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Neural network estimation of balance control during locomotion

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Abstract

Gait patterns of the elderly are often adjusted to accommodate for reduced function in the balance control system and a general reduction in skeletal muscle strength. Recent studies have demonstrated that measures related to motion of whole body center of mass (COM) can distinguish elderly individuals with balance impairment from healthy peers. Accurate COM estimation requires a multiple-segment anthropometric model, which may restrict its broad application in assessment of dynamic instability. Although temporal-distance measures and electromyography have been used in evaluation of overall gait function and determination of gait dysfunction, no studies have examined the use of gait measurements in predicting COM motion during gait. The purpose of this study was to demonstrate the effectiveness of an artificial neural network (ANN) model in mapping gait measurements onto COM motion in the frontal plane. Data from 40 subjects of varied age and balance impairment were entered into a 3-layer feed-forward model with back-propagated error correction. Bootstrap re-sampling was used to enhance the generalization accuracy of the model, using 20 re-sampling trials. The ANN model required minimal processing time (5 epochs, with 20 hidden units) and accurately mapped COM motion (*R*-values up to 0.89). As training proportion and number of hidden units increased, so did model accuracy. Overall, this model appears to be effective as a mapping tool for estimating balance control during locomotion. With easily obtained gait measures as input and a simple, computationally efficient architecture, the model may prove useful in clinical scenarios where electromyography equipment exists.

Keywords: Dynamic stability; Electromyography; Gait; Artificial neural network; Mapping

1. Introduction

As humans age, gait patterns are adjusted to accommodate for reduced function in the balance control system and a general reduction in skeletal muscle strength (Grimby and Saltin, 1983; Fiatarone and Evans, 1993). The temporal-distance (T-D) measures of gait have been widely used in evaluation of overall function and determination of gait dysfunction in the elderly (Heitmann et al., 1989; Ferrandez et al., 1990; Elble et al., 1991; Leiper and Craik, 1991; Judge et al., 1996; Maki, 1997; Menz et al., 2003). These studies showed that while T-D measures of gait do provide an overall impression of walking performance, there is substantial inter-subject variability in the measures. Such variability may contribute to a lack of power in accurately predicting the risk of falling in the elderly. The effect of aging on muscle activation and strength in the elderly has been shown to result in higher electromyographic (EMG) signal amplitudes during gait (Finley et al., 1969; Shiavi, 1985). However, the resulting force production in aged subjects is highly variable (Galganski et al., 1993; Grabiner and Enoka, 1995). None of the previous studies have examined the effect of T-D parameters and EMG activity on control of whole body stability.

Control of whole body stability has been studied in recent years by analyzing motion of the whole-body center of mass (COM), the patterns of which were reported to be quite consistent during locomotion (Jian

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et al., 1993; MacKinnon and Winter, 1993; Prince et al., 1994; Winter, 1995). More recent studies have demonstrated an ability to distinguish elderly individuals with balance impairment from their age-matched healthy peers, using measures of medio-lateral (M-L) COM motion during obstacle crossing (Chou et al., 2003; Hahn and Chou, 2003). Accurate estimation of the whole-body COM requires three-dimensional reconstruction of a multiple segment biomechanical model. This technical requirement alone may restrict broad application of assessing dynamic instability.

In many clinical settings, gait analysis can be performed with accuracy in measures of gait velocity, stride length, stride time and step width. Additionally, with many brands of inexpensive hardware/software currently available, the relative magnitude of muscle activations may be measured with surface EMG during locomotion and other activities of daily living. Using T-D and EMG data to predict dynamic stability would be advantageous by reducing the necessity for a multiple camera motion analysis system (more costly), and reducing the time commitment of data-processing and analysis. A model is therefore needed which would allow accurate description of whole-body balance control, given simple measures of gait such as EMG and T-D parameters.

One approach for mapping interactions between gait measurements and balance control is to construct a nonlinear model using an artificial neural network (ANN). Biological nervous systems are capable of learning by adjustment of the synaptic connections between individual neurons. The ANN is modeled in a similar fashion, allowing the network to be trained by exposure to a set of input data where the output values are known. Weights of the ANN interconnections are iteratively adjusted to attempt correction of the final processed output to match that of known values. Once a network has been trained to a satisfactory level, the knowledge gained by this learning process is stored in the connection weights (synapses), allowing a trained network to solve new problems similar to the task it was trained on. The primary advantages of ANNs in solving real-world classification problems are (1) their resilience in the face of noise and variability within a dataset, and (2) the ability to map relationships between variables that would not otherwise be noticeable. They have been used with high success in problems that are either too complex for conventional methods or are of an exploratory nature (Chau, 2001).

Applications of ANN models in musculoskeletal biomechanics have dealt primarily with joint angles and joint moment estimations in gait simulation (Sepulveda et al., 1993) and estimation of muscle recruitment in static conditions (Nussbaum et al., 1995). Sepulveda and colleagues used traditional back-propagation algorithms to successfully map the relationship between EMG and joint angles, and between EMG and joint moments during gait. Nussbaum et al. also reported success using a back-propagation algorithm to map lumbar muscle recruitment during moderate static exertions. Koike and Kawato (1995) used an architecturally complex ANN model to estimate isometric joint torques and trajectory from surface EMG in upper limb motions. More recent efforts by Luh et al. (1999) showed promising results with use of a simple, three-layer ANN, using an adaptive learning rate back-propagation algorithm in the determination of elbow joint torque from EMG activity.

Although ANN modeling has been used in studies of human locomotion (Holzreiter and Kohle, 1993; Sepulveda et al., 1993; Lafuente et al., 1998; Prentice et al., 1998; Savelberg and de Lange, 1999; Su and Wu, 2000; Prentice et al., 2001; Wu et al., 2001), no previously published work has addressed the ability of such models to map the interaction between basic gait measurements and descriptions of dynamic balance control. The purpose of this study was to demonstrate the effectiveness of an ANN model in mapping gait measurements (normalized lower extremity EMG signals and basic T-D parameters) onto whole body measures of dynamic stability (motion of the COM). It was hypothesized that a relatively simple ANN architecture would be capable of accurately mapping interactions between these variables.

2. Methods

Input/output data of the ANN model were obtained from a database of previously collected subjects (Koshida, 2002; Chou et al., 2003; Hahn and Chou, 2003, 2004). The subject pool ($n = 40$) consisted of 11 healthy young adults, 19 healthy elderly adults, and 10 elderly adults with complaints of imbalance (Table 1). Inclusion criteria for the young and healthy elderly samples required no histories of significant head trauma, neurological disease (e.g., Parkinson's, post-polio syndrome, diabetic neuropathy), visual impairment not correctable with lenses, musculoskeletal impairments (e.g., amputation, joint replacement, joint fusions, joint deformity due to rheumatoid arthritis), or persistent symptoms of vertigo, light-headedness, unsteadiness. Healthy elderly subjects were noted to be active community members, with many of them currently involved in recreational sporting activities. Ten elderly subjects with complaints of imbalance during walking or a history of falls, were recruited from the local community. Three were diagnosed with either unilateral or bilateral vestibular weakness. All elderly subjects with balance disorders were community-dwelling and able to walk more than 100 m without the use of gait aides at the time of testing. The experimental protocol was approved by the Institutional Review Board and

Table 1
Subject information; age, height and mass; Mean (SD)

Group	Female	Male	Age (yrs)	Height (cm)	Mass (kg)
Young ($n=11$)	6	5	24.5 (3.3)	171.5 (7.2)	68.9 (6.8)
Healthy Elderly ($n=19$)	8	11	71.5 (5.6)	167.9 (9.8)	73.3 (14.1)
Elderly/Imbalance ($n=10$)	7	3	78.5 (4.7)	162.0 (9.8)	72.2 (14.4)

experimental procedures were explained to all subjects prior to testing, with verbal and written consent obtained.

The gait analysis protocol included walking on level ground with no obstructions and stepping over an obstacle corresponding to 2.5% of each subject's height. All subjects performed the trials at a self-selected pace, while barefoot. Previous results indicated that an obstacle set at 2.5% of body height ($\sim$5 cm) resulted in the greatest alteration of stability patterns in elderly subjects with balance disorders (Chou et al., 2003). Whole body motion data were collected using a six-camera Expert Vision system (Motion Analysis Corp., Santa Rosa, CA, USA). The COM position was estimated throughout the obstacle crossing stride, using a weighted-sum approach with a 13-link anthropometric model (Meglan, 1991; Jian et al., 1993; Chou et al., 2001). Velocities were calculated using the generalized, cross-validated spline algorithm (Woltring, 1986). Range of M-L displacement and peak M-L velocity values were compiled as target values for the ANN model output. These variables were selected as outputs due to previous findings indicating their ability to distinguish between individuals with and without balance impairment. Comparison of these empirical results between the young, healthy elderly, and elderly with balance impairment was performed using a heteroscedastic t-test (with Bonferroni adjustment of the significance level; $\alpha=0.05/3$ comparisons $=0.017$).

Dynamic EMG measures were taken from surface electrodes placed bilaterally over the bellies of the gluteus medius (GM), vastus lateralis (VL) and medial gastrocnemius (GA). Activation magnitude of each muscle during gait was normalized to values taken during maximal effort manual muscle testing (MMT). Maximal GM activation was tested in 30° of hip abduction, while side lying. For VL maximum, subjects were seated with the knee in 45° of flexion. Maximal GA activation was tested in neutral ankle position, with the subject fixed to a table in prone position. MMT procedures were performed by one examiner for each muscle group, bilaterally. Subjects were verbally encouraged to ensure maximal recruitment.

During gait trials, only the peak phases of activity were used as EMG inputs into the model. Peak phases of activity corresponded to periods of double support for the GM and VL; single support for the GA. Further details about the EMG collection protocol have been reported previously (Koshida, 2002; Hahn et al., 2003). Gait velocity, stride length (normalized to body height), stride time and step width were measured during the obstacle-crossing stride, and used as inputs into the ANN model. A total of ten variables were therefore available for input (6 EMG and 4 T-D measures).

An ANN model was designed and implemented using Matlab's Neural Network Toolbox (v. 6, The MathWorks, Inc., Natick, MA) to estimate M-L COM motion using input from EMG magnitudes of the lower extremity and T-D values during a low-level obstacle-crossing task. The ANN system consisted of a supervised 3-layer feed-forward neural network (Fig. 1) with two cells in the output layer to represent measures of sideways dynamic stability (M-L COM range of displacement and peak velocity), up to 20 processing units in the hidden layer, and an input layer of EMG amplitudes and T-D parameters, normalized to zero mean and unity standard deviation.

The hidden and output units sum incoming connections and derive an outgoing activation signal based upon a sigmoidal transfer function in the hidden units and a pure linear transfer function in the output units. For the output units, the result of the transfer function is the normalized value of the predicted variable. Activation in the hidden units was calculated as

$$a_m = sig\,(n), \tag{1}$$

where sig is a sigmoidal transfer function

$$n = 2/(1+\mathrm{e}^{(-2*n)}) - 1 \tag{2}$$

and n is the result of the weight summation

$$n = \sum_{p=1}^{numP} (i_p w) + b. \tag{3}$$

In Eq. (3), i_p is the input signal from each p parameter, w is the synaptic weight on each input signal, and b represents the bias of the hidden unit. The same calculation steps were carried out in the output units, except with a pure linear transfer function (see Fig. 1). Error correction was performed on the synaptic weights and biases using the Levenberg-Marquardt learning algorithm (Levenberg, 1944; Marquardt, 1963), known to provide rapid convergence and robust generality in small networks being trained on small-to-moderate subsets. Error correction in this algorithm can be described with the following general equation:

$$x_{k+1} = x_k - \alpha_k g_k, \tag{4}$$

where x_k represents the vector of current weights and biases, g_k the current gradient value, α_k the current learning rate, and k indicates the iteration index. The Levenberg-Marquardt algorithm allows for iterative

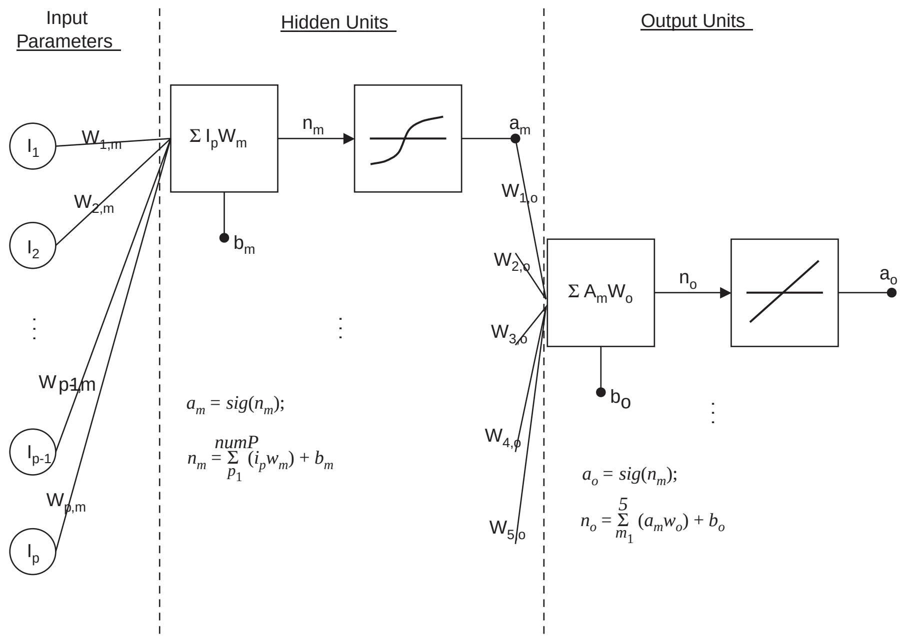

Fig. 1. General diagram describing the neural network architecture. A tangential sigmoid activation transfer function was used in the hidden layer, and a pure linear activation transfer function in the output layer.

adjustment of the learning rate in order to control the rate of convergence. Ideally, the algorithm will adjust the learning pattern from an initial "gradient-descent" style of convergence, with large adjustments made to the weights and biases, to a more controlled convergence allowing smaller adjustments to be made with greater accuracy in the final, converged solution.

The full data set consisted of all subject groups collected, with 3 trials representing each subject (40 subjects $\times 3 = 120$ cases). The training set was selected randomly from the entire data set at a given proportion (i.e. 0.70), with the remainder of subjects entering the testing set. Individual subjects were selected rather than individual trials, so that it was not possible for a particular subject's data to be used in training and testing. Moderate bootstrap re-sampling was utilized, with 20 re-sampling instances used for each of the parameter settings listed below. Bootstrap re-sampling was chosen as a method for improving model generalizability due to the small size of the total data set. The model then ran iteratively on the training set with error correction proceeding until the mean squared error (MSE) of the predictions became less than a preset value. The training set proportion (Pr), training error goal (E), and number of hidden units (H) were manipulated to assess which settings provide the best estimation accuracy. Using three values for each setting [$\mathrm{Pr} = \{0.6, 0.7, 0.8\}$; $E = \{0.01, 0.001, 0.0001\}$; $H = \{5, 10, 20\}$], a total of 27 setting conditions were tested.

After successful training of the ANN, the model's output was transformed back to real-world units (cm, cm/s), and overall model performance was assessed by correlation analysis to detect how well the model estimations fit the target values (reported as the correlation coefficient (R): R_1, for M-L displacement; R_2, for peak M-L velocity) of the entire subject pool. Separate analyses were performed for EMG and T-D inputs, as well as when EMG and T-D were combined as complimenting inputs. Mapping accuracy results were statistically compared using a two sample t-test.

3. Results

Comparisons between young and healthy elderly adults showed no significant differences in the measures of M-L COM displacement or peak M-L velocity (Fig. 2). Elderly adults with balance impairment allowed significantly greater M-L displacement and peak velocity, compared to both the young ($p < 0.001$ and 0.014, respectively), and the healthy elderly ($p = 0.002$ and 0.013, respectively). Empirical results of the COM variables were then compiled as target values for the ANN model output.

The model architecture was shown to be efficient by requiring minimal processing time. Generally, training sessions required less than 5 min to reach the target training goals. Based on correlation analysis, the ANN performed reasonably well in terms of prediction accuracy; mean R_1 values ranged from 0.64 to 0.89 in the estimation of M-L COM motion, and R_2 values from 0.57 to 0.82 for the estimation of peak M-L COM velocity (Table 2). When EMG data were used as the sole input to the model, R-values ranged from 0.57 to

0.82. With T-D parameters as the sole model input, R-values ranged from 0.64 to 0.80. When the two types of data were entered together both R-values improved; ranging from 0.73 to 0.89 and from 0.65 to 0.82 for R_1 and R_2, respectively. When mapping results from the highest training proportion setting ($\mathrm{Pr}=0.8$) were compared, significant differences existed in the goodness of fit (R-values) when comparing between the EMG-only and EMG/T-D combined input ($p=0.006$), and between T-D input and combined input ($p=0.001$). Other mapping result differences were not significant.

As training proportion increased from 0.6 to 0.8, the goodness of fit for the ANN mapping accuracy improved for both the M-L COM displacement and peak M-L velocity, regardless of input type. No noticeable trends developed regarding which training error goal (E) performed best for the mapping networks. Of note however, is that when EMG and T-D parameters were combined as input, the model performed better with a more strict training goal ($E=0.0001$).

For each type of input data (EMG, T-D alone, and combined), it was determined that more hidden units provided quicker convergence within the model, improving the ability to generalize (Fig. 3). With only 5 hidden units the EMG input mapping to COM motion took an average of 460.5 epochs (SD, 77.7) to converge, whereas when the same mapping was performed with 20 hidden units, the system converged in 7.0 epochs on average (SD, 1.2). Similarly, when T-D input was mapped with only 5 hidden units an average of 483.8 epochs was required (SD, 10.1), compared to 12.1 epochs (SD, 2.7) with 20 hidden units. When EMG and T-D measures were combined as input, mapping solutions were reached in 226.6 epochs on average (SD, 129.3) with 5 hidden units, compared to an average of 4.4 epochs (SD, 0.5) with 20 hidden units.

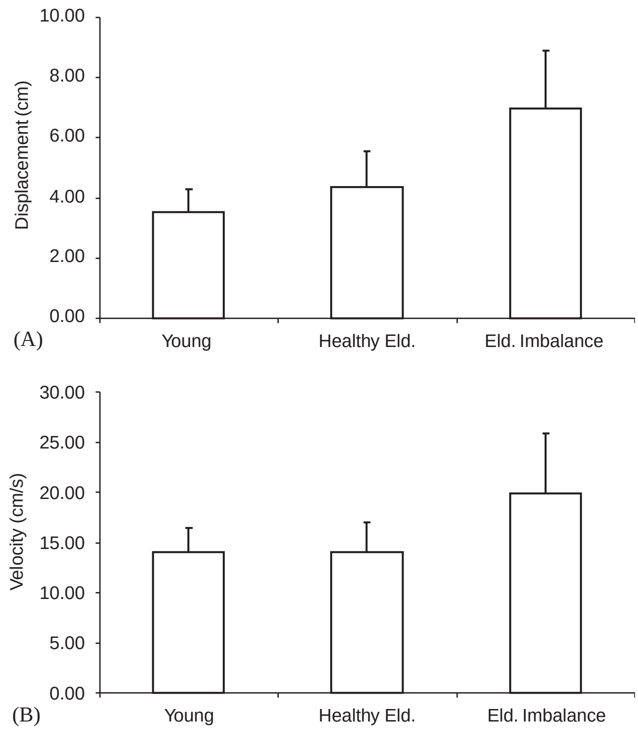

Fig. 2. Empirical results of M-L COM displacement (A) and peak M-L COM velocity (B) during the obstacle crossing stride at an obstacle height of 2.5% body height. Elderly subjects with imbalance exhibited greater displacement and peak M-L velocity than either healthy young or healthy elderly subjects ($p<0.014$).

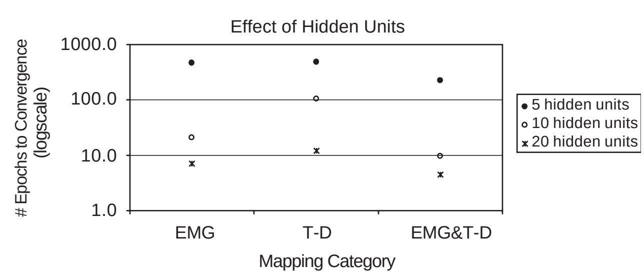

Fig. 3. Average number of epochs necessary to reach convergence with 5, 10, and 20 hidden units (means; SD bars) on a logarithmic scale.

Table 2
Mapping results showing the effect of training proportion and input data type

Input	Proportion	Goal	# hidden units		R_1	R_2
EMG	0.6	0.001	10		0.65 (0.12)	0.57 (0.16)
	0.7	0.01	20		0.72 (0.12)	0.67 (0.16)
	0.8	0.01	20	[a]	0.82 (0.09)	0.77 (0.10)
T-D	0.6	0.001	20		0.64 (0.11)	0.64 (0.13)
	0.7	0.001	20		0.72 (0.12)	0.75 (0.11)
	0.8	0.01	20	[b]	0.80 (0.10)	0.80 (0.10)
EMG & T-D	0.6	0.0001	20		0.73 (0.09)	0.65 (0.13)
	0.7	0.01	20		0.79 (0.09)	0.75 (0.09)
	0.8	0.0001	20	[a,b]	0.89 (0.06)	0.82 (0.09)

The goal and hidden unit values reflect the settings producing highest accuracy. R-values are reported in Mean (SD) of 20 attempts.

[a] Significant difference between EMG and combined input types ($p=0.006$).

[b] Significant difference between T-D and combined input types ($p=0.001$).

4. Discussion

This study sought to demonstrate the ability of an ANN model to accurately map muscular activation levels and T-D parameters onto whole body measures of dynamic stability during gait. Results supported the hypothesis that a relatively simple ANN model architecture is adequate for estimating dynamic stability from the basic measures of normalized EMG activation and T-D parameters.

Given the relatively small size of the sample data set, the model performed reasonably well, with average correlation coefficient (R_1) values from 0.64 to 0.89 in estimation of M-L COM motion, and correlation coefficient (R_2) values from 0.57 to 0.82 for the estimation of peak M-L COM velocity. Further investigation is needed to confirm this stability estimation in a larger, more diverse sample set. By the very nature of the empirical data used in this model (EMG and T-D), variability within subject group was high enough that more distinctive categorization a priori would be beneficial in the initial validation of this model. However, the strength of using neural network theory to model the relationships between these variables and balance control lies in its ability to map non-linear functions in systems that are not clearly defined.

As ANN models are allowed to learn, they have a tendency to solidify the weightings between input parameters, the processing units, and the output. This tendency can sometimes lead to interpretations regarding the predictive strengths of the input parameters. Further examination of the network connections between the input layer and the layer of hidden units revealed no definitive weighting patterns. When EMG data were the sole inputs, the muscles which received strong weighting (values of 2 or greater) would vary between training attempts. The leading limb gluteus medius was the only muscle to continuously receive strong weighting with each training attempt. With T-D input, stride length consistently received stronger weightings, while step width rarely received strong weightings. The lack of strong weightings for step width may appear counterintuitive, as step width may be assumed to have some effect on M-L COM motion. However, recent findings have demonstrated that change in step width does not necessarily indicate greater sway or dynamic instability (Krebs et al., 2002; Chou et al., 2003) as its increase, if any, is variable within groups.

Network weighting for gait velocity and stride time varied between training attempts. As gait velocity is a function of stride length and stride time, it is not surprising that its contributive weighting was sporadic in nature. Inclusion of gait velocity as an input may not be warranted due to its association with the other variables. When EMG and T-D were combined as inputs, no distinct patterns could be detected. Overall, these findings indicate that the present ANN model did not rely on solidifying weight values to reach accurate output estimations. This could be due in part to the rapid convergence of the network. With rapid convergence, the tendency of a network to solidify weightings would be inhibited. The present model's success in prediction accuracy was likely dependent on the generalized weightings of its network connections; however, this reduced the ability to examine network weightings for patterns of learning in the network. Future investigations into this and similar models could include the use of class estimators as utilized in heteroscedastic probabilistic neural network models.

Additionally, it is interesting to note the effect of increasing the number of hidden units on the model's performance. As the number of hidden units increased, the number of epochs necessary for the network to converge on a solution decreased (Fig. 3). Rapid convergence of a system to an accurate solution indicates an enhanced ability to generalize the function in a broader application. Indeed, findings from this study indicate that accuracy was improved with more hidden units, indicating enhanced generality overall (see Table 2). The ability to generalize may be similar to the concept of plasticity in natural neural pathways. Early in the learning of a task, the neural system has a number of pathways/solutions to choose from (i.e. plastic), but the more corrections and repetitions that it takes to converge on a solution, the more rigid the final pathway becomes. In this way, an ANN model that can converge quickly (e.g. 5 epochs, with 20 hidden units) will have a greater number of possible pathways to the solution, compared to an ANN model which converges slowly (e.g. 500 epochs, with 5 hidden units).

Overall, this model appears to be effective as a mapping tool for the estimation of balance control during locomotion. Effectiveness was revealed by the robust performance of the model with different network parameters. When EMG and T-D data were combined as input, R-values ranged from 0.73 to 0.89 in estimating M-L COM displacement. Previous studies have used simple ANN models in human locomotion, reporting general acceptance of training proportion set to 0.70, and model accuracy up to 0.897 (Su and Wu, 2000; Wu et al., 2001). The accuracy achieved through this model is therefore deemed acceptable, considering the range of training proportions used (from 0.60 to 0.80). Moreover, with simple 3-layer architecture, the ANN model is computationally efficient. Further validation of this model is needed with inclusion of a larger, more diverse sample set. A possible application of this model would be categorization of individuals with balance impairment, leading to a risk estimation system for the prevention of traumatic falls. Other applications may be pursued in simulation of age-related strength decline and the resulting effect on balance control during locomotion, as well as simulation of prospective outcomes from a range of strength-enhancing therapeutic interventions.

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