Principal Component Analysis of Accelerometer Data Reveals Differences in Running Style

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Introduction

While accelerometers have been used to study leg motion during running (Nigg et al., 1995), traditional measures extracted from accelerometry waveform data have been limited. The commonly reported temporal measure of peak tibial acceleration uses only a single point during running, while frequency measures are typically limited to the frequencies associated with the impact phase only (Shorten et al., 1992). In contrast, principal component analysis (PCA) offers the ability to explore information from the entire waveform, incorporating both the impact peak and possible subsequent consequences associated with the impact. The purpose of the present study was to compare more traditional analysis techniques of leg accelerometry with the PCA method. The comparison was performed using data from two distinct groups of runners that are differentiated by their kinematic responses to downhill grade (Chu, 2000).

Methods

Ten experienced college-aged runners ran on a treadmill at a fixed velocity (4.17 m/s) at 5 grades ranging from level to 12% downhill. Tibial accelerations (TA) were measured with a light weight accelerometer (1000 Hz), and joint kinematic data were captured with CCD cameras at 200 Hz. Subjects were partitioned equally into two groups (n = 5) based on their kinematic responses to steeper downhill grades: increased joint extension (JXT) or maintenance of body orientation (BOD). The JXT group exhibited more lower extremity joint extension with steeper downhill grades while the BOD group maintained body orientation (Figure 1). While the downhill data were used for subject classification, the analyses of TAs were performed for the level condition only. The temporal measures of peak TA and time to peak were recorded, and mean impact power was calculated by averaging power from the frequencies (12 – 20 Hz) associated with impact (Shorten et al., 1992).

Principal component analysis is a multivariate statistical technique that has been used to capture shape changes in waveform data (Deluzio et al., 1999). Mathematically, principal component analysis consists of an orthogonal transformation that converts time normalized waveforms into new uncorrelated principal components. These components are optimal in the sense that they explain a maximal amount of variance. Although there can be as many uncorrelated principal components as there are original variables (i.e. number of time samples), often only a few are required to adequately capture the observed total variation. The variation in waveform data is related to differences in the pattern or the shape of the individual
waveforms. We used PCA to reduce the TA waveform data to a few principal component scores (PCS), which represented specific features of the waveform data. All TA trials were time normalized to 100% stance and an ensemble waveform for each subject was created. A covariance matrix containing all 10 ensemble waveforms was then used for input to the PCA. The eigenvectors of this covariance matrix represent the loading vectors and the associated eigenvalues are the variances of the principal components. PCS were measured by applying the loading vectors to the raw data. These scores were then used in an attempt to discriminate between the two groups of subjects.

Results and Discussion

No differences were found in the temporal measures (impact peak magnitude, p > 0.5; peak occurrence, p > 0.9) nor frequency measures (impact power, p > 0.3) of TA. The first three principal components (PCS1-3) accounted for 84% of the variance in all TAs, capturing the most pertinent features of the TA (Figure 2). However, of these PCS components only PCS2 significantly differentiated the JXT and BOD groups (p < 0.02; Figure 3). The differences were emphasized at 15, 30, and 40% of the stance cycle, which are associated mainly with the impact peak and two subsequent peaks (Figure 4 and 5). Traditional TA analysis techniques were insensitive to the differences between the two groups. In contrast, the PCA technique was able to objectively identify the two groups that differed in their downhill running responses, using the TA for the level condition only. Moreover, additional information was obtained by examining the explained variance of the waveforms. Further assessment of the data using the PCA technique may provide greater insight into the nature of TA waveforms during running.

![Figure 2: Reconstructed data using PCS1-3 compared to raw data](image1)

![Figure 3: PCS1 and PCS2.](image2)

![Figure 4: % variation explained during stance for PCS2. Circles emphasize periods of high explained variation](image3)

![Figure 5: TA waveforms associated with differing PCS2 scores.](image4)
References