Evaluation of posture signal using entropy analysis and fractal dimension in adults with Down syndrome

C. Rigoldi[a]*, M. Galli[a,b], L. Mainardi[a] and G. Albertini[b]

[a] *Bioengineering Department, Politecnico di Milano, Milan, Italy;* [b]*IRCCS San Raffaele Pisana, TOSINVEST Sanità, Rome, Italy*

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1. Introduction

Maintaining posture is a complex task attained by the postural control system throughout the integration of information from visual, vestibular and somatosensory systems in conjunction with the passive properties of the musculo-skeletal system. Static standing balance is defined as a state, in a quiet stance, of maintaining (or controlling) the position of the whole body's centre of mass within the base of support without falling: for this reason, standing is characterised by repeated adjustments of body position to counteract the constantly occurring small perturbations (Duarte and Zatsiorsky 2000). One of the most widely used experimental measurements to understand the postural system is the recording of postural sway data, which could provide information concerning motor control system. Quantitative analysis of centre of pressure (COP) data in quiet standing was carried out in several experiments using different approaches: some works (Soames and Atha 1982; Shumway-Cook and Woollacott 1985; Winter 1990; Schumann et al. 1995; Westcott et al. 1997; Stoffregen and Smart 1998; Winter et al. 1998; Rocchi et al. 2006) describe the posture control system using the analysis of COP signal in time domain, considering the shifting of COP during the maintenance of standing position in anterior–posterior (AP) and medio-lateral (ML) directions. Others quantify the COP displacements in frequency domain using Fast Fourier Transform or autoregressive (AR) model (Soames and Atha 1982; Massion 1992; Alessandrini et al. 2006; Rocchi et al. 2006).

More recently, the dynamical structure of COP trend during quiet standing has been described using nonlinear approaches (Doyle et al. 2006; Roerdink et al. 2006; Manor et al. 2010). In particlar, fractal dimension (FD) and entropy measurements were investigated.

FD was associated with patient stability (Blaszczky and Klonowsky 2001) with an increase in FD linked to an augmented postural instability. Roerdink et al. (2006) observed an increased dimensionality of the COP displacements in stroke patients in respect to healthy subjects in both sagittal and frontal planes. The finding was interpreted as the sign of a more complex postural control strategy.

In their work, Manor et al. (2010) studied the sample entropy associated with the COP displacements in sagittal plane during quiet standing: they related the sample entropy to the complexity of a system, and consequently to system functionality as defined by the capacity to generate adaptive responses to stressors. Their analysis revealed that biological ageing or diseases are often associated with a sample entropy reduction in AP direction: chronic sensory impairments lower the physiological complexity of postural sway dynamics and consequently lower the adaptive capacity of the system. The changes in sample entropy seem to be related to the pathology and its impairment. In fact, Roerdink et al. (2006) augmented

*Corresponding author. Email: chiara.rigoldi@polimi.it

sample entropy in AP direction in stroke patients in comparison with healthy subjects. Considering postural analysis in subjects with Down syndrome (DS), Rigoldi et al. (2010) displayed the increasing of COP oscillations in both directions, as consequences of compensatory strategies in order to supply to the hypotonia, the ligament laxity and higher time of response that characterised this pathology, resulting in a clumsy movement.

The impairments to one or more subsystems that regulate postural control, such as somatosensory, vestibular and/or visual sensors feedback networks, reduce the complexity of the system diminishing its adaptive ability. Considering the clumsy nature of DS movements and the dynamical approaches previously exposed to analyse these aspects, the aim of this study was to explore new techniques in analysing postural control using nonlinear time-series analysis in the description of posture in subjects with DS.

2. Methods

2.1 Subjects

For the analysis of posture strategies, the data from 35 young adults (Down syndrome group, DSG, range: 20–40 years, body weight: 57.9 ± 10.8 kg) with DS were collected in the Posture and Motion Analysis Lab of IRCCS 'San Raffaele-Pisana', TOSINVEST Sanità (Rome, Italy).

The inclusion criteria for DS participants were presence of trisonomy 21 or mosaic DS, normal vision and hearing, absence of congenital heart defects, no history of seizures, absence of current medications, independence in ambulation and no previous orthopaedic treatment. In order to compare the DSG data, a control group (CG), composed of 10 age-matched healthy subjects (CG: range, 20–40 years; body weight, 68.3 ± 19.2 kg), was taken. The selection criteria for the CG participants were no signs of any orthopaedic or neurological diseases or disorders, no impairment of somatosensory, hearing, vestibular and uncorrectable visual functions and no developmental disabilities. All participants gave their informed consent to participate in the study, and all investigations were done in conformity with the ethical and humane principles of research. The researchers explained the purpose, procedures, risks and benefits of the study to parents who gave their informed consent.

2.2 Instrumentation and data acquisition

The equipment utilised for data acquisition during the posture trials consisted of a force platform (Kistler, Winterthur, Switzerland), used to obtain the COP displacement values, and two TV cameras (VideoController, BTS, Milan, Italy) synchronised with the force platform for the video recording of the participants, used to ascertain whether any undesired behaviour occurred.

The participants were instructed to maintain an upright standing position for 30 s with arms at their sides and feet positioned over sketches representing the foot with an angle of 30° respect to the AP direction. The participant chose the width of the base of support in order to maintain posture in a safety way.

Data were collected in two consecutive trials. In the first, the participants were asked to maintain an upright standing position with eyes open (OE), looking at a black target located 1.5 m far away the subject (a circle with a diameter of 6 cm). The target was positioned vertically to be in the patient's direct line of sight. In the second trial, the participants were requested to keep their eyes closed (CE). Participants were requested to sit for a period of about 120 s after the completion of each trial in order to rest. After that, participants were asked to reassume the aforementioned foot position in preparation for another trial.

2.3 Data processing

The outputs of the force plate are time series of COP displacements in AP and ML directions. The first 10 s interval was discarded in order to exclude the transition phase needed to reach a postural steady state, as previously suggested (Mitchell et al. 1995; Raymakers et al. 2005).

2.3.1 Traditional parameters: time domain analysis

From each of the 2D components of COP displacements, the ML excursion ($ROMP_x$) and the AP excursion ($ROMP_y$) were computed as the difference between absolute maximum and absolute minimum values of COP displacements in both considered directions.

In addition, the trajectory length (TL) of the COP was computed. All traditional parameters were normalised to subject's height.

2.3.2 Frequency domain analysis

In this work, a spectral analysis was carried out using parametric estimators based on AR modelling of the data (Galli et al. 2008). The use of this method allows for the efficient quantification of the centre frequency (CF) and the power of each spectral component. In this work, the AR model order was set to 10.

In order to characterise the spectral patterns, we calculated the CF of the main spectral peak of both the AP COP displacements spectrum (f_y) and the ML COP displacements spectrum (f_x).

2.3.3 Nonlinear approaches: FD and entropy

2.3.3.1 Fractal dimension. FD of COP signal was computed using the box-counting algorithm.

To calculate the FD for a given set S, imagine this fractal set lying on an evenly spaced grid, and count how many boxes are required to cover the set. The box-counting dimension is calculated by seeing how this number changes when the grid is made finer and finer.

Suppose that $N(\varepsilon)$ is the number of boxes of side length ε required to cover the set. Then the box-counting dimension is defined as follows (1):

$$\mathrm{FD} = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log(1/\varepsilon)}. \tag{1}$$

Thus, FD corresponds to the slope of the plot $\log N(\varepsilon)$ versus $\log(1/\varepsilon)$ (see Figure 1). FD was computed for the sway of all participants in both conditions (OE and CE).

2.3.3.2 Entropy measures. Let $x(t)$ be the temporal evolution of a given signal and S its discrete evolution, obtained by a regular sampling, given by

$$S = \{x_k, k = 1, \ldots, K\}, \tag{2}$$

where x_k stands for $x(t_k)$, i.e. the signal value at the time $t_k = k \times T$, where T is the sampling period. Thus, given the sequence S, consisting of K measurements and specified the pattern length m, two patterns, $p_m(i)$ and $p_m(j)$, are considered similar if the difference between any pair of corresponding measurements in the patterns is less than the tolerance r, i.e. if (3)

$$|x_{i+k} - x_{j+k}| < r \quad \text{for } 0 \le k \le m. \tag{3}$$

Considering the set P_m of all patterns of length m within S,

$$C_{im}(r) = \frac{n_{im}(r)}{N - m + 1}, \tag{4}$$

where $n_{im}(r)$ is the number of patterns in P_m that are similar to $p_m(i)$. The quantity $C_{im}(r)$ is the fraction of patterns of length m that resemble the pattern of the same length that begins at interval i. $C_{im}(r)$ is calculated for each pattern in P_m and $C_m(r)$ is defined as the mean of the $C_{im}(r)$ values. The quantity $C_m(r)$ expresses the prevalence of repetitive patterns of length m in S. Finally, the ApEn of S, for patterns of length m and threshold r, is defined as (5)

$$\mathrm{ApEn}(S, m, r) = \ln\left[\frac{C_m(r)}{C_{m+1}(r)}\right], \tag{5}$$

i.e. the natural logarithm of the relative prevalence of repetitive patterns of length m compared with those of length $m + 1$.

In this work, ApEn of COP signal in ML direction ($\mathrm{ApEn_{ML}}$) and in AP direction ($\mathrm{ApEn_{AP}}$) was computed for all the participants.

Methods for estimation of the entropy of a system represented by a time series are not, however, well suited for analysis of the short and noisy data-sets and may lead to inconsistent results. For this reason, the sample entropy (SampEn) was introduced to avoid bias due to the shortening of the data. SampEn over performed ApEn over a broad range of conditions as reported by Richman and Moorman (2000): for this reason, in this work we computed this index also.

2.4 Statistics

To explore the statistical differences, within and between the DS and CG, in computed parameters, we analysed category results (between DS and CG in the same condition) and condition results (within the same population in different conditions of OE and CE) using ANOVA; p value was set at 0.05.

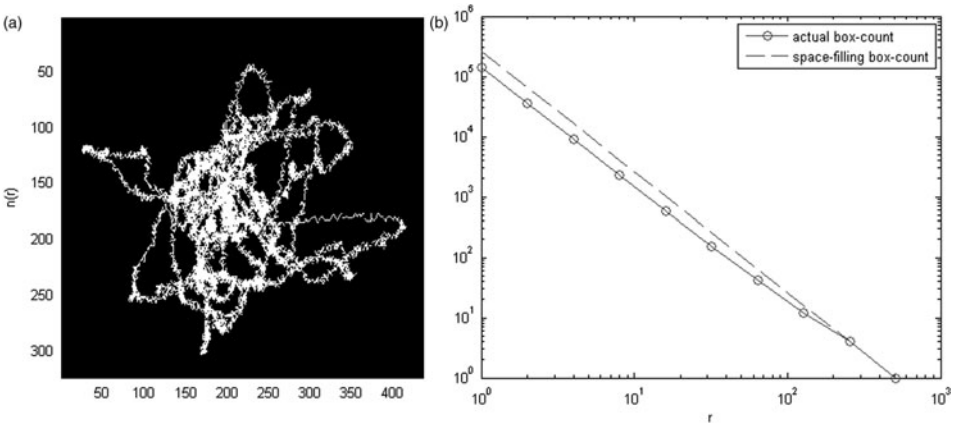

Figure 1. Binarisation of original image in order to prepare the box-counting process (a); FD corresponds to the slope of the plot $\log N(\varepsilon)$ versus $\log(1/\varepsilon)$ (b).

Table 1. Results of traditional parameter analysis for the two groups considered in OE and CE conditions.

	DSG		CG	
	OE	CE	OE	CE
ROMPx (cm/m)	22.28 ± 8.8*	22.81 ± 8.8*	15.78 ± 5.2	20.26 ± 5.8
ROMPy (cm/m)	16.49 ± 7.4*	15.93 ± 7.9*	8.53 ± 3.9	8.95 ± 6.9
TL (cm/m)	226.1 ± 15.6*	225.1 ± 15.4*	157.3 ± 24.8	141.2 ± 18.6
f_x (Hz)	0.26 ± 0.21	0.42 ± 0.32	0.15 ± 0.12	0.18 ± 0.14
f_y (Hz)	0.28 ± 0.22	0.26 ± 0.22	0.15 ± 0.27	0.37 ± 0.29

$^*p < 0.05$ DSG versus CG; $^+p < 0.05$ OE versus CE.

3. Results

3.1 Traditional parameters and frequency analysis

DS participants evidenced a general increase in the ROM in both AP and ML directions in comparison with CG (see Table 1). The increase was evident in both OE and CE conditions.

Frequency analysis pointed out no statistical differences between DS and CG participants and between OE and CE conditions: the value of frequency indicated the rate at which the subject adapts control in order to compensate external forces. DS and CG use the same frequency but DS participants showed an increase in ROM in ML and AP directions, evidencing a precarious balance that they tried to compensate using a 'clumsy' strategy.

3.2 FD and entropy

Nonlinear analysis was computed in terms of the FD and entropy.

As reported in Table 2, DS participants evidenced an increase in the FD in comparison with CG: the dimensionality of DS participants pointed out higher values in both groups and in both conditions.

Concerning entropy analysis results, $ApEn_{ML}$ and $ApEn_{AP}$ did not evidence statistical differences between groups and conditions.

Accordingly, SampEn (Figure 2) pointed out no statistical differences between groups in AP directions: both groups showed the same regular trend of COP AP trajectories. However, a statistical increase in DS participants in ML direction was observed: DS participants exhibited a more irregular sway than healthy subjects in ML COP fluctuations. Moreover, in OE versus CE comparison, SampEn revealed an increase in CE condition, pointing out a less regular signal in both AP and ML directions.

4. Discussion

Postural and in general motor control in DS subjects evidenced many differences in comparison with healthy subjects: the hypotonia and the ligament laxity in union with neurological diseases act on the control of all the inputs the motor system required.

In the first part of this work, we analysed postural control using traditional parameters that describe the movement of COP in ML and AP directions throughout the computation of the excursions during trial.

The movement of COP is connected to the ability of a subject to compensate the movement of centre of mass using vestibular, proprioceptive and visual inputs: the synergic work of these systems let us to maintain posture. The extent of COP movements permits to understand how much the subject has to move to maintain COP inside the base of support. In this work, DS participants exhibited larger movements than normal subjects both in AP and, especially, in ML directions, evidencing a less stable equilibrium. DS participants suffered from hypotonia and ligament laxity that work increasing COP movements: moreover, in CE condition, visual inputs are deleted and the proprioceptive and vestibular system alone cannot supply to the lack of information.

Table 2. Results of nonlinear analysis for the two groups considered in OE and CE conditions.

	DSG		CG	
	OE	CE	OE	CE
$ApEn_{ML}$	0.43 ± 0.38	0.45 ± 0.15	0.42 ± 0.19	0.41 ± 0.17
$ApEn_{AP}$	0.31 ± 0.25	0.39 ± 0.11	0.38 ± 0.16	0.43 ± 0.08
$SampEn_{ML}$	0.4 ± 0.35*	$0.54 \pm 0.3^{*,+}$	0.2 ± 0.09	0.27 ± 0.08
$SampEn_{AP}$	0.26 ± 0.13	$0.32 \pm 0.11^{+}$	0.23 ± 0.09	$0.29 \pm 0.07^{+}$
FD	1.67 ± 0.06*	1.71 ± 0.04*	1.57 ± 0.04	1.6 ± 0.02

$^*p < 0.05$ DSG versus CG; $^+p < 0.05$ OE versus CE.

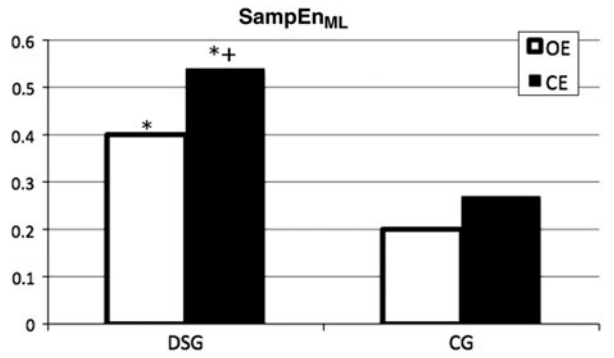

Figure 2. $SampEn_{ML}$ results for DS and CG participants in OE and CE conditions ($^{*}p < 0.05$ in DSG vs. CG comparison, $^{+}p < 0.05$ in OE vs. CE comparison).

Frequency analysis adds information to the traditional parameters, analysing the rate at which the COP direction changes, reflecting the action–reaction times between external perturbations and compensatory movements in order to re-establish balance. DS participants pointed out the same frequency of CG, even if the ROM is higher in all directions.

Nonlinear approach takes into account the dynamic of the signal: we found higher values for DS participants in FD. In agreement with the findings of Blaszczky and Klonowsky (2001), this fact can be interpreted as a decrease in postural stability in DS subjects. In addition, Roerdink et al. (2006) suggested to interpret these findings according to the recruitment of additional control processes (degrees of freedom), for instance to compensate for the reduced efficacy of ankle mechanisms in controlling posture. This is in line with the entropy results that evidenced a stronger involvement of ML direction for DS participants.

SampEn evidenced statistical differences between OE and CE conditions: in CE condition, this index increases in both groups in both directions, revealing a less regular signal in both directions without visual inputs. Moreover, resultant COP trajectories of the DS participants in ML direction were less regular than those of the CG, as indexed by significantly higher sample entropy values.

These findings reflect less effective physiological control, as documented by large use of ML plane in compensatory strategies actuated by DS people in order to conserve balance: since DS participants feel precarious equilibrium controlling postural sway with only AP movements and try to compensate using ML movemets. The increase in SampEnML recording for DS participants revealed a less regular signal and a more complex system, developed in order to supply to the lack of balance in AP direction, which is not for healthy subjects.

The more regular COP trajectories in both directions in the conditions comparison indexed by the increase in SampEn could be explained by an increase in system complexity and adaptability, present in both considered groups.

The system is continuously subjected to external perturbation that a person can contrast integrating the real-time input and the prediction system based on past input: the information given by the nonlinear approach can describe this mechanism.

Considering the neurological aspect of people suffering from DS and given that the entropy and FD could analyse the dynamics of the COP signal, it seems that the complete integration of all the systems required in maintaining posture was not achieved by the examined pathological group.

Moreover, the movements of DS subjects are presented in the literature as ‘clumsiness’: their movements appear as always under perturbation and the adaptation process is longer than the starting of a new perturbation.

The rehabilitative approach would take into account not only the ‘mechanical’ aspect introduced by the presence of ligament laxity and hypotonia but also a re-educational programme that could act on the integration of the systems acting in postural control.

In our work, these indexes are suitable in order to better describe the postural control in DS.

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