Federolf, P., Roos, L., Nigg, B. (2013). Analysis of the multi-segmental postural movement strategies utilized in bi-pedal, tandem and one-leg stance as quantified by a principal component decomposition of marker coordinates. *Journal of Biomechanics, 46*, 2626-2633.

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

Peter Federolf[1,2], Lilian Roos[2,3], Benno M. Nigg[2]

Affiliations:

[1] Norwegian School of Sports Sciences, Oslo, Norway;
[2] Human Performance Lab, Faculty of Kinesiology, University of Calgary, Canada;
[3] Institute of Human Movements Sciences and Sport, ETH Zurich, Zurich, Switzerland

Original article prepared for submission to Journal of Biomechanics

Key Words: coordination of movements; movement synergies; postural control strategy; balance and stability; upright quiet stance; locomotor system; principal component analysis (PCA);

Corresponding author:

Peter Federolf
Norwegian School of Sport Sciences
P.O. box 4014 Ulleval Stadion
0806 Oslo,
Norway
Phone: +47 (232) 62322
Email: peter.federolf@nih.no

Word Count: Abstract: 244 / Text: 3493

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 level; 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-second 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 (PM). 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.

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; Winter et al., 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 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 level. We hypothesized that increased task difficulty would be associated with increased "complexity" of the postural movements. According to Vaillancourt and Newell, the "complexity of a system" may be viewed as a measure of how many states are accessible to the system (Vaillancourt and Newell, 2002). Following an approach suggested by Verrel et al. (Verrel et al., 2009) and Witte et al. (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.

Methods

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.

Measurement Procedures

Three standing tasks of different difficulty level 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; 3) a one-leg stance (OL) on the dominant leg with the foot of the non-dominant leg held in the 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 meters 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 seconds 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).

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, scratching). From each accepted trial, a period of 80 seconds, from second 15 to 95, 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* $\boldsymbol{p}(t_i)$. In each trial, 19,201 posture vectors were collected (80 seconds 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; Federolf et al., 2012b; Federolf et al., 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, $\boldsymbol{p}_{mean}$, 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.

$$\boldsymbol{p}_{\boldsymbol{norm}}(t_i) = (\boldsymbol{p}(\boldsymbol{t}_{\boldsymbol{i}}) - \boldsymbol{p}_{\boldsymbol{mean}})/\boldsymbol{d}_{\boldsymbol{mean}}$$

The normalized and centered posture vectors $\boldsymbol{p_{norm}}(t_i)$ of all subjects were then assembled into one input matrix for the PCA, i.e. for each of the three stance conditions one 556,829x84-input matrix was obtained.

The PCA yielded a set of orthogonal eigenvectors, the *principal component vectors* $\boldsymbol{PC_j}$, 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 $\boldsymbol{PC_j}$. By convention, the $\boldsymbol{PC_j}$ 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 $\boldsymbol{p}(t)$ onto the principal component $\boldsymbol{PC_j}$:

$$c_j(t_i) = \boldsymbol{p_{norm}}(t_i) \cdot \boldsymbol{PC_j},$$

where indices i, j refer to the time frame (i = 1..19,201) and the number of the principal component (j = 1..84), respectively. 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 (Figure 1). Projecting each principal movement back into the original posture space and rescinding the normalization yielded posture vectors, $\boldsymbol{PM_j}(t_i)$,

$$\boldsymbol{PM_j}(t_i) = \boldsymbol{p_{mean}} + a_j \cdot d_{mean} \cdot c_j(t_i) \cdot \boldsymbol{PC_j}$$

representing a subject's principal movement components in the original marker coordinates and therefore allowed to visualize the principal movement with stick figures (Figure 2,3,4) or animations. The amplification factor a_j introduced in this equation alleviated a visual assessment of the principal movement (Figure 2,3,4).

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 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 PM_j to the postural movements in an individual subject was obtained by calculating the *normalized variance*, σ^2_j, from the coefficient-time series $c_j(t)$ of each individual subject. In analogy to the eigenvalues, the σ^2_j were normalized by dividing them by the sum of all σ^2_j of a subject. In addition, the *cumulative normalized variance*, $\Sigma\sigma^2_j$, was calculated as a measure of how much of the entire variance observed in a subject's trial was represented by a given number of principal movements or, conversely, how many PM_j were needed to cover a predefined fraction of variance in the data:

$$\Sigma\sigma^2{}_j = \sum_{k=1}^{j} \sigma_k^2$$

The *cumulative normalized variance*, $\Sigma\sigma^2_j$, can also be seen as a measure of the movement's complexity, in the sense that a movement may be considered as more complex if more one-dimensional movement components are needed to represent a given percentage of the postural variance that occurs in a given movement (Federolf et al., 2012c; Verrel et al., 2009; Witte et al., 2010).

Finally, the *persistence* α was calculated for each $c_j(t)$-time series by performing a DFA (Peng et al., 1995). DFA has been used frequently to determine long-range correlations in stabilographic time series (Duarte 2001; Norris et al. 2005; Amound et al. 2007; Duarte & Stenard 2008, Lamoth et al. 2009). The persistence α is a measure of "smoothness" of the analyzed time series in the sense of a likelihood that the time series changes direction. Reference values for α are $\alpha \approx 0.5$ for white noise, $\alpha \approx 1.5$ for Brownian motion, and $\alpha = 2.0$ for the limiting case of a straight line. DFA was selected since it does not require stationarity of the underlying signal – a condition that is not necessarily satisfied in extended standing experiments (Duarte and Zatsiorsky, 2001).

To determine if the time series characteristics quantified by α had an influence on how the individual subjects structured their postural movement, a Spearman correlation coefficient r_S was calculated between the individual subjects' normalized variance σ^2 and their α-values.

All data analysis procedures were calculated using the software Matlab® (The MathWorks, Inc., Natick, MA, USA) and PASW 18.0 package (SPSS Inc., Chicago, IL, USA). The level of statistical significance was set at 0.05.

Results

The 6 PMs contributing the most to the postural variance in the three stances were graphically represented in Figures 2, 3, and 4. In bipedal stance (Figure 2), PM_1 could be characterized as anterior-posterior ankle sway; PM_2 as lateral weight shift; PM_3 as core flexion; PM_4 as a rotation of the upper body around a vertical axis; PM_5 as lifting of the shoulders in the frontal plane and breathing (note the change in thorax volume); and PM_6 as rotation around an anterior-posterior axis trough the subjects' core. PM_1 explained 71,7% of the postural variance in the whole group, its relative contribution to the postural variance in individual subjects varied between 36.5% and 89.3% (Figure 5 A, B). It was thus the dominant postural control movement in all subjects. The contribution of PM_j ($j \geq 2$) gradually decreased from 9.8% in PM_2 to 1.4% in PM_6 with individual results varying between 1.4% and 33.9% in PM_2 and between 0.4% and 3.2% in PM_6.

In tandem stance (Figure 3), PM_1 could be interpreted as a lateral ankle sway combined with a lateral core sway; PM_2 as anterior-posterior weight shift; PM_3 as rotation around a vertical axis; PM_4 as a core rotation around an anterior-posterior axis; PM_5 as core flexion; and PM_6 as lifting of the arms. In this stance, the dominant postural movement strategy was either PM_1 or PM_2 or a combination thereof with their relative contributions varying between 8.6% to 73.9% and 8.3% to 77.0%, respectively. The higher order PMs – with the exception of two outliers – contributed less than 12.8% in all subjects (Figure 5 C).

In one-leg stance (Figure 3), PM_1 quantified an anterior-posterior ankle sway; PM_2 a lateral ankle sway combined with a lateral core sway; PM_3 a knee flexion of the lifted leg; PM_4 a lateral ankle sway; PM_5 a hip flexion of the lifted leg; PM_6 anterior-posterior motion of the elbows combined with a slight rotation of the thorax around a vertical axis. Similarly to tandem stance, either PM_1 or PM_2 or a combination thereof dominated the postural strategy ($\sigma^2_{1,2}$ varying between 6.0% to 63.4% and 4.4% to 66.4%), however, the higher order PMs together accounted on average for more than 40.1% of the postural variance (Figure 5 D, A).

The results for the cumulative normalized variance $\Sigma\sigma^2_j$ determined for the three stances BP, TA, and OL showed that averaged over all subjects, 4, 8, and 9 PM_j were needed to represent 90% of the total variance, respectively (Figure 6). To represent 95%, 10, 14, and 16 principal movement components were needed. For the following analyses, the first 20 PM_j were therefore considered to ensure that the analyzed PM_j represented at least 95% of the postural variance. Significant differences were found in the movement complexity, quantified by $\Sigma\sigma^2_j$, between BP and TA and between BP and OL in all of the first 20 PM_j (j = 1…20). These differences persisted even after adjusting for 20 comparisons (Bonferroni). Differences between TA and OL were significant for j = 2, 3, 13 and j ≥ 15, but did not persist after adjusting for multiple comparisons.

In all three stances, the persistence α decreased gradually from median values of 1.8 for PM_1 to values of 1.4 (BP) or 1.5 (TA, OL) for $PM_{j>12}$ (Figure 7). The correlation between the persistence of a PM_j's time series and the normalized variances σ^2_j (Table 2) was significant for 11, 16, and 14 of the first 20 PM_j in BP, TA, OL, respectively. All significant correlations were positive.

Discussion

Summary and discussion of the most important findings

A refined analysis methodology was developed and applied in this study to compare the organization of postural movements between subjects in three balance stances. **The hypothesis that increased task difficulty is associated with increased complexity of the postural movements was supported since the cumulative normalized variance was**

consistently higher in BP than in TA and in TA compared to OL. The results further revealed that the structure of the postural movements is highly subject-specific – an observation that is rarely explicitly pointed out (Argatov, 2013; Collins and Luca, 1993; Fujiwara et al., 2009; Torres-Oviedo and Ting, 2010). Only in BP the movement component quantified by PC_1, characterized as an anterior-posterior ankle sway, was the dominant movement component in all subjects. In higher order movement components in BP, and in all movement components in TA and OL, great differences were observed in whether or not a movement component played a role in an individual subject's postural movements. This suggests that different subjects rely on different **postural strategies** to control their upright posture. The hypothesis that the relative importance a principal movement had for a subject's postural control would be correlated with the smoothness of this movement's time series, was supported in a significant fraction of the first 20 principal movements. One interpretation of this observation may be that subjects predominantly utilized those movement components whose movements they could control in such a way that few adjustments or interventions were necessary, whereas movement components exhibiting the characteristics of a stochastic control process (lower α) were less likely to play an important role in the postural movements.

Application of PCA to decompose postural movements

The PCA-based analysis applied in this study decomposed the subjects' postural movements observed during balance trials into one-dimensional multi-segment movement components. In a previous study a PCA-decomposition of postural movements of individual trials proved to be highly sensitive for the detection of intra-subject effects such as differences in the structure of postural movements between shod and barefoot standing (Federolf et al., 2012c) – a highly relevant research question when analysing the risk of a fall in older adults (Koepsell et al., 2004). The current study enhanced this analysis method by applying a normalization technique to filter out anthropometric differences before submitting the data to the PCA. The resultant movement components of different subjects are therefore projected on the same PC-vector basis and thus facilitated a direct comparison of postural movement strategies between subjects.

The principal movement components appeared to represent distinct movement strategies. Some of these movement components agreed well with movement strategies that had been described qualitatively in previous studies, e.g. as ankle or hip strategy (Horak and Nashner, 1986; Horak, 1987), but which were so far difficult to distinguish from other, higher-order multi-segmental movements strategies. The characteristics of the temporal evolution of the different principal movements, here quantified by the persistence α, differed considerably between lower order and higher order PMs. This suggests that their control posed different challenges for the motor control system. Moreover, in all subjects the persistence calculated for the low order PM differed substantially from the reference value for Brownian motion ($\alpha = 1.5$). This suggests that the dominating postural movements – in contrast to the center of pressure motion (Duarte and Zatsiorsky, 2001; Duarte and Sternad, 2008) – may not be controlled by non-linear (chaotic) or random processes.

Particularly in the more difficult stances TA and OL, a relatively large number of principal movements were necessary to represent 90% of the variance in postures. This suggest that at least in these more complex stances, a simple inverted pendulum model or postural control models only relying on ankle and hip strategy may not adequately represent the multi-faceted structure of human postural sway. Our findings therefore support other studies suggesting that multi-segment postural movement patterns should be considered (Alexandrov et al., 2005; Gunther et al., 2011; Hsu et al., 2007; Park et al., 2012; Pinter et al., 2008). A principal component decomposition of the variability in the posture vectors offers a new approach to study the multi-joint nature of postural stability within subjects or within-subject adaptations to changes in external conditions (Federolf et al., 2012c). The normalization proposed in the current study allows for comparison of multi-joint postural movement strategies between subjects or subject groups **without the need for additional scaling and thus facilitated the**

use of marker coordinates rather than joint angles. This enables the visualization of the principal movements and offers other advantages, for instance, marker coordinates are directly measured with a known error and without the need for additional assumptions about joint axis locations or orientations which are necessary when calculating joint angles.

Limitations

The normalization applied in the current study subtracted the mean posture of each subject and standardized the deviation from the mean posture between subjects. This facilitated computation of principal movement components for datasets pooled from several subjects and therefore allowed comparing the structure of the postural movements between subjects, however, it eliminated differences in the movement amplitude. Hence, relative contributions of a principal movement component in relation to the whole postural movements of a subject can be compared between subjects, but absolute amplitudes cannot.

It is also important to note, that the PM_j are a priori mathematical solutions representing correlated, linear changes in the set of marker positions. Hence, they do not exactly represent movements such as “ankle-” or “hip strategy”, but linearized versions thereof. Further, in the assessment and comparison of the principal movement components it needs to be taken into account that different components may have different functions whose primary purpose may not be postural control, for instance, breathing (PM_5 in BP) or involuntary or voluntary movements to ease fatigue (this may have led to the outliers in PM_2 of BP, Figure 5).

When comparing balance movements between subjects, foot positioning may affect the postural movements carried out by the subject. Future studies are needed to assess how foot placement affects the relative difficulty of balance tasks.

Funding

The authors did not receive external funding for conducting this study.

Conflict of interest statement

None of the authors have a conflict of interest.

References

Abe, M. O., Masani, K., Nozaki, D., Akai, M., Nakazawa, K., 2010. Temporal correlations in center of body mass fluctuations during standing and walking. Human Movement Science 29**,** 556-566.

Alexandrov, A. V., Frolov, A. A., Horak, F. B., Carlson-Kuhta, P., Park, S., 2005. Feedback equilibrium control during human standing. Biological Cybernetics 93**,** 309-322.

Argatov, I., 2013. A subject-specific postural instability parameter. Gait & Posture 37**,** 141-143.

Aristidou, A., Cameron, J., Lasenby, J., 2008. Predicting missing markers to drive real-time centre of rotation estimation. In: Perales, F., Fisher, R. (Eds.), Articulated Motion and Deformable Objects. Springer Berlin / Heidelberg, pp. 238-247.

Collins, J. J., Luca, C. J., 1993. Open-loop and closed-loop control of posture: A random-walk analysis of center-of-pressure trajectories. Experimental Brain Research 95**,** 308-318.

Corriveau, H., Hebert, R., Raiche, M., Dubois, M. E., Prince, E., 2004. Postural stability in the elderly: empirical confirmation of a theoretical model. Archives of Gerontology and Geriatrics 39**,** 163-177.

Creath, R., Kiemel, T., Horak, F., Peterka, R., Jeka, J., 2005. A unified view of quiet and perturbed stance: simultaneous co-existing excitable modes. Neuroscience Letters 377**,** 75-80.

Daffertshofer, A., Lamoth, C. J. C., Meijer, O. G., Beek, P. J., 2004. PCA in studying coordination and variability: a tutorial. Clinical Biomechanics 19**,** 415-428.

Dietz, V., Duysens, J., 2000. Significance of load receptor input during locomotion: a review. Gait & Posture 11**,** 102-110.

Duarte, M., Sternad, D., 2008. Complexity of human postural control in young and older adults during prolonged standing. Experimental Brain Research 191**,** 265-276.

Duarte, M., Zatsiorsky, V. M., 2001. Long-range correlations in human standing. Physics Letters A 283**,** 124-128.

Federolf, P., Reid, R., Gilgien, M., Haugen, P., Smith, G., 2012a. The application of principal component analysis to quantify technique in sports. Scandinavian Journal of Medicine & Science in Sports, http://dx.doi.org/10.1111/j.1600-0838.2012.01455.x, in press.

Federolf, P., Tecante, K., Nigg, B., 2012b. A holistic approach to study the temporal variability in gait. Journal of Biomechanics 45**,** 1127-1132.

Federolf, P. A., Roos, L., Nigg, B., 2012c. The effect of footwear on postural control in bipedal quiet stance. Footwear Science 4**,** 115-122.

Fujiwara, K., Tomita, H., Kurokawa, N., Asai, H., Maeda, K., 2009. Effects of stance width on postural movement pattern and anticipatory postural control associated with unilateral arm abduction. Journal of Electromyography and Kinesiology 19**,** e187-e196.

Gage, W. H., Winter, D. A., Frank, J. S., Adkin, A. L., 2004. Kinematic and kinetic validity of the inverted pendulum model in quiet standing. Gait & Posture 19**,** 124-132.

Gatev, P., Thomas, S., Kepple, T., Hallett, M., 1999. Feedforward ankle strategy of balance during quiet stance in adults. The Journal of Physiology 514**,** 915-928.

Gunther, M., Putsche, P., Leistritz, L., Grimmer, S., 2011. Phase synchronisation of the three leg joints in quiet human stance. Gait & Posture 33**,** 412-417.

Hadders-Algra, M., Brogren, E., Forssberg, H., 1998. Development of postural control - Differences between ventral and dorsal muscles? Neuroscience and Biobehavioral Reviews 22**,** 501-506.

Horak, F. B., 1987. Clinical Measurement of Postural Control in Adults. Physical Therapy 67**,** 1881-1885.

Horak, F. B., Nashner, L. M., 1986. Central programming of postural movements: adaptation to altered support-surface configurations. Journal of Neurophysiology 55**,** 1369-1381.

Hsu, W. L., Scholz, J. P., Schöner, G., Jeka, J. J., Kiemel, T., 2007. Control and estimation of posture during quiet stance depends on multijoint coordination. Journal of Neurophysiology 97**,** 3024-3035.

Koepsell, T. D., Wolf, M. E., Buchner, D. M., Kukull, W. A., LaCroix, A. Z., Tencer, A. F., Frankenfeld, C. L., Tautvydas, M., Larson, E. B., 2004. Footwear style and risk of falls in older adults. Journal of the American Geriatrics Society 52**,** 1495-1501.

Kuo, A. D., Zajac, F. E., 1993. Chapter 31 Human standing posture: multi-joint movement strategies based on biomechanical constraints. In: Allum, J. H. J. (Ed.), Progress in Brain Research Natural and Artificial Control of Hearing and Balance. Elsevier, pp. 349-358.

Moghadam, M., Ashayeri, H., Salavati, M., Sarafzadeh, J., Taghipoor, K. D., Saeedi, A., Salehi, R., 2011. Reliability of center of pressure measures of postural stability in healthy older adults: Effects of postural task difficulty and cognitive load. Gait & Posture 33**,** 651-655.

Park, E., Schöner, G., Scholz, J. P., 2012. Functional synergies underlying control of upright posture during changes in head orientation. PLoS ONE 7**,** e41583.

Peng, C. K., Buldyrev, S. V., Goldberger, A. L., Havlin, S., Mantegna, R. N., Simons, M., Stanley, H. E., 1995. Statistical properties of DNA-sequences. Physica A 221**,** 180-192.

Pinter, I. J., van Swigchem, R., van Soest, A. J. K., Rozendaal, L. A., 2008. The dynamics of postural sway cannot be captured using a one-segment inverted pendulum model: A PCA on segment rotations during unperturbed stance. Journal of Neurophysiology 100**,** 3197-3208.

Raymakers, J. A., Samson, M. M., Verhaar, H. J. J., 2005. The assessment of body sway and the choice of the stability parameter(s). Gait & Posture 21**,** 48-58.

Sasagawa, S., Ushiyama, J., Kouzaki, M., Kanehisa, H., 2009. Effect of the hip motion on the body kinematics in the sagittal plane during human quiet standing. Neuroscience Letters 450**,** 27-31.

Ting, L. H., 2007. Dimensional reduction in sensorimotor systems: a framework for understanding muscle coordination of posture. In: P. Cisek, T. Drew & J.F. Kalaska (Eds.) Progress in Brain Research, Vol. 165. Elsevier Science B.V., Amsterdam, pp. 299-321.

Torres-Oviedo, G., Ting, L. H., 2010. Subject-specific muscle synergies in human balance control are consistent across different biomechanical contexts. Journal of Neurophysiology 103**,** 3084-3098.

Troje, N. F., 2002. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. Journal of Vision 2, 371–387.

Vaillancourt, D. E., Newell, K. M., 2002. Changing complexity in human behavior and physiology through aging and disease. Neurobiology of Aging 23**,** 1-11.

Verrel, J., Lovden, M., Schellenbach, M., Schaefer, S., Lindenberger, U., 2009. Interacting effects of cognitive load and adult age on the regularity of whole-body motion during treadmill walking. Psychology and Aging 24**,** 75-81.

Winter, D. A., Prince, F., Frank, J. S., Powell, C., Zabjek, K. F., 1996. Unified theory regarding A/P and M/L balance in quiet stance. Journal of Neurophysiology 75**,** 2334-2343.

Winter, D. A., Patla, A. E., Prince, F., Ishac, M., Gielo-Perczak, K., 1998. Stiffness control of balance in quiet standing. Journal of Neurophysiology 80**,** 1211-1221.

Witte, K., Ganter, N., Baumgart, C., Peham, C., 2010. Applying a principal component analysis to movement coordination in sport. Mathematical and Computer Modelling of Dynamical Systems 16**,** 477-488.

Tables

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)

Table 2: Spearman correlation coefficients calculated for the first 20 principal movements PM_j to quantify the relationship between normalized variance σ^2 and the R/σ-ratio or the persistence α.

	BP	**TA**	**OL**
order of PMj **j**	correlation coeff. α versus σ^2 r_s	correlation coeff. α versus σ^2 r_s	correlation coeff. α versus σ^2 r_s
1	0.33	0.06	**0.58****
2	**0.47***	**0.59****	0.23
3	0.16	0.28	0.32
4	0.23	- 0.18	0.13
5	0.31	**0.59****	0.18
6	**0.41***	**0.42***	- 0.20
7	0.34	**0.51****	**0.53****
8	**0.52****	**0.61*****	**0.39***
9	**0.48***	**0.51****	**0.41***
10	0.28	0.32	**0.45***
11	0.30	**0.49****	**0.76*****
12	**0.60*****	**0.53****	**0.41****
13	**0.50****	**0.49****	**0.52****
14	0.33	**0.46***	**0.53****
15	0.38	**0.62*****	**0.41***
16	**0.74*****	**0.63*****	**0.53****
17	**0.68*****	**0.66*****	0.28
18	**0.40***	**0.65*****	**0.64*****
19	**0.43***	**0.76*****	**0.71*****
20	**0.44***	**0.79*****	**0.43****

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Figures

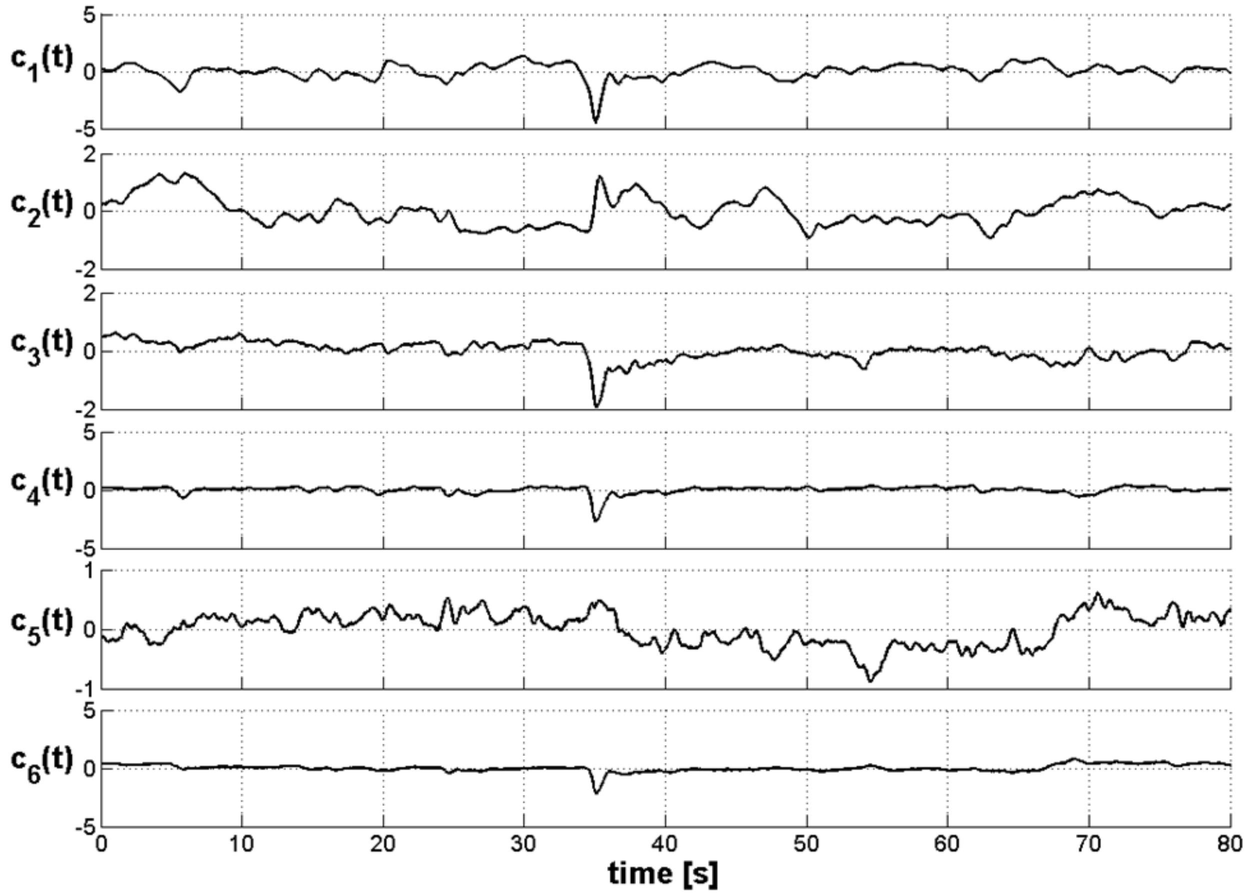

Figure 1: Example of the principal component scores $c_j(t)$ for the first six principal movements PM_j (j = 1..6) of one subject standing in tandem stance for 80 seconds. In this trial the subject was standing quietly for long periods, but at second 35 an instability event occurred characterized by large amplitudes in five of the six first PMs.

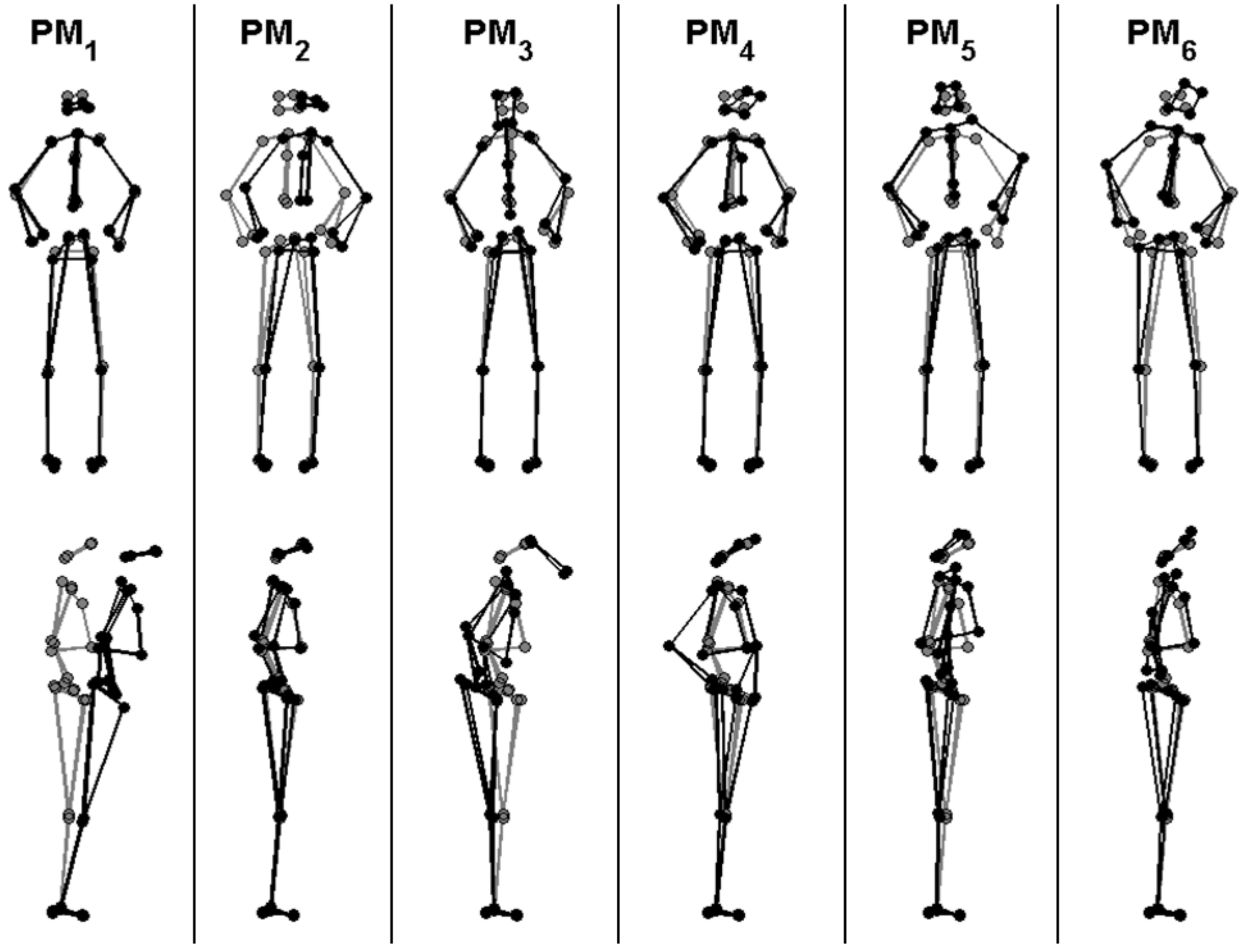

Figure 2: Visualization of the first six principal movements PM_j of bipedal quiet stance in a front view (top row) and sagittal view (bottom). Circles indicate marker positions; lines were added to guide the eye. Grey lines and circles represent the mean posture; black lines and circles represent the average deviation from the mean posture in direction of the principal component PC_j-vector. This deviation was amplified with a factor $a_1 = a_2 = 40$ for PM_1/PM_2 and $a_j = 80$ for higher PM_j to make these differences visible.

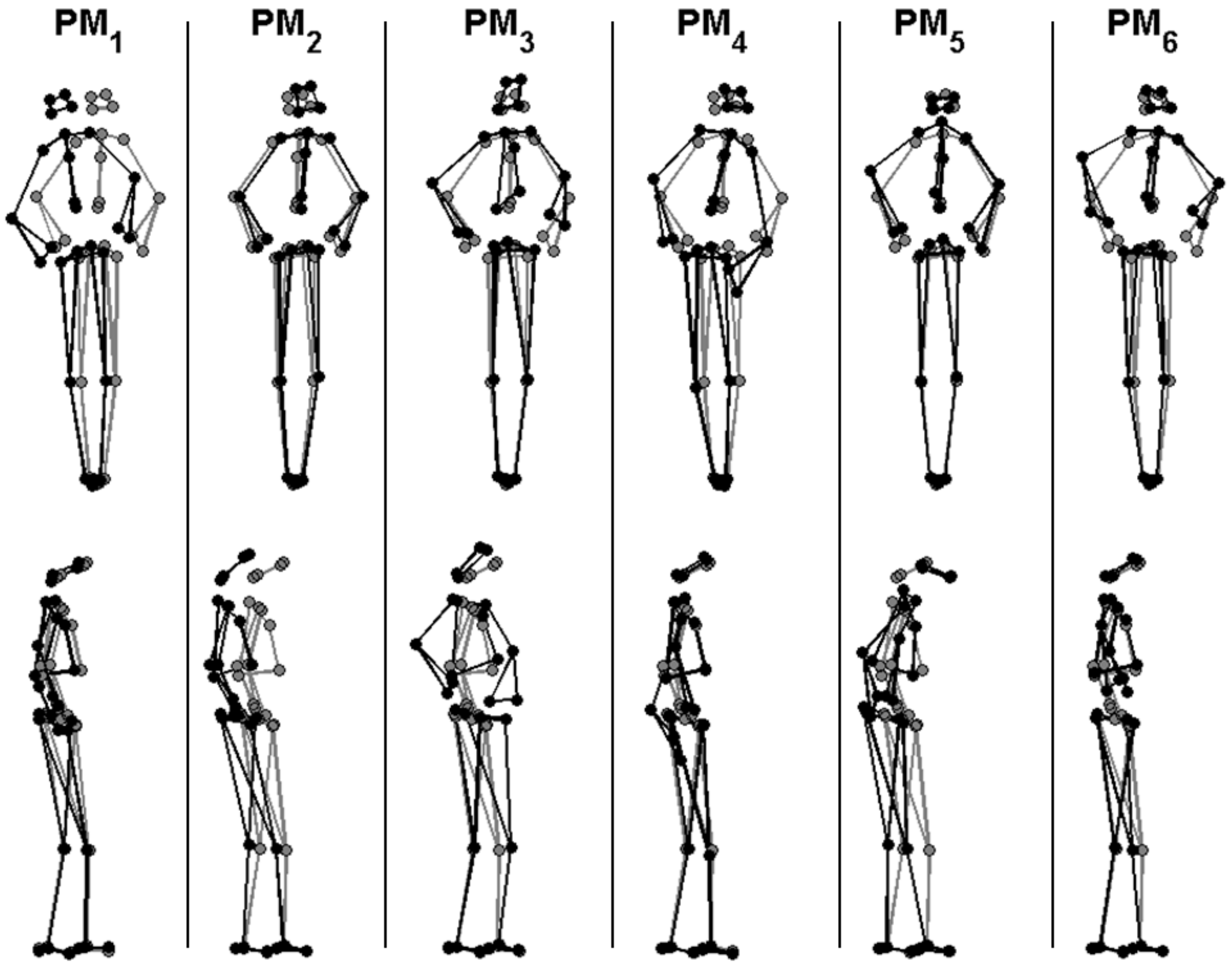

Figure 3: Visualization of the first six principal movements PM_j of tandem stance. The deviation from the mean posture was amplified with a factor $a_1 = a_2 = 40$ for PM_1 and PM_2 and $a_j = 80$ for higher PM_j.

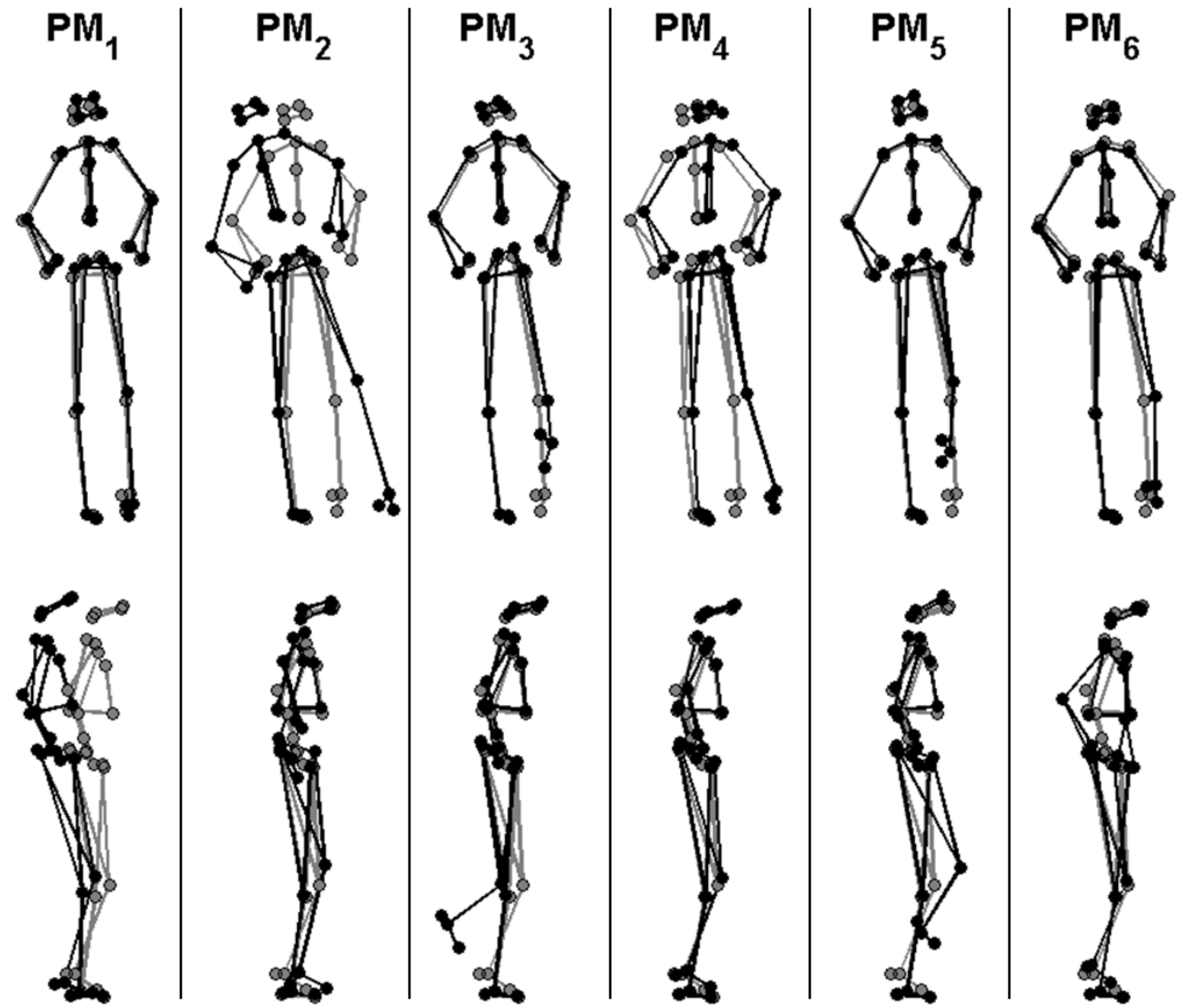

Figure 4: Visualization of the first six principal movements PM_j of one-leg stance. The deviation from the mean posture was amplified with a factor $a_j = 30$ for all PMs.

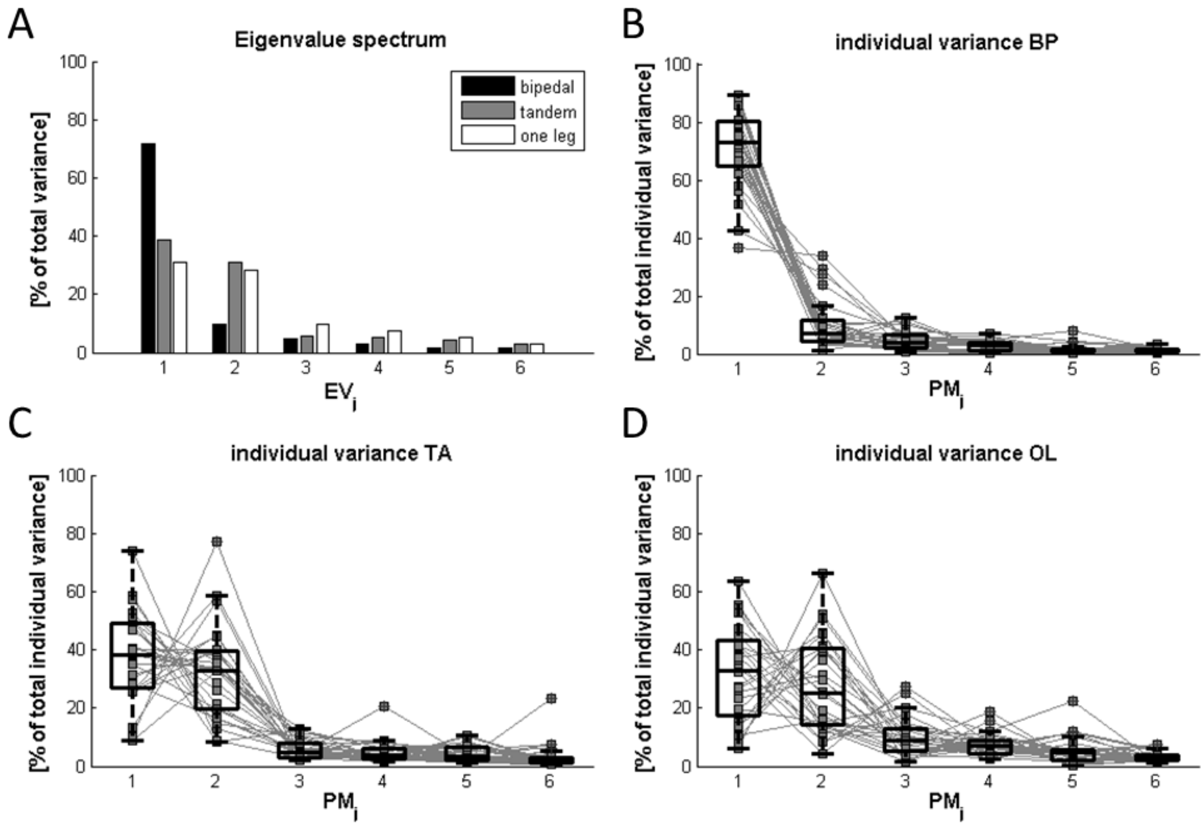

Figure 5. Normalized eigenvalue spectrum calculated for all subjects represented as bar-graph (A) and normalized variance σ^2 displayed for the first six PC-coefficients of each subject in the bipedal stance BP (B), tandem stance TA (C), and one-leg stance OL (D). In the latter three graphs, boxplots (thick black lines) represent the distribution of the results over the whole group; the individual results and how they relate between the principal movements PM_j are indicated as grey squares and connecting lines (thin grey lines).

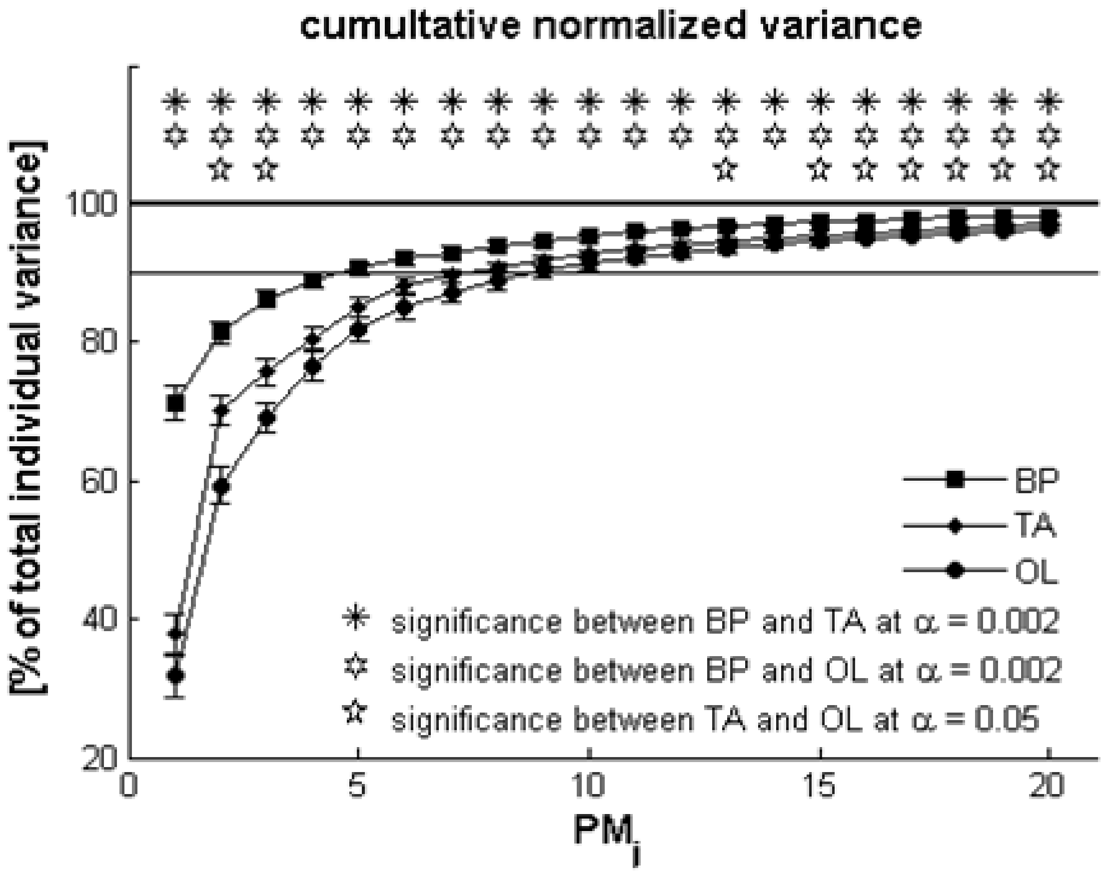

Figure 6. Cumulative normalized variance of the first 20 principal movements PM_j in the three stances bipedal (BP), tandem (TA) and one-leg (OL). The symbols (square, diamond, circle) represent the mean values calculated over all subjects, the error bars represent the standard error of the mean. The threshold representing 90% of the postural variance is indicated as a thin horizontal line. The stars indicate significance in a post-hoc pairwise comparison (paired T-test) as specified in the graph (Bonferroni correction for multiple comparisons: α = 0.002).

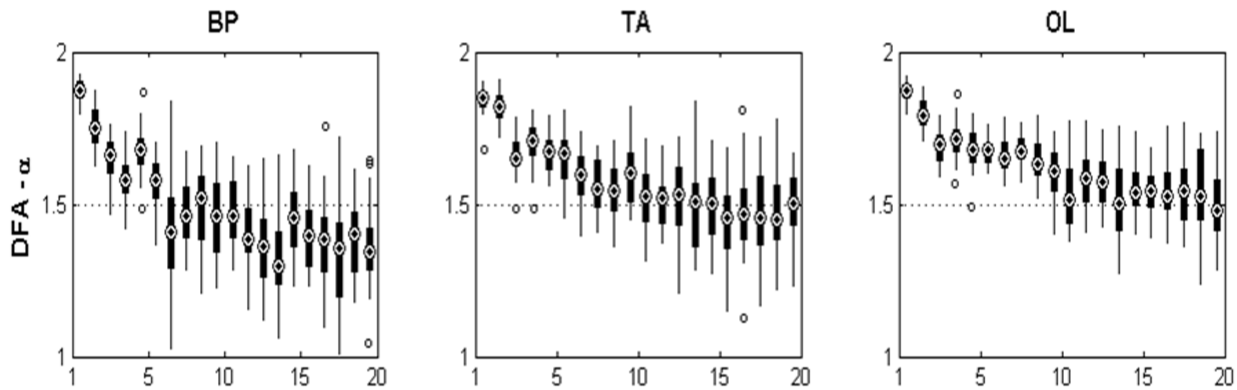

Figure 7. Persistence α (detrended fluctuation analysis, DFA) for the first 20 principal movements PM_j (x-axis) of the three stances bipedal (BP), tandem (TA) and one-leg (OL) represented as box-plots.