Postural Control: A Study of One-Legged Stance

M. R. Semak[1], T. McMillan[1], J. Schwartz[1], and G. Heise[2]
Department of Physics and Astronomy[1], School of Sport and Exercise Science[2]
University of Northern Colorado, Greeley, CO 80639

Abstract

We investigate certain characteristics of human unipedal balance control. Data were collected via a force plate for individuals attempting to maintain upright posture using their dominant and non-dominant legs (with eyes open). The force and jerk concerning the center-of-pressure for each foot has been examined using, among other methods, power spectral and detrended fluctuation analyses. For the sake of space and time, this poster will focus on results for the jerk associated with the dynamics of the subjects' dominant legs. Both the lateral and longitudinal components of the jerk display (what may be seen as) oscillatory behavior on long time scales. On short time scales, the longitudinal component of the jerk shows persistent correlations which can be modeled by fractional Gaussian noise, while the lateral component appears to lack strong temporal correlations. Moreover, we attempt to distinguish behavior associated with the dominant leg's dynamics from that of the non-dominant using sample entropy estimates.

Introduction

The means by which human posture control is maintained is both subtle and complex. Certainly, a great deal of past work by many researchers has afforded us valuable insights particularly for the case of human two-legged quiet stance. In particular, the seminal work by the neuromuscular researchers Collins and DeLuca established a model for the center-of-pressure (please see below) trajectories based on a bounded random walk [1]. Since then, a great deal of work has been generated dedicated to a better understanding of human balance control with a variety of methods.

Careful analysis of this system may lead to insights about the brain's role in balance. We attempt to gain further insight by studying the dynamics involved when a human attempts to maintain a one-legged stance.

Background

The center of pressure (COP) [1] is the point of application of the net force vector on the floor due to, for our case, the bottom surface of a foot being in contact with the ground. As weight shifts, so does the COP. A force plate was used to collect data concerning the COP trajectory of healthy individuals attempting to remain stationary with their eyes open. (The noise profile of this force plate was taken into consideration.) Below we see our original unprocessed COP data (sampled at 100 Hz) for human unipedal quiet stance taken over a 30 second period. The volatility of this data suggests that it may come from a stochastic system.

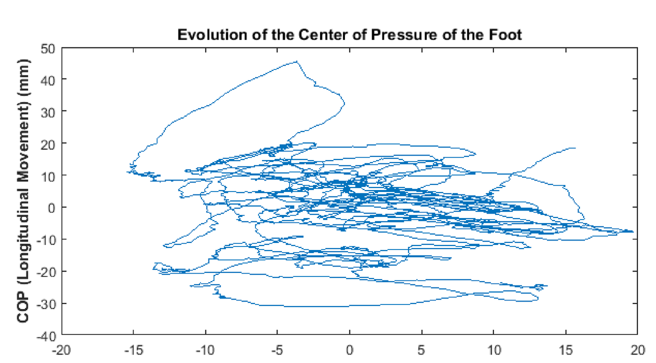


Figure 1: **Typical trajectory of the COP for human one-legged stance**

Detrended Fluctuation Analysis

In short, detrended fluctuation analysis (DFA) is a technique which is useful for exploring the temporal correlations in a time series (a sequence of values in chronological order) [2]. With this method, the time series (with N samples) is integrated. Then, the resulting series, $\{x(i)\}$, is broken up into a set of non-overlapping windows each consisting of n points. A (least squares) linear fit is performed over each window to reveal the local trend, $x_n(i)$ (for each window). The root-mean-square (rms) average of the residuals is calculated giving the rms fluctuation,

$$F(n) = \sqrt{\tfrac{1}{N}\sum_{i=1}^{N}(x(i) - x_n(i))^2}.$$

This calculation is done for all time scales, n. How these average fluctuations scale with n speaks to the character of temporal correlations found in the original time series. DFA can be applied to a variety of signals including those with a stochastic fractal nature which may be stationary or not. Moreover, the scaling behavior referred to above may be indicative of a range of correlations. Typical results for a DFA of the longitudinal component of force for one-legged stance are shown below.

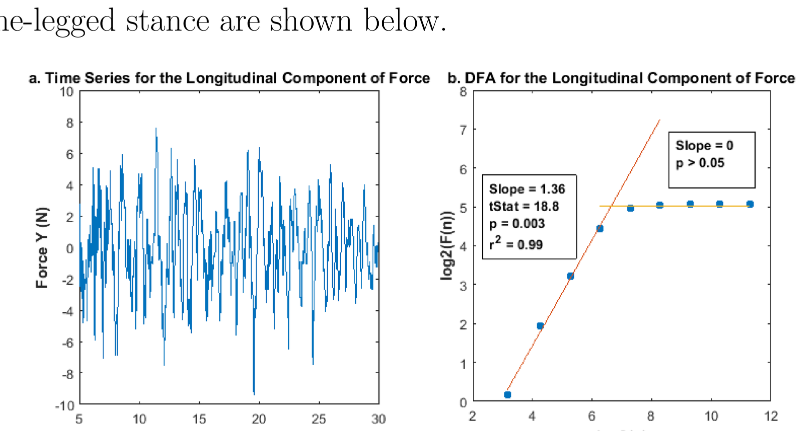


Figure 2: **a. This is the time series (after transients) for the longitudinal component of force for unipedal quiet stance. b. This shows the results of a DFA performed for the time series in Figure 2a (without the transient structure). On short time scales, the scaling of the fluctuations is indicative of fractal Brownian motion (fBm) [3], thus a nonstationary process, whereas, for long time scales, the graph saturates which can be suggestive of of a recurrent temporal structure [4].**

The Jerk

The jerk is taken to be the increment of the force, $\Delta F(i) = F(i+1) - F(i)$, $i = 1..N-1$. Having used various tests, we are fairly confident that this is a stationary process. A Butterworth filter was applied to the data allowing for a passband signal $(0 - 15Hz)$ strength sufficiently above that of the machine noise (checking for filter-induced effects, autocorrelations for i.i.d. white noise remain unchanged for the passband). The data was then linearly detrended and the seasonal component extracted revealing the data's random part (please see below for typical examples).

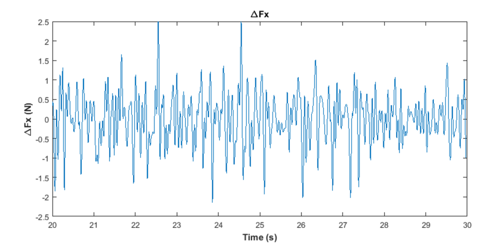


Figure 3: **The lateral component of the jerk**

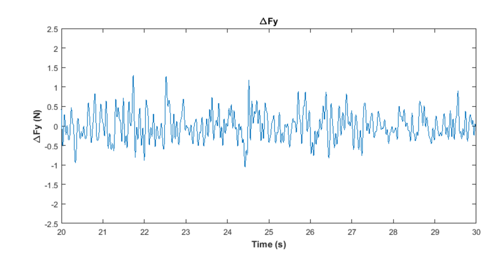


Figure 4: **The longitudinal component of the jerk**

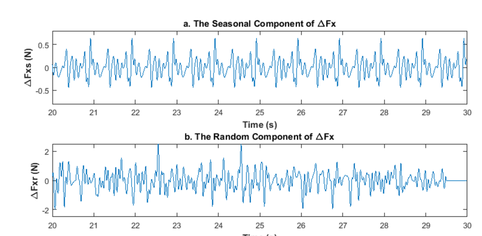


Figure 5: **The seasonal and random components of ΔFx**

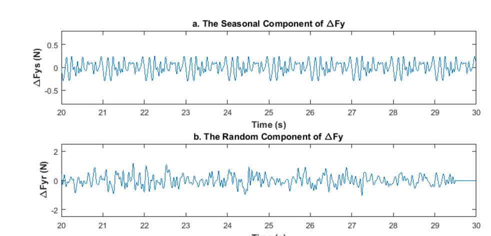
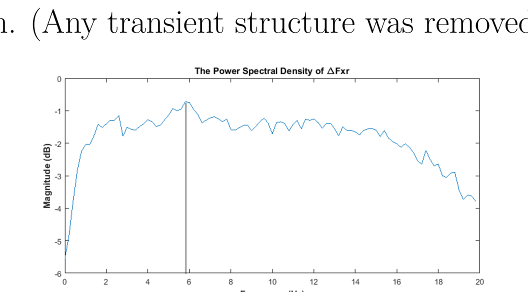
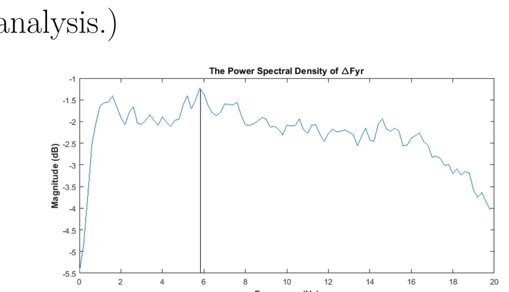


Figure 6: **The seasonal and random components of ΔFy**

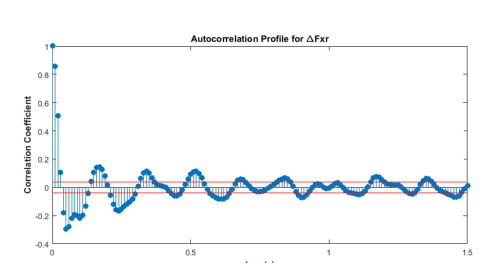
Analyzing the Jerk

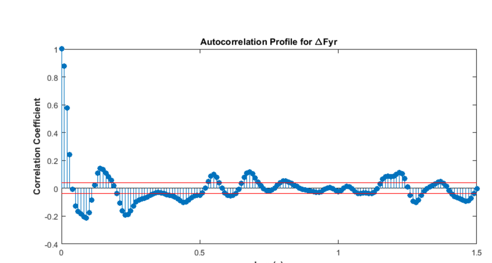
We are particularly interested in the temporal correlation structure of the jerk's random part. This was studied via spectral analysis, DFA, and by examining the autocorrelation profiles. Below some typical results are shown. (Any transient structure was removed before the analysis.)



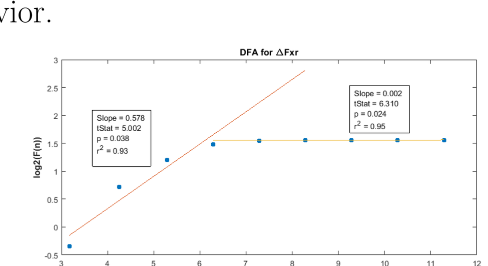


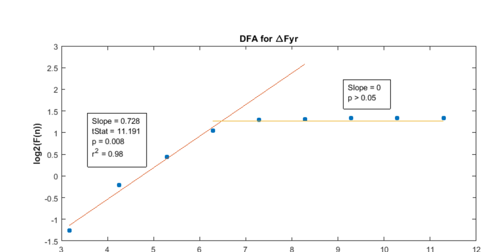
The two figures directly above show a typical example of the power spectral density (log - linear) for the lateral and longitudinal components of the increment of the force. This was done using Welch's method [5]. The frequency range shown is slightly wider than that of the passband discussed earlier. The vertical line indicates where the peak in energy content of each signal occurs; both at just about 5.8 Hz. For the time scales under consideration, this value is considered to be relatively fast. Both spectra show a secondary peak at approximately 1.5 Hz, which, as indicated by the DFA results shown below, is close to the time scale (0.60 s) at which the transition in correlation behavior (thus, the demarcation between what is considered short and long time scales) occurs.





Just above, we see autocorrelation profiles for both components of ΔF characteristic of our study. The horizontal lines enclose the 95% confidence interval for the normal distribution, $N(0, \frac{1}{N})$. Both components show positive correlations over (approximately) a 0.04 s interval. From then on, there are alternating positive and negative correlations possibly indicative of a quasi-periodic temporal structure. This behavior occurs for time scales smaller than the correlation transition time scale (0.60 s) mentioned above. These fluctuations in correlation values may not be able to be resolved through DFA given the set of window sizes that this method must use for this data. Indeed, the smaller window sizes for the DFA correspond to time scales over which there are only positive correlations as indicated by the autocorrelation profiles. More work must be done to understand this behavior.





Here, we see the results of the DFA of both components of the force increment. In both cases we see a transition in correlation character near window sizes of approximately 0.60 s (where $\log_2(n) = 6$, approximately) as spoken of above for the spectral analysis. For the lateral component, behavior on short time scales is indicative of that of white noise with a bias toward positively correlated fractional Gaussian noise (fGn) [3]. On long time scales, the fluctuation average effectively saturates and, given the results above, the behavior appears to be that of some recurrent structure (when the window size is, at least, that of some effective oscillatory period, the fluctuation average becomes constant) [4]. As for the longitudinal component, for short time scales, we again see an indication of positively correlated fGn. On long time scales, similar behavior to that of the lateral component is seen. Overall, it seems that the jerk is persistent in its short term behavior and follows a recurrent pattern during its slower variations.

Sample Entropy

We became interested in knowing whether or not any dynamical differences could be discerned, during unipedal stance (eyes open), between using an individual's dominant and non-dominant leg. To attempt to answer this question, we used the sample entropy algorithm. The sample entropy of a time series of length N, with subsequences of the time series of length m is,

$$SampEn(N, m, r) = -\log\left(\frac{A(r)}{B(r)}\right),$$

where $A(r)$ (respectively $B(r)$) is the total number of subsequences of length, $m+1$, (respectively m) within a certain distance (radius), r of one another. Formally, SampEn is the negative logarithm of the probability that, for a discrete data set of length N, subsequences of m successive data points which are within a distance r of one another will stay this close if one more data point is added to each subsequence (this excludes self matches). In this way, SampEn is a measure of complexity.

A robust SampEn algorithm is provided by *PhysioBank* [6]. There were 5 participants in our study, all of whom had a dominant right leg. We used this algorithm to measure the complexity of the force and jerk generated by an individual during unipedal stance (eyes open). To see how the parameters m and r were determined, and for an introduction to this algorithm, see [7].

An example of our current results for a component of force is shown below in Figure 7.

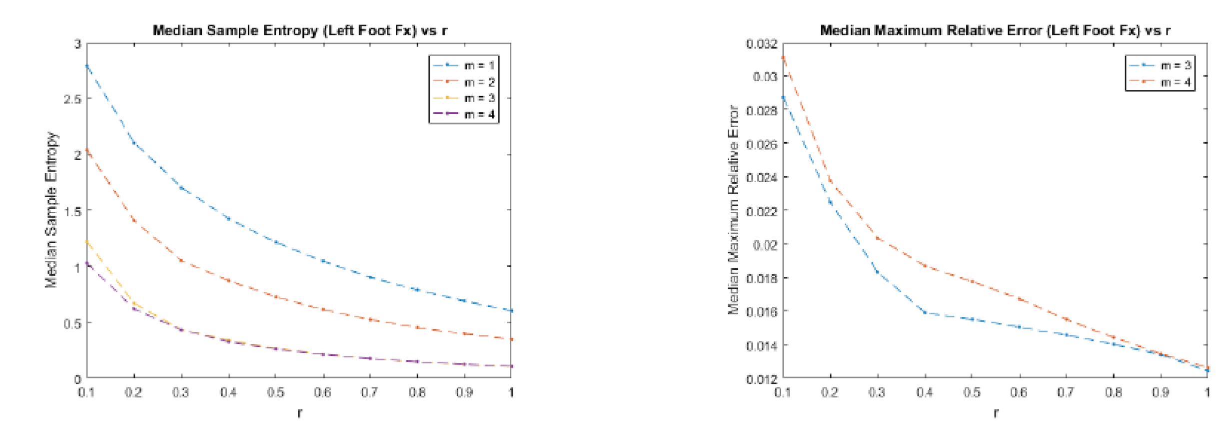


Figure 7: **Just as in the case of [7] our values for the subsequence length are $m = 3$ and $m = 4$ via the convergence criterion [7]. Given our values of m we did not obtain an optimal value for r. It should be noted, however, that the error graph on the right suggests that it does not matter what particular r value we use since all of the error is well within a satisfactory statistical uncertainty.**

Figure 7 suggests that a value of $m = 3$ will suffice for studying our data (as explained in [7]). However, our data did not produce an optimal r value (contrary to what was observed for the case of bipedal stance in [7]), but all of the associated error is well below 5%. We observed this during the balance sessions when subjects used their left and right feet (for the force and jerk).

Below in Table 1 is the average difference in the x-components and y-components of the observed force and jerk.

Sample Entropy Values				
Difference of Average Entropy	**L F_x - L F_y**	**R F_x - R F_y**	**L J_x - L J_y**	**R J_x - R J_y**
|Difference| ± Standard Dev.	0.069 ± 0.001	0.058 ± 0.001	0.044 ± 0.002	0.125 ± 0.002

Table 1: **The results shown above are with $m = 3$ and the values for $r = 0.1, 0.2 \ldots, 1$ averaged. We report the results as follows: absolute value of the entropy ± the average of the set of error values generated by the range of r values (L means left, and R means right). Note that in the case of the force, the result for the left foot shows a higher entropy value than that for the right foot. However, in the case of the jerk, the result for the left foot has a smaller entropy value than that for the right foot.**

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