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RESEARCH ARTICLE

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Effect of altered sensory conditions on multivariate descriptors of human postural sway

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Abstract Multivariate descriptors of sway were used to test whether altered sensory conditions result not only in changes in amount of sway but also in postural coordination. Eigenvalues and directions of eigenvectors of the covariance of shnk and hip angles were used as a set of multivariate descriptors. These quantities were measured in 14 healthy adult subjects performing the Sensory Organization test, which disrupts visual and somatosensory information used for spatial orientation. Multivariate analysis of variance and discriminant analysis showed that resulting sway changes were at least bivariate in character, with visual and somatosensory conditions producing distinct changes in postural coordination. The most significant changes were found when somatosensory information was disrupted by sway-referencing of the support surface (P=3.2·10^{-10}). The resulting covariance measurements showed that subjects not only swayed more but also used increased hip motion analogous to the hip strategy. Disruption of vision, by either closing the eyes or sway-referencing the visual surround, also resulted in altered sway (P=1.7·10^{-10}), with proportionately more motion of the center of mass than with platform sway-referencing. As shown by discriminant analysis, an optimal univariate measure could explain at most 90% of the behavior due to altered sensory conditions. The remaining 10%, while smaller, are highly significant changes in posture control that depend on sensory conditions. The results imply that normal postural coordination of the trunk and legs requires both somatosensory and visual information and that each sensory modality makes a unique contribution to posture control. Descending postural commands are multivariate in nature, and the motion at each joint is affected uniquely by input from multiple sensors.

Key words Posture · Equilibrium · Sway · Posturography · Sensory organization test · Human

Introduction

During quiet stance, humans sway slightly. This sway is indicative of a sensor-based control system maintaining imperfect equilibrium of an inverted pendulum. The control relies of multiple sensory modalities, and sway, defined either as motion of the body's center of mass (COM) or the center of pressure (COP) of vertical ground reaction forces (Black et al. 1982), increases when some sensory inputs are disrupted (Mirka and Black 1990). In addition, subjects with a variety of neurological disorders exhibit greater sway or stereotypical patterns of sway than normals (Nashner et al. 1982; Woollacott et al. 1986; Diener and Dichgans 1988; Furman 1994; Horak and MacPherson 1995). For these reasons and because of ease of measurement, sway and other quantifiers of quiet stance have been proposed as useful measures for detecting balance disorders or determining risk of falling (Maki et al. 1991). These measures are, however, limited in their ability to either diagnose contributing factors or provide insight concerning underlying mechanisms. More advanced sway indicators may address these shortcommings.

There are, however, several drawbacks to such univariate measures. In the case of COP indicators, they inseparably combine information concerning center of mass location and acceleration. Also, some combinations of joint motions such as a "hip strategy" are not accurately represented by COP or COM measurement alone (Horak and Nashner 1986; Barin 1992). Implicit to using sway measure is a single-link inverted pendulum model of balance, in which sensory or neurological dysfunction is manifested by greater sway.

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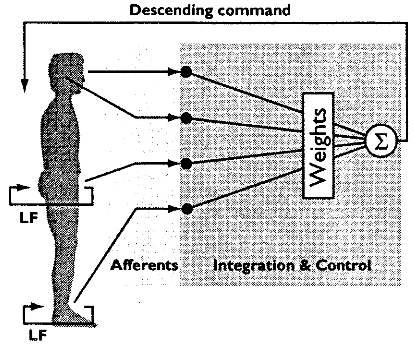
a. Univariate control model



b. Multivariate control model

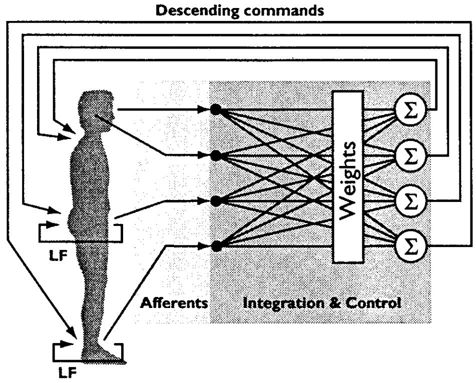


Fig. 1a, b Univariate and multivariate models for multisensory integration and control. Whereas local feedback (*LF*) acts at each joint, afferents from somatosensors, vision, and vestibular organs are also integrated by the central nervous system. **a** In the univariate model, integration is used to generate a univariate (scalar) descending command, such as a command to move the center of mass. **b** In the multivariate model, integration produces multivariate (vector) feedback commands, which may differ for each joint

More information may be obtained by adopting a multi-link, inverted pendulum model of balance and measuring the additional degrees of freedom (Armblard et al. 1985; Accornero et al. 1997). These measurements may be useful for detecting not only *extent* of sway but also *type* of sway. Depending on the organization of postural control within the central nervous system, it is possible that degradation of various components of the control system, due to age, disease, or trauma, could result in changes in postural coordination of sway which cannot be adequately described using a univariate measure such as COP or COM motion.

One way to test for dysfunction-induced changes in sway coordination is to artificially upset certain sensory inputs and look for associated changes in multivariate sway measures. For example, the Sensory Organization Test (SOT), also referred to as dynamic posturography, is an existing clinical test that alters visual and somatosensory conditions to test for balance disorders (Nashner et al. 1982). In fact, multivariate measures including peak-to-peak COP and a "strategy score" basd on horizontal ground reaction force have been proposed for the SOT (NeuroCom International 1990). However, it is difficult to use force plate output, and hence the strategy score, to accurately deduce the relative motion of the ankles and hips (Barin 1992; Peterka and Black 1990). Direct measurements of ankle and hip motion could potentially address this issue.

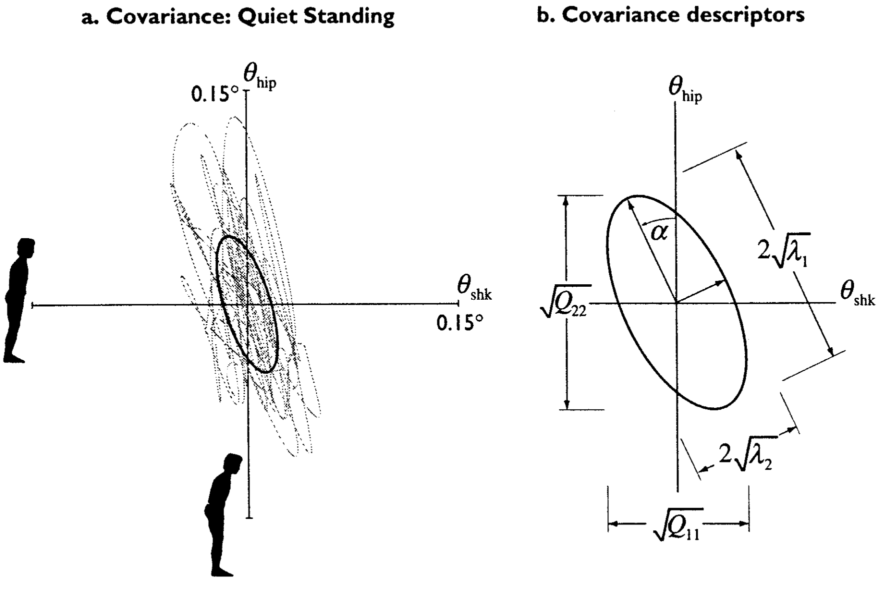
Whether altered sensory conditions do result in altered sway coordination depends on how the central nervous system (CNS) makes use of information from multiple sensors. One simple model places responsibility for control of individual joints at the level of spinal reflexes, leaving a supervisory role to descending vestibulospinal commands. Short-latency local feedback would therefore operate at one level in a hierarchy, stabilizing the joints without regard to the body's overall orientation. At the higher level, visual, vestibular, and possibly somatosensory information would be integrated in the brain to sense overall orientation or COM position (Mergner et al. 1997). The postural control pathway would then deliver descending commands, equivalent to set points, to the lower level without regard to how individual joints are controlled (see Fig. 1a). From the point-to-view of the brain, the body would behave much like a single-link inverted pendulum.

There is, however, evidence to support an alternate model, which gives the brain more responsibility for joint-level motion. First, major responses occur with a latency of at least 90 ms, indicative of a long-loop triggered response reaching at least to the level of the brain stem (Nashner et al. 1979). Second, these postural adjustments, while stereotyped, display context-dependent variations in joint coordination (such as when the support surface is narrow), suggesting that the selection of the appropriate "ankle or hip strategy" (Horak and Nasher 1986) is made within the loop prior to triggering this response. And finally, inertial coupling could cause supervisory commands to the ankles or hips to affect motion about other joints, potentially causing instabilities (Kuo and Zajac 1993). Higher level commands therefore perform best when they coordinate multiple joint motions. In this alternate scenario, the brain treats the body as a multi-link inverted pendulum and forms multiple descending commands contributing to the control of individual joints. Visual, vestibular, and somatosensory information would necessarily be integrated (Dichgans and Diener 1989), possibly forming an overall sense of body orientation, but nonetheless resulting in multiple, heteronymous feedback paths that could compensate for inertial coupling.

These two models are tested by examining postural behavior under altered sensory conditions. In the supervisory model (Fig. 1a), disruption of visual or somtosensory input would be expected to upset the pendulum as a whole, primarily about the ankles. Inertial coupling of body segments could also cause the increased ankle sway to affect other joints, but only in a systematic way. A univariate measure of body sway should be sufficient to characterize such changes. The multi-joint descending command model (Fig. 1b), however, would predict that altered sensory conditions should induce not only changes in amount of sway, but *type* of sway as well. This prediction results from the heteronymous, multi-joint nature of the descending commands, which could afford different contributions of each sensory input to movement at each joint (Allum et al., 1995). If, for example, the ankles and hips were controlled through feedback of visual and vestibular inputs in different proportions, then disruption of vision might primarily affect ankle motion and disruption of vestibular input might primarily affect hip motion. Somatosensory and vestibular loss have been shown to induce different changes in postural control strategies (Horak et al. 1990; Peterka and Benolken 1995). No univariate sway measure would be sufficient to capture these multivariate differences.

We propose that the multivariate model of postural control, in which information from multiple sensors is integrated in multiple feedback paths, is a better description of the posture control system. We hypothesize that the SOT induces changes in sway coordination that can be characterized using multivariate measures. This hypothesis is tested by examining both univariate and multivariate measures for statistically significant differences between sensory conditions and employing discriminant analysis to identify multivariate variability in sway. A graphical method is used to test for more complex nonlinear changes, which cannot be captured using discriminant analysis. This approach suggests that postural commands are multivariate in nature and that availability of sensory information systematically affects coordination of the trunk and legs for orientation and equilibrium control in stance.

Fig. 2a, b Covariance measures for kinetics of human posture. **a** Covariance during quiet standing describes motion of shank and hip angles, as shown by posture icons. Shank angle θ_{shk} is defined as orientation of the shanks measured counterclockwise from the horizontal, and hip angle θ_{hip} is defined as orientation of the trunk measured counterclockwise relative to the legs. Zero for both angles is defined as the mean upright position of the subject over each trial. Knee motion is assumed small. *Gray line* traces shank and hip angles during sample trial, with origin corresponding to upright stance. *Ellipse* shows 1-σ contour of constant standard error, described by components of covariance matrix. **b** Illustration of definitions of covariance descriptors, using matrix entries ($\sqrt{Q_{11}}$and $\sqrt{Q_{22}}$; Q_{12} not shown) and eigenvector parameters ($\sqrt{\lambda_1}$ is the half-length of one axis of the ellipse, $\sqrt{\lambda_2}$ is the half-length of the other axis, α is the angle of the ellipse measured counterclockwise with respect to the ordinate axis)



Method

The first step in testing the multivariate posture control hypothesis was to define an appropriate sway measure to be used in statistical tests. The covariance of body kinematics was proposed as a general measure of multi-joint sway that is compatible with the SOT and is also a superset of univariate COM or ankle sway. A coordinate system for describing this covariance was then devised. Both statistical and graphical methods were then used to test the null hypothesis. Univariate and multivariate analysis of variance, paired contrasts, discriminant analysis, and paired T^2-tests were employed to determine whether the multivariate measures detected altered sway patterns, which the univariate measure cannot. Finally, graphical visualization of the mean descriptor values was used to test whether these multivariate measures were fundamentally dependent on some underlying univariate variable.

Covariance of two body angles, shank angle (θ_{shk}) and hip angle (θ_{hip}) was used as a basis for the multivariate measures of postural coordination and sway (see Fig. 2a). The covariance is defined as the 4×4 matrix.

$$Q = \mathrm{cov}(x) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})^T \qquad (1)$$

where x_i is ith sample out of n of a vector containing the joint angles, $x = [\theta_{shk}\ \theta_{hip}]^T$. The result is a positive definite matrix (described graphically by the 1-σ contour ellipse in Fig. 2a), with diagonal entries equal to the individual joint variances and off-diagonal terms related to interjoint coupling.

The covariance matrix may be described by three graphical measures. The 1-σ contour ellipse has major and minor semi-axis lengths given by the square root of the eigenvalues λ of Q, and the orientation of the ellipse is defined by the eigenvectors $[V_{11}\ V_{12}]^T$ and $[V_{21}\ V_{22}]^T$ of Q (Strang 1988). The major axis orientation is given by the eigenvector $[V_{11}\ V_{12}]^T$ associated with the largest eigenvalue, and is used to calculate the orientation angle α. Another sway measure, the variance of COM motion, can be extracted from

Table 1 Summary of covariance descriptors

Descriptor	Definition	Interpretation
σ^2_{shk}	Q_{11}	Variance of shank motion
σ^2_{hip}	Q_{22}	Variance of hip motion
Q_{12}	Q_{12}	Covariance of shank-hip motion
λ_1	Largest eigenvalue of Q	Square of length of ellipse's major semi-axis
λ_2	Smallest eigenvalue of Q	Square of length of ellipse's minor semi-axis
α	$\tan^{-1}(V_{11}/V_{12})$	Angle of major axis counterclockwise from vertical
σ^2_{COM}	c^TQc	Variance of center of mass motion

Table 2 Summary of sensory organization test sensory conditions

Condition	Visual input	Surface somatosensory input
1	Eyes open, earth-referenced	Earth-referenced
2	Eyes closed	Earth-referenced
3	Eyes open, sway-referenced	Earth-referenced
4	Eyes open, earth-referenced	Sway-referenced
5	Eyes closed	Sway-referenced
6	Eyes open, sway-referenced	Sway-referenced

the covariance as well. Defining a vector $c=[0.98\ -0.23]^T$ based on anthropometric parameters for an average adult (Kuo 1998), the quantity c^Tx is a linearized representation of COM position, and c^TQc is its variance. Table 1 summarizes the most useful descriptors, which are also shown graphically in Fig. 2b.

These eigenvalue-based descriptors may be given a physical interpretation related to postural coordination. Body dynamics have been shown to greatly constrain possible joint accelerations, greatly favoring motion of the ankles and hips in the approximate ratio of −1:3, which may also be taken as a kinematic definition of the hip strategy (Kuo and Zajac 1993). As a result, the covariance ellipse for ankle and hip angles has a major axis which is in approximately the same direction for all sensory conditions. The associated eigenvalue, λ_1, may therefore be loosely interpreted as a measure of the amount of hip strategy used. The second eigenvector is perpendicular to the first and is aligned in the approximate ankle-hip ratio of 3:1. Associated with such motion is considerable movement of COM, which is maximized at a ratio of approximately 4:1 (as seen in the components of c). Loosely speaking, λ_2 may therefore be associated with COM motion. Both of these interpretations are inexact but are useful for summarizing major changes in coordination.

The SOT involves application of six sensory conditions while subjects attempt to stand quietly. The sensory conditions are combinations of three visual conditions and two surface somatosensory conditions. Visual conditions are manipulated using a movable visual surround, which may either be fixed or serve-controlled to match the subject's anterior-posterior COM motion. This sway-referencing of the visual surround has the effect of degrading the accuracy of visual input. The specific visual conditions include eyes open with the visual surround fixed (referred to simply as "eyes open"), eyes closed, and eyes open with visual surround sway-referenced (referred to as "visual sway-referencing"). Somatosensory conditions involve manipulation of sensory input about the ankles using a movable platform that can rotate about an axis aligned with ankle motion in the sagittal plane. This platform may be held fixed to earth or it may be servo-controlled to match the subject's ankle position, which has the effect of altering the relationship between COM position and somatosensory information at the feet and ankles. In earth-referenced somatosensory conditions, θ_{shk} is equivalent to the ankle angle, but under platform sway-referencing the two are not equal. The combinations of visual and somatosensory conditions are summarized in Table 2 and by the icons in Fig. 5.

Fourteen healthy subjects aged 22–35 years performed the SOT. Subjects gave informed consent to be tested under a protocol approved by the R. S. Dow Neurological Sciences Institute. Subjects stood with arms folded across the chest, for 21 s per trial, with one trial each for conditions 1 and 2, and three successive trials for the other conditions. Augmenting the standard SOT, kinematics of hip and shoulder motion were measured in the sagittal plane using sway bars sensed with potentiometers. These measurements were then used to compute approximate shank and hip angles, θ_{shk} and θ_{hip} (assuming relatively little knee motion) and to compute the associated COM position. The shank angle was used to drive the visual surround and platform sway-referencing, which are normally based on force plate measurements in the conventional SOT (NeuroCom International, Clackamas, Ore.). The convention for both angles was defined to that positive measurements denote extension of the ankle and hip joints from zero, which in turn was defined as the mean displacement from each trial. Additional details of the apparatus, procedure, and measurement methods are given by Peterka and Black (1990). Data were sampled at 50 Hz and filtered with a digital, 3rd-order bandpass Butterworth filter, with a high frequency cutoff of 3.5 Hz and a low frequency cutoff of 0.5 Hz. The high cutoff was employed to filter out noise and the low cutoff was used to ensure that covariances were calculated on at least 10 cycles of the lowest frequency component contained in the data.

The recorded measurements of θ_{shk} and θ_{hip} were used to compute covariance matrices Q, as in Eq. 1. For conditions where multiple trials were performed, Q was averaged across trials for each subject. Six of the total of 104 trials recorded overall were discarded because a subject fell or otherwise did not complete a trial, or because the data were corrupted.

A statistical analysis was used to test the multivariate sway hypothesis. The tests included univariate analysis of variance (ANOVA) based on COM and multivariate analysis of variance (MANOVA) with discriminant analysis based on shank and hip angles, all calculated in stages. For both ANOVA and MANOVA, the following tests were performed. First, one-way analysis of variance was used to test for the existence of significant differences in univariate (multivariate in the case of MANOVA) sway descriptions, for any sensory conditions. Then, two-way analyses, in which the visual and somatosensory alterations were treated as factors, were used to test for overall sway differences due to these effects. Paired group contrasts were then used to differentiate between the overall effects of the three levels of the vision factor. Finally, paired individual tests were used to identify specific differences for every possible pair of conditions. Discriminant functions were also calculated to determine the nature of the significant changes and to test for a multivariate basis for these changes. Tests were only administered at each successive level if the previous level showed significant differences, in order to preserve a strong overall experimental P-value (probability of false rejection).

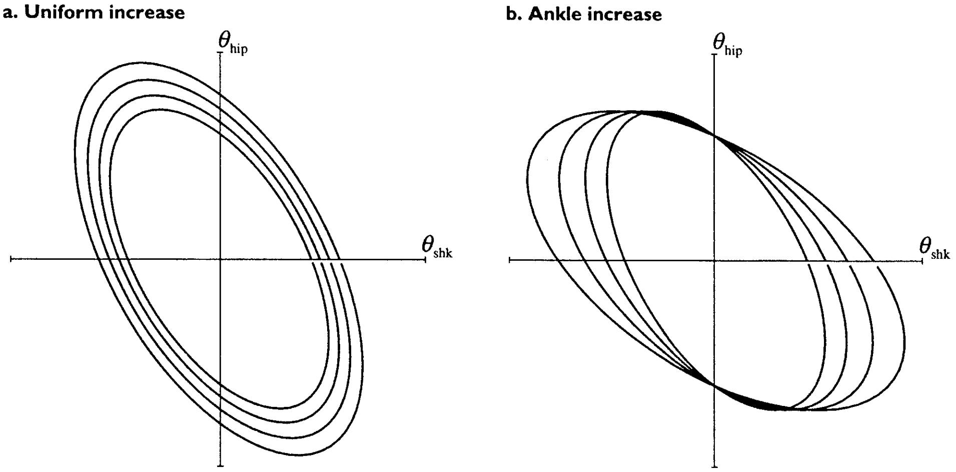
The eigenvector parameters $\sqrt{\lambda_1}, \sqrt{\lambda_2}$, and α were chosen as the coordinates for the multivariate measures (see Fig. 2b). Square roots of eigenvalues were taken to put these values in units of normalized joint position and to make their distributions closer to normal. All three descriptors were also normalized relative to the condition 1 results in order to highlight the within-subject differences between conditions. It was expected that if sensory conditions cause sway to change in a multivariate manner, then the multivariate descriptors would be more useful than COM variance for identifying these changes.

In the first level of tests, one-way univariate ANOVA was applied to the COM descriptor and one-way MANOVA was applied to the eigenvector parameters. Wilks's lambda test was used to calculate P-values for MANOVA. In both tests, the null hypothesis was that there were no significant differences in means across all six SOT conditions. Any further tests were predicated on the existence of significant differences with $P<0.05$. Discriminant analysis was performed to determine which combinations of measures were responsible for any detected differences. The analysis was conducted by computing the eigenvectors and eigenvalues of $\mathbf{W}^{-1}\mathbf{B}$, where **W** is the within-subjects mean-square variability and **B** is the between-subjects variability for the multivariate descriptors. The eigenvalues Λ_i describe the degree to which a particular discriminant i contributes to the overall differences between groups and were expressed as proportions through the equation

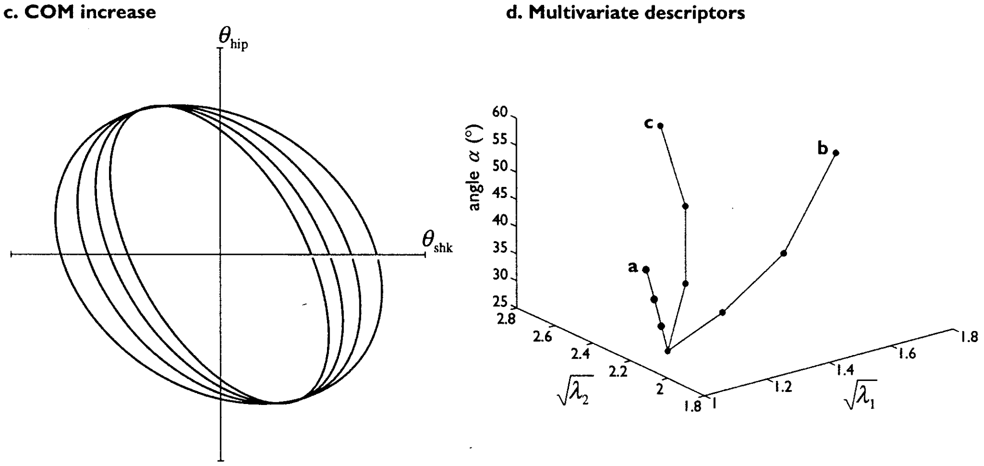
$$\text{proportion}\, i = |\Lambda_i| / \sum_j |\Lambda_j| \qquad (2)$$

where the sum is taken over all eigenvalues. The eigenvectors serve as discriminant vectors, which may be interpreted as the axes of a coordinate system is measurement space that best reveals group separation, or alternatively as planes of projection for ignoring dimensions in which the groups are not different. If the proportion for any one discriminant function is nearly 1, most of the changes in sway can be summarized using a single parameter – a univariate measure. It was expected that, given two possible changes in visual conditions and one possible change in proprioceptive conditions from normal, up to three discriminant functions should be necessary to describe the changes, although the one-way discriminants need not correspond to these treatments.

The second level of tests was conducted to determine how visual and somatosensory conditions affect sway. The three visual conditions (eyes open, eyes closed, and visual sway-referencing) were used as three levels of a vision factor, and the two somatosensory conditions (platform earth-fixed and platform sway-referenced) were used as two levels of a somatosensory factor, in two-way analyses of variance. Two-way ANOVA was applied to the COM descriptor, and two-way MANOVA was applied to the eigenvector parameters. Again, Wilks's lambda test was used for MANOVA, but the null hypothesis for both tests was that there were no significant differences in mean descriptor values across all factors. The first test was for significant interaction between the factors. Further tests on the factor effects, to determine how each factor affected sway, were predicated on the inability to reject the null hypothesis of an interaction ($P>0.05$). These tests identified visual and somatosensory factor discriminants and their associated proportions. There is, however, no guarantee that the two-way vision discriminants properly highlight the differences between the three levels of the visual factor. Therefore, another set of discriminations was computed, along with paired group contrasts, to reveal the specific differences due to these levels. The groups compared were eyes open (a group of conditions 1 and 4) compared with eyes closed (conditions 2 and 5), eyes open compared with visual sway-referencing (conditions 3 and 6), and eyes closed compared with visual sway-referencing. In addition, the MANOVA comparing somatosensory conditions could be interpreted as a group comparison of conditions 1–3 compared with 4–6. It was expected that both visual and somatosensory factors would have significant and unique effects, each requiring at least one discriminant function. Within the vision factor, one or two discriminants were expected to be significant, to differentiate between three levels. Only one discriminant function is possible and necessary for somatosensory conditions, because there are only two levels of that factor. Under the multivariate hypothesis, the proprioceptive discriminant should be different from the vision discriminant(s).


a. Uniform increase

b. Ankle increase


c. COM increase

d. Multivariate descriptors

Fig. 3a–d Possible univariate changes in sway due to altered sensory conditions. **a** In univariate model, changes to sway could be in the form of uniform increases in covariance; **b** increases in sway about the ankles only, keeping hip variance constant; or **c** increases in sway about the center of mass (*COM*) only, keeping other factors unchanged. Other types of variations are possible, but any such univariate changes **d** should fall on a (possibly curved) line when plotted in the multivariate coordinate system of covariance descriptors (see Fig. 2)

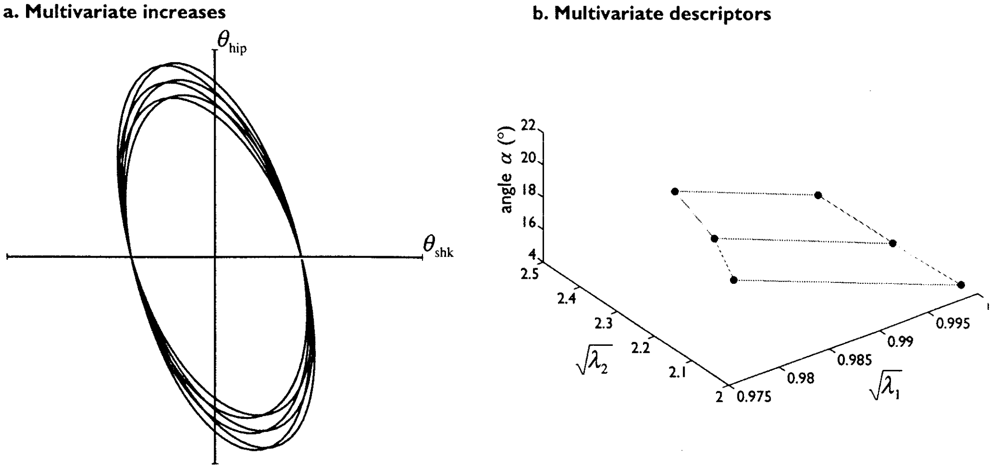


Fig. 4a, b Example of multivariate changes in sway due to altered sensory conditions. **a** Sway may change in character, rather than only in extent. Covariance ellipse shows a possible bivariate variability, in which two parameters of covariance can increase independently. **b** When plotted in multivariate coordinates, such changes full on a two-dimensional surface, rather than on a line. Trivariate changes would be described only by the full three-dimensional coordinate system

The last level of statistical tests involved paired individual comparisons between pair of sensory conditions. Hotelling's T^2 was applied to the multivariate descriptions. Between six sensory conditions, there are 15 unique pairs. Each of these pairs was tested for significant differences. These tests were used to identify where the largest and smallest differences occur.

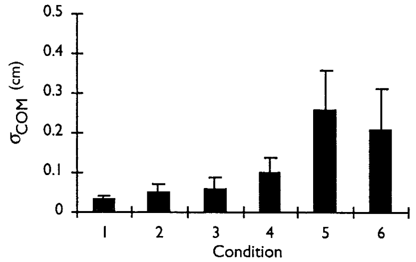
Finally, the eigenvector descriptors were plotted graphically in order to test for more complex, possibly nonlinear, multivariate changes which linear discriminant analysis might not capture. For example, even if univariate changes in sway are nonlinear, the multivariate descriptors should fall on a (possibly curved) line when plotted, as in Fig. 3d. Mean multivariate descriptors were plotted in the three-dimensional eigenvector parameter coordinate system of $\sqrt{\lambda_1}$,$\sqrt{\lambda_2}$,, and α, and assessed qualitatively for a univariate relationship (Fig. 4). These descriptors were also plotted in the coordinate system of the first two discriminant functions from the two-factor MANOVA, in order to provide a simpler view of the changes and to show the variability in the measurements.

Results

Altered sensory conditions resulted in changes in postural coordination during quiet standing. Increases in sway were demonstrated by increased root-mean-square of COM position (with bias removed), averaged across subjects, for each condition (Fig. 5a). These increases were most pronounced for the sway-referenced conditions (4, 5, and 6) compared with their respective earth-referenced conditions and less pronounced for inaccurate visual conditions compared with their respective eyes-open conditions. However, multivariate covariance ellipse plots also showed that, aside from increases in COM sway, there were other changes in postural coordination of the ankles and hips (Fig. 5b). These changes include increased shank angle variance (wider ellipses horizontally) in eyes-closed compared with eyes-open conditions, and increased use of the hip strategy (longer ellipses) in platform sway-referenced compared with earth-referenced conditions.

One-way ANOVA and MANOVA tests confirmed that changes in sway coordination were statistically significant, and the discriminant analysis showed that approximately 90% of the differences across all six conditions could be captured by measuring the amount of hip strategy. The P-values were 6.0e–7 and 4.7e–8 for ANOVA and MANOVA, respectively, indicating that the differences were highly significant. The discriminants had proportions 89.8%, 6.5%, and 3.7% (see Table 3), with the first vector being almost entirely aligned with $\sqrt{\lambda_1}$(the hip strategy).

a. Mean COM standard deviations



b. Mean 1-σ ellipses

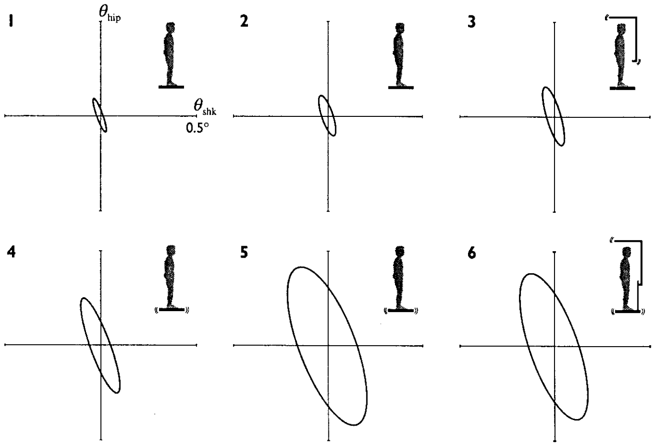


Fig. 5a, b Mean descriptor values from Sensory Organization Test (SOT). **a** Mean COM sway across subjects for each condition. *Error bars* denote 1 SD. Sway for each subject is reported as standard deviation of anterior-posterior COM motion. **b** Mean covariance ellipses across subjects for six SOT conditions: *1*, eyes open, platform fixed; *2*, eyes closed, platform fixed; *3*, vision sway-referenced; *4*, eyes open, platform sway-referenced; *5*, eyes closed, platform sway-referenced; *6*, both vision and platform sway-referenced

Table 3 Results from one-way MANOVA discriminant analysis. Discriminant vector components are reported in standardized form, relative to each component's SD, and scaled to unit length

Discriminant	Proportions (%)	Vector components		
		$\sqrt{\lambda_1}$	$\sqrt{\lambda_2}$	α
1	89.8	0.984	0.151	–0.094
2	6.5	–0.453	0.664	–0.595
3	3.7	–0.530	0.686	0.798

Table 4 Statistical results from two-way ANOVA and MANOVA

	P-values
Two-way univariate ANOVA	
Interaction	1.23e-02*
Vision	6.13e-03*
Platform	2.27e-06*
Two-way MANOVA	
Interaction	4.90e-01
Vision	1.74e-02*
Platform	3.16e-10*

* $P<0.05$, statistically significant

Table 5 Discriminant analysis results

Discriminants	Proportions (%)	Vector components		
		$\sqrt{\lambda_1}$	$\sqrt{\lambda_2}$	α
Vision 1	89.2	0.625	0.517	–0.584
Vision 2	10.8	–0.509	0.717	–0.476
Platform	100	0.0994	0.028	–0.020

Other changes in postural coordination, captured by linear combinations of $\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$, and α in the proportions given by the discriminant vectors, were also significant but accounted for only about 10% of the detectable changes. Thus, the single most obvious change in posture due to altered sensory conditions was increased use of hip strategy.

Two-way results showed that altered surface somatosensory conditions were responsible for the increase in hip strategy, while altered visual conditions induced subtler, more complex changes in coordination. While the univariate test showed significant interaction between the somatosensory and visual factors (P=0.012; see Tables 4, 5), multivariate tests failed to detect interaction (P=0.49). However, both tests revealed significant factor-specific changes in postural coordination due to somatosensory and visual conditions, with the most significant differences attributed to platform sway-referencing (P=2.3e–6 and 3.2e–10 for univariate and multivariate analyses, respectively).

From the multivariate analysis, three discriminant vectors were found. Two vectors, vision 1 and vision 2, show the differences due to altered visual conditions, while a single vector shows the differences due to platform sway-referencing. The platform discriminant is almost entirely aligned with $\sqrt{\lambda_1}$ (hip strategy), with a component value of 0.994, demonstrating that altered somatosensory conditions were responsible for the overall increased hip strategy detected in the one-way results. The first visual discriminant (vision 1) accounted for approximately 90% of the changes associated with altered visual conditions (though the analysis does not attribute these changes to a specific level). Both visual discriminant vectors showed changes in all three measurement variables, in roughly equal proportions, in contrast to the changes seen due to platform sway-referencing. Thus, multivariate measures are required to separate changes in postural coordination due to altered visual or somatosensory input.

Table 6 Paired group contrast results

Pairwise contrasts	*P*-values	Vector components		
		$\sqrt{\lambda_1}$	$\sqrt{\lambda_2}$	α
Eyes open vs eyes closed	3.15e-02*	–0.351	–0.878	0.327
Eyes open vs visual sway-ref.	6.55e-03*	–0.689	–0.332	0.644
Eyes closed vs visual sway-ref.	5.37e-01	–	–	–
Platform	1.12e-04*	0.994	0.028	–0.020

* Statistically significant, $P<0.05$

Paired group contrasts showed that, whereas altered visual conditions induced significant changes relative to eyes open conditions, the eyes closed and visual sway-referencing results were not significantly different from each other (see Table 6). Comparing eyes open (conditions 1 and 4) with eyes closed (conditions 2 and 5) results and eyes open with visual sway-referencing (conditions 3 and 6) results yielded P-values of 0.031 and 0.0065, respectively. Both of the associated discriminants had components associated with each of the measurement variables, but the eyes open or closed difference was mostly accounted for by increased COM motion, $\sqrt{\lambda_2}$, with component value 0.88, and the eyes open or visual sway-referencing difference was mostly accounted for by the other measures, $\sqrt{\lambda_1}$, and α, with component values –0.69 and 0.64, respectively. Despite having different discriminants, however, the eyes closed and visual sway-referencing results were not significantly separated from each other (P=0.54). Altered visual conditions as a whole may therefore be considered to have substantially different effects on coordination than somatosensory conditions, but the difference between eyes closed and visual sway-referencing is subtle.

Individual pariwise comparisons (see Table 7) confirm that platform sway-referencing had a greater effect on coordination than the altered visual conditions, which tended not to be significantly different when compared individually. For example, in the absence of platform sway-referencing, none of the visual conditions (condition 1 vs 2, 1 vs 3, and 2 vs 3) had significantly different results. With platform sway-referencing, the visual conditions (4 vs 5, 4 vs 6, and 5 vs 6) had lower P-values, though not all were significant. Visual conditions had significantly

Table 7 Results from multivariate paired T^2-tests

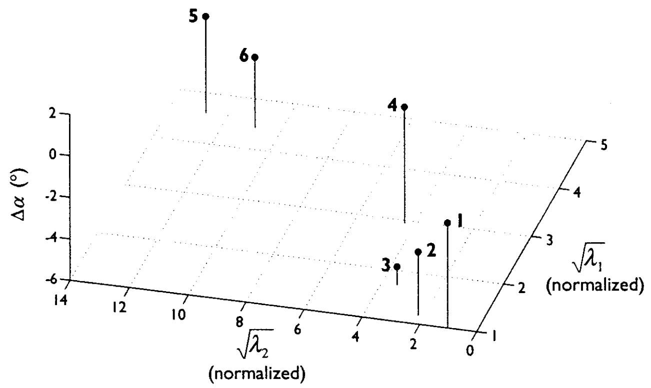
	Condition					
	1	2	3	4	5	6
1	–	0.272	0.060	0.004*	0.037*	0.024*
2	0.272	–	0.321	0.002*	0.048*	0.062
3	0.060	0.321	–	0.005*	0.030*	0.042*
4	0.004*	0.002*	0.005*	–	0.098	0.042*
5	0.037*	0.048*	0.030*	0.098	–	0.761
6	0.024*	0.062	0.042*	0.042*	0.761	–

* Statistically significant, $P<0.05$

different effects only when both somatosensory conditions were lumped, as in the group contrasts above. Each of the somatosensory pairs (1 vs 4, 2 vs 5, and 3 vs 6), however, were significantly different, despite the fact that visual conditions were not lumped. These results suggest that there is some interaction between platform and visual conditions, as might be expected when multiple sensory are severely compromised. Although the univariate test detected interaction between these factors using COM sway alone, this interaction was not confirmed when examining multivarite measures simultaneously. It appears that high variability in measurements for conditions 5 and 6 may explain lack of detectable interaction. It is possible that more subjects or different measures could detect interaction more explicitly.

The graphical analysis demonstrates the multivariate nature of changes in postural coordination. As seen in Fig. 6a, the mean measurement values do not appear to lie on a (possible curved) line, as would be required by the univariate hypothesis. Rather they appear to lie on surface of a least two dimensions, indicating that coordination changes are at least bivariate in character. A two-dimensional view of these values, which highlights differences between levels of the visual and somatosensory factors, is given by projecting the multivariate descriptors into the plane defined by the two-way discriminant vectors. Figure 6b shows such discriminated mean values, along with their variations, which were also projected and are shown in the form of 1-s ellipses. The horizontal axis, corresponding to the visual discriminant, maximizes separation due to visual conditions, and the vertical axis maximizes separation due to platform conditions. This figure shows that platform sway-referencing (conditions 5–6 vs 1–3) results in changes in both $\sqrt{\lambda_1}$ and $\sqrt{\lambda_2}$, though the discriminant vector indicates that this difference is significnt primarily for $\sqrt{\lambda_1}$ (hip strategy), most likely due to excessive variabilitiy in $\sqrt{\lambda_2}$ (COM motion). The changes in α for any conditions do not appear to be large, confirming the fact that the discriminants are biased toward the first two descriptors.

a. Mean multivariate descriptors



b. Projected means & 1-σ ellipses

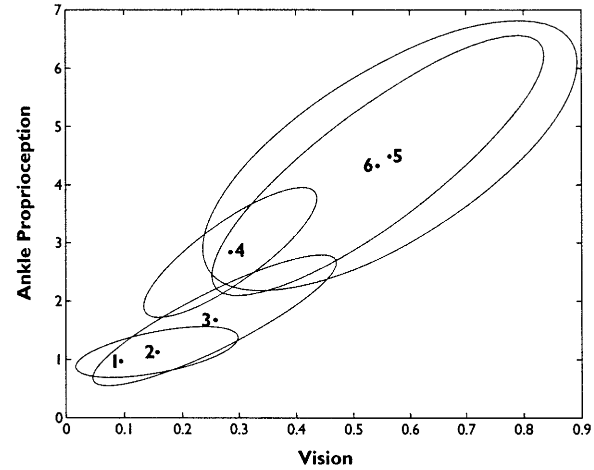


Fig. 6a, b Mean values from Sensory Organization Test, plotted in multivariate descriptor coordinate systems. **a** Mean values plotted using eigenvector parameters as coordinates. *Dotted lines* connect related sensory conditions, while *vertical lines* are references from the planar coordinate grid. **b** Mean values projected onto two-dimensional coordinate system defined by two-way discriminant vectors, along with 1-σ uncertainties. Vision axis emphasis differences due to eyes open or closed, while ankle proprioception axis emphasizes differences due to platform fixed or sway-referenced. MANOVA does not detect significant interaction between visual and proprioceptive factors

Discussion

The univariate and multivariate models of sensorimotor integration predict different types of sway under altered sensory conditions, which may be compared with the statistical results. Under the univarite model (Fig. 1a), altered sensory conditions should result in systematic changes in covariance. In the simplest case, sway would increase uniformly for both shank and hip angles, resulting in changes in size of the covariance ellipse (see Fig. 3a). Some other possibilities are that sway would increase about the ankle joint only, with hip variance remaining constant (Fig. 3b), or COM motion along might increase, with other aspects of the covariance ellipse remaining constant (Fig. 3c). Regardless of the form of the changes, however, a univariate measure such as COM variance would be sufficient to characterize them, as long as the nature of the changes is known. And even in more complex, possibly nonlinear, cases, the multivariate descriptors plotted for each sensory condition would tend to fall on a (possibly curved) line in the descriptor coordinate system (Fig. 3d). In contrast, the multivariate model (Fig. 1b) predicts changes to the covariance ellipse that a univariate measure such as COM variance might not detect (Fig. 4a). Moreover, the multivariate descriptors plotted for each sensory condition would not fall on a line in the descriptor coordinate system, because multivariate sway changes would by definition require two or more parameters to describe them. For the example of Fig. 4a, the descriptors would actually fall on a planar surface (Fig. 4b).

Our results show multivariate differences in sway under the varied sensory conditions of the SOT, suggesting that somatosensory and visual input play distinct roles in stabilizing body segments during quiet standing. As shown in Fig. 5a, a univariate measure shows that platform sway-referencing induces increased COM sway. But the multivariate measures show that disrupted somatosensory input also causes a highly significant increase in hip strategy, $\sqrt{\lambda_1}$ (see Table 5). Disruption of vision, through either closing the eyes or visual sway-referencing, also induces increased sway. However, unlike for platform sway-referencing, the multivariate measures show that this increase is more complex, combining a larger proportional of COM motion ($\sqrt{\lambda_2}$) in addition to hip strategy. This difference in effects due to vision and platform conditions (displayed graphically in Fig. 6) cannot be captured using any univariate measure. It also suggests that descending motor commands are of a multivariate nature, so that disruption of any single signal has an effect distinct from that caused by disruption of another.

The increase in hip strategy with platform sway-referencing is noteworthy because it indicates that disruption of foot somatosensory input actually induces more sway about the hips than about the ankles. This is contrary to the obvious expectation of increased sway localized to the shank angle alone. The observed increase in hip sway could result from the CNS misinterpreting the array of sensory signals as corresponding to hip or trunk motion, for which the feedback response would be to drive motion about the hips. Such a response could therefore be due to incorrect perception of hip motion, rather than incorrect control behavior.

We propose a model for sensory conflict resolution which could explain increased perception of hip motion under platform sway-referencing. Under this condition, visual and vestibular inputs are consistent with each other, but not with ankle or hip inputs. Given no objective means of resolving the inaccurate input, it would be different to identify and suppress the source of sensory conflict. For example, perceptual illusions such as circular-vection demonstrate an inability to suppress confusing signals (Robinson 1981). In posture, a rational perception of movement during platform sway-referencing would be one which is maximally consistent (and hence minimally inconsistent) with all of the sensory data. Because body dynamics greatly favor the hip strategy, it would be most reasonable to attribute the confusing set of inputs primarily to poorly sensed hip motion, possibly induced by an external disturbance. In order for the CNS to function in this manner, it would have to incorporate knowledge of the relative precision of various sensors, as well as expectations of body motion and associated afferent input. An internal model of body and sensory dynamics, consistent with those proposed by others (see Borah et al. 1988; Merfeld et al. 1993; Mergner et al. 1997) could provide these functions.

Regardless of the means of resolving conflicting sensory input, the response must ultimately be driven by one or more of the sensors that are not disrupted. Because the increase in hip strategy occurs with and without vision (i.e., in conditions 4, 5, and 6), it appears that vestibular input is heavily weighted in driving hip motion. This hypothesis is supported both by anatomical evidence of vestibulospinal projections to the trunk and by experiments using active disturbances to posture. Horak et al. (1990) reported that normals and normals subjected to artificial somatosensory loss (induced by hypoxic anesthesia) were able to perform the hip strategy in response to active translation of the support surface. However, vestibular loss patients did not perform the hip strategy while standing on a narrow support surface, suggesting that vestibular inputs are indeed important for controlling hip motion and consequently trunk motion as well. Galvanic vestibular stimulation has also been shown to induce sway with significant components of trunk motion (Inglis et al. 1995).

If sensory signals do not converge for the purpose of producing univariate signals such as a control signal for COM motion, it is reasonable to question whether convergence confers significant advantages over a distributed control architecture, in which sensory signals are delivered to the muslces in appropriate proportions without passing through a common pathway. We have identified two possible purposes for multivariate convergence. First, a CNS internal model requires dynamical processing of sensory signals such that the signals must mix yet still produce multivariate signals. If the internal model is used to predict an expected sensory afference that is compared with actual afference, the mixing occurs when the resulting error signal is used to adjust the state of the internal model. The brain stem performs dynamical processing that combines visual and vestibular signals for control of eye movement (Robinson 1981); similar processing could contribute to posture control. A second justification for multivariate convergence is that motor learning is facilitated by the ability to correlate motor actions with positive and negative features of their outcomes. For adjustments to be made to the appropriate gains (i.e., credit assignment), it is necessary that sufficient multivariate sensory information be available. The cerebellum appears to play a role in these adjustments, and sensory convergence provides inputs to the mossy fiber and climbing fiber systems within the cerebellum (Ghez 1991).

We conclude that multivariate measures may serve as useful supplements to traditional univariate measures of postural sway. Although sophisticated tests such as the SOT can be used to detect severe vestibular loss using only univariate measures (Mirka and Black 1990), other disabilities may induce more subtle changes in postural coordination that are detectable only using multivariate descriptors. The finding that somatosensory and visual sensors have different contributions to sway may also provide clues regarding CNS integration of signals and possibly provide a means for using multivariate measures in a diagnostic manner. While much of the variability in sway is univariate in nature, the multivariate changes were highly significant even with a modest sample size. While they suffer from the drawback of requiring kinematic measurements, the multivariate descriptors are also useful for differentiating between COM and COP motion as well as for separating movement of the body from the resulting feedback response. Further work is underway to use multivariate tests to study CNS sensorimotor integration and postural coordination in patients suffering from balance dysfunction.

Appendix

Two statistical matters must be addressed: the distributions of the results for each condition and the statistical significance of the entire battery of tests. Because each subject's measurements were normalized to condition 1, the descriptors for condition 1 had zero variance, differing from the other conditions. Both ANOVA and MANOVA are technically not applicable to data with unequal distributions. However, they are generally fairly robust to unequal variances (Johnson and Wichern 1992). Nonetheless, the paired tests, which are unaffected by normalization and are highly robust to uneven distributions (Rencher 1995), serve as a check. Because all results are supported by both MANOVA and paired tests, the former results could conservatively be discarded without disrupting the overall conclusions. Finally, it is also important to consider the statistical significance of the entire battery of tests, which as a whole is lower than the significance for any individual test. Statistical significance of the entire experiment is difficult to assess, because successive tests were only performed predicated on significance in the previous level (Rencher and Scott 1990). This design has the effect of preventing the overall *P*-value from degrading drastically from the significance threshold ($P<0.05$) from the first MANOVA (Rencher 1995). In fact, ignoring this preservation still results in a worse-case *P*-value of

$$P_{\exp} = 1 - \prod_{i=1}^{m} (1 - P_i) = 0.055$$

where the product is taken over those *P*-values on which hpyotheses were rejected.

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