



# Analysis of the multi-segmental postural movement strategies utilized in bipedal, tandem and one-leg stance as quantified by a principal component decomposition of marker coordinates



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## ARTICLE INFO

### Article history:

Accepted 11 August 2013

### Keywords:

Coordination of movements  
Movement synergies  
Postural control strategy  
Balance and stability  
Upright quiet stance  
Locomotor system  
Principal component analysis (PCA)

## ABSTRACT

Postural control research describes ankle-, hip-, or multi-joint strategies as mechanisms to control upright posture. The objectives of this study were, first, development of an analysis technique facilitating a direct comparison of the structure of such multi-segment postural movement patterns between subjects; second, comparison of the complexity of postural movements between three stances of different difficulty levels; and third, investigation of between-subject differences in the structure of postural movements and of factors that may contribute to these differences.

Twenty-nine subjects completed 100-s trials in bipedal (BP), tandem (TA) and one-leg stance (OL). Their postural movements were recorded using 28 reflective markers distributed over all body segments. These marker coordinates were interpreted as 84-dimensional posture vectors, normalized, concatenated from all subjects, and submitted to a principal component analysis (PCA) to extract principal movement components (PMs). The PMs were characterized by determining their relative contribution to the subject's entire postural movements and the smoothness of their time series.

Four, eight, and nine PM were needed to represent 90% of the total variance in BP, TA, and OL, respectively, suggesting that increased task difficulty is associated with increased complexity of the movement structure. Different subjects utilized different combinations of PMs to control their posture. In several PMs, the relative contribution of a PM to a subject's overall postural movements correlated with the smoothness of the PM's time series, suggesting that utilization of specific postural PMs may depend on the subject's ability to control the PM's temporal evolution.

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## 1. Introduction

Postural control is facilitated by postural movements that control body sway such that the center of mass remains above the area of support. Many different approaches have been used to quantify postural control movements during quiet stance. Direct measures of the postural control movements quantified the sway angle of the center of mass or the kinematics of specific joints (Corriveau et al., 2004; Gage et al., 2004; Sasagawa et al., 2009). Indirect methods include, for example, the quantification of the center of pressure (COP) movement (Abe et al., 2010; Moghadam et al., 2011; Raymakers et al., 2005; Winter et al., 1996) or the measurement of activation of muscles involved in postural control (Dietz and Duysens, 2000; Hadders-Algra et al., 1998; Ting, 2007). Quantification of joint kinematics in combination with measurements of the

muscle activation of postural control movements has led to the definition of postural control strategies, e.g. ankle or hip strategy (Gatev et al., 1999; Horak, 1987; Winter et al., 1996, 1998). Some studies imply that combinations of the ankle and hip strategies fully explain the postural control movements (Aristidou et al., 2008; Horak and Nashner, 1986; Kuo and Zajac, 1993; Creath et al., 2005). However, more recent studies suggest that higher order, multi-segment movement strategies should also be considered (Alexandrov et al., 2005; Gunther et al., 2011; Hsu et al., 2007; Park et al., 2012; Pinter et al., 2008).

Practical challenges in studies that consider multi-joint movements when investigating postural control are that movement amplitudes are typically small, making multi-joint coordination patterns difficult to determine. In this study, we explore and refine a method to identify, quantify, and visualize postural strategies that builds on approaches developed for gait analysis (Daffertshofer et al., 2004; Federolf et al., 2012b; Troje, 2002; Verrel et al., 2009), which interpret the entirety of the 3D positions of all markers quantifying the movements of a subject as a high dimensional

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posture vector. A principal component analysis (PCA) on these posture vectors extracts the main (“principal”) movement components constituting the subject’s movements (Federolf et al., 2012a). Even when motion amplitudes are as small as during quiet stance, this method proved to be well suited to determine subject-specific multi-segment coordination patterns in postural movements (Federolf et al., 2012c). The current study presents a normalization technique that allowed calculation of principal postural movements for a group of subjects, thus facilitating a direct comparison of postural movement strategies between subjects.

As a first application, the current study compared the postural movements between the three stances of different difficulty levels. We hypothesized that increased task difficulty would be associated with increased “complexity” of the postural movements. According to Vaillancourt and Newell (2002), the “complexity of a system” may be viewed as a measure of how many states are accessible to the system. Following an approach suggested by Verrel et al. (2009) and Witte et al. (2010) we quantified movement complexity by determining how many principal movement components contribute to stabilizing upright stance in a balance task.

Secondly, between-subject differences in structure and organization of postural movements were investigated. We hypothesized that whether or not a specific type of postural movement plays an important role in a subject’s organization of postural control, may depend on this subject’s ability to control the specific movement component. One indication for a subject’s ability to control a movement component may be related to the “smoothness” of the motion, which we quantified by performing a detrended fluctuation analysis (DFA) (Peng et al., 1995).

In summary, the objectives of this study were (1) presentation of an analysis technique that facilitated direct comparison of the structure of multi-segment postural movement patterns between subjects; (2) application of this technique to compare the complexity of postural movements between bipedal, tandem, and one-leg stances, testing the hypothesis that the complexity of postural movements increases from bipedal over tandem to one-leg stance; and (3) investigation of between-subject differences in the structure of postural movements and testing the hypothesis that whether or not a subject utilizes a specific movement strategy may relate to the “smoothness” of the movement’s time series as characterized by DFA.

## 2. Methods

### 2.1. Participants

Twenty-nine subjects (16 male/13 female) participated in this study (Table 1). The study was approved by the appropriate ethics committee and all participants gave informed written consent. The subjects had no recent lower extremity injuries and no other physical or mental conditions that might impair their ability to execute a balance exercise.

### 2.2. Measurement procedures

Three standing tasks of different difficulty levels were completed barefoot: (1) a normal bipedal stance (BP) with the inside of the feet aligned with markings taped onto the ground 15 cm apart; (2) a tandem stance (TA) with the dominant leg in front of the non-dominant leg such that the heel of the front foot touched the

toes of the rear foot; and (3) a one-leg stance (OL) on the dominant leg with the foot of the non-dominant leg held in air a few centimeters above the ground. In all stance conditions the hands rested on the hips and subjects were instructed to focus their gaze on a target in approximately 15 m distance. The trials began with the participants aligning the position of their feet to markings on the ground. Then the subjects stood in the specified stance for 100 s looking straight ahead. A trial was repeated if a participant lost balance or touched the ground with the non-supporting foot in the OL.

Postural control movements were recorded using 28 reflective markers placed on bony landmarks of all major segments of the subjects’ body. The 3D-trajectories of these markers were recorded with eight high-speed video cameras (Motion Analysis Corporation, Santa Rosa, CA, USA) using a sampling rate of 240 Hz and reconstructed with the software Eva Real-Time (“EvaRT”; Motion Analysis Corporation, Santa Rosa, CA, USA).

### 2.3. Data analysis

All trials were visually inspected. Three trials (one in each stance condition) had to be rejected due to substantial voluntary movements superimposing the postural movements (turning the head and scratching). From each accepted trial, a period of 80 s, from 15 to 95 s, was selected for further analysis to avoid movements due to stepping into or out of the balance task. At any given time in the analysis period, a subject’s posture was quantified by the 28 3D-marker coordinates. These 84 spatial coordinates were interpreted as an 84-dimensional posture vector  $\mathbf{p}(t_i)$ . In each trial, 19,201 posture vectors were collected (80 s at 240 Hz measurement frequency) quantifying the entirety of the subject’s movement during the analyzed period. Previous studies calculated a principal component analysis (PCA) directly on such posture vectors yielding trial- and subject-dependent principal movement components (Abe et al., 2010; Daffertshofer et al., 2004; Federolf et al., 2012a, 2012b, 2012c; Troje, 2002; Verrel et al., 2009). The current study employed a normalization technique that allowed combining the posture vectors of different subjects, such that universal principal movements could be calculated. The aim of this normalization was to retain the variability between posture vectors created from postural movements in the input matrix for the PCA, while minimizing those differences between posture vectors that stemmed from anthropometric differences between subjects. This was achieved in three steps: First, a mean posture vector,  $\mathbf{p}_{mean}$ , was calculated for each trial and subtracted from all posture vectors of this trial. Second, the vector norm,  $d(t_i)$ , of these centered posture vectors was calculated. Third, all centered posture vectors were divided by the mean vector norm,  $d_{mean}$ , calculated for the entire trial.

$$\mathbf{p}_{norm}(t_i) = (\mathbf{p}(t_i) - \mathbf{p}_{mean}) / d_{mean}$$

The normalized and centered posture vectors  $\mathbf{p}_{norm}(t_i)$  of all subjects were then assembled into one input matrix for the PCA, i.e. for each of the three stance conditions one  $556,829 \times 84$ -input matrix was obtained.

The PCA yielded a set of orthogonal eigenvectors, the principal component vectors  $\mathbf{PC}_j$ , which indicated the direction of the largest variance of the posture vectors within the 84-dim posture space. Their associated eigenvalues  $EV_j$  quantified the variance in the direction defined by each  $\mathbf{PC}_j$ . By convention, the  $\mathbf{PC}_j$  are ordered according to their eigenvalues. The progression of each one-dimensional principal movement was quantified by a coefficient  $c_j(t_i)$  obtained by projecting the posture vectors  $\mathbf{p}(t)$  onto the principal component  $\mathbf{PC}_j$

$$c_j(t_i) = \mathbf{p}_{norm}(t_i) \mathbf{PC}_j$$

where indices  $i, j$  refer to the time frame ( $i = 1, \dots, 19,201$ ) and the number of the principal component ( $j = 1, \dots, 84$ ). The coefficients  $c_j(t_i)$  formed time series that allowed a quantitative analysis of the principal movements carried out by a subject during a postural control task (Fig. 1). Projecting each principal movement back into the original posture space and rescinding the normalization yielded posture vectors,  $\mathbf{PM}_j(t_i)$ ,

$$\mathbf{PM}_j(t_i) = \mathbf{p}_{mean} + a_j d_{mean} c_j(t_i) \mathbf{PC}_j$$

representing a subject’s principal movement components in the original marker coordinates and therefore allowed to visualize the principal movement with stick figures (Figs. 2–4) or animations. The amplification factor  $a_j$  introduced in this equation alleviated a visual assessment of the principal movement (Figs. 2–4).

### 2.4. Variables quantifying the internal structure of the principal postural movements

Normalized eigenvalues,  $EV_j$ , of the principal movements—normalized by dividing each  $EV_j$  by the sum of all  $EV_j$ —quantify how much the corresponding  $\mathbf{PM}_j$  contributed to the entirety of postural movements observed in all subjects (Daffertshofer et al., 2004; Verrel et al., 2009). An equivalent variable quantifying the contribution of each  $\mathbf{PM}_j$  to the postural movements in an individual subject was obtained by calculating the normalized variance,  $\sigma_j^2$ , from the coefficient-time series  $c_j(t)$  of each individual subject. In analogy to the eigenvalues, the  $\sigma_j^2$  were normalized by dividing them by the sum of all  $\sigma_j^2$  of a subject. In addition, the cumulative normalized variance,  $\Sigma \sigma_j^2$ , was calculated as a measure of how much of the entire variance observed in a subject’s trial was represented by a given number

**Table 1**  
Anthropometrical data of the subjects (mean and SD).

	Women (n=13)	Men (n=16)
Age [years]	23.3 (2.9)	24.6 (3.2)
Weight [kg]	64.0 (8.7)	78.3 (13.2)
Height [m]	1.71 (0.07)	1.80 (0.07)

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