Journal of Biomechanics 40 (2007) 3590–3597

JOURNAL OF BIOMECHANICS

www.elsevier.com/locate/jbiomech
www.JBiomech.com

A balance control model of quiet upright stance based on an optimal control strategy

Xingda Qu[a], Maury A. Nussbaum[a,b,*], Michael L. Madigan[b,c]

[a]Department of Industrial and Systems Engineering, Virginia Tech, 250 Durham Hall (0118), Blacksburg, VA 24061, USA
[b]School of Biomedical Engineering and Sciences, Virginia Tech, 250 Durham Hall (0118), Blacksburg, VA 24061, USA
[c]Department of Engineering Science and Mechanics, Virginia Tech, 250 Durham Hall (0118), Blacksburg, VA 24061, USA

Accepted 7 June 2007

Abstract

Models of balance control can aid in understanding the mechanisms by which humans maintain balance. A balance control model of quiet upright stance based on an optimal control strategy is presented here. In this model, the human body was represented by a simple single-segment inverted pendulum during upright stance, and the neural controller was assumed to be an optimal controller that generates ankle control torques according to a certain performance criterion. This performance criterion was defined by several physical quantities relevant to sway. In order to accurately simulate existing experimental data, an optimization procedure was used to specify the set of model parameters to minimize the scalar error between experimental and simulated sway measures. Thirty-two independent simulations were performed for both younger and older adults. The model's capabilities, in terms of reflecting sway behaviors and identifying aging effects, were then analyzed based on the simulation results. The model was able to accurately predict center-of-pressure-based sway measures, and identify potential changes in balance control mechanisms caused by aging. Correlations between sway measures and model parameters are also discussed.

Keywords: Balance control; Optimal control strategy; Aging; Sway; Simulation

1. Introduction

Upright stance is inherently unstable in that without internal control, even minute amplitude disturbances can compromise stability. Internal control is provided by the postural control system which generates joint torques to control upright stance (Ishida et al., 1997; Peterka, 2000). Thus, investigating balance control mechanisms may aid in understanding the postural control system.

A number of balance control models have been proposed to investigate balance control mechanisms. The most essential aspect of such models is the model neural controller, for which two main approaches have been used. In the first, it is assumed that the neural controller adopts a particular control strategy to maintain balance. These include PID (proportional, derivative, and integral) control (Iqbal and Roy, 2004; Johansson et al., 1988; Maurer and Peterka, 2005), RIPID (recurrent integrator proportional integral derivative) control (Jo and Massaquoi, 2004), and sliding mode control (Bottaro et al., 2005), etc. While providing a basis for applying control theory to the neural controller, a common concern with such models is that it is impossible to validate the fundamental control assumption, since it is still unknown how the neural controller works. In the second approach, the neural controller is completely determined by available experimental data (Fujisawa et al., 2005; Ishida et al., 1997; Kiemel et al., 2002). These models appear more valid, as no assumptions about the controller have to be made, yet are limited by a dependence on experimental data. Further, when using the second type of model, the neural controller has to be modeled as a discrete

*Corresponding author. Department of Industrial and Systems Engineering, Virginia Tech, 250 Durham Hall (0118), Blacksburg, VA 24061, USA. Tel.: +1 540 231 6053; fax: +1 540 231 3322.
E-mail address: nussbaum@vt.edu (M.A. Nussbaum).

0021-9290/$ - see front matter
doi:10.1016/j.jbiomech.2007.06.003

system, which may induce errors related to discretizing continuous data. Such errors can result in instability when modeling upright stance (Ishida et al., 1997).

Human motions are generally effective and efficient. For example, hand paths taken 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 (Morasso, 1981; Ohta et al., 2004), and these movements appear to be organized to minimize energy expended (Soechting et al., 1995). Some type of optimization also appears present in the control of muscle recruitment for generating motions (Fagg et al., 2002). Some investigations of upright stance control have been based on the assumption that sway motions are planned according to optimal objectives, and have yielded realistic motion trajectories (Ferry et al., 2004; Martin et al., 2006). Thus, we may consider that the neural controller is an optimal controller that is able to optimize the generation of sway motion (though we may not know, *a priori*, what is optimized).

The purpose of this study was to develop a new balance control model based on an optimal control strategy. Since center-of-pressure (COP) based sway measures are most commonly used to characterize sway behaviors (Baratto et al., 2002; Peterka, 2000; Prieto et al., 1996), this model was expected to be able to accurately simulate actual COP-based measures. Recent studies have shown that older adults have a reduced ability to maintain balance (Du Pasquier et al., 2003), indicating that aging likely compromises balance control. Thus, results are presented on the ability of the model to simulate spontaneous sway measures, to reflect differences in sway associated with age, and to identify potential internal mechanisms that cause these differences.

2. Methods

2.1. Model structure

The postural control system was modeled as a feedback control system (Masani et al., 2006; Peterka, 2002). The closed loop in the postural control system model consists of three parts: human body dynamics, the sensory (afferent) feedback, and a neural controller. Human body dynamics was described by a single-segment inverted pendulum model (Fig. 1). Sway motion was assumed to be restricted to the sagittal plane, and anthropometry of the simulated subject was set to that of an average adult male (Maurer and Peterka, 2005). The equation of motion for the inverted pendulum model of the body is given by:

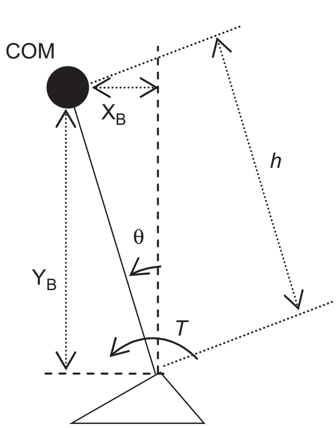

Fig. 1. Single-segment inverted pendulum model of sway dynamics.

$$I\ddot{\theta}(t) - Mgh\sin\theta(t) = T(t), \tag{1}$$

where $I = 66\,\mathrm{kg/m^2}$ is the moment of inertia of the body about the ankle, $M = 76\,\mathrm{kg}$ is body mass, $h = 0.87\,\mathrm{m}$ is the height of the body center of mass (COM), θ is the sway angle, T is the ankle torque, and $g = 9.81\,\mathrm{m/s^2}$ is the acceleration due to gravity. For spontaneous sway, $\theta(t)$ is small enough so that $\sin\theta(t) \approx \theta(t)$. Thus, Eq. (1) can be linearized as

$$I\ddot{\theta}(t) - Mgh\,\theta(t) = T(t). \tag{2}$$

Sensory systems were assumed to provide accurate body orientation measures to the neural controller (e.g. Masani et al., 2006; Peterka, 2000), but with an inherent time delay due to sensory transduction, transmission, and processing (van der Kooij et al., 1999). We assumed that this delay was time-invariant for a given individual under consistent conditions. In order to linearize the sensory system model, the delayed sway angular displacement, $\hat{\theta}(t) = \theta(t - \tau_d)$, was expanded using a Taylor series (Bajpai et al., 1977), and thereby approximated as

$$\hat{\theta}(t) \approx \theta(t) - \tau_d\dot{\theta}(t) + \tfrac{1}{2}\tau_d^2\ddot{\theta}(t), \tag{3}$$

where τ_d is the time-invariant delay time.

According to Eqs. (2) and (3), given a zero initial condition, the properties of body dynamics and sensory systems can be represented by the following transfer functions, respectively:

$$\frac{\theta(s)}{T(s)} = \frac{1}{Is^2 - Mgh}, \tag{4}$$

$$\frac{\hat{\theta}(s)}{\theta(s)} = \frac{1}{2}\tau_d^2 s^2 - \tau_d s + 1,$$

or

$$\frac{\dot{\hat{\theta}}(s)}{\dot{\theta}(s)} = \frac{1}{2}\tau_d^2 s^2 - \tau_d s + 1. \tag{5}$$

To stabilize the postural control system, so that the body is kept upright, the properties of both body dynamics and sensory systems should be taken into account by the neural controller. Thus, the controlled part in the postural control system includes both body dynamics and sensory systems. Derived from Eqs. (4) and (5), the transfer function from joint torque to delayed sway angular displacement is

$$\frac{\hat{\theta}(s)}{T(s)} = \frac{\frac{1}{2}\tau_d^2 s^2 - \tau_d s + 1}{Is^2 - Mgh}. \tag{6}$$

Since the Laplace '*s*' can be directly replaced by the differentiation operator, according to Eq. (6):

$$\ddot{\hat{\theta}}(t) = \frac{Mgh}{I}\hat{\theta}(t) + \frac{1}{I}T(t) - \frac{\tau_d}{I}\dot{T}(t) + \frac{1}{2}\tau_d^2\ddot{T}(t). \tag{7}$$

Thus, we obtained the state equations accounting for the properties of body dynamics and sensory systems as follows:

$$\dot{x}(t) = Ax(t) + Bu(t), \tag{8}$$

where

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ \dfrac{Mgh}{I} & 0 & \dfrac{1}{I} & \dfrac{-\tau_d}{I} \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ \dfrac{\tau_d^2}{2I} \\ 0 \\ 1 \end{pmatrix},$$

the state is

$$x(t) = \begin{pmatrix} \hat{\theta}(t) \\ \dot{\hat{\theta}}(t) \\ T(t) \\ \dot{T}(t) \end{pmatrix},$$

and the control signal is $u(t) = \ddot{T}(t)$.

The neural controller was designed according to the above state equations, and it assumed to be an optimal controller that incorporates an optimal control processor and two integration units. The optimal control processor generates the optimal control signal (u) according to some performance criterion. Two integration units ensure that the output of the neural controller is the joint torque. We also assumed that spontaneous sway was caused by both the torque generated by the neural controller and a random disturbance torque (e.g. Peterka, 2000), the latter modeled as white noise. The complete postural control system model can thus be illustrated as in Fig. 2(a).

2.2. Optimal control processor

The optimal control processor was designed following an optimal control strategy. Since there is no clear final condition for spontaneous sway, the optimal control processor is determined by an infinite-time linear quadratic regulator (LQR). The LQR minimizes a performance index of the standard form

$$J = \frac{1}{2}\int_0^\infty (x'(t)Qx(t) + u'(t)Ru(t))\,\mathrm{d}t, \tag{9}$$

where Q and R are time-invariant weighting matrices for state x and control signal u (see Eq. (8)), and are chosen by regulating certain physical quantities relevant to sway.

State x and control signal u should be able to represent selected physical quantities, and do so in a form that allows the weighting matrices to be easily obtained. Ferry et al. (2004) and Martin et al. (2006) used the criterion of minimum torque change rate to simulate sway motion and found that it could yield realistic trajectories. Humans may also try to minimize the displacement and velocity of the sway angle, and/or other joint torque measures over time in order to maintain balance effectively and efficiently. Therefore, the optimal controller's performance index was defined by:

$$J = \frac{1}{2}\int_0^\infty (w_1\hat{\theta}^2(t) + w_2\dot{\hat{\theta}}^2(t) + w_3T^2(t) + w_4\dot{T}^2(t) + w_5\ddot{T}^2(t))\,\mathrm{d}t, \tag{10}$$

where w_1, w_2, w_3, w_4 and w_5 are weightings of the respective relevant physical quantities. These weights are not predetermined. Rather, they are determined as described below, and are subsequently interpreted as indicating which physical quantities play a more important role in balance control.

In order to apply formulated optimal control equations, the performance index (Eq. (10)) must first be converted into the standard form. Doing so yields the weighting matrices Q and R in Eq. (9) as

$$Q = \begin{pmatrix} w_1 & 0 & 0 & 0 \\ 0 & w_2 & 0 & 0 \\ 0 & 0 & w_3 & 0 \\ 0 & 0 & 0 & w_4 \end{pmatrix}, \quad R = w_5. \tag{11}$$

After determining the weighting matrices of the performance index in the standard form, and state equations of the controlled part in the postural control system, the optimal state feedback gain ($K = \{K_1, K_2, K_3, K_4\}$) is needed. This gain is used to define the optimal control processor

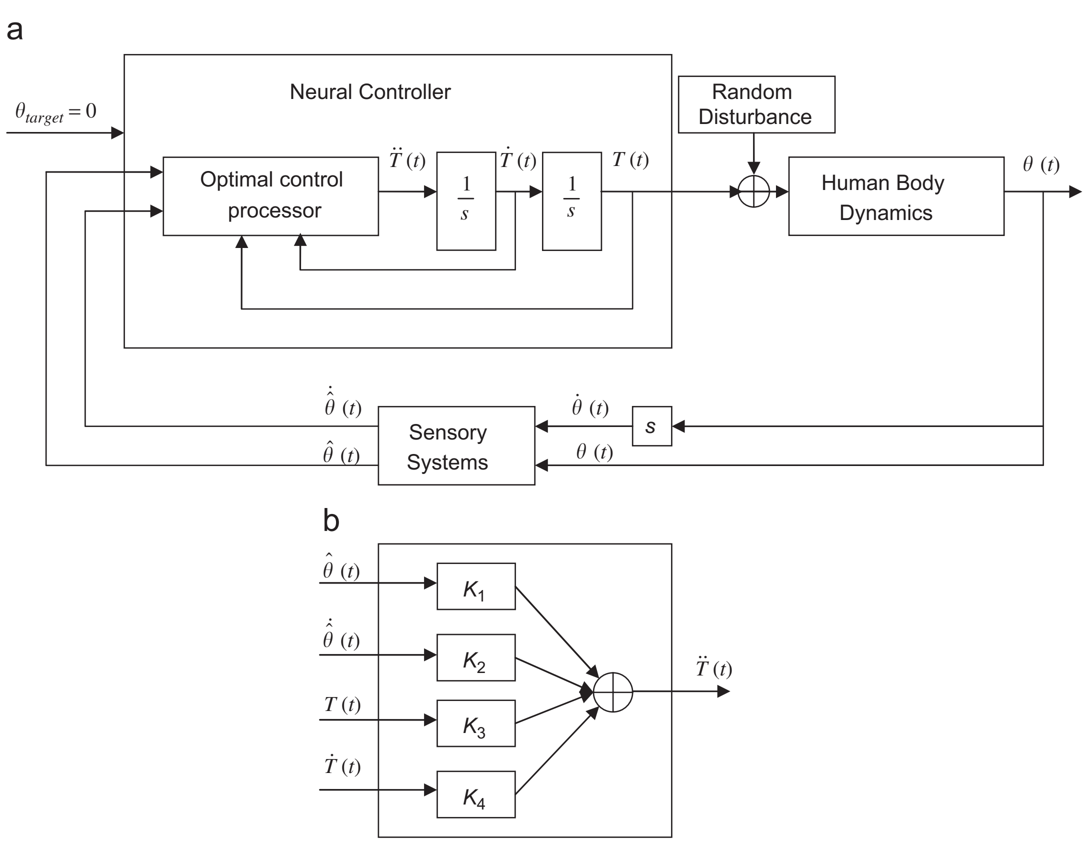

Fig. 2. (a) Human postural control system model of balance control. θ, sway angular displacement; $\hat{\theta}$, delayed sway angular displacement; T, ankle torque; θ_{target}, target sway angle. Human body dynamics is defined by Eq. (4). Sensory systems are defined by Eq. (5). (b) Optimal control processor model. $\{K_1, K_2, K_3, K_4\}$ is the optimal feedback gain.

(Fig. 2(b)), and can be calculated by solving the Riccati equation (Naidu, 2003). Given the state x, the optimal control processor generates the optimal control signal that can minimize the performance index (Eq. (10)):

$$u(t) = -Kx(t) = -(K_1\hat{\theta}(t) + K_2\dot{\hat{\theta}}(t) + K_3T(t) + K_4\dot{T}(t)). \quad (12)$$

Note that when using the Riccati equation to calculate the optimal feedback gain, only the state matrices A and B (see Eq. (8)), and the weighting matrices Q and R (see Eq. (9)) were required, and the properties of the random disturbance torque were not taken into account. This is appropriate since the random disturbance torque is not contained in the closed loop of the postural control system, and thus cannot account for the internal properties of the postural control system.

2.3. Optimization procedure

Unlike the anthropometry of the simulated subject, some model parameters, e.g. sensory delay time, cannot be specified in advance. In addition, the balance control model was expected to be able to accurately simulate sway measures. To this end, an optimization procedure was performed to determine the values of the unspecified model parameters, so that the simulation results can best match the experimental results. These model parameters were the weights of the relevant physical quantities in the optimal controller's performance index, the random disturbance gain, and the sensory delay time.

COP-based measures of sway were desired from the model output for comparison with experimental data. From body dynamics, the COP displacement along the A/P direction (X_{cop}) was determined using (Maurer and Peterka, 2005):

$$X_{\mathrm{cop}} = \frac{(Mh^2 - I)\ddot{\theta} + Mx_{\mathrm{B}}(g + \ddot{y}_{\mathrm{B}}) - My_{\mathrm{B}}\ddot{x}_{\mathrm{B}} - Mh_{\mathrm{F}}\ddot{x}_{\mathrm{B}} + m_{\mathrm{F}}d_{\mathrm{F}}g}{M(g + \ddot{y}_{\mathrm{B}}) + m_{\mathrm{F}}g}, \quad (13)$$

where $m_{\mathrm{F}} = 2.01$ kg is the mass of the feet, $h_{\mathrm{F}} = 0.085$ m is the height of the ankle, and $d_{\mathrm{F}} = 0.052$ m is the A/P distance between the ankle and the COM of the feet (additional terms are as defined above).

We chose nine COP-based sway measures according to the classification suggested by Maurer and Peterka (2005). These measures are: mean distance (MD), root mean square distance (RMS), maximum distance (MAXD), mean velocity (MV), mean frequency (MFREQ), 50% power frequency (P50), 95% power frequency (P95), centroidal frequency (CFREQ), and frequency dispersion (FREQD). The cost function is then given by:

$$E = \sum_{i=1}^{N} \left(\frac{\mathrm{COPM}_i - \widehat{\mathrm{COPM}}_i}{\widehat{\mathrm{SD}}_i} \right)^2, \quad (14)$$

where $N = 9$ is the number of COP-based measures, COPM_i is the mean of the ith COP-based measure from the simulation results, and $\widehat{\mathrm{SD}}_i$ and $\widehat{\mathrm{COPM}}_i$ are, respectively, the standard deviation and mean of the ith COP-based measure from the experimental results of Prieto et al. (1996).

This optimization procedure is sufficiently complex that heuristic approaches are suitable for searching for a good solution (Hillier and Lieberman, 2005). Thus, a genetic algorithm (GA) was implemented to determine the optimal set of model parameters.

2.4. Model simulation

Fig. 3 shows the flow of model simulation. Initially, the state equations of the controlled part in the postural control system were determined. Then, the values of the model parameters were randomly set for a simulation trial. Based on the current model parameters, the weighting matrices of the optimal control processor's performance index were determined, and then the corresponding optimal feedback gain was obtained by solving the Riccati equation. This optimal feedback gain was then used to determine the optimal control processor. At this stage, the kinematics and dynamics during spontaneous sway could be simulated.

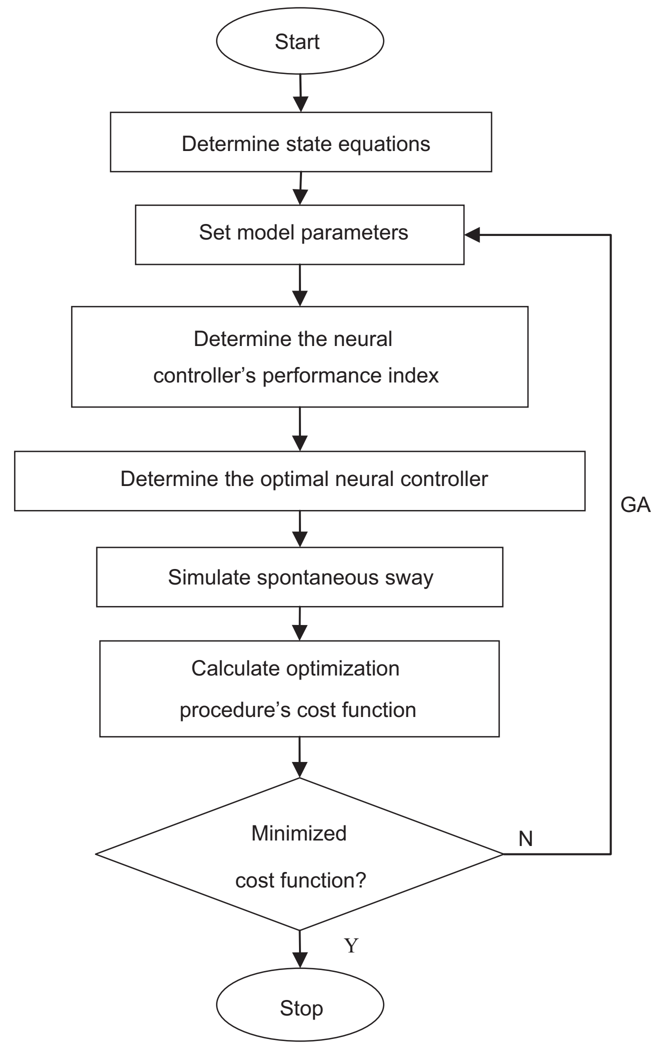

Fig. 3. Flow of model simulations (GA, genetic algorithm).

Based on the simulation output, the cost function (Eq. (14)) was calculated and the GA was used here to determine whether this cost function was minimized. If so, this simulation trial was stopped. Otherwise, the GA would aid in finding another set of model parameters, and the above procedures would be repeated until the cost function was minimized or a stopping criterion (maximum number of generations or iterations = 50) was met.

Thirty-two independent simulations with different initial random disturbance seeds were performed for both younger and older adults. The whole simulation procedure was coded using the Matlab programming language (The MathWorks, Natick, MA), and each simulated sway trial was 40 s in duration. After obtaining the simulation results for all the simulated trials, two-sample t-tests were used to identify significant ($p < 0.05$) differences in any model parameters between younger and older adults. We also determined linear correlations between model parameters and simulated sway measures.

3. Results

3.1. Simulated sway measures

Nearly all the simulated sway measures from the 64 simulation trials were within the one standard deviation ranges of the corresponding experimental data (Fig. 4). The only exception occurred in the measure of MFREQ.

3.2. Model parameters

Several modeled parameters differed between younger and older adults (Table 1). Significant differences were found in the weights of sway angular velocity (w_2), ankle torque (w_3), ankle torque acceleration (w_5), and random disturbance gain (k_n). More specifically, w_2 and w_5 were significantly larger in younger adults, while w_3 and k_n were significantly larger in older adults. In addition, some differences in the parameters approached significance, including the weight of sway angular displacement (w_1) and sensory time delay (τ_d), which were both larger in the older group.

3.3. Correlations between the simulated sway measures and some model parameters

Typically, the simulated sway measures were positively correlated with w_1, w_3, w_4, k_n, and τ_d, and negatively correlated with w_2 and w_5 (Table 2). Two exceptions were that FREQD was positively correlated with w_5, and P95 was uncorrelated ($r = 0.003$) with τ_d. Not all of these correlations were significant. For example, although w_1 seemed positively correlated with all of the simulated sway measures, none of these correlations was significant. However, most of the sway measures (MAXD, MV, MFREQ, P95, CFREQ) were significantly correlated with w_2, w_3, w_5, and k_n. In addition, MD and RMS were significantly correlated with w_2, w_5, and k_n, P50 with w_5, k_n, and τ_d, and FREQD with w_4 and k_n.

4. Discussion

One of the objectives of this study was to develop a balance control model based on an optimal control strategy that could accurately reflect postural sway during quiet upright stance. The simulation results showed that almost all simulated sway measures were completely within a one standard deviation range of the corresponding experimental data. Therefore, the balance control model appears to be capable of simulating realistic COP-based measures of sway.

Since the proposed model was able to simulate realistic COP-based measures, it can be used to identify potential

Table 1
Model parameter means (SD) for younger and older adults (p-values given for age-related differences)

	Younger adults	Older adults	p-Value
Weight w_1	0.330 (0.195)	0.397 (0.188)	0.083
Weight w_2	0.540 (0.198)	0.434 (0.177)	<0.05
Weight w_3	0.072 (0.050)	0.098 (0.063)	<0.05
Weight w_4	0.053 (0.038)	0.069 (0.066)	0.123
Weight w_5	$3.84\ (3.00) \times 10^{-3}$	$1.96\ (2.97) \times 10^{-3}$	<0.05
Disturbance gain k_n	151.8 (23.1)	356.1 (83.3)	<0.05
Sensory delay τ_d (ms)	25.6 (18.0)	33.3 (23.0)	0.073

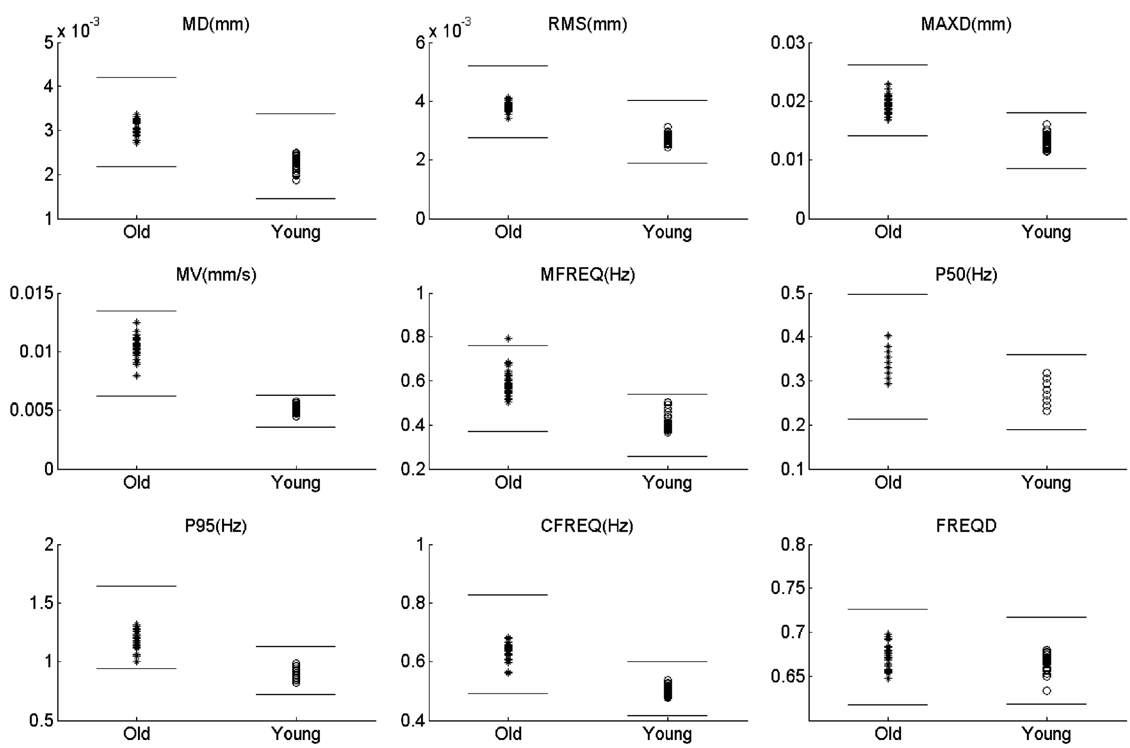

Fig. 4. Simulated sway measures obtained from 32 simulation trials of both younger and older adults. Horizontal solid lines represent the one standard deviation ranges of the corresponding experimental data given by Prieto et al. (1996).

Table 2
Correlations (r) between simulated sway measures and model parameters

	Weight w_1	Weight w_2	Weight w_3	Weight w_4	Weight w_5	Disturbance gain k_n	Sensory delay τ_d
MD	0.181	−0.247*	0.119	0.124	−0.262*	0.832*	0.187
RMS	0.176	−0.247*	0.150	0.112	−0.297*	0.850*	0.177
MAXD	0.160	−0.246*	0.229*	0.083	−0.343*	0.831*	0.108
MV	0.162	−0.276*	0.298*	0.112	−0.335*	0.878*	0.153
MFREQ	0.124	−0.267*	0.409*	0.099	−0.355*	0.812*	0.109
P50	0.112	−0.150	0.074	0.073	−0.259*	0.679*	0.265*
P95	0.133	−0.227*	0.257*	0.083	−0.328*	0.906*	−0.003
CFREQ	0.170	−0.295*	0.260*	0.188	−0.267*	0.839*	0.174
FREQD	0.056	−0.203	0.197	0.312*	0.0917	0.338*	0.115

Correlations noted by * were significant ($p < 0.05$).

underlying causes of the aging effect on balance control. It is generally accepted that aging adversely affects the accuracy of control signals by increasing sensory noise and elevating sensory thresholds (Ahmed and Ashton-Miller, 2005; Gilsing et al., 1995; Tian et al., 2002). Accuracy of the control signal is influenced in the simulation model by the random disturbance gain (k_n). With larger disturbance gains, the accuracy of the control signal decreases. Since the predicted random disturbance gain among older adults was significantly larger than that of younger adults, the proposed model provides a plausible mechanism to explain age-related differences in upright balance control.

Sensory delay has also been generally considered to increase with aging (Mackey and Robinovitch, 2006). From the simulation results, the mean sensory delay time among older adults was larger than that of younger adults, though not significantly ($p = 0.073$). In addition to disturbance gain and sensory delay, other model parameters also showed effects of age (Table 1). For example, the weight of ankle torque acceleration (w_5) was significantly larger in younger adults, so it might be concluded that ankle torque acceleration plays a more important role in balance control in younger versus older adults.

By examining the correlations between simulated sway measures and model parameters, we found that some model parameters (w_2, w_3, w_5, and k_n) may be predictable from more directly observable sway measures. For example, random disturbance gain (k_n) was positively (and significantly) correlated with all sway measures. Hence, knowing certain tendencies regarding sway measures, which can be determined experimentally, may aid in estimating the differences in underlying random disturbance magnitudes among different subject groups.

Predicted sensory delay, accounting for the time delay in the feedback loop, was ~30 ms. This time delay could be interpreted as the latency from the instant that mechanoreceptive afferents (e.g. in the foot) are stimulated, until the instant a sensory evoked potential is recorded in the somatosensory area of the brain (Masani et al., 2006). Applegate et al. (1988) reported that this time delay was in the range of 35.4–40.1 ms, which is comparable to our simulation results. There are clearly other sources of delays, such as the motor command time delay in the postural control system, but these time delays are not in the feedback loop. In order to simplify the model, we did not model these time delays. Note that errors may still be made in estimating sensory delay primarily due to two factors. First, the GA cannot guarantee that exact global optimal solutions are found, so the predicted sensory delay may not be the exact time delay in the feedback loop. Second, the delayed sway angle considered in the model was only an approximation (see Eq. (3)).

A PID control strategy has been widely used to design the neural controller in balance control models. In particular, Maurer and Peterka (2005) obtained realistic simulations of COP-based sway measures using such a controller. The major difference between the presented model and that of Maurer and Perterka (2005) is in the control strategy used to define the neural controller. We assumed that the neural controller adopted an optimal control strategy. As a result, the inherent parameters of the two models are different. Since these model parameters are used to explain how the neural controller works, balance control mechanisms are explained from different perspectives. For example, we used weightings of several physical quantities relevant to sway to indicate which of these plays a more important role in balance control. In contrast, Maurer and Peterka (2005) interpreted the effect of active stiffness on balance control.

Kuo (1995, 2005) and van der Kooij et al. (1999) have also successfully applied optimal control theory when constructing balance control models. However, van der Kooij et al. (1999) only took into account the properties of human body dynamics when specifying the optimal feedback in their model. Sensory systems are also an important aspect of the closed loop portion of the postural control system. In order to optimize the performance of the whole postural control system, properties of sensory systems should be considered by the neural controller. In Kuo's study (1995), the state equations accounted for both body dynamics and sensory properties. However, the system matrices were specified by measuring the feasible acceleration set (FAS) which is derived from many complex factors, e.g. musculoskeletal geometry and muscle properties. In contrast to these earlier models, the model presented here derived the controlled state equations (Eq. (8)) from the transfer functions of human body dynamics and sensory systems, and the neural controller was modeled according to these state equations. In addition, no additional knowledge was necessary when specifying the sensory systems.

The strength of the model presented here is that it was able to accurately simulate sway behaviors. Further, we have presented an approach for determining what to optimize and how to optimize when modeling balance control during spontaneous sway. Modeling the neural controller as an optimal controller stems from a physiological basis, in that it is possible to incorporate physical quantities relevant to sway into the performance index defined in the optimal controller. It is also physiologically plausible that the state x (see Eq. (8)) can be fed back to the neural controller to generate the optimal control signal. Specifically, muscle spindles can sense the joint angular displacement and velocity (van der Kooij et al., 1999), and the state variables T and $\dot{T}$ are internal states of the neural controller. At the same time, this model can be used to analyze potential balance control mechanisms for different groups of subjects by simply comparing their model parameters. In addition, this model may aid in predicting human physiological reactions used in maintaining balance, and facilitate evaluating the potential impact of intervention strategies for the improvement of balance.

The model presented here also has some limitations. First, only a few physical quantities that may have effects on spontaneous sway can be incorporated into the performance index. Second, the neural controller may not use an optimal control strategy to generate the motor plans that lead to spontaneous sway, though based on the simulation results, we may say that such a control strategy can at least partly explain the neural controller. Third, the presented model is only applicable for small amplitudes of planar sway motion, given only ankle torques were considered to contribute to maintaining balance (Kuo, 1995). Fourth, this model depends on experimental data to determine the parameters. Note that in the current work, the same anthropometry was assumed for both younger and older adults. This represents a limitation in implementation, though not necessarily in the modeling approach. Fifth, GAs are a heuristic approach and not good at local searching, which may not guarantee that the obtained set of model parameters were globally optimal.

It can also be argued that the real sensory systems are much more complex than is represented in the model, as a time delay, since to maintain upright stance body orientation information from visual, vestibular, and proprioceptive sensory systems should be integrated and fed back to the neural controller (Kuo, 2005; Peterka, 2002). Two reasons motivated our adoption of a simple time delay to represent sensory systems. First, the focus of this study was not on an investigation of the contributions of sensory systems to balance control. Second, it is easy to linearize sensory systems by simply using a time delay representation, so that the Ricatti equation can be used to calculate the optimal feedback gain. Several studies have also used this simplification to model sensory systems and obtained realistic results (Masani et al., 2006; Maurer and Peterka, 2005; Peterka, 2000). However, we admit that modeling sensory systems as a time delay is rather simplistic, especially when the interest is in studying how sensory systems work during quiet upright stance. Thus, in future research, a balance control model with more complex sensor dynamics should be investigated.

Conflict of interest

The authors declare that all authors have no financial or personal relationship with other persons or organizations that might inappropriately influence our work presented therein.

Acknowledgments

Support for this work was provided by Cooperative Agreement Number R01 OH04089 from the Centers for Disease Control and Prevention (CDC). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the CDC. The authors would also like to thank Bradley Davidson for his comments and suggestions on this paper.

References

Ahmed, A.A., Ashton-Miller, J.A., 2005. Effect of age on detecting a loss of balance in a seated whole-body balancing task. Clinical Biomechanics 20, 767–775.

Applegate, C., Gandevia, S.C., Burke, D., 1988. Changes in muscle and cutaneous cerebral potentials during standing. Experimental Brain Research 71, 183–188.

Bajpai, A.C., Mustoe, L.R., Walker, D., 1977. Advanced Engineering Mathematics. Wiley, New York, pp. 195–198.

Baratto, L., Morasso, P.G., Re, C., Spada, G., 2002. A new look at posturographic analysis in the clinical context: sway-density versus other parameterization techniques. Motor Control 6, 246–270.

Bottaro, A., Casadio, M., Morasso, P.G., Sanguineti, V., 2005. Body sway during quiet standing: is it the residual chattering of an intermittent stabilization process? Human Movement Science 24, 588–615.

Du Pasquier, R.A., Blanc, Y., Sinnreich, M., Landis, T., Burkhard, P., Vingerhoets, F.J.G., 2003. The effect of aging on postural stability: a cross sectional and longitudinal study. Neurophysiologie Clinique 33, 213–218.

Fagg, A.H., Shah, A., Barto, A.G., 2002. A computational model of muscle recruitment for wrist movement. Journal of Neurophysiology 88, 3348–3358.

Ferry, M., Martin, L., Termoz, N., Cote, J., Prince, F., 2004. Balance control during an arm raising movement in bipedal stance: which biomechanical factor is controlled? Biological Cybernetics 91, 104–114.

Fujisawa, N., Tasuda, T., Inaoka, H., Fukuoka, Y., Ishida, A., Minamitani, H., 2005. Human standing posture control system depending on adopted strategies. Medical and Biological Engineering and Computing 43, 107–114.

Gilsing, M.G., van der Bosch, C.G., Lee, S.G., Ashton-Miller, J.A., Alexander, N.B., Schultz, A.B., Ericson, W.A., 1995. Association of age with the threshold for detecting ankle inversion and eversion in upright stance. Age Ageing 241, 58–66.

Hillier, E.S., Lieberman, G.J., 2005. Introduction to Operations Research. McGraw-Hill, New York, pp. 644–652.

Iqbal, K., Roy, A., 2004. Stabilizing PID controllers for a single-link biomechanical model with position, velocity, and force feedback. Journal of Biomechanical Engineering 126, 838–843.

Ishida, A., Imai, S., Fukuoka, Y., 1997. Analysis of the posture control system under fixed and sway-referenced support conditions. IEEE Transactions on Biomedical Engineering 44, 331–336.

Jo, S., Massaquoi, S.G., 2004. A model of cerebellum stabilized and scheduled hybrid long-loop control of upright balance. Biological Cybernetics 91, 188–202.

Johansson, R., Magnusson, M., Akesson, M., 1988. Identification of human postural dynamics. IEEE Transactions on Biomedical Engineering 35, 858–869.

Kiemel, T., Oie, K.S., Jeka, J.J., 2002. Multisensory fusion and the stochastic structure of postural sway. Biological Cybernetics 87, 262–277.

Kuo, A.D., 1995. An optimal control model for analyzing human postural balance. IEEE Transactions on Biomedical Engineering 42, 87–101.

Kuo, A.D., 2005. An optimal state estimation model of sensory integration in human postural balance. Journal of Neural Engineering 2, S235–S249.

Mackey, D.C., Robinovitch, S.N., 2006. Mechanisms underlying age-related differences in ability to recover balance with the ankle strategy. Gait and Posture 23, 59–68.

Martin, L., Cahouet, V., Ferry, M., Fouque, F., 2006. Optimization model predictions for postural coordination modes. Journal of Biomechanics 39, 170–176.

Masani, K., Vetter, A.H., Popovic, M.R., 2006. Controlling balance during quiet standing: proportional and derivative controller generates preceding motor command to body sway position observed in experiments. Gait and Posture 23, 164–172.

Maurer, C., Peterka, R.J., 2005. A new interpretation of spontaneous sway measures based on a simple model of human postural control. Journal of Neurophysiology 93, 189–200.

Morasso, P.G., 1981. Spatial control of arm movements. Experimental Brain Research 42, 223–227.

Naidu, D.S., 2003. Optimal Control Systems. CRC Press, Boca Raton, FL, pp. 125–151.

Ohta, K., Svinin, M.M., Luo, Z., Hosoe, S., 2004. Optimal trajectory formation of constrained human arm reaching movements. Biological Cybernetics 91, 23–36.

Peterka, R.J., 2000. Postural control model interpretation of stabilogram diffusion analysis. Biological Cybernetics 82, 335–343.

Peterka, R.J., 2002. Sensorimotor integration in human postural control. Journal of Neurophysiology 88, 1097–1118.

Prieto, T.E., Myklebust, J.B., Hoffmann, R.G., Lovett, E.G., Myklebust, B.M., 1996. Measures of postural steadiness: differences between healthy young and elderly adults. IEEE Transactions on Biomedical Engineering 43, 956–966.

Soechting, J.F., Buneo, C.A., Herrmann, U., Flanders, M., 1995. Moving effortlessly in three dimensions: does Donder's law apply to arm movement? Journal of Neuroscience 15, 6271–6280.

Tian, J.R., Crane, B.T., Wiest, G., Demer, J.L., 2002. Effect of aging on the human initial interaural linear vestibule-ocular reflex. Experimental Brain Research 1452, 142–149.

van der Kooij, H., Jacobs, R., Koopman, B., Grootenboer, H., 1999. A multisensory integration model of human stance control. Biological Cybernetics 80, 299–308.