ANALYSIS OF HUMAN POSTURAL CONTROL DURING SPONTANEOUS SWAY USING AN OPTIMAL CONTROL MODEL

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Models of human postural control aid in understanding human capabilities and limitations, and may facilitate a reduction in injuries related to loss-of-balance. Such a model is presented here to simulate and interpret the postural control system during spontaneous sway. The human body was represented by a simple inverted pendulum, with the neural controller assumed to be an optimal controller that generates spontaneous sway according to a certain performance criterion. In order to accurately simulate existing experimental data, an optimization procedure was used to specify the set of model parameters. Ten independent simulations were performed for both young and older adults. Aging effects were then analyzed based on the simulation results. The results showed that this model was able to simulate some center-of-pressure measures reported in experimental studies, and indicated potential changes in postural control mechanisms caused by aging.

INTRODUCTION

Falls are a major cause of occupational injuries. In 2003, falls accounted for 272,988 nonfatal occupational injuries and 691 fatalities (Department of Labor, 2005). Fall-related injuries are even more prevalent and serious for older adults. About a third of Americans over 65 experience fall-related injuries annually, and 32% of Americans over 85 die from traumatic falls (Shin et al., 2005). From biomechanical and psychophysiological perspectives, a substantial number of occupational falls are thought to result from loss-of-balance (Hsiao and Simeonov, 2001). Understanding the mechanisms by which humans maintain balance can thus help understand and prevent such injuries. More specifically, postural control models can be used to investigate these mechanisms, to predict human physiological reactions used in maintaining balance, and to evaluate the potential impact of intervention strategies for the improvement of balance.

A number of control strategies have been proposed to model how the central nervous system (CNS) maintains balance. Masani et al. (2006) indicated that a proportional-derivative (PD) neural controller could effectively produce a desired preceding motor command for controlling balance during quiet standing. Proportional-derivative-integral (PID) neural controllers have been able to mimic experimental measures (Peterka, 2000; Maurer et al., 2005). Both PD and PID control strategies are simple and easily modeled, but they lack obvious physiological meaning. Kuo (1995) suggested an optimal control strategy for balance control, but no systematic approach was given to estimate the performance index used in the optimal controller. Bottaro et al. (2005) reported that body sway during quiet standing was an intermittent stabilization process, and that a ‘sliding mode’ control could effectively model this process. However, the authors also admitted that there was little theoretical and experimental evidence to explain the nature of the switching mechanism used in their method. In contrast to the above methods, Ishida et al. (1997) and Fujisawa et al. (2005) determined the neural controller’s transfer function using experimental data. These latter methods appear more valid, as no assumptions about the controller have to be made. However, they depend on the availability of experimental data, and the neural controller has to be modeled as a discrete system. Such discretizing likely yields errors when applied to what is in reality a continuous system.

To overcome some of the limitations of existing work, a new method for modeling postural control during spontaneous sway was developed. The objective of this study was to develop a new optimal control model of postural sway. Preliminary results are presented on the ability of the model to reflect age-related differences observed during spontaneous sway, and the identification of potential internal mechanisms that cause these differences.

METHOD

Human postural control system model

Since humans may be expected to achieve movement and balance tasks in an efficient and effective way, which assumes that the neural controller can at least partially optimize motions, the neural controller was assumed to be an optimal controller that could minimize a combination of certain physical quantities relevant to sway. The performance index in the optimal controller, and several other model parameters, were determined by using an optimization procedure whose objective was to minimize a scalar error function of center-of-pressure (COP) measures, since COP is commonly used to characterize body sway (Peterka, 2000).

There is always random noise acting on the human body which can be generally classified into two types: internal and external (van der Kooij *et al.*, 1999). Some studies explained the random noise as a random torque exerted about the joints along with the torques generated by the neural controller (Masani *et al.*, 2006; Maurer and Peterka, 2005). Other studies have shown that the random noise is from the sensory organs (van der Kooij *et al.*, 2001). Maurer and Peterka (2005) found that simulation results were very similar with different sites of noise injection. Thus, we assumed that the postural control system was a feedback control system, and that spontaneous sway was caused by both the torque generated by the neural controller and a random disturbance torque (Figure 1). For simplicity, the sensory system was assumed to provide an accurate measure of body orientation which has a certain time delay when input to the neural controller (van der Kooij et al., 1999; Maurer et al., 2005).

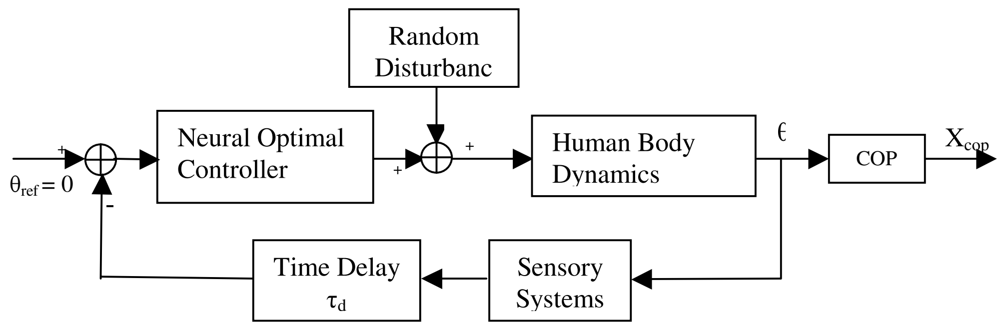

Figure 1: Optimal control model of human postural control

Human body dynamics

For spontaneous sway, the ankle strategy, under which only the ankle torque is considered to contribute to reducing sway angles, is sufficient for balance maintenance under normal sensory conditions (Johansson *et al.*, 1988). Hence, a single-link inverted pendulum model (Figure 2) was used to describe human body dynamics. In this preliminary work, sway was assumed to be restricted to the sagittal plane. The anthropometry of the simulated subject was set to that of an average adult male (Maurer et al., 2005).

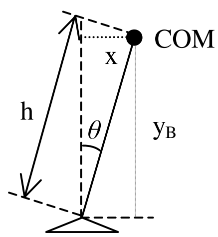

Figure 2: Inverted pendulum model of sway dynamics

The inverted pendulum equation of motion is given by:

$$J_B \frac{d^2\theta}{dt^2} - Mgh\sin\theta = T \tag{1}$$

where J_B is the moment of inertia of the body about the ankle, M is body mass, h is the height of the body center of mass, θ is the sway angle, T is the ankle torque, and g is the acceleration due to gravity. For spontaneous sway, θ is small enough so that $\sin\theta \approx \theta$. Derived from the equation of motion (1), the state equations representing body dynamics are given by

$$\dot{x} = Ax + Bu \tag{2}$$

where $A = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & \mathrm{Mgh/J_B} & 0 \end{pmatrix}$, $B = \begin{pmatrix} 0 \\ 0 \\ 1/J_B \end{pmatrix}$, and the states and control are $x = \begin{pmatrix} \theta \\ \dot{\theta} \\ \ddot{\theta} \end{pmatrix}$, $u = \dot{T}$.

Knowing the body dynamics, the computation of X_{cop}, the COP displacement along anterior-posterior direction, was based on the following equation (Maurer et al., 2005):

$$X_{cop} = \frac{(Mh^2 - J_B)\ddot{\theta} + Mx_B(g + \ddot{y}_B) - My_B\ddot{x}_B - Mh_F\ddot{x}_B + m_F d_F g}{M(g + \ddot{y}_B) + m_F g} \tag{3}$$

where m_F is the mass of the feet, h_F is the height of the ankle, and d_F is the horizontal distance between the ankle and the COM of the feet.

Neural controller

It was assumed that the neural controller was an optimal controller, and was determined by a linear quadratic regulator (LQR) that minimized a performance index of the standard form:

$$J = \int_0^\infty (x^T Qx + u^T Ru + 2x^T Nu)dt \tag{4}$$

where Q, R and N are time-invariant weighting matrixes for state x and control u, and are chosen by regulating certain physical quantities relevant to sway.

Minimum torque change is one of the most popular of several criteria that have been used to predict human motion (Uno et al., 1989; Chang et al., 2001). Ferry et al. (2004) and Martin et al. (2006) used this criterion to model balance control and found that it could yield realistic trajectories. The CNS may also try to minimize the displacement, velocity and acceleration of the sway angle over a time period in order to maintain balance effectively. At the same time, body orientation information received by the CNS has a certain time delay. Therefore, it was concluded that the relevant physical quantities included ankle torque change rate, and delayed body orientation measures. The optimal controller's performance index in this case is defined by:

$$J = \int_0^{\infty} (a_1\hat{\theta}^2 + a_2 \dot{\hat{\theta}}^2 + a_3 \ddot{\hat{\theta}}^2 + a_4 u^2) dt \tag{5}$$

where a_1, a_2, a_3, and a_4 are the weights of different relevant physical quantities. $\hat{\theta}$ is the delayed sway angle received by the CNS and approximated by $\hat{\theta} \approx \theta - \tau_d \dot{\theta}$, where τ_d is the delay time. Converting the performance index (5) into standard form (4), we obtained the weighting matrices mentioned in (4):

$$Q = \begin{pmatrix} a_1 & -a_1\tau_d & 0 \\ -a_1\tau_d & a_1\tau_d^{\,2} + a_2 + a_3(\tau_d Mgh / J_B)^2 & -a_2\tau_d - a_3\tau_d Mgh / J_B \\ 0 & -a_1\tau_d - a_3\tau_d Mgh / J_B & a_1\tau_d^{\,2} + a_3 \end{pmatrix} \tag{6}$$

$$R = a_4 + a_3(\tau_d / J_B)^2 \tag{7}$$

$$N = \begin{pmatrix} 0 & a_3 Mgh(\tau_d / J_B)^2 & -\tau_d / J_B \end{pmatrix} \tag{8}$$

After determining the weighting matrices and state equations, the optimal state feedback gain K can be determined by solving the Riccati equation (Naidu, 2003). Given the state x, the control $u=-Kx$.

Optimization procedure

This model was expected to be able to simulate COP properties, which were obtained from existing experimental studies. An optimization procedure was used to determine the values of several model parameters (decision variables), including the weights of the relevant physical quantities in the optimal controller's performance index, the random disturbance gain, and the delay time, so that the simulation results could best match the experimental results.

Prieto et al. (1996) presented several COP measures of postural steadiness. Maurer et al. (2005) classified these measures into three groups. Measures within each group are highly correlated, and between groups have lower correlations. According to Maurer's classification, we chose mean distance (MD), root mean square distance (RMS), mean velocity (MV), 50% power frequency (P50), 95% power frequency (P95), and centroidal frequency (CFREQ) to define the cost function of this optimization procedure, which is given by:

$$E = \sum_{i=1}^{N} \left(\frac{COPM_i - \hat{COPM}_i}{\hat{SD}_i}\right)^2 \tag{9}$$

where N=6 is the number of COP measures, $COPM_i$ is the mean of the *ith* COP measure from the simulation results, $\hat{SD}_i$ and $\hat{COPM}_i$ are the standard deviation and mean of the *ith* COP measure from the experimental results given by Prieto et al. (1996). (See Appendix for detailed definition of these COP measures)

In order to determine the optimal set of model parameters, a genetic algorithm (GA) was implemented, since GAs can typically find the region that includes the global optimum. In the GA, a feasible solution, which is defined by a set of model parameters in this specific case, is termed a "chromosome", and is usually encoded by a binary string. During each iteration of the optimization procedure, the current chromosomes (the feasible sets of model parameters) were each used to simulate spontaneous sway. The COP measures were calculated from the simulation results for each chromosome, and the corresponding cost function was evaluated. Then, the current chromosomes were selected to generate new chromosomes according to their fitness measured by the cost function – the lower the cost function is, the higher the chance that the chromosome will be selected. Finally, by using the operators of reproduction, crossover, and mutation, the GA made changes to the selected chromosomes in order to obtain better model parameters for the next iteration. This procedure was repeated until the cost function was minimized.

Model simulation

Ten independent simulations with different random disturbance seeds were performed for young and older adults respectively by using Matlab 7.0.4 (The MathWorks, Natick, MA). Simulink of Matlab 7.0.4 was used to model the described postural control system (Figure 1). The optimization procedure was coded using the Matlab programming language.

Initially, the values of the model parameters were randomly set for each simulation trial. Based on the current model parameters, the weighting matrices of the optimal controller's performance index were determined (see equations 6, 7, and 8), and then the corresponding optimal feedback gain was obtained by solving the Riccati equation. This optimal feedback gain was then input to the postural control system modeled in Simulink, to simulate the kinematics and dynamics during spontaneous sway. From this, the several COP measures were obtained. The model parameters that made the simulation results best match the experimental results were finally determined for each simulation trial by using the proposed optimization procedure. Two-sample t-tests were used to identify significant ($P<0.05$) differences in any model parameters between young and older adults.

RESULTS

To evaluate the simulation model performance, 1 SD ranges of the COP measures were derived from the 10 runs (Table 1). Simulated ranges were well within the 1 SD ranges of the corresponding experimental data given by Prieto et al. (1996), indicating that the simulations could yield reasonable estimates of all COP measures.

A number of model parameters were significantly larger in older adults (Table 2), specifically the random disturbance gain (*Kn*) and weights of the sway angular displacement (a_1) and ankle torque change rate (a_4). In contrast, the weight of the sway angular acceleration (a_3) was significantly smaller in this group. No significant differences were found in the weight of the sway angular velocity (a_2) and the delay time (τ_d).

DISCUSSION

COP measures are able to distinguish between older and young adults, for example, COP mean velocity and COP range were found to change with age (Prieto et al., 1996). Since the proposed model was able to accurately simulate COP measures, it can be used to identify potential underlying causes of the aging effect on upright postural control. Further, Ahmed et al. (2005) argued that aging could deteriorate the accuracy of the control signal that is sent to human body dynamics. Accuracy of the control signal is influenced, in the simulation model, by the random disturbance gain (Kn). Specifically, the larger the disturbance gain is, the less accurate the control signal is (Ahmed et al., 2005). Since the predicted random disturbance gain among older adults was significantly larger than that of young adults, the proposed model provides a plausible mechanism to explain age-related differences in postural sway. Ahmed et al. (2005) also suggested that aging could increase delay time in sensory systems. However, the difference in simulated delay time between the young and older adults was not significant. This may be due to the small number of simulation trials. Additional trends found in the simulation results (Table 2) highlight potential effects of age. For example, since the simulation results shows that the weight of ankle torque change rate was significantly larger in older adults, it might be concluded that ankle torque change rate plays a more important role in balance control in older adults than that in young adults.

Human motion is generally considered effective and efficient. For example, hand paths in point-to-point reaching movements are the shortest between the initial hand position and the target since they tend to be straight and smooth (Ohta et al., 2004), and these movements appear to be organized to minimize the amount of energy (Soechting et al., 1995). Thus, it is reasonable to consider that the CNS is able to at least partially optimize the generation of motion. This study systematically introduces an approach for the determination of what to optimize and how to optimize when modeling postural control during spontaneous sway. Modeling the neural controller as an optimal controller can also help to analyze spontaneous sway from a physiological perspective by incorporating relevant physical quantities into the performance index. At the same time, this model can be used to analyze possible postural control mechanisms for different groups of subjects by simply comparing their model parameters. Furthermore, because of the application of an optimization procedure, the simulation results given by this model can accurately reflect experimental studies in most cases. However, this model also has limitations. First, it is infeasible for us to incorporate all the possible physical quantities that may have effects on spontaneous sway. Second, the CNS may not simply use an optimal control strategy to generate the motor plans that lead to spontaneous sway. Third, the inverted pendulum model is only applicable for small amplitudes of sway motion. Fourth, genetic algorithms are a heuristic method and not good at local searching, which may not guarantee that the obtained set of model parameters is globally optimal.

Several steps may be taken to improve the model in future research. In order to improve the accuracy of the model, other physical quantities could be tested and incorporated into the performance index, and additional physical measures could be used to validate the model. By using the proposed model, additional individual-level effects (e.g. fatigue) could be assessed. A more realistic multi-link body model could be generated, such that larger amplitudes of sway motion can be modeled. Additional heuristic methods, that are good at finding local optima, could be used after the genetic algorithms to identify exact global optima. Each of these improvements are being currently investigated. In the longer term, we hope to apply such models in the development and evaluation of interventions, so as to maximize the capacity of the postural control system. In doing so, it is hoped that losses of balance, and associated fall events, can be minimized.

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Table 1: Simulated and experimental results for young and older adults

	Young adults				Older adults			
	Experimental results		Simulation results		Experimental results		Simulation results	
COP Measures	Mean	±SD Range	Mean	±SD Range	Mean	±SD Range	Mean	±SD Range
MD(mm)	2.42	1.45-3.39	2.55	2.44-2.66	3.19	2.18-4.20	3.30	3.23-3.37
RMS(mm)	2.95	1.87-4.03	3.21	3.09-3.33	3.98	2.76-5.20	4.16	4.04-4.28
MV(mm/s)	4.92	3.58-6.26	4.49	4.22-4.76	9.86	6.23-13.49	8.56	7.93-9.19
P50(Hz)	0.275	0.190-0.360	0.210	0.191-0.229	0.355	0.214-0.496	0.26	0.257-0.263
CFREQ(Hz)	0.509	0.418-0.600	0.584	0.550-0.618*	0.659	0.492-0.826	0.680	0.665-0.695
P95(Hz)	0.928	0.724-1.132	1.020	0.908-1.132	1.29	0.941-1.639	1.35	1.30-1.40

* indicates that the 1 SD range of the simulated measure is not completely within the 1 SD range of the corresponding experimental data

Table 2: Model parameters for young and older adults

Model Parameters	Young adults Mean(SD)	Older adults Mean(SD)	P-Value
Weight a_1	0.5549(0.0641)	0.6942(0.1092)	<0.05
Weight a_2	0.0026(0.0018)	0.0263(0.0438)	0.10
Weight a_3	0.4424(0.0632)	0.2795(0.0931)	<0.05
Weight a_4	2.127×10^{-6} (0.242×10^{-6})	2.667×10^{-6}(0.426×10^{-6})	<0.05
Random disturbance gain *Kn*	867(69)	1748(118)	<0.05
Delay time τ_d	0.6256(0.0245)	0.5981(0.0491)	0.15