Postural Control: A Sample Entropy Approach To One-Legged Stance

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Project Overview

We became interested in knowing whether or not there are any measurable dynamical differences between using one's dominant and non-dominant leg for one-legged stance. To attempt to detect these differences, we used the sample entropy algorithm.

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 (COP: is the point of application of the net force vector on the floor due to standing) 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.

Delignieres et al. [2] were the first to show that there are some methodological concerns with the techniques that Collins and De Luca implemented. Furthermore, Delignieres et al. presented a compelling argument as to why the brain's control of the COP is actually based on the velocity of the COP [3] instead of position-based. Although, it should still be noted that the original paper by Collins and De Luca gave a new and insightful understanding of COP control.

More recently, Richard and Moorman [4] have developed an algorithm, dubbed sample entropy (SampEn), to analyze the entropy (in the context of time series and dynamical systems, *entropy* is the rate of information production) of a time series (a sequence of values in chronological order). This is an extension of the approximate entropy algorithm (ApEn) by Pincus [5].

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. Analytic methods [6] and empirical methods [7] have been proposed to calculate the input parameters m and r.

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. To determine the parameters m and r, two different methods have been adopted. In [6] they show that in most cases a value of $m = 2$, or $m = 3$ and a value of $r = 0.2$ (normalized) suffices for most time series, and in [7] they propose an empirical method for determining such parameters.

For our purposes, we focused on the empirical method since the SampEn algorithm we used, provided by *PhysioBank* [8], already had functions for producing this confidence interval, and is known to obtain more consistent results [7]. An example of this is shown in Fig. 1.

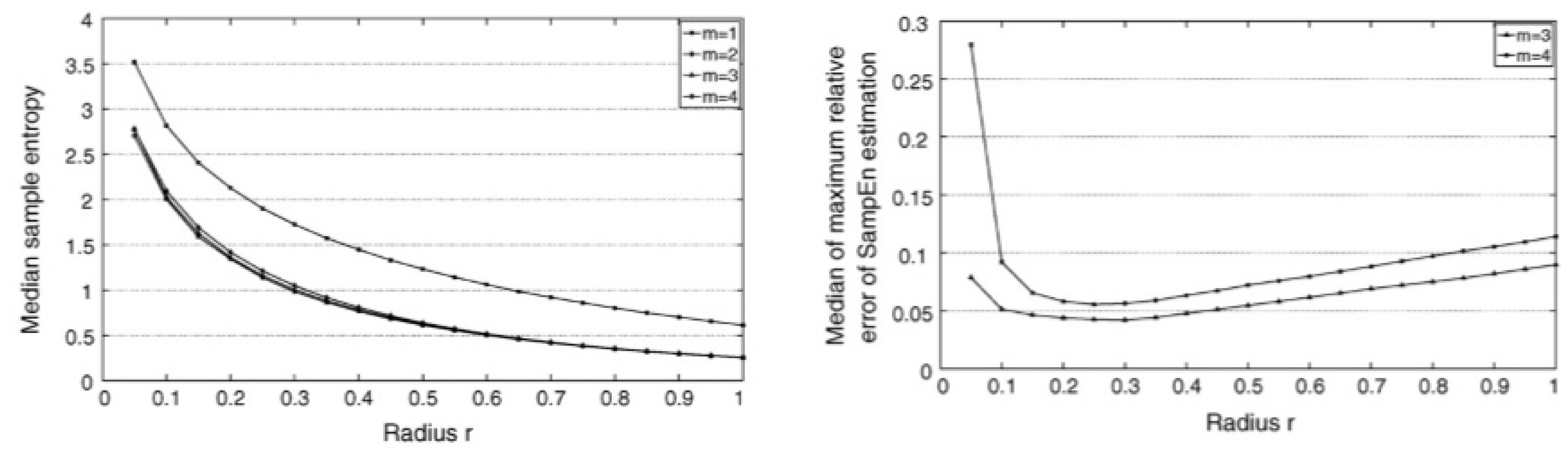

Figure 1: **These graphs were obtained from [7]. The above graphs show an empirical method for determining the parameters m and r. The above graph on the left is a plot of the median sample entropy vs. the tolerance (radius) r. To select an appropriate value for m we use a so called "convergence" criterion [7]. In this case, the authors [7] chose $m = 3$ and $m = 4$. Once the subsequence length is chosen, the next step is to determine the tolerance level r. Given that 3 and 4 were sufficient values, for m, for the given data set in [7], the authors used these values for optimizing r. The above graph on the right is a plot of the median maximum standard error vs. the tolerance r. The authors selected $r = 0.3$, in their case, because it was the value that corresponded to a minimum error value.**

A Comparison

To collect our data, we used a force plate that measured the force at the position of the center of pressure of an individual's foot while that individual maintained a one-legged stance (eyes open). The data was collected at a sampling rate of 100 hertz and $N = 3000$ data points (30 seconds of data) were collected for each balance session. For our analysis, we filtered out frequency components of the data above 20 hertz. Below are our current graphs used in determining the parameters m and r.

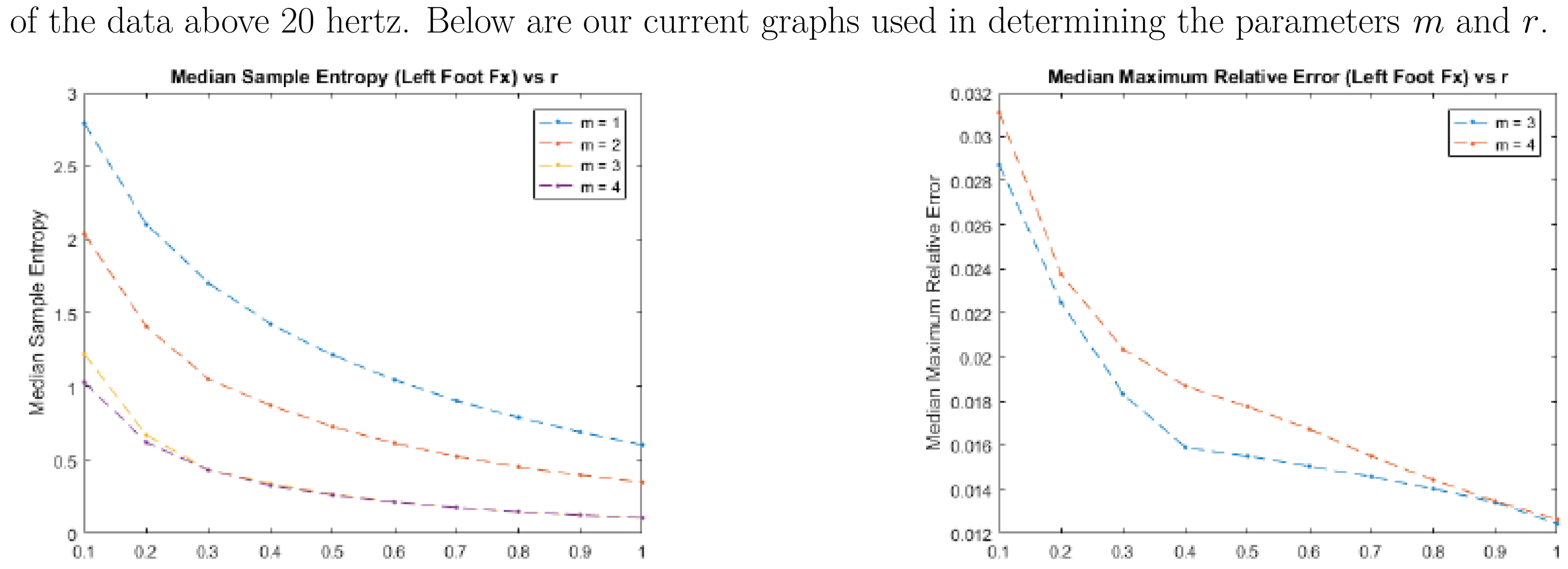

Figure 2: **Just as in the case of [7], our values for the subsequence length are $m = 3$ and $m = 4$ via the convergence criterion [7]. Given our values of m, we did not obtain an optimal value for r. It should be noted, however, that what this graph suggests is that it does not matter what particular r value we use since the error is well within a satisfactory statistical uncertainty.**

Data

Figure 2 suggests that a value of $m = 3$ will suffice for our data (as explained in [7]). However, our data did not produce an optimal r value (contrary to what was observed with 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 both their left and right feet (for the force and jerk).

Below, in Table 1, are the average differences in the x-components and y-components of the observed force and jerk.

Table 1: **The values shown above are with $m = 3$ and $r = 0.1, 0.2 \ldots, 1$. We report the values as follows: absolute value of the average entropy $\pm$ 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 concerning the left foot shows a higher entropy value than that for the right foot, and in the case of the jerk, the result for the left foot has a smaller entropy value than that for the right foot.**

Sample Entropy Values			
L F_x **- L** F_y	**R** F_x **- R** F_y	**L** J_x **- L** J_y	**R** J_x **- R** J_y
0.069 ± 0.001	0.058 ± 0.001	0.044 ± 0.002	0.125 ± 0.002

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