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OPTIMISING GAIT STABILITY ANALYSIS IN PATIENTS WITH MUSCULOSKELETAL DISORDERS

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1. Introduction

Gait stability is vital in musculoskeletal health, directly influencing quality of life. Nonlinear metrics such as entropy and fractal dimension enhance understanding of gait stability beyond traditional measures, thus improving diagnostic and physical therapy assessments. Entropy metrics measure the regularity of time-series data as a number between 0 and 2, with lower values signifying a more regular series. Fractal dimension quantifies the complexity and self-similarity of time-series data.

This study aimed to determine which input variable values influence approximate entropy (*ApEn*), sample entropy (*SampEn*), and Higuchi's fractal dimension (*HFD*) parameters' effectiveness for evaluating the stability of various individuals.

2. Materials and methodology

Eighty-one participants (ages 14–84, weights 43–124 kg, heights 149–189 cm) performed self-paced walking trials on an instrumented treadmill; ten were healthy and 71 had spinal or lower limb orthopaedic issues. Self-paced treadmill walking was recorded on an instrumented Zebris FDM-THM treadmill (Zebris Medical GmbH) for 2 minutes after a 5-minute accommodation to establish a stable gait. The trials were recorded with a sampling frequency of 100 Hz.

The recorder ground reaction force data enabled calculation of centre of pressure (CoP) coordinates during the recorded time interval in both the anteroposterior (AP) and mediolateral (ML) directions. The coordinates were filtered with a zero-phase 6th-order Butterworth filter with a cut-off frequency of 20 Hz. Since the trials were self-paced, participants walked at different speeds, leading to variations in the number of gait cycles. To eliminate the impact of varying gait cycle count on the analysed nonlinear metrics, each measurement was standardised by trimming and resampling to 45 gait cycles, equivalent to 4500 data points.

ApEn values were calculated using the corresponding function from the MATLAB Predictive Maintenance Toolbox. The calculation required defining an embedding dimension (m), a time delay (τ), and a similarity criterion radius (r), expressed as a percentage of the time series' standard deviation (STD) [1]. τ values were estimated using Average Mutual Information (AMI), selecting the first local minimum of AMI as the lag. m was then estimated using the False Nearest Neighbour (FNN) algorithm.

After estimating and selecting the collective embedding dimension and time delay values, the effect of r was examined through iteration. In each direction, for every participant, the *ApEn* values were calculated for every 2% of the STD at a 2–100% interval for the similarity radius.

SampEn, a data-length-independent modification of ApEn, required the same m values but no τ [2]. With the m values already selected, r was determined using the same iterative method. The final variable values can be found in Table 1.

Table 1. Determined input variables for the calculation of *ApEn* and *SampEn*.

Parameter	m [-]	τ [-]	r [% of STD]
AP *ApEn*	4	19	20
ML *ApEn*	4	26	15
AP *SampEn*	4	-	20
ML *SampEn*	4	-	10

HFD values range from 1 to 2, where 1 corresponds to a straight line and 2 to a line that is so complex that it fills the area of a two-dimensional plane [3]. Calculation requires defining the maximum number of sub-series composed of the original time series, herein referred to as $k_{\max}$ [4]. *HFD* values were calculated for all participants on an interval of 4–200, in increments of four. *HFD* values reached their plateau around a $k_{\max}$ of 60 in the AP and a $k_{\max}$ of 120 in the ML directions. All computational procedures, including parameter tuning were executed using MATLAB (The MathWorks Inc., Version R2023a).

3. Results

The purpose of the study was to investigate how the choice of input variables influences nonlinear metrics and their applicability to assessing gait stability. After providing a coherent method for calculating these metrics, it was important to evaluate how parameter tuning impacts the obtained results.

To analyse these effects, another intentionally off-tuned dataset was created with respect to the input parameters. Since most parameter values level out beyond certain input thresholds, further increases would result in minimal variation. Therefore, for calculating the off-tuned data set, much smaller input values were used than those originally determined. For the entropy-based metrics (*ApEn* and *SampEn*) the r was set to 5% of the STD (both Ap and ML). In the case of the *HFD*, a $k_{\max}$ value of 20 was used.

Comparisons between well- and poorly tuned datasets were conducted visually and statistically. For the visual method, we examined CoP trajectories of participants with the lowest and highest parameter values under each tuning condition. The statistical approach compared distribution shapes and outlier counts across calculation methods to determine tuning effects.

Visual inspection of CoP trajectories at entropy extremes showed that tuned AP *ApEn* clearly differentiated between participants: low values linked to short, irregular steps; high values to long, regular cycles. Similarly, higher ML *ApEn* values were usually paired with trajectories that had maintained a constant width. Poor tuning blurred these distinctions, producing heterogeneous trajectories and undermining interpretability. *SampEn* proved largely insensitive to tuning: extreme-value trajectories retained their shapes but overlapped across methods. *HFD*'s fractal dimensions also distinguished gait types regardless of $k_{\max}$, although overlaps persisted. Only with tuned inputs in the ML *HFD* did the end-value trajectories diverge more clearly, with high values corresponding to more consistent step widths.

Statistical comparison of tuned versus off-tuned datasets showed that AP and ML *ApEn* distributions moved closer to normal when tuned, and AP *ApEn*'s outliers disappeared, improving data processability. *SampEn* showed mixed effects: tuned AP *SampEn* lost outliers but became less normal, while ML *SampEn* gained fewer outliers and retained near-normality. Tuning did not improve AP *HFD*'s distribution, but ML *HFD* became slightly more normal and cut outliers from three to two, hinting at a modest benefit.

4. Conclusions

The present study aimed to find suitable calculation methods for *ApEn*, *SampEn,* and *HFD* as these nonlinear metrics lack standardized reference values for gait stability evaluation. The various input variables of these metrics were tuned specifically on data gathered from gait, and the effects of the tuning were determined via comparison with a purposefully badly tuned dataset. The comparisons showed the large effect that input variable choice has on the final values and that the tuning had successfully resulted in values suitable for evaluating gait stability. The dataset incorporated a heterogeneous population, including both healthy participants and those with various musculoskeletal disorders, covering a broad range of age groups, weights, and heights.

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References

[1] The MathWorks, Inc., Predictive Maintenance Toolbox documentation. https://www.mathworks.com/help/predmaint/index.html.

[2] Martínez-Cagigal, V. Sample entropy. https://www.mathworks.com/matlabcentral/fileexchange/69381-sample-entropy. Accessed October 17, 2023.

[3] Higuchi, T. Approach to an irregular time series on the basis of the fractal theory. *Phys D: Nonlinear Phenom*, 1988, 31(4), 277–283.

[4] Monge-Álvarez, J. Higuchi and Katz fractal dimension measures. https://www.mathworks.com/matlabcentral/fileexchange/50290-higuchi-and-katz-fractal-dimension-measures. Accessed October 2, 2024.