A Back-propagation Neural Network Model for Prediction of Loss of Balance

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Abstract -Two neural network models were developed for the prediction of postural sway response due to exposure to risk factors including environmental lighting, job-tasks, standing surface firmness, surface oiliness, work load, peripheral vision conditions, age and gender. Variables used to measure the loss of balance were index of proximity to stability boundary and sway length. Tests showed that job-task is the main risk factor that changes the output while there is some impact by age or gender on the outcome of the model. The results from these models can be used to find risk factors that have great impact on loss of balance and therefore can help in designing intervention programs.

I. Introduction

In recent years there has been a growing interest in the field of biomechanics/ergonomics to apply artificial neural network (ANN) modeling techniques for predicting an outcome based on multiple inputs. While statistical models can also serve this purpose to some extent the advantage of a neural network is that it does not require the input data to be normal distribution in nature. Also, in this method one does not have to measure baseline (under ideal conditions) postural balance on the worker to allow prediction of his/her postural balance response to various fall risk factors. Therefore, the use of neural network modeling for predicting changes in postural sway due to exposure of various types of risk factors was undertaken as a pilot effort. The existing applications of ANN in biomechanics include learning of voluntary movements [1, 2, 3], reaching and balance [4], limb joint positions [5], and limb trajectories [6]. Recently, Sepulveda et al., (1993) [7] used an ANN model to estimate joint angles and moments from muscle activity measured during normal gait and Maury et al., (1995)[8] developed an ANN to predict lumbar muscle activity in response to steady-state external moment loads. Both models made good predictions and gave lower standard errors than other methods. It shows that neural network has strong ability to find the underlying consistencies from a data set.

II. Method

A. Artificial Neural Network

An artificial neural network is an information processing system that is nonalgorithmic, nondigital and intensely parallel. It consists of a number of cells called neurodes, which are connected by a large number of weighted links, over which signals can pass. Each neurode usually has many inputs but only one output. For neurode i in each layer, output is $f(\Sigma w_{ij}x_j)$, where f(x) is the activation function, w_{ij} is the weight between the neurode i with neurode j and x_j is the output from neurode j. When weights between neurodes change, output of the neural network usually changes. Therefore, we can adjust the weights to the output to fit the desired data set. Practically a typical multi-layer neural network model will be used because it can fit the training data better than would be possible with a single-layer model so that better generalization might be achieved. Among the network training algorithms, Back-propagation is currently the most important and most widely used algorithm. The training of a back-propagation network is composed of two steps: a forward propagation step, which makes a bottom-up pass through the network to compute the outputs for every neurode; and a backward propagation step, which makes a top-down pass neurodes through the output and middle neurodes and update the connection weights and bias terms. Weight changes follow the generalized delta rule:

$$\Delta w_{ij}=\beta E[f(I)]+\alpha\Delta w_{if}^{\text{previous}} \tag{1}$$

where E is the error, f(I) is the output from the previous layer's neurode (incoming signal). α is momentum constant and, β is learning constant. Both of them control the speed of convergence. Error is calculated in different way in different layers. For the output layer:

$$E_j^{\text{output}} = y_j^{\text{desired}} - y_j^{\text{actual}} \tag{2}$$

For the middle layer:

$$E_j^{\text{middle}}=(df(I_i^{\text{middle}})/dI)\Sigma_{if}E_j^{\text{output}} \tag{3}$$

The activation function used here is

$$f(x)=1/(1+\exp(-x)) \tag{4}$$

B. Neural Network Model

Two sway variables (Index of Proximity to Stability Boundary and Sway Length) were used in our study because of their lower coefficients of variations (25% and 28% respectively). Index of Proximity to Stability Boundary (IPSB) measures the minimum distance between body's center of pressure (CP) and the boundary of supporting base area. Sway Length (SL) measures the distance travelled by the body's CP during the test period. Two 5-layer back-propagation network (Fig. 1) were constructed, trained, and tested using Professional Neural Network Developer: Risk factors

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→ IPSB; and Risk factors → SL. Risk factors include: Workload (0, 40, 100 watts), Surface Compliance (compliant, firm), Surface Oiliness (dry, oily), Lighting (dim, bright), View (unobstructed, obstructed), Task (Stationary, Bending, Upward reach and Sudden loading), Age group (21-29, 30-37.5, 37.5-45 and 45-55 years) and Gender (male and female). The training set used data from a project from our laboratory dealing with effect of fall risk factors on the industrial workers' ability to maintain upright balance. The data from 52 industrial workers were divided into eight groups according to their age and gender. For each group, there are 10 different test conditions which are a combination of the risk factors. Average values were taken in each group to represent the output of the whole group under each test condition. Therefore we had 80 patterns for each network model. Fifty-six patterns were used in training set and 24 patterns were used in test set for each model. Supervised learning procedures were applied to minimize the error between the desired output and the predicted values. The learning constant α was 0.8 and the momentum constant β was 0.2. The size of middle layers were 20, 10 and 10 respectively. All inputs and outputs were normalized between 0 and 1 according to appropriate absolute maxima for all subjects because the activation function used here only yields values between 0 and 1. The categorical risk factors (view, tasks and gender) were set to be 0 and 1 for different states.

III. Result and Discussion

All weights were randomized at the beginning of the training process. After 50,000 iterations, the predicted values from neural network models were very close to the expected values, as shown in Fig. 2(a) and (c). The errors between the predicted and expected values for the IPSB and SL were 0.009 and 0.008 respectively. To test the ability of prediction of neural network in unknown situations, the data from test sets were applied as inputs to the both trained networks and the results are shown in Fig. 2(b) and (d). The predicted and expected values were still close, which provided evidence that the models are valid. The trained network models made it possible to examine the effect of each risk factor on the output variables separately. The effect of surface oiliness was examined for male subjects of all age groups under the following conditions: 0 Load, Compliant, Dry, Bright, Unobstructed and Upward reach. As shown in Fig. 3, when surface oiliness increased, IPSB decreased implying expected increase in loss of balance for all age groups. The subjects in the two older age groups showed much increased levels of loss of balance compared to those in the younger groups. It suggests that age may be one of the risk factors which has direct impact on IPSB. The same observation can be found for SL, as shown in Fig. 5. In comparison to other tasks types the Upward reach task produced significantly higher response for SL and IPSB was significantly lower (Fig.4 and Fig. 6). These findings suggest that a change in task type increased the level of loss of balance for these test subjects.

Implementation of ANN models does not need baseline

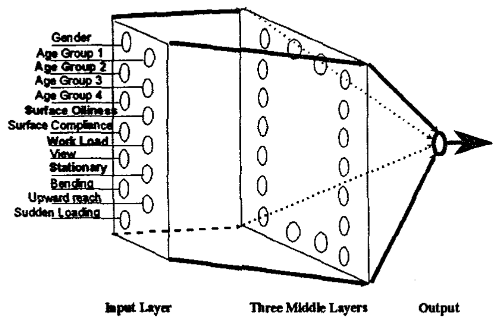

Fig. 1 Illustration of Neural Network Model

postural balance information. Also our trained ANN models can give reasonable predictions when risk factors change. These advantages suggest that an ANN model will be a useful tool towards finding risk factors that have great impact on loss of balance and helping to design intervention programs.

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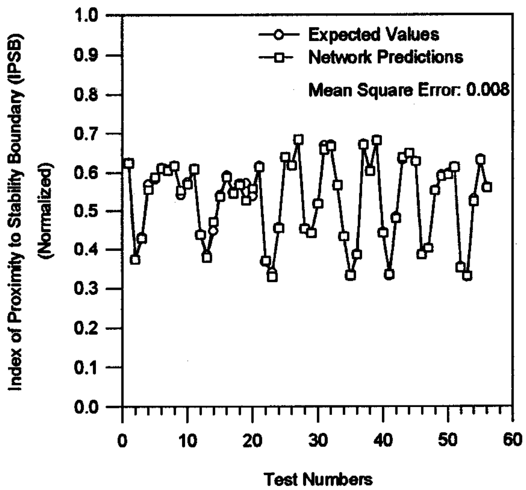

Fig. 2 (a) End of Training After 50,000 iterations Network I

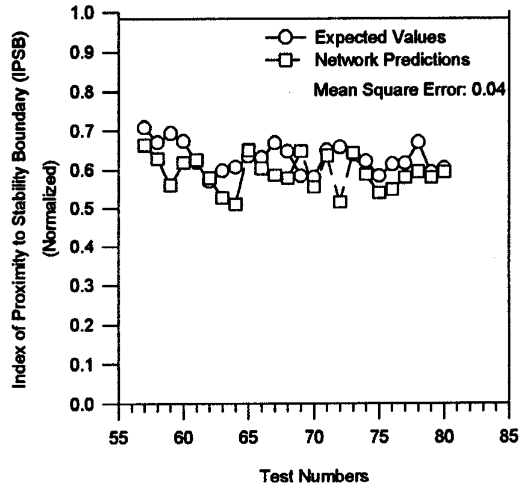

Fig. 2 (b) Validation of Network I

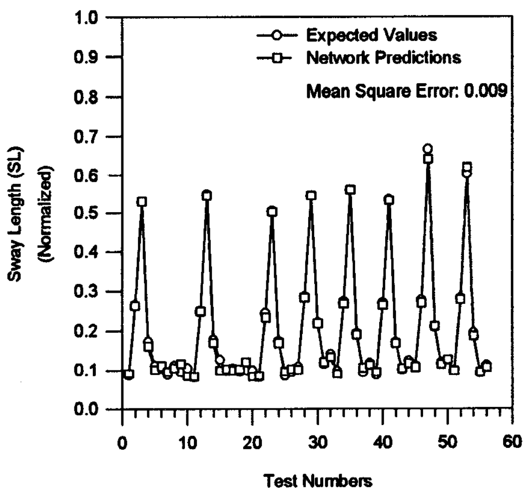

Fig. 2 (c) End of Training After 50,000 iterations Network II

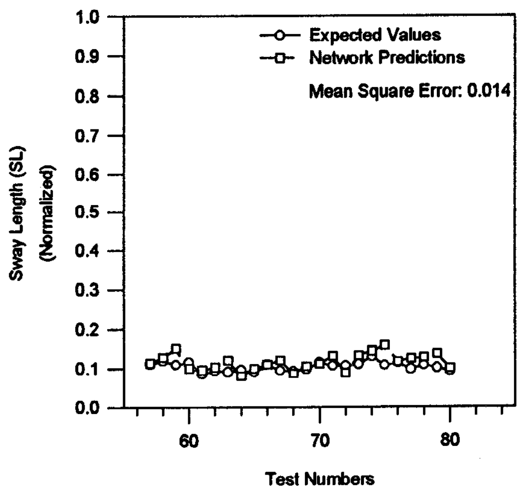

Fig. 2 (d) Validation of Network II

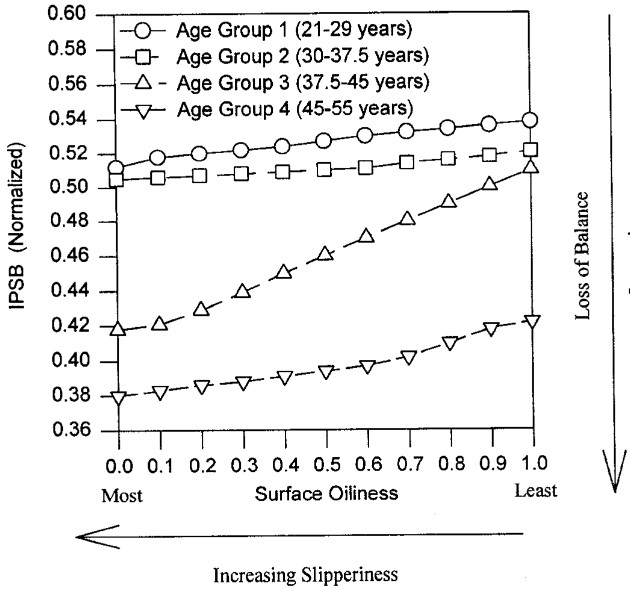

Fig. 3 Network I's Predictions for male subjects for IPSB for Upward Reach Task

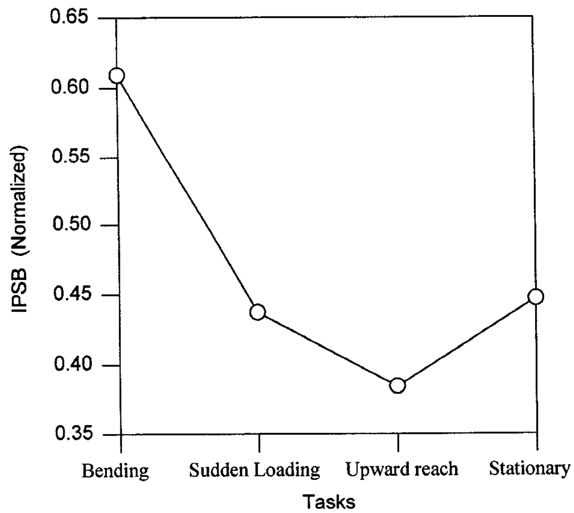

Fig. 4 Network I's Prediction for female subjects (21-29 years)

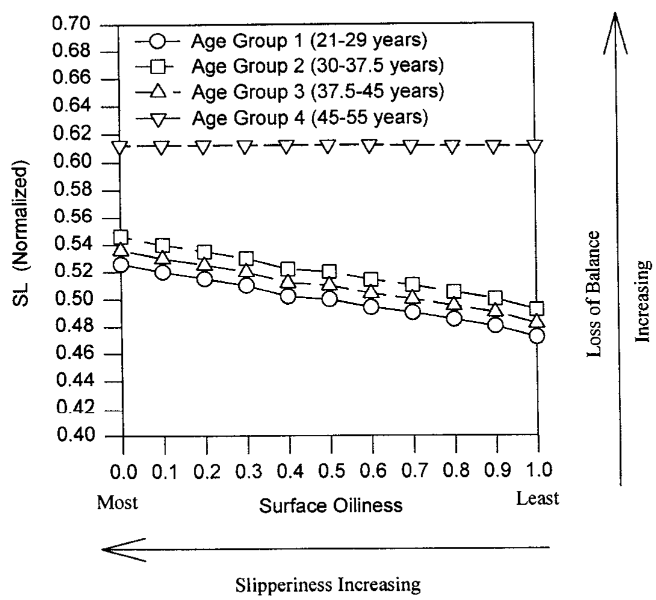

Fig. 5 Network II's Prediction for male subjects for Sway Length for Upward Reach Task

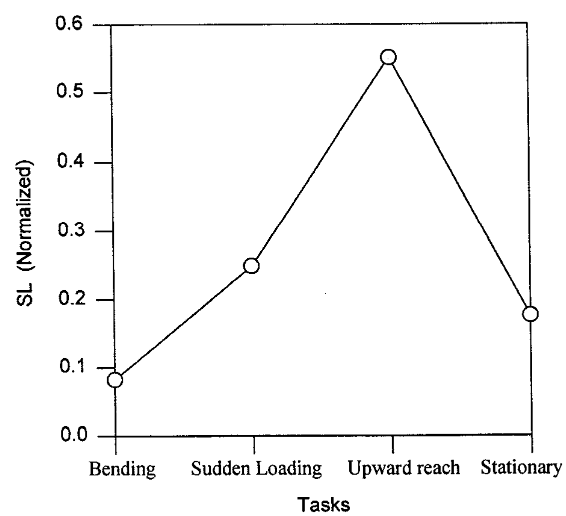

Fig. 6 Network II's Prediction for female subjects (21-29 years)