Characterizing the Complexity of Human Unipedal Balance

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Introduction

We would like to understand the dynamical nature of human unipedal balance. Time series typical of the anterior-postural (A-P, front to back) and medial-lateral (M-L, side to side) jerk during the balance process were studied. Our interest is to classify features found in these measurements as indicative of subjects experiencing certain medical conditions. New data taken with a higher sampling rate and a more restricted filtering scheme (to deal with machine noise) revisits our earlier work in this area [1]. Currently, our data is very limited but typical of our studies at lower resolution. We anticipate more data to be taken soon with a variety of subjects and consider this work as a pilot study to inform preprocessing of future trials.

Our analysis suggests that these signals have a deterministic character with a temporally evolving autocorrelation structure and time-frequency spectrum. We will use the term "nonstationary" for this behavior. Finally, with the Lempel-Ziv complexity having mild but measurable fluctuations throughout the time series, we have been led to pursue a classification scheme that attempts to track the evolution of the complexity with time. The signals have been decomposed into modes using multiresolution analysis. Using the Lempel-Ziv complexity with its coarse-graining application can classify bulk features and find suggestions of determinism playing a role in the jerk. This allows us to pursue an examination of the more nuanced features contained in the signal.

Background

The COP (center of pressure) is the point of application of the net force vector on the floor because the bottom surface of the foot is in contact with the ground in our case. As weight shifts, so does the COP. A force plate was used to collect data concerning the COP trajectory of a healthy individual attempting to remain still (unassisted) standing on one foot with eyes open. (The noise profile of this force plate was taken into consideration.)

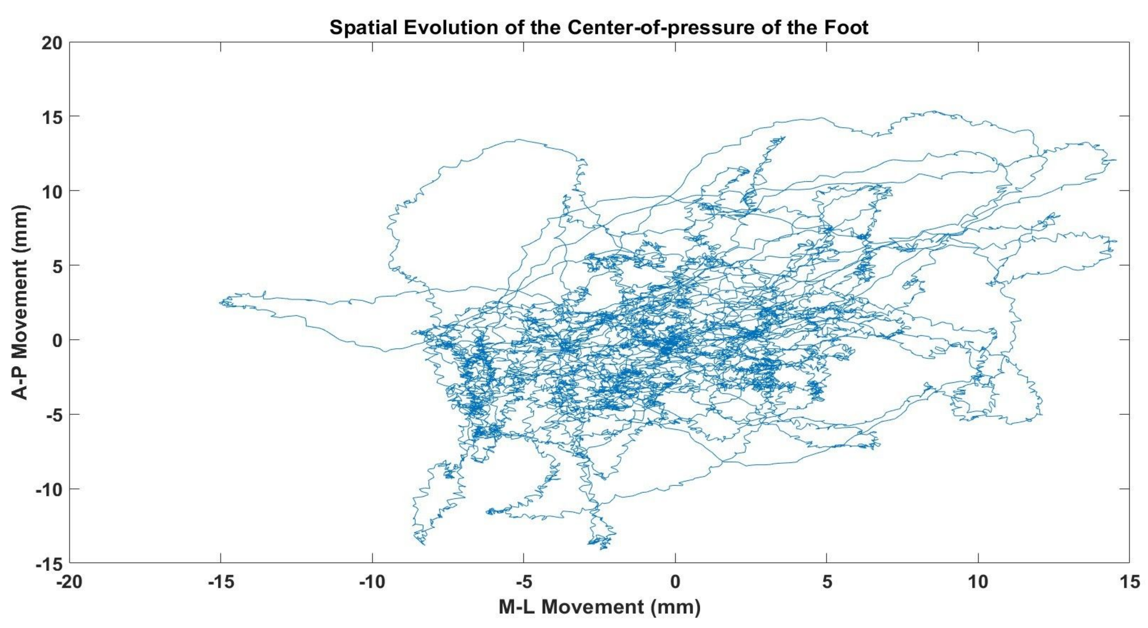

Fig. 1. Here is a typical trajectory of the COP (sampled at 1000 Hz) during a single leg stance.

Data Collection

Force data were collected using a multi-axis force plate for an adult subject who maintained balance (with eyes open looking straight ahead, hands by his sides, and barefoot) using each leg separately for 30-second sessions. Before any data collection, all procedures were explained to the participant and written consent was obtained following local institutional review board policy.

- The data were sampled at 1000 Hz in the spirit of experimentation to see if a higher sample density than in our previous work leads to any alterations in certain results (from what we found, this isn't a major concern).
- Also, given our knowledge of the frequency range of the machine noise, we wanted a fairly high Nyquist frequency to reveal a well-defined region for filtering and to avoid any aliasing effects.
- Machine noise primarily affected frequencies above 15 Hz. Our study concerns behavior below this.
- Notch filters were applied (Butterworth) at 60 and 120 Hz to inhibit AC line noise as well as at certain frequencies for sinusoidal detrending. A low-pass finite impulse response (FIR) filter was applied (sharply) at 12 Hz and a high-pass infinite impulse response (IIR) filter was applied (sharply) at 0.10 Hz. Also, the signal was linearly detrended.

Treatment of Data

Taking the jerk to be proportional to the first difference of the force measurements, we have the time series and autocorrelation (AC) estimates (below, Fig. 2 (a and b)) for the M-L jerk (for the sake of space, we'll only discuss the M-L signal results). The AC estimates are for four sequential one-second nonoverlapping windows of the jerk signal (each enclosing several oscillations) – one can get a sense of the temporal evolution of this profile. This change in the statistics of the signal is indicative of a nonstationary time series.

Also, applying the 2-Sample Kolmogorov-Smirnov Test [2] to such windows (overlapping and not and of varying width), we find that the distributions underlying the data are not significantly the same at the 5% level. Moreover, the variances fluctuate for these sections of the time series. All this suggests nonstationarity.

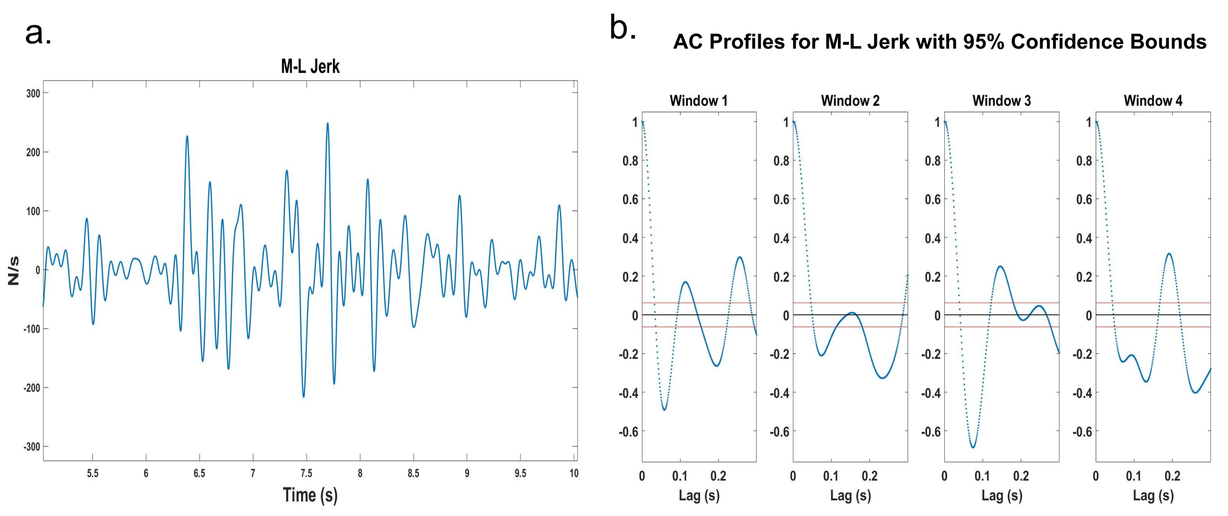

Fig. 2. This is the time series (a) and evolving autocorrelation profiles (b) for the M-L jerk.

Multiresolution Analysis

We used a wavelet multiresolution analysis (MRA) to decompose the signal into modes (see Fig. 3) with frequency bands limited to low, middle, and high ranges of the spectral content of the signal (maximal overlap discrete wavelet transform (MODWT) [3]). This technique is appropriate for nonstationary signals [3]. These modes sum to give the signal and will be used in our complexity analysis.

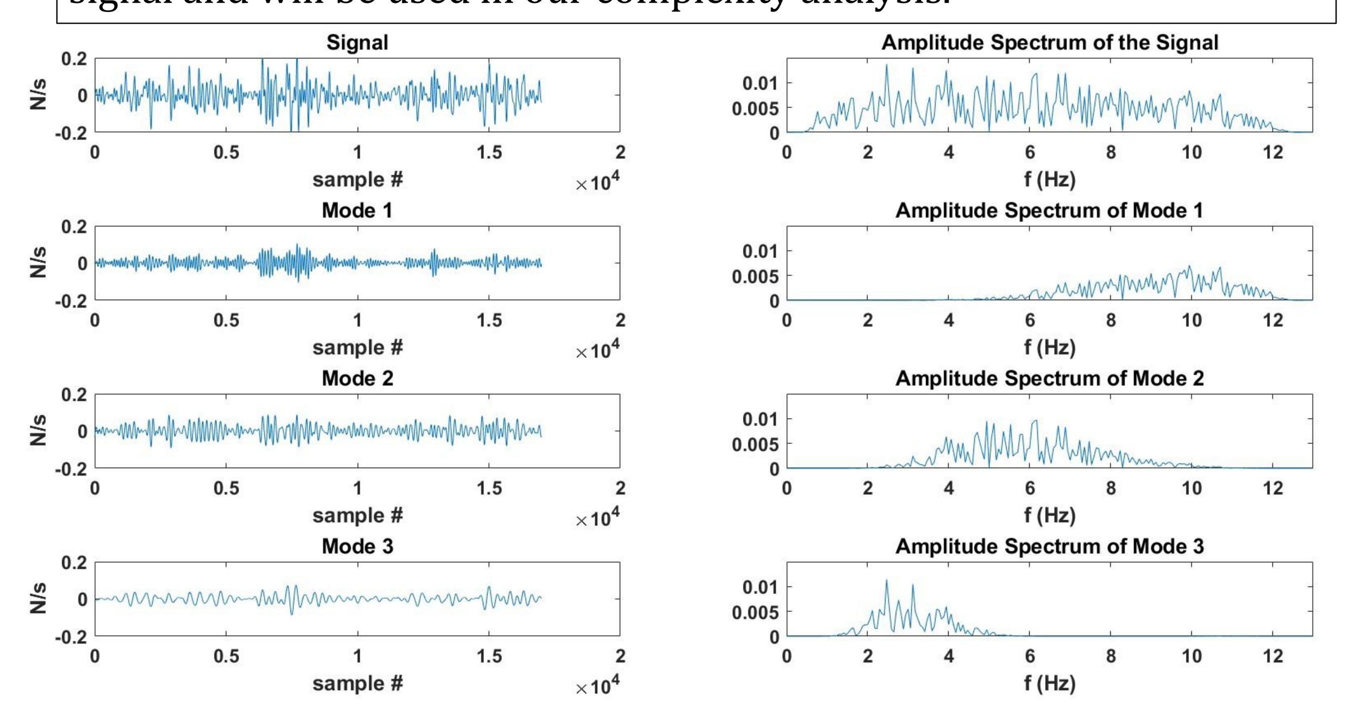

Fig. 3. Here is the filtered jerk signal, three modes, and their frequencies. The signals are scaled (1/1000 of their true value), but we permit this since we are investigating the shape of the data.

A Measure of Complexity

For signals that appear random but may have an underlying nonlinear mechanism [4], the Lempel-Ziv complexity (LZC) measures the irregularity ("randomness") of a sequence of characters by counting the number of copy operations needed to generate it [4].

Subsequences (words) are lists of characters evaluated for uniqueness. If the word is not a subset of the prefix (all characters leading to, but excluding, the one under examination), it is added to a dictionary. The LZC is the number of words in this dictionary (the exhaustive history) [4].

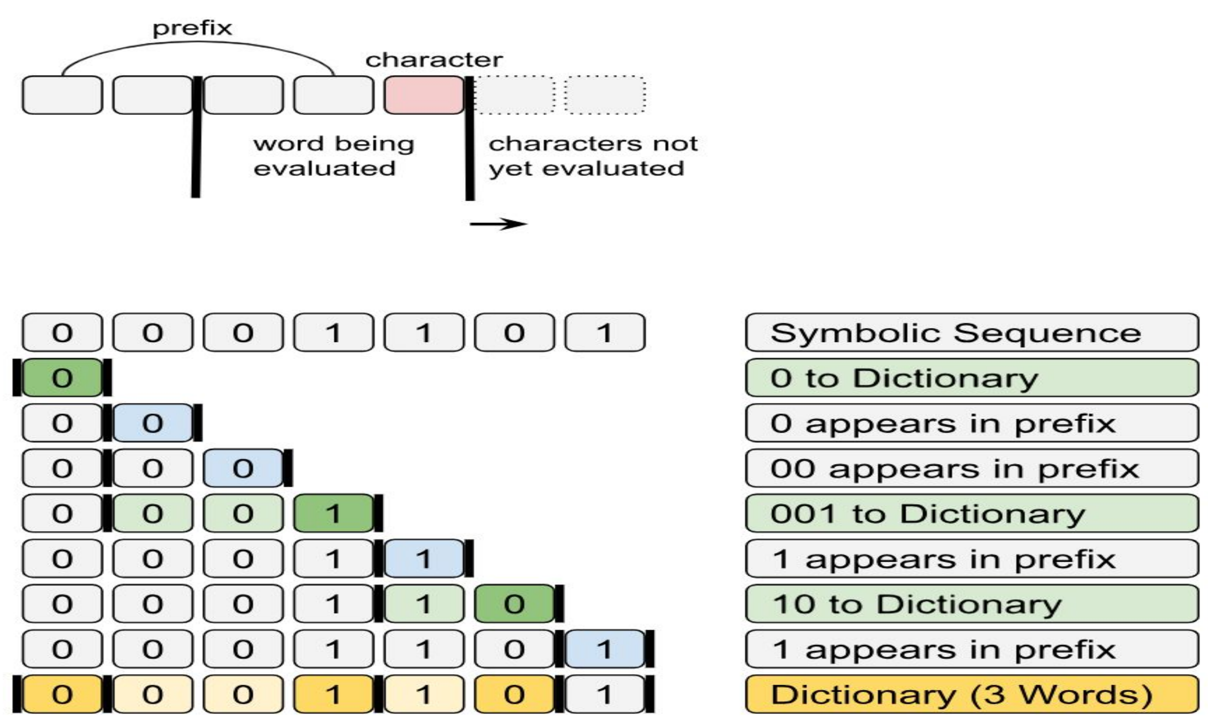

Fig. 4. This is a visual of the Lempel-Ziv algorithm counting the number of unique words in a binary sequence.

Coarse-Graining

Running the LZC on a time series coarse-grained with the Bandt-Pompe method gives the Lempel-Ziv permutation complexity (PLZC) [5]. We chose to work with triplets of adjacent points (embedding dimension and delay: D=3, τ=1) to coarse-grain. Groups of points are assigned a character based on 3! rankings that comprise an alphabet (see Fig. 5 (a)). The existence of orderings that rarely appear in the time series (*forbidden patterns)* is indicative of determinism [5], and we find that using triplets produces a sufficiently large alphabet to highlight these patterns (see Fig. 5 (b)).

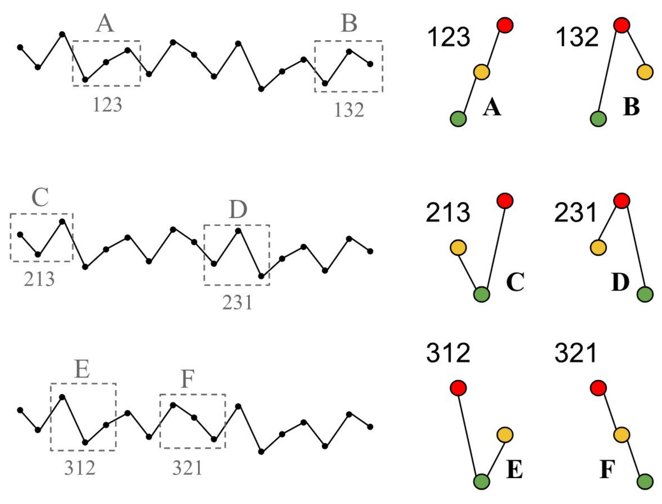

Fig. 5a. This is a visual of the Bandt-Pompe coarse graining procedure.

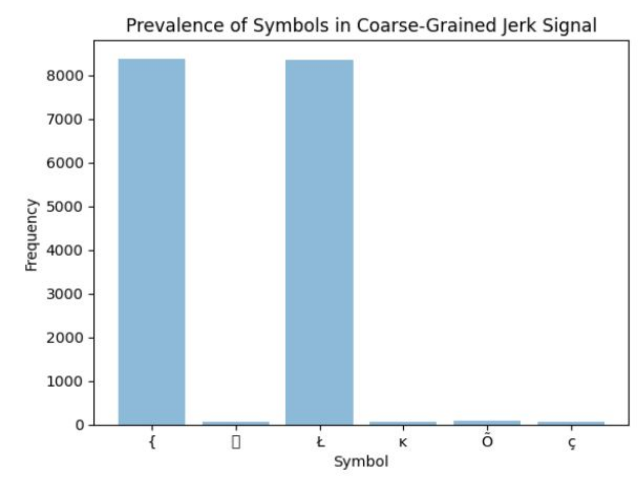

Fig. 5b. The jerk sequence is dominated by characters corresponding to monotonic behaviors. Sequences around extrema are skewed to the left and right with equal probability because their corresponding characters have uniform occurrence frequencies.

Application to Balance Signal

To see how the complexity of the signal changes with time, we chose to examine overlapping 2000-point windows of the signal (see Fig. 6). This window size is large enough to include a sufficient exhaustive history but small enough to prevent averaging behavior.

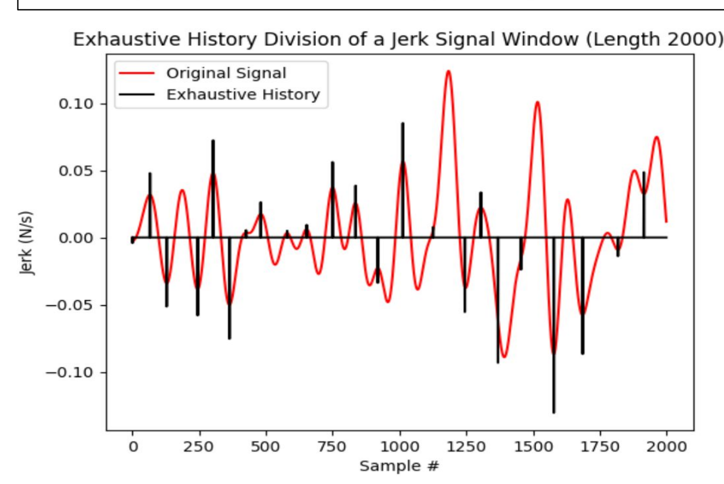

Fig. 6. Breaks indicate a unit increase of the PLZC in a signal window. The breaks of a more periodic signal are spaced far apart–corresponding to a longer duration on the force plate in a balance pattern already recorded.

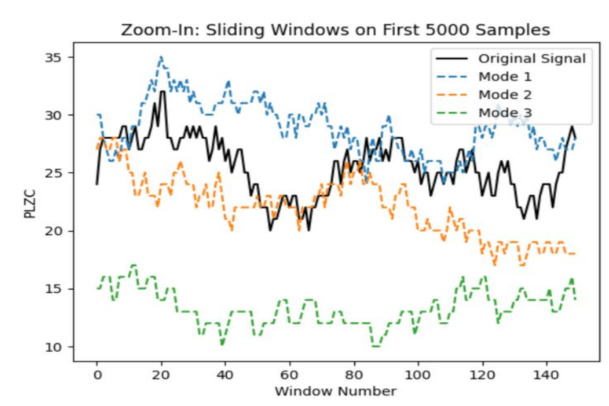

Fig. 7a. Here is the time evolution of the PLZC for the jerk signal and modes.

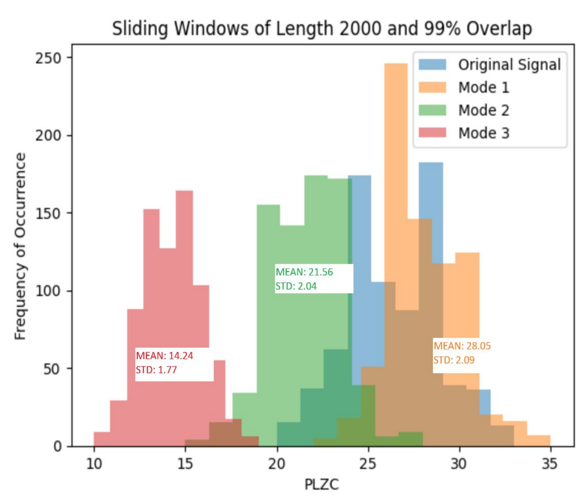

Fig. 7b. Here is the PLZC histogram counted over all windows.

The jerk signal and its modes have significantly lower mean complexity than white noise (≈300)–suggesting that they exhibit more regularity. Although the PLZC signature of the original signal on average lies between the first two modes (Fig. 7 (a)), it has the largest *variance* in complexity (Fig. 7 (b)) likely due to the jerk's wide range of frequencies. Even with a significant overlap of windows (99%), the PLZC was able to differentiate between the modes. This allows for the possible identification of underlying sources of determinism for the signal by tracking forbidden patterns and studying modes with relatively low average PLZC values (mode 3).

Future Research

After taking more data, further research into how the embedding dimension and delay parameters should be chosen to coarse-grain the signal is worth investigating.

Acknowledgments

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