Joseph E. Barton¹

Research and Development Service,
VA Maryland Health Care Center,
Baltimore VA Medical Center,
Baltimore, MD 21201;
Department of Neurology,
University of Maryland School of Medicine,
Baltimore, MD 21201;
Department of Physical Therapy & Rehabilitation Science,
University of Maryland School of Medicine,
Baltimore, MD 21201
e-mail: mailto:jbarton@som.umaryland.edu

Valentina Graci

Research and Development Service,
VA Maryland Health Care Center,
Baltimore VA Medical Center,
Baltimore, MD 21201;
Department of Neurology,
University of Maryland School of Medicine,
Baltimore, MD 21201
e-mail: vgraci@som.umaryland.edu

Charlene Hafer-Macko

Geriatric Research Education and Clinical Center,
VA Maryland Health Care Center,
Baltimore VA Medical Center,
Baltimore, MD 21201;
Department of Neurology,
University of Maryland School of Medicine,
Baltimore, MD 21201
e-mail: cmacko@grecc.umaryland.edu

John D. Sorkin

Geriatric Research Education and Clinical Center,
VA Maryland Health Care Center,
Baltimore VA Medical Center,
Baltimore, MD 21201;
Division of Gerontology and Geriatric Medicine,
Department of Medicine,
University of Maryland School of Medicine,
Baltimore, MD 21201
e-mail: jsorkin@grecc.umaryland.edu

Richard F. Macko

Geriatric Research Education and Clinical Center,
VA Maryland Health Care Center,
Baltimore VA Medical Center,
Baltimore, MD 21201;
Department of Neurology,
University of Maryland School of Medicine,
Baltimore, MD 21201
e-mail: rmacko@grecc.umaryland.edu

Dynamic Balanced Reach: A Temporal and Spectral Analysis Across Increasing Performance Demands

Standing balanced reach is a fundamental task involved in many activities of daily living that has not been well analyzed quantitatively to assess and characterize the multisegmental nature of the body's movements. We developed a dynamic balanced reach test (BRT) to analyze performance in this activity; in which a standing subject is required to maintain balance while reaching and pointing to a target disk moving across a large projection screen according to a sum-of-sines function. This tracking and balance task is made progressively more difficult by increasing the disk's overall excursion amplitude. Using kinematic and ground reaction force data from 32 young healthy subjects, we investigated how the motions of the tracking finger and whole-body center of mass (CoM) varied in response to the motion of the disk across five overall disk excursion amplitudes. Group representative performance statistics for the cohort revealed a monotonically increasing root mean squared (RMS) tracking error (RMSE) and RMS deviation (RMSD) between whole-body CoM (projected onto the ground plane) and the center of the base of support (BoS) with increasing amplitude ($p < 0.03$). Tracking and CoM response delays remained constant, however, at 0.5 s and 1.0 s, respectively. We also performed detailed spectral analyses of group-representative response data for each of the five overall excursion amplitudes. We derived empirical and analytical transfer functions between the motion of the disk and that of the tracking finger and CoM, computed tracking and CoM responses to a step input, and RMSE and RMSD as functions of disk frequency. We found that for frequencies less than 1.0 Hz, RMSE generally decreased, while RMSE normalized to disk motion amplitude generally increased. RMSD, on the other hand, decreased monotonically. These findings quantitatively characterize the amplitude- and frequency-dependent nature of young healthy tracking and balance in this task. The BRT is not subject to floor or ceiling effects, overcoming an important deficiency associated with most research and clinical instruments used to assess balance. This makes a comprehensive quantification of young healthy balance performance possible. The results of such analyses could be used in work space design and in fall-prevention instructional materials, for both the home and work place. Young healthy performance represents "exemplar" performance and can also be used as a reference against which to compare the performance of aging and other clinical populations at risk for falling. [DOI: 10.1115/1.4034506]

Keywords: balance, balance disorders, balanced reach test, internal model

1 Introduction

Bipedal standing balance is inherently unstable and must be actively controlled to prevent falling. This involves coordinated interactions between the sensorimotor and multisegment musculoskeletal systems that are difficult to characterize and not fully understood. Falls typically occur in a larger perturbational context than simply maintaining balance. Standing reach, for example, consists of three subtasks: fixing gaze, reaching to acquire an object, and maintaining balance. These subtasks must be coordinated and sensorimotor resources properly allocated between

them. While young individuals maintain balance across a wide range of perturbational challenges, sensorimotor and musculoskeletal systems gradually deteriorate with aging [1,2], predisposing some to an increased risk of falls. Certain disease and neurological conditions (e.g., peripheral neuropathy, stroke, Parkinson's disease) can also impair balance, magnifying the deleterious effects of aging [3]. An integral part of coordination and resource allocation is the ability to adapt to these sensorimotor and musculoskeletal deficits.

A variety of clinical instruments have been developed to assess balance and fall risk (e.g., Berg Balance Scale [4], Timed Up and Go Test [5], Single Leg Stance Test [6]), but these have proven to be of limited usefulness, or applicable only to select populations. Some employ subjective ordinal scales that do not lend themselves to quantitative analysis. Some lack hierarchical structure and/or include redundant items that artificially inflate scores. Some are relevant only for a narrow range of subject performance,

¹Corresponding author.

Manuscript received February 18, 2016; final manuscript received August 18, 2016; published online November 3, 2016. Assoc. Editor: Zong-Ming Li.

This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States. Approved for public release; distribution is unlimited.

exhibiting floor or ceiling effects when performance falls outside that range [7]. Finally, reports regarding reliability in predicting fall risk are inconsistent [8–12]. These fall short of the practice needs of rehabilitation professionals [13], or provide only limited information beyond that obtained through direct clinical observation [14,15]. Three recent balance instruments (Physiological Profile Assessment [16], Protective Stepping Test [17], and Balance Evaluation Systems Test (BESTest) [18]) begin to address these shortcomings by taking a systems-oriented approach. Sensorimotor functions and biomechanical measures judged important for balance are assessed and scored independently, then combined into an overall score. Overall scores correlate better with fall risk, while component scores provide qualitative indices of the nature of the increased risk. These instruments are still limited in that they cannot specify how performance in any of the component tests will affect balance and fall risk. It can only be said that performance in these tests covaries to some degree with an ability to control and maintain balance.

A comprehensive understanding of balance requires quantitative models with sufficient sensorimotor and biomechanical complexity to enable mathematical characterization of balance control. Movement scientists have long employed engineering concepts such as system identification [19] and feedback control [20] to study balance. While not all (e.g., Refs. [21] and [22]), most have employed simplified balance dynamics to study small perturbations in a single plane for which the standing body is represented by a linear, two-dimensional, single link inverted pendulum rotating about the ankles, controlled by a generic proportional-integral-derivative (PID) controller. While such models convey overall movement mechanics, they are largely limited to cause-and-effect behavior, and lack the complexity to probe the neurophysiological and musculoskeletal bases for balance and falls.

Our long-term objective is to develop an engineering control system model of balance (CSMB) that represents the sensorimotor and musculoskeletal determinates of performance, and quantifies the manner in which performance changes as a function of task difficulty. To accomplish this, we are proceeding along two

complimentary lines. The first is to develop the CSMB [23], which simulates performance in an experimental protocol, the balanced reach test (BRT), whose development and validation constitute the second line. The BRT constitutes a complex reaching and tracking task in three-dimensional space that is relevant to daily function. Our goal is that it be sensitive enough to detect differences in the ability of different population groups (e.g., young healthy, older high fall risk, stroke) to maintain balance under different levels of task difficulty. This report presents the BRT protocol and the analytical methods to quantify performance in tracking and balance maintenance for 32 young healthy subjects (YHSs) across a range of task difficulty.

2 Methods

2.1 The Balanced Reach Test. During the BRT (Fig. 1), subjects stand on a platform with each foot directly underneath its respective shoulder joint and supported by an AMTI Optima series triaxial force plate (AMTI, Watertown, MA). A $6' \times 10'$ reverse-projection screen (Da-Lite, Eden Prairie, MN) is located one arm's length in front of the subject, aligned perpendicular to the anterior–posterior (AP) (z) axis and parallel to the subject's frontal plane. An image of a disk is projected on the screen by a BenQ SP 890 high resolution digital projector (BenQ, Costa Mesa, CA). Subjects are instructed to point with the dominant hand index finger to the center of the disk as it moves, lightly touching the screen, with their hand in the neutral position with respect to wrist pronation/supination. (With either upper arm hanging alongside the trunk and the elbow flexed at 90 deg, the palm of the hand faces medially (toward the body). This is done to ensure consistency of movement in a natural fashion, and also to ensure that the motion detection markers attached to the forearm always remains in view of the motion detection system.)

The medial–lateral (ML) (x) and superior–inferior (SI) (y) positions of the disk at time t are determined by a sum of 14 sine functions, given by

$$x_d(t) = \sum_{i=1}^{14} \frac{1}{2\pi f_i} \sin(2\pi f_i t), \quad y_d(t) = \sum_{i=1}^{14} \frac{1}{2\pi f_i} \sin(2\pi f_i t + \phi_i) \quad (1)$$

Such a stimulus appears random to the observer, but because only discrete frequencies are contained in the stimulus, it produces a Fourier transform with very sharply defined frequency spectra,

Fig. 1 During the balanced reach test, subjects stand on force platforms, fix gaze and point to the projected disk as it moves around the screen. The locations of two landmarks on each foot are used to compute the perimeter of the BoS at each sampling instant. This computation is robust enough to accurately represent the perimeter should the subject shift their stance or momentarily raise up on the ball of one foot (as shown in the figure).

Table 1 Disk motion parameters

#	Predictable frequency set			Unpredictable frequency set		
	f_i (Hz)	Period (s)	ϕ_i (deg)	f_i (Hz)	Period (s)	ϕ_i (deg)
1	0.024	41.67	90	0.024	41.67	90
2	0.048	20.83	76	0.056	17.86	284
3	0.096	10.42	192	0.104	9.62	76
4	0.192	5.21	238	0.184	5.43	215
5	0.288	3.47	99	0.296	3.38	122
6	0.336	2.98	145	0.344	2.91	99
7	0.48	2.08	261	0.488	2.05	330
8	0.576	1.74	30	0.584	1.71	145
9	0.72	1.39	168	0.712	1.40	261
10	0.816	1.23	284	0.824	1.21	238
11	0.912	1.10	215	0.904	1.11	168
12	1.416	0.71	307	1.432	0.70	192
13	2.184	0.46	330	2.104	0.48	30
14	2.928	0.34	122	2.936	0.34	53

Note: Overall excursion amplitudes: 0.5000, 0.6563, 0.8125, 0.9688, 1.1250 arm lengths (ALs).

easing subsequent frequency response analysis and interpretation of results. We use ten frequencies (f_i , Table 1) that lie within a range ($0.05 \leq f_i \leq 3.0$ Hz) that can be visually tracked by healthy subjects [24], and four additional frequencies in the vicinity of 1 Hz where we find tracking gain (Sec. 2.2.2) changes most rapidly. Amplitudes of individual sinusoids are scaled by the inverse of their respective frequencies so that each sinusoid has the same peak velocity. A randomly selected phase shift (ϕ_i , Table 1) is then applied to each term of the vertical sum-of-sines, $y_d(t)$, so that the vertical component of the disk's motion does not appear correlated with the horizontal component. At the beginning of each experiment, arm length (AL) is measured as the distance from the tip of the pointing index finger to the acromion process. Five multiples of arm length ranging from 0.5 to 1.125 (Table 1, bottom) are then computed. Once the disk's overall trajectory is computed, its maximum excursions in the ML and SI directions are normalized to unity, and then multiplied by one of these multiples, depending on the test condition. Increasing the overall excursion amplitude of the disk increases its velocity and thus, task difficulty, since for sinusoidal motion velocity is directly proportional to amplitude. Task difficulty also increases with amplitude in that as the disk moves farther outside the limits of the subject's base of support (BoS), the subject must assume increasingly less stable body poses with respect to the BoS to maintain contact. When the sinusoidal frequencies are integer multiples of one another (Table 1, predictable frequency set), the overall motion is periodic and in theory predictable by the subject [25]. When the frequencies are not integer multiples of one another (Table 1, unpredictable frequency set), the motion of the disk is not periodic, and thus not predictable. The protocol incorporates both frequency sets to determine subjects' ability to predict the disk's motion. Each trial's duration is 90 s, allowing capture of two or more complete cycles of each frequency sinusoid. All combinations of frequency set and disk excursion amplitude (ten in total, 15 min total testing time) are presented to each subject.

To accurately represent movements during the BRT, a triangular "rigid body" is attached to each of the 13 body segments listed in Table 2. Subjects' hands are placed in rigid splints to prevent movement of the hand with respect to the forearm (not shown in Fig. 1); thus subjects' hands are assumed rigidly connected to their respective forearms. Infrared emitting diodes (IREDs) placed at the rigid bodies' vertices (Fig. 1) are sensed by an OptoTrak Certus motion capture system (Northern Digital, Waterloo, Ontario, Canada), allowing construction of a local coordinate system for each body segment. The locations of the joint centers of rotation (CoRs) defining each body segment's endpoints (and thus length) are obtained relative to these local coordinate systems using the motion capture system's digitizing stylus. This

information and the subject's height and weight are used to calculate each body segment's mass and the location of its center of mass (CoM) using sex-specific anthropometric data [26,27]. After the experiment, the positions and orientations of each body segment are computed with respect to the global coordinate system for each sampling instant from the measured positions and orientations of the local coordinate systems. Whole-body CoM is computed as the weighted mean of the positions of the body segments' CoMs, where the weighting is the ratio of body segment mass to total mass. The 13 segment representation thus incorporates actual body segment lengths and CoR locations, as well as any asymmetries (e.g., unequal right/left femur lengths) and other unique aspects of musculoskeletal anatomy.

The positions of the tracking fingertip and other significant landmarks relative to the local coordinate system fixed to the body segment containing those landmarks are recorded. Stable upright balance requires that the projection of the body's CoM onto the ground plane be maintained within the area of its BoS, delimited by the feet [28,29]. The boundaries of the BoS are identified by the positions of the fifth metatarsal joint and the lateral outside of the heel. Projection of these four points onto the ground plane comprises the vertices of a quadrilateral used to compute the center and boundaries of the BoS. Variations in the position of the BoS are minimized by instructing subjects to move their feet as little as possible, and to maintain ground contact with both feet. Occasionally, some subjects shift the position of their feet slightly or raise up on the ball of a foot (Fig. 1). In such cases, resulting changes to the BoS are accounted for since its center and boundaries are computed at each sampling instant. A test is also incorporated in the calculation to determine if the front or back of either foot is off the ground. If so, the associated landmark is excluded and the computed perimeter of the BoS becomes triangular shaped. Shifting stance or raising up on the ball of the foot was observed to occur infrequently, and for only brief periods. Hence, the positions of the center and vertices of the BoS remained very nearly constant throughout each test.

At the end of setup, the projection screen and projector are positioned so that the horizontal limits of the screen's projection area are located approximately $1\frac{1}{2}$ arm lengths from the dominant shoulder joint. Four calibration points are projected onto the screen at known positions (in projector coordinates; pixels) and their global coordinate locations (meter) recorded using the digitizing stylus. Using this data, a function is derived to map the disk's position from projector coordinates to global coordinates, so that the disk's trajectory during each trial can be compared to the subject's movements.

In addition to kinematic data, the subject's weight and the forces and moments applied by each foot are measured by the force plates. Eye motion relative to head is captured using an Eye-Link II eye tracking system (SR Research, Ottawa, Ontario, Canada). Electromyographs (EMGs) of certain muscles (Table 3) used while pointing and responding to the self-induced balance perturbations are recorded using a wireless EMG system (Noraxon, Scottsdale, AZ). Force plate and motion detection data are sampled at 60 Hz, eye tracking data at 250 Hz, and EMG data at 3000 Hz. EMG data are down-sampled to 60 Hz and eye tracking data are interpolated to 60 Hz using a third-order spline interpolation polynomial; so that combined analyses with the force plate

Table 2 Body segments and joints

Segment index	Segment	Joint
1	Right foot	Right ankle
2	Right shank	Right knee
3	Right thigh	Right hip
4	Left foot	Left ankle
5	Left shank	Left knee
6	Left thigh	Left hip
7	Lower trunk	L5/S1 ^a
8	Trunk	C7/T1 ^b
9	Head	Right shoulder
10	Right upper arm	Right elbow
11	Right forearm and hand	Left shoulder
12	Left upper arm	Left elbow
13	Left forearm and hand	

^aIntervertebral disk between the fifth lumbar and first sacral vertebrae.

^bIntervertebral disk between the seventh cervical and first thoracic vertebrae.

Table 3 Measured muscle activations

Right and left soleus
Right and left tibialis anterior
Right and left pectoralis major (caudal head)
Right and left anterior deltoid
Right and left middle deltoid
Right and left sternocleidomastoid
Right and left paraspinal

and motion detection data can be carried out. Measurement data from the force plates and the motion capture, eye tracking, and EMG systems are synchronized and consolidated by a Motion Monitor system (Innovative Sports Training, Chicago, IL). The Motion Monitor also establishes a global coordinate (x_0, y_0, z_0) system whose origin is located between the subject's feet (Fig. 1) and approximately coincident with the center of the BoS. In this system, $+x_0$ points to the subject's left, $+y_0$ in subject's superior direction, and $+z_0$ in subject's anterior direction. All quantities are referred to the global coordinate system. The current analysis is based on kinematic and kinetic data obtained during the BRT. Eye motion and EMG analyses are ongoing and will be reported in subsequent articles.

2.2 Analytical Methods. Overall performance is characterized by analyzing the tracking fingertip and whole body CoM motion relative to the projected target disk. AP (z) motion of the finger is not included, as it is constrained by the planar projection screen aligned perpendicularly to the AP axis. AP CoM motion is also affected (though not to as great a degree) by the presence of the projection screen, but it remains an important aspect of balance in this task and is included where appropriate. Finally, SI motion of the CoM is not included because it does not have a direct bearing on the primary measure of balance considered here, CoM–BoS deviation, which is the deviation between the projection of the CoM onto the ground plane (resulting in an SI component of zero) and the center of the BoS. A more complete description of the factors affecting AP tracking and CoM motion is provided in Appendix A, which is available under the “Supplemental Materials” tab for this paper on the ASME Digital Collection.

Finger tracking, CoM, and BoS trajectories (xyz position versus time) for each trial are visually inspected to identify and remove spurious spikes in the data caused by intermittent noise in the OptoTrak electronics, or abrupt shifts in the location of whole-body CoM that result when a marker falls out of view of the motion detection system, causing the rigid body segment that it was attached to to “disappear.” Since the location of whole body CoM is the weighted average of the locations of the individual body segment CoMs, the disappearance of a body segment removes its contribution to the calculation, bringing about an abrupt shift in the result. Notwithstanding the constraints imposed by the projection screen, subjects engaged in a continuum of complex motions and body positions performing the tracking task. This presented a particular challenge for motion capture: as body segments twisted and turned to track the disk, the IRED's attached to any particular body segment could assume positions that were not visible to the sensors, leaving brief gaps in the data. Because of the strong observed correlation between the motions of the tracking finger and CoM and the sum-of sines motion of the disk, we employed spectral methods [30] to estimate missing data caused by both removal of outliers and out-of-view IRED's. Subsequently, “clean data” refers to measured test data with outliers removed and gaps due to out-of-view IRED's. We used clean data to compute overall performance measures (see Sec. 2.2.1), as these data represent the unaltered tracking and balance performance of each subject, and the calculations can be made with missing data. In no case was missing data extensive enough to compromise validity of the calculations. Group representative performance (see Sec. 2.2.2), however, requires complete data sets and for this, we used “estimated data,” which refers to the result of the spectral estimation process.

2.2.1 Overall Performance Measures. For each subject and condition clean data is used to calculate root mean squared error (RMSE) in the ML and SI directions. This is defined for the ML (x) direction as

$$RMSE_x = \sqrt{\frac{\sum_{i=1}^{n_x} [x_d(i) - x_f(i)]^2}{n_x}} \quad (2)$$

where $x_d(i)$ is the x component of the disk's position at sampling instant i , $x_f(i)$ is the corresponding position of the tracking finger, and n_x is the number of data points associated with the x direction. For the SI (y) direction, the tracking errors are defined similarly. The composite error $RMSE_{xy}$ is also computed according to

$$RMSE_{xy} = \sqrt{\frac{\sum_{i=1}^{n_x} [x_d(i) - x_f(i)]^2}{n_x} + \frac{\sum_{i=1}^{n_y} [y_d(i) - y_f(i)]^2}{n_y}} \quad (3)$$

RMSE can range from zero to $+\infty$. A value of zero represents perfect tracking.

Similarly, we computed RMS CoM–BoS deviation (RMSD) to quantify balance performance

$$RMSD_x = \sqrt{\frac{\sum_{i=1}^{n_x} [x_{BoS}(i) - x_{CoM}(i)]^2}{n_x}},$$

$$RMSD_{xz} = \sqrt{\frac{\sum_{i=1}^{n_x} [x_{BoS}(i) - x_{CoM}(i)]^2}{n_x} + \frac{\sum_{i=1}^{n_z} [z_{BoS}(i) - z_{CoM}(i)]^2}{n_z}} \quad (4)$$

where $x_{CoM}(i)$ and $x_{BoS}(i)$ are the x components of the CoM's and the center of the BoS's position at sampling instant i . Deviations in the AP (z) direction are defined similarly. The deviations presented in Eq. (4) can range from zero to values corresponding to the boundaries of the BoS, at which point a step or fall would ensue. Beyond this, there is no measure or definition of “perfect” control of the CoM within the boundaries of the BoS (see Sec. 4). These quantities are averaged over the entire cohort of young healthy subjects for each disk excursion amplitude.

Clean data is also used to compute the overall correlation coefficient ρ and response delay τ between the target disk trajectories and the tracking finger and CoM response trajectories. ρ is obtained by identifying the maximum correlation coefficient between the response trajectory and numerous lagged versions of the corresponding target disk trajectory. τ is the lag (s) corresponding to this maximum value of ρ . Correlation coefficients and response delays are computed for the disk/tracking finger and disk/CoM, then averaged across the entire cohort of young healthy subjects for each disk excursion amplitude.

2.2.2 Group Representative Disk and Response Trajectories. We next undertook a detailed analysis of the cohort's performance in both the temporal and spectral domains. It is not possible in this analysis to obtain group-representative temporal or spectral response data simply by averaging individual subject responses (in either domain) for each condition. The overall amplitude of the disk's motion and the prescribed distance of the projection screen from the subject varies across subjects. Further, it is not possible to position the high resolution projector and projection screen in exactly the same position relative to each other and the subject for each experiment. If, as an initial review of the experimental data revealed, subjects respond approximately linearly to the disk's motion, then it is possible to compute an empirical transfer function (ETF) [31] for each subject/condition and average these to arrive at a group-representative ETF. Group-

representative responses are then obtained by applying an appropriate input to the ETF.

Fourier transforms of the disk, tracking finger, and CoM-BoS deviation trajectories are computed for each subject and condition. This requires complete data sets, and we employ the method of Ferreira [30] to estimate missing data and compute Fourier transforms in one step. The ETF for each response (Fourier coefficients of the response, divided frequency by frequency by the corresponding Fourier coefficients of disk motion [31]) is then computed. The ETF's corresponding to each overall disk excursion amplitude are averaged together, frequency by frequency, and standard errors computed to obtain group-representative ETF's for each excursion amplitude and associated upper and lower 95% confidence limits. Because the disk's motion is made up of a 14-term sum of sines (Table 1), its Fourier transform is zero for every frequency but those included in the sum (hereafter, referred to as the disk motion frequencies). As a result, the corresponding ETF's are undefined (set to zero) at all nondisk motion frequencies; and the resulting group-representative response trajectories are also composed of only the disk motion frequencies. This calculation serves to "filter out" noise and nonlinear aspects of subjects' responses, leaving only the linear portion. To gauge how much information is lost in the calculation, we estimated missing data and response Fourier transforms for each subject only at the disk motion frequencies, then took the inverse Fourier transforms of the results and compared these estimated response trajectories with the original clean data, using the measure %Fit, given by

$$\%Fit = \left(1 - \frac{\sum_i (r_i - \hat{r}_i)}{\sum_i (r_i - \bar{r})} \right) \times 100 \quad (5)$$

Here, r is the actual response given by clean data, $\bar{r}$ is its mean, and $\hat{r}$ is the estimated response. Fit can range from zero to 100%, with 100% indicating that $\hat{r} = r$, i.e., that the estimated trajectory retains all of the information contained in the clean data trajectory.

Representative disk trajectories for each amplitude are computed using average arm length for the group (76.5 cm), and assuming the projector screen is placed exactly perpendicular to the global z -axis (Fig. 1). Under these conditions, the AP position of the disk is constant throughout the disk's motion. The assumed locations of the projector and projection screen with respect to the global coordinate system are such that the positions of the four calibration dots used to map the disk's motion to global coordinates are averages of the actual calibration points measured for each subject (see Sec. 2.1). By multiplying the Fourier transforms of these trajectories by their corresponding group-representative ETF for each disk excursion amplitude, a group-representative Fourier transform and (by taking its inverse) temporal trajectory of the tracking finger and CoM-BoS deviation response for each disk excursion amplitude are obtained. Because AP CoM motion is a function of disk motion in all three dimensions (Appendix A, which is available under the "Supplemental Materials" tab for this

Fig. 2 Group-average RMSEs, RMSDs, and response delays for 32 young healthy subject

paper on the ASME Digital Collection), the ETF's for AP CoM–BoS deviation responses are computed with respect to overall (xyz) disk motion instead of AP disk motion. ETF's are also used to compute group-representative transfer function gain and phase shift relationships. To gain greater insight into human tracking and balance performance in this task, analytical transfer functions (in the Laplace variable s) are fit to the discrete ETF gain and phase data points, and unit step responses computed. Finally, group-representative data are used to compute RMSE and RMSD as a function of disk motion frequency. In this analysis, we compute one additional tracking error measure, normalized root mean squared error (NRMSE), defined for the ML direction as

$$NRMSE_{x,i} = \frac{RMSE_{x,i}}{a_{x,i}(f_i)} \quad (6)$$

where $a_{x,i}$ is the amplitude of the i th harmonic of disk motion. $NRMSE_{y,i}$ in the SI direction is defined similarly. All data analyses are performed using MATLAB (The MathWorks, Inc., Natick, MA).

2.2.3 Statistical Methods. A nonparametric sign test [32] is used to determine whether overall RMSE and RMSD increase monotonically with amplitude. A standard t-test of the difference between means [32] is employed to determine significance of differences between individual quantities. Group-averaged ETF's are obtained by computing frequency-by-frequency averages of individual subject ETF's for each amplitude. Frequency-by-frequency

standard errors are computed, and 95% confidence intervals defined. All subsequent group-averaged quantities and confidence limits are calculated from these group-averaged ETF's and confidence limits.

3 Results

Performance tracking a disk whose movement is governed by the predictable frequency set is analyzed for 32 young healthy subjects (nine male/23 female, 28 right/four left handed, age: 25.7 ± 3.3 yr, arm length: 76.5 ± 10.0 cm, height: 166.2 ± 10.8 cm, weight: 67.3 ± 12.0 kg, BMI: 23.0 ± 5.0 kg/m² (mean ± 1 standard deviation)).

3.1 Overall Performance Measures. Figure 2 plots average ML, SI, and composite RMSE (Fig. 2(a)), ML, AP, and composite RMSD (Fig. 2(b)), tracking response delays (Fig. 2(c)), and CoM–BoS deviation response delays (Fig. 2(d)) for this group, for each of the five excursion amplitudes tested. Component and composite RMSEs and RMSDs all increase monotonically with increasing amplitude, and a nonparametric sign test shows that these trends are significant ($p \leq 0.03$). Further, a standard t-test of the difference of means shows that ML RMSE is significantly greater than SI RMSE for all amplitudes ($p \leq 0.05$); and ML RMSD is significantly greater than AP RMSD for all amplitudes ($p \leq 0.001$). In contrast, delays associated with the tracking finger remain constant over the range of amplitudes. ML CoM–BoS deviation response delays decrease monotonically with amplitude ($p \leq 0.03$), but AP and composite CoM–BoS deviation delays remain constant with amplitude. Averaging across disk excursion

Fig. 3 Temporal trajectories (a) and frequency spectra (b) of the disk (gray), tip of the tracking finger (black, top two panels) and CoM–BoS deviation (black, bottom two panels). Dotted lines indicate 95% confidence intervals. Tracking fingertip and CoM–BoS deviation ordinates are along the left hand side of the plots, disk ordinates are along the right-hand side. All trajectories have been shifted along their respective ordinate axes so that the overall excursion amplitude of each can be read directly (e.g., 54.5 cm for the tracking fingertip in the x -direction, 47.6 cm in the y -direction). Movements in the positive x -direction are to the subject's left, those in the positive y -direction are up, and movements in the positive z -direction are forward with respect to the subject (see global coordinate axis orientation in Fig. 1). Due to the scale, tracking finger confidence intervals are barely discernable, so their mean "width" is indicated. This shows that all confidence intervals are approximately the same. The reduced ranges of the AP CoM–BoS deviation in the plot "magnifies" this trajectory, making it appear "noisier" than the other trajectories. 1.1250 arm lengths overall excursion amplitude.

amplitude gives an overall composite tracking finger delay of 0.51 ± 0.06 s (mean $\pm$ standard error), and an overall composite CoM–BoS deviation delay of 0.92 ± 0.04 s.

3.2 Group Representative Disk and Response Trajectories. The algorithm employed to estimate missing data (Sec. 2.2) produces tracking finger response trajectories that are very close to the corresponding clean data trajectories. For the ML (x) and SI (y) directions, the %Fit is 93% and 94%, respectively, across all conditions. The ML CoM–BoS deviation %Fit is lower, 78%, but still captures a majority of the response dynamics. AP CoM–BoS deviation %Fit is lower yet at 36%, indicating that significant noise and/or other nonlinearities are associated with CoM motion in this direction. In Fig. 3, we plot group-representative performance maintaining balance and tracking the disk according to the predictable frequency set with amplitude 1.125 AL. Performance for all amplitudes is tabulated in Appendix B, which is available under the “[Supplemental Materials](#)” tab for this paper on the ASME Digital Collection. Finger tracking trajectories (position versus time) in the ML and SI directions (Fig. 3(a), upper two panels, black solid lines) indicate very close tracking of the disk (gray lines). These tracking trajectories are nearly identical in shape to those of the disk movement itself ($\rho = 0.998, 0.996$, respectively), though modest attenuation and delay are present. The shape of the ML CoM–BoS deviation trajectory (Fig. 3(a), third panel, black solid line) is also quite similar to that of the disk ($\rho = 0.936$), but with substantially more attenuation and delay than that of the corresponding finger tracking motion. AP CoM–BoS deviation is not as well correlated with overall disk motion ($\rho = 0.417$).

Figure 3(b) details the frequency spectra (amplitude versus frequency) corresponding to the temporal plots of Fig. 3(a). Table B5 in Appendix B (available under the “[Supplemental Materials](#)” tab for this paper on the ASME Digital Collection) lists the

amplitudes of these spectra versus frequency. For the ML and SI tracking fingertip motions (Fig. 3(b), upper two panels, black lines), the spectra corresponding to the disk motion frequencies have amplitudes approximately 90% as great as the corresponding disk motion amplitudes (gray lines) for the six lowest frequency components. Note the difference between the right and left-hand scales in Fig. 3(b). The spectra for ML CoM–BoS deviation (Fig. 3(b), third panel, black lines) is also similar to the corresponding disk spectra, but attenuation is much greater (approximately 20% for the six lowest frequency components). This complimentary view of the temporal plots of Fig. 3(a) again indicates that these stimulus and response waveforms are similarly shaped. The spectra of AP CoM–BoS deviation (Fig. 3(b), bottom panel, black lines) is dissimilar to that of overall disk motion and highly attenuated, indicating the low correlation previously noted between these two motions.

3.3 Group Representative Gain and Phase Relationships.

Empirical transfer functions relating these responses to corresponding disk motion are computed by dividing the tracking and CoM–BoS deviation frequency spectra by their corresponding disk motion frequency spectra. Gains and phase shifts computed from these transfer functions are presented in the Bode diagrams of Fig. 4 (discrete dots). Note that the gain is reported as the transfer function’s amplitude characteristic (dimensionless) for clarity, rather than converted to decibel. Analytical transfer functions (in the Laplace variable s , solid lines in Fig. 4) are fit to the empirical transfer function data. The lowest order stable transfer functions that fit this data are listed in Table 4 (upper three rows). Note that the fitted transfer functions are mixed phase, since they contain zeros in the right-half s -plane. The corresponding minimum phase transfer functions are listed in the lower three rows of Table 4, and appear as dashed lines in Fig. 4. Because the minimum phase transfer functions have identical gain characteristics as their nonminimum phase

Fig. 4 Gain/phase diagram of ML(y) and SI (z) components of tracking finger motion and ML CoM–BoS deviation. Dots denote the empirical transfer function gain computed at each disk motion frequency. Solid lines denote the analytical transfer functions fit to the empirical data (upper three rows in Table 4). Dotted lines denote the fitted transfer functions’ 95% confidence intervals. Dashed lines denote the minimum phase transfer functions (lower three rows in Table 4). Because minimum phase transfer functions have identical gain characteristics as fitted transfer functions only their phase relationships are visible in the figure. 1.1250 arm lengths overall excursion amplitude. Bode diagrams for other amplitudes are shown in Appendix C, which is available under the “[Supplemental Materials](#)” tab for this paper on the ASME Digital Collection.

Table 4 Best-fit and minimum phase transfer functions for the tracking fingertip and CoM–BoS ($i = \sqrt{-1}$) 1.1250 arm lengths overall excursion amplitude

System (num/den order)	Fitted transfer function
ML finger tracking (num/den = 4/6)	$\frac{[s + 0.5871][s - 10.59][s - (6.933 \pm 10.52i)]}{[s + 0.5821][s + 5.598][s + (5.492 \pm 14.61i)][s + (5.519 \pm 8.035i)]}$
SI finger tracking (num/den = 4/6)	$\frac{[s + 2.958][s - 6.995][s - (6.024 \pm 11.69i)]}{[s + (3.375 \pm 1.614i)][s + (3.674 \pm 14.16i)][s + (4.43 \pm 8.427i)]}$
ML CoM–BoS (num/den = 4/6)	$\frac{[s + 0.04346][s + 5.752][s - (2.570 \pm 6.710i)]}{[s + 0.04558][s + 1.945][s + (1.688 \pm 5.470i)][s + (2.081 \pm 3.066i)]}$
	Minimum phase transfer function
ML finger tracking (num/den = 4/6)	$\frac{[s + 1.233][s + 13.06][s + (6.356 \pm 11.23i)]}{[s + 1.213][s + 6.372][s + (5.346 \pm 14.63i)][s + (5.747 \pm 8.68i)]}$
SI finger tracking (num/den = 4/6)	$\frac{[s + 2.54][s + 9.346][s + (5.488 \pm 11.87i)]}{[s + (3.569 \pm 14.16i)][s + (3.727 \pm 0.9775i)][s + (4.444 \pm 8.765i)]}$
ML CoM–BoS (num/den = 4/6)	$\frac{[s + 0.04484][s + 5.114][s + (2.671 \pm 6.817i)]}{[s + 0.04706][s + 1.908][s + (1.735 \pm 5.432i)][s + (2.093 \pm 3.011i)]}$

counterparts, only their phase characteristics are visible in the figure. Bode diagrams for the other disk excursion amplitudes are given in Appendix C, which is available under the “[Supplemental Materials](#)” tab for this paper on the ASME Digital Collection.

The fitted transfer function plots (solid and dotted lines in Fig. 4) indicate that the finger tracks the disk closely with a gain of approximately 0.9 and a phase lag of less than 32 deg for the lowest four frequencies. At this point, the gain characteristics begin to diverge, with the ML gain decreasing steadily to approximately 0.8 at 1 Hz, while the SI gain gradually increases to a resonant peak of approximately 1.0 at 1 Hz. The phase lags associated with both movement directions remain very close to one another throughout the frequency range. By the fifth frequency, 0.288 Hz, the lags are approximately 50 deg, large enough to seriously compromise tracking accuracy. In contrast, CoM–BoS deviation tracks the disk in the ML direction with a gain of approximately 0.2 for the lowest six frequencies before its response quickly falls off to zero. The response gain and phase characteristics for all five disk excursion amplitudes are plotted together in Fig. 5. These are nearly the same for all amplitudes, indicating that the system is linear with respect to amplitude. Therefore, earlier observations regarding performance at 1.1250 AL amplitude apply to these other amplitudes as well.

The responses of the tracking finger and CoM–BoS deviation to a unit step function (computed using the transfer functions listed in Table 4) are shown in Fig. 6. Fitted transfer function step responses are shown with heavy lines while minimum phase transfer function step responses are represented by the thinner lines. These plots indicate that ML CoM–BoS deviation exhibits the most heavily damped response, followed by ML motion of the tracking finger. SI motion of the tracking finger exhibits the least damping. The dots in the figure locate points at which each response settles to within 5% of its final, steady state value. Based on these data, the tracking finger reaches steady state in the ML direction in 0.30–0.66 s, and in the SI direction in 0.54–0.89 s. ML CoM–BoS deviation reaches steady state in 1.02–1.54 s. The tracking finger settling times are comparable to the response delays determined by correlation analysis and shown in Fig. 2 (ML lag: 0.48 s, SI lag: 0.51 s), while the CoM–BoS deviation settling time is somewhat larger than the previous result (0.73 s).

3.4 Group Representative Tracking Error and CoM–BoS Deviation as Functions of Disk Frequency. To understand how the response at each individual frequency contributes to overall

response, the motions of the disk, tracking finger, and CoM–BoS deviation are decomposed into their sinusoidal components, and RMSEs and RMSDs calculated for each frequency component. These are shown in Fig. 7. The odd-looking variation of these errors with frequency is explained in Appendix D, which is available under the “[Supplemental Materials](#)” tab for this paper on the ASME Digital Collection, which shows that the tracking errors are given by equations of the form

$$RMSE(f_i) = a_i \sqrt{\frac{1 + g_i^2 - 2g_i \cos \chi_i}{2}}, \quad (7)$$

$$NRMSE(f_i) = \frac{RMSE(f_i)}{a_i} = \sqrt{\frac{1 + g_i^2 - 2g_i \cos \chi_i}{2}}$$

where a_i is the amplitude of the i th disk harmonic (frequency f_i) and g_i and χ_i are the associated gain and phase lag. As frequency increases, RMSE generally decreases since gain decreases with frequency (Fig. 4), but it fluctuates due to the $\cos \chi_i$ term. NRMSE shows the same general trend but is not as distorted due to the normalizing effect of division by a_i . For frequencies less than 1.0 Hz, RMSE generally decreases, while NRMSE increases. These observations do not apply to RMSD because that calculation does not involve the stimulus trajectory (Eq. (4)). In this case, both ML and AP RMSD decrease approximately according to $k_1 f_i^{k_2} + k_3$, where the k_i are fitted constants.

4 Discussion

These experimental and analytical results demonstrate that the BRT can quantify young healthy performance in the combined tracking and balance task, and that it has the sensitivity to detect changes in performance based on task difficulty (disk motion amplitude). In particular, they further reveal that the tracking and balance systems respond linearly under these conditions, and that performance in the SI direction is superior to that in the ML direction. The BRT is also able to quantify tracking and balance performance without floor or ceiling effects in this young population, indicating thus far that it is a valid platform for ongoing comparisons to aging and neurological disability populations.

The results presented in this article illuminate several noteworthy aspects of young healthy tracking and balance performance. The lower tracking error (Fig. 2), tighter confidence intervals (Fig. 3), and different gain characteristics between the two tracking finger directions (Fig. 4) suggest that subjects are better able to track the disk, and track it at higher frequencies, in the SI direction than in the ML direction. Moreover, the presence of a resonant frequency associated with SI tracking (Fig. 4) indicates that the “SI tracking system” has less damping and is more responsive than the “ML tracking system,” which can also be discerned from the step responses shown in Fig. 6. For this test subjects oriented their reaching arm with the palm faced medially (toward the center of the body). In such a configuration movement of the tracking finger in the SI direction involves movement of the humerus and forearm/hand in the Sagittal plane. Tracking in the ML direction involves movement of the humerus and forearm/hand in the horizontal and frontal planes, respectively.

Tracking in the SI direction involves elbow flexion/extension, shoulder flexion/extension, and shoulder elevation/depression; which are produced by the elbow, glenohumeral joint, acromioclavicular joint, and the sternoclavicular joint. ML tracking involves shoulder abduction/adduction and internal/external rotation, produced by just the glenohumeral joint. Thus, four joints with their associated degrees-of-freedom and musculature participate in SI tracking while only one joint participates in ML tracking. Moreover, the size, proportion of fibers recruited, and lines of action of muscles involved in SI motion produce more powerful synergy patterns than strictly ML motion. Though neither the tracking task nor the action of the shoulder and elbow can be strictly divided into SI and ML motion (as we have done for illustrative purposes), our findings suggest that more degrees-of-freedom and more powerful movements are likely available for SI tracking than ML tracking, which contributes to the superiority of performance in the SI direction. Elbow and shoulder flexion/extension are

employed in ballistic movements of the hand, as in striking, “clubbing,” and throwing objects. It is widely accepted that the body and particularly the hand, arm, and shoulder evolved, beginning with early hominins, to facilitate such movements [33]. This would have conferred a strong selective benefit to these early hunters [34]. The evolutionary development of the shoulder and arm is most evident in high performance sports that involve over-hand throwing, such as baseball pitching [35]. Movements requiring shoulder abduction/adduction and internal/external shoulder rotation typically do not involve high levels of force or speed. At frequencies below the SI resonant peak, ML tracking system performance is equal to SI performance, which might facilitate precision tasks such as manipulation of objects, writing, or drawing on a vertical surface such as a blackboard.

There is no reason to expect the CoM, which is a function of whole-body orientation, to track the disk’s motion very closely. For this task, the CoM is located approximately within the pelvic region, separated from the center of the target disk by several segments of the reaching body (trunk, upper arm, and forearm/hand). The CoM’s position in space is determined primarily by the positions and orientations of the legs, pelvis, and trunk. Substantial CoM movement entails accelerating these more massive body segments in order to change their position and orientation—an energy-intensive proposition. Moreover, moving the CoM too far from the center of the BoS could result in a fall. A conservative strategy (with respect to both energy expenditure and safety) would involve fixing the legs and pelvis, and then employing smaller trunk movements to the point that still smaller movements of the substantially less massive upper arm and forearm/hand are all that are required to place the tracking finger in contact with the disk’s center. This is largely what is observed in the experiment. Like the motion of the tracking finger, ML CoM motion is highly correlated with ML disk motion, but greatly attenuated. The CoM responds much differently in the AP direction, due at least in part

Fig. 5 Gain/phase diagrams of ML(y) and SI(z) components of tracking finger motion and ML CoM–BoS deviation for all five disk excursion amplitudes. The individual characteristics are nearly the same across amplitude, indicating that these systems respond linearly under these conditions.

to the constraining placement of the projection screen. This, however, is not an unrealistic movement environment. Reaching for objects in overhead or under-counter kitchen shelves, for example, involves just such environments. AP motion of the CoM is not solely predicated upon AP motion of the disk. As the disk moves in the ML and SI directions toward the outer boundaries of the projection screen, subjects must shift forward to maintain contact with the disk. When the disk moves back to the center of the screen, the subjects must shift back to provide room for the arm and hand moving directly in front. AP motion of the CoM (± 1 cm, Fig. 3(a)) is quite small compared to ML CoM motion (± 12 cm) or tracking motion (± 48 – 55 cm), due not only to the placement of the projection screen but also to the BoS's smaller AP dimension (~ 17 cm) relative to its ML dimension (~ 30 cm).

We noted that the analytical transfer functions which best fit the ETF data (Table 4) are not minimum phase transfer functions. Of all transfer functions with the same gain characteristic, the one with the minimum phase characteristic exhibits the shortest group delay, hence the fastest response time. In this regard, they represent an upper limit on the system's performance (see Fig. 6). Not only do the minimum phase transfer functions exhibit substantially shorter response times than their fitted counterparts, they also do not exhibit the initial fluctuations that the best-fit, nonminimum phase tracking transfer functions do. Analysis of tracking errors (Fig. 7) also reveals that for both ML and SI directions RMSE *decreases* with frequency, while NRMSE *increases* for frequencies below 1 Hz. Since the amplitude of each sinusoidal component is inversely proportional to its frequency, the lowest frequency components of motion have the highest amplitudes, and vice versa. At the same time, lower frequency components are easier to track than higher frequency components. Thus, the subject tracks the lower frequency components more accurately than the higher frequency components (as indicated by NRMSE), but the *magnitudes* of the tracking errors are greater due to the greater amplitudes (as indicated by RMSE). We also saw that subjects exhibit better high frequency tracking performance (i.e., higher gains) in the SI direction than in the ML direction. This

superiority is also reflected both in the lower overall tracking errors (Fig. 2), and lower frequency-specific tracking errors (Fig. 7).

A physical limitation of the experiment is the presence of the projection screen in front of the subject. Though this represents an important reaching environment encountered in ADL's, it nonetheless constrains AP motion of the CoM and limits our ability to fully challenge balance in this direction. To address this work has begun on a second generation BRT, which employs a virtual reality environment instead of a projection screen. A second limitation concerns the assumption that the measured responses are substantially linear, and that linear portions can be separated from nonlinear portions and analyzed to give a meaningful characterization of overall response dynamics. This follows the work of McRuer et al. [36], Kleinman et al. [37], and Baron et al. [38], who separated human tracking responses into a linear component and a nonlinear "remnant." We were able to verify that the tracking system responses and ML CoM–BoS deviation response were substantially linear. The %Fit for the tracking system responses was greater than 93%, and for the ML CoM–BoS deviation response it was 78%. Further, Fig. 5 shows that for these responses the gain and phase characteristics did not vary with amplitude, a second test of linearity. An analysis of the nonlinear aspects of performance in this task is not presented in this first article, but will be addressed in a subsequent one.

A number of tracking studies have been undertaken to assess human tracking performance (e.g., Refs. [36–40]). However, these have focused exclusively on performance in the tracking task itself. Performance in a secondary task such as balance has not been considered. Likewise, balance studies generally focus exclusively on the maintenance of balance when subjected to externally applied disturbances of the BoS, visual surround, etc. (e.g., Refs. [19], [20], and [22]). To our knowledge, no prior studies have assessed balance maintenance while performing some other task involving volitional, perturbing movements of the whole body and/or its parts. Nonetheless, prior studies reveal similar control patterns. McRuer et al. [36] found that for a given set of test

Fig. 6 Step responses of ML(y) and SI (z) components of tracking finger motion and ML CoM–BoS deviation. Thick lines represent fitted transfer function step responses (upper three rows in Table 4), while thin lines represent minimum phase transfer function responses (lower three rows in Table 4). Dots indicate time to settle to within 5% of response final value. 1.1250 arm lengths overall excursion amplitude.

conditions, healthy adult subjects adaptively alter tracking response dynamics to respond linearly to an input. Kleinman et al. [37] and Baron et al. [38] also found that healthy subjects respond linearly to a tracking input, and further found evidence that subjects were capable of developing a predictive model of this input to aid in the tracking task. That human movement control employs adaptive and predictive algorithms together implies the existence of internal models [41–43]: highly adaptable neural structures [44] that represent the kinematics and dynamics of the body and its parts, and the forces and constraints imposed by the external environment. The CSMB that we are developing incorporates a controller based on this concept. Paterka [19], Mergner [20], and others have found that the balance system exhibits at least a quasi-linear response to unexpected disturbances. We are inclined to rule this out for the tracking system, given the high %Fit measures associated with it, but we do not rule it out for the balance system, given its lower %Fit measures. It is important to note, though, that while these earlier studies employed *unexpected* balance disturbances, our study employs *expected* disturbances caused by volitional movements of the body and its parts. The response to each is generated by distinctly different regions of the brain (at least initially). Responses to unexpected disturbances are generated by lower level brain stem and spinal cord processes after the disturbance is sensed. Responses to expected disturbances are generated by suprabrainstem (cortex, cerebellum, and basal ganglia) predictive and motor planning processes in advance of the disturbance [23]. These latter regions are also where reaching and tracking motor commands are generated. Responses to the expected balance disturbances encountered in this study are closely predicated upon the tracking motions for which they are designed to compensate, and so we posit that these responses exhibit greater linearity than those associated with unexpected balance disturbances.

The BRT was designed to challenge balance and to bring subjects with and without balance impairments to the limits of their

balance (without substantially moving their feet), just short of inducing a fall. Young healthy subjects do not have appreciable fall risk and are able to perform the test with relative ease because their uncompromised sensorimotor and musculoskeletal systems are able to anticipate expected, impending balance perturbations and execute compensatory actions far enough in advance of the disturbance to eliminate any threat of falling. Their performance still has limits, however, and it is important to characterize and quantify them. Moreover, even though this population is free from the confounding effects of age and disease, we still cannot (yet) determine even young healthy response to a particular balance disturbance from “first principles,” given the high degree of complexity and redundancy associated with the sensorimotor and musculoskeletal systems and our limited knowledge of their functions and interactions. Our approach to this goal lies in measuring and quantifying young healthy performance both to advance our knowledge of normal function and as a reference against which to compare and assess high fall risk populations. Young healthy performance data has a number of more immediate applications. It can inform work space design, for example, in the home and on the job. Many athletic and job-related activities involve reaching. It is important not only to know when to step to prevent a fall, but also how to stand or step when at the limits of balance in order to provide an optimal base of support for the upper extremity to achieve maximal performance. Finally, given its sensitivity, variants of the BRT could be useful for movement training whose goal is to achieve high fidelity and optimal human performance within a prescribed movement or sequence of movements. We are currently using the results reported here as a reference against which to compare the performance of healthy older adults, otherwise healthy older adults with a history of falls, and older adults whose balance has been further compromised by stroke. We hypothesize that such comparisons will enable us to better characterize the multisegmental nature of functional balance in health,

Fig. 7 RMS (solid lines) and NRMS (dashed lines) finger tracking errors and CoM-BoS deviations (solid lines) with 95% confidence intervals (dotted lines). For tracking errors (Figs. 7(a) and 7(b)), dots (RMS error) and stars (NRMS error) correspond to errors computed from the ETF gains and phase lags (dots in Figs. 4(a) and 4(b)), while the solid and dashed lines correspond to those computed by the fitted analytical transfer function gains and phase lags (solid lines in Figs. 4(a) and 4(b)). For CoM-BoS deviations (panels C and D), dots correspond to deviations computed from the ETF gains and phase lags (dots in Figs. 4(c) and 4(d)), and solid lines represent fitted equations of the form $k_1 f_i^{k_2} + k_3$. The lower 95% confidence bound for AP CoM-BoS deviation is zero. 1.1250 arm lengths overall excursion amplitude.

aging, and disease to enhance diagnostic specificity, better target movement therapy, and quantify treatment response, including changes in balance, referenced against young healthy controls.

Acknowledgment

This study (PI: Joseph Barton) was supported by a Veterans Administration Career Development Award, CDA Grant No. B7160-W (PI: Joseph Barton), a Pepper Center Development Project (PI: Joseph Barton) supported by NIA Grant No. P30-AG028747 (PI: Andrew Goldberg), the Baltimore Veterans Administration Medical Center Geriatric Research, Education and Clinical Center (GRECC), and the Baltimore VA Maryland Exercise and Robotics Center of Excellence (VA Grant No. B9215-C), PI: Richard Macko.

The authors thank Dr. Vincent Conroy and Dr. Douglas Savin of the University of Maryland Physical Therapy and Rehabilitation Science Department for their expert advice on shoulder anatomy and motion.

Nomenclature

a_i	= amplitude of the i th disk frequency harmonic
f	= sum of sines frequency (Hz)
f_i	= i th frequency harmonic
G	= transfer function gain
g_i	= transfer function gain at the i th frequency harmonic
i	= $\sqrt{-1}$
k_i	= fitted constants
$\bar{r}$	= mean of clean data trajectory
r_i	= i th element of clean data response trajectory
$\hat{r}_i$	= i th element of estimated data response trajectory
s	= Laplace variable
t	= time (s)
x	= ML (x) position relative to global coordinate system
$x_d(t)$	= horizontal trajectory of disk
y	= SI (y) position relative to global coordinate system
$y_d(t)$	= vertical trajectory of disk
z	= AP (z) position relative to global coordinate system
%Fit	= percent fit
ρ	= correlation coefficient
τ	= response lag
ϕ	= sum of sines phase shift
χ_i	= transfer function phase lag at the i th frequency harmonic

Abbreviations

ADL	= activities of daily living
AL	= arm length
AP	= anterior–posterior
BoS	= base of support
BRT	= balanced reach test
CoM	= center of mass
CoM–BoS deviation	= deviation between the projection of the CoM onto the ground plane and the center of the BoS
CoR	= center of rotation
CSMB	= control system model of balance
C7/T1	= intervertebral disk between the seventh cervical and first thoracic vertebrae
EMG	= electromyography

ETF	= empirical transfer function
IREDD	= infrared emitting diode
L5/S1	= intervertebral disk between the fifth lumbar and first sacral vertebrae
ML	= medial–lateral
NRMSE	= normalized root mean squared finger tracking error
PID	= proportional–integral–derivative
RMS	= root mean squared
RMSD	= root mean squared CoM–BoS deviation
RMSE	= root mean squared finger tracking error
SI	= superior–inferior
YHS	= young healthy subject

References

- [1] Woollacott, M. H., 2000, "Systems Contributing to Balance Disorders in Older Adults," *J. Gerontol., Ser. A*, **55**(8), pp. M424–M428.
- [2] Woollacott, M. H., and Shumway-Cook, A., 1990, "Changes in Posture Control Across the Life Span—A Systems Approach," *Phys. Ther.*, **70**(12), pp. 799–807.
- [3] Jorgensen, L., Engstad, T., and Jacobsen, B. K., 2002, "Higher Incidence of Falls in Long-Term Stroke Survivors Than in Population Controls: Depressive Symptoms Predict Falls After Stroke," *Stroke*, **33**(2), pp. 542–547.
- [4] Berg, K., Wood-Dauphinee, S., Williams, J. I., and Gayton, D., 1989, "Measuring Balance in the Elderly: Preliminary Development of an Instrument," *Physiother. Can.*, **41**(6), pp. 304–311.
- [5] Podsiadlo, D., and Richardson, S., 1991, "The Timed Up & Go: A Test of Basic Functional Mobility for Frail Elderly Persons," *J. Am. Geriatr. Soc.*, **39**(2), pp. 142–148.
- [6] Fregly, A. R., and Graybiel, A., 1968, "An Ataxia Test Battery Not Requiring Rails," *Aerosp. Med.*, **39**(3), pp. 277–282.
- [7] Tyson, S., and Connell, L., 2009, "How to Measure Balance in Clinical Practice—A Systematic Review of the Psychometrics and Clinical Utility of Measures of Balance Activity for Neurological Conditions," *Clin. Rehabil.*, **23**(9), pp. 824–840.
- [8] Hyndman, D., Ashburn, A., and Stack, E., 2002, "Fall Events Among People With Stroke Living in the Community: Circumstances of Falls and Characteristics of Fallers," *Arch. Phys. Med. Rehabil.*, **83**(2), pp. 165–170.
- [9] Hyndman, D., and Ashburn, A., 2003, "People With Stroke Living in the Community: Attention Deficits, Balance, ADL Ability and Falls," *Disability Rehabil.*, **25**(15), pp. 817–822.
- [10] Harris, J. E., Eng, J. J., Marigold, D. S., Tokuno, C. D., and Louis, C. L., 2005, "Relationship of Balance and Mobility to Fall Incidence in People With Chronic Stroke," *Phys. Ther.*, **85**(2), pp. 150–158.
- [11] Belgen, B., Beninato, M., Sullivan, P. E., and Narielwalla, K., 2006, "The Association of Balance Capacity and Falls Self-Efficacy With History of Falling in Community-Dwelling People With Chronic Stroke," *Arch. Phys. Med. Rehabil.*, **87**(4), pp. 554–561.
- [12] Oliver, D., Daly, F., Martin, F. C., and McMurdo, M. E. T., 2004, "Risk Factors and Risk Assessment Tools for Falls in Hospitalised Patients: A Systematic Review," *Age Ageing*, **33**(2), pp. 122–130.
- [13] Sibley, K. M., Straus, S. E., Inness, E. L., Salbach, N. M., and Jaglal, S. B., 2013, "Clinical Balance Assessment: Perceptions of Commonly-Used Standardized Measures and Current Practices Among Physiotherapists in Ontario, Canada," *Implementation Sci.*, **8**(33), pp. 1–8.
- [14] McGlynn, M., and Cott, C. A., 2007, "Weighing the Evidence: Clinical Decision Making in Neurological Physical Therapy," *Physiother. Can.*, **59**(4), pp. 241–254.
- [15] McGinnis, P. Q., Hack, L. M., Nixon-Cave, K., and Michlovitz, S. L., 2009, "Factors That Influence the Clinical Decision Making of Physical Therapists in Choosing a Balance Assessment Approach," *Phys. Ther.*, **89**(3), pp. 233–247.
- [16] Lord, S. R., Menz, H. B., and Tiedemann, A., 2003, "A Physiological Profile Approach to Falls Risk Assessment and Prevention," *Phys. Ther.*, **83**(3), pp. 237–252.
- [17] Hilliard, M. J., Martinez, K. M., Janssen, I., Edwards, B., Mille, M.-L., Zhang, Y., and Rogers, M. W., 2008, "Lateral Balance Factors Predict Future Falls in Community-Living Older Adults," *Arch. Phys. Med. Rehabil.*, **89**(9), pp. 1708–1713.
- [18] Horak, F. B., Wrisley, D. M., and Frank, J., 2009, "The Balance Evaluation Systems Test (BESTest) to Differentiate Balance Deficits," *Phys. Ther.*, **89**(5), pp. 484–498.
- [19] Paterka, R. J., 2002, "Sensorimotor Integration in Human Postural Control," *J. Neurophysiol.*, **88**(3), pp. 1097–1118.
- [20] Mergner, T., 2007, "Modeling Sensorimotor Control of Human Upright Stance," *Prog. Brain Res.*, **165**, pp. 283–297.
- [21] Barin, K., 1989, "Evaluation of a Generalized Model of Human Postural Dynamics and Control in the Sagittal Plane," *Biol. Cybern.*, **61**(1), pp. 37–50.
- [22] Kuo, A. D., 2005, "An Optimal State Estimation Model of Sensory Integration in Human Postural Balance," *J. Neural Eng.*, **2**(3), pp. S235–S249.
- [23] Barton, J. E., Roy, A., Sorkin, J. D., Rogers, M. W., and Macko, R., 2015, "An Engineering Model of Human Balance Control Part 1: Biomechanical Model," *ASME J. Biomech. Eng.*, **138**(1), p. 014502.

- [24] Kiemel, T., Oie, K. S., and Jeka, J. J., 2006, "The Slow Dynamics of Postural Sway Are in the Feedback Loop," *J. Neurophysiol.*, **95**(3), pp. 1410–1418.
- [25] Jagacinski, R. J., and Flach, J. M., 2003, *Control Theory in Humans: Quantitative Approaches to Modeling Performance*, Lawrence Erlbaum Associates, Mahwah, NJ.
- [26] Zatsiorsky, V. M., Seluyanov, V. N., and Chugunova, L. G., 1990, "Methods of Determining Mass-Inertial Characteristics of Human Body Segments," *Contemporary Problems of Biomechanics*, G. G. Chernyi, and S. A. Regirer, eds., Mir Publishers, Moscow, Russia, pp. 272–291.
- [27] de Leva, P., 1996, "Adjustments to Zatsiorsky–Seluyanov's Segment Inertia Parameters," *J. Biomech.*, **29**(9), pp. 1223–1230.
- [28] Horstmann, G. A., and Dietz, V., 1990, "A Basic Posture Control Mechanism: The Stabilization of the Centre of Gravity," *Electroencephalogr. Clin. Neurophysiol.*, **76**(2), pp. 165–176.
- [29] Patla, A., Frank, J., and Winter, D. A., 1990, "Assessment of Balance Control in the Elderly," *Physiother. Can.*, **42**(2), pp. 89–97.
- [30] Ferreira, P. J. S. G., 1996, "Interpolation in the Time and Frequency Domains," *IEEE Signal Process. Lett.*, **3**(6), pp. 176–178.
- [31] Ljung, L., 1999, *System Identification: Theory for the User*, Prentice Hall, Upper Saddle River, NJ.
- [32] Spiegel, M. R., Schiller, J., and Srinivasan, A. A., 2000, *Probability and Statistics*, McGraw-Hill, New York.
- [33] Gorman, J., 2013, "Scientists Unlock Mystery in Evolution of Pitchers," *New York Times*, p. A3.
- [34] Roach, N. T., Venkadesan, M., Rainbow, M. J., and Lieberman, D. E., 2013, "Elastic Energy Storage in the Shoulder and the Evolution of High-Speed Throwing in *Homo*," *Nature*, **498**(7455), pp. 483–487.
- [35] Roach, N. T., and Lieberman, D. E., 2014, "Upper Body Contributions to Power Generation During Rapid, Overhand Throwing in Humans," *J. Exp. Biol.*, **217**(12), pp. 2139–2149.
- [36] McRuer, D., Graham, D., Krendel, E., and William, R., 1965, "Human Pilot Dynamics in Compensatory Systems," Wright Patterson Air Force Base, OH, Report No. AFFDL-TR-65-15.
- [37] Kleinman, D. L., Baron, S., and Levison, W. H., 1970, "An Optimal Control Model of Human Response—Part I: Theory and Validation," *Automatica*, **6**(3), pp. 357–369.
- [38] Baron, S., Kleinman, D. L., and Levison, W. H., 1970, "An Optimal Control Model of Human Response—Part II: Prediction of Human Performance in a Complex Task," *Automatica*, **6**(3), pp. 371–383.
- [39] Boer, E. R., and Kenyon, R. V., 1998, "Estimation of Time-Varying Delay Time in Nonstationary Linear Systems: An Approach to Monitor Human Operator Adaptation in Manual Tracking Tasks," *IEEE Trans. Syst., Man, Cybern.—Part A: Syst. Hum.*, **28**(1), pp. 89–99.
- [40] Vercher, J.-L., Sares, F., Blouin, J., Bourdin, C., and Gauthier, G., 2003, "Role of Sensory Information in Updating Internal Models of the Effector During Arm Tracking," *Prog. Brain Res.*, **142**, pp. 203–222.
- [41] Shadmehr, R., and Wise, S. P., 2005, *A Computational Neurobiology of Reaching and Pointing*, MIT Press, Cambridge, MA.
- [42] Kawato, M., and Wolpert, D. M., 1998, "Internal Models for Motor Control," Novartis Found. Symp., **218**, pp. 291–307.
- [43] Abe, N., and Yamanaka, K., 2003, "Smith Predictor Control and Internal Model Control—A Tutorial," *SICE 2003 Annual Conference*, Aug. 4–6, pp. 1383–1387.
- [44] Kawato, M., 1999, "Internal Models for Motor Control and Trajectory Planning," *Curr. Opin. Neurobiol.*, **9**(6), pp. 718–727.