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Approximate and Sample Entropy of Center of Pressure in Unperturbed Tandem Standing: Contribution of Embedding Dimension and Tolerance

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Approximate and Sample Entropy of Center of Pressure in Unperturbed Tandem Standing: Contribution of Embedding Dimension and Tolerance

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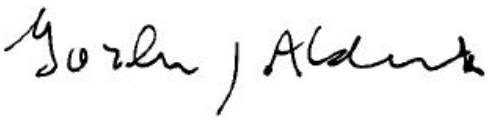
Thesis Approval Form

GRAND VALLEY STATE UNIVERSITY

The signatories of the committee below indicate that they have read and approved the thesis of Jayla Mashae Wesley in partial fulfillment of the requirements for the degree of Master of Science in Engineering, Electrical/Computer Engineering.

4/26/2023

Samhita S. Rhodes, Thesis committee chair — Date



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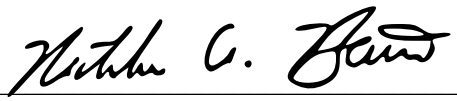

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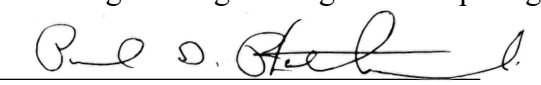

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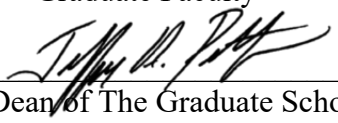

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Abstract

Approximate entropy (ApEn) and sample entropy (SampEn) are statistical methods designed to quantify the regularity or predictability of a time series. Although ApEn has been a prominent choice for use, it is currently unclear as to which method and parameter selection combination is optimal for its application in biomechanics. The goal of this thesis was to examine the difference between ApEn and SampEn related to center of pressure (COP) data during standing balance tasks, while also refining tolerance *r*, to determine entropy optimization. Six participants completed five 30-second, feet together and tandem standing, trials under eyes-open and eyes-closed conditions. Ground reaction force platform data (1200 Hz) was collected and downsampled to provide a 60 Hz COP time series. ApEn and SampEn were calculated using a constant pattern length, i.e., $m = 2$, and multiple values of *r* (tolerance). Four separate one-way analysis of variance analyses (ANOVA) were conducted for ApEn and SampEn in the anterior posterior (AP) and medial lateral (ML) directions. Dunnett's intervals were applied to the one-way ANOVA analyses to determine which conditions differed significantly. ApEn and SampEn provided comparable results in the predictability of patterns for different stability conditions, with increasing instability being associated with greater unpredictability. The selection of *r* had a relatively consistent effect on mean ApEn and SampEn values across $r = 0.15 – 0.25$*SD, where both entropy methods tended to decrease as *r* increased. Mean SampEn values were generally lower than ApEn values. The results suggest that both ApEn and SampEn indices were equally effective in quantifying the level of center of pressure signal regularity during quiet tandem standing postural balance tests.

Keywords: approximate entropy, sample entropy, center of pressure, complexity, tolerance, downsampling

Abbreviations

ApEn – approximate entropy

COP – center of pressure

EC – eyes closed

EO – eyes open

FT – feet together

SampEn – sample entropy

SD – standard deviation

TanDB – tandem dominant foot in back

TanDF – tandem dominant foot in front

Introduction

Two commonly used methods for quantifying physiological data are approximate entropy (ApEn) and sample entropy (SampEn). Entropy is defined as the loss of information in a time series or signal, i.e., it quantifies the amount of uncertainty regarding the order of an output signal[10]. Within the past twenty years, the use of entropy methods to define predictability or regularity in human physiological and biomechanical data has become quite prevalent[47]. Entropy quantifies the likelihood of the next state of a system, based on what is known about the present state of a time series, and has been used to quantify physiological changes with aging[2,41], as well as cardiovascular[14,40] and respiratory pathology[8,10,13]. ApEn and SampEn are both also useful tools for understanding more about the function of changes in postural control system[6,16,21,36,310] such as human gait mechanics[50,51] and standing balance[5,6,7,36,47,48].

In 1991, Pincus developed approximate entropy as a mathematical instrument for measuring regularity to quantify levels of complexity within a time series[31]. It was meant to be a statistical measure of regularity whose foundations are similar and correctly quantifies finite data series[47]. ApEn was devised to quantify the rate of regularity in time data series, motivated by applications for relatively short, noisy data sets. Specifically, ApEn (and SampEn) have been shown to demonstrate changes in the complexity of various physiological signals such as chronic stroke[28], electrocardiograms (ECG)[4], electroencephalograms (EEG)[49], heart rate variability[30], and neural respiration signals[8,19]. Complex systems such as these do not equate to being unmeasurable. Information entropy has been used to quantify complex systems where a time series with repeated patterns and less randomness will produce small entropy values whereas a time series with more randomness will equate with larger entropy values[29,40]. Equally, lower ApEn values reflect that a

system is very persistent, repetitive, and predictive, with apparent patterns that repeat themselves throughout the series, while greater values of entropy mean independence between the data and greater randomness. So, it is more appropriate to use terms like probability, predictability, regularity, when describing the nature of a measurable complex system. In summary, the use of ApEn (and SampEn) was not meant to comprehensively analyze complex systems, but to statistically analyze the dynamics of time series related to complex systems[12].

When this understanding of entropy is applied to postural sway in human stability, changes in entropy may provide insight into the control of static and dynamic balance. Cavanaugh et al.[7] evaluated the effect of cognitive task performance on postural control during quiet standing, revealing changes in ApEn as changes in the randomness of COP data occurred. ApEn showed the evolution of its complexity, providing meaningful comparisons to the detection of subtle influences on postural control after cerebral concussion in the alteration of the complex nature of motor control. Similarly, Ramdani et al.[36] analyzed the irregularity of postural sway during quiet standing comparing two sensory conditions using SampEn and concluded that the ability to successfully discriminate between levels of complexity, e.g., eyes open to eyes closed conditions, may provide insight toward characterizing the postural effects of aging and diseases. Hence, entropy provided researchers with the ability to quantify complexity within relatively short data sets based on meaningful experimental comparisons to control groups[47].

Approximate entropy is calculated over a scale of time. Both ApEn and SampEn methods utilize three input parameters: N is the data length, m is the length of the window of the different vector comparisons, and r is the tolerance, i.e., function criterion of similarity or type of signal filter. Given the input parameters, ApEn (*m, r, and N*)[30] is denoted by:

$$ApEn(m,r,N) = -\frac{1}{N-m}\sum_{i=1}^{N-m} log\frac{A_i}{B_i} \quad (1)$$

ApEn measures the logarithmic probability that nearby pattern runs remain close in the next incremental comparison[7]. $B_i(r)$ is the probability that two sequences are similar for *m* points with self-counting and $A_i(r)$ is probability that two sequences are similar for *m* + 1 matches with self-counting. Self-counting suggests that given one template, that segment in the sequence is compared to all the blocks in the sequence, including itself. For ApEn, self-counting is needed in the calculation of conditional probabilities to ensure the logarithms remain finite. Statistically, selecting *m* and *r* as input parameters would be the equivalent of dividing the space of states into cells of width *r*, to estimate the conditional probabilities of the *m*-th order[7]. Higher *m* and smaller *r* describe details of sharper, more probabilistic parameters[7]. However, when dealing with stochastic processes, the analysis of conditional probabilities causes large values of *m* or minimal values of *r* to produce statistically low estimates. Ultimately, the value of the estimate depends on *m* and *r*. Pincus[29] suggested taking *m* as 2 and *r* as 0.2*SD_x where SD_x is the standard deviation of the original data <*x(n)*>, i.e.,

$$SD_x = \sqrt{\frac{1}{N-1}\sum_{n-1}^{N}\left[x(n) - \frac{1}{N}\sum_{n-1}^{N} x(n)\right]^2} \quad (2)$$

Pincus[29] suggested that one of the advantages of ApEn is that the algorithm is finite for stochastic, noisy deterministic, and composite processes, i.e., models for complicated biological systems. It can differentiate between different mixed methods of deterministic and random components occurring with a different probability. ApEn is also robust to outliers because the pattern formed by wild points will rarely be repeated in the waveform[32]. An increasing ApEn corresponds to intuitively increasing process complexity in a biological modeling platform. However, the

limitations of ApEn include that the relative consistency is not guaranteed, and depending on the value of *r*, the ApEn values will change[10]. Additionally, the value of ApEn depends on the length of the data series. Lastly, the self-counting portion of the algorithm implies a statistical bias that is important in situations with small data sets, where when only a few or even no matches are present, the entopic result is biased toward zero[10].

Although the development of ApEn made a significant contribution to the understanding of complex physiological time series, its shortcomings may be significant. Richman and Moorman[40] introduced SampEn as an algorithm to counteract the limitations of ApEn, claiming that SampEn, as a statistical alternative, solved the self-counting problem to eliminate that bias. Eliminating self-counting is justified given that entropy is conceived as a measure of the rate of information production. ApEn uses the whole series to determine its value, needing only a that a template vector find a match of length $m + 1$ to be defined[7]. SampEn contrasts with ApEn, where each template vector must find a match to be determined[47]. SampEn (*m, r, and N*) is defined as the negative value of the logarithm of the conditional probability that two similar sequences of *m* points remain identical at the next point $m + 1$, counting each vector over all the other vectors except on itself[7].

$$SampEn(m, r, N) = -log \frac{A^m(r)}{B^m(r)} \quad (3)$$

$B^m(r)$ is the probability that two sequences are similar for *m* points, $A^m(r)$ is the probability that two sequences are similar for $m + 1$ matches, the ratio is a conditional probability. The use of

SampEn appears to quantify regularity more effectively and eliminates many of the problems associated with ApEn[40]. **S**ampEn maintains the relative consistency and is also mostly independent

of the length of the series[40]. SampEn was created to address the bias and inconsistencies of ApEn, yet both methods retain similarities[40]. However, the literature is unclear about which method is preferable.

Important consideration must be given to parameter selection, as these choices may have the greatest impact on the final entropy value even in the presence of noise[52]. Given a time series with N data points, the calculation of entropy requires *a priori* determination of two unknown parameters, embedding dimension m and threshold r[20]. Multiple pairings of parameter selections allow one to examine relative consistency where a better discrimination capacity can be accomplished. Incorrect parameter choice, and lack of due diligence in selecting m, r, N, can undermine the entropy results.

The parameter N is the length of the data series. According to Yentes et al.[51], data sets larger than $N = 200$ points are recommended over data lengths that consist of less than 200 points. It appears that both ApEn and SampEn stabilize around 2000 points. When the sampling rate is too high, i.e., frequency collection rates greater than 1000 Hz, too much redundancy likely exists within the data, which tends to artificially decrease entropy values[48]. Redundancy, i.e., repetitiveness of or repeating values, results in a reduced entropy and more signal regularity secondary to the counting of repeated matches. The over-redundant data problem can be solved by downsampling overly redundant time series data sets. Although downsampling removes real data, sensitivity analyses have demonstrated that the loss of data does not impact the subsequent application of the revised data set[21,50]. Rhea et al.[38], for instance, examined the effect of downsampling on metrics that measure the magnitudes and structure of COP displacement and velocity variability. The results suggested that excessive downsampling, e.g., to 25 Hz, artificially

altered standing center of pressure displacement and velocity SampEn values. When analyzing changes in CoP variability, it is therefore essential to differentiate between those caused by the neuromotor system and those caused by data processing methods.

The parameter *m* determines the length of the sequences to be compared, and an estimation of its selection can be obtained by calculating the false closest neighbor[20]. Based on previous studies that include clinical applications, $m = 1$ or $m = 2$ appeared to produce good statistical validity for entropy calculations, where $m = 2$ was the most popular[30,52].

The third parameter, *r*, is the tolerance level for allowing similar patterns between two segments. It has been suggested that it be within 0.1-0.25 times the standard deviation (SD) for both deterministic and stochastic processes in order to be clinically useful[25]. These recommendations were largely based on its applications in heart rate analysis'[4,19], neural processes as it relates to cognitive behaviors[6], and long gait datasets[50]. Theoretically, with a greater *r* value, more randomized data are accepted, which produces a lower entropy value. With a smaller value of *r,* more similar data are rejected, only counting matches within a criterion thus producing a higher entropy value. Tipton's[48] work exposed the use of an unconventional *r* value. In the Tipton study, center of pressure data were analyzed at 1200 Hz, i.e., a very high sampling rate for purposes of estimating entropy. Because of the high sampling rate used by Tipton, a non-traditional method to determine *r* was used. Given the recommended range of *r*, authors[4,19,20,50,51] have shown that for ApEn values vary significantly even within the defined range of $r = 0.1 - 0.25*SD$, suggesting that additional studies are needed to accurately tighten this range.

The purpose of this master's thesis was to compare the analysis methods, ApEn and SampEn of the center of pressure data, to determine which entropy measure is less biased and most consistent. Center of pressure data were chosen because it represents a single measurement of the complex postural control mechanism used to maintain balance and incorporates all somatosensory and neuromotor inputs that influence stability[48]. ApEn and SampEn methods of analysis quantify these data regularity and unpredictability in its fluctuations over time and will determine an estimated baseline signal for different stability conditions. The goal was to examine distinctions in bias and consistency between ApEn and SampEn. We hypothesized that ApEn would be lower than SampEn for all calculations overall. Further, this study examined downsampling methods of the standing balance data to remove redundancy contained in high sampling rates, and to evaluate the effect of altering input tolerance *r* to determine the best *r* value for optimization.

Materials and Methods

Participants

Eight participants, between 18 – 34 years of age, participated in this research study after voluntarily providing their signed informed consent. Center of pressure force plate data were collected from participants but participants whose COP data contained any signal dropout were omitted. Therefore, six participants' data from the original cohort were included in the analysis. All participants were in good health and with no history of neurological or muscular disorders or injuries[23]. Before data collection commenced, foot dominance for each subject was determined based on the leg with which they preferred to kick a ball. This study was approved by the Grand

Valley State University Institutional Review Board (18-246-H), and data from a previous data collection were used in this study for the purpose of extending a prior analysis.

Instrumentation

Marker trajectories were captured at 120 Hz using Vicon Nexus v2.8 motion capture software (Vicon Motion System Ltd., Oxford Metrics, UK) and Vicon 16 MX and T40 cameras. Reflective markers were affixed to anatomical landmarks using two-sided hypoallergenic tape to track the movement trajectories of a modified Full-Body Plug-in-Gait model. Two floor embedded AMTI (Advanced Mechanical Technology Inc., Watertown, MA) force plates were used to synchronously collect ground reaction force data (1200 Hz). Data from six MA-411 surface pre-amplifiers, using the 16-channel MA300-XVI patient unit acquisition system (Motion Lab Systems Inc., Baton Rouge, LA) were synchronized with motion and ground force data to measure the electromyographic (EMG) signals of the medial gastrocnemius, soleus, and tibialis anterior bilaterally at a 1200 Hz sampling frequency. The MA300 has a fixed 10 – 1000 Hz (-3dB) bandwidth and uses a 500 Hz low-pass anti-aliasing filter.

Only force plate data were analyzed for this study. The force plates were oriented with one directly in front of the other (Figure 1). Center pressure data were extracted using Vicon NEXUS motion capture software v2.8 (Oxford Metrics, Oxford, UK) and exported to Excel for later analysis.

Experimental Procedure

Data for each trial were collected at 1200 Hz per second for 30 seconds until 5 successful trials were completed per stability condition (Table 1). Therefore, the time series of data collected totaled 36,000 data points. The standing postural condition of feet together with eyes open (EOFT) was defined as the most stable and hence was used as a baseline for all entropy comparisons. The subject was asked to hold this quiet standing position for thirty seconds without moving their body or stepping out of position. Balance tasks were performed barefoot with the arms positioned with the index finger pointed towards the shoulder on the same side of the body and the elbows pulled in and the knees extended. The subject then progressed through increasingly unstable balance conditions by changing visual status, with 2-minute breaks between each. Conditions included eyes open or closed, and changing foot position, i.e., feet together on force plate 5 or tandem stance using force plate 3 and 5 shown in Figure 1.

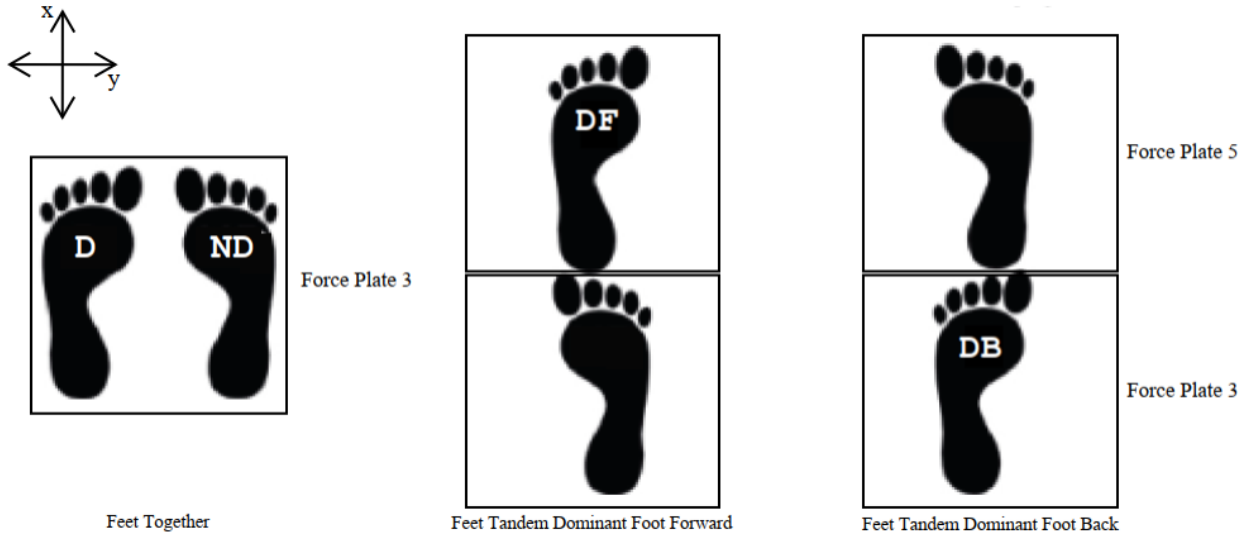

Figure 1. Force plate foot placement for feet together and feet tandem standing balance conditions, where the x-axis (anterior posterior (AP) direction) y-axis (medial lateral (ML) direction define the center of pressure orientation. Note: D =dominant foot; ND = non dominant foot; DF = dominant foot forward; and DB = dominant foot back[23,48]

Table 1. Quiet Standing Balance Conditions

Balance Condition	Description
EOFT	Eyes Open, Feet Together
ECFT	Eyes Closed, Feet Together
EOTanDF	Eyes Open, Feet Tandem, Dominant Foot Forward
ECTanDF	Eyes Closed, Feet Tandem, Dominant Foot Forward
EOTanDB	Eyes Open, Feet Tandem, Dominant Foot Back
ECTanDB	Eyes Closed, Feet Tandem, Dominant Foot Forward

Determining total body center of pressure from two force plates

The extracted COP data files were analyzed using nonlinear analysis in the time and frequency domains. The tandem trial output data sets differed from the feet together trials in that two separate COP signals for tandem balance conditions were produced (one for data from each of the force plates), while feet together resulted in data from a single force plate. The two-column tandem trials were combined into one resultant COP to be directly compared to the feet together conditions using Equation 4.

$$COP_{net} = COP_L \frac{F_{zL}}{F_{zL}+F_{zR}} + COP_R \frac{F_{zR}}{F_{zL}+F_{zR}} \quad (4)$$

where COP_{L} and COP_{R} are the values of the COP signal from the left and right foot, respectively, and F_{zL} and F_{zR} are the vertical forces exerted on the force plates under the left and right foot, respectively[41]. The magnitude of the x and y axes of each subject and corresponding balance conditions were populated into curated databases. These data were then used for further estimation

of COP in the AP and ML directions using Approximate Entropy (ApEn) and Sample Entropy (SampEn).

Downsampling and sensitivity analysis

The total number of data points, *N*, required revaluation based on previous estimation by Tipton[48]. The original COP datasets, recorded at 1200 Hz for 30 seconds, produced 36,000 data points. Sampling data beyond 1000 Hz has been shown to lead to redundant information[48]. MATLAB's built-in downsample function was used to decrease the 1200 Hz sample rate by

keeping the first sample, and then every n^{th} sample, i.e., 20, after the first. Consequently, *N* was downsampled from 36,000 data points by a factor of 20 to 1,800 data points. Simple downsampling typically exposes a system to aliasing; however, aliasing was not an issue because a fourth-order, zero-lag, low-pass Butterworth filter was applied with a cutoff frequency of 6 Hz via Nexus motion capture software v2.8 (Oxford Metrics, Oxford, UK) during preprocessing to eliminate any noise present in the signal that could not be attributed to each participant's postural control mechanism[48]. Simple sensitivity analyses as illustrated in Figures 2 and 3 and Figures 4 and 5 demonstrate the change in the time series before (Figs. 2 and 4) and after (Figs. 3 and 5) downsampling from a representative participant from an eyes open feet together and eyes closed tandem standing postures, respectively. Observation of the figures suggest that elimination of data points by downsampling did not impact the revised data set. These results are due to signal preprocessing and elements of eliminating redundancy, as disclosed by sensitivity analysis.

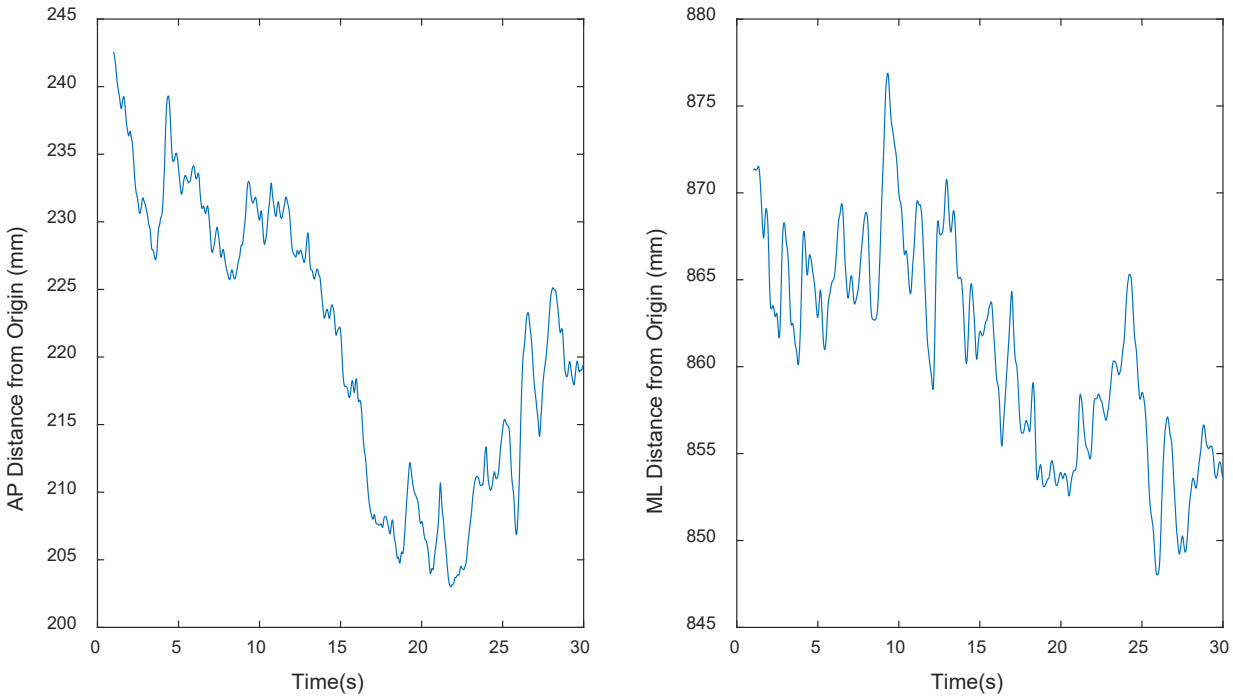

Figure 2. Representative time series for raw center of pressure (COP) data of Subject 1 eyes open, feet together (EOFT) Trial 4, where $N = 36{,}000$ datapoints, in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

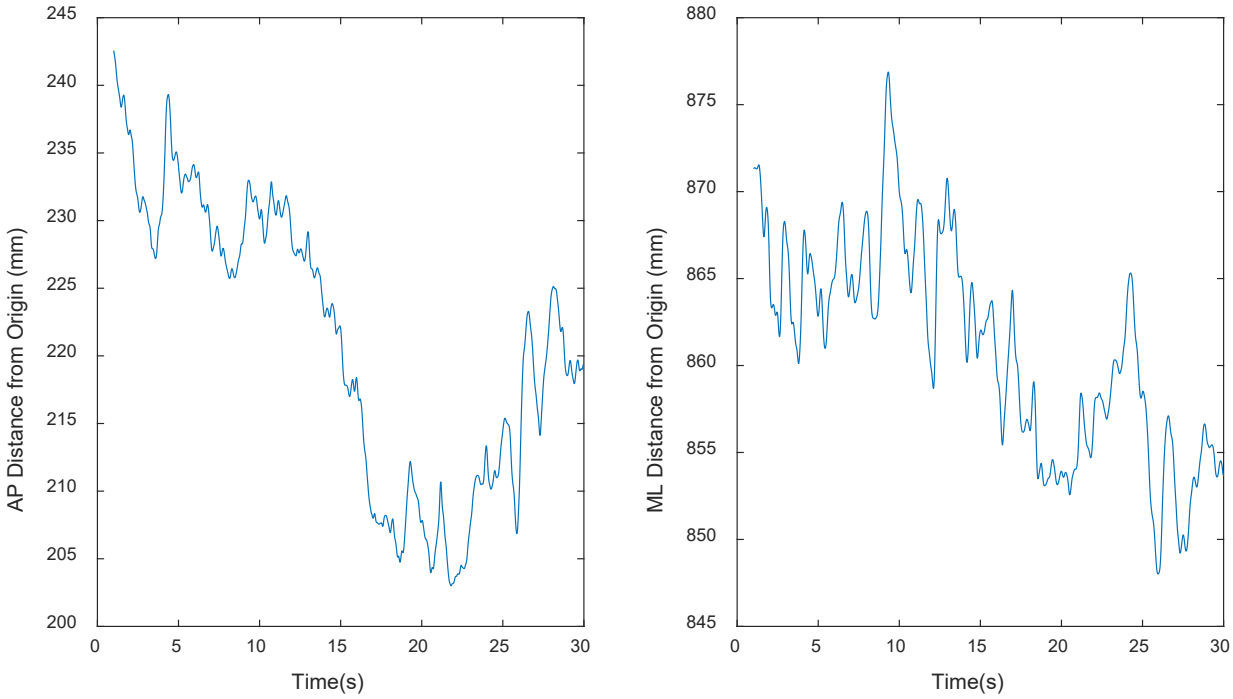

Figure 3. Representative time series for downsampled center of pressure (COP) data of Subject 1 eyes open, feet together (EOFT) Trial 4, where $N = 1{,}800$ datapoints, in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

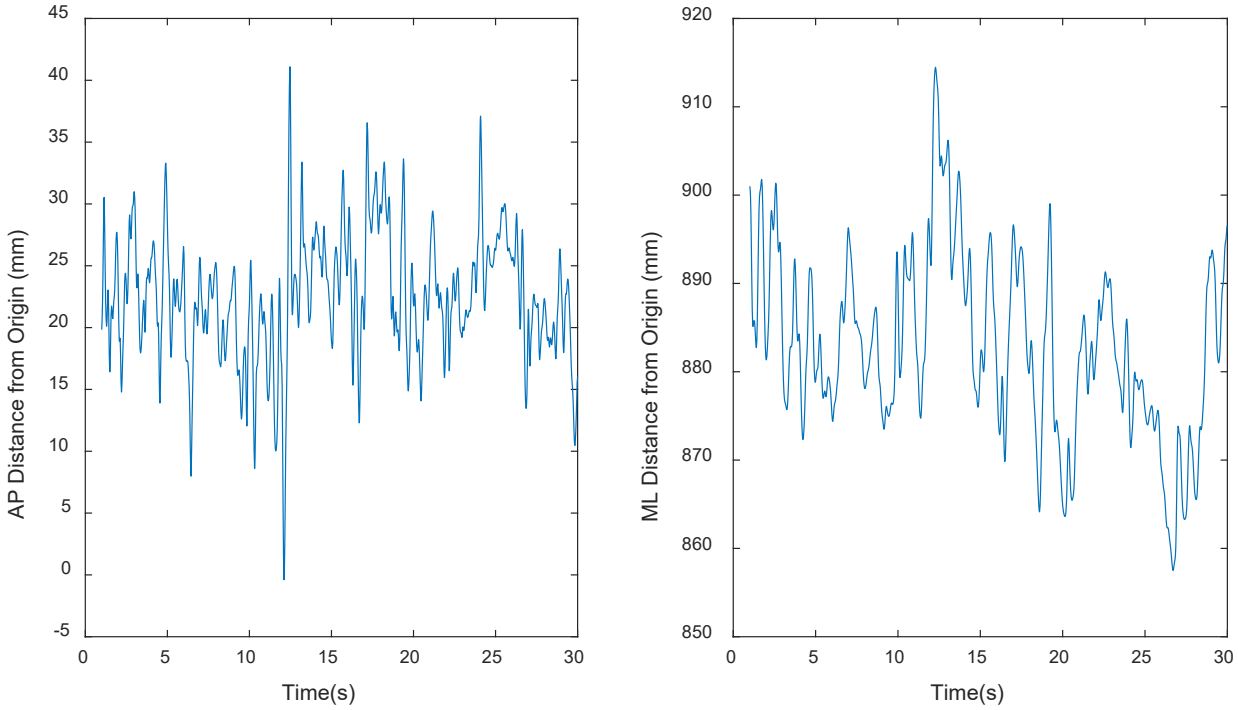

Figure 4. Representative time series for raw center of pressure (COP) data of Subject 1 eyes closed, feet tandem, dominant foot forward (ECTDF) Trial 29, where $N = 36{,}000$ datapoints, in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

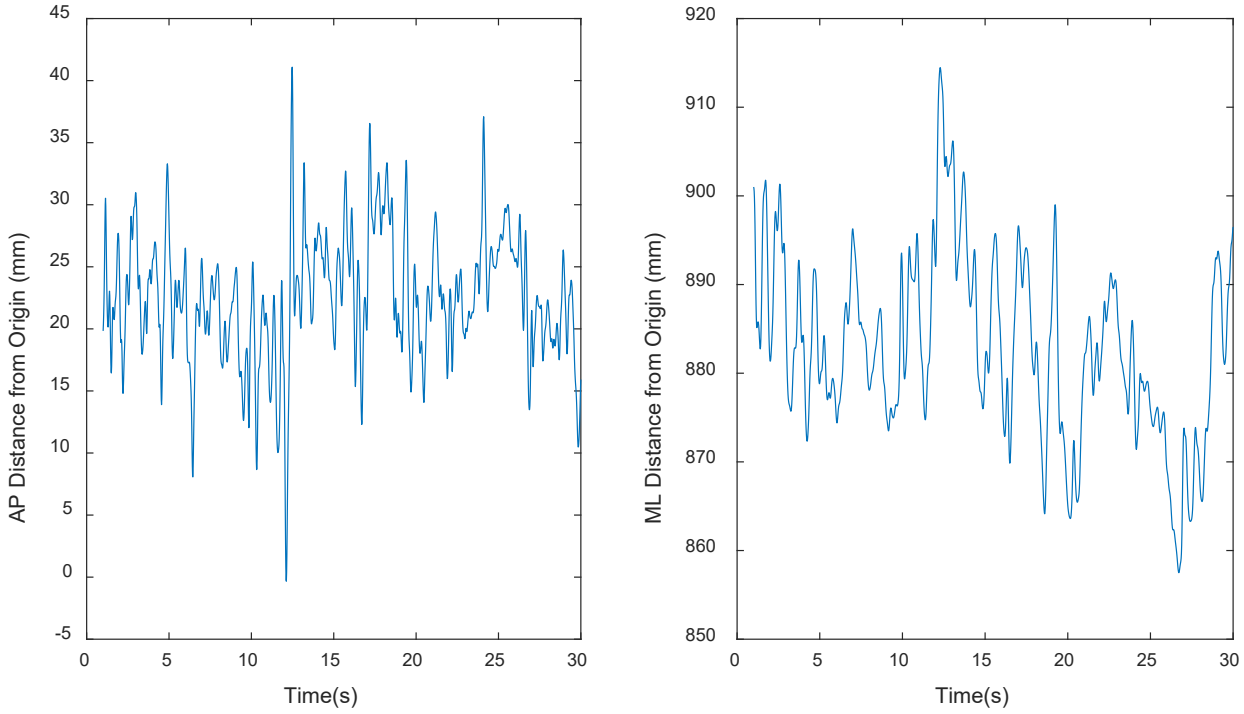

Figure 5. Representative time series for downsampled center of pressure (COP) data of Subject 1 eyes closed, feet tandem, dominant foot forward (ECTDF) Trial 29, where N = 1,800 datapoints, in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

Determination of Approximate and sample entropy

Approximate (ApEn) and SampEn were determined for all five trials under each condition using custom MATLAB® (The MathWorks, Natick, MA) code. Given each COP time series, where N = 1800 datapoints, a sequence of m = 2 length vectors was formed. Comparisons were then made against each data segment that was 2 numbers long. Vectors were considered alike if vector components fell within a tolerance level, $\pm r * SD$[29]. The similarity criteria were evaluated over a range of r = 0.05 – 0.3*SD. The total number of like vectors' logarithm sum was divided by $N - m + 1$ to get the total number of like vectors, including a template comparison to itself[51].

Looking one vector higher, m was raised by 1, i.e., $(m+1)$, the procedure was repeated. By deducting the conditional probabilities of $m+1$ from m, ApEn was calculated.

$$ApEn(m,r,N) = -\frac{1}{N-m}\sum_{i=1}^{N-m} log\frac{A_i}{B_i} \quad (5)$$

SampEn uses a different approach. It uses the whole series together, requiring only that a template vector find a match of length $m+1$ to be defined[33]. This contrasts with ApEn where each template vector (including itself) must find a match to be defined. So, the use of SampEn eliminates many of the problems associated with ApEn, in that it is useful to quantify regularity in a system more effectively[33]. The same input parameters as ApEn were used, and vectors were deemed similar if both their tail and head fell under the predetermined tolerance level. The sum of the total number of like vectors for m points was divided by $N-m+1$ and defined as $B^m(r)$. Further, SampEn defined $A^m(r)$ as the subset of $B^m(r)$ that two sequences are similar for $m+1$[51]. SampEn is then calculated as the conditional probability $-\ln(A^m(r)/B^m(r))$.

$$SampEn(m,r,N) = -log\frac{A^m(r)}{B^m(r)} \quad (6)$$

Statistical Analysis

Trials and stability conditions were independent of one another due to the breaks given between each of them[23]. The subject's ability to rest and then reset allows for this assumption. Four separate one-way analysis of variance (ANOVA) tests were performed for ApEn and SampEn in each of the AP and ML axial directions. The ANOVA testing revealed that each one-way ANOVA assessed for a difference of means between the baseline and increasingly difficult stability conditions within each subject. Additionally, the one-way ANOVA tests were run with Dunnett's

intervals to determine which conditions varied significantly. This test compared the baseline EOFT condition to each increasingly less stable condition.

Results

Comparison of Approximate and Sample Entropy Time Series

Approximate and sample entropy were determined for all trials and conditions, yet it was important to first examine the ApEn and SampEn values over the 30-second time series for $m = 2$, $r = 0.02$*SD for the purpose of establishing the fidelity of the data. Note that since $N = 1800$ data points each second of COP data consisted of 60 points. Figures 6 and 7 illustrate these data for one trial of an eyes open, feet together condition and one trial of an eyes closed feet tandem condition for one representative participant. Visual inspection of each plot suggest that the ApEn and SampEn magnitude of the values were comparable to each other and the spikes over the 30-second time series appeared similar. Having established this for a representative participant and trial it seemed appropriate to determine the mean ApEn and SampEn values for the purpose of further statistical analysis.

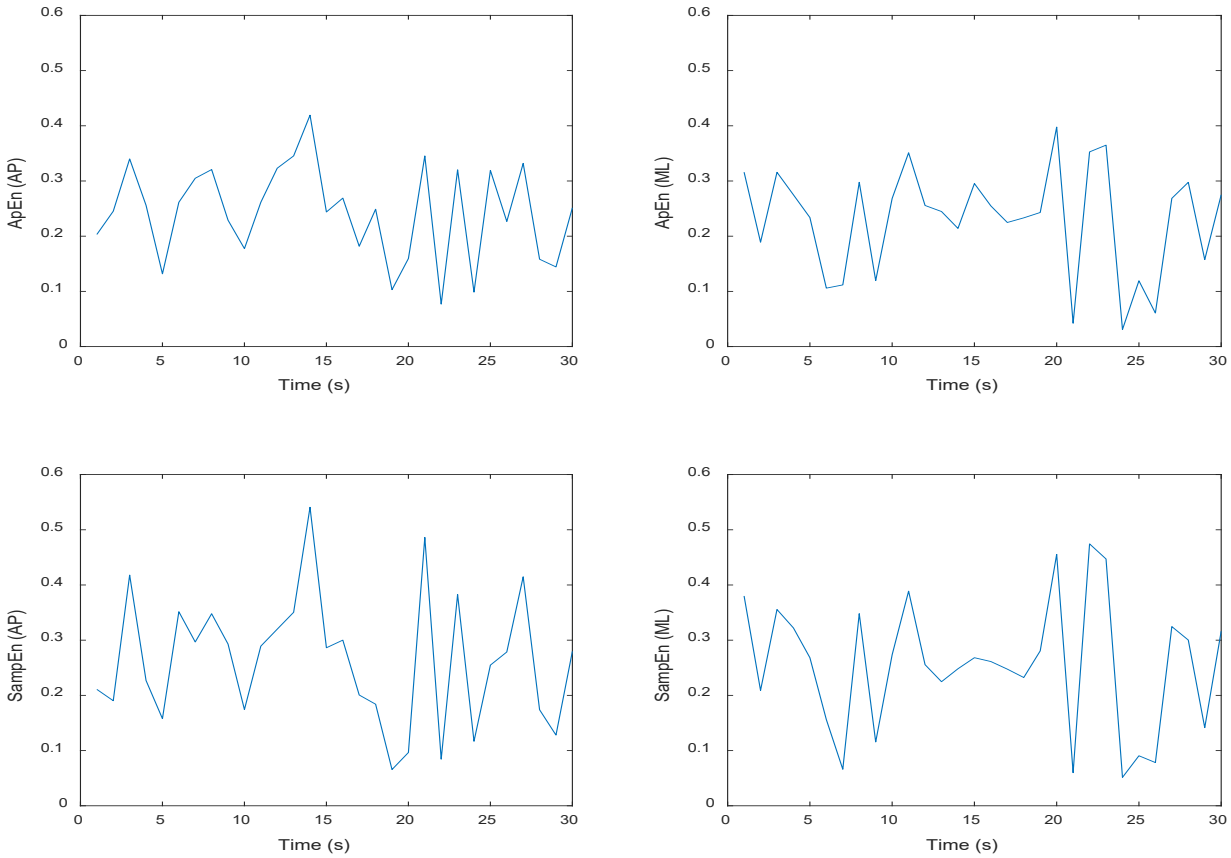

Figure 6. Representative time series for ApEn and SampEn calculated over thirty 60-point segments of Subject 1 eyes open, feet together (EOFT) Trial 03 COP data; where N = 1,800 datapoints, m = 2, and r = 0.02*SD; in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

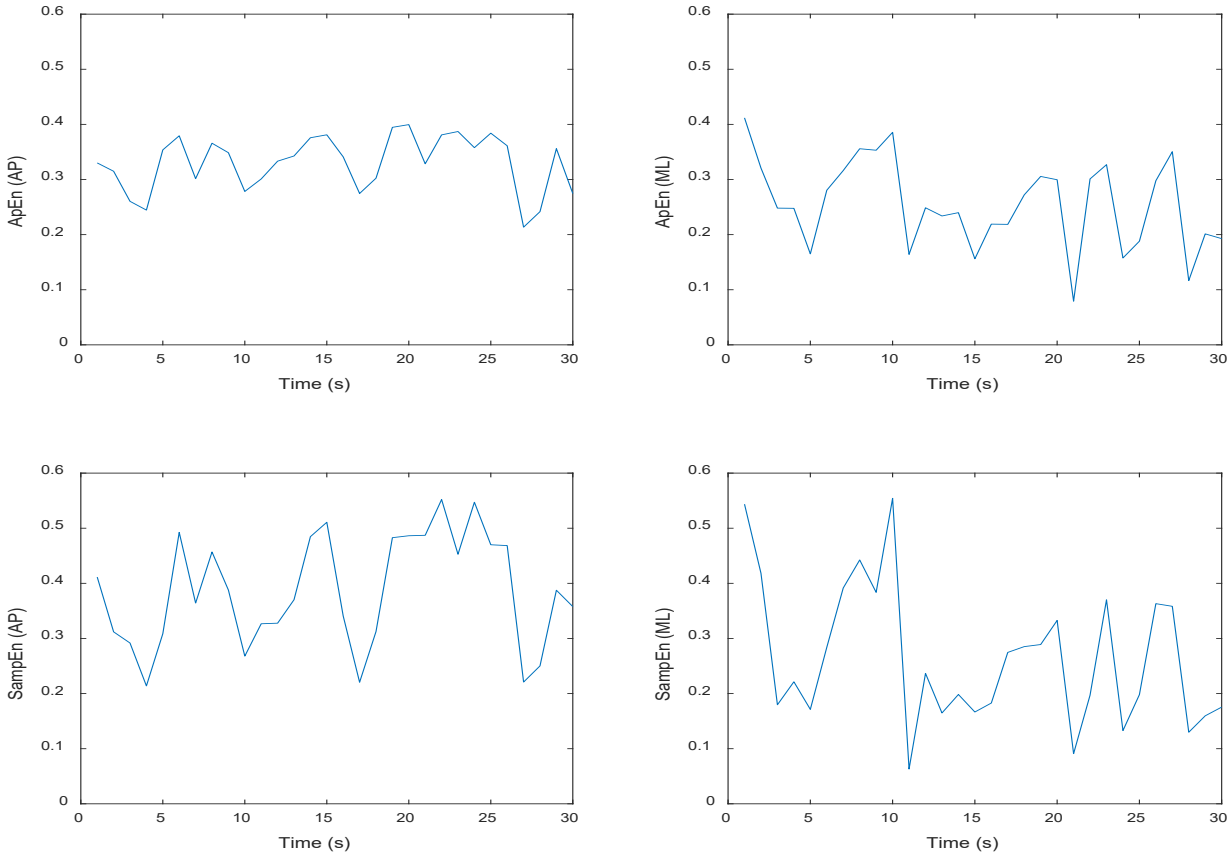

Figure 7. Representative time series for ApEn and SampEn calculated over thirty 60-point segments of Subject 1 eyes closed, feet tandem, dominant foot back (ECTDB) Trial 19 COP data; where N = 1,800 datapoints, m = 2, and r = 0.02*SD; in the anterior posterior (AP) and medial lateral (ML) directions, respectively.

Examination of ApEn and SampEn under different postural conditions

Mean ApEn and SampEn values were obtained for all trials and conditions. Since one purpose of this study was to compare differences in the analysis methods in conjunction with the differing *r* parameter chosen, compilations of one-way ANOVAs with Dunnett's Test outputs for each condition were compared to baseline. These 144 analyses were condensed into summary graphics where Figures 8 – 12 depict subjects by column Average ApEn and SampEn values, charted in orange and blue respectively, are plotted in either row, where groups were separated by

data in the medial lateral (ML) and anterior posterior (AP) direction, based on if the entropy value was significantly different from baseline. The upper "No" row demonstrate that differences in entropy, with respect to the confidence interval, were not significantly different from baseline. The lower "Yes" row demonstrates that difference in entropy values were significantly different from baseline. The stature of 'significance' is based on an equivalent of 720 tests at $\alpha = 0.05$, where on average 36 "Yeses" are to be expected even if there are no statistically significant differences between the data. Notably there are a lot more than 36 significant instances found.

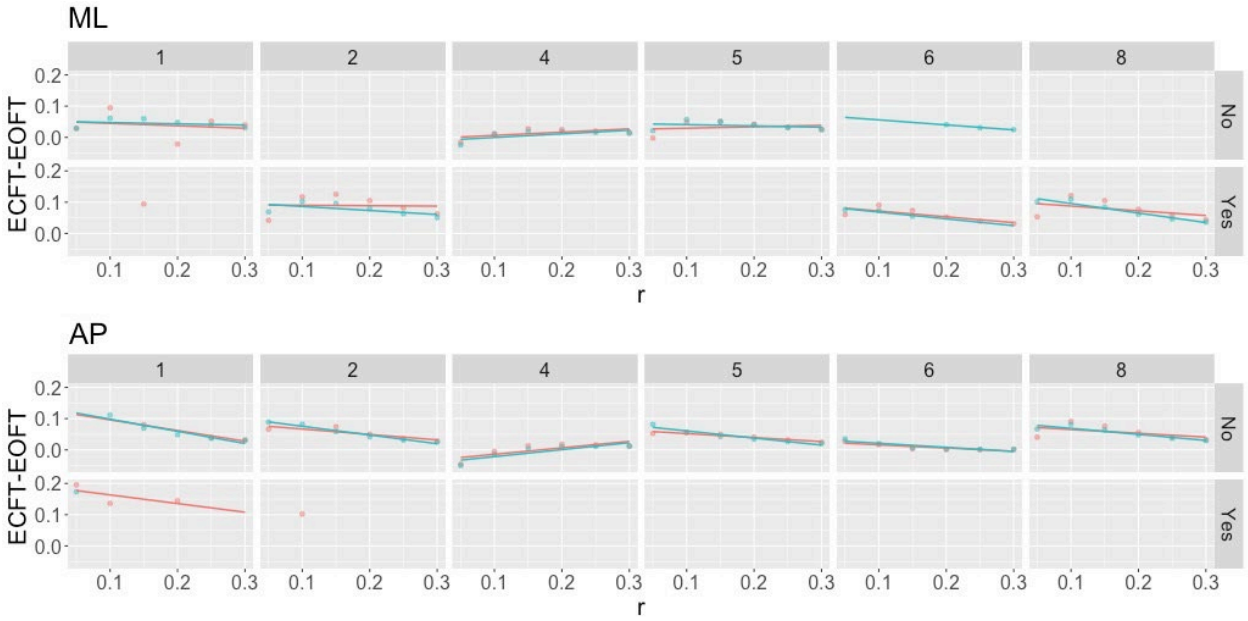

Figure 8. One-way ANOVA with Dunnett's Tests Outputs summary graphic, comparing the difference of eyes close, feet together (ECFT) trials of mean ApEn(orange) and SampEn(blue) values to baseline condition eyes open, feet together (EOFT), in the medial lateral (ML) and anterior posterior (AP) directions; where $N = 1{,}800$ datapoints, $m = 2$, and r ranges from 0.05-0.3*SD, for all subjects.

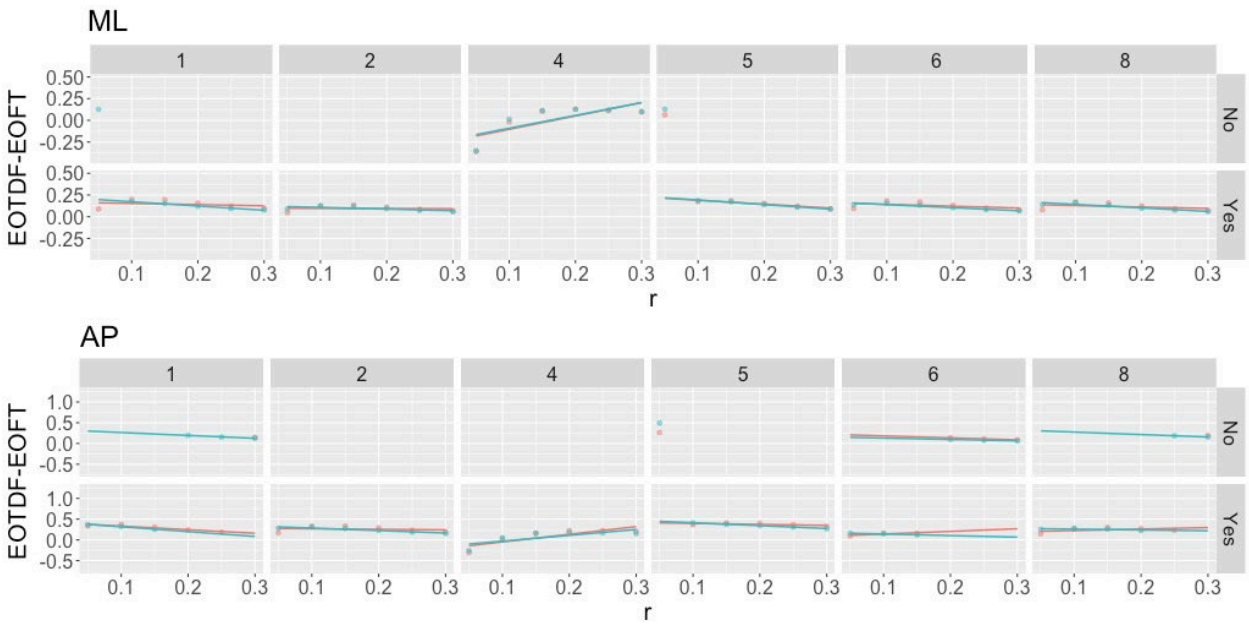

Figure 9. One-way ANOVA with Dunnett's Tests Outputs summary graphic, comparing the difference of eyes open, feet tandem, dominant foot forward (EOTDF) trials of mean ApEn(orange) and SampEn(blue) values to baseline condition eyes open, feet together (EOFT), in the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, and r ranges from 0.05-0.3*SD, for all subjects.

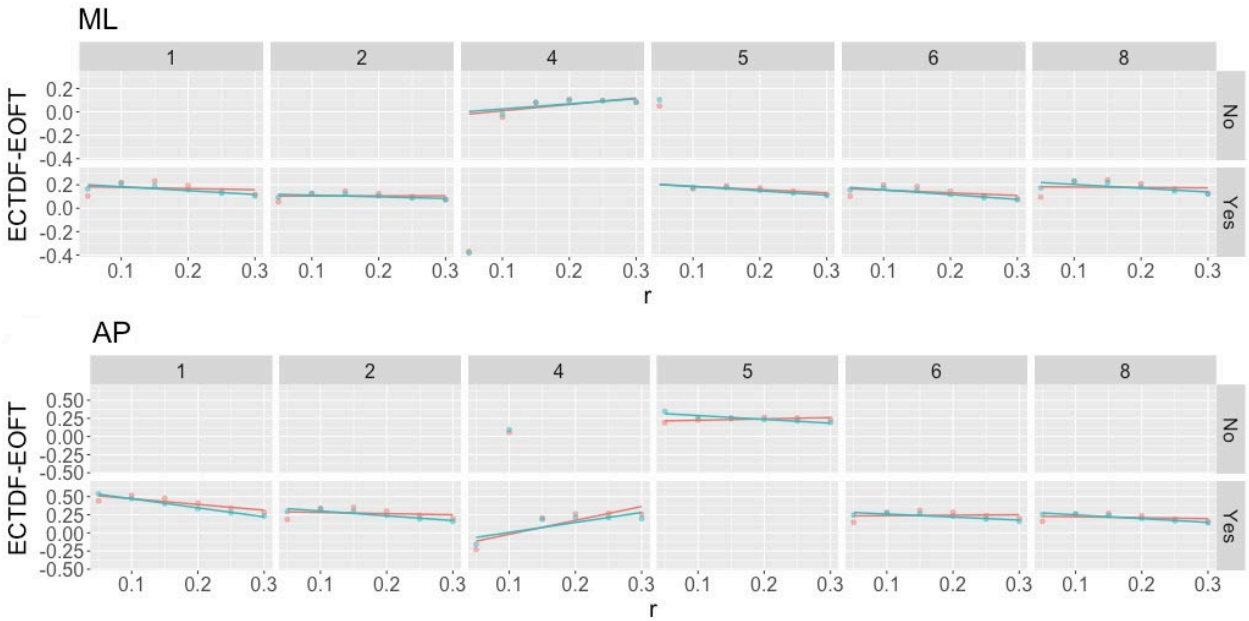

Figure 10. One-way ANOVA with Dunnett's Tests Outputs summary graphic, comparing the difference of eyes closed, feet tandem, dominant foot forward (ECTDF) trials of mean ApEn(orange) and SampEn(blue) values to baseline condition eyes open, feet together (EOFT), in the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, and r ranges from 0.05-0.3*SD, for all subjects.

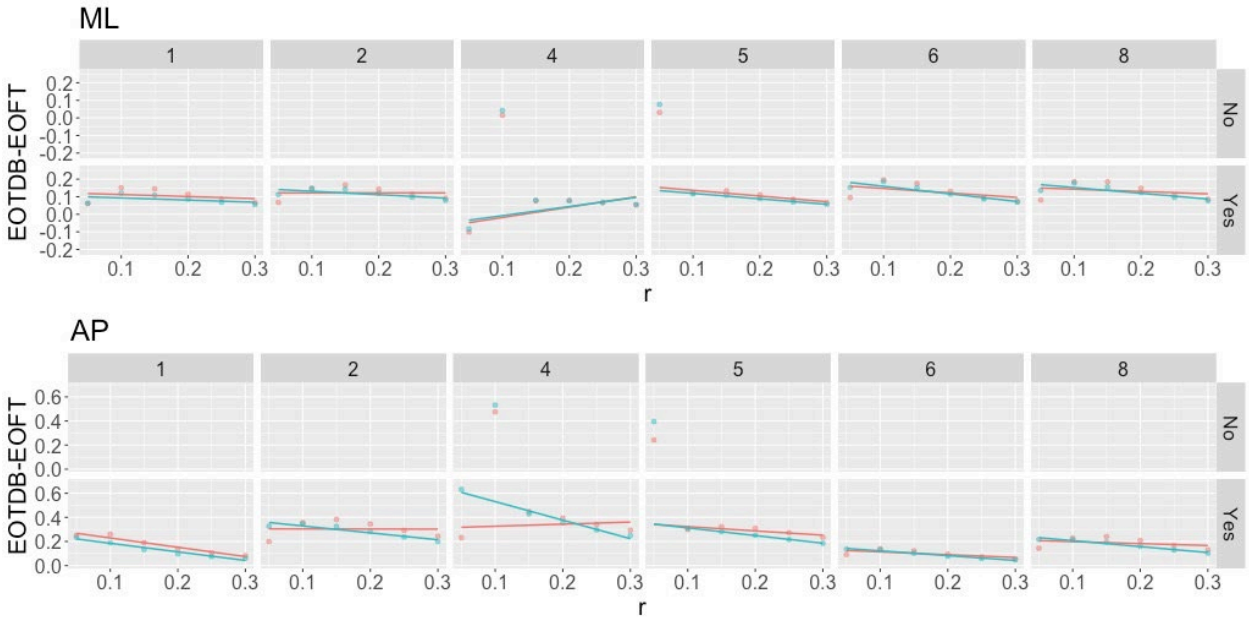

Figure 11. One-way ANOVA with Dunnett's Tests Outputs summary graphic, comparing the difference of eyes open, feet tandem, dominant foot back (EOTDB) trials of mean ApEn(orange) and SampEn(blue) values to baseline condition eyes open, feet together (EOFT), in the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, and r ranges from 0.05-0.3*SD, for all subjects.

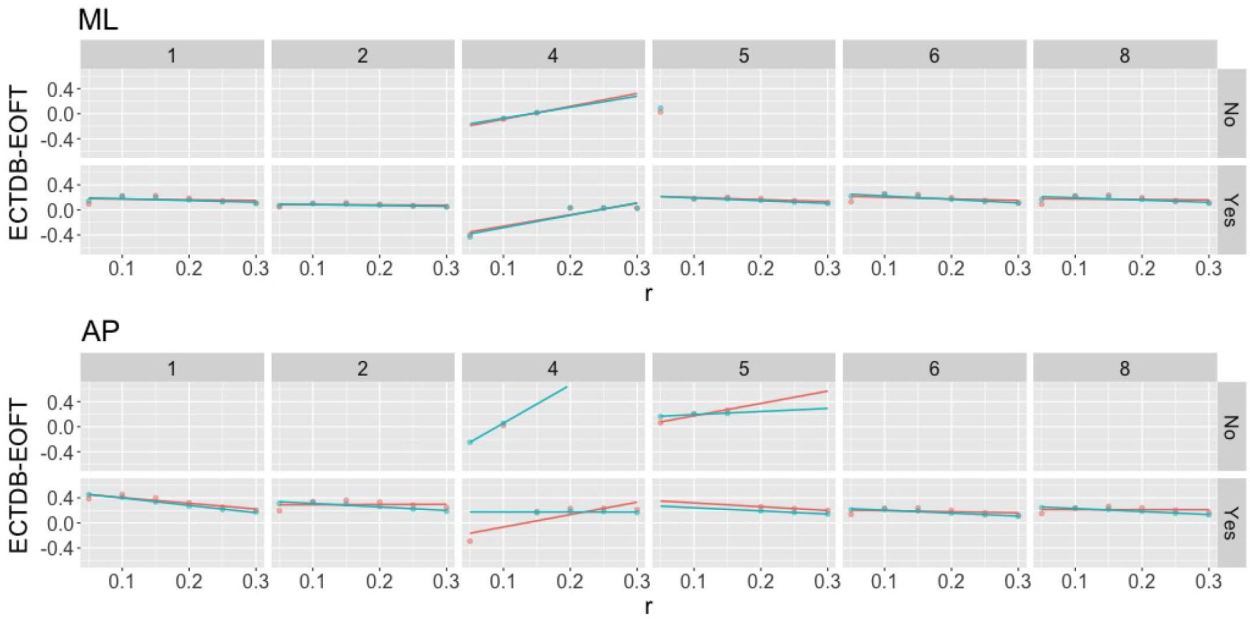

Figure 12. One-way ANOVA with Dunnett's Tests Outputs summary graphic, comparing the difference of eyes closed, feet tandem, dominant foot back (ECTDB) trials of mean ApEn(orange) and SampEn(blue) values to baseline condition eyes open, feet together (EOFT), in the medial lateral (ML) and anterior posterior (AP) directions; where $N = 1{,}800$ datapoints, $m = 2$, and r ranges from 0.05-0.3*SD, for all subjects.

Assessment of each plot compares the "Yes" rows to the "No" rows in evaluating significance in the differences from baseline. Meaningful deviations from baseline conditions were found in the ML direction in cases of ECFT, EOTDB, ECTDB, EOTDF, and ECTDF. Considerable deviations were also found in the AP direction in cases of EOTDB, ECTDB, EOTDF, and ECTDF. The ECFT trials compared to baseline in the AP direction display majority insignificant results, implying there exists no tangible evidence that conditions were substantially different from baseline. The EOTanDB trails in both ML and AP directions, notably had the highest difference in entropy, and greatest amount of significances difference from baseline across all values of *r*. The consistent number of "Yeses" in Tandem trials suggest differences from baseline can be quantified for tandem standing. Overall, all trial mean entropy data assessed and

output into an ANOVA summary graphic, show that the significance of the difference from baseline is the equivalent, using either ApEn or SampEn approximation. Having determined that the significance of using either entropy calculation is equivalent when assessing the difference from baseline for all tandem trial data, it made sense to examine mean ApEn and SampEn entropy across varying *r* values.

Examination of the changes in tolerance level, r, on ApEn and SampEn; bias and consistency

Selection of parameters is the most important factor when evaluating entropy, and given *r* was determined using trial and error until reasonable values of ApEn were found in a previous study[48], it was important to examine the effect of the *r* parameter for each entropy method. Figure 13 displays mean ApEn and SampEn values for all stability conditions, where each column separated by participant numbers, rows depicted by each ML and AP axial direction, and ranged over values of $r = 0.05 – 0.3*SD$. Figure 14 illustrates participants by method are separated into each column, grouping all subjects. See Appendix B. ANOVA Data Tables for participants by method and conditions by method mean entropy values.

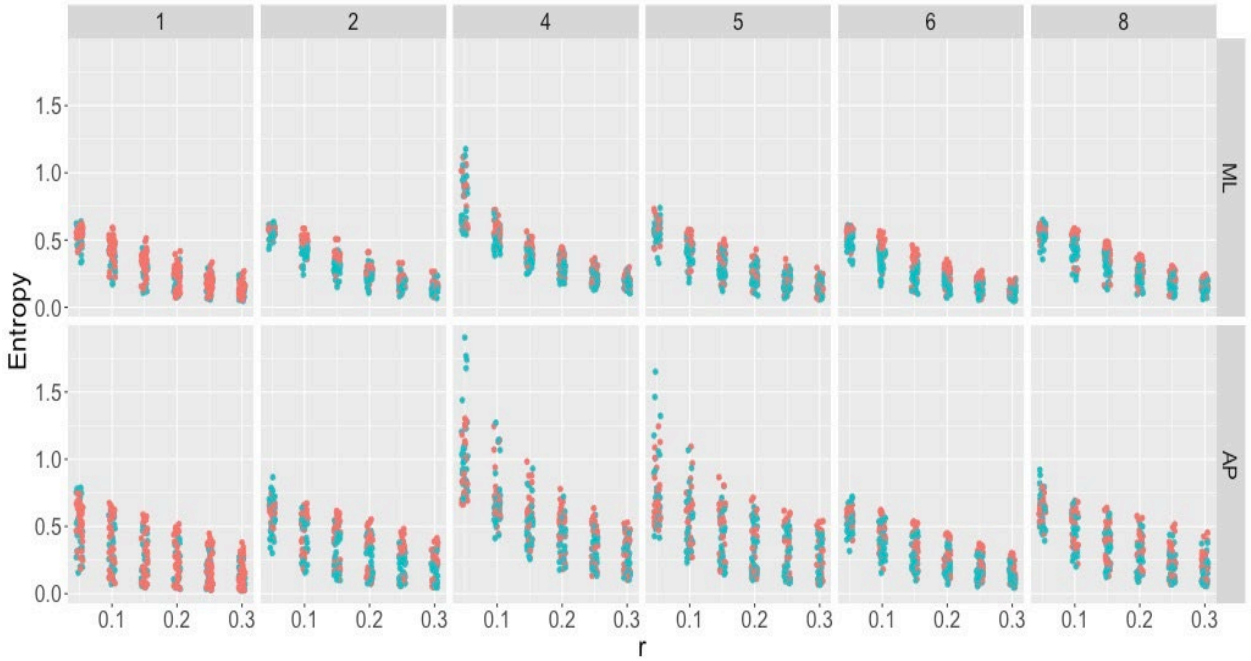

Figure 13. Summary plot of all mean ApEn (orange) and SampEn (blue) values of all trials of stability conditions, separated by participant, in the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, across r range from 0.05-0.3*SD.

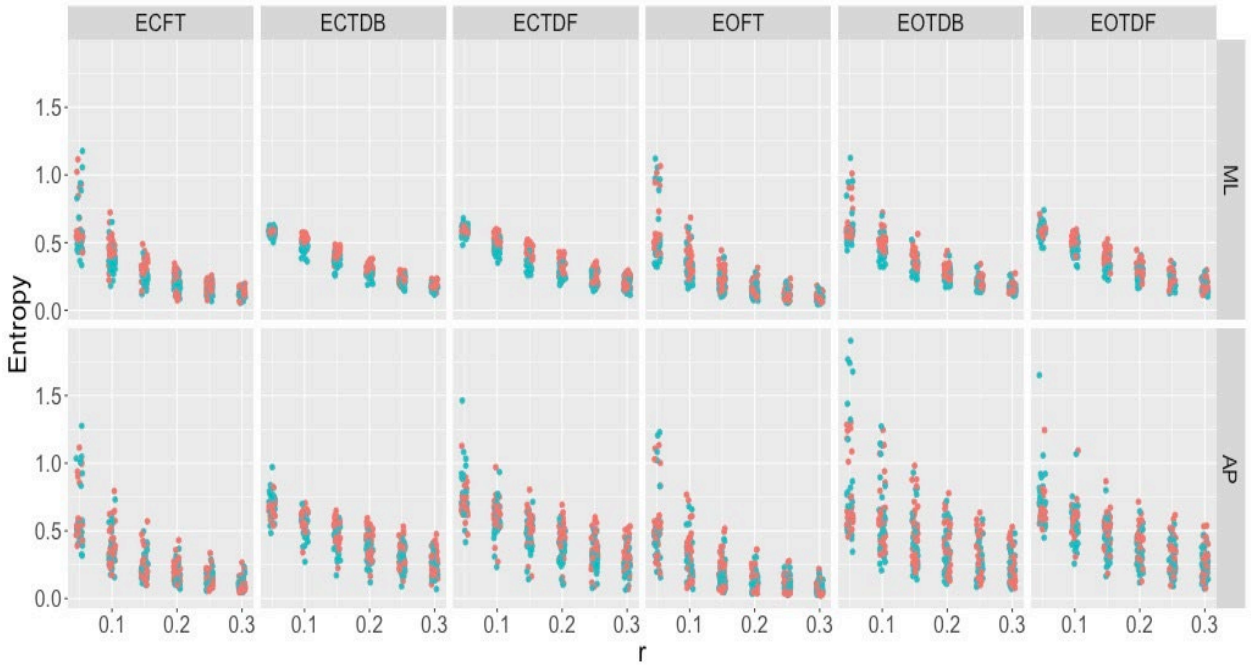

Figure 14. Summary plot of all mean ApEn (orange) and SampEn (blue) values of all participants, separated by trials of stability conditions, in the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, across r range from 0.05-0.3*SD.

Visual examinations of each plot indicate that ApEn and SampEn tended to decrease as *r* increased, with relative directionality evident between *r = 0.15 – 0.25*SD*. Outliers that distorted this line of regression were most prominent in the range *r = 0.05 – 0.1*SD.* Participants 4 and 5 revealed notable outliers in the AP directions within this range as calculated by the SampEn. Coincidingly, less rejected matches revealed themselves in the lowest entropy values, where *r = 0.3*SD*. Despite comparing mean entropy values across all values of *r,* it does not appear that one method, i.e., ApEn and SampEn, is superior.

Comparison of the magnitude of ApEn and SampEn

Though the significance of the differences from baseline are consistent using either entropy calculation, differences in ApEn and SampEn values were apparent. This gave the purpose to directly compare outputs by taking the differences between the data derived from the ApEn and SampEn calculations in both medial lateral and anterior posterior directions. This comparison is shown in Figure 15 as a histogram of the SampEn and ApEn relationship of all the data, where the difference in value of the two calcuations are distributed across the x-axis, and the total number of calculations for all trials and conditions conducted are displayed on the y-axis.

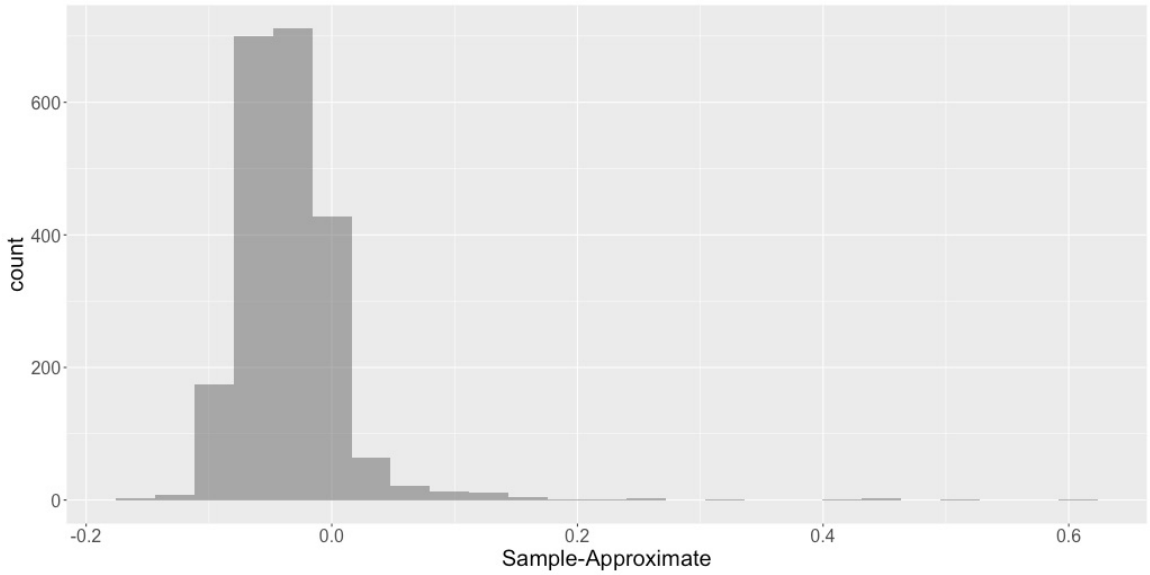

Figure 15. SampEn versus ApEn histogram of each COP data timeseries of all subjects and stability conditions, including both the medial lateral (ML) and anterior posterior (AP) directions; where N = 1,800 datapoints, m = 2, across r range from 0.05-0.3*SD.

Evidence of a right skewed histogram indicates that the sample-approximate relationship is primarily negative, i.e., SampEn on average is smaller than ApEn. Given the bias in the ApEn calculation, ApEn estimates were expected to converge closer to 0; therefore, this result contradicted initial hypotheses. The sample-approximate relationship is anticipated to be positive based on previous research; however, these results are unique to this study's data set and should be reported.

Discussion

Understanding how a healthy brain responds to different stability conditions and utilizing the best method to measure those conditions is important when accurately comparing how a healthy brain responds versus how an injured brain responds to the same conditions. Previous research that has examined children and adults with mild traumatic brain injury, e.g., concussion, have

suggested that the use of the center of pressure (COP) data can be useful in delineating a normal from an abnormal response to the perturbations of static and dynamic balance[5,6,35,36,37,46]. Since it has been shown that the COP time series is non-linear, traditional methods of assessing various COP parameters, e.g., statistical use of means and standard deviation, have not been effective[3]. Previous work using non-linear methods, such as approximate and sample entropy, to study normal and pathological balance has been useful[1,2,26,42]. However, a consensus on the best methodological use of ApEn and SampEn has not yet been established. For example, previous work[48] in our laboratory used ApEn to examine healthy college-aged participants to describe changes in ApEn under more and less stable standing positions. Based on the need described in the literature for more work using ApEn and SampEn, and the methodological limitations of the previous research in our laboratory, the purpose of this study was to compare ApEn and SampEn under various stability conditions, and when altering tolerance (i.e., *r*) values. The results revealed that even though SampEn tend to yield lower mean values than ApEn, both indices were equally effective in quantifying the regularity of a COP signal given that the significance of using either entropy calculation is equivalent when assessing the difference from baseline. Further, the selection of *r* had a relatively consistent effect with both entropic statistical analyses, as the similarity criterion was increasingly tightened, more similarities were rejected, and therefore larger entropy values.

Tipton's[48] study was the most similar to ours in terms of the methodologies used to investigate conditions. Downsampling the COP data in this study was necessary because previously, entropy values were an artifact of quantifying an oversampled COP signal with an *r* value that was found through trial and error. Yentes et al.[51] recommend, as best practice, when using ApEn or SampEn for the analysis of human gait data that *N* not exceed sampling data beyond 1000 Hz because it's

over this frequency that may lead to redundant information. In the current study, previous entropy estimates at 1200 Hz yielded low entropy values between 0.005 and 0.030, where N = 36,000 consisted of many closely spaced data points with identical values. In a different study, Lubetsky et al.[21] conducted sample entropy on COP data for prolonged standing tasks on normal and compliant surfaces. The study found that while down-sampling had increased SampEn values, it had an insignificant effect on the comparisons to the original datasets; however, if such procedures are performed, they should be well justified. In the present study, the waveforms were virtually identical when comparing the raw COP trial data to the downsampled trial data. Downsampling was necessary for the processing of our entropy results. Utilizing 1,800-point arrays, the entropy values in this study ranged from 0.08 to 0.90. However, it is suggested that it is essential for researchers to evaluate the influence that downsampling has on their particular dataset.

Incorrect parameter selection of the vector length, m, threshold, r, or data length, N, can undermine the ApEn and SampEn discrimination capacity[9]. The embedding dimension, $m = 2$, and dataset length, N, were fixed input parameters in this study. Many approaches of calculating r have been suggested, including utilizing the standard deviation (SD) of the whole time series[26,30], the standard error of the entropy values[18], predefined tolerance levels[15,45] and using a heuristic stochastic model[9]. Typically, it is suggested that for clinical data, r is to be set 0.02*SD when utilizing an entropy algorithm. In Tipton's study (which use the same data set as the present study), only one value of r value was used. Therefore, one of the focusses of this study was placed on the filter parameter, r, to determine which or which are optimal for the objectives of this study. Center of pressure data sets demonstrated significant differences between the range of r values, r = 0.05, r = 0.1, r = 0.15, r = 0.2, r = 0.25, and r = 0.3 times standard deviation. Overall, the variations in

entropy values by ApEn and SampEn calculations as *r* changed imply that the usual choice of *r* = 0.2*SD allows for contemplation. The stability of a metric is referred to as relative consistency. As r increased, ApEn and SampEn values decreased, where both calculations exhibited relative directional consistency; therefore, *r* had the same effect on both entropy calculations. In a different study Yentes et al.[50], found that for walking trials of gait data SampEn decreased as *r* increased, which is consistent with our findings. However, for ApEn, different *r* values resulted in some variability[50]. For the current study, since ApEn showed relative consistency in a similar manner as SampEn, it is suggested that *r* be selected based on the individual study's criteria for parameters, and then examine the relative consistency across *r* = 0.15, 0.2, and 0.25 times the standard deviation.

Outliers and spikes were apparent in SampEn values for *r* = 0.05 and *r* = 0.1*SD due to the overly stringent conditions. In a study that evaluated the impact of abnormal spikes on the interpretation of entropy results in the context of biosignal analysis, Molina-Picó et al.[25] suggested removing these results, as they can misrepresent the signal regularity. Therefore, it is illogical to assume that the anomalies exhibited by SampEn represent data that ApEn was incapable of detecting in any way. The obvious deviation of entropy values from the overall trend line of the data, within the range of *r* = 0.05 and *r* = 0.1*SD, suggests that such small entropy values should not be used, removing *r* = 0.05 and *r* = 0.1*SD from the list of recommendations for use.

The performance of ApEn and SampEn calculations of standing balance condition-based time series were able to differentiate between circumstances that were different from the baseline EOFT condition, in that the tandem stance trials indicated higher entropy values. ECFT was not consistent enough in indicating entropy values that were significantly higher than the baseline

entropy values in this study. In a similar study assessing balance by altering visual conditions, Ramdani[36] used SampEn to analyze human postural sway and was able to distinguish between eyes open and eyes closed conditions of participants standing on a single force plate. Importantly, in conditions with eyes closed, SampEn was lower than in conditions with eyes open. Some concur with these findings[11], while others find them contradictory[43]. Given the equal significance in distinguishing between eyes closed, feet together (ECFT) and eyes open, feet together (EOFT) in our present study, it is suggested that ECFT condition not be a method primarily used to differentiate ECFT from baseline conditions.

All the participants showed a consistent significant difference from baseline under tandem conditions in both AP and ML directions. As expected, the tandem was the least stable condition, under both eyes open and eyes closed conditions. With tandem standing, placement of the dominant foot in the back or front did not seem to affect the entropy values. In contrast to other participants for tandem standing, participants 4 and 5 repeatedly exhibited insignificances when comparing ECTDF, EOTDB, and ECTDB trials to baseline in the one-way ANOVA with Dunnett's Tests Outputs summary graphics; however, previously discussed outliers may contribute to this. Though clear significances are found for differentiating from baseline in both ApEn and SampEn, which entropic measure is "better"? Few studies have compared ApEn and SampEn for standing balance data by altering only the tolerance parameter. However, Yentes[50] investigated postural control of walking trials and evaluated various combinations of *N, m*, and *r* and concluded that SampEn appeared to be more trustworthy for brief data sets and demonstrated fewer difficulties with relative consistency. As opposed to Yentes et al.'s[50]findings that generally mean ApEn values were lower than mean SampEn values in the analysis of gait data, in the present

study it was found that mean SampEn values were lower. Given Our findings in that ApEn and SampEn are almost equally significant to distinguish from baseline for standing balance data, additional research needs to re-examine differences between ApEn and SampEn across similar values of *m* and *r*.

There are several limitations to this study beyond its use of a small sample of healthy participants. First, differentiating comparisons between ApEn and SampEn might be feasible utilizing alternative statistical practices. Future studies may propose the use of significantly more sophisticated statistical methods that permit testing across subjects concerning ANOVA analysis. Researchers may also consider comparing the time frequency analysis of the anterior posterior and medial lateral directions of ApEn and SampEn when considering directional differences. Secondly, additional methodologies exist for determining an optimal *r*. In addition to a few methodological propositions of *r,* such as using the standard error of the entropy values[18] and employing fixed tolerance values[15, 45], I would propose comparing ApEn and SampEn using a method proposed by Chon et al[9]. In this study, the authors implement a heuristic stochastic model employing equations that autonomously determine the $ApEn_{max}$ value, such that the accuracy of the entropic output is unaffected by the different data lengths. Lastly, the outcomes of this study may be influenced by the resolution of the selected downsampling technique. Typically, downsampling by selecting every nth point, rather than averaging across each window, introduces aliasing into the system. However, a low-pass Butterworth filter was implemented during preprocessing to mitigate this effect. Though the resulting COP waveforms of the unprocessed and downsampled data appeared to be identical in this study, the results should be compared to other sampling techniques, such as

the use of the MATLAB decimate function rather than downsample. Or evaluate the effect of obtaining a windowed average by downsampling an average of 20, 30, 40, etc. points at a time.

This study's objective was to investigate the impact of varying the input parameter *r*, the similarity criterion, required for the calculations of both ApEn and SampEn, in order to determine the optimal choice. Choosing a suitable input *r* value is necessary to ensure relative consistency. The selection of *r* had a relatively consistent effect on both statistical analyses, as the similarity criterion was increasingly tightened, more similarities were rejected, resulting in larger entropy values. For optimal results, values between $r = 0.15$ and 0.25*SD are deemed optimal. It is these ranges of *r* values that the entropic data is less susceptible to outliers while maintaining a critical threshold in lieu of retaining low experimental error. Further, the purpose of this master's thesis was to compare the analysis methods, ApEn and SampEn of center of pressure balance data, to determine which entropy measure is most consistent. ApEn and SampEn analysis methods accurately quantify the varying stability conditions, i.e., both methods could accurately decipher between the stability conditions appropriately. It can be concluded that both systems are highly predictable over time and share equivalent significance in terms of their ability to differentiate from baseline. Consequently, one estimation technique was not particularly "better" than the other. Since both methods of statistical data analysis produce the same overall pattern of results, it can be concluded that both indices were equally effective in quantifying the level of center of pressure signal regularity during quiet tandem standing postural balance tests and it is thereby suitable to use either methodology. However, it was discovered that mean SampEn values were typically lesser than ApEn values. In order to substantially advance the determination of the optimal

technique for clinically diagnosing concussions, additional research will be required to demonstrate what this really implies for our data.

Appendix A. ANOVA with Dunnett's Test Figures

Supplementary data associated with this master's thesis can be found below. Participant 1 serves as the representative for all subjects' one-way ANOVA statistics with Dunnett's tests in Appendix A. The data from graphics such as those in Appendix A were compiled into summary graphics for methods section, Figures 8 – 12.

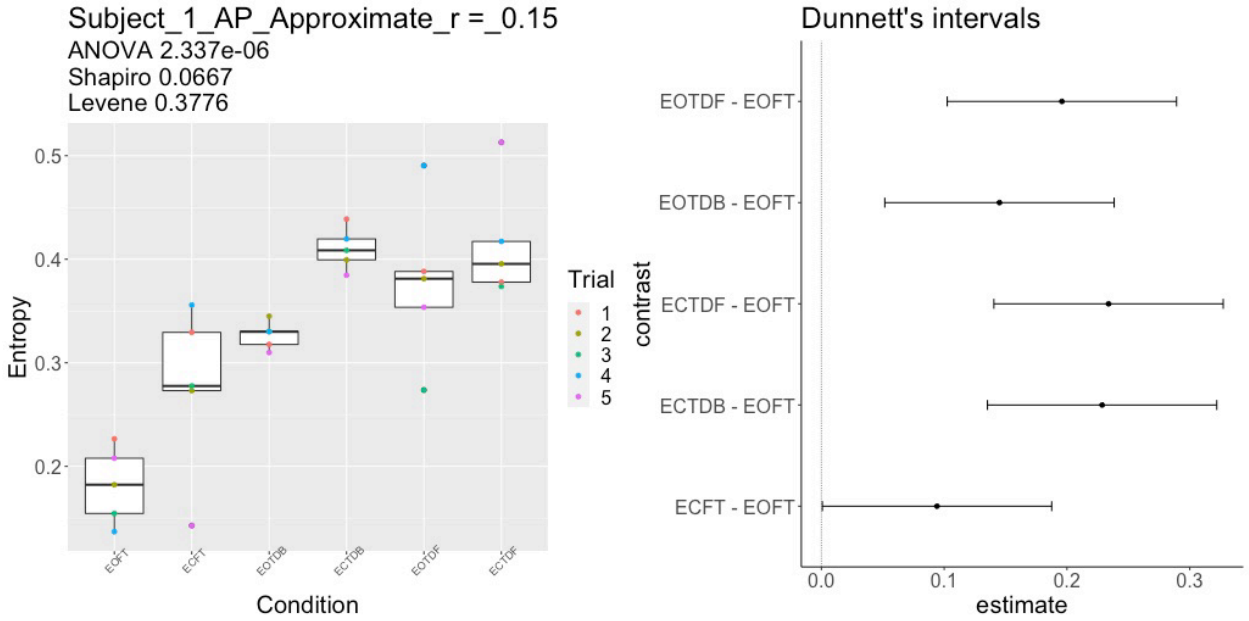

Figure A.1. One-way ANOVA, mapping the 5 mean ApEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.15*SD.

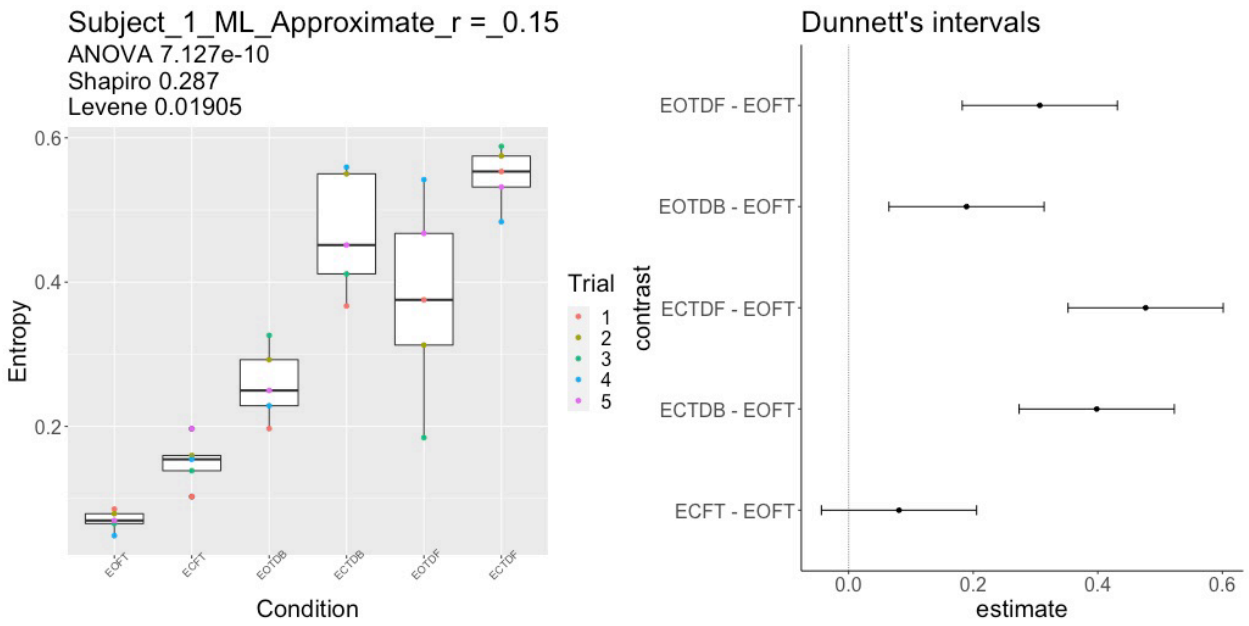

Figure A.2. One-way ANOVA, mapping the 5 mean ApEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.15*SD.

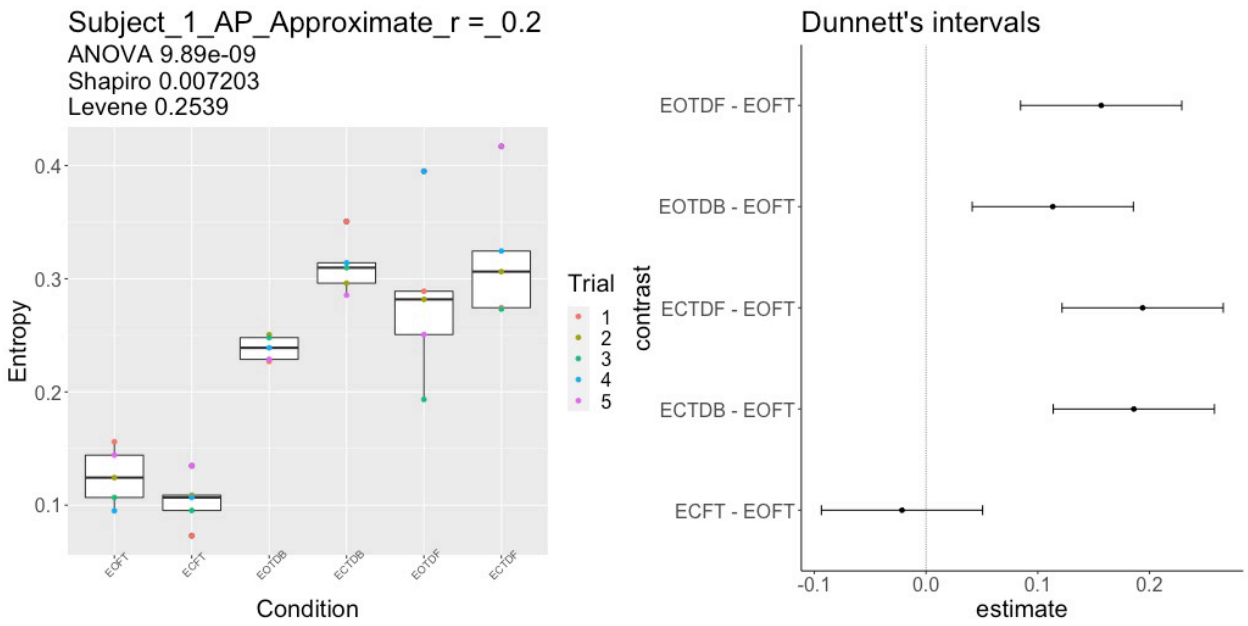

Figure A.3. One-way ANOVA, mapping the 5 mean ApEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.2*SD.

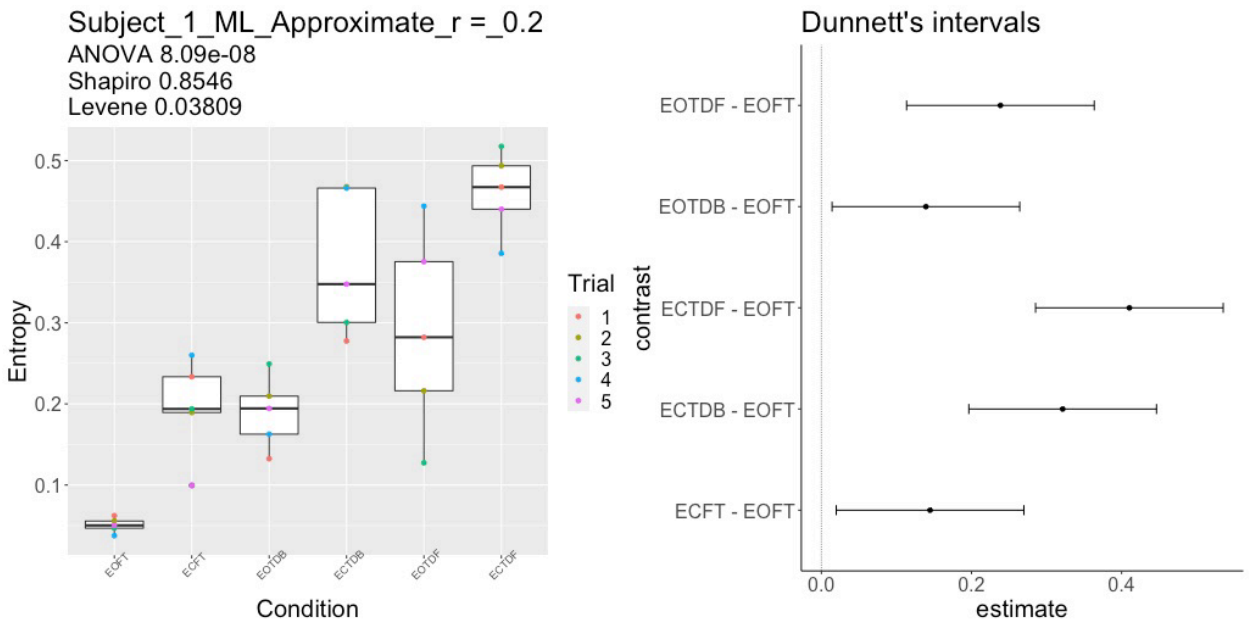

Figure A.4. One-way ANOVA, mapping the 5 mean ApEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.2*SD.

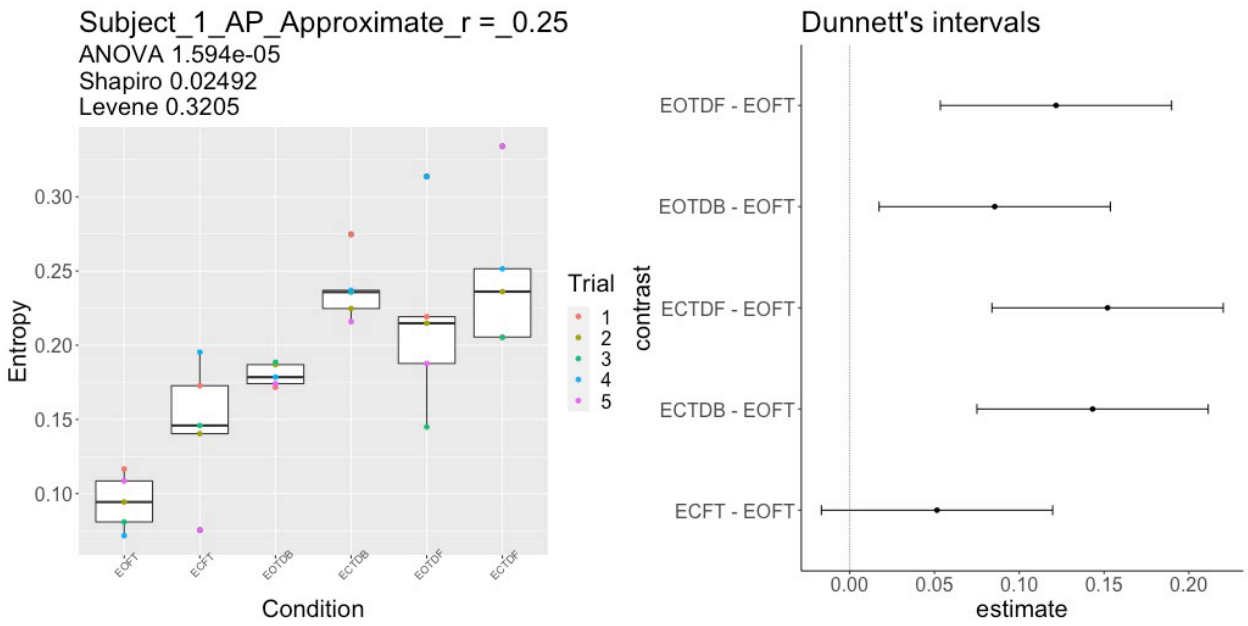

Figure A.5. One-way ANOVA, mapping the 5 mean ApEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.25*SD.

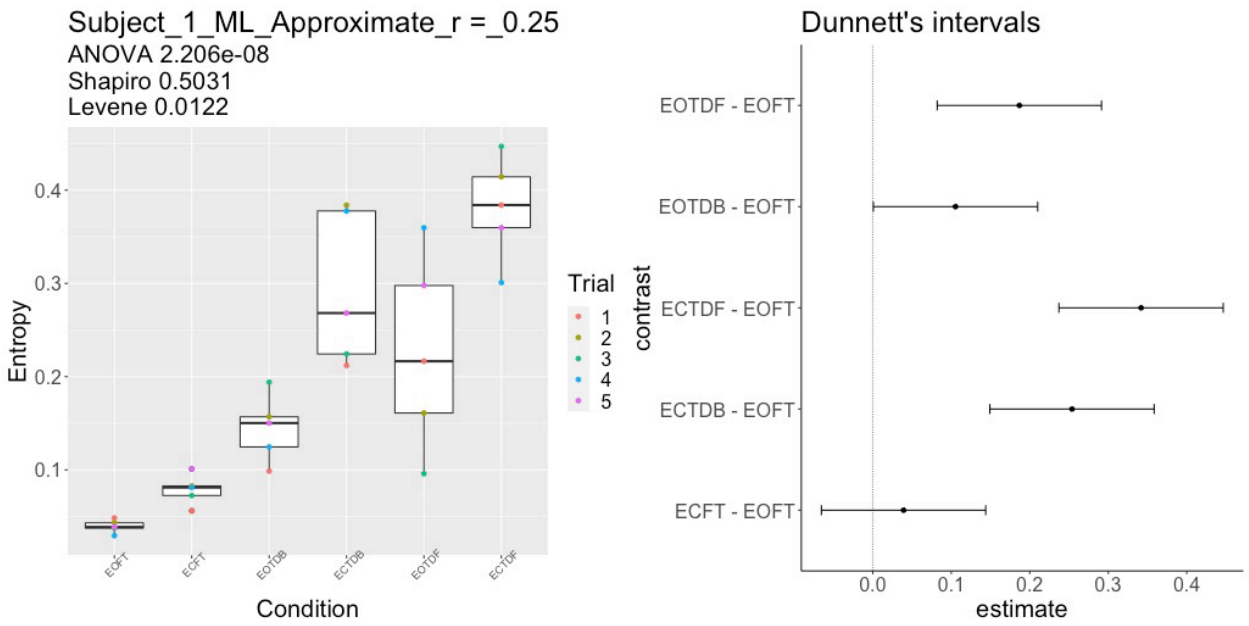

Figure A.6. One-way ANOVA, mapping the 5 mean ApEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.25*SD.

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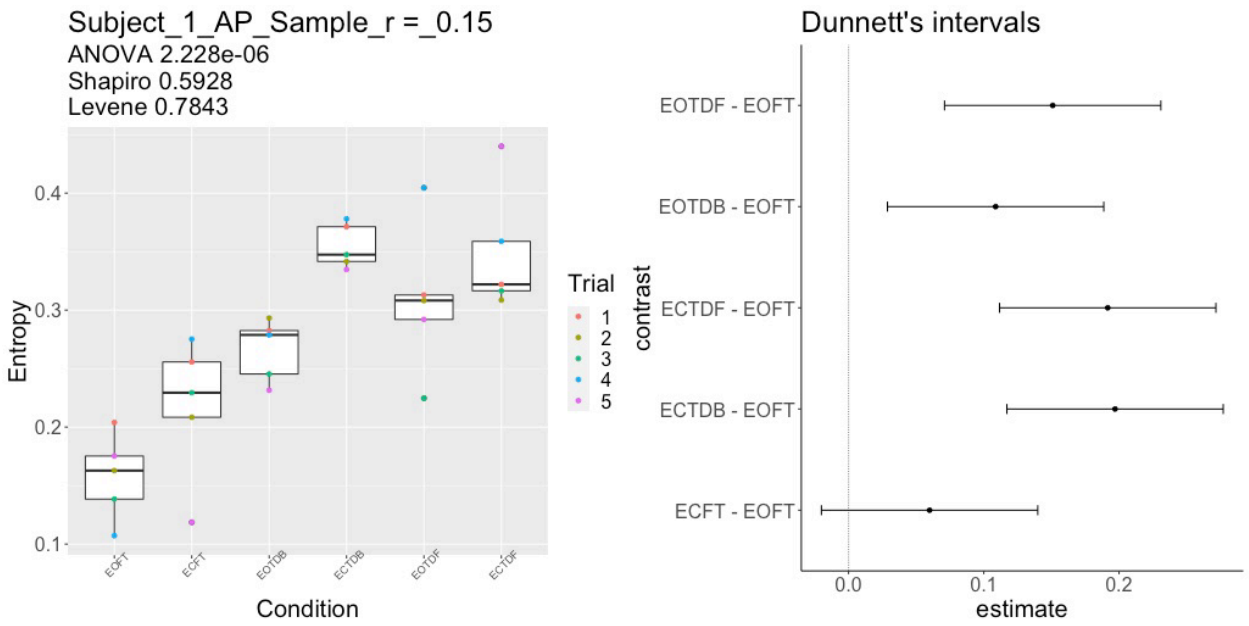

Figure A.7. One-way ANOVA, mapping the 5 mean SampEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.15*SD.

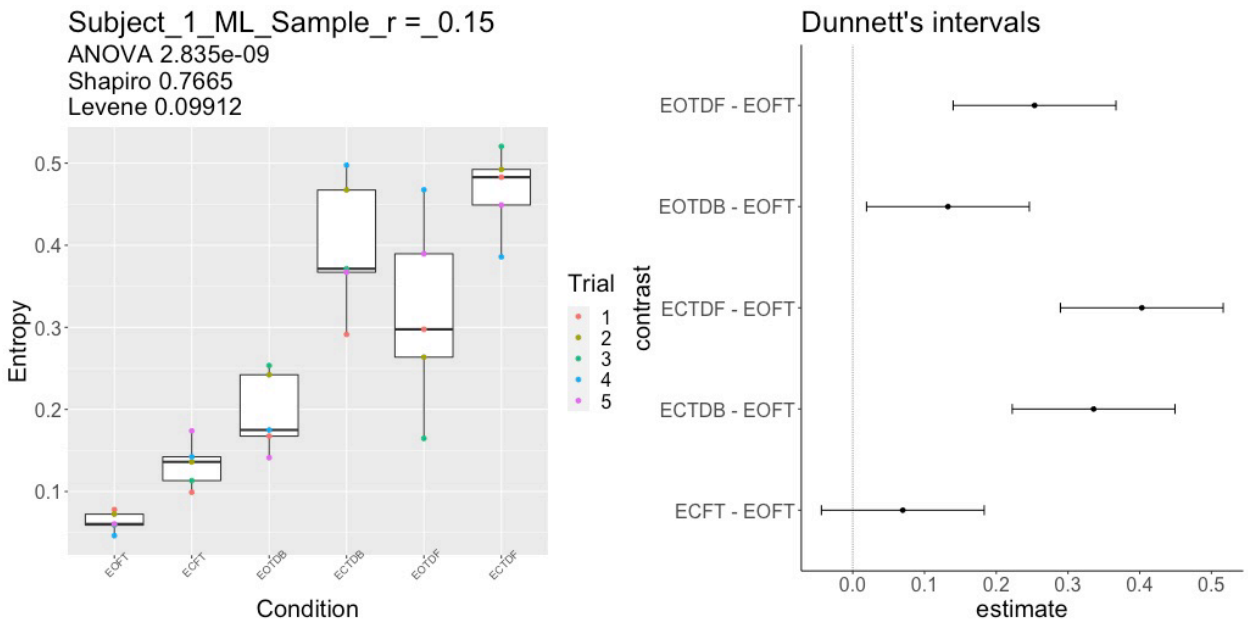

Figure A.8. One-way ANOVA, mapping the 5 mean SampEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.15*SD.

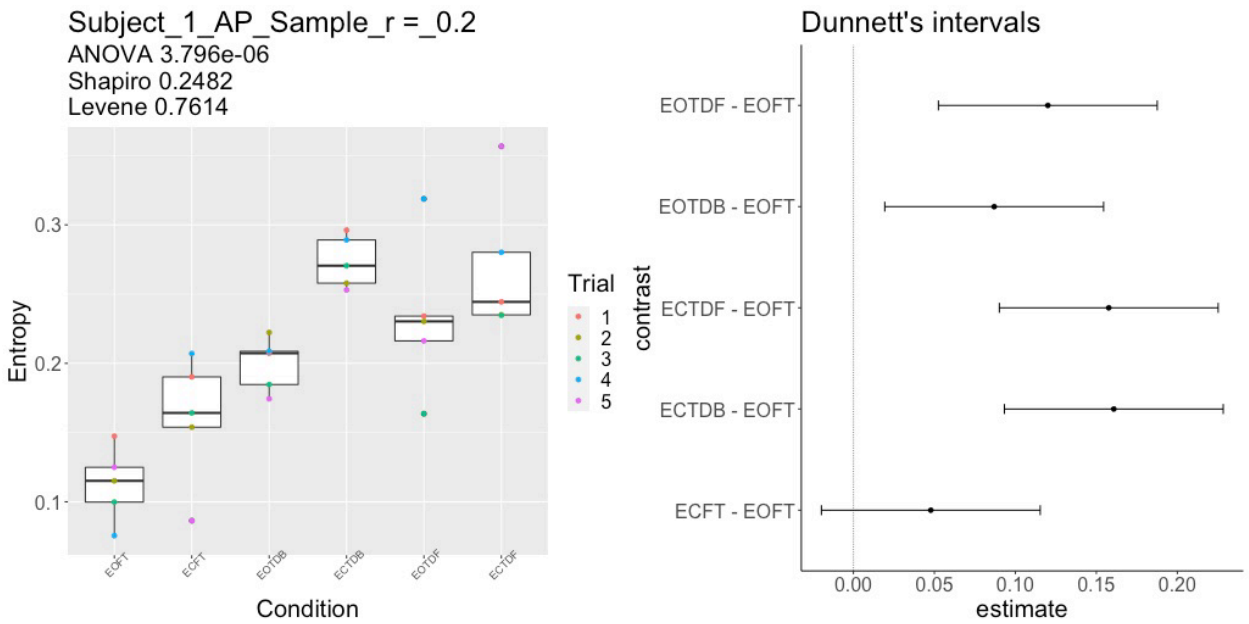

Figure A.9. One-way ANOVA, mapping the 5 mean SampEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.2*SD.

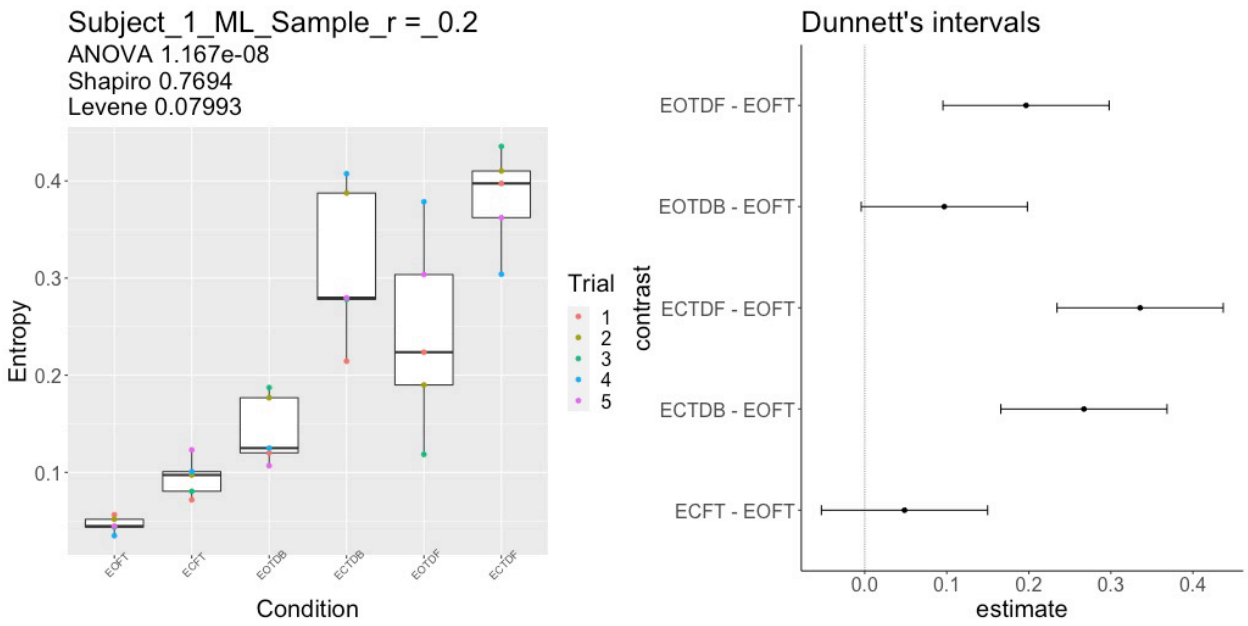

Figure A.10. One-way ANOVA, mapping the 5 mean SampEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.2*SD.

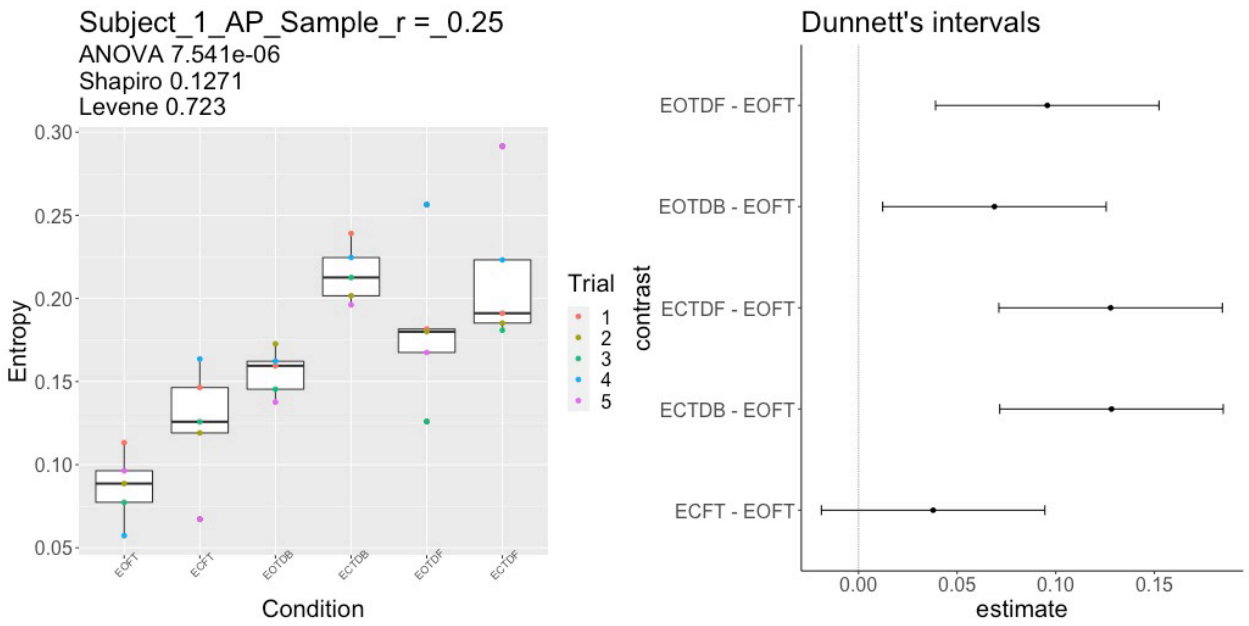

Figure A.11. One-way ANOVA, mapping the 5 mean SampEn trial values in the anterior posterior (AP) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.25*SD.

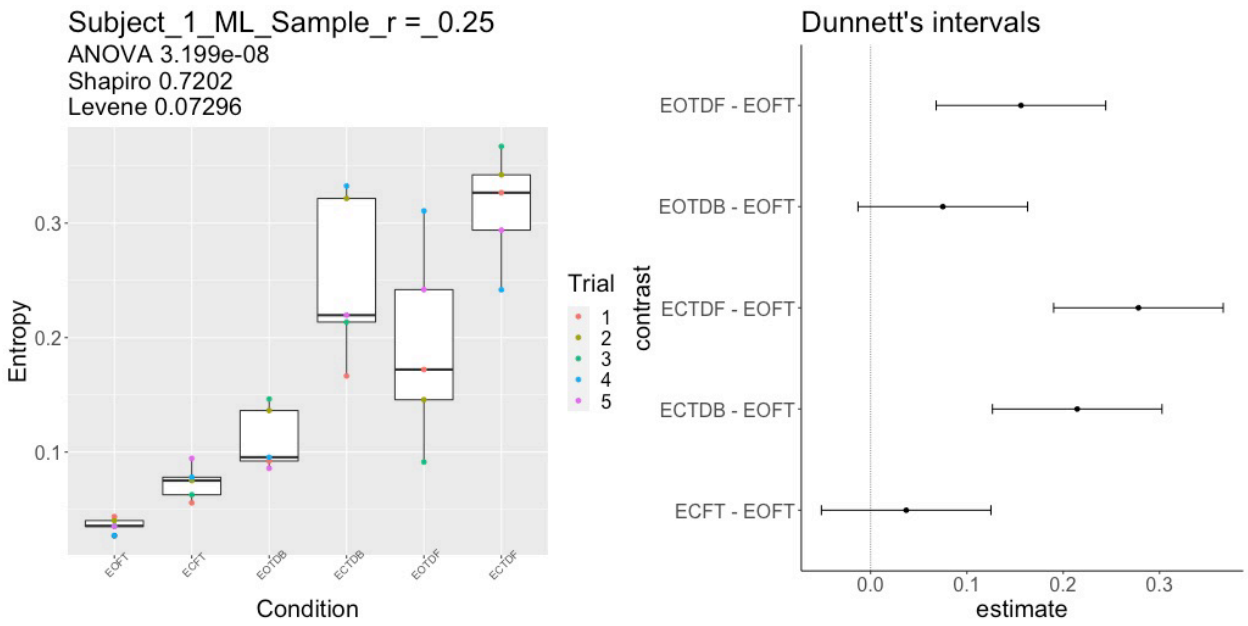

Figure A.12. One-way ANOVA, mapping the 5 mean SampEn trial values in the medial lateral (ML) direction for each stability condition; with Dunnett's tests, comparing eyes closed, feet together (ECFT); eyes open, feet tandem, dominant foot back (EOTDB); eyes closed, feet tandem, dominant foot back (ECTDB); eyes open, feet tandem, dominant foot forward (EOTDF); and eyes closed, feet tandem, dominant foot forward (ECTDF); to baseline (EOFT); where N = 1,800 datapoints, m = 2, and r = 0.25*SD.

Appendix B. ANOVA Data Tables

Supplementary data associated with this master's thesis can be found below. Table B.1 and Table B.2 depict the associated ApEn and SampEn values plotted in Figures 13 and 14. Each mean entropy value is a result of a compilation of each of the columns, i.e., value of *r*, axis direction, participant, stability condition, and entropy estimation method.

Table B.1. All Subjects by Axis and Method Mean and Standard Deviation Data

	r	Axis	Subject	Method	mean	std
1	0.05	AP	1	Approximate	0.552923336033609	0.0488963051243597
2	0.05	AP	1	Sample	0.513363004523101	0.0754283729720997
3	0.05	AP	2	Approximate	0.573654693622424	0.0271048578781064
4	0.05	AP	2	Sample	0.555312510534061	0.0462103755086795
5	0.05	AP	4	Approximate	0.773897907699981	0.183724893881889
6	0.05	AP	4	Sample	0.789084817867085	0.202248702651556
7	0.05	AP	5	Approximate	NA	NA
8	0.05	AP	5	Sample	NA	NA
9	0.05	AP	6	Approximate	0.543356457836966	0.0490237753617992
10	0.05	AP	6	Sample	0.496973395612704	0.0769347412887044
11	0.05	AP	8	Approximate	0.574055805788667	0.0383543544455246
12	0.05	AP	8	Sample	0.55617824887009	0.0681921869237874
13	0.05	ML	1	Approximate	0.532937654547443	0.153309748577886
14	0.05	ML	1	Sample	0.513974937202097	0.194325970349666
15	0.05	ML	2	Approximate	0.594209164205528	0.0864580077985201
16	0.05	ML	2	Sample	0.598869208020955	0.14416650843452
17	0.05	ML	4	Approximate	0.914593728118234	0.208024389784852
18	0.05	ML	4	Sample	1.05959078000325	0.334259652183477
19	0.05	ML	5	Approximate	NA	NA
20	0.05	ML	5	Sample	NA	NA
21	0.05	ML	6	Approximate	0.573649856971166	0.0648231736059189
22	0.05	ML	6	Sample	0.552868221749671	0.103898283656662
23	0.05	ML	8	Approximate	0.619926536346686	0.0824860324099032
24	0.05	ML	8	Sample	0.625694031364102	0.135668768455753
25	0.1	AP	1	Approximate	0.448215894627326	0.0969965564832068
26	0.1	AP	1	Sample	0.375800257292317	0.0928149762734519
27	0.1	AP	2	Approximate	0.488664106635178	0.0598657503255546
28	0.1	AP	2	Sample	0.415247057735097	0.0603946849773664

29	0.1	AP	4	Approximate	0.567474916011697	0.0674951459009477
30	0.1	AP	4	Sample	0.507756510572	0.0740456583489741
31	0.1	AP	5	Approximate	NA	NA
32	0.1	AP	5	Sample	NA	NA
33	0.1	AP	6	Approximate	0.434524366535238	0.0929176707999807
34	0.1	AP	6	Sample	0.361046116190021	0.0890553086859567
35	0.1	AP	8	Approximate	0.488806534591956	0.0873956779977639
36	0.1	AP	8	Sample	0.4200755908704	0.0865508217796465
37	0.1	ML	1	Approximate	0.404874158362073	0.192762801119961
38	0.1	ML	1	Sample	0.351251734395586	0.180134099429366
39	0.1	ML	2	Approximate	0.497240541960855	0.150571400929271
40	0.1	ML	2	Sample	0.44167733872721	0.153063084087885
41	0.1	ML	4	Approximate	0.724012860580689	0.192703471077284
42	0.1	ML	4	Sample	0.689399718148441	0.210328197002203
43	0.1	ML	5	Approximate	NA	NA
44	0.1	ML	5	Sample	NA	NA
45	0.1	ML	6	Approximate	0.462801212161836	0.121618643059573
46	0.1	ML	6	Sample	0.398742435299288	0.117513438324011
47	0.1	ML	8	Approximate	0.504738434619346	0.126702858792856
48	0.1	ML	8	Sample	0.447999220908179	0.132658512628974
49	0.15	AP	1	Approximate	0.331166920743155	0.0977156344566747
50	0.15	AP	1	Sample	0.275587815871537	0.0837687624778456
51	0.15	AP	2	Approximate	0.368904586523714	0.0676511602065315
52	0.15	AP	2	Sample	0.307308752378951	0.0584798721351914
53	0.15	AP	4	Approximate	0.423956400795699	0.0652935183933577
54	0.15	AP	4	Sample	0.371413665346407	0.0688236995377513
55	0.15	AP	5	Approximate	NA	NA
56	0.15	AP	5	Sample	NA	NA
57	0.15	AP	6	Approximate	0.311864233690721	0.0888345225970193
58	0.15	AP	6	Sample	0.260436520563862	0.0766220258314184
59	0.15	AP	8	Approximate	0.369898452376085	0.0923825418569759
60	0.15	AP	8	Sample	0.311935991132178	0.0813270834234804
61	0.15	ML	1	Approximate	0.311578828305287	0.184140234278394
62	0.15	ML	1	Sample	0.262285487807663	0.15823408979534
63	0.15	ML	2	Approximate	0.404553774931911	0.165596114970691
64	0.15	ML	2	Sample	0.340858145272437	0.145166613101269
65	0.15	ML	4	Approximate	0.578333770648374	0.166638880358923
66	0.15	ML	4	Sample	0.517695366653017	0.162140589221939
67	0.15	ML	5	Approximate	NA	NA
68	0.15	ML	5	Sample	NA	NA
69	0.15	ML	6	Approximate	0.34944517013498	0.131862873670127
70	0.15	ML	6	Sample	0.2936829724187	0.11050134347345
71	0.15	ML	8	Approximate	0.392663305443923	0.145553641702517

72	0.15	ML	8	Sample	0.336527434654231	0.130053955280431
73	0.2	AP	1	Approximate	0.229989193447657	0.095439556431448
74	0.2	AP	1	Sample	0.208093540150848	0.0691431029159029
75	0.2	AP	2	Approximate	0.273942460731057	0.0591606081786695
76	0.2	AP	2	Sample	0.232088390501253	0.0494807683376879
77	0.2	AP	4	Approximate	0.319773546818795	0.0655011689461831
78	0.2	AP	4	Sample	0.284060920026601	0.065389649428505
79	0.2	AP	5	Approximate	NA	NA
80	0.2	AP	5	Sample	NA	NA
81	0.2	AP	6	Approximate	0.226197637843229	0.0706261219789934
82	0.2	AP	6	Sample	0.193656589980495	0.0604156169763611
83	0.2	AP	8	Approximate	0.274705903934411	0.0780543335198408
84	0.2	AP	8	Sample	0.235549915301517	0.0678789954169452
85	0.2	ML	1	Approximate	0.259524933281401	0.151202205497115
86	0.2	ML	1	Sample	0.203724010669376	0.132990871182964
87	0.2	ML	2	Approximate	0.326523945594658	0.153225836609389
88	0.2	ML	2	Sample	0.269548834700058	0.12704735547884
89	0.2	ML	4	Approximate	0.47189137870991	0.155219919881618
90	0.2	ML	4	Sample	0.409149942460809	0.139219384241739
91	0.2	ML	5	Approximate	NA	NA
92	0.2	ML	5	Sample	NA	NA
93	0.2	ML	6	Approximate	0.265912195267243	0.117716028732856
94	0.2	ML	6	Sample	0.224154224914164	0.0944933745582462
95	0.2	ML	8	Approximate	0.307407840344365	0.139878313456619
96	0.2	ML	8	Sample	0.260273957945955	0.116950811373516
97	0.25	AP	1	Approximate	0.186741690269226	0.065558389891597
98	0.25	AP	1	Sample	0.162993488953873	0.0562979323549168
99	0.25	AP	2	Approximate	0.208154703830785	0.0488285231253674
100	0.25	AP	2	Sample	0.181527870854991	0.0409101571597724
101	0.25	AP	4	Approximate	0.2458249755349	0.0574401252167571
102	0.25	AP	4	Sample	0.223689535314665	0.0571197554314075
103	0.25	AP	5	Approximate	NA	NA
104	0.25	AP	5	Sample	NA	NA
105	0.25	AP	6	Approximate	0.17102255372337	0.054005379375082
106	0.25	AP	6	Sample	0.150608224521617	0.0471764402357288
107	0.25	AP	8	Approximate	0.209211649452499	0.0614182315540103
108	0.25	AP	8	Sample	0.183791996389714	0.0546864600108072
109	0.25	ML	1	Approximate	0.193929612507069	0.133641956388092
110	0.25	ML	1	Sample	0.163011561472537	0.110695625914642
111	0.25	ML	2	Approximate	0.264358145625547	0.133504137866843
112	0.25	ML	2	Sample	0.217632259556432	0.107825895936438
113	0.25	ML	4	Approximate	0.391345291029995	0.143730107625575
114	0.25	ML	4	Sample	0.333627456449931	0.122075236518685

115	0.25	ML	5	Approximate	NA	NA
116	0.25	ML	5	Sample	NA	NA
117	0.25	ML	6	Approximate	0.207186730634017	0.0980794582018656
118	0.25	ML	6	Sample	0.176988769866324	0.0782941305485083
119	0.25	ML	8	Approximate	0.244696727592634	0.124487145447648
120	0.25	ML	8	Sample	0.207408219078263	0.101614949747247
121	0.3	AP	1	Approximate	0.147413586034671	0.0518672659890784
122	0.3	AP	1	Sample	0.131962574805219	0.0459571907503602
123	0.3	AP	2	Approximate	0.16388583641981	0.0390441019200517
124	0.3	AP	2	Sample	0.146801678879389	0.0337274095388648
125	0.3	AP	4	Approximate	0.194206631964223	0.0476272709196575
126	0.3	AP	4	Sample	0.180739110430945	0.0481953037370043
127	0.3	AP	5	Approximate	NA	NA
128	0.3	AP	5	Sample	NA	NA
129	0.3	AP	6	Approximate	0.134879717826831	0.0416876733790984
130	0.3	AP	6	Sample	0.12168185097051	0.0374015752515928
131	0.3	AP	8	Approximate	0.164974361215884	0.0477887043158255
132	0.3	AP	8	Sample	0.148274547353833	0.0438802271151863
133	0.3	ML	1	Approximate	0.156971276857867	0.110095250592128
134	0.3	ML	1	Sample	0.133732045614251	0.092158732785613
135	0.3	ML	2	Approximate	0.216016175947946	0.113356088509414
136	0.3	ML	2	Sample	0.17941797306955	0.091253195428536
137	0.3	ML	4	Approximate	0.328574546195869	0.129810217731111
138	0.3	ML	4	Sample	0.278120656533204	0.10725972063412
139	0.3	ML	5	Approximate	NA	NA
140	0.3	ML	5	Sample	NA	NA
141	0.3	ML	6	Approximate	0.16591360343697	0.0799861047818259
142	0.3	ML	6	Sample	0.143981036209407	0.0646059827742168
143	0.3	ML	8	Approximate	0.199078641904989	0.107871255326046
144	0.3	ML	8	Sample	0.169858737868292	0.0878226919358317

Table B.2. Conditions by Axis and Method Mean and Standard Deviation Data

	r	**Axis**	**Condition**	**Method**	**mean**	**std**
1	0.05	AP	ECFT	Approximate	0.615446673585895	0.169093235110817
2	0.05	AP	ECFT	Sample	0.580214089499568	0.199021823941436
3	0.05	AP	ECTDB	Approximate	NA	NA
4	0.05	AP	ECTDB	Sample	NA	NA
5	0.05	AP	ECTDF	Approximate	0.594363845494992	0.0221672593236419
6	0.05	AP	ECTDF	Sample	0.586488512105544	0.0447277591604153
7	0.05	AP	EOFT	Approximate	0.587716078648704	0.189821927006716
8	0.05	AP	EOFT	Sample	0.534773836071416	0.226848466546936

9	0.05	AP	EOTDB	Approximate	0.626824610678242	0.123532524458569
10	0.05	AP	EOTDB	Sample	0.611232690255824	0.156626155034266
11	0.05	AP	EOTDF	Approximate	0.590217410341068	0.0348647167159653
12	0.05	AP	EOTDF	Sample	0.579906841048275	0.0600261134756815
13	0.05	ML	ECFT	Approximate	0.609174901449631	0.191514606156255
14	0.05	ML	ECFT	Sample	0.577913808971904	0.240535136725473
15	0.05	ML	ECTDB	Approximate	NA	NA
16	0.05	ML	ECTDB	Sample	NA	NA
17	0.05	ML	ECTDF	Approximate	0.701660921000785	0.119905466423849
18	0.05	ML	ECTDF	Sample	0.765063521649689	0.197208870541617
19	0.05	ML	EOFT	Approximate	0.553029788779079	0.241374268367437
20	0.05	ML	EOFT	Sample	0.511906513474842	0.282350754201994
21	0.05	ML	EOTDB	Approximate	0.746297053124038	0.264366907464697
22	0.05	ML	EOTDB	Sample	0.835454520263187	0.446693873974837
23	0.05	ML	EOTDF	Approximate	0.670481593173265	0.131675637805314
24	0.05	ML	EOTDF	Sample	0.727134821186554	0.2227647217722
25	0.1	AP	ECFT	Approximate	0.456242755943474	0.100340577839872
26	0.1	AP	ECFT	Sample	0.378321230873911	0.0968529837431867
27	0.1	AP	ECTDB	Approximate	NA	NA
28	0.1	AP	ECTDB	Sample	NA	NA
29	0.1	AP	ECTDF	Approximate	0.525054281199565	0.0446363766126562
30	0.1	AP	ECTDF	Sample	0.459824150996151	0.0540321343500852
31	0.1	AP	EOFT	Approximate	0.375494033641188	0.120400066317457
32	0.1	AP	EOFT	Sample	0.309460277788605	0.111990799713221
33	0.1	AP	EOTDB	Approximate	0.511694226384145	0.0654797919568866
34	0.1	AP	EOTDB	Sample	0.440855849565787	0.0788975313729291
35	0.1	AP	EOTDF	Approximate	0.513915472559543	0.0467065695385829
36	0.1	AP	EOTDF	Sample	0.445901835566377	0.0614488773256967
37	0.1	ML	ECFT	Approximate	0.404748255912342	0.139078140706425
38	0.1	ML	ECFT	Sample	0.346114267493604	0.130752850738477
39	0.1	ML	ECTDB	Approximate	NA	NA
40	0.1	ML	ECTDB	Sample	NA	NA
41	0.1	ML	ECTDF	Approximate	0.618061578251138	0.118180138649981
42	0.1	ML	ECTDF	Sample	0.572730135955645	0.132101293709322
43	0.1	ML	EOFT	Approximate	0.338577642188683	0.175820068500834
44	0.1	ML	EOFT	Sample	0.290059610379686	0.158441042685206
45	0.1	ML	EOTDB	Approximate	0.632050253618183	0.252243138484633
46	0.1	ML	EOTDB	Sample	0.577264605626455	0.28122788302594
47	0.1	ML	EOTDF	Approximate	0.591074350893299	0.133873488251142
48	0.1	ML	EOTDF	Sample	0.543130431989346	0.153326895759643
49	0.15	AP	ECFT	Approximate	0.317727666704173	0.0776354623159107
50	0.15	AP	ECFT	Sample	0.261555770389475	0.0662947808289264
51	0.15	AP	ECTDB	Approximate	NA	NA

52	0.15	AP	ECTDB	Sample	NA	NA
53	0.15	AP	ECTDF	Approximate	0.41876901929844	0.061204036869183
54	0.15	AP	ECTDF	Sample	0.357917839374826	0.0589140959294864
55	0.15	AP	EOFT	Approximate	0.238357227130369	0.0836575322073203
56	0.15	AP	EOFT	Sample	0.200788497674001	0.0723956852100691
57	0.15	AP	EOTDB	Approximate	0.385525853546339	0.0621370724389266
58	0.15	AP	EOTDB	Sample	0.325434825645317	0.0639396148194999
59	0.15	AP	EOTDF	Approximate	0.396388655647414	0.0587380510550414
60	0.15	AP	EOTDF	Sample	0.337146252345819	0.0623000887991572
61	0.15	ML	ECFT	Approximate	0.26432042432904	0.106935187310751
62	0.15	ML	ECFT	Sample	0.227563915350218	0.091576528004677
63	0.15	ML	ECTDB	Approximate	NA	NA
64	0.15	ML	ECTDB	Sample	NA	NA
65	0.15	ML	ECTDF	Approximate	0.526353790179524	0.125396075045685
66	0.15	ML	ECTDF	Sample	0.459097688853714	0.122009177186753
67	0.15	ML	EOFT	Approximate	0.214790672338941	0.12035928414717
68	0.15	ML	EOFT	Sample	0.186966416656634	0.103337038594578
69	0.15	ML	EOTDB	Approximate	0.499184322686777	0.212831856781852
70	0.15	ML	EOTDB	Sample	0.431496255731315	0.210675281843379
71	0.15	ML	EOTDF	Approximate	0.494223660375179	0.137825217613009
72	0.15	ML	EOTDF	Sample	0.428180011716297	0.137768476263633
73	0.2	AP	ECFT	Approximate	0.211851797605485	0.072321625176192
74	0.2	AP	ECFT	Sample	0.191537073954868	0.0489272910230612
75	0.2	AP	ECTDB	Approximate	NA	NA
76	0.2	AP	ECTDB	Sample	NA	NA
77	0.2	AP	ECTDF	Approximate	0.323947093287654	0.0627097583240227
78	0.2	AP	ECTDF	Sample	0.280251149918314	0.0562058109209532
79	0.2	AP	EOFT	Approximate	0.165030719179868	0.0585189928969483
80	0.2	AP	EOFT	Sample	0.143709332858276	0.0510872379940733
81	0.2	AP	EOTDB	Approximate	0.285563359750933	0.054166028000021
82	0.2	AP	EOTDB	Sample	0.245350334742472	0.0524208537819914
83	0.2	AP	EOTDF	Approximate	0.298941071486615	0.0578673405310776
84	0.2	AP	EOTDF	Sample	0.257696017505767	0.0576902549027792
85	0.2	ML	ECFT	Approximate	0.201088624662743	0.0752666981198356
86	0.2	ML	ECFT	Sample	0.163613930974187	0.067970584651304
87	0.2	ML	ECTDB	Approximate	NA	NA
88	0.2	ML	ECTDB	Sample	NA	NA
89	0.2	ML	ECTDF	Approximate	0.442166452956038	0.129500060220738
90	0.2	ML	ECTDF	Sample	0.37523239536124	0.11597570879329
91	0.2	ML	EOFT	Approximate	0.149425677916381	0.0840580041878042
92	0.2	ML	EOFT	Sample	0.132867407869736	0.071971769706746
93	0.2	ML	EOTDB	Approximate	0.397673106299343	0.18424453003594
94	0.2	ML	EOTDB	Sample	0.336678392962461	0.170365676436763

95	0.2	ML	EOTDF	Approximate	0.408686960217003	0.13995417051965
96	0.2	ML	EOTDF	Sample	0.344976072136868	0.126658075167603
97	0.25	AP	ECFT	Approximate	0.170478168814785	0.0442232980524086
98	0.25	AP	ECFT	Sample	0.147957144102735	0.0374696738875929
99	0.25	AP	ECTDB	Approximate	NA	NA
100	0.25	AP	ECTDB	Sample	NA	NA
101	0.25	AP	ECTDF	Approximate	0.251764144067622	0.0558148364681049
102	0.25	AP	ECTDF	Sample	0.223529111796983	0.0495546725525944
103	0.25	AP	EOFT	Approximate	0.12340644104425	0.0425677296083877
104	0.25	AP	EOFT	Sample	0.110442639127105	0.0381334824537455
105	0.25	AP	EOTDB	Approximate	0.216963189650859	0.0445380277615436
106	0.25	AP	EOTDB	Sample	0.19141978090801	0.0425491654078806
107	0.25	AP	EOTDF	Approximate	0.229773397175633	0.0498813997147656
108	0.25	AP	EOTDF	Sample	0.202526494279519	0.0496301903180321
109	0.25	ML	ECFT	Approximate	0.139909743891459	0.0619350377984523
110	0.25	ML	ECFT	Sample	0.125883444130559	0.0524948279074408
111	0.25	ML	ECTDB	Approximate	NA	NA
112	0.25	ML	ECTDB	Sample	NA	NA
113	0.25	ML	ECTDF	Approximate	0.369055784167554	0.126237157050676
114	0.25	ML	ECTDF	Sample	0.310403284501171	0.108135874823766
115	0.25	ML	EOFT	Approximate	0.112376507273484	0.0621317543503756
116	0.25	ML	EOFT	Sample	0.101634558800668	0.0536047920425661
117	0.25	ML	EOTDB	Approximate	0.320944709267668	0.159828141276398
118	0.25	ML	EOTDB	Sample	0.270258550765251	0.141637217247445
119	0.25	ML	EOTDF	Approximate	0.338105756724756	0.135308770941955
120	0.25	ML	EOTDF	Sample	0.28309100151512	0.115277541711683
121	0.3	AP	ECFT	Approximate	0.134302820395314	0.0336873938061658
122	0.3	AP	ECFT	Sample	0.119260052001676	0.0294757680394505
123	0.3	AP	ECTDB	Approximate	NA	NA
124	0.3	AP	ECTDB	Sample	NA	NA
125	0.3	AP	ECTDF	Approximate	0.199655209774259	0.0466416895643456
126	0.3	AP	ECTDF	Sample	0.182112496237088	0.04205408807522
127	0.3	AP	EOFT	Approximate	0.0978094282532174	0.0323626112783335
128	0.3	AP	EOFT	Sample	0.0892037423352866	0.0298435032348492
129	0.3	AP	EOTDB	Approximate	0.170911455476799	0.0357141178716424
130	0.3	AP	EOTDB	Sample	0.154511214465163	0.0345399689921685
131	0.3	AP	EOTDF	Approximate	0.181579494875872	0.0410319917069211
132	0.3	AP	EOTDF	Sample	0.163636000480095	0.0415007349082736
133	0.3	ML	ECFT	Approximate	0.111193452490954	0.048173989658354
134	0.3	ML	ECFT	Sample	0.101550176393256	0.0416250531101957
135	0.3	ML	ECTDB	Approximate	NA	NA
136	0.3	ML	ECTDB	Sample	NA	NA
137	0.3	ML	ECTDF	Approximate	0.309914710556836	0.119386552888959

138	0.3	ML	ECTDF	Sample	0.260774020604223	0.099268136612955
139	0.3	ML	EOFT	Approximate	0.0893767048750164	0.0482604035843592
140	0.3	ML	EOFT	Sample	0.0817352480809925	0.0421309354408963
141	0.3	ML	EOTDB	Approximate	0.263296360895647	0.137944776188303
142	0.3	ML	EOTDB	Sample	0.222444063464105	0.119281330826695
143	0.3	ML	EOTDF	Approximate	0.281882236387636	0.124585738437153
144	0.3	ML	EOTDF	Sample	0.236233335293836	0.102861273053559

Appendix C. Code

C.1 *Downsampling COP Data*

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Title: Downsample_COP.m
% Author: Jayla Wesley
% Notes: this script file loads subject data into a usable structure for
% further analysis
%   1. Cx is the Anterior-Posterior direction
%   2. Cy is the Medial Lateral direction
%   3. Downsampling by a factor of 20, 1200Hz to 60Hz
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clc; close all; clear;

% load trial condition
filtdata = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 01\Subject 01 Trial Data
Raw\SB01_Trial04.csv');

% separate COP data into axial vectors
Cx_filt = filtdata(6:36005,18);
Cy_filt = filtdata(6:36005,19);
Cz_filt = filtdata(6:36005,20);
t1 = linspace(1,30,36000);

% downsample by factor of 20
Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);
t2 = linspace(1,30,1800);

% plot generation
figure(1)
subplot(1,2,1), plot(t1,Cx_filt)
xlabel('Time(s)','FontSize', 12), ylabel('AP Distance from Origin (mm)','FontSize',
12);
subplot(1,2,2), plot(t1,Cy_filt)
xlabel('Time(s)','FontSize', 12), ylabel('ML Distance from Origin
(mm)','FontSize',12);

figure(2)
subplot(1,2,1), plot(t2,Cx_filtds)
xlabel('Time(s)','FontSize', 12), ylabel('AP Distance from Origin (mm)','FontSize',
12);
subplot(1,2,2), plot(t2,Cy_filtds)
xlabel('Time(s)','FontSize', 12), ylabel('ML Distance from Origin
(mm)','FontSize',12);
```

C.2 *Approximate Entropy Function*

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [AE] = ApEntr( data, dim, r )
% Title: ApEntr(data,m,R): returns the approximate entropy value, function
% Adapted from Jenna Yentes [44].
% inputs - data, single column (transpose COP) time series
```

```
%        - m, length of vectors to be compared
%        - R, filter for accepting matches (as a proportion of the
%          standard deviation)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% variable declaration
r = r*std(data);   % tolerance, r, times the standard deviation
N = length(data);  % data length
phim = zeros(1,2); % phi m and phi m + 1

% ApEn calculation
for j = 1:2
    m = dim+j-1;                        % define vector length
    phi = zeros(1,N-m+1);
    dataMat = zeros(m,N-m+1);
    for i = 1:m
        dataMat(i,:) = data(i:N-m+i); % divide data series into blocks
    end
    for i = 1:N-m+1                     % calculate the conditional probability of each
vector
        tempMat = abs(dataMat - repmat(dataMat(:,i),1,N-m+1));
        AorB = any( (tempMat > r),1); % count m and m + 1 matches within tolerance
r*SD
        phi(i) = sum(~AorB)/(N-m+1);  % sum of natural log for ea cond. proab m and m
+ 1
    end
    phim(j) = sum(log(phi))/(N-m+1);  % sum of natural log for ea cond. prob divide by
N - m + 1 and N-m
end
AE = phim(1)-phim(2);                 % phi m - phi m + 1
End
```

C.3 *Sample Entropy Function*

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [SE] = SampEntr(data, m, R)
% Title: SampEntr(data,m,R): returns the sample entropy value, function
% Adapted from Jenna Yentes [44].
% inputs: - data, single column (transpose COP) time series
%         - m, length of vectors to be compared
%         - R, filter for accepting matches (as a proportion of the
%           standard deviation)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% variable declaration
r = R * std(data); % tolerance, r, times the standard deviation
N = length(data);  % data length

dij=zeros(N-m,m+1);
dj=zeros(N-m,1);
dj1=zeros(N-m,1);
Bm=zeros(N-m,1);
Am=zeros(N-m,1);

% SampEn calculation
for i = 1:N-m
    for k = 1:m+1
        dij(:,k) = abs(data(1+k-1:N-m+k-1)-data(i+k-1));
    end
    dj = max(dij(:,1:m),[],2); % divide series into m blocks
```

```
    dj1 = max(dij,[],2);        % divide series into m + 1 blocks
    d = find(dj<=r);            % count m matches within tolerance r*SD
    d1 = find(dj1<=r);          % count m + 1 matches within tolerance r*SD
    nm = length(d)-1;           % subtract the self-match
    Bm(i) = nm/(N-m);           % number of similar vector for m points
    nm1 = length(d1)-1;         % subtract the self-match
    Am(i) = nm1/(N-m);          % number of similar vector for m + 1 matches
end
Bmr = sum(Bm)/(N-m); % sum of natural log for cond. prob two sequences
                     % are similar for m points divided by N - m

Amr = sum(Am)/(N-m); % sum of natural log for cond. prob two sequences
                     % are similar for m + 1 matched divided by N - m

SE = -log(Amr/Bmr); % negative natural log of A/B
end
```

C.4 *ApEn and SampEn over Time Series*

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Title: ApEn_SampEn_TimeSeries.m
% Author Jayla Wesley
% Notes: this script file loads subject data into a usable structure for
% further analysis
%   1. Cx is the Anterior-Posterior direction
%   2. Cy is the Medial Lateral Direction
%   3. Downsampling by a factor of 20, 1200Hz to 60Hz
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
close all; clear all; clc;

filtdata = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 01\Subject 01 Trial Data
Raw\SB01_Trial19.csv');

Cx_filt = filtdata(6:36005,27);
Cy_filt = filtdata(6:36005,28);
Cz_filt = filtdata(6:36005,29);

% downsample the data 1200Hz to 60Hz
Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);


%% Center of Pressure (COP) Calculation %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Get COP data by window - choose filtered because overtime difference is
insignificant.
% 1 second %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x1 = Cx_filtds(1:60);    % 1 second of data 1-60
y1 = Cy_filtds(1:60);
z1 = Cz_filtds(1:60);

% 2 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x2 = Cx_filtds(61:120);  % 1 second of data 61-120
y2 = Cy_filtds(61:120);
z2 = Cz_filtds(61:120);

% 3 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
x3 = Cx_filtds(121:180); % 1 second of data 121-180
y3 = Cy_filtds(121:180);
z3 = Cz_filtds(121:180);

% 4 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x4 = Cx_filtds(181:240); % 1 second of data 180-240
y4 = Cy_filtds(181:240);
z4 = Cz_filtds(181:240);

% 5 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x5 = Cx_filtds(241:300); % 1 second of data 240-300
y5 = Cy_filtds(241:300);
z5 = Cz_filtds(241:300);

% 6 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x6 = Cx_filtds(301:360); % 1 second of data 300-360
y6 = Cy_filtds(301:360);
z6 = Cz_filtds(301:360);

% 7 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x7 = Cx_filtds(361:420); % 1 second of data 361-420
y7 = Cy_filtds(361:420);
z7 = Cz_filtds(361:420);

% 8 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x8 = Cx_filtds(421:480); % 1 second of data 421-480
y8 = Cy_filtds(421:480);
z8 = Cz_filtds(421:480);

% 9 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x9 = Cx_filtds(481:540); % 1 second of data 481-540
y9 = Cy_filtds(481:540);
z9 = Cz_filtds(481:540);

% 10 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x10 = Cx_filtds(541:600); % 1 second of data 541-600
y10 = Cy_filtds(541:600);
z10 = Cz_filtds(541:600);

% 11 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x11 = Cx_filtds(601:660); % 1 second of data 601-660
y11 = Cy_filtds(601:660);
z11 = Cz_filtds(601:660);

% 12 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x12 = Cx_filtds(661:720); % 1 second of data 661-720
y12 = Cy_filtds(661:720);
z12 = Cz_filtds(661:720);

% 13 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x13 = Cx_filtds(721:780); % 1 second of data 721-780
y13 = Cy_filtds(721:780);
z13 = Cz_filtds(721:780);

% 14 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x14 = Cx_filtds(781:840); % 1 second of data 781-840
y14 = Cy_filtds(781:840);
z14 = Cz_filtds(781:840);

% 15 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x15 = Cx_filtds(841:900); % 1 second of data 841-900
```

```
y15 = Cy_filtds(841:900);
z15 = Cz_filtds(841:900);

% 16 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x16 = Cx_filtds(901:960); % 1 second of data 901-960
y16 = Cy_filtds(901:960);
z16 = Cz_filtds(901:960);

% 17 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x17 = Cx_filtds(961:1020); % 1 second of data 961-1020
y17 = Cy_filtds(961:1020);
z17 = Cz_filtds(961:1020);

% 18 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x18 = Cx_filtds(1021:1080); % 1 second of data 1021-1080
y18 = Cy_filtds(1021:1080);
z18 = Cz_filtds(1021:1080);

% 19 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x19 = Cx_filtds(1081:1140); % 1 second of data 1081-1140
y19 = Cy_filtds(1081:1140);
z19 = Cz_filtds(1081:1140);

% 20 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x20 = Cx_filtds(1141:1200); % 1 second of data 1141-1200
y20 = Cy_filtds(1141:1200);
z20 = Cz_filtds(1141:1200);

% 21 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x21 = Cx_filtds(1201:1260); % 1 second of data 1201-1260
y21 = Cy_filtds(1201:1260);
z21 = Cz_filtds(1201:1260);

% 22 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x22 = Cx_filtds(1261:1320); % 1 second of data 1261-1320
y22 = Cy_filtds(1261:1320);
z22 = Cz_filtds(1261:1320);

% 23 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x23 = Cx_filtds(1321:1380); % 1 second of data 1321-1380
y23 = Cy_filtds(1321:1380);
z23 = Cz_filtds(1321:1380);

% 24 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x24 = Cx_filtds(1381:1440); % 1 second of data 1381-1440
y24 = Cy_filtds(1381:1440);
z24 = Cz_filtds(1381:1440);

% 25 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x25 = Cx_filtds(1441:1500); % 1 second of data 1441-1500
y25 = Cy_filtds(1441:1500);
z25 = Cz_filtds(1441:1500);

% 26 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x26 = Cx_filtds(1501:1560); % 1 second of data 1501-1560
y26 = Cy_filtds(1501:1560);
z26 = Cz_filtds(1501:1560);

% 27 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x27 = Cx_filtds(1561:1620); % 1 second of data 15611-1620
y27 = Cy_filtds(1561:1620);
```

```
z27 = Cz_filtds(1561:1620);

% 28 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x28 = Cx_filtds(1621:1680); % 1 second of data 1621-1680
y28 = Cy_filtds(1621:1680);
z28 = Cz_filtds(1621:1680);


% 29 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x29 = Cx_filtds(1681:1740); % 1 second of data 1681-1740
y29 = Cy_filtds(1681:1740);
z29 = Cz_filtds(1681:1740);

% 30 seconds %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x30 = Cx_filtds(1741:1800); % 1 second of data 1741-1800
y30 = Cy_filtds(1741:1800);
z30 = Cz_filtds(1741:1800);


%% Entropy Variable Declaration
dim = 2; % embedded dimension = 2
r = 0.2; % tolerance

% Sample Entropy(SampEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%
% AP direction
SE1_AP = SampEntr(x1',dim,r);
SE2_AP = SampEntr(x2',dim,r);
SE3_AP = SampEntr(x3',dim,r);
SE4_AP = SampEntr(x4',dim,r);
SE5_AP = SampEntr(x5',dim,r);
SE6_AP = SampEntr(x6',dim,r);
SE7_AP = SampEntr(x7',dim,r);
SE8_AP = SampEntr(x8',dim,r);
SE9_AP = SampEntr(x9',dim,r);
SE10_AP = SampEntr(x10',dim,r);
SE11_AP = SampEntr(x11',dim,r);
SE12_AP = SampEntr(x12',dim,r);
SE13_AP = SampEntr(x13',dim,r);
SE14_AP = SampEntr(x14',dim,r);
SE15_AP = SampEntr(x15',dim,r);
SE16_AP = SampEntr(x16',dim,r);
SE17_AP = SampEntr(x17',dim,r);
SE18_AP = SampEntr(x18',dim,r);
SE19_AP = SampEntr(x19',dim,r);
SE20_AP = SampEntr(x20',dim,r);
SE21_AP = SampEntr(x21',dim,r);
SE22_AP = SampEntr(x22',dim,r);
SE23_AP = SampEntr(x23',dim,r);
SE24_AP = SampEntr(x24',dim,r);
SE25_AP = SampEntr(x25',dim,r);
SE26_AP = SampEntr(x26',dim,r);
SE27_AP = SampEntr(x27',dim,r);
SE28_AP = SampEntr(x28',dim,r);
SE29_AP = SampEntr(x29',dim,r);
SE30_AP = SampEntr(x30',dim,r);

%ML direction
SE1_ML = SampEntr(y1',dim,r);
SE2_ML = SampEntr(y2',dim,r);
SE3_ML = SampEntr(y3',dim,r);
SE4_ML = SampEntr(y4',dim,r);
```

```
SE5_ML = SampEntr(y5',dim,r);
SE6_ML = SampEntr(y6',dim,r);
SE7_ML = SampEntr(y7',dim,r);
SE8_ML = SampEntr(y8',dim,r);
SE9_ML = SampEntr(y9',dim,r);
SE10_ML = SampEntr(y10',dim,r);
SE11_ML = SampEntr(y11',dim,r);
SE12_ML = SampEntr(y12',dim,r);
SE13_ML = SampEntr(y13',dim,r);
SE14_ML = SampEntr(y14',dim,r);
SE15_ML = SampEntr(y15',dim,r);
SE16_ML = SampEntr(y16',dim,r);
SE17_ML = SampEntr(y17',dim,r);
SE18_ML = SampEntr(y18',dim,r);
SE19_ML = SampEntr(y19',dim,r);
SE20_ML = SampEntr(y20',dim,r);
SE21_ML = SampEntr(y21',dim,r);
SE22_ML = SampEntr(y22',dim,r);
SE23_ML = SampEntr(y23',dim,r);
SE24_ML = SampEntr(y24',dim,r);
SE25_ML = SampEntr(y25',dim,r);
SE26_ML = SampEntr(y26',dim,r);
SE27_ML = SampEntr(y27',dim,r);
SE28_ML = SampEntr(y28',dim,r);
SE29_ML = SampEntr(y29',dim,r);
SE30_ML = SampEntr(y30',dim,r);

SampEn2_AP = [SE1_AP SE2_AP SE3_AP SE4_AP SE5_AP SE6_AP SE7_AP SE8_AP SE9_AP SE10_AP
SE11_AP SE12_AP SE13_AP SE14_AP SE15_AP SE16_AP SE17_AP SE18_AP SE19_AP SE20_AP
SE21_AP SE22_AP SE23_AP SE24_AP SE25_AP SE26_AP SE27_AP SE28_AP SE29_AP SE30_AP];
tS_AP = 1:length(SampEn2_AP);

SampEn2_ML = [SE1_ML SE2_ML SE3_ML SE4_ML SE5_ML SE6_ML SE7_ML SE8_ML SE9_ML SE10_ML
SE11_ML SE12_ML SE13_ML SE14_ML SE15_ML SE16_ML SE17_ML SE18_ML SE19_ML SE20_ML
SE21_ML SE22_ML SE23_ML SE24_ML SE25_ML SE26_ML SE27_ML SE28_ML SE29_ML SE30_ML];
tS_ML = 1:length(SampEn2_ML);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%
% AP direction
AP1_AP = ApEntr(x1',dim,r);
AP2_AP = ApEntr(x2',dim,r);
AP3_AP = ApEntr(x3',dim,r);
AP4_AP = ApEntr(x4',dim,r);
AP5_AP = ApEntr(x5',dim,r);
AP6_AP = ApEntr(x6',dim,r);
AP7_AP = ApEntr(x7',dim,r);
AP8_AP = ApEntr(x8',dim,r);
AP9_AP = ApEntr(x9',dim,r);
AP10_AP = ApEntr(x10',dim,r);
AP11_AP = ApEntr(x11',dim,r);
AP12_AP = ApEntr(x12',dim,r);
AP13_AP = ApEntr(x13',dim,r);
AP14_AP = ApEntr(x14',dim,r);
AP15_AP = ApEntr(x15',dim,r);
AP16_AP = ApEntr(x16',dim,r);
AP17_AP = ApEntr(x17',dim,r);
AP18_AP = ApEntr(x18',dim,r);
AP19_AP = ApEntr(x19',dim,r);
AP20_AP = ApEntr(x20',dim,r);
AP21_AP = ApEntr(x21',dim,r);
AP22_AP = ApEntr(x22',dim,r);
```

```
AP23_AP = ApEntr(x23',dim,r);
AP24_AP = ApEntr(x24',dim,r);
AP25_AP = ApEntr(x25',dim,r);
AP26_AP = ApEntr(x26',dim,r);
AP27_AP = ApEntr(x27',dim,r);
AP28_AP = ApEntr(x28',dim,r);
AP29_AP = ApEntr(x29',dim,r);
AP30_AP = ApEntr(x30',dim,r);

%ML direction
AP1_ML = ApEntr(y1',dim,r);
AP2_ML = ApEntr(y2',dim,r);
AP3_ML = ApEntr(y3',dim,r);
AP4_ML = ApEntr(y4',dim,r);
AP5_ML = ApEntr(y5',dim,r);
AP6_ML = ApEntr(y6',dim,r);
AP7_ML = ApEntr(y7',dim,r);
AP8_ML = ApEntr(y8',dim,r);
AP9_ML = ApEntr(y9',dim,r);
AP10_ML = ApEntr(y10',dim,r);
AP11_ML = ApEntr(y11',dim,r);
AP12_ML = ApEntr(y12',dim,r);
AP13_ML = ApEntr(y13',dim,r);
AP14_ML = ApEntr(y14',dim,r);
AP15_ML = ApEntr(y15',dim,r);
AP16_ML = ApEntr(y16',dim,r);
AP17_ML = ApEntr(y17',dim,r);
AP18_ML = ApEntr(y18',dim,r);
AP19_ML = ApEntr(y19',dim,r);
AP20_ML = ApEntr(y20',dim,r);
AP21_ML = ApEntr(y21',dim,r);
AP22_ML = ApEntr(y22',dim,r);
AP23_ML = ApEntr(y23',dim,r);
AP24_ML = ApEntr(y24',dim,r);
AP25_ML = ApEntr(y25',dim,r);
AP26_ML = ApEntr(y26',dim,r);
AP27_ML = ApEntr(y27',dim,r);
AP28_ML = ApEntr(y28',dim,r);
AP29_ML = ApEntr(y29',dim,r);
AP30_ML = ApEntr(y30',dim,r);

ApEn2_AP = [AP1_AP AP2_AP AP3_AP AP4_AP AP5_AP AP6_AP AP7_AP AP8_AP AP9_AP AP10_AP
AP11_AP AP12_AP AP13_AP AP14_AP AP15_AP AP16_AP AP17_AP AP18_AP AP19_AP AP20_AP
AP21_AP AP22_AP AP23_AP AP24_AP AP25_AP AP26_AP AP27_AP AP28_AP AP29_AP AP30_AP];
tA_AP = 1:length(ApEn2_AP);

ApEn2_ML = [AP1_ML AP2_ML AP3_ML AP4_ML AP5_ML AP6_ML AP7_ML AP8_ML AP9_ML AP10_ML
AP11_ML AP12_ML AP13_ML AP14_ML AP15_ML AP16_ML AP17_ML AP18_ML AP19_ML AP20_ML
AP21_ML AP22_ML AP23_ML AP24_ML AP25_ML AP26_ML AP27_ML AP28_ML AP29_ML AP30_ML];
tA_ML = 1:length(ApEn2_ML);

%% PLOT GENERATION %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
figure(1)
subplot(2,2,1), plot(tA_AP, ApEn2_AP)
xlabel('Time (s)','FontSize', 12), ylabel('ApEn (AP)','FontSize', 12),ylim([0 .6]);
subplot(2,2,2), plot(tA_ML, ApEn2_ML)
xlabel('Time (s)','FontSize', 12), ylabel('ApEn (ML)','FontSize', 12),ylim([0 .6]);
subplot(2,2,3), plot(tS_AP, SampEn2_AP)
xlabel('Time (s)','FontSize', 12), ylabel('SampEn (AP)','FontSize', 12),ylim([0 .6]);
subplot(2,2,4), plot(tS_ML, SampEn2_ML)
```

```
xlabel('Time (s)','FontSize', 12), ylabel('SampEn (ML)','FontSize', 12),ylim([0
.6]);
```

C.5 *ApEn and SampEn Averages*

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Title: ApEn_SampEn_Averages.m
% Author Jayla Wesley
% Notes: this script file loads subject data into a usable structure for
% further analysis. estimates the average of entire data set EOFT: Trials 2 - 6
%   1. Cx is the Anterior-Posterior direction
%   2. Cy is the Medial Lateral Direction
%   3. Downsampling by a factor of 20, 1200Hz to 60Hz
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
close all; clear; clc;

%% Trial 02 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
filtdata2 = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 04\Subject 04 Trial Data
Raw\SB04_Trial02.csv');
Cx_filt = filtdata2(4:36003,9);
Cy_filt = filtdata2(4:36003,10);
Cz_filt = filtdata2(4:36003,11);

% downsample the data 1200Hz to 60Hz
Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);

x = Cx_filtds(1:1800);
y = Cy_filtds(1:1800);
z = Cz_filtds(1:1800);

% Calculate Center of Pressure
data_COPAP = x'; % get transpose for time series AP calculation
data_COPML = y'; % get transpose for time series ML calculation

% Entropy Variable Declaration Trial 2
dim = 2; % embedded dimension = 2
r = 0.2; % tolerance

% Sample Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%%
% ranging r values
SampEntropy22ML = SampEntr(data_COPML,dim,r);
SampEntropy22AP = SampEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
SampEntropy052ML = SampEntr(data_COPML,dim,r);
SampEntropy052AP = SampEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; % tolerance
SampEntropy12ML = SampEntr(data_COPML,dim,r);
SampEntropy12AP = SampEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
SampEntropy152ML = SampEntr(data_COPML,dim,r);
SampEntropy152AP = SampEntr(data_COPAP,dim,r);
```

```
% r = .25
r = 0.25; % tolerance
SampEntropy252ML = SampEntr(data_COPML,dim,r);
SampEntropy252AP = SampEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; % tolerance
SampEntropy32ML = SampEntr(data_COPML,dim,r);
SampEntropy32AP = SampEntr(data_COPAP,dim,r);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%
% ranging r values
r = 0.2; % tolerance
AproxEntropy22ML = ApEntr(data_COPML,dim,r);
AproxEntropy22AP = ApEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
AproxEntropy052ML = ApEntr(data_COPML,dim,r);
AproxEntropy052AP = ApEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; %tolerance
AproxEntropy12ML = ApEntr(data_COPML,dim,r);
AproxEntropy12AP = ApEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
AproxEntropy152ML = ApEntr(data_COPML,dim,r);
AproxEntropy152AP = ApEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
AproxEntropy252ML = ApEntr(data_COPML,dim,r);
AproxEntropy252AP = ApEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; %tolerance
AproxEntropy32ML = ApEntr(data_COPML,dim,r);
AproxEntropy32AP = ApEntr(data_COPAP,dim,r);



%% Trial 03 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
filtdata3 = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 04\Subject 04 Trial Data
Raw\SB04_Trial03.csv');
Cx_filt = filtdata3(4:36003,9);
Cy_filt = filtdata3(4:36003,10);
Cz_filt = filtdata3(4:36003,11);

Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);

% Center of Pressure (COP) Calculation %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x = Cx_filtds(1:1800); % 1 second of data 1-60
y = Cy_filtds(1:1800);
z = Cz_filtds(1:1800);

% Calculate Center of Pressure
data_COPAP = x'; % get transpose for time series AP calculation
data_COPML = y'; % get transpose for time series ML calculation

% Entropy Variable Declaration Trial 3
dim = 2; % embedded dimension = 2
```

```
r = 0.2; % tolerance

% Sample Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% range of r values
SampEntropy23ML = SampEntr(data_COPML,dim,r);
SampEntropy23AP = SampEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
SampEntropy053ML = SampEntr(data_COPML,dim,r);
SampEntropy053AP = SampEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; % tolerance
SampEntropy13ML = SampEntr(data_COPML,dim,r);
SampEntropy13AP = SampEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
SampEntropy153ML = SampEntr(data_COPML,dim,r);
SampEntropy153AP = SampEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
SampEntropy253ML = SampEntr(data_COPML,dim,r);
SampEntropy253AP = SampEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; % tolerance
SampEntropy33ML = SampEntr(data_COPML,dim,r);
SampEntropy33AP = SampEntr(data_COPAP,dim,r);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%
% range of r values
r = 0.2; % tolerance
AproxEntropy23ML = ApEntr(data_COPML,dim,r);
AproxEntropy23AP = ApEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
AproxEntropy053ML = ApEntr(data_COPML,dim,r);
AproxEntropy053AP = ApEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; %tolerance
AproxEntropy13ML = ApEntr(data_COPML,dim,r);
AproxEntropy13AP = ApEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
AproxEntropy153ML = ApEntr(data_COPML,dim,r);
AproxEntropy153AP = ApEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
AproxEntropy253ML = ApEntr(data_COPML,dim,r);
AproxEntropy253AP = ApEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; %tolerance
AproxEntropy33ML = ApEntr(data_COPML,dim,r);
AproxEntropy33AP = ApEntr(data_COPAP,dim,r);



%% Trial 04 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
filtdata4 = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 04\Subject 04 Trial Data
Raw\SB04_Trial04.csv');
```

```
Cx_filt = filtdata4(4:36003,9);
Cy_filt = filtdata4(4:36003,10);
Cz_filt = filtdata4(4:36003,11);

Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);

% Center of Pressure (COP) Calculation %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x = Cx_filtds(1:1800); % 1 second of data 1-60
y = Cy_filtds(1:1800);
z = Cz_filtds(1:1800);

data_COPAP = x'; % get transpose for time series AP calculation
data_COPML = y'; % get transpose for time series ML calculation

% Entropy Variable Declaration Trial 4
dim = 2; % embedded dimension = 2
r = 0.2; % tolerance

% Sample Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%%
% ranges of r
SampEntropy24ML = SampEntr(data_COPML,dim,r);
SampEntropy24AP = SampEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
SampEntropy054ML = SampEntr(data_COPML,dim,r);
SampEntropy054AP = SampEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; % tolerance
SampEntropy14ML = SampEntr(data_COPML,dim,r);
SampEntropy14AP = SampEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
SampEntropy154ML = SampEntr(data_COPML,dim,r);
SampEntropy154AP = SampEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
SampEntropy254ML = SampEntr(data_COPML,dim,r);
SampEntropy254AP = SampEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; % tolerance
SampEntropy34ML = SampEntr(data_COPML,dim,r);
SampEntropy34AP = SampEntr(data_COPAP,dim,r);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%
% ranges of r
r = 0.2; % tolerance
AproxEntropy24ML = ApEntr(data_COPML,dim,r);
AproxEntropy24AP = ApEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
AproxEntropy054ML = ApEntr(data_COPML,dim,r);
AproxEntropy054AP = ApEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; %tolerance
AproxEntropy14ML = ApEntr(data_COPML,dim,r);
AproxEntropy14AP = ApEntr(data_COPAP,dim,r);
% r = .15
```

```
r = 0.15; % tolerance
AproxEntropy154ML = ApEntr(data_COPML,dim,r);
AproxEntropy154AP = ApEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
AproxEntropy254ML = ApEntr(data_COPML,dim,r);
AproxEntropy254AP = ApEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; %tolerance
AproxEntropy34ML = ApEntr(data_COPML,dim,r);
AproxEntropy34AP = ApEntr(data_COPAP,dim,r);



%% Trial 05 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
filtdata5 = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 04\Subject 04 Trial Data
Raw\SB04_Trial05.csv');
Cx_filt = filtdata5(4:36003,9);
Cy_filt = filtdata5(4:36003,10);
Cz_filt = filtdata5(4:36003,11);

Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);

% Center of Pressure (COP) Calculation %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x = Cx_filtds(1:1800); % 1 second of data 1-60
y = Cy_filtds(1:1800);
z = Cz_filtds(1:1800);

data_COPAP = x'; % get transpose for time series AP calculation
data_COPML = y'; % get transpose for time series ML calculation

% Entropy Variable Declaration Trial 5
dim = 2; % embedded dimension = 2
r = 0.2; % tolerance

% Sample Entropy(SampEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%%%
% ranges of r
SampEntropy25ML = SampEntr(data_COPML,dim,r);
SampEntropy25AP = SampEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
SampEntropy055ML = SampEntr(data_COPML,dim,r);
SampEntropy055AP = SampEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; % tolerance
SampEntropy15ML = SampEntr(data_COPML,dim,r);
SampEntropy15AP = SampEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
SampEntropy155ML = SampEntr(data_COPML,dim,r);
SampEntropy155AP = SampEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
SampEntropy255ML = SampEntr(data_COPML,dim,r);
SampEntropy255AP = SampEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; % tolerance
```

```
SampEntropy35ML = SampEntr(data_COPML,dim,r);
SampEntropy35AP = SampEntr(data_COPAP,dim,r);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%
% ranges of r
r = 0.2; % tolerance
AproxEntropy25ML = ApEntr(data_COPML,dim,r);
AproxEntropy25AP = ApEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
AproxEntropy055ML = ApEntr(data_COPML,dim,r);
AproxEntropy055AP = ApEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; %tolerance
AproxEntropy15ML = ApEntr(data_COPML,dim,r);
AproxEntropy15AP = ApEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
AproxEntropy155ML = ApEntr(data_COPML,dim,r);
AproxEntropy155AP = ApEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
AproxEntropy255ML = ApEntr(data_COPML,dim,r);
AproxEntropy255AP = ApEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; %tolerance
AproxEntropy35ML = ApEntr(data_COPML,dim,r);
AproxEntropy35AP = ApEntr(data_COPAP,dim,r);



%% Trial 06 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
filtdata6 = readmatrix('C:\Users\jmwesley\OneDrive - Newkirk Electric Associates,
Inc\Documents\GVSU Masters 22\EGR 695 Masters Thesis\Subject 04\Subject 04 Trial Data
Raw\SB04_Trial6.csv');
Cx_filt = filtdata6(4:36003,9);
Cy_filt = filtdata6(4:36003,10);
Cz_filt = filtdata6(4:36003,11);

Cx_filtds = downsample(Cx_filt,20);
Cy_filtds = downsample(Cy_filt,20);
Cz_filtds = downsample(Cz_filt,20);

% Center of Pressure (COP) Calculation %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
x = Cx_filtds(1:1800); % 1 second of data 1-60
y = Cy_filtds(1:1800);
z = Cz_filtds(1:1800);

data_COPAP = x'; % get transpose for time series AP calculation
data_COPML = y'; % get transpose for time series ML calculation

% Entropy Variable Declaration Trial 6
dim = 2; % embedded dimension = 2
r = 0.2; % tolerance

% Sample Entropy(SampEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%%%
% ranges of r
SampEntropy26ML = SampEntr(data_COPML,dim,r);
SampEntropy26AP = SampEntr(data_COPAP,dim,r);
```

```
% r = .05
r = 0.05; % tolerance
SampEntropy056ML = SampEntr(data_COPML,dim,r);
SampEntropy056AP = SampEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; % tolerance
SampEntropy61ML = SampEntr(data_COPML,dim,r);
SampEntropy61AP = SampEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
SampEntropy156ML = SampEntr(data_COPML,dim,r);
SampEntropy156AP = SampEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
SampEntropy256ML = SampEntr(data_COPML,dim,r);
SampEntropy256AP = SampEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; % tolerance
SampEntropy36ML = SampEntr(data_COPML,dim,r);
SampEntropy36AP = SampEntr(data_COPAP,dim,r);

% Approximate Entropy(ApEn) Calculation (Function) %%%%%%%%%%%%%%%%%%%%%%%%%%
% ranges of r
r = 0.2; % tolerance
AproxEntropy26ML = ApEntr(data_COPML,dim,r);
AproxEntropy26AP = ApEntr(data_COPAP,dim,r);

% r = .05
r = 0.05; % tolerance
AproxEntropy056ML = ApEntr(data_COPML,dim,r);
AproxEntropy056AP = ApEntr(data_COPAP,dim,r);
% r = .1
r = 0.1; %tolerance
AproxEntropy61ML = ApEntr(data_COPML,dim,r);
AproxEntropy61AP = ApEntr(data_COPAP,dim,r);
% r = .15
r = 0.15; % tolerance
AproxEntropy156ML = ApEntr(data_COPML,dim,r);
AproxEntropy156AP = ApEntr(data_COPAP,dim,r);
% r = .25
r = 0.25; % tolerance
AproxEntropy256ML = ApEntr(data_COPML,dim,r);
AproxEntropy256AP = ApEntr(data_COPAP,dim,r);
% r = .3
r = 0.3; %tolerance
AproxEntropy36ML = ApEntr(data_COPML,dim,r);
AproxEntropy36AP = ApEntr(data_COPAP,dim,r);



%% Results %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

format long

[AproxEntropy052ML AproxEntropy053ML AproxEntropy054ML AproxEntropy055ML
AproxEntropy056ML AproxEntropy12ML AproxEntropy13ML AproxEntropy14ML
AproxEntropy15ML AproxEntropy61ML AproxEntropy152ML AproxEntropy153ML
AproxEntropy154ML AproxEntropy155ML AproxEntropy156ML AproxEntropy22ML
AproxEntropy23ML AproxEntropy24ML AproxEntropy25ML AproxEntropy26ML
AproxEntropy252ML AproxEntropy253ML AproxEntropy254ML AproxEntropy255ML
AproxEntropy256ML AproxEntropy32ML AproxEntropy33ML AproxEntropy34ML
```

AproxEntropy35ML AproxEntropy36ML]

[AproxEntropy052AP AproxEntropy053AP AproxEntropy054AP AproxEntropy055AP
AproxEntropy056AP AproxEntropy12AP AproxEntropy13AP AproxEntropy14AP
AproxEntropy15AP AproxEntropy61AP AproxEntropy152AP AproxEntropy153AP
AproxEntropy154AP AproxEntropy155AP AproxEntropy156AP AproxEntropy22AP
AproxEntropy23AP AproxEntropy24AP AproxEntropy25AP AproxEntropy26AP
AproxEntropy252AP AproxEntropy253AP AproxEntropy254AP AproxEntropy255AP
AproxEntropy256AP AproxEntropy32AP AproxEntropy33AP AproxEntropy34AP
AproxEntropy35AP
AproxEntropy36AP]

[SampEntropy052ML SampEntropy053ML SampEntropy054ML SampEntropy055ML
SampEntropy056ML SampEntropy12ML SampEntropy13ML SampEntropy14ML
SampEntropy15ML SampEntropy61ML SampEntropy152ML SampEntropy153ML
SampEntropy154ML SampEntropy155ML SampEntropy156ML SampEntropy22ML
SampEntropy23ML SampEntropy24ML SampEntropy25ML SampEntropy26ML
SampEntropy252ML SampEntropy253ML SampEntropy254ML SampEntropy255ML
SampEntropy256ML SampEntropy32ML SampEntropy33ML SampEntropy34ML
SampEntropy35ML SampEntropy36ML]

[SampEntropy052AP SampEntropy053AP SampEntropy054AP SampEntropy055AP
SampEntropy056AP SampEntropy12AP SampEntropy13AP SampEntropy14AP
SampEntropy15AP SampEntropy61AP SampEntropy152AP SampEntropy153AP
SampEntropy154AP SampEntropy155AP SampEntropy156AP SampEntropy22AP
SampEntropy23AP SampEntropy24AP SampEntropy25AP SampEntropy26AP
SampEntropy252AP SampEntropy253AP SampEntropy254AP SampEntropy255AP
SampEntropy256AP SampEntropy32AP SampEntropy33AP SampEntropy34AP
SampEntropy35AP SampEntropy36AP]

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