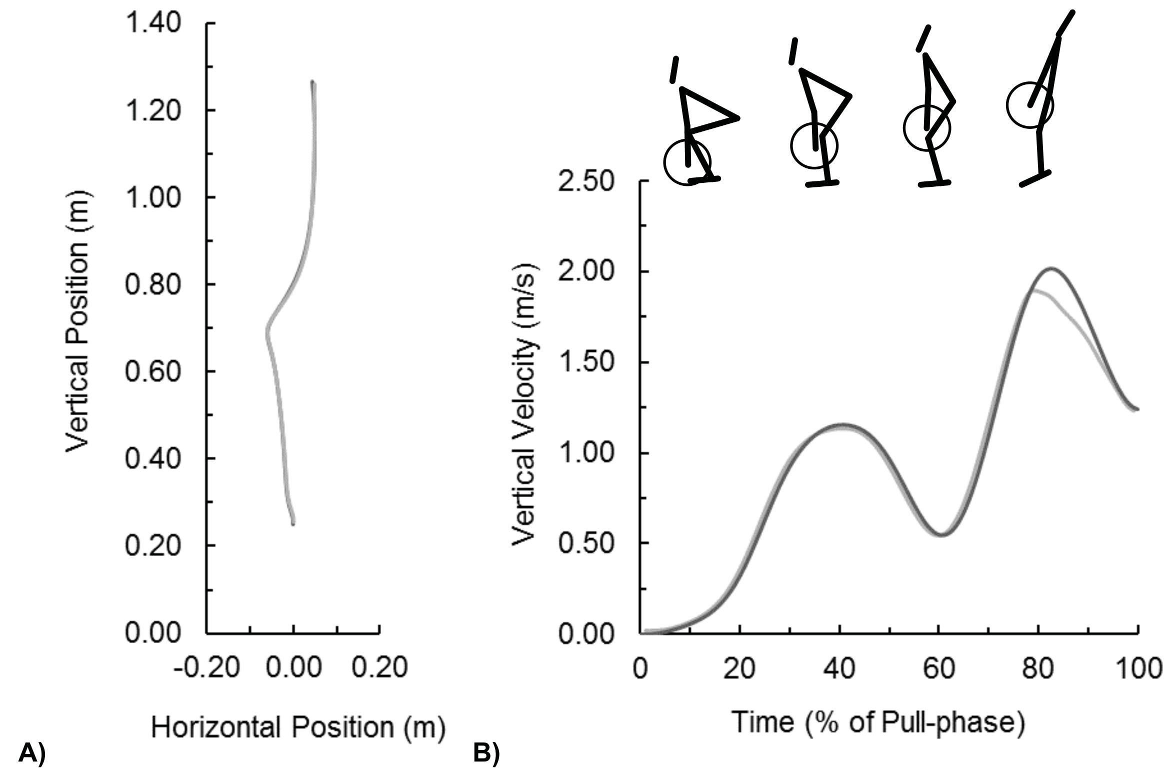

Figure 1: A) Predicted (grey) and actual (black) barbell trajectories in the horizontal and vertical directions for the test case (positive values in the x-direction indicate barbell motion away from the weightlifter). B) Predicted (grey) and actual (black) barbell vertical velocities for the test case.

DISCUSSION: The purpose of this study was to develop and train neural networks to predict barbell motion and velocity from hip, knee, and ankle joint torques during a weightlifting exercise. Based on the final errors obtained from the training of both networks, it appears that the networks effectively capture the relationship between barbell kinematic data and joint kinetic data during the clean exercise. Furthermore, the results also showed that given additional test data from another weightlifter, both networks were able to accurately predict discrete barbell kinematic data based off of the joint kinetic data from that weightlifter; although the network predictions for barbell displacement data were slightly better than for barbell velocity data.

Barbell kinematic data are highly relevant to weightlifting performance (Gourgoulis et al., 2000; Isaka, Okada & Funato, 1996). Appropriate backward and forward motion of the barbell along with optimal vertical barbell velocity are hallmarks of efficient weightlifting technique (Bottcher & Deutscher, 1999; Garhammer 1985). The results of the current study indicate that the joint torques produced by the lower extremity muscles can predict the trajectory of the barbell to within an accuracy of 0.03% for three of the primary kinematic variables. Such high accuracy suggests that the motion of the barbell is directly influenced by the activation patterns of the lower extremity muscles. With respect to the vertical velocity of the barbell, the results indicate that the joint torques can predict the speed of the barbell to an accuracy of approximately 6%. Although this percentage may seem small, the pragmatic consequence of this difference may have larger implications. Vertical barbell velocities are a critical component of an optimal weightlifting profile (Bartonietz, 1996; Bottcher & Deutscher, 1999), and the absolute difference (~0.10 m/s) captured by the 6% difference may be too large to provide useful information to guide the training process.

Given that joint torque data were able to predict barbell kinematics it would be of future interest to determine how perturbations in joint torques affect the motion and velocity of the barbell during weightlifting exercises. Determining such effects would provide weightlifters and coaches with actionable information that could be used to optimize weightlifting technique e.g., by strengthening a particular muscle group in an effort to alter joint kinetics. Another future direction should be to determine the effects of reducing the amount of input data on the prediction accuracy of the neural networks (Hahn & O'Keefe, 2008). Such an analysis would identify if certain joint torques in isolation, or combination, can predict barbell kinematics and help us better understand the role of individual joints in relation to barbell kinematics, and weightlifting technique and performance.

CONCLUSION: This study highlighted the ability of neural networks to predict barbell kinematic data from joint kinetic data. The results suggest that muscle-generated joint torques are strongly associated with barbell displacements, and to a lesser extent barbell velocity. Joint torques should therefore be considered an integral part of weightlifting technique, similar to barbell kinematics.

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