PREDICTION OF ANKLE JOINT TORQUES USING ARTIFICIAL NEURAL NETWORKS

Kaitlyn Kopke[1], Jerrod Braman[1], Charles Bardel[2], Tariq Khan[2], John Powell[3], Lalita Udpa[2], Roger Haut[1]

[1]Orthopaedic Biomechanics Laboratories, Michigan State University, East Lansing, MI, USA
[2]Non Destructive Evaluation Lab, Michigan State University, East Lansing, MI, USA

[3]Department of Kinesiology, Michigan State University, East Lansing, MI, USA

Major ankle sprains in sports are thought to be due to high levels of ankle torsion. The purpose of this study was to develop a method for measuring *in vivo* ankle torques developed by athletes. Motion capture, force plate, and insole pressure measurements were used to develop generalized regression neural networks to predict maximum ankle torque and rate of ankle torque based on insole pressures. It was found that network prediction accuracy depended on the number of subjects used for training, as well as the method of pressure sensor grouping. Further work will be performed to determine optimal subject and pressure sensor groupings.

KEY WORDS: ankle torque, sports injury, neural network, motion capture, insole pressure

INTRODUCTION: Ankle injuries are prevalent in sports. Among these injuries are a group referred to as ‘eversion’ ankle sprains or ‘high ankle sprains’. While these injuries are less frequent than the ‘inversion’ sprain, they require a longer time for rehabilitation (Williams et al., 2007). Clinical (Boytim et al., 1991) and experimental (Villwock et al., 2009) studies suggest high ankle sprains occur due to excessive torque, or external rotation of the foot. Recent studies by Villwock et al suggest that the shoe-surface interface conditions may be important factors in the generation of high levels of external torque on the ankle. However, the levels of torque developed by athletes on playing surfaces are unknown at this time. The objective of this study was to investigate the use of an in-shoe pressure measurement system to determine the maximum torque as well as rate of torque generation developed by subjects twisting under controlled laboratory conditions. It is believed that maximum torque can be a predictor of injury while the rate of torque generation is directly related to performance. In sports it is important to optimize performance while minimizing the risk of injury. The findings of the study will assist in the development of techniques to determine torques developed by athletes with various shoe designs on various types of synthetic and natural turfs.

METHODS: Data from two male subjects, performing ten trials each, were used in the current study. A six-camera Vicon MX Motion Capture System (OMG plc., Oxford, UK) was used to capture 3-dimensional marker data at a sample rate of 100 Hz. The standard lower body Vicon Plug-in Gait marker set was used for this study. A force plate sampling at 1000 Hz (Advanced Medical Technology, Inc., Watertown, MA) was used to measure ground reaction forces. Plantar pressures were measured with 24 sensors in the Parotec insole pressure measurement system (Paromed, Neubern, Germany). Prior to any recorded trials, the subject was instructed on how to perform the torque motion. Subjects stood with their feet shoulder width apart with the right foot on the force plate and their knees slightly bent. The subject then internally rotated his right shank with respect to the stationary right foot. Internal/external ankle moment data was recorded using the Plug-in Gait kinetic and kinematic packages. The right Parotec insole data and the output ankle torque values were put into a file for each subject trial. The method used to model the maximum torque and rate of torque generation was a neural network.
Generalized regression neural networks (GRNN) have the ability to model complex functional mappings between inputs and outputs. However, GRNN’s suffer from dimensionality which is characterized as a possible overabundance of input variables (Kiyan,

2004). In order to investigate optimization of dimensionality of the input vector from 24 individual sensor inputs, the pressure sensors were grouped four different ways based on their relative contribution to the output torque. All sensor groupings took into account knowledge that the pressure distribution during the torque motion changes from uniform pressure distribution across the foot to more pressure on the medial side. Using this premise, sensor grouping A divided the insole into medial and lateral halves, leaving out the sensors that fell along the center line (sensors 8 and 11). Sensor grouping B divided the sensor data into three groups, medial, lateral, and a center group. It was assumed that this grouping would improve upon Sensor Grouping A by adding a group in the center to track the lateral to medial pressure change. Groupings C and D further refined the clusters by breaking up sensor groupings across the foot. This was done to allow the networks to have better prediction capabilities due to possible changes in pressure in the anterior/posterior direction during the motion.

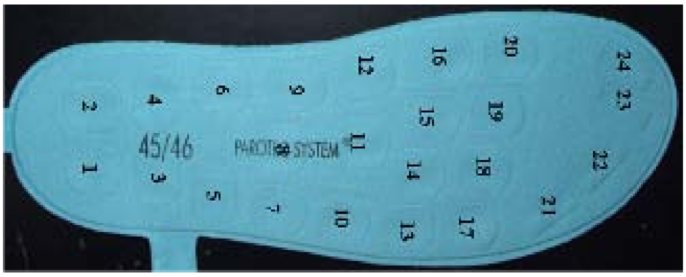

Figure 1: A Numbered Parotec Insole (right foot)

Table 1: Four different sensor groupings

Sensor Grouping A (2 Dimensions)	**Sensor Grouping C (8 Dimensions)**		
1,3,5,7,10,13,14,17,18,21,22	1,3	2,4	5,7,10
2,4,6,9,12,15,16,19,20,23,24	6,9,12	21,22	23,24
	13,14,17,18		15,16,19,20
Sensor Grouping B (3 Dimensions)	**Sensor Grouping D (11 Dimensions)**		
1,3,5,7,10,13,17,21,22	1,3	2,4	5,7,10
8,11,14,15,18,19	6,9,12	8,11	13,17
2,4,6,9,12,16,20,23,24	14,18	15,19	16,20
	21,22		23,24

In order to develop a neural network, the network must first be trained using representative data. Four different networks were trained and tested to determine which led to the most accurate prediction of maximum torque and rate of torque generation. The first two networks used data from both subjects for training and one subject to test, i.e. 19 of the 20 trials were used to train and 1 trial was chosen at random to test the network's ability to predict the torque data based on the insole pressure measurements alone. The other two networks were trained and tested with each subject's data independently, i.e. 9 of the 10 trials from one subject were used to train and 1 out of 10 trials was used to test. Each of these four networks was run with four different sensor groupings. A total of sixteen neural networks were constructed and tested. The success of each network was determined by how accurately the actual and predicted curves aligned, based on an error analysis. The time trace error value represented the square root sum of the squares between the predicted and actual torque values at individual time points. The peak torque error represented the difference between the actual and predicted maximum torque values.

RESULTS: The time trace error values, as well as the peak torque errors, are shown in Table 2 for each of the networks. Table 3 provides averages for the error values produced by each sensor grouping. The smallest error values were seen when both subjects were used to train the network, Networks 1 and 2. Sensor grouping D produced the lowest time trace error value regardless of the network. Looking specifically at Network 1, sensor grouping D was best at predicting the rate of loading with an error value of 15.00. Sensor grouping A was best at predicting the peak torque, its average error value across all networks was 1.71%. Looking specifically at Network 2, the difference between the actual and predicted maximum torque values for sensor grouping A was 0.07%.

Table 2: Error values recorded for each network and sensor grouping

	Subject(s) used for Training	Subject used for testing	Sensor Grouping	Time Trace Error (Nm)	Peak Torque Error (%)
Network 1	1,2	1	A	19.23	2.70
	1,2	1	B	16.72	14.28
	1,2	1	C	18.68	14.75
	1,2	1	D	15.00	11.39
Network 2	1,2	2	A	34.49	0.07
	1,2	2	B	18.22	4.67
	1,2	2	C	18.65	2.29
	1,2	2	D	17.94	3.35
Network 3	1	1	A	27.52	2.73
	1	1	B	20.94	13.78
	1	1	C	28.45	2.80
	1	1	D	17.61	0.73
Network 4	2	2	A	18.22	1.37
	2	2	B	19.52	0.45
	2	2	C	18.66	2.29
	2	2	D	17.94	3.35

Table 3: Average Error Values for sensor groupings

Sensor Grouping	Time Trace Error (Nm)	Peak Torque Error (%)
A	24.87	1.72
B	18.85	8.30
C	21.11	5.53
D	17.12	4.71

DISCUSSION: The findings support the notion that a properly trained neural network could be used successfully to predict torque values based on insole pressure measurements alone. It was found that a network trained on two subjects was more precise than those that were trained and tested on only one subject. This is supported in other studies that have shown networks tend to be most accurate predictors when they are trained on data from many test subjects (Haykin, 1999). The current study also showed that the prediction accuracy of maximum torque and rate of torque generation was greatly affected by sensor groupings. Grouping A, which had two dimensions (medial-lateral), best predicted the maximum torque (Figure 2b). This may be due to the fact that at peak torque, the pressure distribution was concentrated on the medial border of the insole. Sensor grouping D, which was based on eleven dimensions, best predicted the rate of loading (Figure 2a).

** Actual values calculated from inverse dynamics, predicted values calculated from the neural network

a) b)

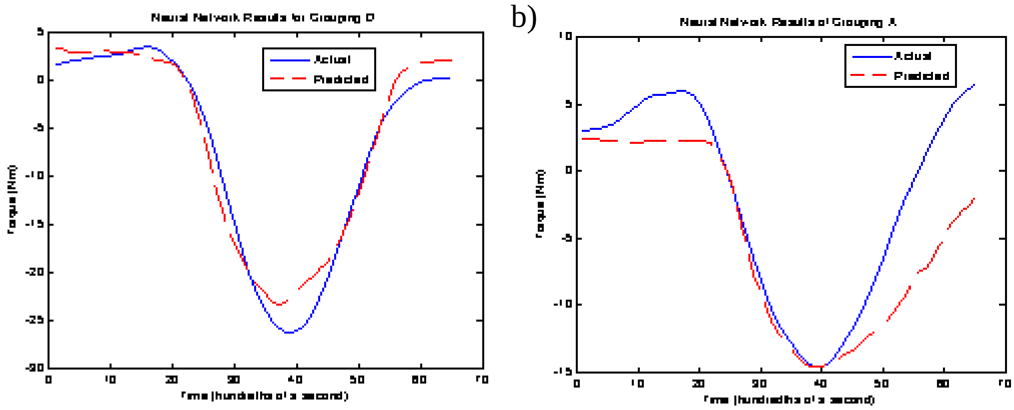

Figure 2: Torque results from training with Subjects 1 and 2, a) and tests on Subject 1 in sensor grouping D, b) and tests on Subject 2 in sensor grouping A

This result may suggest that adding dimensions may be required to better predict temporal torque data. (Erkmen & Yildirim, 2008). It is not uncommon to use different prediction methods and levels of dimensions to optimize the prediction capabilities of various physical parameters, based on pressure insole data (Cordero et al, 2004).

CONCLUSION: This study demonstrates that a neural network based on insole pressures could successfully predict ankle torque and rate of torque generation. Findings indicate that different sensor groupings influenced the accuracy of the neural network. Depending on the aim of the tests, an optimal sensor grouping could be selected. Future work should be continued to determine the optimal sensor grouping for both maximum torque and rate of torque loading, as well as determine if an individualized network will produce more accurate outputs than combined subject networks. The use of artificial neural networks to predict torque and rate of torque generation by subjects on current playing surfaces with various shoes could prove valuable in determining optimal combinations of shoes and playing surfaces. Future studies may utilize this testing technology to develop combinations of shoes and playing surfaces that optimize performance and limit injury risk.

REFERENCES:
Boytim M. J., Fischer, D. A., & Neumann, L. (1991). Syndesmotic ankle sprains. *American Journal of Sports Medicine*, 19(3), 294-298.
Erkmen, B., & Yildirim, T. (2008). Improving classification performance of sonar targets by applying general regression neural network with PCA. *Expert Systems with Applications*, 35(1-2), 472-475.
Forner Cordero A., Koopman H.J.F.M., & van der Helm F.C.T. (2004). Use of pressure insoles to calculate the complete ground reaction forces. *Journal of Biomechanics*, 37(9), 1427-1432.
Haykin, S. (1999). Neural Networks: A Comprehensive Foundation (2nd ed.). Upper Saddle River,NJ: Prentice-Hall.
Kiyan, T. (2004). Breast cancer diagnosis using statistical neural networks. *Journal of Electrical & Electronics Eng.*, 4 (2), 1149-1153.
Villwock, M., Meyer, E., Powell, J., Fouty, A., & Haut, R. (2009). Football playing surface and shoe design affect rotational traction. *American Journal of Sports Medicine*, 37(3), 518-525.
Williams, G. N., Jones, M. H., & Amendola, A. (2007). Syndesmotic ankle sprains in athletes. *American Journal of Sports Medicine*, 35(7), 1197-1207.

ACKNOWLEDGEMENTS: The authors would like to thank Clifford Beckett for his contribution to this project. The authors would also like to express their gratitude towards Michigan State University (VPRGS New Directions Grant) for their support of this research.