# Measuring Robustness of the Postural Control System to a Mild Impulsive Perturbation

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***Abstract*—We propose a new metric to assess robustness of the human postural control system to an impulsive perturbation (in this case, a mild backward impulse force at the pelvis). By applying concepts from robust control theory, we use the inverse of the maximum value of the system's sensitivity function (*1/MaxSens*) as a measure for robustness of the human postural control system, e.g., a highly sensitive system has low robustness to perturbation. The sensitivity function, which in this case is the frequency response function, is obtained directly using spectral analysis of experimental measurements, without need to develop a model of the postural control system. Common measures of robustness, gain and phase margins, however require a model to assess system robustness. To examine the efficacy of this approach, we tested thirty healthy subjects across three age groups: young (YA: 20–30 years), middle-aged (MA: 42–53 years), and older adults (OA: 71–79 years). The OA group was found to have reduced postural stability during quiet stance as detected by center of pressure measures of postural sway. The proposed robustness measure of *1/MaxSens* was also found to be significantly smaller for OA than YA or MA ($p = 0.001$), implying reduced robustness among the older subjects in response to the perturbation. Gain and phase margins failed to detect any age-related differences. In summary, the proposed robustness characterization method is easy to implement, does not require a model for the postural control system, and was better able to detect differences in system robustness than model-based robustness metrics.**

***Index Terms*—Postural control, robustness, sensitivity, stability.**

## I. Introduction

THE word "stability" which is defined as the ability of a system to maintain equilibrium has been frequently used to characterize human postural behavior. For example, aging and visual input have been reported to modify postural stability (e.g., [1]–[5]). Along with stability, robustness is frequently used to describe a controlled system, but not necessarily the human postural control system. Robustness is the quality of being able to withstand a perturbation in order to satisfy the performance specification [6]. Besides providing simple yes/no information about whether a closed-loop system is stable, robustness also provides a clear indication of how close the system is to instability [7]. Therefore, robustness measures give more information on the human postural control system performance than stability criterion alone.

This study falls within the scope of "robustness analysis" in control systems theory, where metrics have been developed to measure and quantify sensitivity of a dynamic system to modeling uncertainties such as external disturbances. These metrics enable quantification and comparison of the relative stability of different systems [8]. Recently, Masani *et al.* [9] outlined the robust space for a model of the postural control system based on a time-delayed proportional-derivative (PD) controller by computing the gain and phase margins of the systems. This work demonstrated validity of a PD-control-based model of the human postural control system, but did not evaluate its robustness to external perturbations. Peterka [10] developed a postural control model for upright stance during a persistent perturbation (rotating support surface and/or visual surround) using a spectral analysis system identification technique [10], [11]. However, the robustness of the postural control system to external disturbances was also not studied in this work.

In this study, we define robustness of the human postural control system as the measure that quantifies how insensitive the human postural control system is to perturbations. With this definition, we will discuss the sensitivity function. The sensitivity function describes how a system output is proportional to various frequency contents of external perturbations. A greater value of the sensitivity function at a given frequency implies that it is more sensitive to disturbances having that frequency component. A greater sensitivity also indicates a more sensitive or less robust system that is closer to instability. The sensitivity function of a closed-loop system can be calculated by examining the output response of the system to a known input perturbation. Even though gain and phase margins are popular measures for robustness, the sensitivity function is a direct and more accurate measure of robustness [6]. This is because gain and phase margins depend upon the specific model of the control system. Therefore, the reliability of the gain and phase margins as measures of robustness is affected by the accuracy of the control model. In contrast, the sensitivity function defined in this paper is independent of the specific postural control model, since it relates only the output response to the input perturbation.

Previous studies of dynamic postural control have focused mainly on using persistent perturbations, such as continuous translations or rotations of a moving platform to perturb balance [12]–[15]. However, real-life loss of balance is typically sudden, caused by impulses such as a slip while walking or a bump while standing on a bus. Therefore, it is important to understand how balance and postural control mechanisms respond to unexpected and transient disturbances. Studies that

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have used impulse perturbations have not addressed subject response from a control-systems perspective, but have rather focused on the whole-body and included how joint kinematics or kinetics, muscle activation, and system dynamics are affected by the disturbance (e.g., [16]–[21]). In this investigation, both the impulse loading and impulse response control-theory paradigm are used to examine the postural control system and its response to a mild backward tug at the pelvis.

In this study, we propose that the *robustness* of the postural control system to a mild impulsive backward perturbation be assessed using a new metric, *1/MaxSens*. Robustness is the inverse of sensitivity, i.e., a highly sensitive system has low robustness to perturbation and vice versa. It should therefore be possible to quantify a system's robustness by determining the inverse of the maximum value of the sensitivity function. The efficacy of this assessment method was then evaluated using experimental data.

## II. Methods

The sensitivity function of the postural control system to a mild impulse force was determined using spectral analysis system identification techniques. The robustness of the system was quantified from the inverse of the maximum value of the sensitivity function. This assessment method was evaluated using experimental data from young, middle, and older healthy adults. In the experiments, a single impulse force was applied at the pelvis to produce a mild sway response about the ankle. Additionally, the postural control system was modeled using a controlled single link inverted pendulum in order to calculate gain and phase margins of the modeled system. These more traditional metrics of robustness were then compared to the results calculated using the sensitivity function.

### A. Determination of the Sensitivity Function

*1) Frequency Response Function:* Spectral analysis system identification [10], [11] was used to compute the frequency response function, which expresses the structural response of the system to an input in the frequency domain. The input and output signals of the model are the impulsive tug force $(F)$ and body lean angle $(\theta)$, respectively. Therefore, the sensitivity of the body to the tug force is characterized by the closed-loop transfer function (frequency response) from the input $F$ (tug force) to the output $\theta$ (lean angle). We refer to this transfer function as the sensitivity function [6], [10].

*2) Sensitivity Function:* To identify the system, the experimental lean angle is first detrended to have zero mean using a 3 s window of quiet pre-tug data, which ended 0.3 s before the peak tug force. This range is chosen to avoid influence of the perturbation on the sway while still setting the zero value close to when the perturbation occurred. Input and output data are then truncated to a 5 s window (3 s before and 2 s after the peak tug force). The windowed input and output data are converted to the frequency domain using a fast Fourier transform algorithm with Hamming windows to minimize leakage [22]. The auto power spectrum of the input, $G_{FF}(j\omega)$, and the cross power spectrum between the input and output signals, $G_{F\theta}(j\omega)$, are used to determine the frequency response function, $H(j\omega)$. The frequency response function, and therefore the sensitivity function, is defined as

$$H(j\omega) = \frac{G_{F\theta}(j\omega)}{G_{FF}(j\omega)} \tag{1}$$

where $\omega$ ranged over from 0.1–3 Hz. Frequencies were chosen in this range since it was observed that there was no reliable information above this value. The magnitude and phase of the sensitivity function are computed by

$$|H(j\omega)| = \sqrt{H^*(j\omega)H(j\omega)} \tag{2}$$

and

$$\angle H(j\omega) = \frac{180}{\pi}\tan^{-1}\left(\frac{\mathrm{Im}\left(H(j\omega)\right)}{\mathrm{Re}\left(H(j\omega)\right)}\right) \tag{3}$$

where $H^*(j\omega)$ is the complex conjugate of $H(j\omega)$ and $|\bullet|$ represents the absolute value of $(\bullet)$. Finally, magnitude and phase plots of the sensitivity function were averaged over ten trials for each subject.

*3) Definition of Robustness (1/MaxSens):* We propose a metric based on the sensitivity function to quantify the robustness of the postural control system. More specifically, the maximum value of the sensitivity function (*MaxSens*) represents the amplification of the *worst*-case disturbance (corresponding to the most sensitive frequency); therefore its reciprocal serves as a good metric for robustness [6]. This choice is apt for the robustness analysis of postural control systems since disturbances with appreciable "worst-case" frequency content are critical to the stability of a posture. Additionally, this metric does not suffer from the disadvantages of other popular measures of robustness such as gain and phase margins. Generally, larger gain and phase margins suggest a more robust system. However, large gain and phase margins do not always guarantee robustness of the system. Fig. 1 shows an

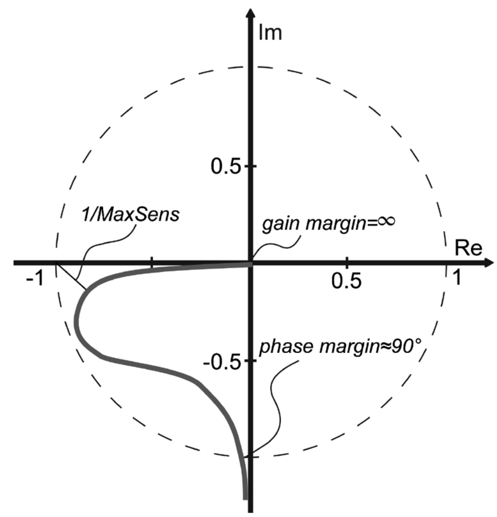


Fig. 1. Sample Nyquist plot illustrating a situation when gain margin and phase margin measures incorrectly suggest a very robust and stable system. Gain margin is infinity and phase margin is 90°, yet this system is very close to instability because the open-loop transfer function (grey) nearly encircles the critical point $-1$ as indicated by the small *1/MaxSens*. (Encirclement of the critical point indicates an unstable system.)

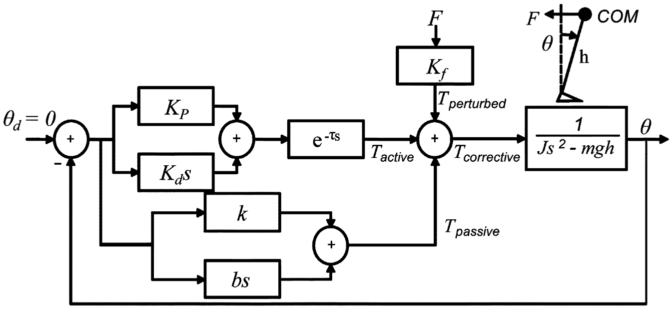


Fig. 2. Block diagram of the postural control system in the Laplace domain. PD control with time delay, passive torque generator, and unity sensory feedback were used. Total corrective torque, $T_{\text{corrective}}$, is sum of torque from active control, $T_{\text{active}}$, torque from passive control, $T_{\text{passive}}$, and torque from the impulsive perturbation, $T_{\text{perturbed}}$.

example of a Nyquist plot with excellent gain and phase margins but where a relatively small combined perturbation of gain and phase suffices to destabilize the system. The distance of the Nyquist plot trajectory away from $-1$, which is equivalent to *1/MaxSens* [6], directly represents the robustness. Therefore, a high value of *1/MaxSens* guarantees robustness. Also since we are investigating robustness with respect to a tug, which can be thought of as an approximation of an impulse function whose spectrum spans the infinite range (on the real line), this "worst-case disturbance" accounts for more possible cases than persistent excitations whose frequencies are weighted around their fundamental harmonics. This generality, in addition to the fact that the causes for loss of balance are typically sudden, reinforces our choice of impulse function for investigation.

### B. Model-Based Gain and Phase Margins

*1) Model Description:* In order to compare our new measure *1/MaxSens* of robustness with conventional measures of gain and phase margins, it was necessary to develop a model of the postural control system. We used a model consisting of a single link inverted pendulum modulated by an active time-delayed proportional-derivative (PD) controller, passive torque generator, and a negative unity feedback loop (Fig. 2).

It is assumed that balance after a mild perturbation is maintained using an ankle strategy, that is, postural movement was predominantly controlled by ankle joint torque [23]. In this model, the height of the body center of mass (COM) above the ankle is represented by $h$ and is approximated as 0.559 of the subject's height [24]. Mass $m$ is total body mass. The body's moment of inertia about the ankle is given by $J = mh^2$. The sensory system along with the control system (i.e., combined vestibular, visual, and proprioceptive systems) is modeled by a unit-gain feedback system as shown in Fig. 2.

Three torque components (perturbed, active, and passive) are summed to create the corrective torque applied to the pendulum. The input tug force, a backward impulsive force $(F)$ applied at the waist of the subject, is transformed to a perturbation torque through a scaling factor $(K_f)$ that represents the lever arm $h$ of the tug force around the ankles. Active torque due to neural control is modeled by a PD controller with proportional and derivative gains $K_p$ and $K_d$ and time delay $\tau$. PD-based control models have been validated through experiments as described in [10], [25], [26]. The time delay $\tau$ is introduced to account for sensory transmission, signal processing in the brain, and muscle activation delays [9], [10]. Passive torque due to musculoskeletal stiffness and damping properties of the ankle complex are modeled as a passive torque generator with stiffness $(k)$ and damping ratio $(b)$ [10].

*2) Open Loop Transfer Function:* Gain and phase margins are derived from the open-loop transfer function of the system. Gain and phase margins represent how far the open-loop transfer function is from $-1$. Negative gain margin or phase margin implies instability. For our modeled system, the open-loop transfer function (OLTF) is

$$\text{OLTF} \equiv \frac{(K_p + K_d s)e^{-\tau s} + k + bs}{Js^2 - mgh} \tag{4}$$

where $g$ represents gravitational acceleration (9.81 $\mathrm{m/s^2}$).

*3) Model-Based Sensitivity Function and Curve Fitting:* Model parameters ($K_p$, $K_d$, $\tau$, $k$, and $b$) were identified by spectral system identification technique [11]. That is, model parameters were identified such that the empirical sensitivity function (1) was best approximated by a model-based sensitivity function [(5)]. We defined the model-based sensitivity function as a transfer function between the backward tug force and lean angle. The model-based sensitivity function is given by

$$S(s) \equiv \frac{K_f}{Js^2 + bs + k - mgh + (K_p + K_d s)e^{-\tau s}}. \tag{5}$$

The sensitivity function [(5)] was fit to the experimentally-determined sensitivity function [(1)] using the MATLAB optimization command *fmincon* (v2007a; The MathWorks, Natick, MA) with initial values of the model parameters of $K_p = 1000$ Nm/rad, $K_d = 400$ Nms/rad, $\tau = 100$ ms, $k = 100$ Nm/rad, and $b = 40$ Nms/rad. The optimization cost function [(6)] was defined as the error between the magnitude of the modeled sensitivity and experimental frequency response function normalized by the magnitude of the experimental frequency response function and summed over all 20 discretized frequencies, logarithmically spaced from 0.1 to 3 Hz

$$\text{Error} = \sum_{i=1}^{20} \frac{|S(j\omega_i) - H(j\omega_i)|}{|H(j\omega_i)|} \tag{6}$$

Thus, with the model parameters derived, it is possible to compute the gain and phase margins from the OLTF [(4)]. Gain margin is defined as the magnitude of the OLTF (in dB) when the phase is $-180°$. Phase margin is defined as the sum of 180° and the phase of the OLTF when its magnitude is 0 dB [8]. Smaller gain and phase margins suggest that the system is near instability. Negative gain and phase margins mean that the system is unstable.

### C. Experimental Protocol

*1) Subjects:* Thirty (14 males, 16 females) subjects participated in this study. Subjects were divided into three groups of ten subjects: young adults (YA), middle-aged adults (MA), and older adults (OA). All other parameters of gender, weight and height except age were matched as much as possible such that

TABLE I
SUBJECT DEMOGRAPHICS, MEAN ± S.E., FOR YOUNG ADULTS (YA), MIDDLE-AGED ADULTS (MA), AND OLDER ADULTS (OA)

| Parameter | YA<br>n = 10 | MA<br>n = 10 | OA<br>n = 10 | $p$* |
|---|---|---|---|---|
| Females | 5 | 5 | 6 | -- |
| Age (y) | 22.9 ± 1.0 | 47.1 ± 1.2 | 75.6 ± 0.8 | <0.001 |
| Age Range (y) | 20 – 30 | 42 – 53 | 71 – 79 | -- |
| Weight (kg) | 69.3 ± 2.6 | 76.1 ± 4.1 | 70.0 ± 2.3 | 0.44 |
| Height (cm) | 170.0 ± 5.9 | 169.1 ± 3.8 | 164.0 ± 3.5 | 0.60 |

* $p$-value from ANOVA examining effect of age

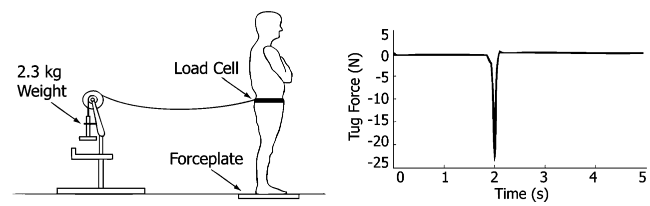


Fig. 3. (a) Experimental setup. The subject stood on a force plate, which recorded the center of pressure. A load cell recorded the impulse force that was transmitted to a belt located around the pelvis. The perturbation was created by activating a mechanical trigger that released a 2.3 kg mass and spooled the tether. After the mass fell, it became detached from the spool such that the tether quickly slackened allowing the subject to readjust to an upright posture. (b) Sample time series of impulsive tug force that illustrates the 5 s of analyzed data. Positive force is in anterior direction.

there were no significant differences in these parameters except age (Table I). All subjects were community-dwelling and had no neurological, gait, or postural disorders. Informed consent was given by all subjects and the study was approved by the university institutional review board.

*2) Experimental Procedure:* Each subject performed twenty 30 s trials randomized between 10 quiet-standing and 10 perturbed trials. For all trials, the subject was instructed to stand on a force plate (AMTI, model BP600900; Watertown, MA) in a self-selected, comfortable stance with arms crossed at the chest while looking ahead at a picture placed at eye level 3 m in front of the subject. A tracing was made of the subject's feet to ensure the same foot positioning for all trials. Subjects were instructed to stand quietly throughout the entire trial. During perturbed trials, a mild, quick-release, backward tug was applied to the pelvis [27]. The test subject wore a belt that was attached to a custom tug device via a loose tether such that normal postural sway was unhindered before and after the tug (Fig. 3). To generate the impulse disturbance, a mechanical trigger was activated to release a weight. After the brief tug, the mechanism allowed the tether to quickly slacken, allowing the subject to adjust to an upright posture. Timing of the perturbation was randomized between 5–20 s after the start of a trial so that the subject was not given cues as to if or when the tug would occur during the trial. The perturbation magnitude was small enough to only elicit a sway response about the ankles. Tug force was measured from a load cell (PCB Piezotronics, model 208C02; Depew, NY). Average tug force was 29.2 N ± 3.9 N with a duration of 0.111 s ± 0.023 s. All forceplate data were sampled at 1000 Hz and were low-pass filtered at 10 Hz with a fourth-order, zero-lag Butterworth filter. Forceplate data were used to compute anterior–posterior center of pressure (AP COP). The COP is the location of application of the ground reaction force vector on the forceplate. Then, the AP position of the center of mass (COM) was computed from AP COP and AP force data from the forceplate using a modified gravity line projection algorithm [28]. Even though there might be slight inaccuracies in calculations by the gravity line projection algorithm during the periods when the impulsive perturbation is applied, these inaccuracies can be ignored due to the small magnitude and short application period of the impulsive force. Finally, the lean angle was computed from the AP COM position $(x)$ and $h$ using the linearized relationship, $\theta h \approx x$.

### D. Supplemental Balance Parameters

Supplemental assessment of balance was done using quiet stance postural sway measures of the COP. It has been shown that postural sway becomes significantly greater in older adults [2], [29], [30]. In this study, traditional and newer stochastic measures of quiet stance postural sway were computed to compare balance or postural stability characteristics of our test groups. Since postural sway information provides insight into the system response to internal perturbation, we assume that greater postural sway implies reduced robustness.

*1) Traditional Stabilometric Parameters of Quiet Stance:* COP data have typically been analyzed using measures that describe the shape or speed of the trajectory. In this study, we examined seventeen traditional (*TRAD*) parameters of COP [2], [31]: standard deviation (*SD*), path length (*PathLen*), mean sway velocity (*MeanVel*), mean frequency (*MeanFreq*), and 95% power frequency (*Freq95*) in the 1-D anterior–posterior (AP) and medial–lateral (ML), and the 2-D radial (Rad) directions. We also examined the angular deviation of the principal sway direction from the AP axis (*AngDev*) and total swept area (*TotalArea*).

*2) Stabilogram Diffusion Analysis for Quiet Stance:* Collins and De Luca [32] modeled the COP trajectory as a correlated one or two dimensional random walk, and applied a stabilogram diffusion analysis (SDA) to characterize short term (open loop) and long term (closed loop) postural control mechanism. In our study, we examined twelve parameters: short term (*DS*) and long term (*DL*) diffusion coefficients, and short term (*HS*) and long term (*HL*) scaling exponents in AP, ML, and Rad directions.

### E. Statistical Analysis

One-way analysis of variance (ANOVA) was used to examine whether *1/MaxSens*, gain margin, phase margin, model parameters, *TRAD* and *SDA* parameters of quiet-stance sway were affected by the factor of age (YA, MA, or OA). Tukey's Honestly Significant Differences (HSD) test was used for post hoc comparisons. The level of significance was set to $\alpha = 0.05$. Statistical analyses were run on SPSS (SPSS Inc., v15).

## III. RESULTS

ANOVA test results for the newly proposed robustness metric, *1/MaxSens*, found significant age-related differences (Table II, $p = 0.001$). Mean and standard error values of *1/MaxSens* for young adult (52.82 ± 0.73 dB) and middle-aged adult (53.81 ± 0.93 dB) groups were similar to each other; however, *1/MaxSens* for older adults (48.15 ± 1.23 dB) was

TABLE II
MODEL-BASED MEASURES, MEAN AND ± S.E., FOR YOUNG ADULTS (YA), MIDDLE-AGED ADULTS (MA), AND OLDER ADULTS (OA)

| Parameter | YA n = 10 | MA n = 10 | OA n = 10 | p* |
|---|---|---|---|---|
| *1/MaxSens* (dB) | 52.8 ± 0.7† | 53.8 ± 0.9‡ | 48.2 ± 1.2 | 0.001 |
| *GainMargin* (dB) | 7.0 ± 0.5 | 7.1 ± 0.8 | 6.5 ± 0.7 | 0.84 |
| *PhaseMargin* (deg) | 23.8 ± 1.1 | 25.4 ± 1.3 | 22.8 ± 1.4 | 0.35 |
| $K_p$ (N m/rad) | 952.8 ± 36.7 | 991.3 ± 31.9 | 841.3 ± 27.4 | 0.06 |
| $K_d$ (N m s/rad) | 318.7 ± 23.2 | 358.5 ± 18.2 | 278.1 ± 32.9 | 0.10 |
| $\tau$ (ms) | 116.7 ± 3.9 | 112.3 ± 4.3 | 136.7 ± 11.1 | 0.06 |
| $k$ (N m/rad) | 67.9 ± 14.8 | 100.0 ± 19.0 | 39.1 ± 24.0 | 0.11 |
| $b$ (N m s/rad) | 0.0 ± 0.0 | 0.0 ± 0.0 | 0.0 ± 0.0 | - |

* $p$-value from ANOVA examining effect of age
† YA and OA are significantly different, based on Tukey HSD post-hoc test
‡ MA and OA are significantly different, based on Tukey HSD post-hoc test

TABLE III
STATISTICALLY SIGNIFICANT TRADITIONAL (TRAD) AND STABILOGRAM DIFFUSION ANALYSIS PARAMETERS (SDA) STABILOMETRIC PARAMETERS OF QUIET-STANCE SWAY, MEAN AND ± S.E., FOR YOUNG ADULTS (YA), MIDDLE-AGED ADULTS (MA), AND OLDER ADULTS (OA)

| Parameter | YA n = 10 | MA n = 10 | OA n = 10 | p* |
|---|---|---|---|---|
| TRAD | | | | |
| $SD_{ML}$ (mm) | 19.9 ± 3.3 | 13.53 ± 1.27‡ | 27.78 ± 4.05 | 0.012 |
| $PathLen_{AP}$ (mm) | 2377 ± 199† | 2291 ± 152‡ | 3125 ± 246 | 0.013 |
| $PathLen_{Rad}$ (mm) | 2898 ± 243 | 2791 ± 153‡ | 3672 ± 301 | 0.030 |
| $MeanVel_{AP}$ (mm/s) | 79.2 ± 6.6† | 76.38 ± 5.07‡ | 128.4 ± 20.5 | 0.012 |
| $MeanVel_{Rad}$ (mm/s) | 96.6 ± 8.1† | 93.04 ± 5.08‡ | 151.0 ± 24.6 | 0.020 |
| $MeanFreq_{AP}$ (rad/s) | 7.84 ± 0.49 | 7.81 ± 0.51‡ | 10.21 ± 0.95 | 0.028 |
| $Freq95_{AP}$ (rad/s) | 9.2 ± 0.4† | 9.69 ± 0.61 | 11.8 ± 0.9 | 0.027 |
| *TotalArea* ($mm^2$) | 3464 ± 648 | 2733 ± 322‡ | 5229 ± 848 | 0.031 |
| SDA | | | | |
| $DS_{AP}$ ($mm^2$/s) | 12.7 ± 2.4 | 10.41 ± 1.15‡ | 25.5 ± 7.1 | 0.048 |
| $HL_{AP}$ | 0.19 ± 0.03† | 0.21 ± 0.03‡ | 0.08 ± 0.02 | 0.005 |
| $HL_{Rad}$ | 0.19 ± 0.03 | 0.21 ± 0.03‡ | 0.10 ± 0.02 | 0.012 |
| $HS_{ML}$ | 0.86 ± 0.01 | 0.89 ± 0.01‡ | 0.84 ± 0.01 | 0.019 |

* $p$-value from ANOVA examining effect of age
† YA and OA are significantly different, based on Tukey HSD post-hoc test
‡ MA and OA are significantly different, based on Tukey HSD post-hoc test

significantly smaller. Post hoc tests revealed statistically significant differences between YA and OA, and MA and OA, but not YA and MA. This result suggests that the robustness of the OA group to mild perturbations was significantly reduced compared to both YA and MA, while there was no difference in robustness between YA and MA. No statistically significant differences $(p > 0.05)$ due to age, however, were found for traditional robustness measures of gain and phase margins. Still, values of these metrics for the older adult group suggest slightly reduced postural control performance compared to young and middle-aged adults, i.e., smaller values for gain margin and phase margin (Table II). Statistically significant differences $(p < 0.05)$ in supplemental quiet-stance (TRAD and SDA) balance parameters were found between age groups (Table III). Significant differences in parameter values were found between YA and OA, and MA and OA, but not YA and MA. These results indicated that OA swayed significantly farther and faster than YA and MA, especially in the anterior–posterior and radial directions.

The mathematical model of a single link inverted pendulum with PD controller, time delay, passive torque generator, and

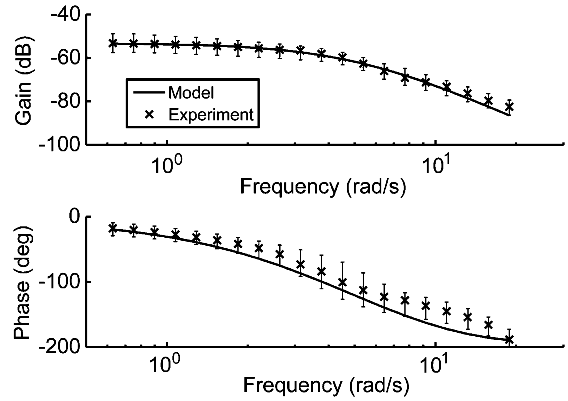


Fig. 4. Example of Bode plots of the frequency response function (FRF) from experimental data of a young adult (×), sensitivity function (solid line) which best fit the FRF. Error bars represent one standard deviation. Experimental data are averaged over ten FRF of a single subject.

unity sensory feedback was found to represent the human postural control system quite well (Fig. 4). There were no statistically significant differences due to age in model parameters $(K_p, K_d, k, b, \tau)$.

## IV. DISCUSSION

We proposed that the robustness of the system could be quantified using the sensitivity function; specifically the reciprocal of peak magnitude of the sensitivity function (*1/MaxSens*). Since robustness has been defined as a measure that quantifies how insensitive the human postural control system is to perturbations, the sensitivity function which is a frequency response to an impulsive perturbation could serve as a robustness quantifier. Thus, a more robust system has a greater value of *1/MaxSens*. To test this idea, we conducted a cross-sectional study involving young, middle-aged, and older adults. Results from the supplemental balance measures indicated that there were significant differences in quiet-stance postural sway and stability between the older adult group and both the young and middle-aged groups (Table III). Our proposed metric of robustness, *1/MaxSens*, detected similar age-related differences, such that OA also demonstrated less robustness to postural disturbances than YA and MA (Table II).

Model-based gain and phase margins are the most frequently used metrics for measuring robustness of a system. OA tended to have slightly smaller gain and phase margins compared to YA and MA; however, these were not significantly different ($p = 0.8$ for gain margin and $p = 0.4$ for phase margin). *1/MaxSens*, however, indicated statistically significant differences between OA and both YA and MA ($p = 0.001$), demonstrating that *1/MaxSens* is a better discriminator of age-related changes. This suggests that the sensitivity function, and more specifically the *1/MaxSens* value, is a better measure for robustness of the postural control system to mild perturbations. It should be noted that the above conclusion is validate only for models that assume that all the subjects used an ankle strategy to control posture. Since it has been suggested that older adults may use a hip strategy more often than young populations [33], gain and phase margins could possibly provide more meaningful results in measuring robustness of the human postural control system when a two-link model of hip strategy is used. However, given the assumption of ankle strategy, even though both gain and phase margins and *1/MaxSens* can be used for robustness measures, *1/MaxSens* could be a better robustness measure in the sense that postural control systems are closed-loop systems and *1/MaxSens* can capture the worst-case margin. Furthermore, in the context of the definition of robustness of the human postural control system in this paper, *1/MaxSens* may be a better robustness measure.

In the current study, we additionally introduced a mathematical model of postural control system in order to compute gain and phase margin. We represented the body and postural control system with a single link inverted pendulum modulated by an active time-delayed proportional-derivative (PD) controller, passive torque generator, and negative unity sensory feedback loop (Fig. 2). In this model, we assume that the body responded to the perturbation as a single link inverted pendulum. The impulse force in the current study is of a small magnitude in order to limit the amount of hip and knee flexion used when responding to the perturbation; therefore, it is assumed that the subject uses an ankle strategy and rotates only about the ankles. A number of studies have used PD controllers and found that a PD controller can represent the postural control system quite well [9], [10], [25], [26]. Although our perturbation differed from those conditions, this model appears to be a good approximation for representing the behavior of the postural control system during the response to an impulse disturbance (Fig. 4). The model parameters found in this study (Table II) were in good agreement with previous studies that used time-delayed PD controlled models of the postural control system. Peterka [10] and Masani *et al.* [9] found similar values for the controller parameters ($K_p$: 570–1200 and 750–1150 N m/rad, $K_d$: 170–515 and 300–550 N m s/rad, and $\tau$: 140–250 and 75–135 ms, respectively). Among these parameters, we found that $K_d$ was the most significantly correlated $(r = 0.77)$ with *1/MaxSens* suggesting that angular velocity information plays important roles for maintaining robustness of the human upright stance using ankle strategy. This result is supported from the previous study [26] that body sway velocity information is important in controlling ankle extensor during quiet stance. $\tau$ was also significantly correlated $(r = 0.70)$ with *1/MaxSens* implying that time delay can significantly affect robustness of the human postural control system.

There has been limited research investigating how the postural control system responds to an impulsive perturbation. Previous studies using impulse perturbations have focused on whole-body kinematics, muscle activation, and the sway-to-step transition [16]–[21], [34]. We addressed these deficiencies by using a backward, quick-release tug at the waist to explore the AP postural sway response to an impulse perturbation.

Recent experimental studies report that postural sway behavior in the medial–lateral (ML) direction may be a better indicator of fall risk than the anterior–posterior (AP) direction (for review see [35]). Our study applied system identification of the postural control system only in the AP direction and proposed *1/MaxSens* to quantify robustness of the system to the external perturbation. The same methodology can be applied to assessments in the ML direction. Future studies comparing *1/MaxSens* values and other control parameters of postural control systems in both AP and ML directions may help improve understanding about why the ML direction may be a better indicator of fall risk compared to the AP direction.

In conclusion, a metric for measuring robustness of the postural control system *1/MaxSens* is proposed. *1/MaxSens* was derived from the sensitivity function which is actually the frequency response function. Greater values of *1/MaxSens* suggest greater system robustness or less system sensitivity to an external perturbation. Age-related changes in the postural control system were detected by *1/MaxSens*. This finding was verified by supplemental balance parameters; however, model-based metrics, gain and phase margin, failed to detect differences. Importantly, *1/MaxSens* provides a measure of robustness of a system without need for developing computational models of the system. Therefore, regardless of the structure of the controller in the feedback loop, the closed-loop sensitivity function can be derived experimentally from the frequency response function. These features make *1/MaxSens* an easy to use and more effective robustness measure.

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