Examining Human Unipedal Quiet Stance: Smoothness

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Abstract

We investigate the quality of smoothness for human unipedal balance. In particular, we are interested in its temporal scaling behavior as well as its general dynamic character. Smoothness is quantified by the time rate of change of the forces, or jerks, associated with the motion of the foot. The presence of jerk during the process of balance is seen to indicate a certain lack of control. Specifically, our study will focus on the jerk concerning the center-of-pressure (COP) for each foot. Data were collected via a force plate for individuals attempting to maintain upright posture using both legs (with eyes open). Positive tests for stochasticity allowed us to treat the time series as a stochastic process. Then, the jerk is seen as proportional to the increment of the force realizations. Detrended fluctuation analysis is the primary tool used to explore scaling behavior. Results suggest that both the medial-lateral and anterior-posterior components of the jerk display persistent and antipersistent correlations which can be modeled by fractional Gaussian noise over different temporal scaling regions.

Background

The COP 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 still (unassisted) standing on one foot with their eyes open. (The noise profile of this force plate was taken into consideration.) Below, we see our (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.

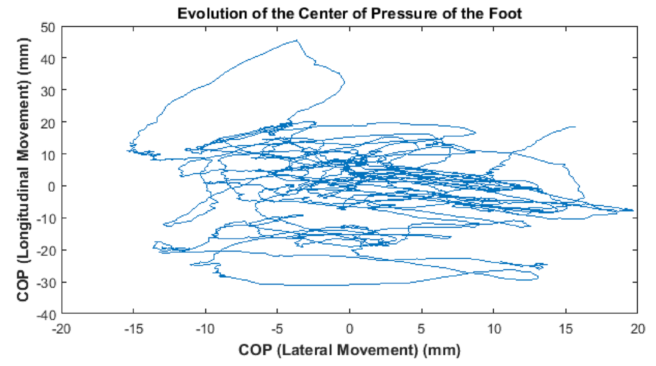

Figure 1: Typical trajectory of the COP for human single leg stance

Data Collection

Force data were collected using a multi-axis force plate for five adult subjects who each maintained balance (with eyes open looking straight ahead, hands by their sides, and barefoot) using each leg separately for 30 second sessions. The ages of these subjects range from 20 to 60 years (mean being 34 years). Prior to any data collection, all procedures were explained to each participant and written consent was obtained in accordance with local institutional review board policy.

One foot was placed squarely on the force plate while the other hovered at approximately 30 cm above the plate. These data were sampled at 100 Hz producing a time series for the force generated by M-L as well as A-P sway. We found 100 Hz to be an optimal rate as with a collection time of no more than 30 seconds (we were concerned about the effect of fatigue on the subjects), 3000 data points for each balance session was taken as adequate (our estimates for certain statistics didn't change significantly for data sets with at least 1500 measurements over a 30 second balance session).

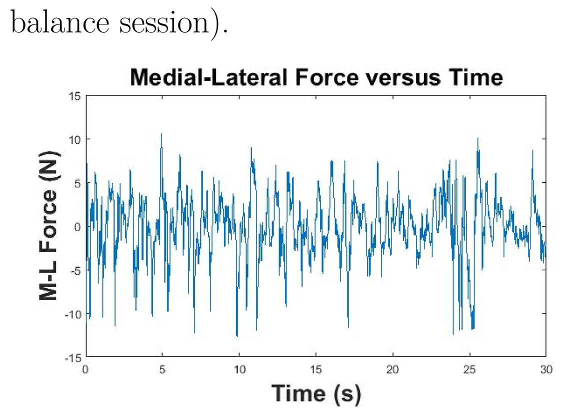

Figure 2: Typical time series for the M-L force.

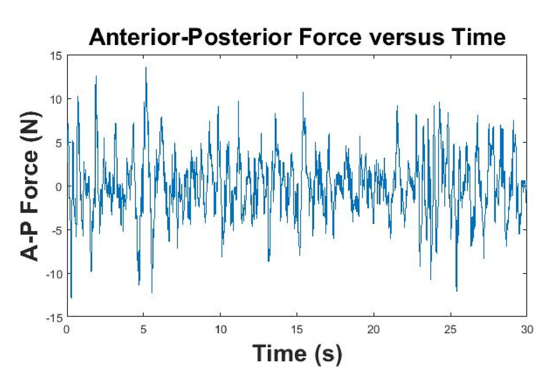

Figure 3: Typical time series for the A-P force.

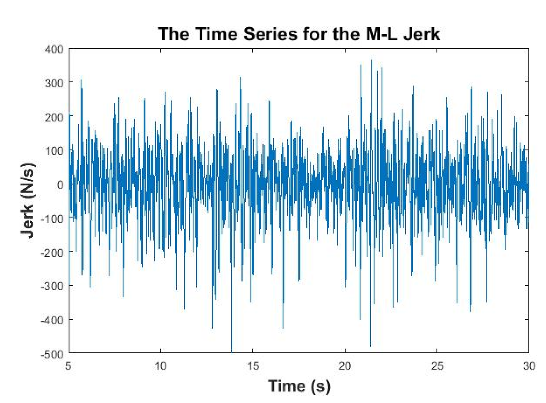

Figure 4: Typical time series for the M-L jerk.

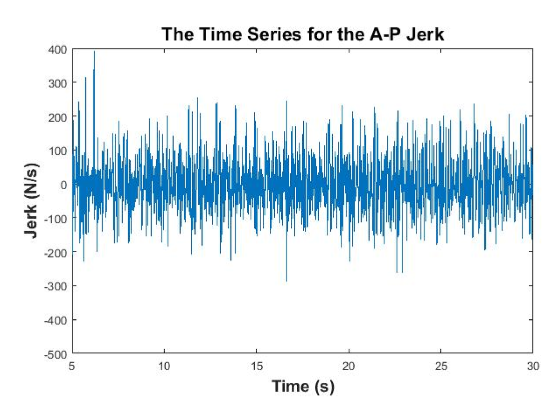

Figure 5: Typical time series for the A-P jerk.

Plotted above are typical examples of the force and corresponding jerk during single leg stance showing both the M-L and A-P cases. Considering the force data as a realization of a stochastic process, the jerk was taken as the increment, $\Delta F = F(i+1) - F(i)$, $i = 1..N-1$ (where N is the number of observations making up the time series for the forces) divided by the sampling period (0.0100 s). Here, the data concerning a subject's dominant leg are shown.

Stationarity Concerns

The quality of stationarity concerns variations in time of the statistics of the time series. This refers to wide-sense stationarity by which it is meant that the mean and autocovariance of the time series do not change with time. [1]. We are concerned with the stationarity of our data in that we would like to not only characterize it, but, also, use analytic tools (such as a power spectral density/autocorrelation function) which depend on stationarity for them to be well-defined in their application.

- All times series under study were linearly detrended (no other processing done).
- Detrended fluctuation analyses indicate the force to be nonstationary and the jerk to be stationary.
- The autocorrelation function have been estimated for the jerk data (see below). The correlation profiles for jerk with their rapid falloff does appear to be indicative of stationary behavior [1].
- An Augmented Dickey-Fuller test for stationarity was performed on jerk data. All test critical values were surpassed for each time series with the probability value, $p < 0.001$, indicating stationary behavior. (This test's statistics also indicated that the data hasn't any deterministic trends linear in time that could be removed, i.e. trend stationarity [1].)
- The Phillips-Perron test for stationarity was also used on the jerk data [2]. There was significant evidence to suggest that the jerk data are stationary (without any deterministic trends linear in time) with $p < 0.001$.

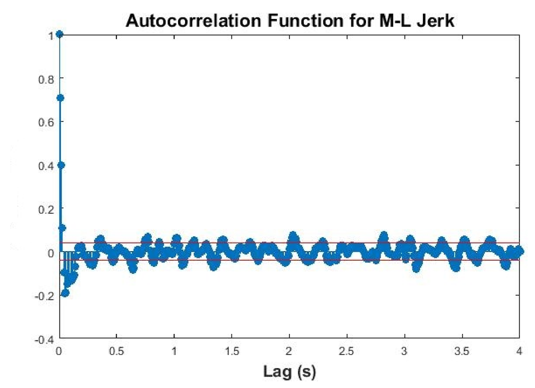

Figure 6: M-L Jerk: dominant leg

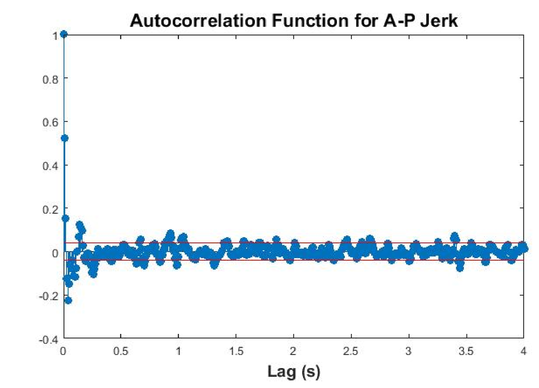

Figure 7: A-P Jerk: dominant leg

The autocorrelation functions for the M-L and A-P jerk are shown above. The horizontal lines indicate the 95 % confidence bounds. In this case, the relatively rapid falloff of the autocorrelation functions to such small values is indicative of a stationary signals. These qualities are generally representative of the jerk data.

Surrogate Data Testing

We wanted to gain insight as to the stochastic and dynamical character of the time series. For this, we used linear surrogate techniques. For a given set of data, a surrogate data set may be generated. Although different from the original data, the surrogate sets are generated in a way that preserve key properties of the original data. This methodology is appropriate for our stationary data in that periodicity and far reaching trends didn't appear to be present (quasi-periodicity could certainly play a role) [3]. We used what are known as Algorithm 0 (testing surrogate time series generated by randomly shuffling the original time series) and Algorithm 1 (testing surrogates constructed using Fourier transforms of the original time series) [3]. We used these two algorithms given their ability to provide insight concerning random behavior. For this study we wanted to test primarily for the stochastic character of the data to establish the context for properly interpreting any scaling behavior.

Once the surrogate data is generated, we can test a null hypothesis. Data sets showing significant evidence to reject the null hypothesis under Algorithm 0 are then tested under Algorithm 1. The hypotheses for the Algorithms 0 and 1 are shown below.

- **Algorithm 0**: The null hypothesis is that there is not a statistically significant difference between the data and uncorrelated (independent and identically distributed (IID)) noise [3].
- **Algorithm 1**: The surrogates under this algorithm are consistent with the null hypothesis of data being linearly filtered IID noise.

We must, then, choose and calculate a discriminating statistic for the original and surrogate data and, using statistical techniques, see how well these results compare. This will allow us to determine whether or not a null hypothesis can be rejected. Sample entropy, a measure of complexity of the time series, was used for the discriminating statistic [4].

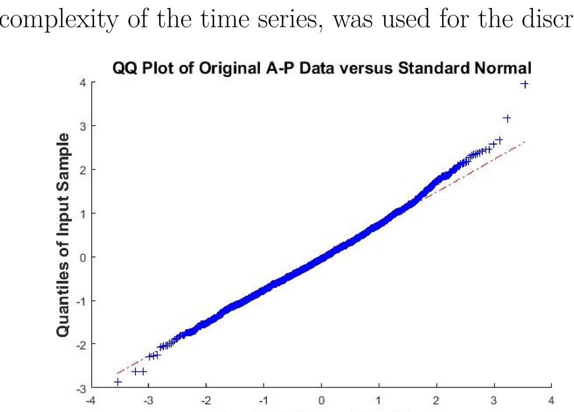

Figure 8: Quantile - quantile plot of the original data

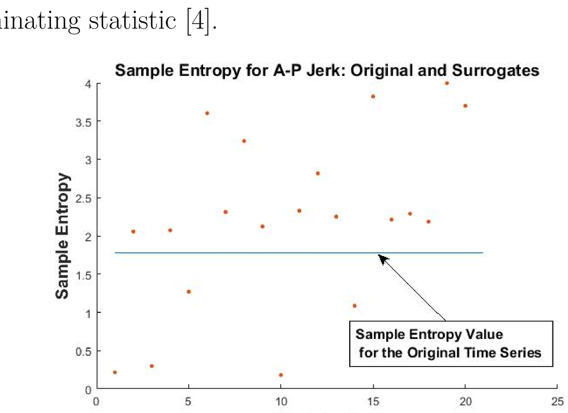

Figure 9: Sample entropy - the discriminating statistic

Above we see typical characteristics for data tested using Algorithm 0 with the null hypothesis failing to be rejected. This occurred at the 95 % level for data sets corresponding to A-P movements for three subjects. Figure 8 shows a quantile - quantile plot of the original data indicating that these data follow a fairly normal distribution with some asymmetric tail deviation. A rank-ordered criterion was applied for Algorithm 0 and, we saw that, for this test, there was a failure to reject the null hypothesis. This suggests that the original time series has the character consistent with IID noise.

A rank-ordered criterion was also applied for Algorithm 1, and there were failures to reject the null hypothesis for several data sets. This was true for three subjects in the case of M-L movements and for three in the A-P case. This indicated that the original time series has a character consistent with linearly filtered IID noise. From this point on in our study, we will only be considering the data sets which fall in one of two categories: ones for which surrogate testing found the null hypotheses unable to be rejected for the two algorithms.

Acknowledgments

We would like to thank Chris Koehler, Bernadette Garcia, the Colorado Space Grant Consortium along with NASA for their continued support, financial and otherwise, of our research. As always, we thank Cynthia Galovich and Robert Walch of UNC's Department of Physics and Astronomy. Also, we would like to thank Jennifer McCamley for being so generous in sharing her revised code for calculating sample entropy [4].

Detrended Fluctuation Analysis

In short, detrended fluctuation analysis (DFA) is a technique which is useful for exploring the temporal correlations in a time series. 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,

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

This calculation is done for all time scales, n. How these average fluctuations scale with n (quantified by a scaling exponent) speaks to the character of temporal correlations found in the time series. DFA can be applied to a variety of signals including those with a stochastic fractal nature which may be stationary or not. For example, the scaling may be indicative of fractional Brownian motion (fBm) or fractional Gaussian noise (fGn). Moreover, the scaling behavior may be indicative of a range of correlations, both positive and negative.

For the scaling exponent, α (the slope of the log(F(n)) - log(n) plot) the following holds [5].

- $\alpha = 0.5$ indicates a signal of white noise, or an integrated signal which corresponds to a random walk. The autocorrelation relation is 0 for this signal.
- $0.5 < \alpha < 1$ corresponds to a positively correlated (power law), or persistent, (stationary) fGn signal. This means that increases (decreases) in the signal will, on average, be followed by increases (decreases).
- $0 < \alpha < 0.5$ corresponds to a negatively correlated (power law), or antipersistent, (stationary) fGn signal. So, increases (decreases) in the signal will, on average, be followed by decreases (increases).
- $\alpha = 1$ is indicative of pink noise.
- $\alpha > 1$ speaks to fBm, a nonstationary signal with correlations, but not of power law form.
- $\alpha = 1.5$ indicates Brownian motion.

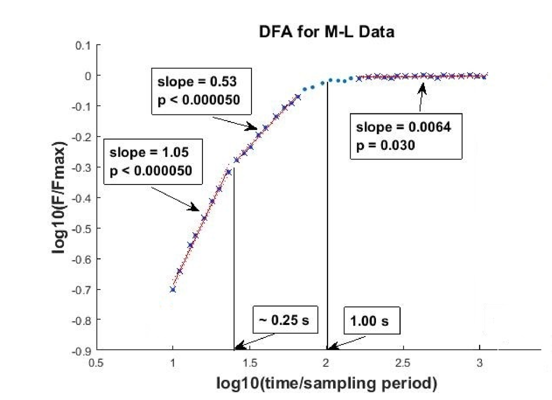

Figure 10: Example of DFA for M-L jerk

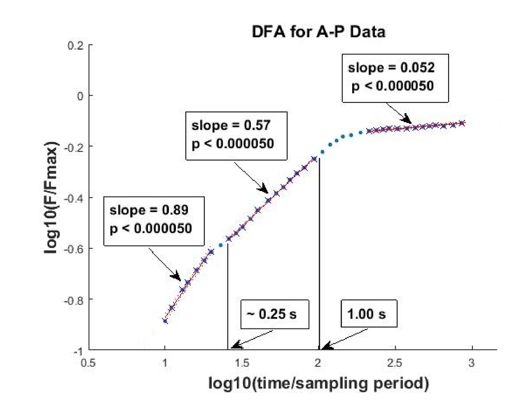

Figure 11: Example of DFA for A-P jerk

Displayed are rather typical fluctuation profiles generated by performing a detrended fluctuation analysis on our data. Temporal scaling regions common to all data are shown. Figures 10 and 11 show results for M-L and A-P jerk data, respectively, indicating these realizations are characteristic of (stationary) fractional Gaussian noise. Moreover, for the analysis seen in Figure 10, one can argue that a crossover from persistent to antipersistent behavior is made at the time scale of 1.00s. Three common temporal scaling regions were revealed with 0.160s being the limit of resolution for the analysis. The scaling boundary values, 0.250s and 1.00s were found by visual inspection and are, therefore, approximate, yet, certainly fall in regions of scaling transition observed in all of the data.

Scaling exponents are shown in Table 1 for each of the three scaling regions. The relevant fit statistics are listed. Also, notice that crossovers from persistence to antipersistence can be found between various regions as well as the suggestion of behavior indicative of pink noise in Region 1. The scaling exponents found for Regions 1 for the jerk data are primarily characteristic of persistent fGn for the sets concerning M-L movement thereby indicating correlated changes in force over time. With exponents also corresponding to fGn, the exponents seen for Region 2 speak to anti-correlated, (what could be argued to be) uncorrelated, and correlated behavior. Region 3 has relatively low value exponents indicative of anti-correlated fGn.

Table 1: DFA Results: This table summarizes the results of the detrended fluctuation analysis. Here scaling exponents are shown for each of the three scaling regions. These exponents were found using linear regression to 95 % confidence limits. For each fit, the p-value < 0.05. The relevant fit statistics are listed. Also, notice that crossovers from persistence to antipersistence can be found between various regions.

Region 1: $0.10s < t < 0.25s$ Region 2: $0.25s < t < 1.00s$ Region 3: $t > 1.00s$

Data Set		**Region 1**		**Region 2**		**Region 3**	
#	Movement	exponent	R^2	exponent	R^2	exponent	R^2
1	A-P	0.89	0.992	0.57	0.999	0.052	0.855
2	A-P	0.76	0.991	0.56	0.996	0.034	0.820
3	A-P	0.90	0.998	0.42	0.998	0.016	0.519
4	A-P	0.95	0.996	0.63	0.997	0.039	0.698
5	A-P	0.63	0.998	0.40	0.993	0.050	0.627
6	M-L	0.80	0.991	0.35	0.988	0.029	0.775
7	M-L	0.94	0.992	0.77	0.993	0.042	0.410
8	M-L	0.95	0.996	0.78	0.988	0.025	0.751
9	M-L	1.05	0.995	0.53	0.995	0.0064	0.262

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