TOWARD A MINIMAL INPUT MODEL FOR JOINT MOMENT ESTIMATION DURING GAIT

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INTRODUCTION

There is a perceived disconnect between laboratory-based locomotion research and broad spectrum clinical application. Use of neural networks and other machine learning (ML) techniques may provide a viable solution to bridge that gap. These techniques have become more common in niche areas of biomechanics and have shown effectiveness in mapping surface measures onto internal mechanical outcomes (Hahn, 2007; Liu et al., 1999; Luh et al., 1999; Wang and Buchanan, 2002). Two previous ML models estimated lower extremity kinematics and kinetics during gait (Goulermas et al., 2005; Sepulveda et al., 1993). However, their findings have been limited in clinical application. The long-term goal of this research is to provide a joint dynamics estimation model which may be accessed and implemented with minimal equipment. With this objective in mind, the purpose of the current study was to develop a model to estimate joint moments for the lower extremity during gait using a minimized list of input data.

METHODS AND PROCEDURES

Nineteen healthy young subjects were recruited for this study (12 female, 7 male; 22.3 ± 1.6 years; 1.73 ± 0.08 m; 72.0 ± 13.3 kg) within the guidelines of the Institutional Review Board. Informed consent was obtained from each subject before participation. All participants were self-reported to be free of neuromuscular and musculoskeletal pathologies.

Standard gait analysis procedures were used to collect all data types: demographics (D), anthropometrics (A), electromyography (E), kinematics (K), and ground reaction forces. Inverse dynamics was used to calculate net internal joint moments for the hip, knee and ankle. All subjects walked at a self-selected pace, wearing comfortable walking/running shoes.

The ML modeling technique used in this study was a three layer feed-forward neural network structure, with 11-fold cross-validation. A unique network was trained and tested for each joint. The input layer contained a variable list of data types, based on category. The hidden layer contained 30 processing units. The output layer contained the experimental net internal moment, serving as the target against which the network was trained. The hidden layer used a sigmoidal transfer function and the output layer contained a linear transfer function. A Levenberg-Marquardt algorithm was used for error correction, with an error goal of 0.01.

The input data set was varied by category (see Table 1) to determine which combination of inputs is best suited to provide a balance between accurate estimation and ease of measurement in the clinical setting. Accuracy was assessed for general model performance using the coefficient of determination (r^2). Case-specific validation was tested with root mean squared error (RMSE) magnitude between experimental and estimated joint moments in a single representative case.

RESULTS

Joint moment estimation accuracy was acceptably high with all data types entered as input (r^2 from 0.94 - 0.99). Next best accuracy was seen in models with all data but electromyography, followed by an input list of just kinematics and demographics (K, D; see Table 1). Case-specific validation revealed similar effects, with the most accurate joint moment estimation coming from models without electromyography (RMSE from 0.02 – 0.07 Nm/kg). The best fit joint moment curve came from an input list of kinematics and demographics (see Figure 1).

DISCUSSION

Model accuracy was comparable to that reported by Goulermas et al. (2005) and Sepulveda et al. (1993). Results indicate that estimation accuracy was not enhanced by the inclusion of electromyography; requiring only kinematic and demographic data to achieve accurate joint moment patterns.

SUMMARY

These findings provide progress towards the goal of a minimal input joint moment estimation model. Use of electrogoniometers and a record of demographics would be sufficient to utilize these models in the non-research setting. Future efforts will include clinical cases and test the field application validity of these models.

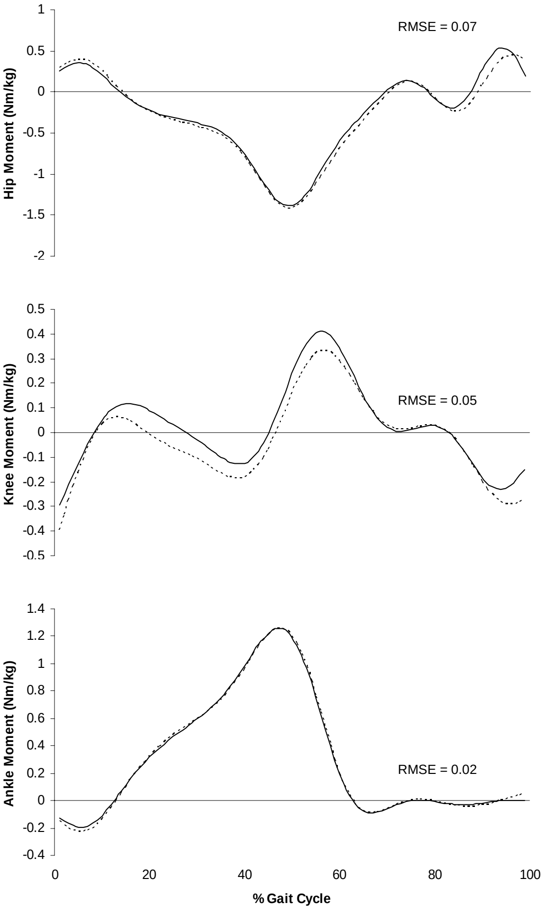

Figure 1. Joint moment estimation, with input list of K, D; solid = experimental, dashed = estimated.

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Table 1. Coefficient of determination (r^2) values for each joint model based on input categories.

	All Input	**K, A, D**	**E, A, D**	**K, D**	**E, D**	**K**	**E**
Hip	0.95	0.96	0.77	0.95	0.75	0.93	0.58
Knee	0.94	0.94	0.81	0.94	0.78	0.70	0.54
Ankle	0.99	0.98	0.92	0.98	0.91	0.96	0.84