Gait stability during shod and barefoot walking and running on a treadmill assessed by correlation entropy

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Abstract. This study tests correlation entropy, K_2, as a measure of stability for gait analysis. An average of 13 strides from 10 participants in each combination of one footwear (barefoot vs shod) condition and one gait mode (walking vs running) were collected during treadmill walking and running. Sagittal plane ankle, knee and hip angular displacement and velocity data were used for analysis. Two-way repeated measures ANOVA showed a main effect for gait mode ($p = .03$) – running had lower K_2 than walking, indicating higher stability. Although the sample of strides and participants was small, we speculate that the greater inertia for running helped stabilize movement control, making the running coordination pattern more resilient against small stride-to-stride perturbations.

Keywords: correlation entropy, gait, biomechanics, dynamical systems

1 Introduction

Human gait is a complex process involving the coordinated action of many muscles to mobilize the body in such a way as to satisfy the demands of the task. According to the concept of *motor abundance*, a vast number of configurations at the musculoskeletal level can be assembled to accomplish the same task [16]. This abundance is said to provide the movement system with flexibility to operate in the presence of numerous combinations of varying constraints, e.g., locomotion speed, obstacle avoidance. The interaction between the ground and the foot is one of the most important constraints as the dynamics between the two determine how forces are transmitted through the body, braking and propulsive forces, vertical acceleration of the center of mass and the stability of the movement system. With the term *stability* here, we refer to the resistance of the neuromuscular system to perturbations [9].

Barefoot gait has received an increasing amount of attention in the biomechanics literature in recent years. Barefoot gait presents an opportunity to investigate how the runner adapts to the changing foot-ground interface; however, its effects have mostly been measured in terms of extracted, discrete measures such as loading rates [5, 3], joint moments [23], angles and angular velocities [12] and spatio-temporal parameters [4]. Moreover, gait variability is typically characterized by scalar values such as standard deviation [19]. Such measures of variability have been shown not to reflect the control of the movement system in response to varying constraints [8].

The emergence of coordinated movement in gait has been treated as a dynamical system [2]; therefore, measures that analyse the development of the system over time, so-called dynamic invariants, should be applied. In particular, the greatest Lyapunov exponent (λ^*) provides information on whether the trajectories of a dynamical system converge ($\lambda^* < 0$) or diverge ($\lambda^* > 0$) with respect to its starting conditions. Thus, λ^* assesses whether the investigated dynamical system is chaotic [7]. However, estimating the Lyapunov exponents usually requires thorough phase space reconstruction when scalar measurements are used [7].

Different types of entropy measures also assess the predictability of an investigated dynamical system. One such measure is the Kolmogorov-Sinai (K) entropy, which is, however, difficult to calculate from experimental data. Therefore, in practice, different approaches are used to approximate K. A frequently used approach is to estimate K through the correlation entropy, K_2. There are several methods for computing K_2, including the recurrence plot approach. K_2 can be derived from the structure of diagonal lines in a recurrence plot [18]. An advantage of this approach is that K_2 can be determined without phase space reconstruction [24]. Bypassing the phase space reconstruction also affords the analysis of multivariate datasets – an attractive prospect for biomechanics.

The following interpretations can be drawn from K_2: $K_2 \approx 0$ means that the system under investigation is nearly regular or periodic, $K_2 > 0$ means the system is chaotic and if K_2 is infinite the system is random.

The purpose of this study is to test K_2 as a measure for determining differences in dynamical stability between barefoot versus shod gait and for walking versus running. We expected that, since the study participants were new to barefoot running, shod gait would be more stable, and also that the greater momentum associated with the comfortable running speed would stabilize the dynamics of the system compared to walking and result in greater K_2 for walking.

2 Material and Method

2.1 Procedures

After giving written consent and following a seven minute warm-up and familiarization trial, ten participants (five male, five female; age 26.8 ± 7.7 years) walked and ran for 30 s at two speeds normalized to leg length. The dimensionless Froude number was used to set the treadmill speed to limit the effect of body size on gait parameters. Based on pilot data [1], the Froude numbers 0.28 and 1.08 were used, which roughly corresponded to comfortable walking and running, respectively. Treadmill speeds, v, were determined by

$$v = \sqrt{F\,l\,g}, \tag{1}$$

where F is the Froude number, l is the leg length of the participant, without shoes, measured from the greater trochanter of the femur to the ground, and g is the acceleration due to gravity [6]. Mean speeds for walking and running were 1.43 m/s and 2.79 m/s, respectively. Each of the speeds were performed in two conditions: barefoot and shod. In the shod condition, participants wore their own running shoes. One of the participants' running shoes were considered minimalist [11]. None of the participants were experienced in barefoot running. All procedures in the study were approved by the Human Ethics Committee of the University of Otago.

Data were collected at 100 Hz using a ten-camera Vicon system (Oxford Metrics Ltd., UK). Local coordinate systems were established for the lower limbs according to the procedures in Robertson et al. [20]. Joint centers and subsequent ankle, knee and hip Cardan angles and angular velocities for the left leg were calculated in Visual3D (C-Motion, Germantown, MD). Stride movement times varied such that the number of strides available for analysis differed between participants; therefore, between 12 and 14 strides in each condition were selected for analysis. Toe-off and touchdown events were determined by finding local minima in vertical spatial position of the foot markers at the calcaneus and the head of the second metatarsal. Trials were then trimmed to individual strides from right toe-off to the next toe-off. A dual-pass 2nd order Butterworth filter with a cutoff of 10 Hz was applied to remove noise from the joint angular data [21]. All processing and analysis procedures were performed in MATLAB (The Mathworks, Natick, MA).

2.2 Method

The data analysis involved several steps and was conducted for each participant and condition individually. The analysis is based on the multivariate time series $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$, where $\mathbf{x}_i \in \Re^{6\times 1}$ consisting of the six kinematic variables described in the previous section. Since the value ranges of the variables were different, each variable was normalized using the z-score transformation. Further, each variable was resampled to 400 Hz using a cubic spline interpolation since a proper approximation of K_2 requires a certain length of the time series [18]. Additionally, to reduce correlation effects between the variables of the multivariate dataset, a principle component analysis was conducted to the respective multivariate dataset $D \in \Re^{n\times 6}$ with sampling rate τ. Based on the resulting principal component coefficients $C \in \Re^{6\times p}$, p is the number of principal components, the new feature set N was prepared through

$$N = D \times C \tag{2}$$

The next step is the calculation of the recurrence matrix on which recurrence plots are based. A recurrence plot is a method to visualize recurring states of a dynamical system. It is computed based on a trajectory containing measurement(s) of the system under investigation. Determining a recurrence plot usually requires phase space reconstruction which, however, is not necessary for the determination of the invariant K_2 [24]. In our case, the recurrence matrices were calculated with respect to the trajectory represented by N. According to Marwan et al. [18] the recurrence matrix is

$$\mathbf{R}_{i,j} = \Theta(\epsilon - \|N_{i,\cdot} - N_{j,\cdot}\|) \tag{3}$$

where ϵ is a predefined threshold, $\Theta(\cdot)$ is the Heaviside function, and $N_{i,\cdot}$ denotes the i-th row of N.

Finally, the correlation entropy K_2 can be estimated from a set of recurrence plots calculated for a range of ϵ [18]. For each $\mathbf{R}(\epsilon)$ the cumulative distribution of diagonal lines $P^c_\epsilon(l)$ must be determined. The probability of finding a diagonal line of at least length l in a $\mathbf{R}$ is given by

$$P^c_\epsilon(l)\ \epsilon^{D_2} \exp(-K_2(\epsilon)\tau) \tag{4}$$

For large l's and independent of ϵ, $P^c_\epsilon(l)$, represented on a logarithmic scale, should become a straight line with slope $-K_2\,\tau$ [24]. In this study, $P^c_\epsilon(l)$ was determined for 101 different $\epsilon \in [1, 3]$. The final K_2 values were determined as the mean of the 101 values of $K_2(\epsilon)$.

2.3 Statistical analysis

A two-way repeated measures ANOVA was conducted to compare the effects of footwear condition (barefoot versus shod) and gait mode (walk versus run) on the K_2 values of stability. Significance was set at $\alpha = 0.05$. All statistical procedures were conducted in MATLAB.

3 Results

Exemplar kinematics for Participant 1 walking at a comfortable speed are shown in fig. 1, and running at a comfortable speed in fig. 2. The ankle angle was defined so that neutral standing position is 0°, plantarflexion is negative and dorsiflexion is positive. Generally, throughout most of the stride the foot was more dorsiflexed when barefoot. Knee and hip angles were similar between barefoot and shod conditions (0° is extended, positive is flexed and negative hyperextended). Angular velocities were also similar between conditions, but statistical analysis of range of motion and angular velocities was not included in this paper.

Fig. 3 illustrates for Participant 3 how K_2 values were determined. Panel A) shows the log of the cumulative line distributions of the respective recurrence plots for each ϵ. To derive the K_2 values from such a histogram one identifies a line length l_t, the longer the better, where the distribution lines are roughly parallel for all ϵ. Subsequently, panel B) shows the $K_2(\epsilon)$ which are related to the respective absolute value of the slope at l_t times the sampling frequency

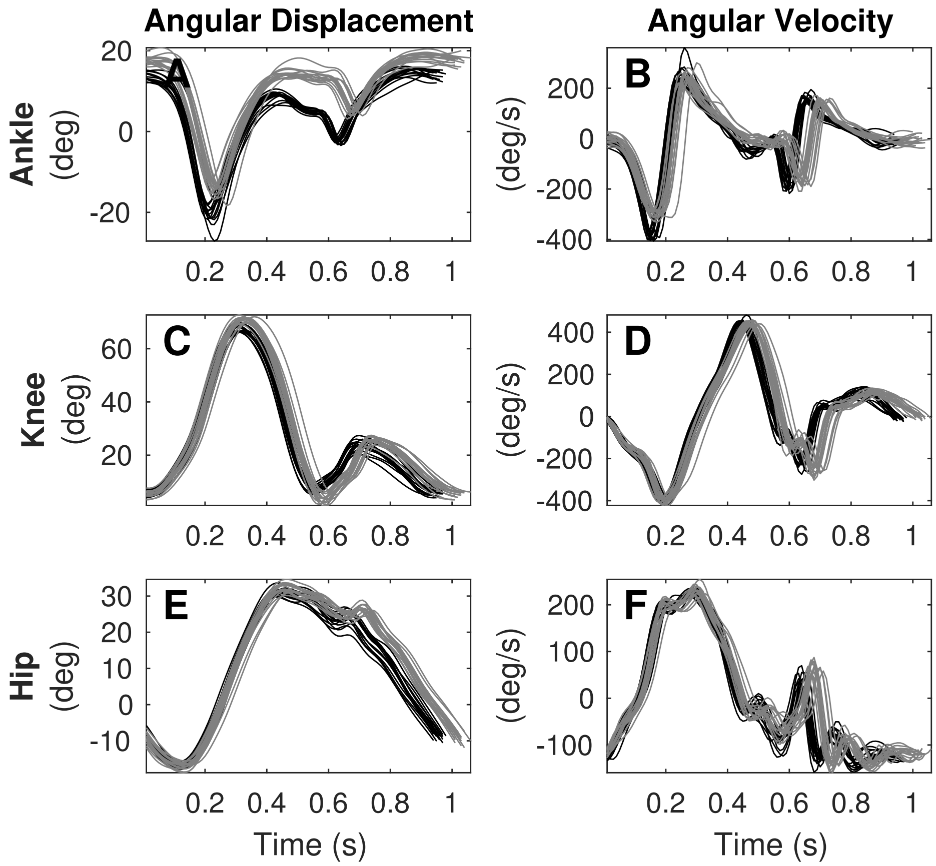

Fig. 1. Kinematic data for one example participant at the respective walking speed. A) ankle angle, B) ankle angular velocity, C) knee angle, D) knee angular velocity, E) hip angle and F) hip angular velocity. Barefoot strides are shown in black and shod in grey. Strides begin and end with right foot toe-off.

for ϵ. The resulting K_2 that was used for further analyses was determined as the mean of the $K_2(\epsilon)$. For the exemplar participant in fig. 3, l_t was 500 and $K_2 = 0.70 \pm 0.07$.

K_2 values were significantly higher for the walking strides compared to running, $F_{(1,9)} = 6.90, p = .03$ (fig. 4). K_2 values did not differ between barefoot compared to shod, $F_{(1,9)} = 0.01, p = .92$, and there was no significant interaction between gait mode and footwear, $F_{(1,9)} = 0.02, p = .73$. We also note that the variability in K_2 was high for all conditions (fig. 4).

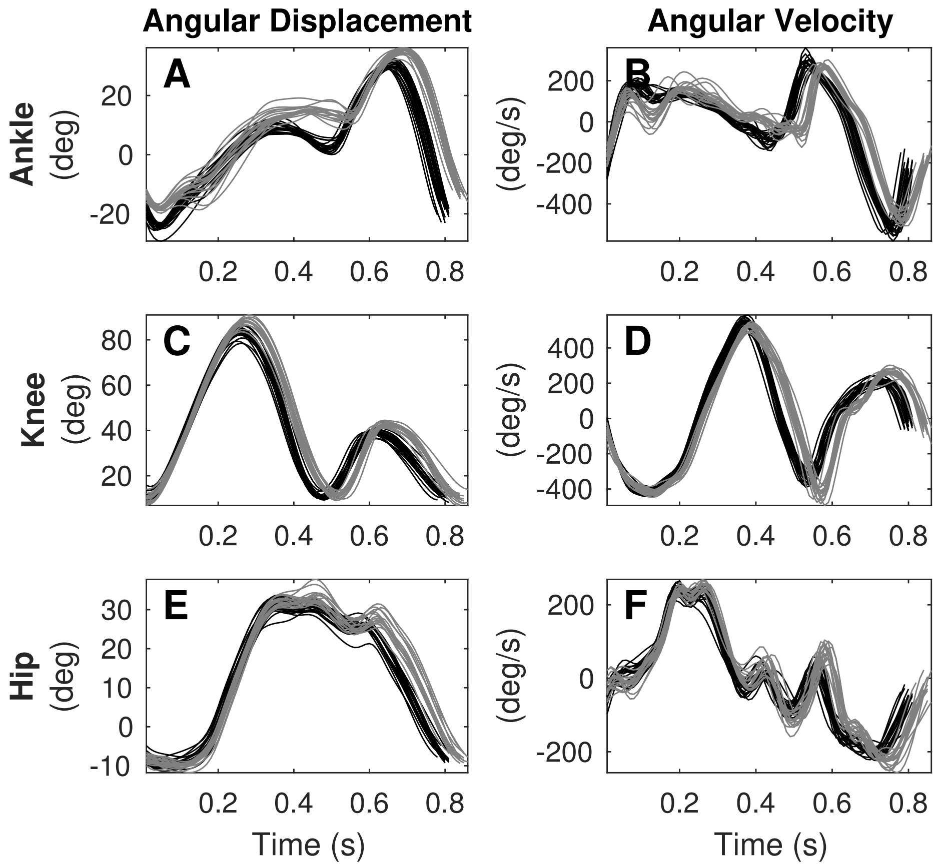

Fig. 2. Kinematic data for one example participant at the respective running speed. A) ankle angle, B) ankle angular velocity, C) knee angle, D) knee angular velocity, E) hip angle and F) hip angular velocity. Barefoot strides are shown in black and shod in grey. Strides begin and end with right foot toe-off.

4 Discussion

This study tested the correlation entropy value K_2 as a measure of stability in gait when representing strides by unilateral sagittal plane kinematics. K_2 is a measurement to assess the predictability of the investigated dynamical system and, thus, describes the (chaotic) variability of the system's behaviour; the more variable a system is, the less predictable it is. We expected shod running to be the most stable combination of gait mode and footwear condition, but only the main effect of running achieved significance. If the main effect of gait mode on stability is real, we suggest that increased momentum or inertia of the runner limits the complexity of the movement. When considering compensations along the kinematic chain of the lower extremity, running at comfortable pace is less complex

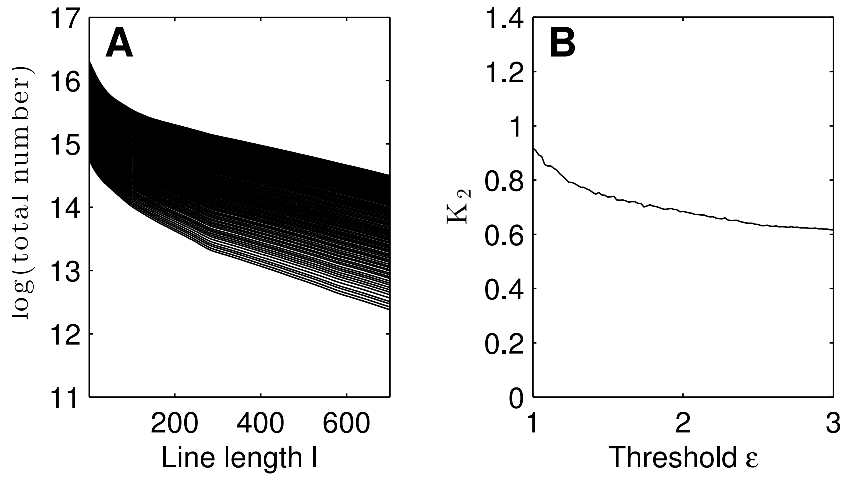

Fig. 3. A) Distribution of line length l of one participant at one condition, B) resulting $K_2(\epsilon)$ for $\epsilon \in [1, 3]$ at line length 500.

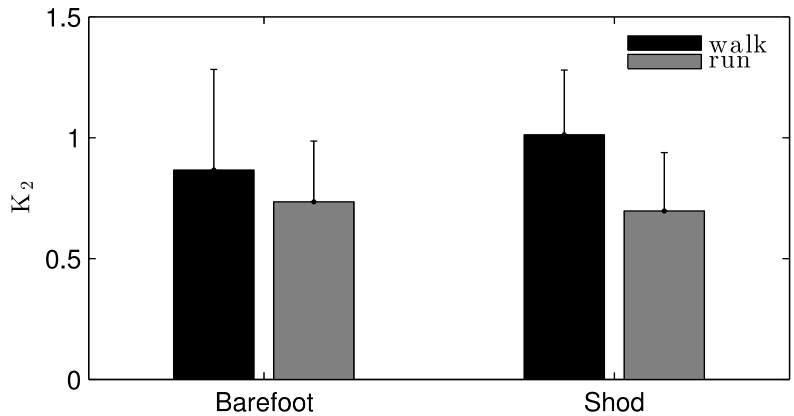

Fig. 4. Mean K_2 values for both walking and running in barefoot and shod conditions for all participants. Error bars represent one standard deviation.

than comfortable walking. In other words, the greater inertia associated with running simplified movement control, making the running coordination pattern more resilient against small stride-to-stride perturbations. However, we would need to use data from more participants to substantiate these interpretations.

Jordan and colleagues showed that stability increased at the preferred walking speed [15] as well as at the preferred running speed [14]. Furthermore, they showed greater ankle displacement stability during running compared to walking [13], although head displacement was more stable for walking. Given that Latt et al. [17] showed that preferred walking speeds stabilize head displacement and correlation entropy allows the analysis of stability using multivariate data, in future work we may look to combine lower extremity kinematics, as in the current study, with upper body kinematics to compare our work with that of Jordan et al. Conversely, England and Granata [10] showed greater stability at the slowest walking speeds assessed by λ^*. We did not look at speeds slower than the preferred walking speed, but future work may focus on these speeds as well as speeds around the transition speed to gain a better comparison between the multidimensional K_2 and λ^* used by [10].

Correlation entropy might be a promising measure of stability for biomechanical data. According to [22], K_2 is a lower bound for the sum of the positive Lyapunov exponents, which enables the stability of the system to be investigated. K_2 and λ^*, however, are different measures, which makes comparisons between studies difficult. Moreover, there are several different algorithms for calculating the phase space reconstruction as well as for approximating λ^*, which further complicates comparisons between e.g. [14] and [10]. K_2, calculated using the recurrence plot method alleviates the necessity to reconstruct the phase space; furthermore, it allows multi-dimensional time-series to be used – two features that make K_2 attractive for studying stability in biomechanical systems.

A major limitation of this analysis is the small sample of participants and the number of strides per condition. The approximation of K_2 values is based on time series of length $\sim 5,500$ in this research. According to [18] more than 10,000 data points are needed to achieve good K_2 approximations through the proposed recurrence plot based method. However, the measurements did not contain enough strides to achieve such long time series. Further resampling would not have added more information to the time series; therefore, we suggest for future research either to collect data for more strides, or to use bootstrapping techniques based on the measured strides to extend the respective time series for K_2 approximations using the proposed recurrence plot approach.

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