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Recurrence quantification analysis of postural fluctuations

M.A. Riley *, R. Balasubramaniam, M.T. Turvey

Center for the Ecological Study of Perception and Action, Department of Psychology, University of Connecticut, 406 Babbidge Road, Storrs, CT 06269, USA

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Abstract

A technique (recurrence quantification analysis; RQA) for analyzing center of pressure (COP) signals is presented and applied to data obtained by having participants stand with the head forward or sideways and with eyes open or closed. RQA is suitable for short, nonstationary signals and quantifies dynamical (deterministic) structure and nonstationarity. Results indicated that vision affects the deterministic structure (in degree and complexity) of COP motions and that differential optical flow structure (radial versus lamellar flow) induced by spontaneous sway under different head orientations affects COP nonstationarity. Implications of these findings and the sensitivity of RQA to subtle time-evolutionary properties of the COP are discussed. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

A recent concern in the postural control literature has been that of developing analytic techniques which go beyond characterizing gross properties of postural sway (i.e. variability measures). It is hoped that such methods may shed light on underlying control processes by revealing meaningful structure in spontaneous postural fluctuations that occur in the absence of external perturbations. For example, Collins and De Luca [1] have applied methods from statistical mechanics which reveal structure in postural sway in terms of the correlation functions of center of pressure (COP) signals over various time scales. The analysis has formed the basis for several proposed models of postural control, ranging from the dual correlated random walk model consisting of open- and closed-loop control regimes [1,2], to a refinement of this view in terms of a pinned-polymer model of postural control [3,4], and to a conception of the role of postural fluctuations in terms of a perceptual, exploratory function [5,6]. This work has also spurred the development of models based upon similar stochastic processes (e.g. the Ornstein–Uhlenbeck model [7]). There have also been attempts to distinguish deterministic and stochastic sway components. While these have thus far yielded inconsistent results [7], present evidence favors a stochastic account [8].

Another concern has been that of characterizing COP nonstationarity [7,9–11]. COP time series show what is termed bounded nonstationarity—within the bounds of the base of support (usually, the anterior–posterior (AP) and the lateral extents of the feet), fluctuations of the COP are typically nonstationary in both the first and second moments (mean and variance).[1] Nonstationarity violates the assumptions of many preferred analyses, including the Fourier transform. Largely, spectral techniques based on the Fourier transform are inappropriate—with the exception of

* Corresponding author. Tel.: +1-860-486-4969; e-mail: mar95003@uconnvm.uconn.edu.

[1] This reflects the fact that, from a purely biomechanical perspective (i.e. not considering the role of supra-postural task constraints), postural control is underconstrained [5,12–14].

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time-frequency methods [11] designed to yield evolving spectral representations of nonstationary signals—as are other analyses such as estimates of correlation dimension and Lyapunov exponents [15]. In short, the nonstationary properties of postural sway may limit such attempts as discussed above to provide a deeper account of the structure of postural sway (and, in turn, to provide a deeper account of postural control processes and mechanisms). An exception is stabilogram-diffusion analysis [1,2], which is designed to provide measures for data exhibiting random walk (such as COP signals). One hallmark characteristic of random walk processes is nonstationarity in the form of drift.

The recent interest in these aspects of COP dynamics has largely followed the development of analytic techniques. These techniques promise insights into a number of the deeper issues confronting an understanding of postural control. For example, fundamental to such an understanding is the issue of whether spontaneous motions of the body are purely random, largely stochastic (but not statistically independent), deterministic, or perhaps a blend of deterministic and stochastic elements. The importance of this aspect of COP dynamics becomes apparent when one considers that postural fluctuations are primarily produced by the postural system, and yet must also be resolved and possibly countered by the postural system. Whereas external factors such as gravity and the support surface obviously contribute to postural fluctuations, the major source of the fluctuations (in the absence of external perturbations) is the postural system itself.

In this paper, we present an application of a recently developed method, recurrence quantification analysis (RQA), a nonlinear and multi-dimensional technique which does not assume data stationarity (and, moreover, which places no restrictions on the statistical distribution of data or on data set length) and which provides a characterization of a variety of features of a given time series, including a quantification of deterministic structure and of nonstationarity [16–18]. These features of RQA make it an ideal tool for the analysis of COP data with respect to the above concerns. We demonstrate the utility of RQA through an examination of the role of vision and of optic flow structure in the control of upright, unperturbed stance. The data were previously reported under a different analysis—a variant of stabilogram-diffusion analysis [1]—by Riley et al. [19]. A reexamination of these data here is useful because the previous results provide a basis for comparison, and, moreover, because multiple methods of analysis of complex behaviors such as upright standing may prove more useful than any one method alone. We discuss the potential insights provided by this analysis regarding the nature of postural sway and postural control and regarding the effects of vision and differential optical structure on postural sway. Some caveats and notes on implementing the analysis are also discussed.

1.1. Recurrence plots and recurrence quantification

The basic idea behind RQA is that of local recurrence, or neighborliness, of data points in reconstructed phase space. The notion of phase space reconstruction (see, e.g. Abarbanel [20]) is based upon a mathematical proof, known as the embedding theorem [21], that knowledge of the dynamics of a potentially multivariate system (e.g. the motions of which may be governed by a system of one or more equations written in terms of one or more dynamical variables) may be obtained through the measurement of only one scalar time series. This is because the influence of these other dynamical variables is contained in the measured signal. The system is then studied by reconstructing the space of the true dynamics using a coordinate system of surrogate observables. Since it is unlikely that all of the dynamical variables of a system can be measured, or even known, a coordinate system of surrogate variables is created by taking the measured signal and a number of time-lagged copies of the signal. This is termed embedding the measured signal into a higher-dimensional, reconstructed space. The space created using these ‘fake’ observables allows us to study the true dynamics of the system in question because the reconstructed space is related to the original phase space by smooth, differentiable transformations; this preserves certain invariant features of the original dynamics, which may then be studied in the reconstructed space. There are several criteria for choosing the time lag to use in creating the reconstructed coordinate system and for establishing how many coordinates to use in reconstructing the space (i.e. establishing the embedding dimension of the reconstructed space); these will be discussed later.

Once the process of phase space reconstruction is completed, one proceeds in RQA by identifying data points that are neighbors (points which are close to each other) in the reconstructed space. Points separated in time but which are (spatial) neighbors in the reconstructed space reflect recurrence in time—as time progresses and the observed dynamics evolve, data points return to the same region of phase space (they recur). The basic idea is to take a sphere of radius r centered on a point $x(i)$ in the reconstructed space and to count the number of points which are within the distance r from $x(i)$. This is achieved for each $i = 1,\ldots, N$ (where N is the total number of data points), by measuring the distance between data points $x(j)$, where $j = 1,\ldots, N$, and $x(i)$. That is, for each data point in the embedded series, the distance between it and every other data point is calculated. If this distance is less than or equal to r, then the points are considered to be recurrent. The degree and nature of recurrence in a time series is represented graphically through the recurrence plot, developed by Eckmann et al. [22]. Fig. 1 displays a recurrence plot created by analysis of a COP time series from the data set discussed below. Each darkened pixel on the recurrence plot represents a recurrent point.

It is useful to reiterate the above process with reference to Fig. 1. Begin with a value of i along the abscissa; then, for each value of j along the ordinate, calculate the distance between $x(i)$ and $x(j)$. If this distance is less than or equal to r, darken a pixel at (i, j). Then, continue this process for all i. When $i = j$, a point is compared with itself, which will obviously result in a distance of 0 and identification of recurrence. This is seen in the central diagonal line in the plot. Also, for fixed r, the two triangular halves of the plot will be reflections of one another [16,17]; for the original [22] algorithm, r was allowed to vary adaptively (to accommodate a predetermined number of neighboring data points), and thus the two halves of the plot would not necessarily be mirror images. It should be noted at this point that several input parameters are required for RQA (e.g. time lag, embedding dimension, and r). One of the more difficult aspects of implementing and interpreting RQA lies in choosing input parameters. This will be discussed below in more detail.

Before presenting the quantitative measures derived from recurrence plots, some qualitative features [17,22] will be reviewed. A basic distinction may be made between large-scale typologies and small-scale textures [22]. There are three types of large-scale typologies: homogeneity, drift, and periodicity. Homogeneity refers to a homogeneous distribution of points throughout the plot, resulting in a roughly uniform plot. This is expected for white noise, which is random and uniformly distributed (there is no dynamical structure). However, such a typology may also be associated with deterministic chaos; the distinction between this and the previous example is apparent in the small-scale texture (see below). Fig. 1 does not display a homogeneous typology, as recurrent points tend to be clustered in distinguishable regions. Drift refers to a tendency of the plot

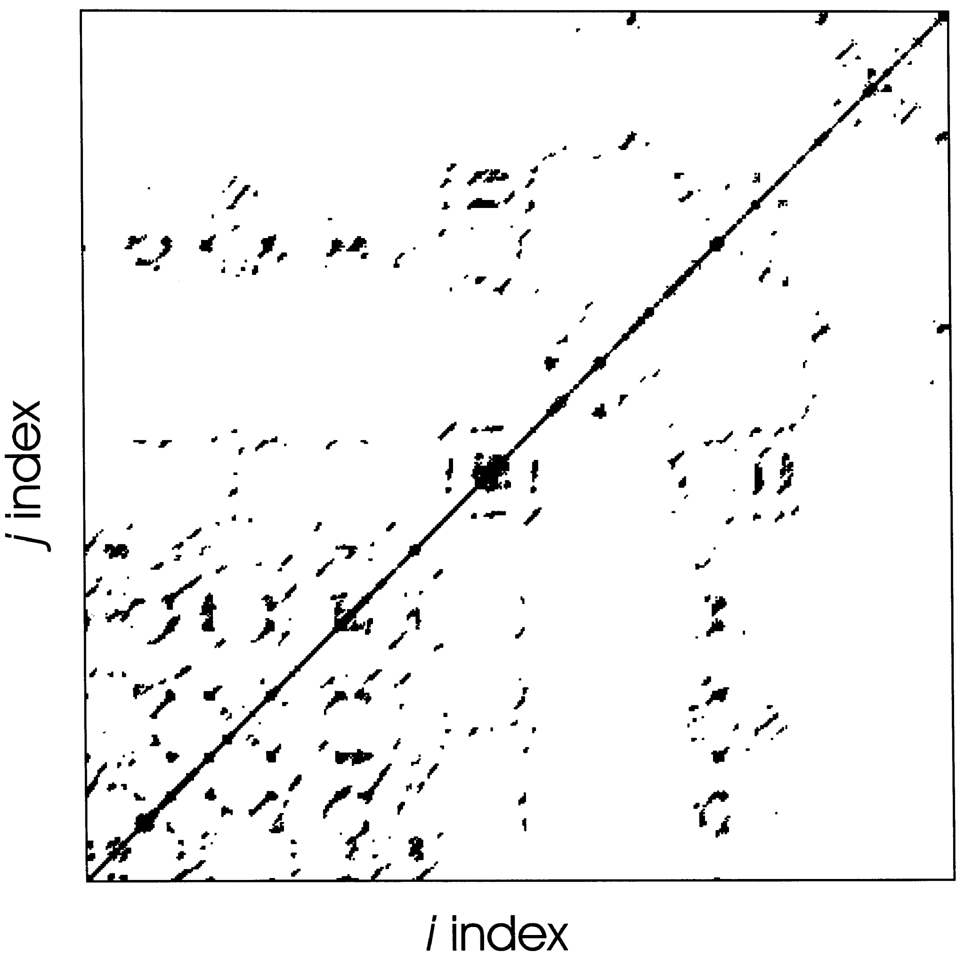

Fig. 1. Example recurrence plot of 30 s of COP data. Darkened points represent points which are recurrent in time (which are neighbors in reconstructed phase space). The main diagonal line results from comparing a point with itself. Input parameters were: embedding dimension = 10; time lag = 0.04 s; and radius $r = 10\%$ of the mean distance between data points in the reconstructed space (these parameters are discussed later in the text).

to pale with increasing distance from the main diagonal (the farther away from the diagonal, the fewer the points). If the paling is uniformly progressive, this may reflect nonstationarity in the form of a gradual trend. If the density changes abruptly, this may reflect a sudden change in level. Drift is readily apparent in Fig. 1. Finally, periodicity is indicated by the presence of long diagonal lines parallel to the main diagonal. As the name suggests, this typology reflects a strong rhythmic structure in the data. Fig. 1 does not exhibit periodicity.

Several types of small-scale texture may be identified. First, single, isolated recurrent points reflect random, stochastic behavior. Several such points may be seen in Fig. 1. Second, short line segments may be observed. If the segments are diagonal and parallel to the main diagonal, this means that strings of vector patterns in the time series repeat themselves multiple times over the observation period—this indicates determinism. In terms of attractor dynamics, this means the system revisited the same region of the attractor at different times. White noise would not be expected to show diagonal segments, but a deterministic system (a sine wave, a chaotic attractor, etc.) would. The length of the segments is inversely proportional to the magnitude of the largest Lyapunov exponent of the signal [22], and thus the maximum observed line length may itself be a measure of interest (we did not analyze this variable here). Several upward diagonal segments may be seen in Fig. 1. If the segments are diagonal but perpendicular to the main diagonal, vector sequences at different locations in the series are mirror images of one another. This is expected for simple oscillations such as sine waves—if a wave is bisected at a peak or trough, the resulting halves are mirror images. Such texture is not widespread in Fig. 1, but is present. If the segments are horizontal or vertical, isolated vector sequences match closely with a repeated string of vectors farther along the dynamic (separated in time). This is also present in Fig. 1. The third texture is the checkerboard texture, the grouping of line segments into small regions of the plot. This reflects the system visiting different areas of the attractor, and switching back and forth between them (e.g. for the Lorenz system, alternation between the attractor's two lobes). This texture is not present in Fig. 1.

Two more features may be identified [17]. First, bands of white space (no recurrent points) indicate transient activity or an abrupt level change, and may reflect an underlying state change. Large bands of white space are seen in Fig. 1. Second, there may be a sudden change in density of recurrent points as one moves along the axes of the plot. This indicates a possible change of dynamical regime, and may be observed after a transient period (e.g. it may be seen after a band of white space). This is not seen in Fig. 1.

While visual inspection of recurrence plots may be revealing, a significant advance was the quantification of recurrence plots (RQA) [17]. Five measures may be obtained by RQA: Percent recurrence (%RECUR), percent determinism (%DET), the ratio of these quantities (ratio), entropy, and trend. All of these variables are computed based on recurrent points in one triangular half only of the recurrence plot. The measures are briefly explained below; see Webber and Zbilut [17] for more details.

%RECUR is the number of recurrent points in the plot expressed as a percentage of the number of possibly recurrent points (i.e. of the total number of $i-j$ distance comparisons, with the exception of when $i=j$—the main diagonal). It is thus a measure of the extent to which the recurrence plot is covered by recurrent points, or, equivalently, the percentage of points within a distance r of one another. The level of %RECUR obtained for a given time series will depend to an extent upon the specified value of r. For Fig. 1, %RECUR = 0.59 (computations were made with input parameter values discussed below).

%DET is the percentage of recurrent points which fall on upward diagonal line segments. Observed levels of %DET will depend upon the specified definition of the number of points forming a line segment. This is usually set as two adjacent recurrent points with no intervening white space (larger, more conservative values may be chosen). %DET reflects the degree of determinism observed because, as stated above, upward diagonal line segments indicate that the system is revisiting the same region of the attractor (or of the reconstructed space) repeatedly. That is, the dynamics are reliable or repeat themselves, which is, essentially, what 'determinism' means. In Fig. 1, %DET = 59.60.

Ratio (%DET/%RECUR) may be useful in detecting changes in physiological state [16]. During changes in states, %RECUR usually decreases while %DET usually changes very little. This quantity is more useful to this end if RQA is performed using a moving window (over repeated epochs of data windows). In fact, all of the measures discussed here may be obtained in this fashion if changes in underlying state are of interest. We do not pursue this analysis here, but believe that this may be a valuable future direction.

Entropy is computed as the Shannon entropy of a histogram of line segment lengths (a simple frequency histogram in which the number of observed upward diagonal lines of different lengths are counted). Segments of particular lengths are counted and distributed over integer bins of a histogram, where each bin represents a possible line length. Entropy E is computed as

$$E = -\sum P_b \log_2(P_b) \quad (1)$$

where the P_b indicate bin probabilities of all nonzero bins greater than or equal to the number of recurrent points defining a line [17]. Bin probabilities are empirically determined based on the frequency with which lines of different lengths are observed. For example, if 100 upward diagonal lines—ten each of ten different lengths—are observed, then the probability of a given line falling in a given nonzero bin is 0.1. Entropy is a reflection of the complexity of the deterministic structure of the time series. This is because the entropy measure is computed not with respect to the entire recurrence plot, but only with respect to the upward diagonal lines which reflect deterministic structure. It is important to note, as recent debates have shown, that no one measure of overall system complexity has emerged as sufficient [23]. Nevertheless, entropy is a useful characterization of the deterministic structure of a given data set, as more complex dynamics will contain more line segments of longer lengths than is to be ordinarily expected (the probability of observing a line segment of a given length usually decreases with increasing line length [17]). Thus, a larger number of bits will be required to represent the distribution of line segments for more complex dynamics (resulting in a higher entropy value). Thus, we would expect deterministic chaos to yield a higher entropy value than either a noiseless sine wave (simple deterministic structure) or white noise (for which we would expect no, or at most a few, upward diagonal line segments, because it has no deterministic structure). Entropy computed for the distribution of line lengths for Fig. 1 was 1.73 bits.

Trend is a quantification of the paling of recurrence plots away from the main diagonal, and is computed as the slope of the line of best fit drawn for %RECUR as a function of distance from the main diagonal. Non-zero trend indicates drift in the system, while zero (or very close to zero) values indicate stationarity. Trend is expressed in units of %RECUR per 1000 data points, and, since trend is a quantification of the paling of recurrence plots away from the diagonal, trend values will usually be negatively signed (i.e. if %RECUR decreases with increasing distance from the diagonal, the regression line will have a negative slope). Computed trend for Fig. 1 was -0.51.

RQA is an ideal analytic tool for the analysis of COP data, and of physiological or biological movement data in general, in that it does not require data stationarity (nor does stabilogram-diffusion analysis [1,2]), any particular statistical distribution of the data, or any particular data set size. With respect to the latter point, it has been suggested that RQA may provide meaningful results even if the observation period is shorter than the characteristic times of the dynamic in question [17].

1.2. Vision and postural control

In the present paper RQA is applied to determine the effects of vision and of the specifics of optical structure on spontaneous postural sway. A well-known result under more basic analyses is that the body sways more, in both the AP and mediolateral (ML) directions, when vision is unavailable [24–26]. Recent experiments [2,5,6] on unperturbed stance have examined the effect of vision (eyes-open versus eyes-closed) on the short- and long-time scales of postural sway identified in the analysis of Collins and De Luca [1]. The results of these experiments suggest that postural variability (as indexed by the level of stochastic activity) and correlated COP activity decrease with eyes-open. The latter finding suggests that postural control is, in a sense, more on-line or moment-to-moment when vision is available then when it is not—decreased correlations may mean that the current postural state is less dependent upon previous postural states. A decrease in correlated activity with eyes-open means that, on average, COP motions are more similar to Brownian motion (a stochastic process with uncorrelated or independent increments) than with eyes-closed. One possible interpretation of this—an interpretation which is readily tested using RQA—is that with the eyes-closed, COP motions are characterized by increased deterministic structure. The increase in correlations with eyes-closed could also simply indicate a change in the bias of the correlated random walk process, however, and may not relate to increased determinism.

The experiment reported here was originally reported by Riley et al. [19] (their Experiment 2), who analyzed the data under stabilogram-diffusion analysis. In the experiment, participants looked at a layout of objects arranged in depth at a distance of approximately 1 m—a layout designed to enhance motion perspective and parallax (see description below). Participants' bodies were aligned perpendicular or parallel to the environmental arrangement (they either directly faced the arrangement or viewed it with the head turned to the side). The issue was whether vision's effect on postural fluctuations depended on the particulars of optical structure induced by the two head orientations. One hypothesis regarding the visual control of stance is that since AP sway results in radial transformations (expansions, dilations) of closed optical contours corresponding to frontal surfaces [27,28], this optical information is available for the control of stance. This makes sense if one is looking straight ahead, but not when one is looking to the side. For the latter case, it has been suggested that motion parallax may be more relevant [29]. ML sway is associated with motion parallax with the head facing forward and radial expansion/dilation with the head facing the side. If vision's effect on posture depends upon the details of optical structure, the effects of the particular environment that is viewed and the person's orientation to the environment should be seen in the structure of postural sway. Certain work [30] suggests, however, that optical specifics may be irrelevant—i.e. vision's effect is general, and the difference between eyes-open and eyes-closed depends only on the availability of perceptual information, whatever its form. Furthermore, these is reason to believe that vision is not necessarily a dominant modality in postural control. Perceptual information about posture and orientation from light fingertip contact with a nearby surface has the same effect on postural fluctuations as vision [6,31,32].

Riley et al. [19] found that the head-forward versus head-to-side manipulation resulted in one effect: negatively correlated COP activity over long time scales decreased for AP sway for eyes-open relative to eyes-closed, but only with the head-to-side. That effect means when the head faced the side and the eyes were open, AP sway showed a decreased tendency to reverse direction. They also found reduced effective stochastic activity with eyes-open, and, with the exception of the above finding regarding head orientation, that vision generally reduced correlated COP activity over both time scales. Collins and De Luca [2], Riley et al. [5], and Riley et al. [6] also observed these vision effects.

1.3. Aims of the present work

The current application of RQA to these data was designed to: (a) provide a baseline assessment of COP signals with respect to the degree of observed deterministic dynamical structure (%DET), the complexity of this deterministic structure (entropy), and COP nonstationarity (trend); (b) compare these measures across experimental conditions of eyes-open and eyes-closed and head-forward or head-to-side; and (c) evaluate the interpretation of an increase in correlated COP activity with eyes-closed as reflecting an increase in deterministic structure. In general, we expected COP data to show a blend of stochastic and deterministic dynamics (we expected to observe $0 < \%DET < 100$). We also evaluated if the nature of this blend would change as a function of the visual manipulations of eyes-open versus eyes-closed and head-forward versus head-to-side. Investigation of these issues is expected to provide significant insights into postural control mechanisms and processes. Classification of COP dynamics with respect to deterministic structure, complexity, and nonstationarity—and how these characteristics change under the present experimental manipulations of visual information—may reveal significant features of postural behavior for which models of postural control must account. For example, if observed, a blend of deterministic and stochastic behavior would indicate that both purely stochastic and purely deterministic models would be limited.

2. Method

2.1. Participants

Ten participants, four graduate students and six undergraduate students at the University of Connecticut, participated in the experiment. The graduate students volunteered, and the undergraduates received partial course credit. Five participants were male and five were female. All had normal or corrected-to-normal vision, and none reported a history of skeleto-muscular disorder or an injury at the time of the experiment. Participants' ages ranged from 17 to 31 years, heights ranged from 149 to 176 cm (mean of 158 cm), and weights ranged from 43.12 to 82.65 kg (mean of 59.93 kg).

2.2. Apparatus and data collection

COP data were obtained at a sampling rate of 100 Hz using a Kistler multicomponent force platform (Type 9281B) and Kistler charge amplifier (Type 9865) set to 10 000 pC on both principal axes of the platform. For each trial, participants stood barefoot on the platform, arms relaxed at the sides, feet abducted 10°, and heels 3 cm apart mediolaterally. Participants were instructed to stand still yet relaxed and to look at the depth-grating apparatus shown in Fig. 2. The depth-grating apparatus consisted of three rows of nine wooden dowels, with each dowel 0.8 cm in diameter. The dowels in a given row were 10 cm apart, and the distance between successive rows was 18 cm. Participants were positioned 122 cm from the nearest row. The whole apparatus was 92 cm wide (subtending a horizontal visual angle of 41.32° at the nearest row) and 105.6 cm high (subtending a vertical visual angle of 46.8° at the nearest row), and was positioned such that participants' eyes were directed roughly at its center. Participants were instructed simply to 'look at the apparatus', and were not instructed to focus specifically on the dowels or the wall behind the apparatus. Data collection was initiated after participants took position on the platform and signaled the experimenter that their breathing was normal and that they were ready to begin. There were ten trials in each of four experimental conditions: (1) eyes-open, head straight, (2) eyes-closed, head straight, (3) eyes-open, head sideways, and (4) eyes-closed, head sideways. Trials lasted 30 s each (yielding 3000 data points per trial), and participants were allowed to rest as needed.

2.3. Analysis procedure

Detailed instructions for implementing RQA may be found in Webber [33]. Here, we present a summary of the analysis. The first step in RQA is to determine appropriate choices of the following input parameters:

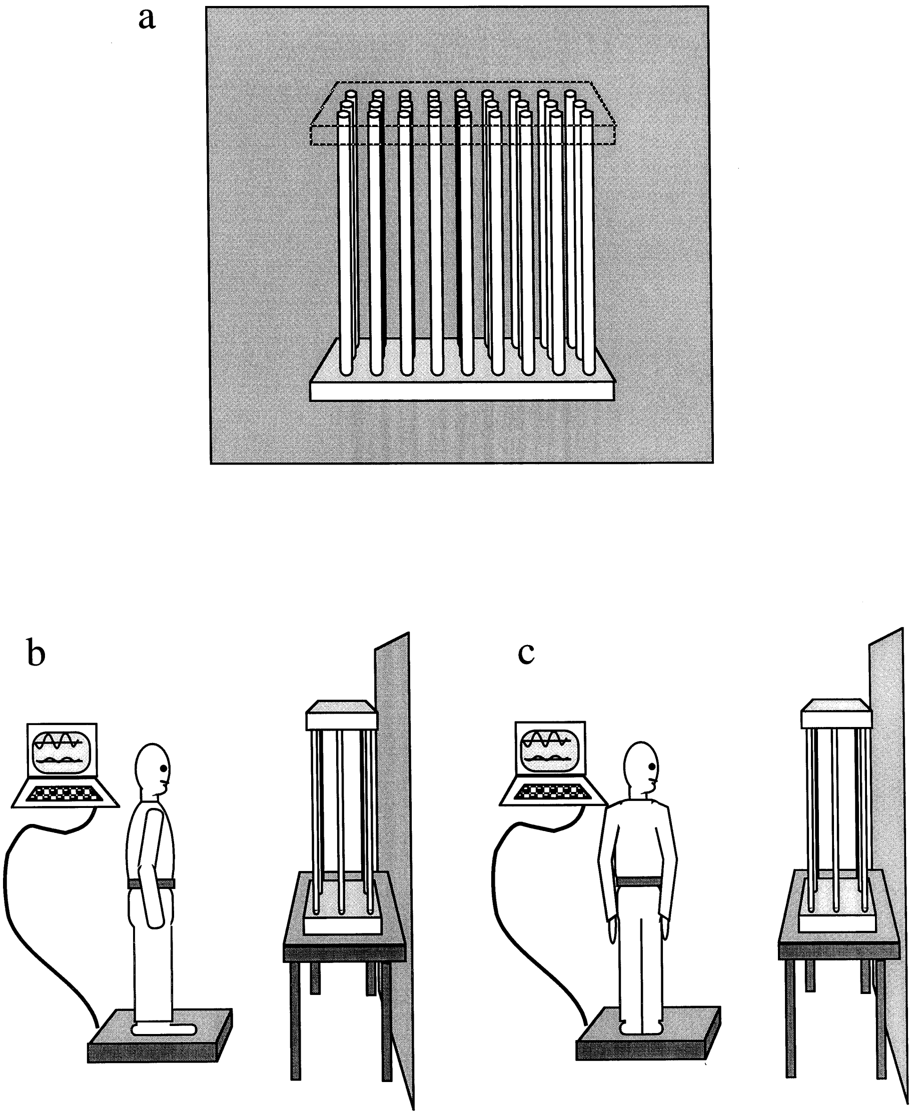

Fig. 2. Experimental apparatus. Panel (a) shows the depth-grating apparatus, and panels (b) and (c) show the two head orientations assumed by participants in relation to the apparatus. The depth-grating apparatus was designed to enhance optical transforms resulting from spontaneous postural sway.

time lag, embedding dimension, *r* (radius), and line length. With respect to choosing a time lag, there are two predominant prescriptions. The first is to choose the lag at which the first zero-crossing of the autocorrelation function (ACF) for the data occurs, or, if there is no zero-crossing, at which the first local minimum of the ACF occurs. However, for nonstationary data (including the present COP data), the ACF decays very slowly [33]. One option is to difference the data, and compute the ACF for this differenced series. This may not always be suitable, however [34]. Another prescription is to choose the first local minimum of the average mutual information (AMI) function [35]. However, because COP signals are usually stochastic and irregular and not periodic, the AMI function is rather 'messy' and shows no obviously distinct minima. Another option is to choose a time lag based upon obtained output measures [36]. Basically, as long as a time lag of 1 is not chosen (this tends to falsely linearize the data [33]), the choice of time lag for RQA is not utterly crucial. However, there is one strategy that may yield more optimal results for the choice of time lag (and for the other input parameters): compute RQA measures for a range of input parameter settings, and choose these settings from a range in which small increments in parameter settings yield smooth (i.e. not large, discontinuous jumps) changes in the output measures. In support of this strategy, Trulla et al. [37] noted that recurrence measures computed from the logistic equation changed little under changes in input parameters. As a method of checking the extent to which output measures may reflect artifactual results, RQA measures may be compared with those obtained from analyzing randomly shuffled data (samples are randomly re-ordered to create a new time series) under the same input parameter values as the intact data [17,38,39]. Random shuffling destroys time-correlation information in the series, and this should be reflected by a substantial drop in the magnitude of RQA measures. If random shuffling fails to substantially change obtained RQA measures, the choice of input parameters should be re-examined. Using this strategy, the time lag chosen here for COP time series was four samples (0.04 s). We also computed the ACF for several short, stationary segments of data taken from several randomly chosen time series. First zero-crossings were in the range of three to five samples, in agreement with the time lag chosen using the above strategy.

The situation is similar for choosing an embedding dimension. While there exist techniques for arriving at the embedding dimension [20], the point of RQA is not to obtain estimates of dimensionality. Thus, the same strategy as presented above is generally the optimal one: choose an embedding dimension from a range in which small changes in embedding dimension lead to correspondingly small changes in output measures, and check the validity of the setting by comparing the RQA measures of randomly shuffled data. The most important idea with respect to this parameter is to choose a high enough embedding dimension to allow for the interplay of a reasonable number of dynamical variables. It is generally best to err on the 'too high' side than the 'too low'. However, if too high an embedding dimension is chosen, the effects of noise may be amplified. Webber [33] recommends, for the analysis of physiological data, beginning with an embedding dimension in the range of 10–20 and working downward from there.

The choice of the radius r of the sphere to center on $x(i)$ is more principled. If one chose a radius $r = 0$, then only exactly matching points would be considered recurrent. Exact matches would be expected only for pristine mathematical examples, however. Thus, instead of exact matches, look for 'ball-park' matches. Generally, one prescription is to choose $r = 10\%$ of the mean distance between data points in the reconstructed space. Since the idea behind RQA is to look for local recurrences, using a very large r would result in deviation from this idea (e.g. approaching global recurrence). Furthermore, since r will affect observed values of %RECUR and %DET, one can track the behavior of %RECUR and %DET over changes in r, in accordance with the above strategy. Choose r such that obtained %RECUR responds smoothly and is not too high (e.g. stay local; $\%\text{RECUR} = 1 - 2$ is not too low) and such that %DET does not saturate at the floor of 0 or the ceiling of 100, as approaching these limits will tend to suppress variance in the measure (Webber, personal communication, March 1998). This strategy yielded a choice of $r = 10\%$ of the mean distance between data points in the embedding space for the present analysis. Another strategy is to plot, in log–log coordinates, obtained %RECUR over a range of r values and for a fixed time lag and embedding dimension (Zbilut, personal communication, June 1998). For values of r which are too low, the plot will oscillate (reflective of noise), while for an appropriate range of r the plot will be roughly linear.

Generally, the number of successive points defining a line segment should be 2. A value of 1 would be too low (all recurrent points would be 'lines'). Defining this number to be higher than 2 is a conservative approach, and may be wise if measurements contain a high degree of contamination. If the more liberal value of 2 is used, results may still (and always should) be checked against randomly shuffled data.

Given these choices of parameter settings, we proceeded as follows for each trial. The measured AP COP time series were embedded in a space of embedding dimension 10, using the measured signal and time-lagged (lag = 0.04 s) copies of the measured signal as coordinates.[2] Distances between points $x(i)$ and $x(j)$, for $i, j, = 1, \ldots, N$ were computed (using a Euclidean normalization [36]) to create the recurrence matrix. The recurrence matrix was rescaled by the maximum distance between points (other rescaling options are available; see Webber [33]), and computed distances were then compared to the pre-determined radius size $r = 10\%$ of the mean distance in the reconstructed space. Points separated by distances less than or equal to r were considered recurrent. %RECUR was computed as the percentage of recurrent points (the ratio of the number of observed recurrent points to the total possible number). %DET was computed as the percentage of recurrent points falling on an upward diagonal line, using a defined line length of two points. Ratio is the simple ratio of %DET to %RECUR. Entropy and trend were computed as defined above. These RQA measures were averaged across trials per condition for each participant and submitted to analysis of variance (ANOVA) with vision (eyes-open versus eyes-closed)

[2] Given the multi-dimensional aspect of RQA, and that the embedding theorem [21] states that measurement of only one variable of a system contains information about all of the dynamical variables in operation, ML sway was not analyzed separately in the present case. It is assumed that AP and ML sway are dynamically linked properties of postural control. In this case, analysis and comparison of both sway components would be redundant and illogical, and thus was not performed. However, this assumption is subject to scrutiny. Winter et al. [40] have argued for the independent control of AP and ML sway. This does not necessarily mean, though, that AP and ML sway are not dynamically linked variables in the manner in which the embedding theorem is concerned. Future studies to address this problem are certainly warranted.

and head orientation (facing forward or to the side) as independent factors. One trial for one participant was identified as an outlier based upon an observed value of %RECUR greater than the median for that condition plus two standard deviations [41]; data from this trial were discarded.

3. Results

Sample recurrence plots from each experimental condition from one participant are pictured in Fig. 3. All of the plots contain isolated single recurrent points (indicating the presence of noise), upward diagonal line segments (indicating deterministic structuring) as well as downward diagonal line segments and vertical/horizontal line segments, and bands of white space (indicating short-term transient behavior). These plots are representative of plots for each condition, though there was a great deal of inter-subject variability—and, for each subject, inter-trial variability—in the qualitative features of the plots. The most notable qualitative differences between these plots which are consistent with the quantitative measures reported below are: (1) an increase in the number of upward diagonal line segments for eyes-closed (most easily observed by comparing the two vision conditions in the head-forward condition); (2) more pronounced paling of the plot with increasing distance from the main diagonal (drift, or trend) for eyes-open than eyes-closed conditions with the head to the side, while no such difference between eyes-open and eyes-closed was observed with the head facing forward; and (3) increased drift (trend) with the eyes-open for the head-to-side relative to the head-forward condition. The large degree of within-condition variability in the plots, and the difficulty in determining consistent qualitative differences across conditions, highlight the need for the quantitative measures.

3.1. Time correlation and deterministic dynamics in COP trajectories

%RECUR is a quantification of time correlation—it quantifies the percentage of points which, over time, return to the same local neighborhood in the reconstructed phase space. ANOVA on %RECUR with vision (eyes-open versus eyes-closed) and head orientation (facing forward or to the side) as indepen-

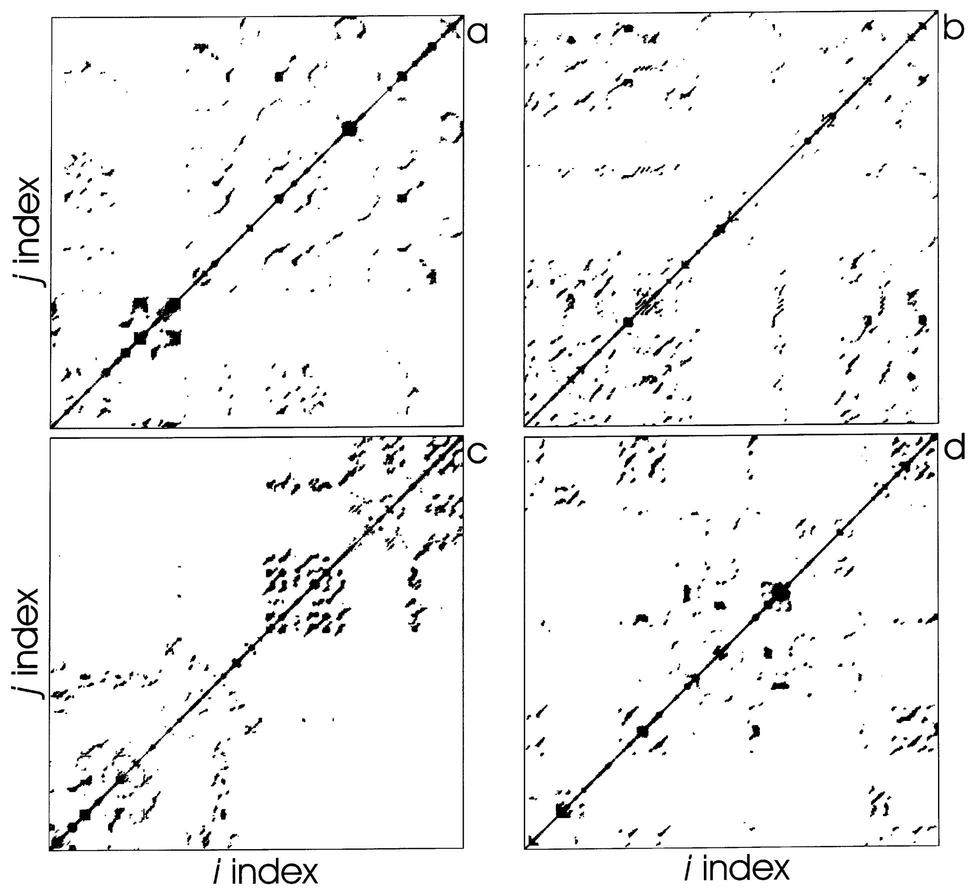

Fig. 3. Sample recurrence plots of COP data from each of the 4 experimental conditions: (a) head straight, eyes-open; (b) head straight, eyes-closed; (c) head-to-side, eyes-open; (d) head-to-side, eyes-closed. Input parameters were: embedding dimension = 10; time lag = 0.04 s; and radius $r = 10\%$ of mean distance.

dent factors revealed no reliable (e.g. $p < 0.05$) effects. However, the interaction between vision and head orientation was marginally significant ($F(1,10) = 4.54$, $p = 0.059$). There was a tendency for %RECUR to increase with eyes-open with the head facing the side, while with the head facing forward there was no difference in %RECUR as a function of vision.

One of the fundamental issues in the present paper was to determine if COP series contained deterministic structure. Deterministic dynamics in the COP time series were observed (overall mean %DET = 64.23). Random shuffling of the data destroyed this structure, suggesting that the finding reflects a true property of COP dynamics (see below). Another issue examined here was that of the effects of the availability of visual information on COP dynamics. ANOVA on %DET revealed a main effect of vision ($F(1,10) = 8.56$, $p < 0.05$). %DET was higher with eyes-closed (mean of 66.49) than with eyes-open (mean of 61.96). Vision's effect on the deterministic structure of COP series was largely a gross one—%DET increased when vision was not available, but was not affected by the specifics of optical structure (no effect of head position was observed).

ANOVA on ratio (%DET/%RECUR) revealed the main effect of vision as well ($F(1,10) = 8.16$, $p < 0.05$). This essentially stems from the main effect observed for %DET. The interaction between vision and head position approached but did not reach significance ($F(1,10) = 3.9$, $p = 0.077$). The eyes-open versus eyes-closed difference tended to be more pronounced in the head-to-side condition.

3.2. Complexity of COP dynamics

Entropy is one quantification of the complexity of deterministic dynamics observed in the data. For the present data, ANOVA on entropy revealed a main effect of vision ($F(1,10) = 5.29$, $p < 0.05$). The number of bits of information required to describe the distribution of line lengths was higher for eyes-closed (mean of 1.99) than eyes-open (mean of 1.83). This result suggests that deterministic COP dynamics were more complex when the eyes are closed. However, since entropy values are computed from the deterministic structure (upward diagonal line segments) of the time series, and since entropy values are not normalized with respect to %DET, observed entropy values may have depended upon the observed level of %DET. Thus, it is possible that the main effect of vision observed for entropy was a simple consequence of the corresponding main effect observed for %DET. Simple linear regression revealed a significant positive correlation between the two dependent variables ($r^2 = 0.84$, $p < 0.01$). To control for this correlation, multiple analysis of variance (MANOVA) was computed with the same independent factors as above and with %DET and entropy as dependent factors. Under MANOVA, the effect of vision on entropy approached but did not reach significance ($F(1,40) = 3.15$, $p = 0.08$).

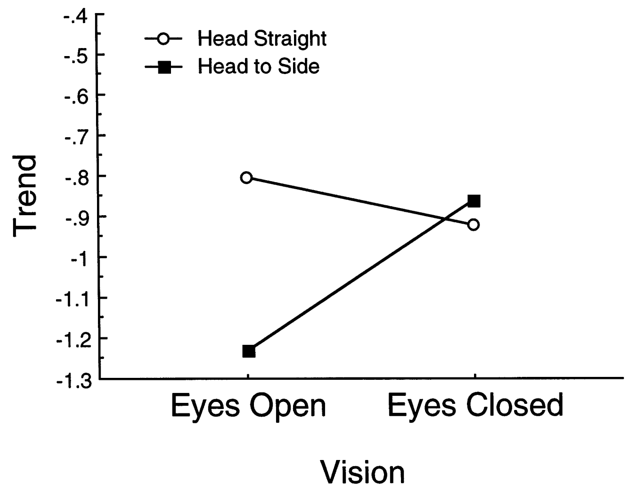

Fig. 4. Interaction between vision and head orientation for trend (the measure of COP nonstationarity). No differences in trend were observed with eyes-closed or when looking straight ahead. Trend increased in magnitude with eyes-open relative to eyes-closed when looking to the side, and with eyes-open was greater in magnitude when looking to the side relative to looking straight.

3.3. COP nonstationarity

Trend reflects the paling of the recurrence plot with increasing distance from the main diagonal, and is computed as the line of best fit drawn for %RECUR as a function of distance from the main diagonal. Trend is expressed in units of %RECUR per 1000 data points. ANOVA on trend revealed a significant interaction between vision and head orientation (head facing forward or to the side), $F(1,10) = 4.73$, $p = 0.05$. This interaction is pictured in Fig. 4. Looking at the depth-grating apparatus in the head-forward condition tended to maximize radial expansions and contractions of closed optical contours, while looking at the apparatus in the head-to-side condition tended to maximize motion parallax. Planned comparisons revealed that trend magnitude (all trend values were negatively signed) was significantly lower for eyes-closed (mean of -0.86) than for eyes-open (mean of -1.23) when the head faced the side ($F(1,10) = 5.41$, $p < 0.05$). There was no effect of vision in the head-forward condition. Planned comparisons also revealed that the difference between eyes-open/head-forward (mean of -0.80) and eyes-open/head-to-side (mean of -1.23) was significant ($F(1,10) = 7.33$, $p < 0.05$). COP nonstationarity increased with the head to the side when the eyes were open (i.e. in the experimental condition designed to enhance motion parallax information).

3.4. Surrogate data testing

The results of RQA for several randomly chosen trials were compared with results obtained after shuffling the data point order for these trials. Random shuffling effectively destroyed all structure revealed under the input parameter values chosen (for example, %DET dropped to around 0–5%). Furthermore, in order to obtain comparable levels of %RECUR for the randomly shuffled trials, r had to be set to nearly 50% of the mean distance (compared with 10% for the intact data). Even with such a high r, the %DET, entropy, and trend measures were still dramatically lower for the randomly shuffled data, and, furthermore, recurrence plots showed the homogeneous typology and did not at all resemble those for the intact data. Thus, it may be concluded that the results obtained under the present parameterization reflect true properties of the temporal evolution of the COP, and that COP dynamics contain a degree of deterministic structure. It must be emphasized, however, that slight changes in input parameters did yield slight changes in output measures, and therefore the obtained RQA measures may not be interpreted as absolute quantities (e.g. it is fair to say that COP signals contain deterministic structure, but it is not fair to say that 'postural sway is about 65% deterministic').

4. Discussion

In this paper, we provided a quantification of certain dynamical properties of COP signals and showed how these properties changed under manipulations of the availability of vision and of the available optical structure. The present analysis suggests potentially important features of postural fluctuations which may shed light on underlying mechanisms and processes. First, we observed that COP signals contain a degree of deterministic structure (%DET was $\approx 60–65\%$ under the current parameterization for the intact data, and $\approx 0–5\%$ for the randomly shuffled data). This reinforces the view that postural sway is not purely random, and contains subtle structure in the form of time correlation information which may be extracted by advanced analytic techniques [1,5,6,19]. This further suggests the possibility that deterministic and stochastic processes are perhaps braided together in the control of posture, such that numerous and effectively random small-scale fluctuations co-exist with deterministic dynamics (which may reflect perceptually-guided control). One example of such a braiding is piecewise-deterministic dynamics, which involves trajectories that are deterministic but that also are influenced by noise near singular points (i.e. noise can cause jumps to unique trajectories) [18]. The existence of piecewise determinism in COP dynamics remains to be explored.

Nonstationarity in COP data, as has been previously noted [7,9–11], was also observed. Nonstationarity of the COP is expected from a consideration of COP trajectories as fractional Brownian motion [1,2,5,6,19]. COP nonstationarity may be a fundamental characteristic of postural control, and may reflect motions about a moving, rather than static, set-point or frame of reference [42–44]. Set-point dynamics would account for global trends in COP motions, while local variability would reflect deviations about the set point [44]. This scheme is generally consistent with the braiding of deterministic and stochastic dynamics discussed above. From this perspective, set-point dynamics are stochastic, and local variability is due to stabilization with respect to the set point via closed-loop, deterministic (damped nonlinear oscillator) dynamics [42]. Nonstationarity might also be an intrinsic feature of dynamic stabilization of an unstable state, such as maintaining the upright posture or balancing an inverted pendulum through motions of the hand. Treffner and Kelso [45] have noted that one strategy in balancing an inverted pendulum is a 'running' strategy, wherein relatively large though brief displacements result in an overall change in level in the time series. This strategy is one of going with, rather than resisting, the dynamics of the system (e.g. not countering a brief tendency to lean) until a constraint (such as a stability boundary) threatens task performance, at which time the run must be countered through appropriate muscular action. If nonstationarity stemming from the sources postulated above is a typical feature of postural control, then perhaps one clinically-oriented use of RQA would be to assess if and how COP nonstationarity changes with disease or aging.

An increase in deterministic structure when the eyes were closed was observed, in accordance with the above interpretation of results from stabilogram-diffusion analysis. There was also a tendency for this structure to increase in complexity when the eyes were closed. An increase in deterministic structuring of postural sway in the absence of vision is perhaps a counterintuitive idea if only the common finding of an increase in sway variability or amplitude is considered [24–26], but is consistent with other results [2,5,6,19]. This may reflect a process of increased exploratory, information-generating behavior with the eyes-closed, if, as is commonly held, postural control is in some sense made easier when vision is available (but see Stoffregen and Smart [46]). An alternative interpretation is that increased determinism with eyes-closed reflects a conservative strategy adopted by participants—a strategy of increasing the controllability of sway to compensate for decreased perceptual sensitivity associated with the absence of vision. The notion of a conservative strategy would have to be reconciled, however, with the increase in variability observed with eyes-closed (and observed by Riley et al. [19] for these data, in particular).

We also observed a change in the nonstationary properties of postural sway as a result of the head orientation manipulation. With the head-forward, AP sway results in radial expansions and dilations of closed optical contours, while ML sway results in motion parallax. With the head facing the side, AP and ML body sway (with sway defined with respect to trunk orientation, not head orientation) produce the reverse effects. Given that AP sway is usually of higher magnitude than ML sway (due to greater biomechanical range of motion in the AP direction; increased sway variability in the AP direction was also empirically demonstrated in these data by Riley et al. [19]), the effect of turning the head to the side is to increase motion parallax relative to radial transformations. The result of this optical manipulation (effected by changing the orientation of the head with respect to the layout of environmental surfaces) was increased trend for eyes-open relative to eyes-closed that was observed only when the head faced the side. When the head faced forward, there was no change in trend as a function of eyes-open versus eyes-closed. Furthermore, the RQA trend measure was higher for eyes-open when the head faced the side than when the head faced forward. These results suggest that increased motion parallax information resulted in an increase in COP nonstationarity. In accordance with the above interpretation of COP nonstationarity, this could mean that when motion parallax information is heightened, the running strategy—which would tend to momentarily further heighten parallax information as the body moves in one direction for a brief, though sustained, period—becomes more prominent (i.e. increased drift in the dynamic set point is observed). Such a possibility would reflect the postural control system's exploitation of enhanced visual information.

The findings regarding increased COP nonstationarity highlight the importance of being able to quantify nonstationarity. The stabilogram-diffusion technique used by Riley et al. [19] only quantified the degree of stochastic activity of the COP and the correlation structure of COP signals over short and long time scales. With respect to the head orientation/optical structure manipulation, the effect that Riley et al. observed was that when the head faced the side, negative correlations between data points separated by large time intervals decreased in strength for AP sway. Such a decrease in negative correlations indicates that when the head faced the side the tendency of the COP to reverse direction decreased with the eyes-open relative to eyes-closed. This result is interpretable with respect to the present finding of an increase in nonstationarity (if the COP reverses direction less often, COP signals will tend to drift), but without the present finding of an increase in the RQA trend measure, such an interpretation of Riley et al.'s data is not as readily apparent.

5. Conclusions

These findings regarding vision and optical structure suggest that RQA may be a valuable tool for the analysis of COP data. An appealing feature of RQA is that it may be used to quantify the extent and nature of observed deterministic structure in a series. Furthermore, RQA can also quantify nonstationarity, and the attained quantification may then be compared across experimental conditions. Future applications of RQA could include the computation of RQA measures over time for measured COP signals (e.g. the moving window analysis mentioned above) in order to determine if underlying changes in physiological state occur over the course of experimental trials. For example, the presence of fatigue could be examined in prolonged standing. Webber et al. [47] have examined (using RQA) the signature of fatigue in EMG signals taken from the biceps brachii of human participants. In this case, fatigue was induced by adding heavy loads during the task of maintaining a constant joint posture for a prolonged period of time. An analysis of postural motions could easily be compared to these EMG data. Other applications could include the effects of aging or of disease on postural fluctuations. With respect to the latter application, a common understanding of disease, from a dynamical perspective, is as increasingly stereotyped or regular (e.g. periodic) behavior in a system whose healthy function is not characterized by such regularity [48]. This hypothesis—and the issue of COP nonstationarity and disease, as discussed above—could be assessed using RQA of COP signals in the context of various vestibular, skeletal, or neuromuscular disorders in which postural control and stability are jeopardized. Furthermore, RQA might also be used, as an alternative to stabilogram-diffusion analysis, if strong periodic components in the data (which might arise, for example, when participants are exposed to a periodic visual display) render parameter estimates from the stabilogram-diffusion plot unreliable.

As a final note, the initial difficulties associated with choosing RQA input parameters are re-emphasized. Deciding upon the correct parameterization requires careful examination of the data under a variety of parameter settings. Results obtained under each parameterization must be compared against randomly shuffled data in order to confirm that they reflect actual processes revealed by the time evolution of the series in question rather than some form of chance occurrence or measurement error. It must also be re-emphasized that obtained RQA measures cannot be considered as absolute; they must be taken with respect to shuffled data and with respect to levels of a manipulated variable (e.g. degrees of change in RQA measures as a function of experimental conditions). With these caveats in mind, RQA may prove to be a valuable means of analyzing COP data as well as data from other biological movement contexts.

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