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Original Article / Technical note

A holistic approach to study the temporal variability in gait.

Peter Federolf[1,2] Karelia Tecante[2], Benno Nigg[2]

1 Norwegian School of Sport Sciences, Oslo, Norway

2 Human Performance Laboratory, University of Calgary, Calgary, Canada

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Abstract

Movement variability has become an important field of research and has been studied to gain a better understanding of the stability or the neuro-muscular control of human movements. In addition to studies investigating "amplitude variability" there are a growing number of studies assessing the "temporal variability" in movements by applying non-linear analysis techniques. One limitation of the studies available to date is that they quantify variability features in specific, pre-selected biomechanical or physiological variables. In many cases it remains unclear if and to what degree these pre-selected variables quantify characteristics of the whole body movement. This technical note proposes to combine two analysis techniques that have already been applied for gait analysis in order to quantify variability features in walking with variables whose significance for the whole movements are known. Gait patterns were recorded using a full-body marker set on the subjects whose movements were captured with a standard motion tracing system. For each time frame the coordinates of all markers were interpreted as a high-dimensional "posture vector". A principal component analysis (PCA) conducted on these posture vectors identified the main one-dimensional movement components of walking. Temporal variability of gait was then quantified by calculating the maximum Lyapunov Exponent (LyE) of these main movement components. The effectiveness of this approach was demonstrated by determining differences in temporal variability between walking in unstable shoes and walking in a normal athletic-type control shoe. Several additional conceptual and practical advantages of this combination of analysis methods were discussed.

Introduction

Analysis of movement variability has become an important field in motor-control and biomechanical research. Bernstein pointed out that for any given motor task there are an infinite number of possible solutions (Bernstein, 1967). He attributed this observation to the fact that the multitude of joints and muscles in the human body create redundant degrees of freedom. Variability in movements is therefore not only caused by external perturbations, but also needs to be considered as an inherent property of the system itself. Changes in movement variability might be a sign of injury (Cavanaugh, Guskiewicz, & Stergiou, 2005; Stergiou, Harbourne, & Cavanaugh, 2006; Harbourne & Stergiou, 2009), disorder (Hausdorff, Cudkowicz, Firtion, Wei, & Goldberger, 1998; Moraiti, Stergiou, Ristanis, & Georgoulis, 2007; Stolze et al., 2001; Ebersbach et al., 1999; Rosengren et al., 2009; Webster, Merory, & Wittwer, 2006; Dingwell & Cusumano, 2000) or aging of the neuro-muscular system (Kang & Dingwell, 2008; Verrel, Lövdén, & Lindenberger, 2012; Verrel, Lövdén, Schellenbach, Schaefer, & Lindenberger, 2009; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Callisaya, Blizzard, Schmidt, McGinley, & Srikanth, 2010; Brach, Studenski, Perera, VanSwearingen, & Newman, 2007).

The term “variability” is used with different meaning in different contexts. It is therefore important to specify what features of variability are analyzed. In general, this manuscript studies aspects of the intra-subject motion variability. Inter-subject variability, while related to the topic of this study, will not be discussed further. In most fields of sciences the term “variability” refers to any kind of variations in an observed variable, however, in the field of motor-control “variability” is often used in a very specific meaning as a quantification of the variability in the amplitude of a time series. If a time series is stationary, “amplitude variability” can be quantified by descriptive statistical measures such as standard deviation (Dingwell, Cusumano, Cavanagh, & Sternad, 2001). Aspects of temporal variations in gait variables have been quantified by different non-linear analysis methods such as the *maximum Lyapunov Exponent* (LyE) (Jordan, Challis, Cusumano, & Newell, 2009; Terrier & Deriaz, 2011; England & Granata, 2007; Dingwell & Marin, 2006; Dingwell & Cusumano, 2000; Bruijn et al., 2009), approximate entropy (ApEn) (Goldberger, Peng, & Lipsitz, 2002; Georgoulis, Moraiti, Ristanis, & Stergiou, 2006), or Poincare analyses (Granata & Lockhart, 2008; Dingwell, Robb, Troy, & Grabiner, 2008; Dingwell & Kang, 2007). In this study the *maximum Lyapunov Exponent* (LyE) was used. LyE quantifies how fast the waveform of a time series changes from step cycle to step cycle. Thus, in a sense, LyE quantifies the "predicatability" of the time series. A common interpretation is also that LyE is a measure of the "dynamic stability" of the process that produced the analysed time series (Dingwell et al., 2001; Segal, Orendurff, Czerniecki, Shofer, & Klute, 2008).

Studies employing nonlinear approaches to study temporal variability features in gait have so far been conducted on specific pre-selected variables, for example, joint angles (ankle, knee, hip) or trunk movements (Dingwell & Cusumano, 2000; Buzzi et al., 2003; Dingwell & Kang, 2007; Park, Son, Kim, & Seo, 2008; Segal et al., 2008; Nessler, De Leone, & Gilliland, 2009; Son, Park, & Park, 2009; Myers, Stergiou, Pipinos, & Johanning, 2010). However, in many cases it remains unclear if and to what degree the temporal variation of such pre-selected variables might be representative for the movement characteristics of the whole body. Pre-selection of variables also carries a certain risk of investigator bias influencing the study and it is possible that other important variability features, which would be visible in variables not selected for analysis, might be missed.

The purpose of this technical note was the introduction of a method to study aspects of the variability in the movement of the whole loco-motor system that does not require the pre-selection of specific variables. The underlying idea of the approach presented here was to first capture the subjects' multi-segment gait movements with a full-body marker set tracked by a standard motion capture system. These multi-segment movement patterns were decomposed into one-dimensional movement components using a principle component analysis (PCA) according to a method described by Troje (2002), Daffertshofer and colleagues (2004), or Verrel and colleagues (2009). The temporal variability features of gait were then quantified by calculating the LyE for these principal movement components. It is demonstrated in this paper that the proposed method is able to distinguish temporal variability characteristics when walking in two types of footwear.

Methods

Data collection

Twenty healthy subjects volunteered for this study (6 female, 14 male; age 24 ± 2; weight 71 ± 11 kg; height 1.77 ± 0.04 m [mean ± SD]). All participants gave informed written consent, and the study was approved by the appropriate Institutional Review Board. None of the subjects had any known orthopedic or neurological conditions that would affect their gait.

All subjects walked on a treadmill at a pre-determined self-selected speed. To select the speed, subjects were first instructed that they should choose a pace as if they were late for an appointment, but at which they could walk for 20 minutes. Then they walked on a treadmill while the speed was stepwise increased by the experimenter until the subject indicated that the speed was too high. From this point the speed was successively reduced until the subject felt confident that he or she could maintain this pace for 20 min. This procedure was followed by 5-minute warm-up walking at the selected speed. If the subject felt it was necessary, small adjustments of the speed were allowed during the first 2 minutes. The final walking speed was on average 3.8 ± 0.1 m/s.

For this technical note two walking trials were analyzed, one with subjects walking in an athletic-type casual shoe ("Ekiden 100" manufactured by Kalenji®, Decathlon SA., France) and one with subjects walking in an unstable shoe ("Mwalk" manufactured by Masai Barefoot Technology Inc. (MBT™), Switzerland). Each trial consisted of an acclimatization period of 30 seconds, then a measurement of 100 seconds was collected. Subjects were informed of the beginning and the end of the data collection period and were asked to focus their gaze on a target in front of them, however, for safety reasons and to allow the subjects to verify their position on the treadmill it had no consequences if a subject looked away from the target.

The subjects' individual walking patterns were recorded using a full-body marker set consisting of 28 markers placed on bony landmarks on all body segments (Figure 1). Specifically, the markers were placed on the left and right lateral malleolus, lateral epicondyle of the knee, anterior and posterior superior iliac spine, acromio-clavicular joint, lateral epicondyle of the elbow joint, both sides of the wrist joint, on the sternum, claviculum, 7th cervical vertebrae, and four markers were attached to a head band. Additional markers were placed on the shoe surfaces as close as possible to the calcaneous and on the second metatarsal head. The other markers were not changed between conditions. The three-dimensional marker trajectories were acquired at a sampling rate of 240 Hz using a standard eight camera motion capture system (Motion Analysis Corporation, Santa Rosa CA, USA). EVa Real-Time Software (EVaRT, Motion Analysis Corporation, Santa Rosa CA, USA) was used for real-time motion capture and for post-processing of the marker trajectories. The recorded spatial coordinates were not filtered during post-processing to retain an accurate representation of the variability within the locomotor system.

Outline of the data analysis steps

The data analysis consisted of the following main steps. 1) Detection of gait cycles from the vertical position of the heel marker and selection of 65 consecutive cycles for further analysis; 2) Principal component analysis (PCA) on posture vectors defined with all marker data to identify the main movement patterns of walking ("*principal movements*"); 3) Transformation of the posture vectors onto the first five principal component vectors, which contained >95% of the entire postural variability; 4) Analysis of the *temporal variability* by analyzing the time series formed by the principal component scores.

Principal movement components of walking

PCA is a statistical technique frequently used to reduce the number of variables necessary to explain a process (e.g. locomotion) while retaining most of the variation present in the original data set (Jolliffe, 2002). PCA is based on an eigenvalue decomposition of the covariance matrix of the data set into eigenvectors called principal component vectors (PCs). These components are arranged in decreasing order of their sample variance. Typically the majority of variation is contained in the first few PCs. Omitting higher order principal components allows to reduce the number of variables that describe the system while retaining of most of the variability, i.e. information.

In this study, the PCA was applied for the analysis of gait patterns similarly to the method described in detail by Troje (2002), Daffertshofer et al. (2004) or Verrel et al.(2009). Specifically, each trial returned a matrix of 84 spatial coordinates (28 3D marker positions) in 24000 time frames (100 seconds collected at 240Hz) of which the time frames corresponding to 65 consecutive steps were selected. Each row of the matrix was interpreted as an 84-dimensional "*posture vector*" representing all available information about the subject's posture in the given time frame. The *mean posture vector* calculated over all 65 steps was subtracted from each row of this matrix but no other normalization was performed.

Performing a PCA on this matrix yielded a) orthogonal principal component vectors, PC_k, in the direction of the largest variances in *posture vectors* (Figure 2 A,B,C and video files 1 to 3); b) eigen values, EV_k, which quantified the amount of variance explained by the corresponding PC_k; c) coefficients $c_k(t)$ (in some publications also called *scores*) obtained by projecting each posture vector onto the PK_k (Figure 2 D,E,F). Applying the PCA to walking decomposes this complex multi-segment movement into one-dimensional movement components that originate from a mean posture, i.e. from a mean marker configuration. The 84-dimensional PC_k-vectors determine for each movement component k in what direction the markers move. The coefficients $c_k(t)$ quantify for each time point *t* how far the momentary posture (=momentary marker configuration) deviates from the mean posture in the direction of the associated PC_k. The EV_k quantify how much deviations from the mean posture in the direction of the associated PC_k were observed during the whole trial. The EV_k were expressed as percentage of the sum of all 84 EV_ks. Thus they quantify how much of the total variance in posture vectors observed during the trial occurred in the associated PC_k (Troje, 2002; Verrel et al., 2009; Daffertshofer et al., 2004). For simplicity we refer to these one-dimensional movement components as "*principal movements* (PM_k)". The PCA calculations conducted in this study were implemented in Matlab (MathWorks Inc., Natic, MA, USA).

<u>Assessment of *temporal variability* using the maximum Lyapunov exponent (LyE)</u>

The temporal characteristics of the whole body movement patterns of walking were then analyzed by assessing the temporal variability characteristics of the time series $c_k(t)$. The LyE was determined by first constructing a state space representation of the time series. Thereto, the time delay τ was determined by an algorithm finding the first minimum of the average mutual information (AMI) as described by Fraser and Swinney (Fraser & Swinney, 1986). The appropriate embedding dimension was determined using a false nearest neighbor algorithm (Kantz & Schreiber, 1997). An embedding dimension of $n=5$ minimized the number of false nearest neighbors in most time series and was therefore used for the analysis of all principal movements in all trials. Following reconstruction of the state space (Figure 2 G,H,I), mean divergence curves and LyE values were calculated for the time series based on Kantz's algorithm (Hegger & Kantz, 1999; Kantz, 1994). Kantz's algorithm is conceptually equal to the algorithm proposed by Rosenstein et al. (Rosenstein, Collins, & De Luca, 1993) and is implemented in the software package TISEAN (version 3.0.1) (Hegger & Kantz, 1999) which was combined with the Matlab codes used for the calculating the PMs.

Results

The variance in posture vectors represented in each of the first five PMs is listed in Table 1 for both types of test shoes. No statistical differences between the two test shoes were found. For all subjects, the first three principal components represented the same type of movement in both test shoe conditions (Figure 2 and video files 1 to 3 give a graphic visualization). PM_1 represented the posture variation due to anterior-posterior arm and leg swing. PM_2 quantified a synchronous flexion-extension of both knees with an in-phase vertical movement of the upper body. PM_3 quantified an asynchronous flexion of the knee with an in-phase medial shift of the upper body (and thus the body weight) onto the stance leg. Higher order movement components represented adjustments of these basic movement components. For example, PC_4 and PC_5 portrayed small additional ankle, knee and elbow flexion-extension movements in most subjects. However, the movement components represented by the PMs became increasingly subject specific with increasing PM order.

Table 1 Eigen value spectrum of the first five principal movement components of walking when wearing a normal athletic shoe or an unstable shoe.

Principal movement	EV normal shoe Mean (SD)	EV unstable shoe Mean (SD)	paired T-test p-value
PM_1	84.2% (4.3%)	84.2% (3.6%)	0.98
PM_2	6.6% (3.7%)	6.3% (3.2%)	0.80
PM_3	3.2% (0.3%)	3.2% (0.4%)	0.52
PM_4	2.3% (0.8%)	2.4% (0.7%)	0.41
PM_5	1.3% (0.5%)	1.3% (0.4%)	0.58

The LyE values characterizing the temporal variability of the first five PMs are listed in Table 2 for both types of footwear. The difference between walking in a normal shoe and walking in an unstable shoe was significant in PM_1 and PM_2. In higher movement components no significant differences were found.

Table 2 Maximum Lyapunov Exponent (LyE) determined for the first three principal movement components of walking in different test shoes.

Principal movement	EV normal shoe Mean (SD)	EV unstable shoe Mean (SD)	paired T-test p-value
PM_1	0.063 (0.007)	0.138 (0.045)	**<0.001 ***
PM_2	0.095 (0.018)	0.122 (0.038)	**0.020 ***
PM_3	0.095 (0.012)	0.093 (0.015)	0.633
PM_4	0.099 (0.021)	0.097 (0.022)	0.866
PM_5	0.105 (0.029)	0.115 (0.030)	0.235

***** indicates significance at the $\alpha = 0.05$ level

Discussion

The combination of a PCA decomposition of the main movement patterns of gait with non-linear analysis methods to analyze temporal variability characteristics was able to identify differences in the temporal variability characteristics when walking in an unstable shoe as compared to walking in a normal athletic-type control shoe. The analysis approach developed in this study has, in the opinion of the authors, several important advantages as compared to previously employed analysis methods. First, the contribution of each principal movement component to the entire postural variability in walking is known since it is directly quantified by the normalized eigenvalues (Table 1). Quantifying the temporal variability of these movement components rather than that of selected variables such as joint angles or selected marker positions therefore has the advantage that the significance of these variables for the behavior of the whole system is known. Moreover, the first three PMs quantified similar movements in all subjects and the functional implications of these PMs for the whole motion can directly be assessed. PM_1 was the main contributor to forward propagation, PM_2 quantified a vertical motion, and PM_3 a lateral weight shift during gait (video files 1 to 3). Considering these functional implications it will become easier in future studies to develop directional hypotheses for how external factors, such as unstable shoes, might influence the variability characteristics of the gait.

Secondly, PCA is an unbiased, data-driven method to identify correlations in the multiple movement variables that can be observed in gait (Daffertshofer et al., 2004). Quantifying variability characteristics in the PMs rather than investigating variability in selected variables is therefore also conceptually a better approach when studying motor control questions.

Finally, non-linear analysis methods are known to be sensitive to noise (Argyris, Andreadis, Pavlos, & Athanasiou, 1998). However, random noise will affect different marker coordinates in an uncorrelated manner. Applying a PCA to the dataset containing all marker positions has therefore also the advantage that random noise will have a small effect on principal components with large eigenvalues (Romero, 2010). The first few PMs, which are of particular interest for the analysis of the system's behavior, are therefore less affected by noise than the original marker coordinates or than any variable that is calculated from only a few markers. Assessing temporal variability features in human movement in the *principal movements* therefore also has the practical advantage of being less affected by measurement noise and therefore more sensitive for differences due to the test conditions.

<u>Limitations and other considerations</u>

One limitation of the approach outlined in this study is that PCA decomposes the movements into linear movement components while the actual segment movements are typically rotations and thus non-linear. One consequence of the linear movement decomposition is that at least two linear variables (PMs) are needed to quantify a rotational motion. The decomposition provided by the PCA will therefore not yield functionally independent movement components and an appropriate non-linear decomposition method might be able to reduce the number of PMs that are necessary to accurately describe the entire movement.

The chosen marker set and the normalization procedures will influence the resultant PMs and the relative postural variability that each PM explains. While PM_1 represented the same movement component of walking in all studies that we are aware of, the movements represented by PM_2 and higher PMs observed in this study differed from those reported by Verrel and colleagues (2009), who performed an additional normalization step in which the subject's position on the treadmill was removed before entering the analysis. We abstained from additional normalization steps, such as the removal of relative movements on the treadmill (Verrel et al, 2009) or the normalization to equal variance (Daffertshofer et al., 2004), because they distort the actual variability observed in the marker positions and would thus also affect the assessment of the temporal variability in the gait patterns. However, the EV observed in this study can be directly compared to the results of Troje (2002) who also did not normalize the marker positions before applying the PCA. We found that EV_1 agreed very well with Troje's results, however, the higher order EV differed between the two studies. We speculate that differences in the marker sets might be responsible for these discrepancies.

Conclusions

For the analysis of temporal variability characteristics of the whole neuro-muscular system we combined a common non-linear analysis method (calculating LyE) with the PCA decomposition of gait patterns proposed by Troje (2002) or Daffertshofer (2004). This approach was effective in identifying differences between unstable shoes and normal shoes. The combination of these analysis methods has several conceptual and practical advantages as compared to the analysis of temporal variability in pre-selected variables such as individual marker positions of joint angles.

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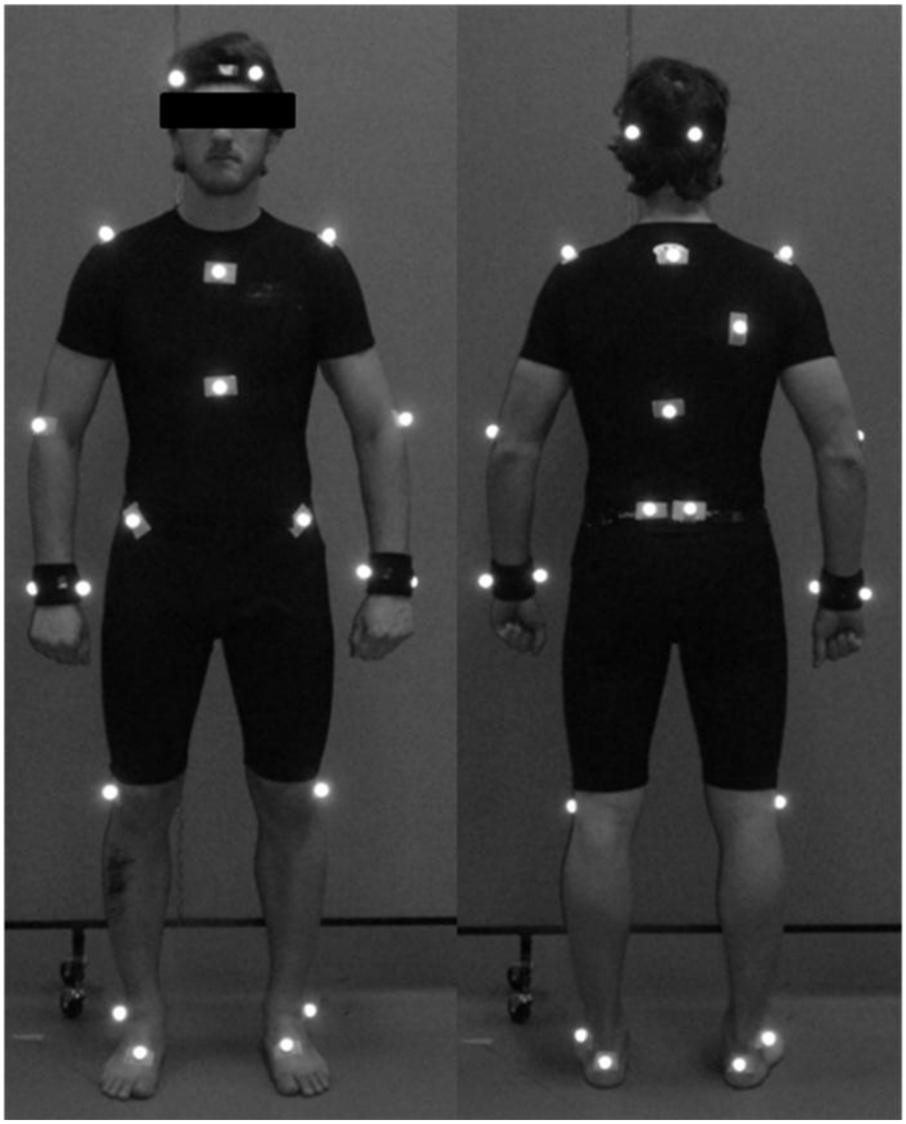

Figure 1. Positions of twenty-eight reflective markers for the quantification of the whole-body kinematics.

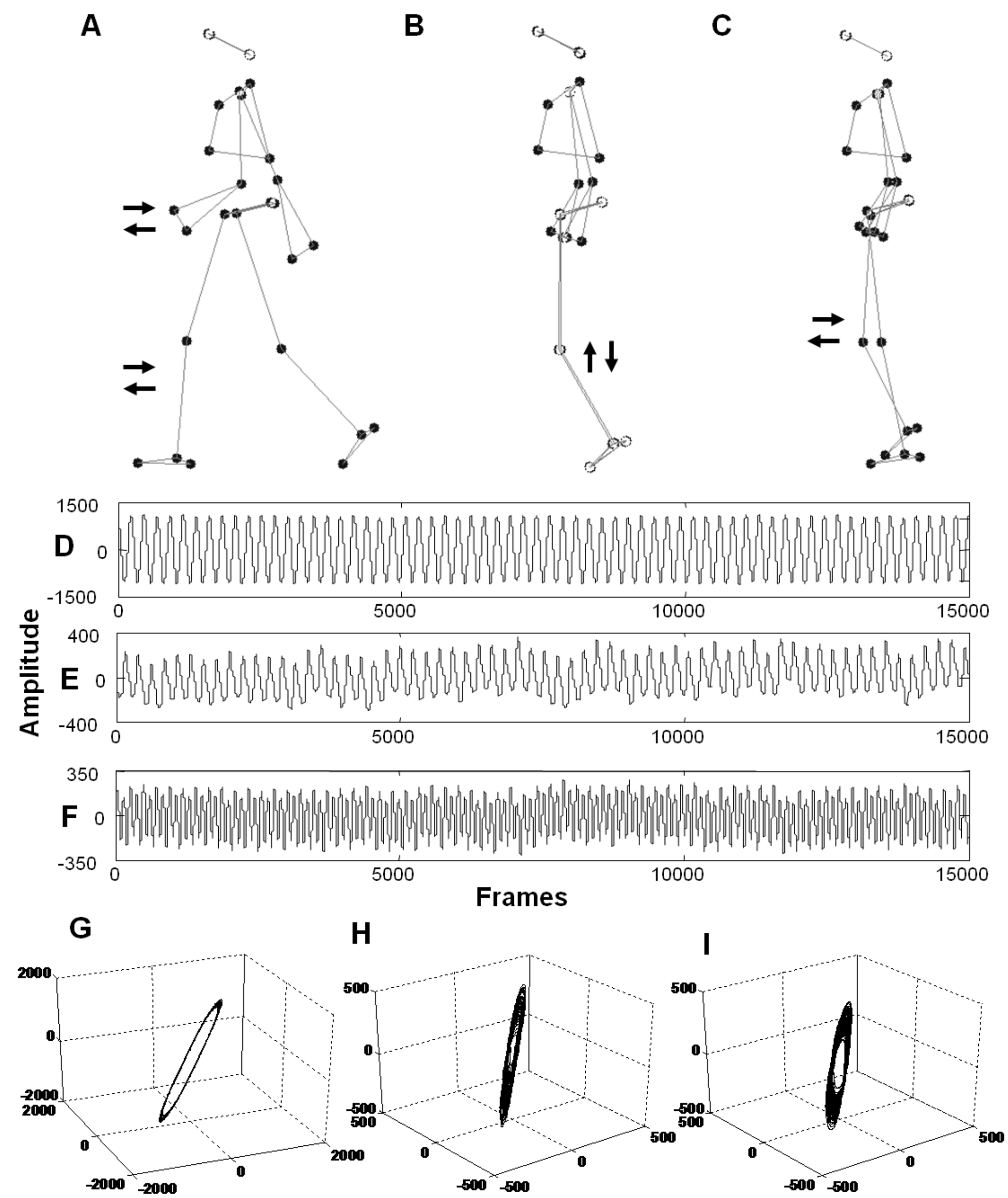

Figure 2. (A), (B) and (C) illustrate the main movement patterns corresponding to the first three principal components calculated from the marker trajectories recorded from a representative subject during walking. (D), (E), and (F) represent the time series obtained from the projection of all posture vectors onto the first three principle components. (G), (H), (I) show a three dimensional representation of the state space trajectories of the first three principal movements.