Postural stability and fractal dynamics

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Abstract. Methods of non-linear dynamics and deterministic chaos may provide us with effective quantitative descriptors of the dynamics of postural control. The goal of this study was to introduce a new measure, which would allow to determine the fractal structure of posturographic signals and to measure the effect of the loss of visual feedback information in postural control. The results of the study show that fractal dimension (D_f) is a very useful, reliable and sensitive measure of the complexity of posturographic signals. Therefore D_f can be used for the evaluation of postural stability and its changes due to pathology or an age-related decline.

Key words: posture, postural stability, elderly, non-linear dynamics, fractal dimension

INTRODUCTION

The upright posture is defined by mutual relationships of the body segments and the global, vertical orientation of the body in the gravitational field. Such the orientation in addition to a narrow base of support and multi-segmental body architecture determines a potential instability of the posture. The classical definition of the postural stability is based upon the center-of-mass (COM) position and its displacements within the base of support (Blaszczyk et al. 1994a). Only due to an active control of the COM position in the space and particularly in respect to the psycho-physiological stability borders, the system remains stable (Błaszczyk et al. 1994a). The nature of the control i.e., nonlinearities of the neuro- muscular control causes that COM is not maintained in a single point of the space but oscillates around it. These tiny movements in the literature are described as a postural sway. In the research on postural control an easy accessible sway component, the center of foot pressure (COP) is usually exploit. The COM position signal, while transmitted to the support surface is transformed by the dynamical, multi-linked system of the body. The final effect of this transmission is observed at the base of support as a compound COP signal. Thus, the COP reflects not only characteristics of the COM excursions but also exhibits properties of active signals used in the control of equilibrium (Maki 1986, Prieto et al. 1993, Blaszczyk et al. 1994b, Winter 1995). Thus, as can be expected the COP signal may give a better insight into quality of the equilibrium control. This hypothesis gained a strong support from the studies of Sheldon (1963). He first showed that the inability to control sway in the elderly is a major cause of their postural instability. Postural instability is, in turn, a commonly accepted risk factor that contributes to falls in the elderly population.

The COP is an easily accessible signal. In posturography the COP is measured by a force plate, therefore as a simple noninvasive technique it is frequently used in medical diagnostics. The major drawback of posturography is lack of reliable and sensitive sway determinants that could be used for the evaluation of pathological changes (Baloh et al. 1998). This results in a rather limited diagnostic value of this method (Hufschmidt et al. 1980, Takagi et al. 1985, Carroll and Freedman 1993, Blaszczyk et al. 1993).

It is implicitly assumed that postural sway is a stationary process. This assumption is not true in most cases (Carroll and Freedman 1993). For this reason Collins and De Luca (1994, 1995) applied the theory of stochastic (random) processes to the analysis of postural control mechanisms. They hypothesized that there are two processes in the control of posture: open- and close-loop. However, more profound analysis of postural control suggests that consideration of the two mechanisms may be inadequate to for its analysis and thus premature. The stochastic properties of the random walk of the COP trajectory in quiet, upright stance remains to be elucidated (Newell et al. 1997).

In the present research, the problem of characterizing postural control is approached from the perspective of nonlinear dynamics and chaos theory. Nonlinear dynamics brought us new concepts and tools for detecting chaos in physiological systems (West 1990, Schiff et al. 1994, Myklebust et al. 1995, Accardo 1997). Chaotic phenomena may be observed only in systems exhibiting nonlinear characteristics, i.e. where reactions are not simply proportional to the applied stimuli. "Chaotic" is a term assigned to a deterministic process which, because of extreme sensitivity to initial conditions and system's parameters, for an observer may seem to behave completely randomly. Chaotic systems are deterministic and should not be confused with random (stochastic) systems i.e., systems govern by laws of probability. Unlike random systems, deterministic chaos may be rather easily controlled (Schiff et al. 1994). Many physiological systems including postural ones are chaotic (West 1990, King 1991, Myklebust et al. 1995).

In the postural system there exist strong nonlinearities due to elastic and damping properties of muscles and nonlinear feedback control (delays and thresholds) in the nervous system. Thus, displacements of the COM and correlated with them the COP oscillation during quiet stance are good candidates to measure the chaotic movements of stance (Myklebust et al. 1995). Since methods of non-linear dynamics and chaos theory (Schuster 1988) may supply us with effective quantitative descriptors of underlying dynamics in complex systems, we hypothesize that one can determine the properties of neuromuscular control based upon the COP signal analysis. If postural sway is really chaotic one can expect that there exists a relatively simple dynamical mechanism of balance regulation that will make possible to introduce new therapeutic and preventive strategies for treatment of postural instability.

Commonly used posturographic measure - the center of foot pressure - is a non-stationary signal. Therefore standard time and frequency analysis methods may not be adequate for monitoring the dynamic changes in the body sway. The ability to classify the nature of COP oscillations can provide a clue for controlling them. Classical methods of spectral analysis of posturographic recordings (Soames and Atha 1982, Powell and Dzendolet 1984, Yoneda and Tokumasu 1986, McClenaghan et al. 1994, Winter 1995) and other simple methods of analysis (Hufschmidt et al. 1980, Taguchi 1985, Takagi et al. 1985, Jeong 1994) turned out to be not sensitive enough. Methods of non-linear dynamics and quantitative descriptors (e.g., attractor's fractal dimension, Lyapunov exponents etc.) may be applied for the analysis of these signals, thus permitting assessment of various normal and pathological states of the posture control system (Myklebust et al. 1995). However, to compute the above mentioned chaotic quantifiers it is necessary to reconstruct from raw data astrange attractor in multi-dimensional phase space. Reconstruction of chaotic attractors from experimentally measured signals in the form of time series is far from trivial. It consumes a lot of time, needs high computing power and the results are difficult to comprehend for most clinicians. Thus, we must search for the characteristics of the measured signals that might be relatively easily computed and which would help the doctors in diagnostics. Here we consider application of the COP and the COM fractal dimension (D_f) for analysis of postural stability. We posit that this analysis will give researchers a new measure that can be used for the evaluation of quality of the postural system which will allow a better understanding of the postural sway behavior.

METHODS

Twelve healthy elderly subjects mean age 71.5 ± 3.6 years volunteered, signed an informed consent, and agreed to participate in the experiment. All subjects reported having no neurological or movement disorders and that they were engaged in regular physical activity. During the test, subjects were asked to stand barefoot on the force platform in a comfortable stance and to stay still for 2 minutes. Their body sway was recorded during two trials separated with a five-minute break. The task was performed in the two experimental conditions: first, while standing with eyes open (EO), and next, with eyes closed (EC). The postural sway was assessed by recording both: the center of mass (COM) and the center of foot pressure (COP) displacements. The COP was recorded using an AMTI (Model OR65-1) force platform. The COM position was calculated from 21 infrared light--emitting diodes attached bilaterally to anatomical landmarks that define a fourteen-segment model (Yeadon and Morlock 1989). The force platform and Optotrack data were sampled at the same frequency of 20 Hz.

Complexity of the COM and the COP were evaluated using fractal dimension of the signals. D_f was calculated independently for the anteroposterior (AP) and mediolateral (ML) components of the COP and the COM, for all subjects and for both experimental conditions. The data analysis was made off-line using custom-design software for calculation of fractal dimension (cf. Appendix). T-tests for dependent samples were performed to compare the fractal dimensions of the COM and the COP data and to analyze the effect of the experimental conditions (EO *versus* EC).

RESULTS

Fractal dimension analysis was applied for the evaluation of the postural control in elderly subjects. Validity of this method has been evaluated by analyzing characteristics and relationships between the COP and the COM in two commonly used experimental situations: while standing quietly with eyes open and eyes closed. Examples of such recordings are given in Fig. 1.

In the COP signals, there was a significant difference between fractal dimension of anteroposterior (AP) and mediolateral (ML) sway components. In the eyes-open condition the mean (± SD) fractal dimension of the COP for AP excursions was much greater than that in the ML direction (1.57 ± 0.13 and 1.29 ± 0.14 for AP and ML respectively). The difference was statistically highly significant ($t = 9.8$, $P<0.00001$).

Fractal dimensions of the COM displacements were significantly smaller than these parameters describing the COP excursions. Fractal dimension of the COM was 1.39 ± 0.16 for the AP direction and 1.09 ± 0.12 for the ML displacements. The t-test for dependent variables revealed a significant difference between the COM and the COP fractal dimensions ($t = 12.95$, $P<0.000001$ for AP movements, and $t = 4.47$, $P<0.001$ for the ML component).

Eyes closure resulted in the increase of the postural sway and in changes of its characteristics. The changes were reflected by the increase of sway fractal dimension. During the eyes closed trials the mean fractal dimension of the anteroposterior COP increased to 1.63 ± 0.16 and the mediolateral D_f was also greater (1.32 ± 0.17) in

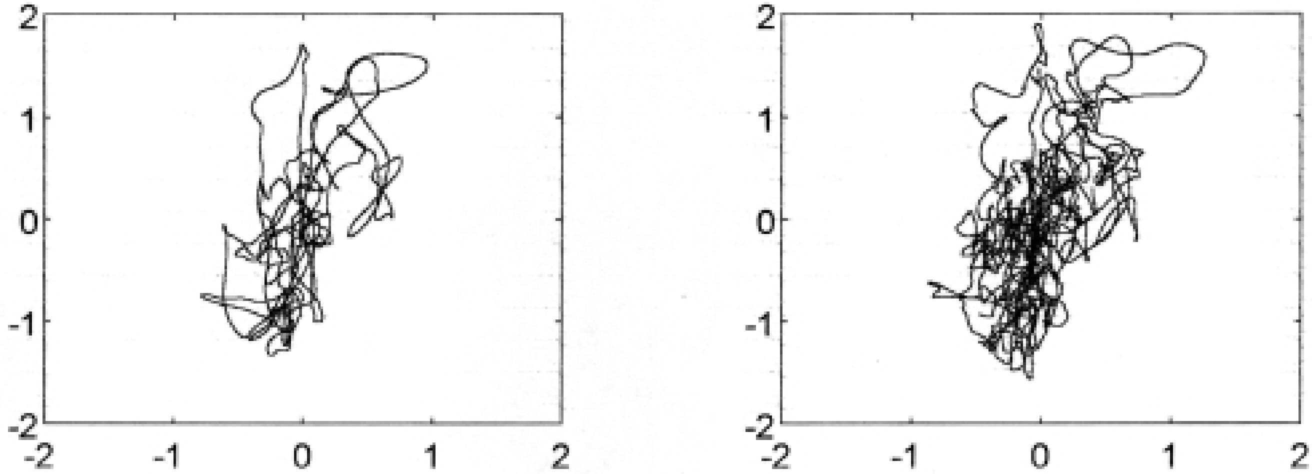

Fig. 1. Example of the COM (left panel) and the COP (right panel) signals recorded simultaneously during quiet stance in a 2-minute trial (subject EN/01, age 74 years). Orthogonal axes show the displacements in millimeters.

these conditions. The increase of the fractal dimension reached the level of significance for the AP direction only ($t = -3.29$, $P<0.008$). The results of this analysis are summarized in Fig. 2.

The same tendency i.e., an increase of fractal dimension was seen in the COM data. Both AP and ML components exhibited a higher fractal dimension in the EC conditions compared to the EO trials. D_f values for COM were 1.43 ± 0.16 for the AP excursions and 1.14 ± 0.16 for the ML displacements. These differences, however, did not reach the level of significance. Results of the COM fractal dimension analysis are depicted in Fig. 3.

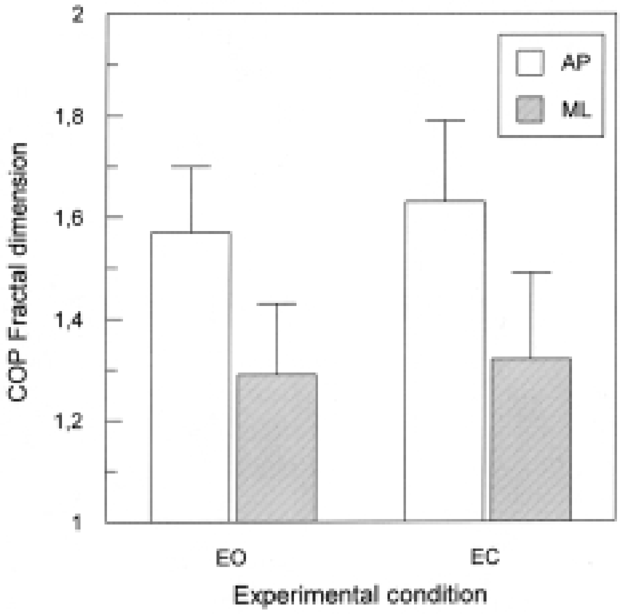

Fig. 2. Mean value of the center-of-foot pressure fractal dimension in the elderly subjects while standing on the force platform with eyes open (EO) and eyes closed (EC).

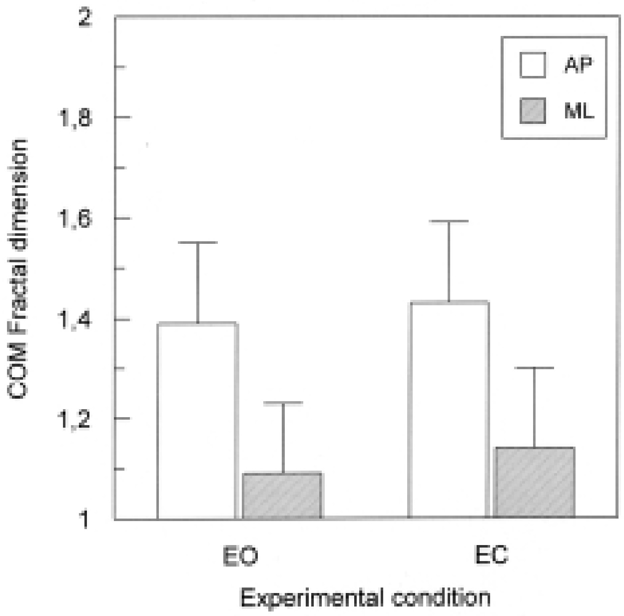

Fig. 3. Mean value of the COM fractal dimension in the elderly group during quiet stance with eyes open and eyes closed.

DISCUSSION

We applied the fractal dimension method to two major posturographic signals: the COP and the COM measured in the elderly subjects. We showed that a decrease of postural stability is accompanied with an increase of signals' fractal dimension. Both signals were collected in two experimental conditions: while standing still with eyes open and with eyes closed. In the latter case the absence of visual feedback was followed by an increased oscillation of the COM and the COP. As the result, an increase of chaos in the postural signals was observed.

Our studies showed that chaos in physiological systems may be characterized and quantified by calculating fractal dimension, D_f, of the time series representing a biological signal (Accardo 1997). This method, in contrast to an attractor's fractal dimension, does not require preliminary reconstruction of the system's phase space but can be directly applied to experimental data. So it is more intuitive to apply and a less time-consuming method. D_f denotes the fractal dimension of the signal's time series itself and should not be confused with attractor's fractal dimension measured in the system's phase space. For a simple smooth curve its fractal dimension is equal 1; for a curve which nearly fills out a two-dimensional plane, D_f is close to 2. D_f of the curve representing the signal under consideration is a measure of complexity of this curve, thus it may be used as a useful characteristic of this signal and so of the dynamics of the processes that generate it. So far the applicability of D_f has been demonstrated on EEG-signal analysis (Accardo 1997). It is worth to notice that the fractal dimension allows to reduce the amount of data without losing diagnostically important information which spectral analysis supplies. For calculation of D_f the box-counting procedure (also called "capacity dimension") or the even more convenient method proposed by Higuchi (1988) may be applied.

The COP and the COM characteristics were analyzed in order to evaluate their applicability in the diagnostics of postural stability. Because the difference between COP and COM signals is directly related to the horizontal acceleration of the COM, it can be considered as the error signal that the balance control system is sensing (Winter 1995). The magnitude and frequency of this error signal is of importance in the interpretation of the balance control system. The postural control system integrates information from the visual, vestibular, and proprioceptive inputs. If one or more of these inputs is impaired as part of the aging process, or in neurologic disease, then the postural system must adjust the relative weighting factors of the inputs to maintain balance (Prieto et al. 1993). Thus a decrease of feedback would elevate the amplitude of an error signal and its distortions. Frequency changes, however, are not so straightforward due to specific frequency characteristics of each feedback channel. An increased amplitude of COP in the elderly population has been reported as a result of progressing postural discontrol (Sheldon 1963, Dornan et al. 1978, Brocklehurst et al. 1982, Horak et al. 1989, Błaszczyk et al. 1994b, Collins and De Luca 1995). In all studies of normal subjects the COP amplitude was higher when the subjects stood with their eyes closed (Brocklehurst et al. 1982, Black et al. 1982, Diener et al. 1984, Prieto et al. 1992). In our studies elimination of the visual input resulted also in the increase of the chaos in each posturographic signal. Standing with eyes closed is a commonly used test in posturography. Such a test excludes one of the major inputs to the postural system. The impoverished control must inevitably challenge the postural balance (Horak et al. 1989, Błaszczyk et al. 1993, 1994a, Winter 1995, Collins and De Luca 1995). It results in the increase of sway fractal dimension. This effect could be clearly observed in the COP signal but not in the COM. This may suggest that the COP is a more sensitive measure of instability. As we suggested previously (Blaszczyk et al. 1993) increased sway might act as noise in postural control especially in the proprioceptive control of the equilibrium. Therefore, the postural stability might be further decreased by a significant decline of the signal-to-noise ratio and resultant decline of sensory sensitivity. However, the effect of noise in the nervous system is not so obvious. An increase of the noise in some instances may improve the control due to a stochastic resonance phenomenon (Noest 1995, Ivey et al. 1998).

Our results are in good agreement with all well-documented facts about postural control. The fractal dimension analysis showed that upright posture is asymmetrical in the frontal and the sagittal plane (Błaszczyk et al. 1993, 1994a, Winter et al. 1996). Higher fractal dimension of the antero-posterior sway component indicates a higher tendency for instability in this direction. This observation can be simply derived from the anatomy of the human body (Błaszczyk et al. 1994). As could be expected, the age-related decline in the control of stability showed a greater effect in the antero-posterior plane, which is the weakest element of the postural control. It was documented in our previous studies that in particular, the posterior border of stability is mostly deteriorated in the elderly and they are prone to fall in this direction (Błaszczyk et al. 1994a,b). The effect of the increase of instability was not clearly pronounced in the COM due to low-passed inertial filtering of the signals by the body mass (Benda et al. 1994).

In summary, the fractal dimension is an easy accessible measure that could be used for the study of COP and

COM complexity and thus postural control. Our results confirmed that the COP signal is more useful and sensitive in the evaluation of the age-related decline of postural stability than the COM. This method may be particularly useful when analyzing subtle changes in stability caused by some pathologies.

APPENDIX

Fractal Dimension

A signal may be represented by a set of points (a binary image, called a bitmap) on a plane, either in amplitude-time coordinates (a, t), where a denotes amplitude of the signal at the moment t, or in Euclidean coordinates (x,y) , where x and y are amplitudes in two independent direction at the same moment of time, e.g. in posturography excursions in ML and in AP directions respectively. Any digitized image in form of a bitmap is a pattern stored as a rectangular data matrix. There exist one-to-one relation between a bitmap and its representation by the matrix. Bitmaps are matrices where pixels belonging to the pattern are stored as 1, pixels from the background are stored as 0. The opposite assignment of the pixels is also valid. On a video screen the 1 pixels are rendered as black, the 0 pixels as white or *vice versa*.

Sets have dimensions, which can be defined in various ways. A bitmap, and so the signal it represents, also has certain dimension. The most popular mathematical dimension is so called Hausdorff Besicovitch dimension, which is often difficult to compute, but is well-defined and interesting. Other dimensions of interest include the "box-counting" dimension (also called capacity dimension), the correlation dimension, and the information dimension. When non-integer in value, any of these are loosely referred to as the *fractal dimension*, below denoted D_f.

A fractal is a set for which dimension exceeds its topological dimension (Mandelbrot 1983). An alternative definition of a fractal says that fractal is a self-similar object. A set is called strictly self-similar if it can be broken into arbitrary small pieces, each of which is a small replica of the entire set. Natural objects, like coastlines or roots, do not show the same shape but look quite similar when they are scaled down; due to their statistical scaling invariance they are called statistical self-similar. The same concerns biosignals, like EEG or posturographic signals.

If one connects in a certain order a set of points on a plane it forms a curve. Topological dimension of a curve is always equal 1, while fractal dimension, D_f, of a curve on a plane is between 1 and 2 and measures its "texture" or complexity. When estimators for the fractal dimension of curves (and so of the signals represented by these curves) or of digitized images (and so of structures represented by these images) serve as parameters to quantify textural information and so to supply classification problems, the structures under consideration do not necessarily have to be strict fractals.

Box Dimension

There are different methods of computing fractal dimension of a curve. A comfortable estimator for the fractal dimension, D_f, of a curve (or practically of any arbitrary binary structure) is box dimension, D_B. The plane is covered with a grid of square cells with cell size r (for binary images it is appropriate to choose the grid length as numbers of pixels). The number of cells containing a part (at least one pixel) of the structure, N(r) , is counted, and the length of the curve is then approximately equal to

$$L(r) = N(r) * r$$

A double logarithmic plot of the number N(r) *versus* the boxsize r , so called Richardson Mandelbrot plot, gives the regression line corresponding to the relation

$$N(r) = const * r^{-D_B}$$

from which the box dimension, D_B of the structure can easily be determined.

This procedure is a proper method to estimate the Hausdorff Besicovitch dimension of binary structures (Kraft and Kauer 1995). Several similar procedures, all based on the Richardson Mandelbrot plot, where different measures of a set are plotted against the box size r on double logarithmic axis and the dimension is then determined from the slope of the regression line, have been proposed. To calculate box fractal dimension the data have to be firstly transformed into a bitmap, e.g. by using a scanner. Higuchi (1988) proposed another method to estimate fractal dimension of a fractal curve that may be applied directly to the raw data.

Higuchi's Algorithm

Higuchi's algorithm is based on the measures of the mean length of the curve L(k) by using a segment of k samples as a unit of measure (Accardo et al. 1997). One takes the series representing the signal under consideration (samples taken at a regular interval):

$a(1), a(2), a(3),..., a(N)$

where $a(i)$ is the signal amplitude at the i-th discrete point (moment of time) (i =1,...,N) and N is the total number of points. From this one then constructs k new time series, a(m,k):

a(m,k): $a(m), a(m+k), a(m+2k), \ldots , a(m+int[(N-m)/k]* k)$
(m=1,2,...,k)

where int[...] denotes the greatest integer not exceeding the number in the square brackets; m and k are integers indicating, respectively, the initial time and the time interval. For example, if N=100 and k=3 one obtains three time series:

a(1,3): $a(1), a(4),..., a(97), a(100)$
a(2,4): $a(2), a(5),..., a(98)$
a(3,4): $a(3), a(6),..., a(99)$

The length, $L_m(k)$, of each curve a(m,k) is then calculated as:

$$L_m(k) = \{[S| a(m+i * k) - a(m+(i-1) * k)|] * (N-1) / [(\text{int}[(N-m)/k)]) * k]\} / k$$

i=1,int [(N-m) / k]
where N is the total number of samples and (N-1)/[(int[(N-m)/k])*k] is a normalization factor.

The length of the curve for the time interval k, L(k), is calculated as the mean of the k values $L_m(k)$ for m=1,2,...k:

$$L(k) = (SLm(k)) / k \qquad \text{m=1,k}$$

The procedure is repeated for several k=1,2,...,k_{max} . If the L(k) value is proportional to k^{-D_H}, the curve is fractal-like, with the fractal dimension D_H. Higuchi's dimension, D_H, may serve as still another comfortable estimator for the fractal dimension, D_f , of the curve, and so to serve as a parameter to quantify "textural information" and to supply classification problems of the signal $a(i)$ represented by this curve. D_H is easily evaluated as the angular coefficient of the linear regression of the graph ln(L(k)) versus ln(1/k) .

While k_{max} has some influence on the results and should be selected appropriately (cf. Accardo et al. 1997), it is important that scaling of the signal amplitude, $a(i)$, has no influence on the results, since it causes only parallel shifting of the regression line along the ln(L(k)) axis, without changing its angular coefficient.

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