



## IDENTIFICATION OF DYNAMIC PATTERNS OF BODY SWAY DURING QUIET STANDING: IS IT A NONLINEAR PROCESS?

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During quiet standing, the human body continuously moves about an upright posture in an erratic fashion. Many researchers characterize postural fluctuations as a stochastic process while some others suggest chaotic dynamics for postural sway. In this study, first we examined these assumptions using principles of chaos theory in normal healthy and in patients with deteriorated postural control mechanisms. Next, we compared the ability of a nonlinear dynamics quantifier correlation dimension to that of a linear measure standard deviation to describe variability of healthy and deteriorated postural control mechanisms during quiet standing. Our findings did not provide convincing evidence for existence of low dimensional chaos within normal and abnormal sway dynamics but support the notion that postural fluctuations time series are distinguishable from these generated by a random process. The results indicated that although linear variability measures discriminated well between groups, they did not provide any information about the structure of postural fluctuations. Calculated correlation dimension as a complexity measure which describes spatio temporal organization of time series may be useful in this regard.

*Keywords:* Postural control; quiet standing; nonlinear dynamics; balance impairment.

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## 1. Introduction

Balance control during quiet standing is one of the essential activities that human being learn in childhood and perform at subconscious level. Despite its apparent simplicity, the task of maintaining an upright posture involves a complex sensorimotor control system. Various mechanisms and neurophysiologic sensory systems including visual, vestibular, and somatosensory systems contribute to our stability during quiet standing and respond to internal or external perturbations [Shumway-Cook & Woollacott, 2006].

The complex behavior of standing still postural control mechanism have been studied using different mathematical linear and nonlinear quantifiers to characterize postural sway, to study influences of different factors on postural steadiness and to detect differences in postural control mechanisms. Many researchers have used linear posturographic measures and summary statistics of center of pressure (COP) time series, which by definition ignore temporal structure of time series, to analyze postural sway during quiet standing [Nichols *et al.*, 1995; DeHaart *et al.*, 2004; Norris *et al.*, 2005; Raymakers *et al.*, 2005; Blaszczyk *et al.*, 2007; Esteki *et al.*, 2009]. Highly irregular outputs of postural control system, as illustrated in Fig. 1, make it a candidate for physiological chaos.

It has been suggested that the complex and unpredictable behavior exhibited by sensorimotor control system may be instances of deterministic chaos and many authors claimed the existence of chaos in human postural control [Yamada, 1995; Pascolo *et al.*, 2005; Ladislao & Fioretti, 2007] while some others believe that this is a random correlated noise [Collins & Luca, 1993; Duarte & Zatsiorsky, 2000; Amoud *et al.*, 2007]. Newell *et al.* [1993] used correlation dimensions of COP trajectories as the

dimensionality quantifier to evaluate stability of normal subjects and tardive dysknetic (TD) adult patients during quiet standing. They found low dimensional attractors within COP dynamics and COP trajectories of TD patients were of a lower dimension than that produced by normal subjects. Same as Newell *et al.*, Yamada [1995] found low dimensional chaotic attractors for COP fluctuations during quiet standing of normal subjects (Fig. 2) and calculated largest Lyapunov exponents. The calculated Lyapunov exponents were consistently greater than zero. Thus, Yamada concluded that there is a chaotic regime within human postural control.

Ladislao and Fioretti [2007] investigated the effect of different visual conditions on postural steadiness time series of normal subjects along anteroposterior (AP) direction using traditional linear posturographic measures and nonlinear dynamical system quantifiers. They assumed chaotic attractors within standing postural control system and then calculated largest Lyapunov exponents. They found positive values for largest Lyapunov exponents and claimed that postural control system demonstrates a weakly chaotic behavior. Their three-dimensional reconstructed embedding space was the same as that found by Yamada. In another literature, Pascolo *et al.* [2005] used correlation dimension and largest Lyapunov exponent to distinguish healthy subjects from Parkinsonians. They claim that postural control system is indeed chaotic and found low dimensional attractors for sway dynamics in both groups. Their estimated dimensions suggest attractors closer to limit cycle attractors with potentially some noise. They also calculated positive Lyapunov exponents for both healthy subjects and Parkinsonians. However their analysis could not discriminate healthy subjects from Parkinsonians.

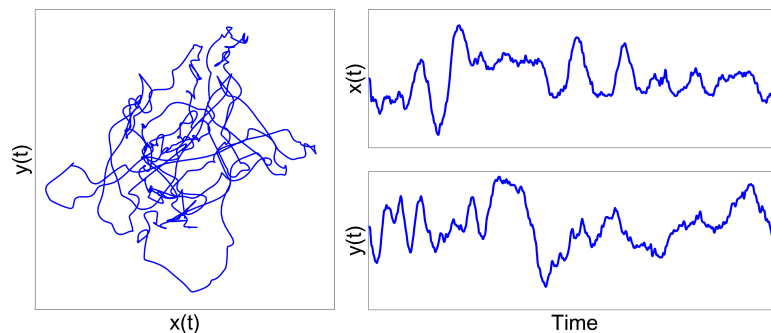


Fig. 1. Left panel: a typical 20 seconds COP trajectory where  $x$  and  $y$  respectively correspond to mediolateral and anterior posterior directions. Right panel: corresponding time series.

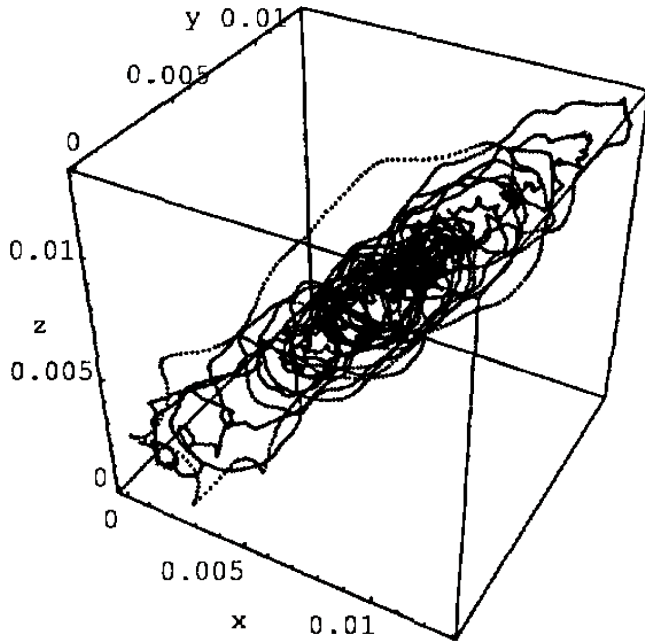


Fig. 2. Three-dimensional embedding space of a sample COP time series. Figure is adapted from [Yamada, 1995].

Roerdink *et al.* [2006] with the aim of unraveling standing postural control mechanism reanalyzed the COP data of Dehaart's study [2004] using non-linear dynamical system quantifiers and other complexity measures. They did not explicitly claim that any chaotic nature exists behind the postural control system but they interpreted correlation dimensions as the number of active dynamical degrees of freedom and largest Lyapunov exponents as the postural instability criterion. Their findings indicated that stroke patients recruit additional control processes during quiet standing and are more locally instable. Donker *et al.* [2007] investigated the influence of attention on dynamical structure of postural sway of young healthy adults using a variety of linear and nonlinear measures. Same as Roerdink *et al.*, they interpreted correlation dimension and largest Lyapunov exponent as the criteria for evaluating dimensionality and local stability of postural sway.

The results of these studies indicate that these authors found low dimensional chaotic attractors in postural fluctuations, and then they calculated Lyapunov exponents to evaluate behavior of trajectories nearby the attractors. For short noisy time series, the aforementioned quantifiers may give spurious results. They may indicate the presence of chaos in systems that are not chaotic.

Standing posture is still poorly understood and weakness of postural control mechanism certainly

plays a role in balance control during quiet standing. Characterization of postural oscillations and its underlying control system may improve our understanding about interactions between components to achieve postural balance. In this study, first we examined sway dynamics of healthy and deteriorated quiet standing postural control mechanisms using principles of chaos theory to investigate the existence of low dimensional chaos in normal and abnormal standing posture and changes that are associated with deterioration of postural control mechanism. Next, the possibility of using chaotic quantifiers as the pathologic measures to evaluate balance impairments and distinguish healthy from deteriorated neuromuscular control systems is investigated.

## 2. Methods

### 2.1. Participants and procedures

In this study, with the aim of investigation of sway dynamics of normal and deteriorated postural control systems, two distinctly different groups are considered. One implies normal dynamics of postural control system and the other indicates abnormal or changed postural control dynamics. Postural control system of healthy young adults is considered as the system with normal dynamics and of elderly stroke patients with severe balance disorders is considered as the abnormal dynamical system. Thirty two stroke patients (17 male and 15 female) with a first hemispheric intracerebral infarction or hematoma with less than one year ( $6.9 \pm 4.2$  months) post stroke time with the age of  $60.59 \pm 8.64$  years old and body mass index (BMI) index of  $25.01 \pm 4.51$  and 29 healthy young adults (16 male and 13 female) with the age of  $25.90 \pm 3.32$  years old and  $23.54 \pm 2.88$  BMI index, without known motor impairments or movement-related disorders, participated in the experiment. There was no significant difference between BMI indexes of two groups.

Postural fluctuations were evaluated using a dynamic dual force platform (SOT#1, EquiTest testing system, NeuroCom International Inc., Clackamas, OR). The system was equipped with a movable visual surround and support surface that could rotate in the AP plane. Two  $22.9 \times 45.7$  cm force plates connected by a pin joint were used to collect COP coordinates at 100 Hz.

Participants were instructed to stand in an upright posture in a standardized foot placement

on the platform based on each subject's height according to the manufacturer's protocol [Equi-Test System Version 8.0, Operator's Manual, 2001]. Participants stood barefoot with their arms relaxed at their sides, their eyes open and look straight ahead fixed on a point in front of them. They were instructed to concentrate on their stability, stand freely, and have no other mental tasks. Each participant performed a set of three trials each lasting 20 sec.

## 2.2. Data analysis

Prior to all analyses, mean and linear trends of the signals were removed. The signals are denoted as  $x(t)$  and  $y(t)$  where  $x$  and  $y$  respectively correspond to mediolateral and anteroposterior components of COP displacements. Since filtering is potentially dangerous activity that can affect dimension estimates and other calculations [Stergiou, 2004], filtering was avoided in this study. Correlation dimensions ( $D_C$ ) of COP components' time series were calculated to investigate the existence of low dimensional attractors within sway dynamics of healthy and deteriorated standing still postural control mechanisms and standard deviations ( $\sigma$ ) were calculated to evaluate postural variability during quiet standing.

## 2.3. Correlation dimension

Correlation dimension is the attractor dimension and may provide an estimate of the number of active dynamical degrees of freedom involved in postural control system. Chaotic systems are generally characterized by finite, noninteger (fractal) values for correlation dimension.

Numerical algorithms have been proposed to quantify this property and detect the presence of chaos in experimental time series [Grassberger & Procaccia, 1983; Hilborn, 2000; Sprott, 2003; Kantz & Schreiber, 2004]. In this study to calculate correlation dimension of the time series we used Chaos Data Analyzer (CDA) software package (Physics Academic Software, by J. C. Sprott and G. Rowlands). This software follows the Grassberger and Procaccia algorithm for calculating correlation dimension [Sprott & Rowlands, 2003]. For scalar time series, these algorithms require reconstruction of system's attractor by embedding the time series in  $m$ -dimensional phase space by delayed vectors as  $x(t_i), x(t_i + \tau), x(t_i + 2\tau), \dots$ . In order to reconstruct the attractor of a dynamical system,

two problems will need to be solved. The first concerns how to select the time delay ( $\tau$ ), for reconstructing the trajectory in phase space. With very small delays, the resulting delayed vectors will be nearly the same, and so the trajectories in the embedding space will all be compressed into a long thin volume equivalent to a diagonal line in the state space. On the other hand, a large delay may produce coordinates which are essentially unrelated. For nonlinear systems one of the favored approaches is choosing the delay coincides with the first local minimum of auto mutual information function that maximizes independence between state vectors. This value was not repeatable in COP time series of neither healthy subjects nor stroke patients but it can be characterized by a mean value  $\pm$  standard deviation in each group of COP time series. So, the average of first local minimums of auto mutual information function of each group of COP time series is considered as the proper time delay.

The second problem concerns how to determine the embedding dimension ( $d$ ) of the system. Our approach to this problem was to use an analytic method known as False Nearest Neighbors. Embedding dimension is chosen when the percentage of false nearest neighbors as a function of the embedding dimension drops or closest to zero (Fig. 3). Correlation dimensions of COP time series were calculated according to abovementioned method.

## 2.4. The method of surrogate data (nonlinearity hypothesis testing)

Surrogation is a technique used to determine whether a deterministic source exists for a given time series. The idea is to compare the original data set to artificially randomly generated data sets which mimic certain prescribed features of the original data set and are consistent with null hypotheses of random processes [Theiler *et al.*, 1992]. The discriminating statistic (correlation dimension) is computed for the original and each respective surrogate data sets. If the results of the surrogates and the original time series are statistically significantly different, then the null hypothesis is rejected. In this study phase, randomization surrogate data generation algorithm is used to identify nonlinearity in COP time series. Thirty surrogate time series are generated for each original COP time series by Chaos Data Analyzer software package. These surrogate data sets have the same power spectra as the

original data, but all other information encoded in the phases is lost.

The most important point is that the surrogate technique does not tell us the original data set is chaotic; it only rejects the null hypotheses of being noise and detects nonlinearity in time series.

### 2.5. Statistical analyses

All statistical analyses were performed using SPSS software package version 11.5 (SPSS Inc., Chicago, IL, USA). Normality of standard deviations and calculated correlation dimensions were checked, independent samples T tests with 95% level of confidence were used for the effect of subject group on estimations of the variables  $\sigma$  and  $D_C$ , and paired samples T tests with 95% level of confidence were used to evaluate statistical differences between AP and mediolateral (ML) variables in each group. To evaluate the effects of deterioration of postural control mechanism on the amount of changes of the variables in each direction Cohen's d statistic was used. Cohen's d is appropriate for comparison between two means and is defined as the difference between two means divided by pooled standard deviation.

Intra class correlation coefficients (ICC) were calculated to document the intra session reliability of  $\sigma$  and  $D_C$  within two groups. The ICC values were categorized as follows: excellent (0.75–1), moderate (0.4–0.74), and poor (0–0.39) [Fleiss, 1986].

To evaluate statistical differences between calculated correlation dimensions of each original data set and its 30 surrogate counterparts one sample T test was used and to evaluate statistical group differences between calculated correlation dimensions of original time series and surrogate time series independent samples T tests were implemented.

### 3. Results

The results of calculating embedding parameters are listed in Table 1. Median of first local minimums of auto mutual information functions of each group of COP time series was considered as the proper time delay and false nearest neighbors algorithm was used to determine embedding dimension of each COP time series (Fig. 3).

Correlation dimensions and standard deviations of COP time series were calculated and the results are shown in Fig. 4. Marked differences are found between linear and nonlinear sway characteristics of elderly stroke patients and young

Table 1. Descriptive statistics of first local minimums of auto mutual information functions and embedding dimensions in both healthy and patient groups.

Index	Group			
	Healthy Median (IQR <sup>a</sup> )		Patient Median (IQR)	
	AP	ML	AP	ML
$\tau$	8 (2)	9 (2)	10 (4)	9 (3)
d	4 (1)	6 (1)	4 (0)	5 (1)

<sup>a</sup>Interquartile range.

healthy subjects and also between sway characteristics along AP and ML directions in each group.

The results indicate that due to degradation of postural control system, postural variability increased, whereas calculated correlation dimension of COP time series were decreased. In both groups, postural variability was higher along AP direction, but calculated correlation dimensions of AP COP time series were lower than ML ones.

The results of calculating Cohen's d indicate that postural variability along AP direction and calculated correlation dimensions along ML direction are more affected by deterioration of postural control mechanism (Table 2).

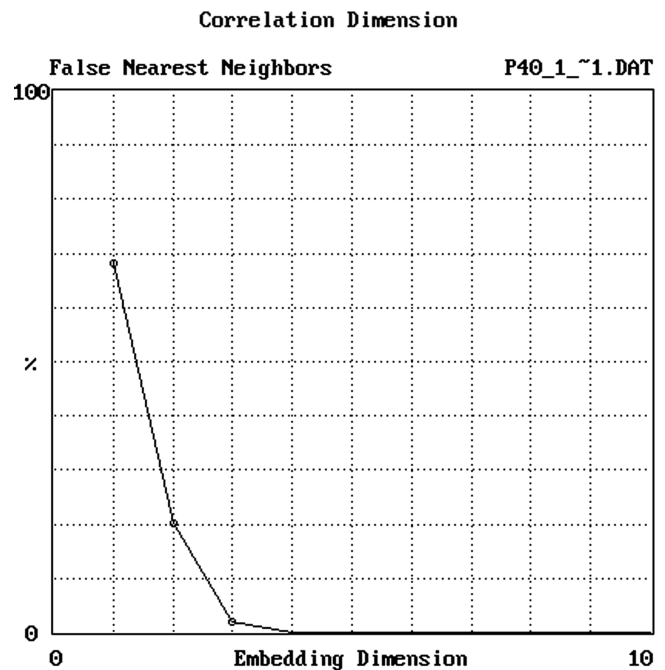


Fig. 3. FNN versus Embedding dimension plot for a sample ML COP displacements of a stroke patient (for this time series a four-dimensional embedding space is estimated using FNN algorithm).

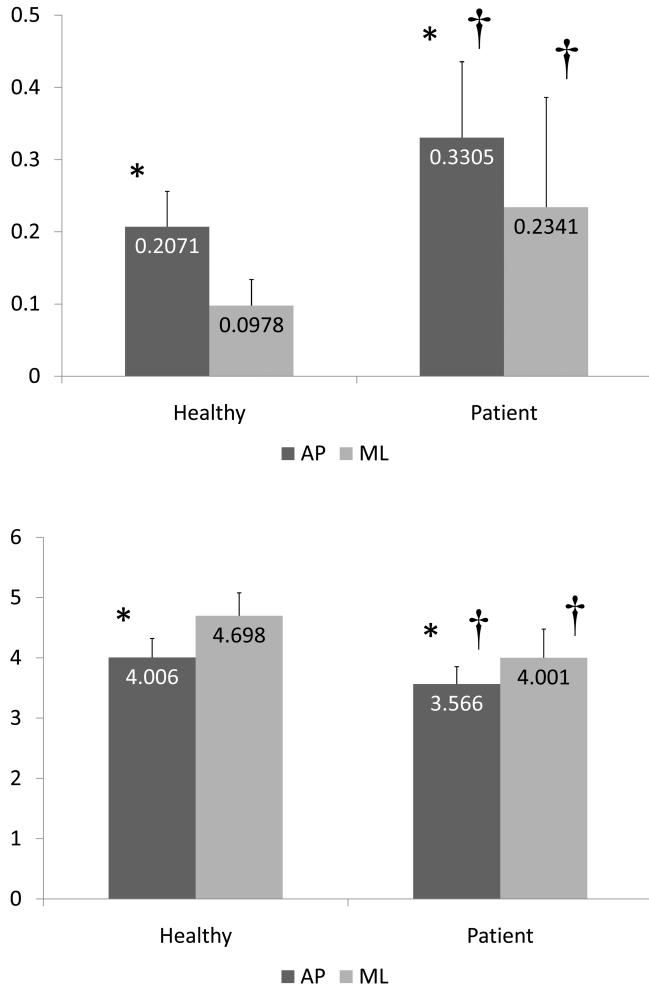


Fig. 4. The effects of health status on variability measures (top panel) and calculated correlation dimensions (bottom panel). †: Patients are significantly different from healthy subjects along both directions ( $p = 0.000$ ). \*: AP is significantly different from ML in each group ( $p = 0.000$ ).

The ICC values of standard deviations and calculated correlation dimensions are listed in Table 3. Sway characteristics demonstrated excellent intra session reliability for stroke patients (average = 0.8211) and moderate level for healthy subjects (average = 0.6591).

Table 2. The results of calculating Cohen’s d to evaluate the effects of health status on the amount of changes of AP and ML COP variability and calculated correlation dimensions.

Index	Direction	Cohen’s d
$\sigma$	AP	1.50
	ML	1.23
$D_C$	AP	1.48
	ML	1.63

Table 3. ICC values of standard deviations and calculated correlation dimensions.

Index		Group	
		Healthy	Patient
$\sigma$	AP	0.6851	0.7467
	ML	0.6794	0.8432
$D_C$	AP	0.6620	0.8883
	ML	0.6098	0.8062

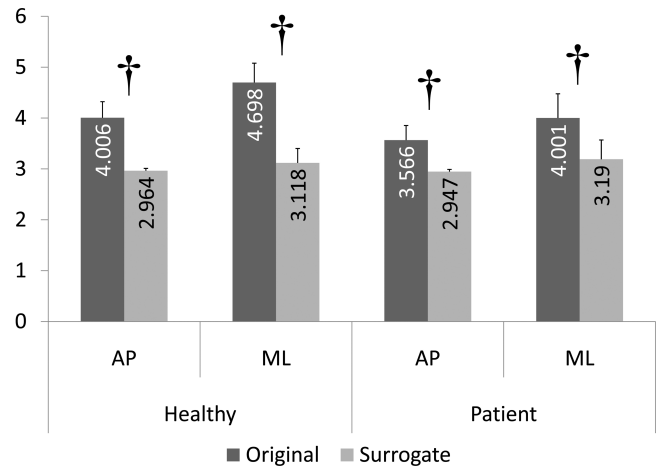


Fig. 5. Randomization effects on calculated correlation dimensions. †: Original time series and phase randomized surrogates all differed significantly from each other ( $p = 0.000$ ).

One sample T tests demonstrated significant differences between calculated correlation dimensions of each original COP time series and surrogate counterparts. Independent samples T test results of calculated correlation dimensions of each group of original COP time series and their surrogate data sets are shown in Fig. 5. The results indicate significant differences between calculated correlation dimensions of COP time series and their surrogate data sets.

## 4. Discussion

### 4.1. Groups

In this study, the authors did not intend to compare stroke patients with age matched controls and investigate changes which are caused by stroke. Here, we examined the assumption of existence of low dimensional chaos in sway dynamics of both healthy and deteriorated quiet standing postural control mechanisms. Due to this reason, two distinctly different groups were considered to better indicate differences between normal and abnormal patterns of balance control during quiet standing.

### 4.2. Linear variability measure

Our results indicate that postural variability is increased due to deterioration of postural control mechanism. Increasing of postural variability may be interpreted as the higher postural instability and more variable postural control system. But bear in mind that linear variability measures only quantify the magnitude of sway and not temporally evolving dynamics of postural control system [Stergiou, 2004; Harbourne & Stergiou, 2009]. Postural instability defined by linear variability measures should not be viewed from dynamical systems theory and higher postural instability in deteriorated postural control system does not imply higher order dynamics.

Although linear variability measures well discriminate normal and abnormal postural control systems during quiet standing, they did not give useful information about underlying control system and its hidden dynamics. These measures ignore temporal characteristics of time series, so dynamical system approaches seem to be useful in this regard and may provide new openings to underlying control structure.

### 4.3. Nonlinear dynamical system quantifiers

Our findings indicate that calculated correlation dimensions well discriminate two groups. Both of them have noninteger calculated correlation dimensions and healthy subjects have higher calculated correlation dimensions than the patients. However finding fractal dimensions for COP trajectories does not prove that there is a low dimensional chaotic nature behind the postural control mechanism. In this study, we have examined this assumption carefully using principles of chaos theory. Finding a plateau in the plot of calculated correlation dimensions versus embedding dimensions is not sufficient for concluding that the correlation dimension is saturated at a specific embedding dimension and thus is independent of next embedding dimensions (Fig. 6), it should be examined with equivalent figures.

Although at each embedding dimension a linear scaling region whose slope is correlation dimension can be approximated in logarithmic plot of correlation sum versus distance  $r$  (Fig. 7), but this linear scaling region does not have significant length at least for two decades of distance  $r$  at each embedding dimension (Fig. 8).

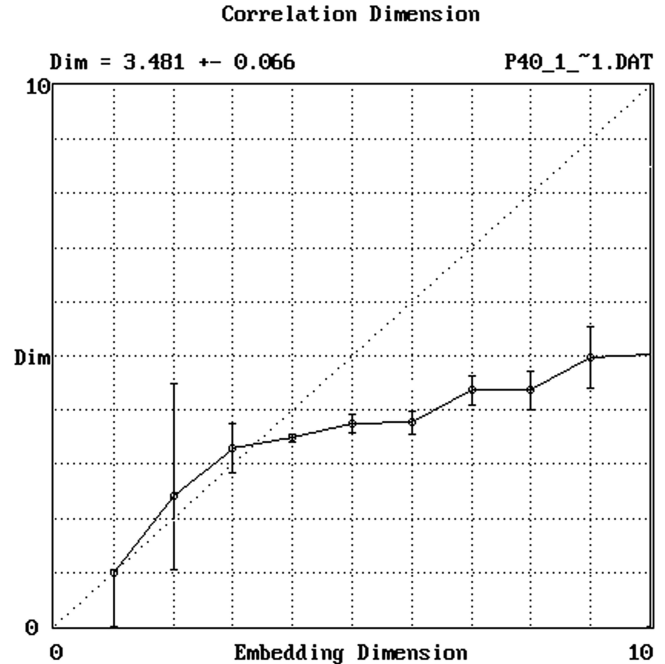


Fig. 6. Plot of calculated correlation dimensions versus embedding dimensions of a sample ML COP displacement of a stroke patient. Saturation of correlation dimension can be seen in the five-dimensional embedding space (as shown in Fig. 3, FNN algorithm suggests four-dimensional embedding space for this time series).

These findings do not provide convincing evidence for existence of low dimensional chaotic attractors for standing still postural fluctuations. Even if there is a chaotic regime within sway dynamics of quiet standing postural control, it could be of a dimension too high to detect or it could be

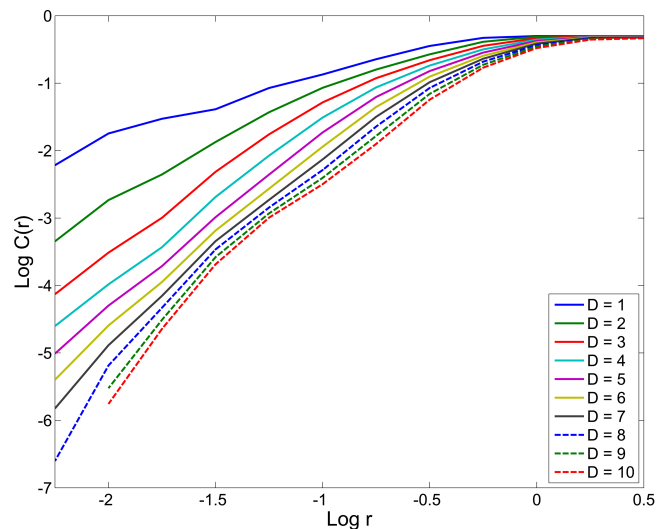


Fig. 7. Logarithmic plot of  $C(r)$  versus  $r$  at different embedding dimensions for the same sample time series as in Fig. 6.

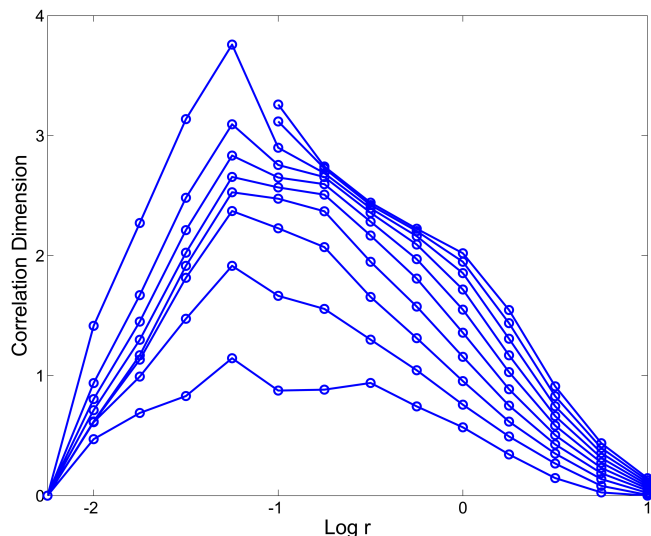


Fig. 8. Slope of correlation sum (correlation dimension) versus  $r$  at different embedding dimensions for the same sample time series as in Figs. 6 and 7.

buried in the noise. Since no low dimensional attractors are found, calculating Lyapunov exponents is meaningless and may give spurious results.

Any claim about the presence of low dimensional deterministic chaos based on noninteger values obtained from dimensionality analyses of finite time series should be done with great caution. However, dimensionality analysis with the aim of finding a discriminating criterion or screening method for evaluating postural control system seems to be useful, but the results should be checked against surrogate data test.

#### 4.4. Randomization

In order to guarantee validity of dimensionality analysis applied here, we used phase randomized surrogate data generation algorithm. We compared calculated correlation dimensions of COP time series with those obtained from surrogate data (Fig. 5). The results show that the null hypothesis of linearly correlated noise is rejected. Rejection of null hypothesis does not demonstrate that a chaotic nature exists for postural fluctuations; it only detects a source of nonlinearity in COP trajectories and indicates that its structure is significantly different from random noise.

#### 4.5. Filtering effects

Yamada [1995] found correlation dimensions between 2.1–2.5, Newell *et al.* [1993], Donker *et al.*

[2007], and Roerdink *et al.* [2006] found similar values of  $2.30 \pm 0.52$ , 2.23 and about 2.5, respectively for normal subjects. All the above mentioned studies have filtered the COP time series using low pass filters. Yamada [1995] used a low pass filter with 5 Hz cutoff frequency, Newell *et al.* [1993] and Donker *et al.* [2007] used 10.5 Hz and 12.5 Hz cutoff frequencies, and Roerdink *et al.* [2006] used the COP time series of Dehaart's study [2004] in which the COP signals were filtered with 6 Hz cutoff frequency. With regards to sensitivity of nonlinear quantifiers to filtering and noise reduction of the signals and its effect on dimension estimates and other calculations, the COP signals have not been low pass filtered in this study and that is the reason we obtained higher correlation dimensions in comparison with related literatures.

#### 4.6. Variability: Correlation dimension versus standard deviation

There are different methods to evaluate variability. The amount of variability is measured by linear measures such as rang, interquartile range, standard deviation, etc., and the structure of variability is measured by complexity quantifiers like entropy [Stergiou, 2004]. Complexity is something that is hidden within the time series and captures variation in the system's behavior across time. Amount and structure of variability are often inversely related and change in opposite directions [Harbourne & Stergiou, 2009]. In this study, we found the same results if calculated correlation dimension is considered as a complexity measure which quantifies state space behavior (spatio-temporal variability) of COP time series. The results in Fig. 4 indicate that the amount of variability is increased in deteriorated postural control system whereas the complexity is decreased. This makes sense, in deteriorated postural control system less complex programs which alter the structure of postural fluctuations are utilized to maintain balance during quiet standing. It supports the notion that complexity would arise from fine tuned adjustments with selected, adaptive and flexible programs for maintaining balance during quiet standing [Harbourne & Stergiou, 2009] like which are used in healthy postural control system. These results are well consistent with the results of many other literatures which indicate loss of complexity in elderlies, and in neurological



and physiological diseases [Kaplan *et al.*, 1991; Lipsitz & Goldberger, 1992; Pincus & Goldberger, 1994; Lipsitz, 2004; Kunhimangalam *et al.*, 2007].

Analyzing both components of COP time series reveals that in both groups AP postural fluctuations are more variable yet more structured than ML. Although the two components of the COP trajectories are often analyzed separately, they represent the output of an integrated control system and in case of postural control impairments, both of them are changed in a same manner. This may be the reason that many researchers concentrated only on a component of COP trajectories (especially AP) to study postural control behavior during quiet standing [Nichols *et al.*, 1995; Ladislao & Fioretti, 2007; Esteki *et al.*, 2009]. In this study we found the same results, both AP and ML postural variability as well as their complexity are changed due to deterioration of postural control mechanism but the Cohen's *d* statistics show that rigidity of balance program is more increased along ML direction. These may interpreted as the reduced ability of symmetrical weight distribution between load bearing limbs, lower ability of loading the paretic side and/or load shifting from non-paretic to paretic side and vice versa. The results of frequency analysis of these two groups show that mean frequency of ML COP time series is decreased due to deterioration of postural control system whereas the mean frequency of AP COP time series did not significantly change [Rajabali, 2009]. It implies that due to neurological impairments, it takes longer to have side-to-side load shifting which causes greater sideway sway range, variability, and more repeatable sway patterns comparing to that of healthy subjects which leads to more structured (less complex) movement patterns. It may be the reason that complexity is more decreased along ML direction in impaired postural control system.

#### 4.7. Reliability analysis

Since ICC values of linear and nonlinear postural sway quantifiers demonstrate excellent intra session reliability for the patients and moderate reliability for the normal subjects, we cannot define which one better describes postural fluctuations. But it should be noted that amount and structure of variability are complementary and do not negate each other, but their interpretations are different. However, from the ICC results, it is concluded that

deterioration of postural control mechanism causes greater reliability. Higher ICC values of patients' sway characteristics indicates decrease of within subject variation in patient group which may be interpreted as more stationarity in sway dynamics of stroke patients.

## 5. Conclusion

In this study, we investigated sway dynamics of normal and abnormal postural control mechanisms using a linear statistical measure and a nonlinear dynamics quantifier correlation dimension. In spite of the fact that linear variability measures ignore the temporal structure of time series, they can be used as the pathological discriminating criteria for balance disorders.

We have examined the assumption of chaotic behavior of standing still postural control mechanism by means of principles of chaos theory. Notwithstanding that fractal dimensions were calculated for postural fluctuations time series, but we could not find any evidence to document existence of low dimensional attractors in COP dynamics of neither healthy nor deteriorated postural control mechanism. Thus, it is not practical to calculate Lyapunov exponents. We never disprove the existence of chaos within sway dynamics of normal and abnormal quiet standing postural control systems but none of them may be modeled as a low dimensional chaotic process and if there is any chaos within dynamics of quiet standing postural fluctuations it might be of a dimension too high to detect.

Although using randomization technique non-linearity was detected within the COP time series, this nonlinearity necessarily may not have a deterministic chaotic origin. It is important to recognize that there are orderly patterns within these outwardly unorganized and noisy looking fluctuations which are the outcomes of distinguishable different postural control programs. Calculated correlation dimension as well as many other complexity measures may provide new insights to underlying structure of postural control mechanism. The results justify the inclusion of nonlinear quantifier correlation dimension in the clinical assessment of postural fluctuations but specifying low dimensional chaotic nature or finite number of active dynamical degrees of freedom for quiet standing postural control based on short noisy data sets should be done with great caution.

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