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J. J. Collins · C. J. De Luca

The effects of visual input on open-loop and closed-loop postural control mechanisms

Abstract In an earlier posturographic investigation (Collins and De Luca 1993) it was proposed that open-loop and closed-loop control mechanisms are involved in the regulation of undisturbed, upright stance. In this study, stabilogram-diffusion analysis was used to examine how visual input affects the operational characteristics of these control mechanisms. Stabilogram-diffusion analysis leads to the extraction of repeatable center-of-pressure (COP) parameters that can be directly related to the resultant steady-state behavior and functional interaction of the neuromuscular mechanisms underlying the maintenance of erect posture. Twenty-five healthy male subjects (aged 19–30 years) were included in the study. An instrumented force platform was used to measure the time-varying displacements of the COP under each subject's feet during quiet standing. The subjects were tested under eyes-open and eyes-closed conditions. The COP trajectories were analyzed as one-dimensional and two-dimensional random walks, according to stabilogram-diffusion analysis. Using this technique, it was found that visual input affects the performance of the postural control system in one of two different ways – either it significantly modifies the steady-state behavior of the open-loop postural control mechanisms, or it significantly alters the characteristics of the other closed-loop feedback mechanisms that are involved in balance control. This result is interpreted as an indication that the visual system is integrated into the postural control system in one of two different ways. The experimental population was roughly evenly divided between these two schemes. For the first group (13 of 25 subjects), visual input principally caused a decrease in the "effective" stochastic activity of the open-loop control mechanisms in both the mediolateral and anteroposterior directions. For the second group (12 of 25 subjects), visual input caused an increase in the effective stochastic activity and uncorrelated behavior of the closed-loop control mechanisms in the anteroposterior direction only. On the basis of these results, it is hypothesized that visual input, in both schemes, serves to decrease the stiffness of the musculoskeletal system. In the former case, this may be accomplished by decreasing the level of muscular activity across the joints of the lower limb, whereas, in the latter case, reduced stiffness may be achieved by reducing the gain(s) of the other postural feedback mechanisms, i.e., the proprioceptive and/or vestibular systems. Using stabilogram-diffusion analysis, it was also found that the two groups of subjects behaved similarly under eyes-closed conditions. This result suggests that the open-loop postural control mechanisms and reflex-based feedback systems, respectively, of healthy, young individuals are organized in functionally equivalent ways.

Key words Postural control · Vision Closed-loop control · Open-loop control Center of pressure · Stabilograms · Human

Introduction

Human postural control involves several different sensory modalities, i.e., the visual, vestibular, and somatosensory systems. In order to understand better the relative contributions of these physiological systems to the maintenance of balance, investigators remove or modify one such modality and then examine the resultant performance of a subject's postural control system in an experimental setting. In the case of the visual system, the most popular protocol is the Romberg test (Dichgans et al. 1976; Black et al. 1982; Paulus et al. 1984, 1989; Ring et al. 1989). This test involves the comparison of an individual's quiet-standing postural sway under eyes-open and eyes-closed conditions. Postural sway is typically quantified by using a force platform to determine the maximum displacement, mean squared displacement, and/or total distance traversed by the

J.J. Collins (✉) · C.J. De Luca
NeuroMuscular Research Center
and Dept. of Biomedical Engineering, Boston University, 44
Cummington St., Boston, MA 02215, USA;
FAX no: 617-353-5737

center of pressure (COP) under a subject's feet. From a clinical standpoint, the Romberg test has been utilized to assess patients with various neurological disorders, such as disequilibrium or ataxia (e.g., Njiokiktjien and De Rijke 1972; Cernacek 1980). From a motor control standpoint, however, the physiological insights gained from this protocol have largely been limited to the conclusion that postural sway, as measured by the aforementioned COP summary statistics, increases when a subject closes his or her eyes (Paulus et al. 1984, 1989; Ring et al. 1989).

Several researchers have extended the Romberg test to dynamic situations (Ishida and Imai 1980; Vidal et al. 1982; Werness and Anderson 1984; Maki et al. 1987; Johansson et al. 1988). Maki et al. (1987), for example, analyzed the postural responses of individuals to pseudorandom external perturbations. The subjects were tested both with their eyes open and blindfolded. Other investigators have studied the role of vision in the control of posture by manipulating the visual scenes in front of quietly standing subjects (Dichgans et al. 1976; Lestienne et al. 1977; Amblard et al. 1985; Bronstein 1986; Asten et al. 1988; Bronstein et al. 1990). Bronstein (1986), for instance, placed subjects on an earth-fixed force platform inside a movable room and examined the COP excursions (under the subjects' feet) that were induced by linear displacement of the visual surrounds.

In an earlier study (Collins and De Luca 1993), we examined quiet-standing COP trajectories as one-dimensional and two-dimensional random walks. This work was based on the assumption that the movements of the COP represent the combined output of coexistent deterministic and stochastic mechanisms. These analyses revealed that over short-term intervals of time during undisturbed stance open-loop control schemes are utilized by the postural control system, whereas over long-term intervals of time closed-loop control mechanisms are called into play. Our approach, known as *stabilogram-diffusion analysis,* has the advantage that it leads to the extraction of repeatable COP parameters which can be directly related to the resultant steady-state behavior and functional interaction of the neuromuscular mechanisms underlying the maintenance of upright stance. Within this stochastic modelling framework, one can thus formulate and test hypotheses concerning the relative contributions of different sensorimotor subsystems and strategies to "quasi-static" postural control.

In the present study, we utilize stabilogram-diffusion analysis and the above open-loop/closed-loop hypothesis to examine and interpret the results from the classic Romberg test. In particular, we analyze how visual input affects the operational characteristics of the open-loop and closed-loop postural control mechanisms.
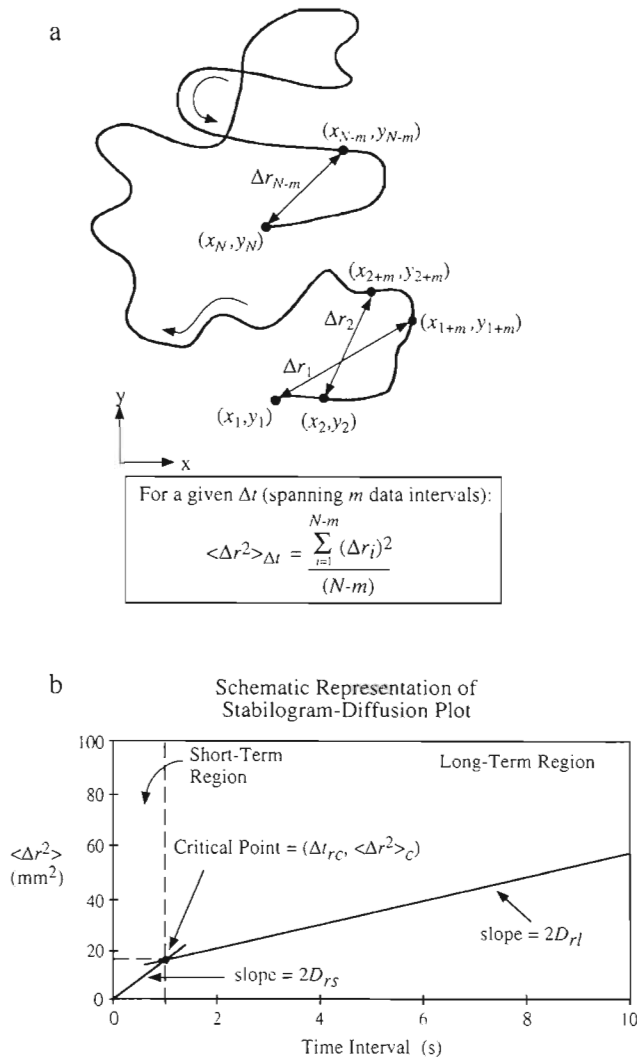
Materials and methods

Experimental methods

Twenty-five healthy male subjects of similar age (19–30 years, mean 22 years) and size (mean ± SD body weight 70.7 ± 8.4 kg; height 173.8 ± 5.9 cm) were included in the study. The subjects had no evidence or known history of a gait, postural, or skeletal disorder. Informed consent was obtained from each subject prior to participation. (This study was approved by the Boston University Charles River Campus Institutional Review Board.) Postural sway was evaluated by using a Kistler 9287 multicomponent force platform to measure the time-varying displacements of the COP under a subject's feet. (The noise characteristics of the platform were described in Collins and De Luca (1993).) Each subject was instructed to stand in an upright posture in a standardized stance on the platform. In the standardized stance, the subjects' feet were abducted 10° and their heels were separated mediolaterally by a distance of 6 cm. During testing, the subjects stood barefoot with their arms relaxed comfortably at their sides. Each trial lasted for a period of 30 s and the force platform data were sampled at a frequency of 100 Hz. A series of ten trials was conducted for each subject with his eyes open. During these tests, the subjects were instructed to fix their eyes on a point in front of them. An additional ten trials were conducted for each subject with his eyes closed and blindfolded. The order of testing, i.e., eyes-open versus eyes-closed trials, was randomized for the subject population. Rest periods of 60 s and 5 min were provided between each trial and between each set of ten trials, respectively.

Stabilogram-diffusion analysis

The COP trajectories were studied as one-dimensional and two-dimensional random walks, according to stabilogram-diffusion analysis (Collins and De Luca 1993). This technique is based on fundamental concepts and principles from statistical mechanics. The general driving principle of this discipline is that although the outcome of an individual random event is unpredictable, it is possible to obtain definite expressions for the probabilities of various aspects of a stochastic process or mechanism. A classic example of a statistical-mechanics phenomenon is Brownian motion, the simplest case of which is the random movement of a single particle along a straight line. This construct is known as a one-dimensional random walk. Einstein (1905) studied Brownian motion and showed that the mean square displacement of a one-dimensional (and higher-dimensional) random walk is linearly related to the time interval (see Eq. 1). As will be described below, this result, in part, forms the analytical foundation of stabilogram-diffusion analysis.

In stabilogram-diffusion analysis, the displacement analysis of COP trajectories is carried out by computing the square of the displacements between all pairs of points separated in time by a specified time interval Δt (Fig. 1a). The square displacements are then averaged over the number of Δt making up the COP time series. This process is repeated for increasing values of Δt. A plot of mean square COP displacement (e.g., $\langle \Delta r^2 \rangle$) versus Δt is known as a *stabilogram-diffusion plot.*[1] Fig. 1b. Stabilogram-diffusion plots are computed for each subject trial and then ten such curves are averaged to obtain a resultant stabilogram-diffusion plot for a particular subject. In the present study, two resultant plots were thus generated for each subject – one for eyes-open conditions and one for eyes-closed conditions. It is important to note that with stabilogram-diffusion analysis only the resultant plots are parameterized, i.e., the individual stabilogram-diffusion plots computed for each 30-s trial are not parameterized separate-

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[1] In the present study, $\{x_i\}$ and $\{y_i\}$ are the mediolateral and anteroposterior COP time series, respectively, and $\langle \Delta r^2 \rangle = \langle \Delta x^2 \rangle + \langle \Delta y^2 \rangle$. Thus, r designates planar COP measurements and displacements. The brackets $\langle \cdot \rangle$ denote an average over time or an ensemble average over a large number of samples

a

For a given Δt (spanning m data intervals):

$$<\Delta r^2>_{\Delta t} = \frac{\sum_{i=1}^{N-m} (\Delta r_i)^2}{(N-m)}$$

b

Schematic Representation of
Stabilogram-Diffusion Plot

Fig. 1 a The method for calculating mean square planar displacement $<\Delta r^2>$ as a function of time interval Δt for a center-of-pressure (COP) trajectory made up of N data points $(x_1, y_1; x_2, y_2; \ldots; x_N, y_N)$. In this case, Δt does not represent the sampling interval; instead, Δt represents a moving time window spanning m data intervals. The summation for calculating mean square displacement for a given time interval is for $(N-m)$ computed displacements. Thus, the last displacement which can be and is considered in the random-walk analysis is that between the $(N-m)$th point and the Nth point of the time series. **b** A schematic representation of a typical resultant planar stabilogram-diffusion plot ($<\Delta r^2>$ vs Δt) generated from COP time series according to the method shown in **a**. The "effective" diffusion coefficients D_{rs} and D_{rl} are computed from the slopes of the lines fitted to the short-term and long-term regions, respectively. The critical point, $(\Delta t_{rc}, <\Delta r^2>_c)$, is defined by the intersection of the lines fitted to the two regions of the plot. The scaling exponents H_{rs} and H_{rl} are calculated from the slopes of the log-log plots of the short-term and long-term regions, respectively (from Collins and De Luca 1993)

ly. Due to the stochastic nature of stabilograms, it is difficult, conceptually and practically, to obtain repeatable parameters from individual 30-s COP time series. In our earlier study (Collins and De Luca 1993), it was demonstrated that this task is greatly simplified by looking at ensemble averages of a relatively small number of experimental sequences, i.e., ten 30-s tests. The use of trial averaging in stabilogram-diffusion analysis was motivated by

the fact that experimental studies concerned with diffusion-like processes typically analyze either long time series of data measurements or a large number of smaller time series of such measurements (Shlesinger and West 1984; Montroll and Lebowitz 1987).

A schematic representation of a typical resultant stabilogram-diffusion plot is shown in Fig. 1b.[2] In order to parameterize such plots, two regions are identified – a short-term region and a long-term region (Fig. 1b).[3] These regions are separated by a transition or critical period over which the slope of the stabilogram-diffusion plot changes considerably. Stabilogram-diffusion analysis involves the extraction of three sets of posturographic parameters – diffusion coefficients, scaling exponents, and critical point coordinates. These parameters can be directly related to the steady-state behavior and functional interaction of the open-loop and closed-loop control mechanisms that are involved in maintaining "quasi-static" balance (Collins and De Luca 1993). The methods for calculating these parameters and their physiological relevance will be described and discussed below.

Diffusion coefficients reflect the level of stochastic activity and/or energy of the COP along the mediolateral or anteroposterior axis or about the plane of support.[4] From a physiological standpoint, the short-term and long-term COP diffusion coefficients characterize the stochastic activity of the open-loop and closed-loop postural control mechanisms, respectively. In our earlier study (Collins and De Luca 1993), it was found for all subjects that the short-term diffusion coefficients were much larger than the long-term diffusion coefficients. Thus, during quiet standing, the open-loop control schemes (which dominate short-term intervals of time) have a higher level of stochastic activity than the closed-loop feedback mechanisms (which are utilized over long-term intervals of time).

Diffusion coefficients D_j are calculated from the slopes of the resultant linear-linear plots of mean square COP displacement versus Δt, according to the general expression:

$$<\Delta j^2> = 2D_j \Delta t \qquad (1)$$

where $<\Delta j^2>$ is the mean square COP displacement, and $j = x, y, r$. Diffusion coefficients are computed for both the short-term and the long-term regions of resultant stabilogram-diffusion plots (Fig. 1b).

Scaling exponents, which can be any real number in the range $0 < H_j < 1$, quantify the correlation between the step increments making up an experimental time series. The correlation function, in this case, is given by the expression (Feder 1988):
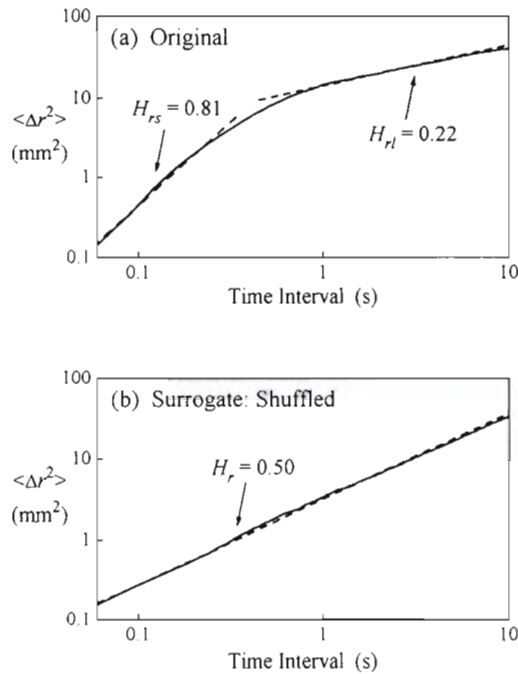
$$C = 2(2^{2H-1} - 1) \qquad (2)$$

Note that for $H_j = 0.5$, the increments in displacement are statistically independent, i.e., $C = 0$. This is the result expected for classical Brownian motion. If $H_j \neq 0.5$, then past increments in the time series are correlated with future increments and the associated

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Fig. 2 Raw-data resultant log-log plots of mean square planar displacement versus time interval for: **a** the original COP time series for a representative subject, and **b** shuffled surrogate random-walk data sets that were generated from the original COP time series in **a**. Shown also are the fitted regression lines (*dashed lines*) for the different scaling regions and the computed values of the respective scaling exponents

stochastic process is referred to as *fractional Brownian motion.*[5] For example, for $H_j > 0.5$, past and future increments are positively correlated, i.e., $C > 0$. In this case, a fractional Brownian particle moving in a particular direction for some t_0 will tend to continue in the same direction for $t > t_0$. In general, an increasing (decreasing) trend in the past implies an increasing (decreasing) trend in the future. This type of behavior is known as persistence (Feder 1988; Saupe 1988). For $H_j < 0.5$, on the other hand, the stochastic process is negatively correlated, i.e., $C < 0$. In this case, increasing (decreasing) trends in the past imply on the average decreasing (increasing) trends in the future. This type of behavior is referred to as antipersistence (Feder 1988; Saupe 1988). In our previous investigation (Collins and De Luca 1993), it was found that over short-term intervals of time during quiet standing, the COP behaves as a positively correlated random walk, i.e., one which tends to move or drift away from a relative equilibrium point following a perturbation. This type of behavior, i.e., persistence, is indicative of open-loop control. On the other hand, it was found that over long-term intervals of time during quiet standing, the COP behaves as a negatively correlated random walk, i.e., one which tends to return to a relative equilibrium point following a perturbation. This type of behavior, i.e., antipersistence, is indicative of closed-loop control.

Scaling exponents H_j are calculated from the slopes of the resultant log-log plots of mean square COP displacement versus Δt, according to the generalized scaling law:

$$< \Delta j^2 > \sim \Delta t^{2H_j} \tag{3}$$

[5] The term *fractional Brownian motion* was introduced by Mandelbrot and van Ness (1968) to designate a generalized family of Gaussian stochastic processes. This mathematical concept is an extension of classical or ordinary Brownian motion. Accessible introductions to the subject are provided by Feder (1988), Saupe (1988), and Voss (1988)

where the symbols correspond to those of Eq. 1. As with diffusion coefficients, scaling exponents are computed for both the short-term and the long-term regions of resultant stabilogram-diffusion plots. In the present study, the respective slopes needed to calculate the COP diffusion coefficients and scaling exponents were determined by utilizing the method of least squares to fit straight lines through defined portions of the aforementioned plots. All parameters were determined by a single investigator.

The critical point coordinates – the critical time interval Δt_{jc} and critical mean square displacement $< \Delta j^2 >_c$, where $j = x, y, r$ – approximate the transition region that separates the short-term and long-term regions. An estimate for each critical point was determined as the intersection point of the straight lines fitted to the two regions of the linear-linear version of each resultant stabilogram-diffusion plot (Fig. 1b). From a physiological standpoint, these coordinates approximate the temporal and spatial characteristics of the region over which the postural control system switches from open-loop control to closed-loop control. In our earlier study (Collins and De Luca 1993), it was found that this crossover region occurred at relatively small time intervals, i.e., $\Delta t_{jc} \approx 1.0$ s, and mean square displacements, i.e., $< \Delta j^2 >_c$ was less than 20 mm².

The above approach involves the fitting of two different models (when $H_j \neq 0.5$) to the same data sets, i.e., diffusion coefficients representing the slope of a linear model (see Eq. 1), and scaling exponents representing the exponent of a scaling-law model (see Eq. 3). In order to test the relative validity of these linear and nonlinear data-analysis techniques as applied to COP trajectories, we conducted the following study. We randomly shuffled the temporal order of the increments making up the COP time series from ten healthy, young subjects and then recombined the increments to form surrogate random-walk sequences (Collins and De Luca 1994, in press). For each subject, an ensemble of ten different shuffled surrogate sets was generated from each of the original COP time series and subsequently analyzed according to stabilogram-diffusion analysis. We calculated the significance of the difference between the computed values of the scaling exponents for the original COP time series and the surrogates according to the method described by Theiler et al. (1992). (We also used techniques described therein to estimate the error bars on the significance.) With this approach, the significance is defined by the difference between the value of H_j for the original COP time series and the mean value of H_j for the surrogates, divided by the standard deviation of the H_j values for the surrogates.

As noted above, double-logarithmic plots of mean square COP displacement versus time interval exhibit two scaling regions (e.g., see Fig. 2a): a short-term region over which the time series behaves as a positively correlated random walk ($H_j > 0.5$) and a long-term region over which it behaves as a negatively correlated random walk ($H_j < 0.5$). In contrast, we found that the double-logarithmic plots of mean square displacement versus time interval for the shuffled surrogates displayed only a single scaling region (e.g., see Fig. 2b), as would be expected for an uncorrelated random walk. The calculated values of H_j for the short-term and long-term scaling regions of the original COP time series and for the shuffled surrogates for the ten different subjects are given in Fig. 3a, c, e. The H_j values for the surrogates (range 0.47–0.54; mean 0.50 ± 0.02) were similar to those expected for a classical random walk (Fig. 3a, c, e). (The regression lines fitted for the computation of the respective surrogate scaling exponents had r^2 values that ranged from 0.97 to 1.00.) It is important to note that the variance of the estimated values of H_j for the surrogates was exceptionally small, i.e., a standard deviation of ± 0.02, and the mean value of these measures was exactly equal to that expected for an uncorrelated random walk.

The significance of the differences between the computed H_j values for the original COP time series and the surrogates are shown in Fig. 3b, d, f. It can be seen that the H_j values for the surrogates were significantly different from those computed for the original COP time series. This study thereby demonstrates that COP trajectories are significantly different from uncorrelated random walks and that the aforementioned correlations in the

Fig. 3a–f Random-walk analyses of COP time series and shuffled surrogate data sets. **a** Calculated values of H_x for the short-term (□) and long-term (△) scaling regions of the original COP times and for the shuffled surrogates (+) for ten different subjects. **b** Significance of the differences between the computed H_x values for the original COP times series and the surrogates in **a**. The significance values and error bars were calculated according to the techniques described by Theiler et al. (1992). Here σ_x is the standard deviation of the H_x values for the surrogates and ΔH_x is the difference between the value of H_x for the original COP time series and the mean value of H_x for the surrogates. A *dashed line* is plotted at the significance level which corresponds to a P value of 0.005. **c** As in **a**, but for the anteroposterior scaling exponent (H_y). **d** As in **b**, but for the computed values of H_y in **c**. **e** As in **a**, but for the planar scaling exponent (H_r). **f** As in **b**, but for the computed values of H_r in **e** (from Collins and De Luca, in press)
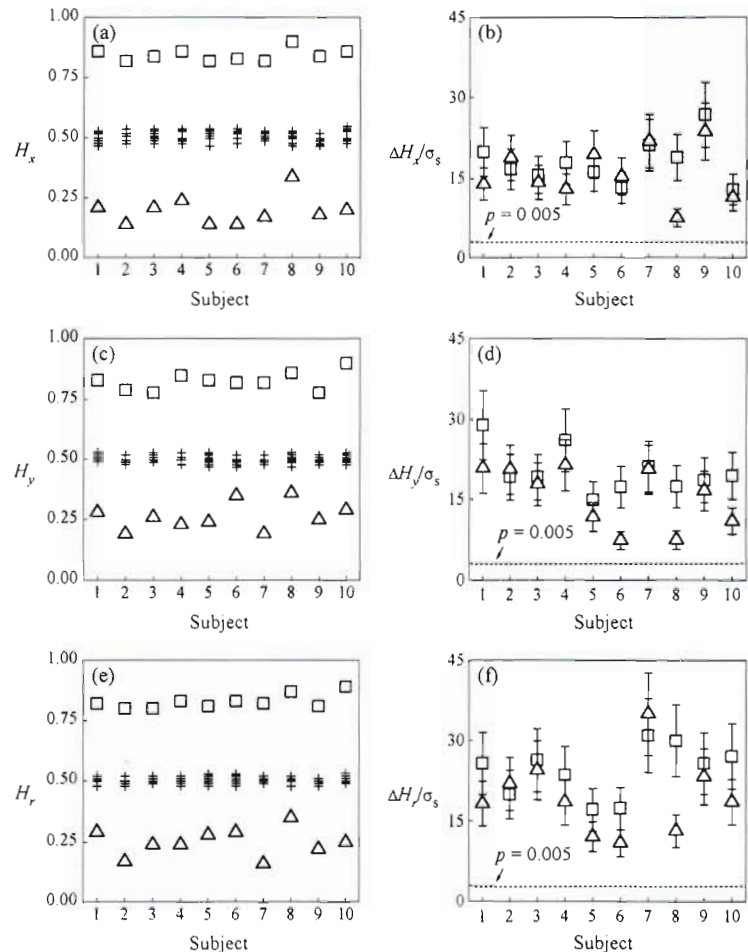
COP time series are due to underlying dynamic processes, i.e., they are not artifacts of the analysis. This result implies that the nonlinear data-analysis technique is more valid than the linear data-analysis technique.

Given this result, the COP diffusion coefficients, which are calculated using the linear data-analysis technique, should be viewed as "effective" diffusion coefficients. (Such measures represent "actual" diffusion coefficients only when $H_j = 0.5$, which, as noted above, is rarely the case with quiet-standing COP trajectories.) As such, these parameters approximate the effective diffusion of the COP about the base of support. Such a measure is useful, nonetheless, for characterizing the steady-state behavior of the postural control system because, in this instance, we are interested in measuring and characterizing the manifestation of a phenomenon, namely, the average postural sway of an individual for a given time interval. From this perspective and from the standpoint of our postural control hypothesis, the short-term and long-term effective diffusion coefficients should be interpreted as approximate measures of the effective stochasticity of the open-loop and closed-loop control mechanisms, respectively.

Traditional COP parameters and statistical analyses

The following commonly used COP parameters were also calculated from the stabilogram time series: maximum anteroposterior displacement, maximum mediolateral displacement, root-mean-square (RMS) displacement, total sway path, and radial area. COP radial area was defined as "the area of the circle whose radius was the average of all the radial distances of the center of pressure at each sampling interval from the mean position of the

center of pressure" (Hasan et al. 1990, p 784). The above parameters were computed for each subject trial and then the respective values were averaged for each set of ten trials to obtain two resultant measures for each parameter – one for eyes-open conditions and one for eyes-closed conditions – for each subject.

Student's t-test for paired observations was used to compare the respective stabilogram-diffusion parameters and traditional COP parameters that were calculated for the eyes-open and eyes-closed trials for each subject.
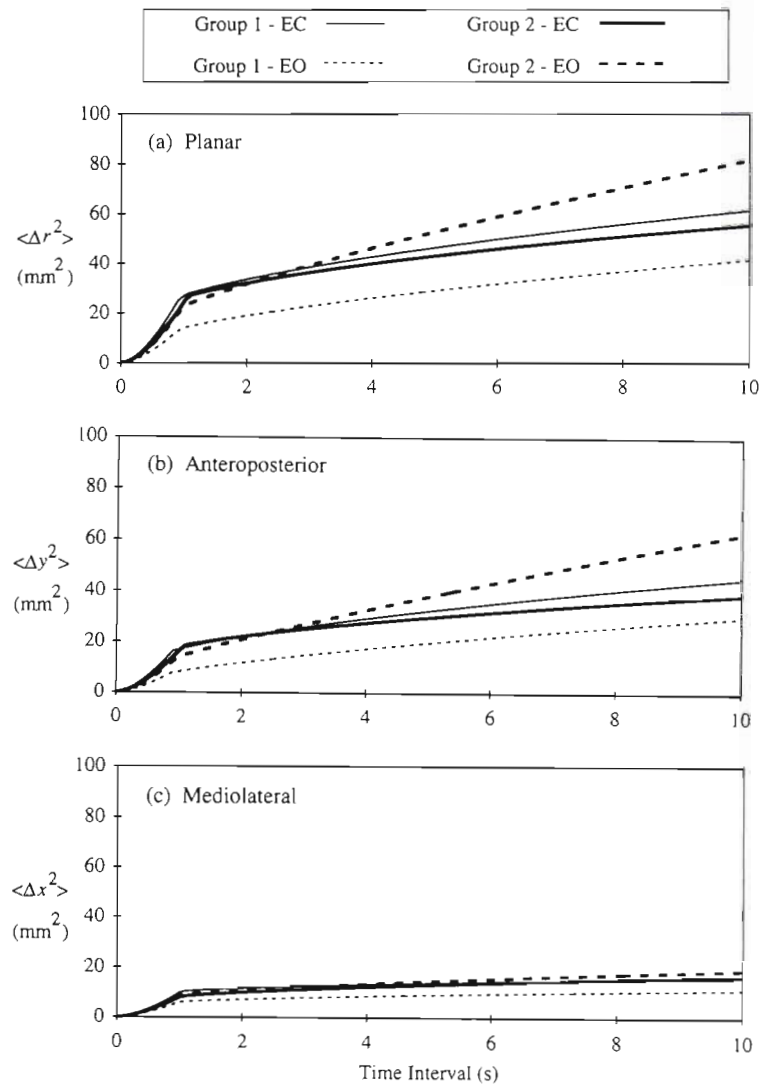
Results

As stated in the previous section, effective COP diffusion coefficients quantify the level of effective stochastic activity exhibited by the open-loop and closed-loop postural control mechanisms during quiet standing. These parameters can therefore be related to a subject's average level of postural sway, i.e., in general, for a given time interval, $D_{ji} \propto$ average postural sway (see Eq. 1), where $j = x, y, r$ and $i = s, l$. It is typically reported that the amplitude of postural sway increases when an individual closes his or her eyes (e.g., Paulus et al. 1984, 1989; Ring et al. 1989). In the present study, 13 of the subjects had, as expected, planar long-term effective diffusion coefficients D_{rl} under eyes-closed conditions that were larger than those under eyes-open conditions.

Fig. 4 A histogram of the relative changes in the planar long-term effective diffusion coefficient (between eyes-closed, *EC*, and eyes-open, *EO*, conditions) for all subjects ($n = 25$)

Number of Subjects

Group 2

Group 1

$$\frac{D_{rl}(EC) - D_{rl}(EO)}{D_{rl}(EO)} \times 100$$
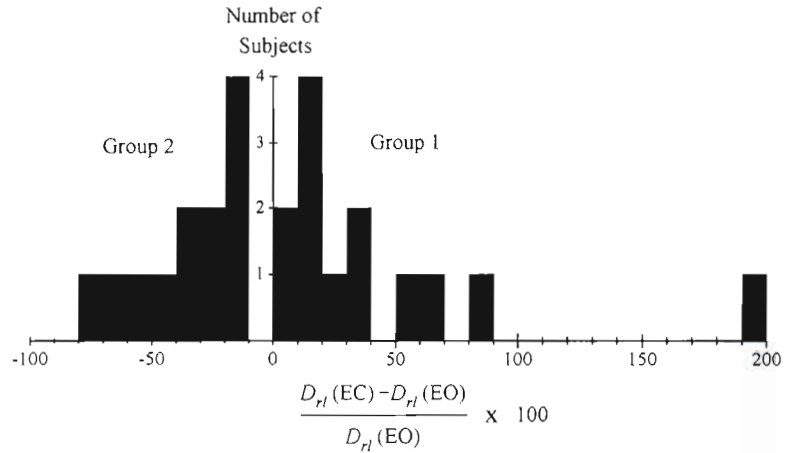
Fig. 5 Resultant stabilogram-diffusion plots for groups 1 and 2 under eyes-closed (*EC*) and eyes-open (*EO*) conditions: **a** planar, **b** anteroposterior, and **c** mediolateral. The plots were generated from the group means of the respective stabilogram-diffusion parameters

Group 1 - EC ——   Group 2 - EC ——
Group 1 - EO ------   Group 2 - EO – – –

(a) Planar

$<\Delta r^2>$
(mm^2)

(b) Anteroposterior

$<\Delta y^2>$
(mm^2)

(c) Mediolateral

$<\Delta x^2>$
(mm^2)

Time Interval (s)

However, for the remaining 12 subjects, the reverse situation was true, i.e., the planar long-term effective diffusion coefficients under eyes-closed conditions were, in fact, *smaller* than those under eyes-open conditions. On the basis of this result, the subjects were divided into two subpopulations: group 1, where D_{rl} (eyes closed) > D_{rl} (eyes open); and group 2, where D_{rl} (eyes closed) < D_{rl} (eyes open). (There were no significant anthropometric or age differences between the two groups – body weight 71.6 ± 8.4 kg (group 1) vs 69.8 ± 8.6 kg
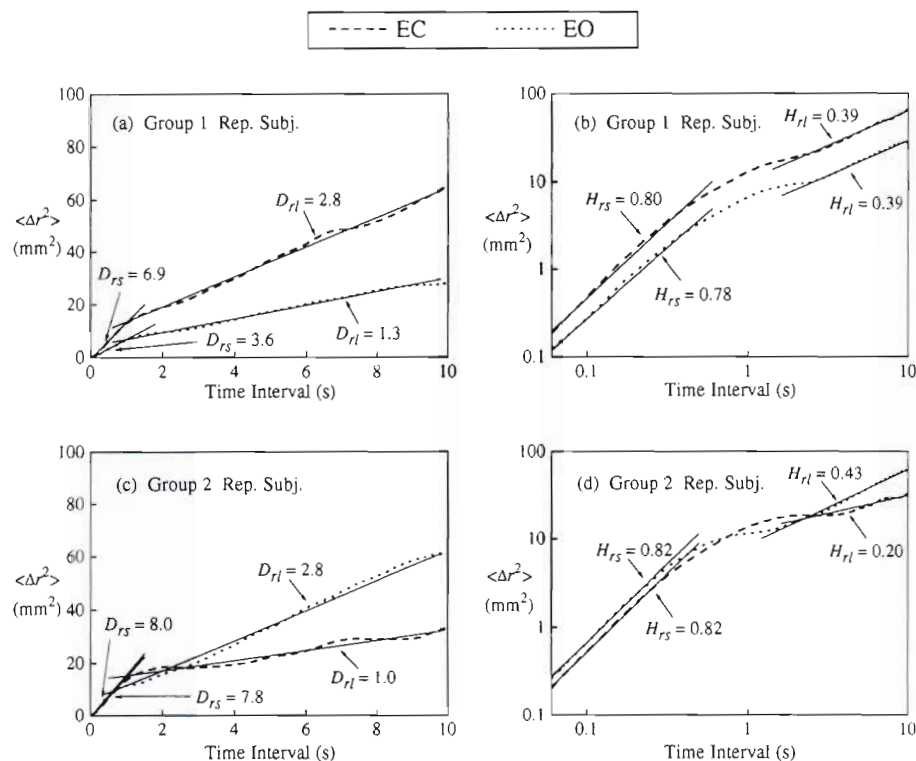
Fig. 6a–d Raw-data resultant planar stabilogram-diffusion plots and fitted regression lines for representative subjects from the two groups under eyes-closed (EC) and eyes-open (EO) conditions. Group 1 representative subject: **a** linear-linear plots, and **b** log-log plots. Group 2 representative subject: **c** linear-linear plots, and **d** log-log plots. Values for the computed short-term and long-term effective diffusion coefficients (in units of square millimeters per second) are given in **a** and **c**. Values for the computed short-term and long-term scaling exponents are given in **b** and **d**. In **a**, the computed critical point coordinates are: $\Delta t_{rc} = 1.0$ s (EC), 1.0 s (EO); and $<\Delta r^2>_c = 13.6$ mm^2 (EC), 6.7 mm^2 (EO). In **c**, the computed critical point coordinates are: $\Delta t_{rc} = 1.0$ s (EC), 0.7 s (EO); and $<\Delta r^2>_c = 15.3$ mm^2 (EC), 10.7 mm^2 (EO). The lines fitted for computation of D_{rs}, D_{rl}, H_{rs}, and H_{rl}, respectively, for the representative subject from group 1 had r^2 values of: 1.0, 0.99, 0.98, and 0.99 (eyes open), and 1.0, 0.99, 0.99, and 0.99 (eyes closed). The lines fitted for computation of D_{rs}, D_{rl}, H_{rs}, and H_{rl}, respectively, for the representative subject from group 2 had r^2 values of: 0.98, 1.0, 1.0, and 0.99 (eyes open), and 1.0, 0.95, 0.99, and 0.90 (eyes closed)

(group 2); height 175.3 ± 5.4 cm (group 1) vs 172.2 ± 6.3 cm (group 2); age 22 ± 3 years (group 1) vs 22 ± 2 years (group 2). There were also no significant differences between the two groups in terms of visual deficits, orthopedic injuries, athletic experience and skill, or occupational training and skill.) A histogram of the relative changes in the planar long-term effective diffusion coefficient (between eyes-closed and eyes-open conditions) for all subjects ($n = 25$) is given in Fig. 4. The distribution of these data can be characterized as being bimodal, albeit skewed toward zero (as would be expected with healthy, young subjects), with modes at -20 to -10 and 10 to 20. This distribution is significantly different ($P < 0.05$) from a normal distribution, as indicated by the Wilk-Shapiro test. This is visually evident from the plot in Fig. 4 given the paucity of points in the -10 to 0 and 0 to 10 bins.

A computer program was designed to generate resultant stabilogram-diffusion plots from the group means of the respective random-walk COP parameters, i.e., short-term and long-term effective diffusion coefficients, short-term and long-term scaling exponents, and critical point coordinates. The corresponding planar, anteroposterior, and mediolateral stabilogram-diffusion plots for groups 1 and 2 are shown in Fig. 5. (It is important to emphasize the fact that the concept of time in a stabilogram-diffusion plot corresponds to a moving time window as opposed to the passage of real time; see Fig. 1.) Several general points about the stabilogram-diffusion plots of Fig. 5 should be noted. Firstly, the eyes-closed results for groups 1 and 2 were remarkably similar. Consequently, the eyes-closed results were used as the starting point for the description and comparison of the quantitative findings for the respective groups. Secondly, it can be seen in Fig. 5a that the slope of the long-term region, i.e., $\Delta t > \sim 1.0$ s, of the planar stabilogram-diffusion plot for group 1 *decreased* under eyes-open conditions whereas that of group 2 *increased*.[6] This result reflects the aforementioned differences in the behavior of the two groups' planar long-term effective diffusion coefficients D_{rl}. Similar results were found in the anteroposterior stabilogram-diffusion plots (Fig. 5b); this effect, however, was not as significant in the mediolateral plots (Fig. 5c).[7] Finally, for all three plots, the

[6] It should be pointed out that the appearance of the slopes of the plots in Fig. 5a is visually deceiving, i.e., the differences in the long-term slopes for group 1 are not immediately obvious by visual inspection

[7] Since $<\Delta r^2> = <\Delta x^2> + <\Delta y^2>$, it follows that each planar stabilogram-diffusion plot corresponds to the linear sum of the respective mediolateral and anteroposterior plots

Fig. 7 Group means and standard deviations for the short-term and long-term stabilogram-diffusion parameters for groups 1 and 2 under eyes-closed (*EC*) and eyes-open (*EO*) conditions: **a** short-term effective diffusion coefficients, **b** long-term effective diffusion coefficients, **c** short-term scaling exponents, and **d** long-term scaling exponents. The symbols * and ** denote statistically significant intra-group differences at $P < 0.05$ and 0.005 levels, respectively. For **c** and **d**, a *dashed line* is drawn at the value expected for classical Brownian motion, i.e., $H_{ji} = 0.50$
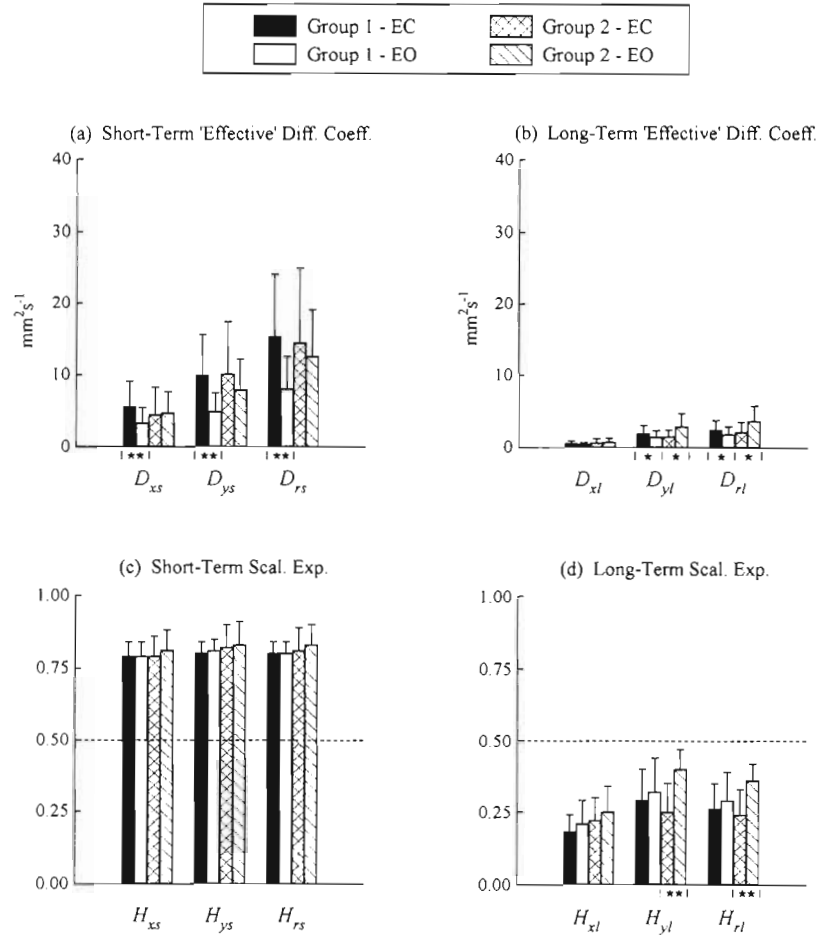
slopes of the short-term region, i.e., $\Delta t < \sim 1.0$ s, for group 1 under eyes-closed conditions and for group 2 under both eyes-closed and eyes-open conditions were similar. For group 1, however, the slopes of the short-term region decreased significantly under eyes-open conditions; this effect implied that the eyes-open short-term effective diffusion coefficients for group 1 were significantly smaller than the respective eyes-closed parameters. Raw-data resultant planar stabilogram-diffusion plots for representative subjects from the two groups are given in Fig. 6.

The group means and standard deviations of the calculated posturographic parameters for group 1 are given in bar-plot form in Figs. 7 and 8. (The lines fitted for computation of D_{js}, D_{jl}, H_{js}, and H_{jl} (where $j = x, y, r$) for groups 1 and 2 had r^2 values that ranged 0.93–1.00, 0.71–1.00, 0.98–1.00, and 0.70–1.00, respectively. In the significant majority of cases, the r^2 values for a given data set were all greater than 0.95.) Firstly, it can be seen that there were statistically significant differences ($P < 0.005$) between the short-term effective diffusion coefficients D_{js} for the eyes-closed and eyes-open trials (Fig. 7a). The group mean values for the eyes-open parameters were approximately one-half the respective values for the eyes-closed cases. As noted above, this result is reflected in the respective resultant stabilo-

gram-diffusion plots (Fig. 5) as a decreased slope over the short-term region for the eyes-open trials. There were also statistically significant differences ($P < 0.05$) between the respective anteroposterior and planar long-term effective diffusion coefficients, i.e., the eyes-open parameters were significantly smaller than the eyes-closed parameters (Fig. 7b). Secondly, it can be seen from Fig. 7c, d that, for both experimental conditions, the COP exhibited persistence ($H_{js} > 0.5$) and antipersistence ($H_{jl} < 0.5$) over the short-term and long-term regions, respectively. Moreover, there were no significant differences between the respective short-term and long-term scaling exponents for the two experimental conditions. Thirdly, there were no significant changes in the critical time intervals when the subjects of group 1 opened their eyes – for all three resultant plots (planar, anteroposterior, mediolateral) for both experimental conditions, the computed Δt_{jc} were approximately 1.0 s (Fig. 8a). There were, however, statistically significant differences between the group mean values for the critical mean square displacements (Fig. 8b). More specifically, $< \Delta j^2 >_c$ (eyes open) were significantly smaller than $< \Delta j^2 >_c$ (eyes closed).

The group means and standard deviations of the computed random-walk COP parameters for group 2 are also given in bar-plot form in Figs. 7 and 8. Firstly,

Fig. 8 Group means and standard deviations for the critical point coordinates for groups 1 and 2 under eyes-closed (*EC*) and eyes-open (*EO*) conditions: **a** critical time intervals, and **b** critical mean square displacements. The symbols * and ** denote statistically significant intra-group differences at $P < 0.05$ and 0.005 levels, respectively
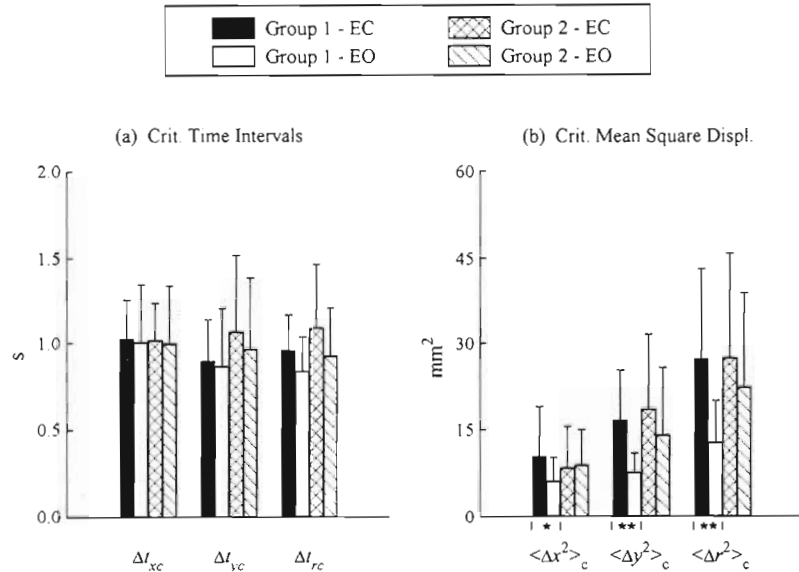
it can be seen from Fig. 7a that for group 2 there were no significant differences between the eyes-closed and eyes-open short-term effective diffusion coefficients D_{js}. This is in contrast to the results for group 1. For group 2, there were, as with group 1, statistically significant differences ($P < 0.05$) between the respective anteroposterior and planar long-term effective diffusion coefficients (Fig. 7b). However, in this case, the group means for the eyes-open parameters were significantly larger than the values for the respective eyes-closed parameters. Secondly, as with group 1, the COP trajectories for the subjects in group 2 behaved as positively and negatively correlated random walks over the short-term and long-term regions, respectively, for both experimental conditions. However, for group 2, there were statistically significant differences ($P < 0.005$) between the respective anteroposterior and planar long-term scaling exponents (Fig. 7d). With eyes open, the group mean values for H_{yl} and H_{rl} increased from 0.25 and 0.24 to 0.40 and 0.36, respectively. Thus, under eyes-open conditions during undisturbed stance, the COP trajectories became less negatively correlated over long-term intervals. Finally, there were no significant differences between the eyes-closed and eyes-open critical point coordinates (Fig. 8a, b). As with group 1, the critical time intervals were approximately 1.0 s for the three resultant stabilogram-diffusion plots for both experimental conditions.

Table 1 summarizes the major parameter changes for the two experimental subpopulations. For group 1, the

Table 1 Summary of the significantly different parameter changes for the two groups resulting from the integration of visual input

	Stabilogram-diffusion parameters	Changes
Group 1	D_{xs}	⇓
	D_{ys}	⇓
Group 2	D_{yl}	⇑
	H_{yl}	⇑

primary changes were seen in the mediolateral and anteroposterior short-term effective diffusion coefficients. For group 2, on the other hand, the primary changes were seen in the anteroposterior long-term effective diffusion coefficient and scaling exponent. (As noted above, changes in planar stabilogram-diffusion parameters, e.g., D_{rs} and D_{rl}, are directly related to changes in the respective mediolateral and/or anteroposterior parameters. Moreover, as will be discussed in the next section, the change in the anteroposterior long-term effective diffusion coefficient for group 1 may be a direct consequence of the change in the respective short-term effective diffusion coefficient. Finally, the significant differences between the eyes-closed and eyes-open critical mean square displacements for group 1 can be directly attributed to the fact that the critical time intervals for the two experimental conditions were equivalent, but the short-term effective diffusion coefficients for the eyes-open trials were significantly smaller than those for the eyes-closed trials.) In light of our open-loop/closed-loop postural control hypothesis, the results for group 1 can be summarized as follows: with visual input, the effective stochastic activity of the open-loop control mechanisms *decreased* in both the x and y directions. Similarly, the results for group 2 can be summarized as: with visual input, the effective stochastic activity and uncorrelated behavior (i.e., decreased levels of antipersistence) of the closed-loop control mechanisms *increased* in the y direction only.

The group means and standard deviations of the traditional COP parameters for the two groups are shown in bar-plot form in Fig. 9. As with the stabilogram-diffusion parameters, the eyes-closed results for the two groups were similar. In addition, for group 1, there were statistically significant differences ($P < 0.005$) between the eyes-closed and eyes-open trials for each of the traditional parameters, i.e., the eyes-open parameters were significantly smaller than the respective eyes-closed

Fig. 9 Group means and standard deviations for the traditional COP parameters for groups 1 and 2 under eyes-closed (*EC*) and eyes-open (*EO*) conditions: **a** maximum anteroposterior displacement (Max AP), maximum mediolateral displacement (Max ML), and root-mean-square displacement (RMS); and **b** total sway path (TSP) and radial area (RA). The symbols * and ** denote statistically significant intra-group differences at $P < 0.05$ and 0.005 levels, respectively. The RMS values and the results in **b** were derived from the two-dimensional COP trajectories, i.e., they represent planar values
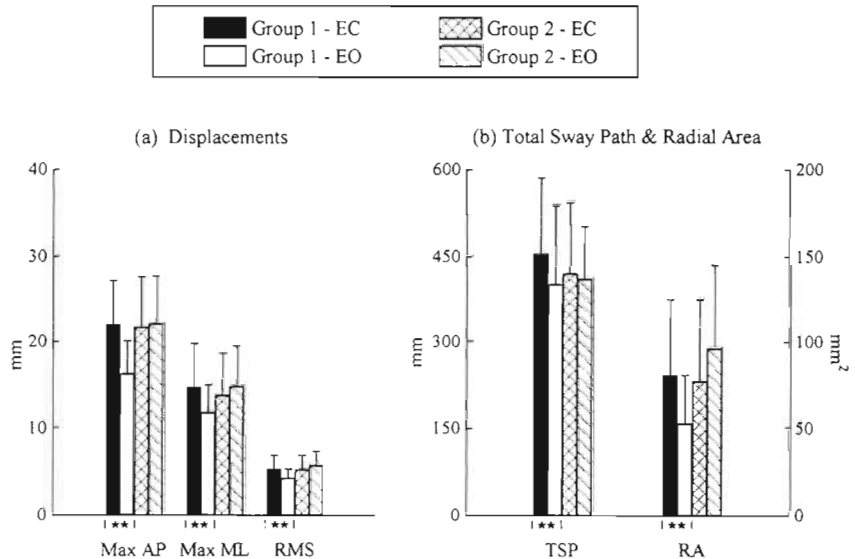
parameters. For group 2, on the other hand, there were *no* significant differences between the eyes-closed and eyes-open trials for *any* of the traditional COP parameters.

Discussion

Using stabilogram-diffusion analysis and our open-loop/closed-loop hypothesis, we found that visual input affects the performance of the postural control system in one of *two* different ways – either it significantly modifies the steady-state behavior of the open-loop postural control mechanisms, or it significantly alters the characteristics of the other closed-loop feedback mechanisms that are involved in the maintenance of upright stance. We interpret this result as an indication that the visual system is integrated into the postural control system in one of *two* different ways. Our experimental population of healthy, young subjects was roughly evenly divided between these two schemes.

For the first group (group 1), visual input principally caused a decrease in the effective stochastic activity of the open-loop control mechanisms in both the x and y directions, i.e., D_{xx} and D_{ys} decreased significantly under eyes-open conditions. On the basis of this result, we hypothesize that the subjects of group 1 used visual input to reduce the stiffness of their musculoskeletal systems by decreasing the level of muscular activity across the joints of their lower limbs. A potential advantage of this hypothesized strategy is that "less stiff" muscles exhibit a lower level of stochastic activity. Since fluctuations are always present in the mechanical output of skeletal muscles (De Luca et al. 1982) and since the average amplitude of these noise-like fluctuations decreases as the amount of force produced by a muscle decreases (Joyce and Rack 1974), the above postural control strategy would lead to lower average levels of short-term postural sway and smaller eyes-open short-term effective

diffusion coefficients D_{js}, as were calculated for group 1. These changes occurred in both the x and y directions, implying that the muscles involved act in both the mediolateral and anteroposterior directions. The importance of muscle stiffness as a load-compensating mechanism for the regulation of balance has been emphasized by a number of researchers (e.g., Grillner 1972; Dietz 1992). For the subjects of group 1, it appears that with visual input they may have reduced their reliance on muscle stiffness to correct for destabilizing influences, e.g., muscle force fluctuations, slight displacements due to respiration, etc., during quiet standing. With sensitive, i.e., extremely low-noise, surface EMG electrodes, it should be possible to test this hypothesized postural control strategy. However, this was not considered as part of the study at the outset; it will be part of future work. (Although the relationship between recorded EMG signals and resultant joint stiffness has not been well established, it is expected that the EMG RMS value for a particular muscle will decrease if the muscle's level of activity, and hence it stiffness, is decreased.)

It was also found that the anteroposterior long-term effective diffusion coefficient D_{yl} of group 1 decreased significantly under eyes-open conditions, along with an associated decrease in D_{rl}. (There was also a decrease in the mediolateral long-term effective diffusion coefficient D_{xl}, although this change was not statistically significant ($P = 0.22$).) This effect may have been a direct consequence of the decreased short-term effective stochastic activity described above and not the result of some change in the steady-state behavior of the closed-loop control mechanisms. It is plausible that a decrease in short-term fluctuations across the multiple joints of the human body could lead to a decrease in the long-term fluctuations of the overall system. In addition, since bipedal stance is inherently more stable in the mediolateral direction, the significant decrease in D_{xs} may not have been sufficient to cause a significant decrease in D_{xl}. This biomechanical argument, as opposed to a mo-

Fig. 10 A possible schematic diagram of how the visual system is integrated into the postural control system. Visual input influences the system in either one of two different ways: (1) it affects the output of the open-loop postural control mechanisms (group 1), or (2) it affects the operational characteristics of the other closed-loop postural control mechanisms, i.e., the proprioceptive and/or vestibular systems (group 2). For both schemes, the integration of visual input serves to decrease the stiffness of the musculoskeletal system. Here G is a gain modulation factor
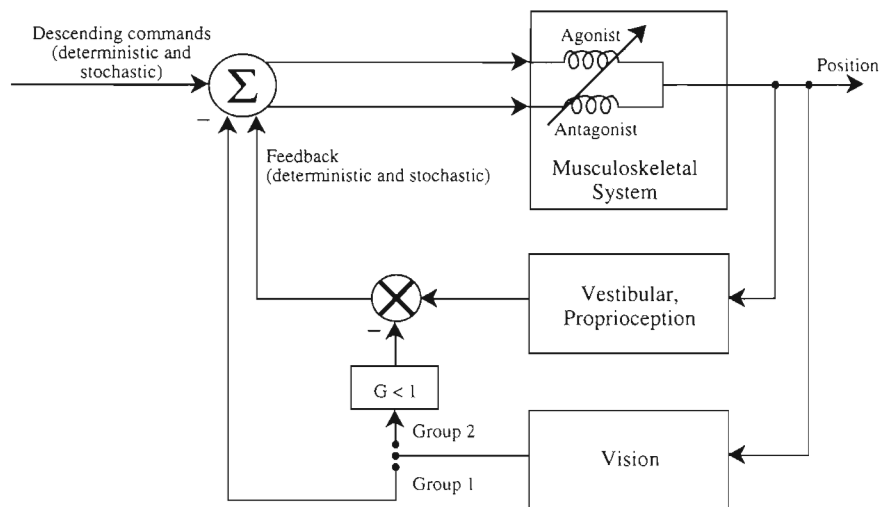
tor control argument, is strengthened by the fact that group 1 did not exhibit any significant changes in the long-term scaling exponents H_{jl}, i.e., visual input did not significantly modify the antipersistent behavior of the closed-loop control mechanisms.

For the second group (group 2), visual input caused an increase in the effective stochastic activity and uncorrelated behavior of the closed-loop control mechanisms in the y direction only, i.e., D_{yl} and H_{yl} increased significantly under eyes-open conditions. This finding does not support the conventional notion that postural sway necessarily decreases under eyes-open conditions. The majority of previous studies in static posturography have limited the analysis of stabilograms to summary statistics, i.e., total sway path length, sway area, maximum displacement, etc. (e.g., Diener et al. 1984; Paulus et al. 1984, 1989; Kirby et al. 1987; Hasan et al. 1990). For group 2, which was made up of nearly *half* the subjects tested (12 of 25), there were no significant differences between the eyes-closed and eyes-open trials for any of five different traditional COP parameters (Fig. 9). (The subjects in group 1, on the other hand, exhibited significant differences in each of the traditional parameters; these differences between the two subpopulations, as indicated by classical measures, could account for the conflicting reports, e.g., Leroux et al. (1973), on the effects of vision on undisturbed balance.) However, as noted above, stabilogram-diffusion analysis was able to detect statistically significant differences between the eyes-closed and eyes-open tests for the subjects of group 2. These differences with previous analyses can largely be attributed to the fact that stabilogram-diffusion analysis takes account of the dynamic features and, hence, the long-term behavior of quiet-standing COP trajectories. By doing so, this technique was able to reveal alterations in the performance of the closed-loop feedback mechanisms involved in maintaining balance.

As with group 1, we hypothesize that the aforementioned stabilogram-diffusion results for group 2 may be due to an eyes-open balance strategy which decreases

the stiffness of the musculoskeletal system. In this case, however, the changes may be produced by reducing the gain of either or both of the remaining closed-loop control mechanisms. With a reduction in feedback gain, the system's behavior would become less tightly correlated, i.e., there would be a decreased probability that slight movements away from a relative equilibrium point would be offset by corrective adjustments back toward the equilibrium position. A control strategy of this nature would result in larger long-term scaling exponents, i.e., H_{jl} would be closer to 0.5, the result expected for classical Brownian motion. Moreover, this effect would increase the probability of the COP moving a greater distance away from some relative equilibrium point and thereby lead to larger long-term effective diffusion coefficients D_{jl}.[8] Functional adaptations of the settings and characteristics of the feedback mechanisms underlying postural control have been well documented (Prochazka 1989; Dietz 1992; Massion 1992). For group 2, it appears that the "quasi-static" behavior of their closed-loop postural control mechanisms in the anteroposterior direction may be context-dependent. With input from the visual system, for example, this group may have become less sensitive to sensory information from the proprioceptive and/or vestibular systems, i.e., their inputs may have been adaptively reweighted, and thereby reduced their reliance on these feedback systems to correct for anteroposterior displacements during undisturbed stance. This hypothesis, which was based on findings derived from quiet-standing COP trajectories, is consistent with the results of a number of dynamic posturographic studies (e.g., Nashner and Berthoz 1978;

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[8] It should be emphasized that the proposed eyes-open balance strategy for group 2 directly affects the long-term dynamics of the postural control system, e.g., causing an increase in D_{yl}, whereas the proposed eyes-open balance strategy for group 1 directly affects the short-term dynamics of the postural control system, e.g., causing a decrease in D_{ys}. As discussed above, the changes associated with the latter strategy could have an indirect effect on the long-term dynamics of the postural control system, e.g., causing a decrease in D_{yl}

Berthoz et al. 1979; Soechting and Berthoz 1979; Ishida and Imai 1980).

It is further interesting to note that the temporal co-ordinates of the critical points for groups 1 and 2 did not change significantly when the subjects opened their eyes. In all cases, the group mean values for Δt_{jc} were approximately 1.0 s. As stated earlier, the critical point approximates the transition from open-loop control to closed-loop control. The present results suggest that during quiet standing the time delays in the visuomotor feedback system neither set nor affect the value for the critical time interval. A number of alternative physiological explanations for this "setting" phenomenon were presented in our earlier paper (Collins and De Luca 1993), including: (1) it may be due to a proprioceptive "dead-zone", i.e., a region over which slight variations in body-segment position and orientation are left unchanged; (2) it may be due to a dead-zone that arises from the interaction of postural responses with the body's inertia; or (3) it may be established by fixed, pre-programmed central commands that are utilized in quiet stance. The speculative proposal of a proprioceptive dead-zone, however, is called into question by the computed results for group 1 (Figs. 5, 7, 8). It was found that the respective critical mean square displacements for their eyes-open trials were significantly smaller than those for their eyes-closed tests. Thus, under eyes-open conditions, the subjects' COP traversed, on average, smaller displacements over shorter periods of time. If the critical points were set by some displacement-based feedback threshold, it would be expected that the critical time intervals for group 1 would have correspondingly shifted to larger values during the eyes-open tests. As stated above, this was not the case – there were no statistically significant differences in the critical time intervals for the two experimental conditions. It is unlikely, furthermore, that the subjects in group 1, with visual input, would have adopted a postural control strategy that involved smaller displacement-based feedback thresholds, i.e., smaller variations in body-segment orientation and position would be allowed before corrective mechanisms are called into play. It is unlikely that such a systematic modification would be necessary when additional sensory feedback information, i.e., visual input, is provided to the postural control system.

A possible schematic diagram for the emerging postural control models is given in Fig. 10. As noted earlier, we interpret our posturographic results as suggesting that the visual system is integrated into the human postural control system in one of two different ways. In a model that is appropriate for group 1, vision influences the output of the open-loop control mechanisms (Fig. 10). (In this case, visual input serves to alter the set point(s) of the open-loop control mechanisms; it does not, however, serve to adjust continually the output of these mechanisms, i.e., it does not transform the open-loop control schemes into feedback-based mechanisms.) In a model that is appropriate for group 2, on the other hand, the visual system affects the output of the propri-

oceptive and vestibular systems, via gain modulation (Fig. 10). In each case, as hypothesized, visual input serves to decrease the stiffness of the musculoskeletal system. It should be noted, moreover, that the two models are equivalent with the removal of vision, i.e., each consists of two general components – open-loop control schemes and closed-loop control schemes (corresponding to the somatosensory and vestibular systems) – that have deterministic and stochastic (noisy) features. Thus, in a visually deprived environment, the net output of these proposed models would be similar. This feature is consistent with our finding that the two groups behaved similarly under eyes-closed conditions, which suggested that the open-loop postural control mechanisms and reflex-based feedback systems, respectively, of healthy, young individuals are organized in functionally equivalent ways.

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