LOWER LIMB COORDINATIVE STRUCTURE IN HUMAN WALKING

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Human movement engages many body segments which are highly coupled. These couplings, known as synergies, have been widely investigated using principal components analysis (PCA). A primary limitation of the correlation matrices underlying PCA is that they do not account for phase differences or frequency-dependent variations in amplitude ratio between signals, yet such properties are widespread in relations between signals in the sensorimotor system. Coherence derived from dynamic linear systems analyses was introduced here to PCA applied to lower limb movements during normal walking. The results showed that one component could account for over 90% of the total variance in 26 joint angles. The findings confirm that the coordinative structure of walking is very low dimensional, comprising only a single degree of freedom.

KEY WORDS: gait, synergy, coordination, principal component analysis.

INTRODUCTION: The control of human movement is simplified by organising actions such as walking or reaching into linkages or couplings between limb segments known as 'synergies' or 'coordinative structure' (Bernstein, 1967). The musculoskeletal and neural elements become linked and operate as one functional unit to reduce the dimensionality of executive control. Many biomechanical studies support the existence of such functional units and demonstrate that multi-segmental movements are highly coupled and correlated (Kelso, Putnam, & Goodman, 1983; Lacquaniti, Soechting, & Terzuolo, 1986; Winter, 1990). Principal components analysis (PCA) is widely used for the investigation of data dimensionality and is increasingly employed to detect the pattern and identify the potential principal components in human walking (Yamamoto, Suto, Kawamura, Hashizume, Kakurai, & Sugahara, 1983; Wootten, Kadaba, & Cochran, 1990; Daffertshofer, Lamoth, Meijer, & Beek, 2004).

Mathematically, PCA can provide a smaller number of independent or orthogonal variables named as principal components (PC) that maximally preserve the variance in the original data. Three to five PCs, which were the linear combination of EMG signals and temporal kinematic parameters, have been shown to reveal details of walking strategies (Yamamoto, et al., 1983; Wootten, et al., 1990; Deluzio, Wyss, Zee, Costigan, & Sorbie, 1997; Olney, Griffin, & McBride, 1998; Cappellini, Ivanenko, Poppele, & Lacquaniti, 2006). The coordinative structure of human walking has also been investigated by applying PCA on the time series of movement patterns of body segments in terms of coordinates and joint angles. It was suggested that four PCs could account for over 90% of data variance and represent the information collected from segment coordination during normal human walking (Daffertshofer, et al., 2004).

Previous studies used either Pearson's product moment correlation coefficient (PCC) or covariance to describe the relationships between the movements of each pair of segments for the PCA. The PCC requires that signals be in phase and have a fixed amplitude ratio throughout the cycle in order to generate a high correlation. Yet phase shifts and frequency-dependent amplitude ratios between segments are frequently manifest in dynamic human movements. This limitation of the PCC can be overcome by conducting a cross-correlational and spectral analysis (Bendat & Piersol, 1971) which takes into account both phase differences and frequency-dependent amplitude ratios. The coherence square function (COH) derived from this analysis quantifies the variance accounted for by the dynamic linear relation between the signals. The current study therefore investigated the dimensional properties of lower limb segments coordination during walking at a self-selected pace by introducing the use of coherence in PCA analysis. The aim was to provide a better insight into the kinematic coordinative structure during walking.

METHODS: Six male adult subjects aged between 24 and 30 years (mean 27.7; SD 2.4) with no walking abnormalities, musculoskeletal or neurological disorders were involved in the study. A total of 29 reflective markers were attached on each subject's lower limbs in order to define 11 body segments and 26 joint angles. The subjects walked barefoot along a 10 m walkway at a self-selected speed in the laboratory environment. The walking speed ranged from 1.14 to 1.51 m/s (mean: 1.30; SD: 0.12). The 3D trajectories of the markers were captured at 60 Hz by a motion analysis system (Motion Analysis Corporation, Santa Rosa CA, USA with Cortex 1.1.4 software) and converted to angular data (KinTrak Version 7.1.4). The joint angles were low-pass filtered using an 8th order dual pass Butterworth filter with a cut-off frequency of 5 Hz.
Given the phase difference between joint angles and the limitations of PCC, the relationship between each pair of joint angles was analysed using two methods: conventional PCC and COH derived from cross-correlational and spectrographic analysis. A 26×26 matrix was obtained from each PCC and COH analysis of the 26 joint angles for each subject and PCA was performed on each matrix. Each PCA generated a series of components in the sequence of decreasing eigenvalues; large eigenvalues contribute more to the total variance of the original data. The dimensionality of the original data could therefore be reduced and the PCs could be identified to account for a particular proportional variance. Statistical analyses were conducted to compare the performance of the PCC and COH approaches in detecting the coordinative structure of human walking.

RESULTS: The contribution of each component to the total variance and the cumulative contribution of the PCs were averaged across all the subjects (Figure 1). From the results of the PCA with the PCC matrix, the first 5 components were extracted because these components accounted cumulatively for approximately 86% of the total variance (Peres-Neto, Jackson, & Somers, 2005). The 1st component contributed 36% of the total variance. The 6th and 7th components were not considered significant because their eigenvalues were 0.86 and 0.63 respectively and their combined contribution was only an additional 5% of the total variance. In contrast to the PCA with PCC matrix, the PCA with the COH matrix demonstrated a dramatic increase (from 36% to 94%) in the variance accounted for by the 1st component, while the 2nd component explained only 1.7% of the total variance.

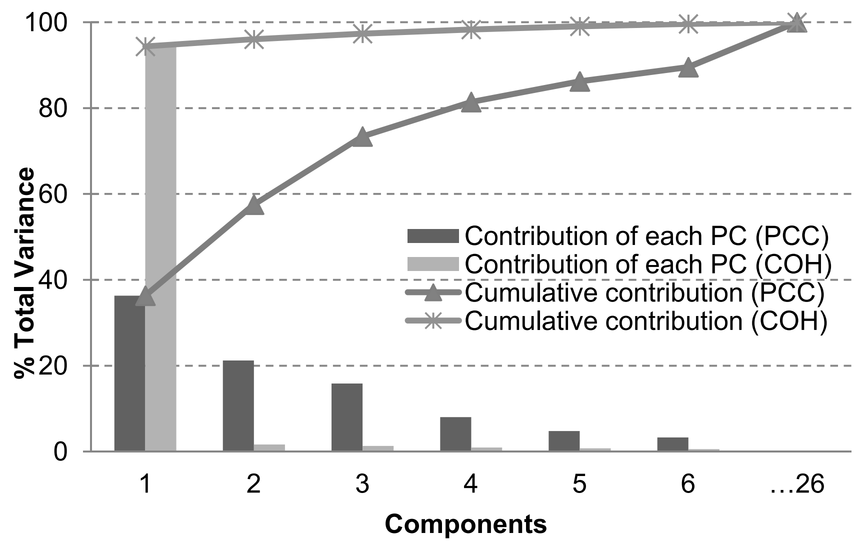

Figure 1: Percentage of variance explained by PCs from PCC or COH matrices.

A series of paired *t* tests were performed to detect significant differences between the number of PCs and the variance explained by the PCs extracted using the two methods (Figure 2). A significantly lower number of PCs was found in the PCA with COH (p <0.001). One PC from the analysis of the PCA with COH explained over 90% of total variance, while more than 6 PCs would be required to explain a similar proportion of variance from PCA with PCC. A significantly higher variance explained by the PC extracted from PCA with COH was noted (*p* <0.001). Therefore, the PCA with COH matrix resulted in a fewer PCs that accounted for a greater proportion of variance in comparison with the PCA with PCC matrix.

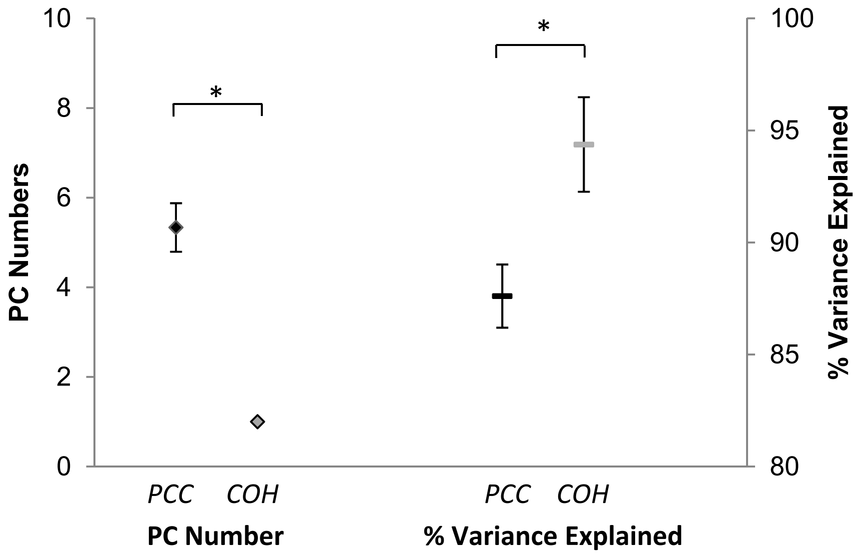

Figure 2: Mean and 95% confidence interval across 6 subjects of the number of PCs extracted and their percentage of variance explained derived from the PCAs with PCC and COH.

DISCUSSION: The present study demonstrated the advantages of using coherence in principal components analysis by overcoming a primary limitation of the Pearson correlation coefficient for assessing dynamic relations between joint angles. The cross-correlational and spectrographic analysis applied to lower limb segments in terms of joint angles was demonstrated to enhance the power of principal components analysis in identifying coordinative structure in human walking. Although not investigated here, this approach would be expected also to enhance the power of other statistical techniques of matrix factorisation for capturing redundancies in high-dimensional data sets.
In the previous studies, PCA based on correlation or covariance matrices has been applied to gait kinematics. Mah, Hulliger, Lee & Ocallaghan (1994) studied four frontal-plane and four sagittal-plane lower limb angles (including hip, knee and ankle flexion-extension) and found that three PCs accounted for at least 91% of the variance of the data set. Daffertshofer et al. (2004) studied the 3-D coordinates of 23 joint markers placed throughout the body (69 signals in total) and found that the first four PCs accounted for about 90% of the variance of the data set. We used 29 markers to capture lower limb movement and calculate 26 joint angles. Five PCs were found in the present study to be necessary to represent the main features within the original data, which was comparable to the previous studies.
The first 5 components from the PCA with PCC matrix accounted for 36%, 21%, 16%, 8% and 5% of variance, cumulatively accounting for over 85% of the total variance. In contrast, the first component from the PCA with COH matrix accounted for 94% of the total variance, while the second component only accounted for 1.7% of variance. This pattern indicates that there was only a single functionally significant principal component in the data. This finding shows that the coordinative relations between joint angles throughout the body during walking are more complex than the scalar relations described by regression analysis, which are limited to closely in-phase or anti-phase timing and fixed amplitude ratios throughout the cycle. The coordination can be described by linear dynamic relations that accommodate intermediate phase relations and frequency-dependent amplitude ratios, and yield a coordinative structure in human walking of only one degree of freedom.

CONCLUSION: This study demonstrated the benefits of using a dynamic linear systems analysis which overcomes the limitation of the Pearson correlation coefficient in that it takes into account the phase shifts between signals in enhancing the performance of principal components analysis in finding principal components. For the particular walking analysis, the coherence approach could be an advantage to reveal the potential correlations between each pair of angles by taking phase differences into account.

One component instead of five was identified through the enhanced principal components analysis. This finding may indicate that the lower limbs during walking could be surprisingly highly correlated when linear dynamic relationship between joint angle pairs are considered. The lower limbs coordinative structure during walking was suggested to be very low dimensional and could be only one degree of freedom. The coordinative structure revealed in the current study could potentially benefit practitioners in their coaching, training and rehabilitation of participants in sports.

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