**TITLE**

Motor Variability in Sports: A Nonlinear Analysis of Race Walking.

**RUNNING TITLE**

Nonlinear Analysis of Race Walking Dynamics.

**KEYWORDS.**

Sample entropy; surrogate time series; biomechanics; locomotion; motor skills.

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**ABSTRACT**

This study aimed to analyse the nature of movement variability and to assess whether entropy measures may represent a valuable synthetic index of neuromuscular organisation. The regularity of kinematic/kinetic time series during race walking, the changes in the structure of intra-individual variability over the testing session and the influence of athletic skill in (inter)national rank athletes were investigated.

Motion analysis techniques were used. Sample entropy (*SampEn*) was adopted to examine fluctuations in lower-limb angles and ground-reaction-forces. The regularity of both original and surrogate time series was assessed and compared, by estimating *SampEn*, to verify the presence of nonlinear features in movement variability.

*SampEn* was statistically lower in original data than in surrogates. In contrast, the regularity of time series did not significantly change throughout the subsequent intra-individual repetitions. Hip and ankle joint angles and vertical ground reaction force manifested increased entropy for skilled athletes.

Results suggested that race walking variability was not only the product of random noise but also contained information about the inherent propriety of the neuro-musculo-skeletal system. Furthermore they provided some indications about the neuromuscular control over lower limb joints during race walking gait, and about the differences between more and less skilled subjects.

## INTRODUCTION

Consecutive repetitions of the same motor task are associated with kinematic or kinetic variables that appear as pseudo-periodic time series functions. Every time a subject repeats the same movement, a certain number of changes is registered between the successive trials. Motor variability (MV) is inherently present throughout the multiple levels of movement organisation and occurs not only between but even within individuals (e.g. Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006; Bartlett, Wheat, & Robins, 2007; Preatoni, Squadrone, & Rodano, 2005; Preatoni, 2007). MV results from the extreme complexity of the neuro-musculo-skeletal system and of the redundancy of its degrees of freedom. The neuro-muscular-skeletal system is always subjected to perturbations that may originate from both internal processes and external influences: biomechanical, morphological/anatomical, environmental and task constraints may all be factors that affect the final outcome (e.g. Müller & Sternad, 2004; Newell et al., 2006).

According to the control theory approach, movement variability is considered a negative property of the motor system which is not able to organize the multiple degrees of freedom and to make the final output match the planned program. MV is thus reduced to the concept of error (Bartlett et al., 2007). In contrast with this view, new interpretations of MV have been proposed. Variability ($V_{tot}$) is no more seen as detrimental instability but as a combination (Equation [1]) of random fluctuations (i.e. error, $V_e$) and functional changes that may be associated with proprieties of the neuromotor system ($V_{nl}$) (Hamill et al., 1999):

[1] $V_{tot} = V_e + V_{nl}$

where $V_e$ may in turn be partitioned into (Equation [2]): (i) the biological noise that is present within the neuro-musculo-skeletal system ($V_{eb}$); (ii) measurement and data processing errors ($V_{em}$); (iii) other external sources of variation ($V_{ee}$) that may come from changes in the environment or in goal settings.

[2] $$V_e = V_{eb} + V_{em} + V_{ee}$$

$V_{nl}$ may be interpreted as the flexibility of the system to explore different strategies to find the most proficient one among many available. This flexibility allows for learning a new movement or adjusting the already known one by gradually selecting the most appropriate pattern for the actual task (e.g. Dingwell, Cusumano, Cavanagh, & Sternad, 2001; Riley & Turvey, 2002). The subject is thus able to gradually release the degrees of freedom that have been initially frozen to gain a greater control over an unfamiliar situation (e.g. Hamill et al., 2005; Newell et al., 2006). Changes in the contributions of $V_e$ and $V_{nl}$ to the total variability may be signs of pathology or aging effects (e.g. Dingwell, Cusumano, Sternad, & Cavanagh, 2000).

Therefore, the most challenging issues are not only the quantification of MV, but also the insight into its origin and meaning (Bartlett et al., 2007). Unlike conventional statistics (e.g. SD, CV, ICC), which only quantify the overall variability, nonlinear dynamics tools may also help in evaluating the information MV conveys. Among them, entropy measures, such as approximate entropy, *ApEn* (Pincus, 1995), or sample entropy, *SampEn* (Richman & Moorman, 2000), are considered particularly suitable for the analysis of biological signals whose variability is of both deterministic and stochastic origin. Entropy indices measure the predictability of the signal: the higher the entropy, the less regular and predictable the time series. Changes in the regularity of motor patterns may be related to changes in motor strategies and may thus reveal the effects of adaptations, pathologies and skills learning (Bartlett et al., 2007).

Only recently and only a few authors (Newell et al., 2006) have used nonlinear dynamics to investigate movement variability, and to associate nonlinear indexes to pathologies (e.g. Dingwell et al., 2000; Vaillancourt, Slifkin, & Newell, 2001) or behavioural development concerning human posture and locomotion (e.g. Dingwell et al., 2001; Newell et al., 2003, 2006).

Moreover, it appears there are few research publications that apply nonlinear tools to the study of MV in sports and with elite athletes in particular. Nonlinear tools may be very useful in sports, because there are extraneous factors influencing variability that are easily masked by the overall MV. In fact, even elite performers cannot precisely replicate identical movement patterns after many years of training. Hence, the traditional quantification of variability in kinematic and kinetic measures is not enough, but the study of its likely nonlinear origin (i.e. $V_{nl}$ in Equation [1]) may reveal important information for understanding how MV may affect performance, for the design and monitoring of training programs, and for injury prevention. The modifications in the time-dependent structure of motor variability may emerge even when there is no apparent change in kinematic and kinetic variables concerning the overall magnitude of MV (Newell et al., 2006; Bartlett et al., 2007).

Among the huge variety of sports disciplines, race walking (RW) was chosen because of its unique locomotor peculiarities. *“Race Walking is a progression of steps so taken that the walker makes contact with the ground, so that no visible […] loss of contact* *occurs. The advancing leg shall be straightened […] from the moment of first contact with the ground until the vertical upright position"* (IAAF, 2006). RW is not a natural motor strategy because at the speed that race walkers are able to achieve, the athlete would naturally turn from normal walking (NW) to running (Cavagna & Kaneko, 1977). The specific constraints that the RW rules impose generate very particular biomechanical and coordinative demands. Furthermore, those restrictions add further control over the execution and make race walking rather stereotyped. Because of our interest in the analysis of motor variability, the choice of a very repeatable movement seemed a good basis for gaining more insight into a particularly complex and little known issue. Finally, RW is the motor task that most resembles normal walking, thus giving the chance of a straight comparison with one of the most studied movements in literature.

Therefore, the aims of the present study were:

1) to investigate the content of variability during a sports motor task, performed by high level athletes;

2) to understand whether the repetition of the same task in the lab could affect MV throughout the acquisitions;

3) to demonstrate how nonlinear dynamics could be a valuable tool for studying the kinematics and kinetics of a sports movement.

## METHODS

PARTICIPANTS

Four male and three female skilled race walkers of national and international rank were the subjects of this study. Their age, height and body mass were (mean±standard deviation): 19.7±2.1 years; 1.75±0.10 m; 58.3±8.3 kg. Detailed information about competitive results are reported in Table 1. From data in Table 1 and information provided by coaches, it emerged that the race walking velocity of the analysed athletes ranged from 3.34 to 4.17 $m \cdot s^{-1}$ during competitions and approximately from 2.75 to 5 $m \cdot s^{-1}$ during training. All subjects trained from a minimum of 6 to a maximum of 12 sessions a week. They did not report any lower limb injury or dysfunction at the time of the experiments.

**** Table 1 near here ****

The study was approved by the local institutional review board and every athlete was properly informed about aims of the research, testing procedures, personal data treatment and the possibility of withdrawal from the experiment at anytime. The subjects provided written informed consent before participation.

INSTRUMENTATION.

The kinematics of race walking were investigated using an eight TV-cameras (TVC) optoelectronic system (ELITE2002, BTS, Milan, Italy) to capture the three-dimensional coordinates of anatomical landmarks. The sampling rate was fixed at 100 Hz. TVC were positioned and set so that their field of view properly covered the acquisition volume and so that markers on both sides of the subject could be simultaneously detectable by the largest number of sensors. The optoelectronic system was calibrated before each experimental session, and its accuracy was assessed. A rigid wand with two markers fixed at a mutual distance of 600 mm was moved throughout the acquisition volume (approximately 8x2x4 metres). A maximum mean error of 1.0 mm concerning the distance between markers was obtained. Ground reaction forces (R) were measured by a force platform (AMTI OR6-7-1000, Watertown, USA) at a sampling frequency of 500 Hz.

DATA COLLECTION.

The SAFLo (Frigo, Rabuffetti, Kerrigan, Deming, & Pedotti, 1998) marker set (Figure 1) was adopted because it is a valid compromise between simplicity during acquisition procedures and reliability of measures (Frigo et al., 1998; Preatoni, 2007). It allowed for the measurement of the total body kinematics and let the athletes move naturally.

**** Figure 1 near here ****

The subjects were prepared by gluing 19 retro-reflective hemispherical markers (15 mm diameter), with a 1 cm pin support, onto selected anatomical landmarks (Figure 1(a)). Particular care was devoted to fixing the marker to the skin, so that both rapid movements and sweating could not threaten their correct and stable position.

After a standard 20 minutes warm up routine, and an average of 10-15 trials to better familiarise the athlete with the experimental settings, each participant was asked to race-walk across a 15 m long walkway. The dimensions of the laboratory were sufficient to let subjects perform their action continuously and to maintain an adequate, approximately constant speed through the acquisition volume. The force platform was positioned at two-thirds of the available path, in order to have enough space to accelerate and reach a stable velocity while being acquired. The athletes had previously been instructed not to alter or adjust their pace by targeting the plate. Only the trials in which they randomly put their left or right foot on the force platform were recorded. Twenty suitable race walking trials (Rodano & Squadrone, 2002; James, Herman, Dufek, & Bates, 2007; Preatoni, 2007), performed at a self-selected training pace, were collected for each athlete's left and right side. The athletes' coach always supervised the trials to visually check the appropriateness of performance in terms of both technique and intensity.

DATA PROCESSING.

Anthropometric measures and specially designed algorithms were used to estimate the three dimensional coordinates of internal joint centres (Figure 1(c) and Figure 1(d)), joint angles and their derivatives (Pedotti & Frigo, 1992). Data were filtered following the procedures proposed by D'Amico and Ferrigno (D'Amico & Ferrigno, 1990), which are particularly indicated for sports movements and granted that measurement noise could be reduced without losing possible useful information coming from the neuro-musculo-skeletal system (D'Amico, Ferrigno, & Rodano, 1989; D'Amico & Ferrigno, 1990). The power spectrum (PSD) of each raw signal was estimated by adopting an autoregressive model (AR) of order 9. The denoising filter was constructed as a low-pass filter. As automatic motion analyzers guarantee a known level of noise and its stationarity along the measurements, the frequency of the filter was simply obtained by considering the frequency $f_1$ at which signal to noise ratio (SNR) falls below 50%. The frequency $f_2$ which bounds 99.5% of the signal power and the frequency $f_3$ bounding the 99% of the signal power were assessed as well, in order to verify the consistency of the estimation. The filtering procedure is important for a reliable parameters evaluation. In general, it is recommended to be in the better condition of SNR before proceeding with the investigation of variability, otherwise measures of MV might be much more related to noise than to physiological factors.

Five time varying measures were considered: antero-posterior and vertical ground reaction forces ($R_{ap}(t)$, $R_v(t)$); and hip, knee and ankle joint angles in the sagittal plane ($A_{hs}(t)$, $A_{ks}(t)$, $A_{as}(t)$). These variables were chosen, at this stage, because they are considered the most reliable and representative measures of lower limb kinematics and kinetics during gait (e.g. Ferber, Davis, Williams, & Laughton, 2002; Queen, Gross, & Liu, 2006; Preatoni, 2007).

Only the stance phase of every acquisition was used. Therefore, the analysed movement was defined as the interval ($\Delta t$) between heel strike, when $R_v(t)$ overcomes a 5 N threshold, and toe off, when $R_v(t)$ reaches the base line again. Movement variability had to be extensively and finely investigated; hence, a high accuracy in determining the beginning and the end of the movement was necessary.

Non-normalised curves were used for nonlinear analyses of motion variability. No time normalisation procedures were performed in order to avoid any kind of alteration that re-sampling to a common number of points might have induced in the dynamics of time series. Individual kinematic and kinetic time series ($Y_i(t)$, where $Y$ stands for the analysed variable, $i$ for the $i$-th subject/side, and $t$ for the time points) were created by aligning the 20 available curves (Figure 2), so that they composed a sequence of similar events (stance phases) with an overall length that was consistently longer than the natural timescale of the single movement (Newell et al., 2006). The time series derived, thereof, might present discontinuities at the 19 junctions between subsequent trials. However, the loss of continuity involved a number of points that was far smaller (less than 2% in the worst case) than the overall length of the signal.

**** Figure 2 near here ****

A strictly continuous time series could have been obtained only by collecting data from consecutive strides performed on a treadmill. However, the chance of using a treadmill was discarded because: (1) it would have not allowed the estimation of ground reaction forces; and (2) it might have altered the natural movement of race walkers and might have influenced the outcoming movement variability which was the most relevant issues of this research (e.g. Alton et al., 1998; Wank et al., 1998; Dingwell et al., 2001; Wheat et al., 2005).

The regularity of each sequence of data was assessed by using sample entropy (*SampEn*) (Richman & Moorman, 2000). *SampEn*, similar to the more known approximate entropy (*ApEn*) (Pincus, 1995), measures the regularity of the signal (see the Appendix for a more detailed explanation of *ApEn* and *SampEn*). That is, it gauges the presence of similar patterns in a time series. Given a series, $Y(t)$, of $T$ points ($t$ = 1, …, $N$), *ApEn* and *SampEn* measure the logarithmic probability that two similar sequences of $m$ points extracted from $Y(t)$, remain similar (i.e. within tolerance given by $r$) on the next incremental comparison (i.e. for $m$+1 sequences) (Pincus, 1995; Richman & Moorman, 2000). *ApEn* and *SampEn* tend to 0 for regular or periodical time series, while the higher the *SampEn* (or *ApEn*) the more unpredictable patterns (Pincus, 1995; Richman & Moorman, 2000). Regularity relates to the complexity of the system generating the signal (Pincus, 1995). Thus a decrease in this characteristic may indicate a loss of complexity of the system.

*SampEn* shows a more consistent behaviour than *ApEn* for different choices of $m$ and $r$, and is largely independent upon record length (Richman & Moorman, 2000). Thus, although *ApEn* is a more common parameter in scientific research, *SampEn* was preferred for race walking gait variables. Since the analysed data sequences showed an apparent great regularity, $m$ was set to 1 and $r$ to 0.1·SD (where SD is the overall standard deviation of the time series) (Richman & Moorman, 2000).

Different levels of analysis concerning the regularity of time series were carried out.

First, the contribution of the different sources of variability (i.e. $V_e$ and $V_{nl}$ in Equation [1]) was investigated. To verify the presence of nonlinear features in MV of race walking we estimated the difference between the entropy content of original kinematic and kinetic waveforms ($Y_i(t)$) and of their surrogate counterparts ($\hat{Y}_i(t)$).

Surrogation is a procedure that alters a time series by removing the small scale structure of original data (chaotic, linear/nonlinear-deterministic) keeping the original large scale behaviour (periodicity, mean, variance and spectra). Surrogation methods are usually applied to test the hypothesis that an observed data series is the outcome of a certain type of dynamics of the analysed system (e.g. Small, Yu, & Harrison, 2001). A particularly suitable surrogation algorithm, the pseudo-periodic surrogate method (PPS) was applied for the analysis (Small et al., 2001; Miller et al., 2006). PPS provides a robust method to test pseudo-periodic time series data against the *null hypothesis* of a periodic sequence with uncorrelated noise. Its advantages consist in destroying the eventual nonlinear structure that characterises time series, without eliminating their periodic nature. Hence, if *SampEn* of $Y_i(t)$ is lower than *SampEn* of $\hat{Y}_i(t)$, the variability that occurs between trials (periods) of the *i*-th subject is not only the outcome of random processes. Figure 3 shows an example of surrogation performed by PPS. PPS is compared to a more common but less appropriate procedure (Schreiber & Schmitz, 2000), referring to the present application (Miller et al., 2006).

The following procedure was followed for each variable and subject: *SampEn* of $Y_i(t)$ was calculated. Ten surrogates of the original signal were created by using PPS. *SampEn* of $\hat{Y}_i(t)$ was defined as the average entropy calculated over those 10 surrogated counterparts of the original time series. Differences between entropy of $Y_i(t)$ and of $\hat{Y}_i(t)$ were evaluated through Wilcoxon tests ($\alpha$ = 0.05) and were expressed not only referring to absolute values but also as the percentage variation produced by surrogation. Differences in *SampEn* magnitude among the 5 analysed variables were tested by applying Kruskal-Wallis statistics ($\alpha$ = 0.05) and Bonferroni post-hoc comparison.

**** Figure 3 near here ****

Second, the *40* trials performed by each subject were split into two parts based on the execution order (i.e. first *20* and last 20 repetitions, each containing an equal number of left and right foot contacts). The regularity of the MV from the first 50% of the trials for each subject was compared to the regularity from the last 50%, so that eventual changes in the variability structure over the testing session could be detected. *SampEn* was calculated, for each variable and subject, on the time series created by aligning the first 20 trials ($Y_{Fi}(t)$) and on the time series made up of the last 20 ones ($Y_{Li}(t)$). The significance of differences between the entropy content of $Y_{Fi}(t)$ and of $Y_{Li}(t)$ were assessed by applying Wilcoxon tests ($\alpha$ = 0.05).

Finally, the MV of more and less skilled athletes was compared by investigating the regularity of the kinematic and kinetic waveforms they produced. The hypothesis was that sample entropy represents a synthetic index of neuromuscular organisation, and that it is useful for gauging and distinguishing performance proficiency and ability, even in a population of (inter)national rank individuals. Race walkers were assigned to 2 groups according to their skill level. This was determined by coupling competition results (Table 1) with the evaluation of an expert coach who judged their technical ability. s2, s5 and s6, who were under age 23 continental medallists, formed the more skilled group (MS); s1, s3, s4 and s7, who were good athletes at a national level, constituted the less skilled one (LS). Mann-Whitney tests ($\alpha$ = 0.05) were applied for the assessment of between groups differences concerning *SampEn* of every kinematic and kinetic variable considered.

Statistical analysis was completed by the estimation of the effect size to gauge the meaningfulness of significance tests (Cohen, 1990; Cohen, 1992). Cohen's *d* greater than 0.5 denoted a medium effect size, while values over 0.8 corresponded to a large effect.

**RESULTS**

Individual progression velocity ($v$) was determined by the average antero-posterior velocity of the centre of mass over $\Delta t$. The overall $v$ of the population was 2.72±0.23 m/s, comparable to a training pace. Intra individual coefficients of variation revealed very low levels of variability with the distribution of intra-individual CV at a 95$^{th}$ percentile of 4.6%.

The comparison between the *SampEn* content of individual time series and of their surrogate counterparts showed that *SampEn* of the former was significantly lower than the surrogates for all the kinematic and kinetic variables considered (Figure 4). Both angular and ground reaction measures revealed higher regularity in $Y_i(t)$ than in $\hat{Y}_i(t)$. The Wilcoxon tests were always positive showing statistically significant differences in terms of unpredictability: P values were all lower than 0.0015 ($A_{as}$) and Cohen's d greater than 0.806 ($A_{ks}$). *SampEn* median values ranged from 0.07 ($A_{as}$) to 0.21 ($R_{ap}$) referring to original time series; from 0.14 ($A_{as}$) to 0.40 ($R_{ap}$) referring to surrogates. Antero-posterior $R$ was the variable which showed both the greatest values of entropy and the largest difference between $Y_i(t)$ and $\hat{Y}_i(t)$ (0.19 between median values). The percentage differences showed an increase of *SampEn* after surrogation had been performed with a median percentage increase between 16% for the vertical component of ground reaction force and 59% for the hip angle in the sagittal plane.

Kruskal-Wallis tests evidenced higher magnitudes of *SampEn* in ground reaction force variables than in angular ones, and increased regularity at the hip and ankle joint with respect to the knee (P=0.03).

**** Figure 4 near here ****

No changes of regularity occurred throughout the testing session. Results generally reported stable values of *SampEn* between the first and the last half trials that every subject performed (Figure 5). *SampEn* significantly changed only for $R_{ap}$: median values increased from 0.20 ($Y_{Fi}(t)$) to 0.22 ($Y_{Li}(t)$).

**** Figure 5 near here ****

The more and less skilled groups manifested statistically different values of entropy for three of the five considered variables (Figure 6). $A_{hs}$ , $A_{as}$ and $R_v$ showed a significant increase of *SampEn* in MS, compared to LS (median and IQR): 0.10 (0.04) vs. 0.07 (0.01), with P = 0.017 and Cohen's d = 1.401; 0.11 (0.05) vs.0.06 (0.01) , with P = 0.017 and Cohen's d = 1.846; 0.21 (0.04) vs. 0.18 (0.04) , with P = 0.045 and Cohen's d = 1.430. *SampEn* concerning $R_{ap}$ was greater for less skilled race walkers, 0.19 (0.02) vs. 0.23 (0.05), with no statistical relevance (P = 0.070) but a large effect size (1.236). Knee joint waveforms evidenced a comparable level of predictability: 0.13 (0.07) vs. 0.13 (0.06).

**** Figure 6 near here ****

## DISCUSSION

The aim of this study was to gain insight into the content of movement variability during multiple repetitions of a sport activity. Race walking gait was the movement under investigation, and *SampEn* measures were used. The analysis was conducted at three levels.

The first step concerned the nature of MV and was carried out to understand whether the fluctuation that occurred over many repetitions of the same task were the outcome of noisy processes or were induced by nonlinear properties of the neuromotor dynamics (Newell et al., 2006). The *SampEn* of the measured waveforms was estimated and compared to the entropy of their PPS surrogates. *SampEn* values (Figure 4) were low (Richman & Moorman, 2000) and close to zero for every considered variable. Results confirmed what visual impression suggested: defining rules and practice make race walking a very stereotyped action. The regularity of signals has even greater relevance if we consider that the time series did not originate from continuous strides, but from the alignment of stance phases during subsequent passages in the acquisition volume. Despite the small magnitude of measured *SampEn*, significant differences between the original time series and their surrogates were reported for all the considered kinematic and kinetic measures. The meaningfulness of statistical tests was supported by the large effect sizes reported. The percentage decrease of regularity after original data had undergone surrogation was considerable and spanned between 16% for $R_v$, and 59% for $A_{hs}$. This would support the hypothesis that race walking variability was not only the product of random noise, but also contained a nonlinear structure that surrogation had eliminated. Therefore, in agreement with other authors' findings (e.g. Dingwell et al., 2001; Riley & Turvey, 2002; Newell et al., 2003, 2006; Müller & Sternad, 2004; Hamill et al., 2005; Bartlett et al., 2007), MV might possess functional information concerning the organisation of the neuro-musculo-skeletal system. This information may be an indicator of athletic condition, of enhancements due to motor learning/adaptation, or to anomalies due to latent pathologies and detrimental motor behaviours.

*RW* revealed an increase of regularity (i.e. a decrease of *SampEn*) passing from the knee to the ankle and hip joints. This was in contrast with the proximal to distal increase of regularity reported in the literature on normal and pathological behaviour (e.g. Newell & Vaillancourt, 2000). The difference may be related to RW rules that impose an unnatural pattern for knee flex-extension and shift the task of absorbing the initial impact and of accepting the load of body weight and inertial forces to the hip/pelvis and to the ankle (Murray et al., 1983; Cairns et al., 1986; Preatoni, 2007). The change from normal gait might thus imply an increased control over proximal and distal joints and, consequently, an increased regularity of related time series.

The issue of whether the individual MV can change during the testing session was also addressed. To our knowledge, there are not published works that study intra-session changes in movement variability. A comparison between first and last trials executed over a single testing session was carried out to understand whether the structure of variability changed over subsequent repetition of the same motor task. Namely, the effects of possible adaptations were investigated. In fact, athletes might progressively become more familiar with the experimental setting and thus modify the complexity of their motor strategy. The results indicated that the first trials and the later ones did not differ significantly in terms of pattern regularity (Figure 5). This could sustain the validity of the adopted experimental protocol which let race walkers be acquainted with testing procedures from the beginning.

The third level of this study was to show how the information MV conveys can be used practically. Nonlinear tools were thus used for the fine discrimination between more and less skilled athletes, and regularity of data sets was studied as a function of athletic ability in a population where all individuals had mastery of the movement (Figure 6). After dividing race walkers according to skill level, *SampEn* differences between more and less skilled groups were evaluated. Less skilled individuals manifested statistically significant differences from more skilled ones. Due to the limited number of subjects that composed MS and LS, a problem concerning low statistical power may arise. The numerosity of the two groups was due to their being made up of only high-level athletes. Hence, larger groups with the same characteristics would hardly be collected. Effect size analysis appeared to support the meaningfulness of these results, but also suggested that for one of the variables ($R_{ap}$, where P=0.07 and d=1.236) the small sample size may induce a type II error. *SampleEn* of $A_{hs}$ and $A_{as}$ was noticeably lower in group LS than in group MS suggesting that LS needed to add further control on those joints to compensate for the extended knee and to maintain a correct technique. These findings concurred with researchers who mostly investigated the influence of pathologies or aging effects (Vaillancourt et al., 2001; Newell et al., 2006). Greater values of entropy may be interpreted as a better flexibility and adaptability to unpredictable environmental changes. That is, subjects possessing an improved coordinative ability and mastery of movements, have a better and less rigid control over the body's degrees of freedom. The measures concerning the knee joint in our study seemed to support this hypothesis. In fact, the race walkers' knee pattern was imposed by external constraints (i.e. RW rules about knee locking), and time series regularity was comparable in the two groups. Force variables manifested increased magnitude of *SampEn*, compared to kinematic variables. *R* may be seen as the final outcome of the whole movement, so both the higher values of *SampEn*, and the greater predictability of $R_v$ for less skilled individuals were not unexpected.

## CONCLUSIONS

The present work proposed that an entropy measure (*SampEn*) could be used to address the issue of movement variability. MV is always present when the same action is repeated and even elite athletes cannot reproduce identical motor patterns. Environmental changes, training procedures, latent pathologies or incomplete recoveries may affect the organisation of the neuromuscular system. These influences are subtle and not easily detectable by using traditional analyses (Preatoni, 2007). Nevertheless, MV may be functional and the information it conveys may be important for performance monitoring.

*SampEn* indicated very interesting potential in addressing this issue. First, it presented theoretical interpretations of MV: although variability may appear as a negative propriety of the neuro-musculo-skeletal systems, it is not exclusively the outcome of random, noisy processes, but it most likely contains also information about the system's health and its flexibility to unstable external conditions. Second, it gave indications for experimental procedures, by showing that intra-individual regularity of patterns do not change over the acquisition process. Third, it characterised athletic ability by differentiating the performance of more and less skilled athletes.

The study illustrated how innovative methodologies and apparently complex mathematical tools could enhance the use of motion analysis and could be turned into practical applications. In fact, the method that was described and applied has the merit of being a synthetic index of the neuromuscular organisation. It may represent an important means for investigating individual peculiarities that may relate to fine performance technique, training/rehabilitative procedures, motor learning and underlying injury. Therefore, nonlinear analysis might be included in longitudinal monitoring of athletes in order to quantitatively support coaches' decisions and training procedures.

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**APPENDIX**

Pincus (1995) proposed a family of statistics, called Approximate Entropy (*ApEn*), which measures the recurrences of similar patterns in a time series. The computation of *ApEn* is based on the construction and comparisons of patterns of length *m*.

Given N data points {$u(i)$} with $i=1,..,N$, the algorithm constructs sequences $x_m(i)$ obtained by taking $x_m(i)=[u(i),\ldots,u(i+m-1)]$ and it computes, for each $i \leq N-m+1$, the quantity:

$$C_i^m(r) = N^{-1}\{\text{number of } x_m(j) \text{ such that } d[x_m(i), x_m(j)] \leq r\}, \qquad (1)$$

where $d[x_m(i), x_m(j)]$ is the distance between the vectors, defined as $\max\{|x(i)-x(j)|,\ldots,|x(i+m-1)-x(j+m-1|\}$.

$C_i^m(r)$ measures, with a tolerance *r*, the regularity of patterns by comparing them to a given pattern of length *m* (*m* and *r* are fixed values: *m* is the detail level at which the signal is analysed, *r* is a threshold, which filters out irregularities).

The regularity parameter is defined as *ApEn*(*m,r*)=lim $_{N\to\infty}[\Phi^m(r)-\Phi^{m+1}(r)]$, where $\Phi^m(r)=(N-m+1)^{-1}\sum_{i=1}^{N-m+1}\ln C_i^m(r)$.

*ApEn*(*m,r*,N)= $[\Phi^m(r)-\Phi^{m+1}(r)]$ is the estimator of this parameter for an experimental time series of fixed length N.

Richman and Moorman (2000) developed a modification of the aforementioned algorithm in order to improve *ApEn*; the name of this new statistic is Sample Entropy (*SampEn*).

The differences between *SampEn* and *ApEn* are: (1) self-matches are not counted; (2) only the first N-*m* vectors of length *m* are considered; and (3) the conditional probabilities are not estimated in a template fashion (they do not adopt as probability measure the ratio of the logarithmic sums, but they compute directly the logarithm of conditional probability).

After defining the following quantities, for $i,j \leq N\text{-}m$

$\mathrm{A}_i^m(r)$ =($N$-$m$-1)$^{-1}${number of $x_{m+1}(j)$ so that $d[x_{m+1}(i), x_{m+1}(j)] \leq r$ , $i \neq j$} (2)

$\mathrm{B}_i^m(r)$ =($N$-$m$-1)$^{-1}${number of $x_m(j)$ so that $d[x_m(i), x_m(j)] \leq r$ , $i \neq j$} (3)

$$\mathrm{A}^m(r) = (N-m)^{-1} \sum_{i=1}^{N-m} \mathrm{A}_i^m(r) \tag{4}$$

$$\mathrm{B}^m(r) = (N-m)^{-1} \sum_{i=1}^{N-m} \mathrm{B}_i^m(r) \tag{5}$$

the parameter *SampEn*($m$,$r$) is given by $\lim_{N\rightarrow\infty}\{-\ln[A^m(r)/B^m(r)]\}$ and the associated statistics *SampEn*($m$,$r$,N)= $-\ln[A^m(r)/B^m(r)]$.

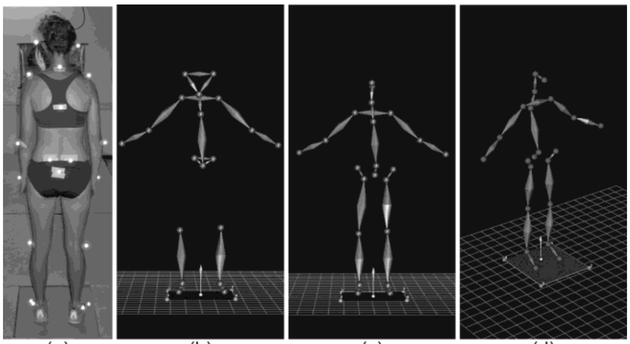
**TABLES**

**Table 1:** Athletes' season best over the most common distances of race walking competitions. The performances achieved over the 5, 10 and 20 km events are reported.

| subject | gender | 5 km | 10 km | 20 km |
|---|---|---|---|---|
| s1 | M | 0:20:06.61 (4.14) | 0:42:59.95 (3.88) | - |
| s2 | M | 0:21:03.68 (3.96) | 0:42:22.59 (3.93) | - |
| s3 | F | 0:23:25.60 (3.56) | 0:48:34.43 (3.43) | 1:39:47.0 (3.34) |
| s4 | F | 0:24:04.61 (3.46) | - | - |
| s5 | M | 0:19:58.00 (4.17) | 0:40:56.74 (4.07) | 1:25:39.0 (3.89) |
| s6 | F | 0:22:55.20 (3.64) | 0:46:38.53 (3.57) | - |
| s7 | M | 0:21:56.33 (3.80) | 0:44:24.97 (3.75) | 1:33:06.0 (3.58) |
| *mean* (speed) | | 3.82 | 3.77 | 3.60 |
| *SD* (speed) | | 0.28 | 0.24 | 0.28 |

Data are presented in the following format: *h:mm:ss.cc*, where *h* stands for hours, *m* for minutes, *s* for seconds and *c* are decimal places. Dashes mean that the athlete did not compete over that distance. Average progression speed ($m \cdot s^{-1}$) is reported between brackets.

**FIGURES**



(a) (b) (c) (d)

**Figure 1:** Example of subject prepared with the SAFLo marker set and the corresponding body model. (a) shows the anatomical landmarks where markers were glued: lower prominence of the sacrum, posterior superior iliac spines, lateral femoral condyles, lateral malleoli, and fifth metatarsal heads (for the pelvis and lower limbs section); seventh cervical vertebra and point of maximum kyphosis (for the column); acromion bones, lateral humerus epicondyles and styloideus processes (for the upper limbs section); parieto-occipital areas of the head. (b) reports the technical markers reconstruction. (c) and (d) display two different views of the stick diagram built on estimated joint centres.

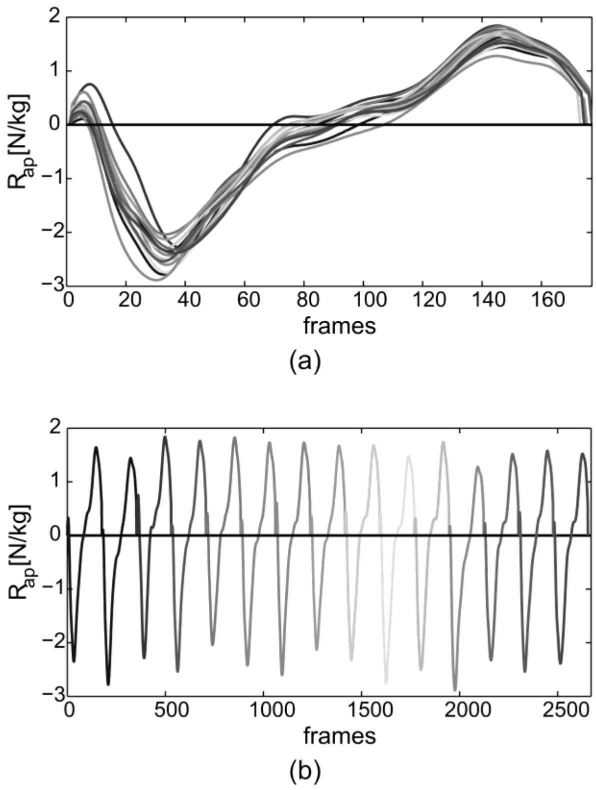



**Figure 2:** Example of creation of an individual pseudo-periodic time series. The original curves concerning the stance phase (a) were aligned to form a continuous sequence of similar events (b). The reported variable was $R_{ap}$ for s2 left limb.

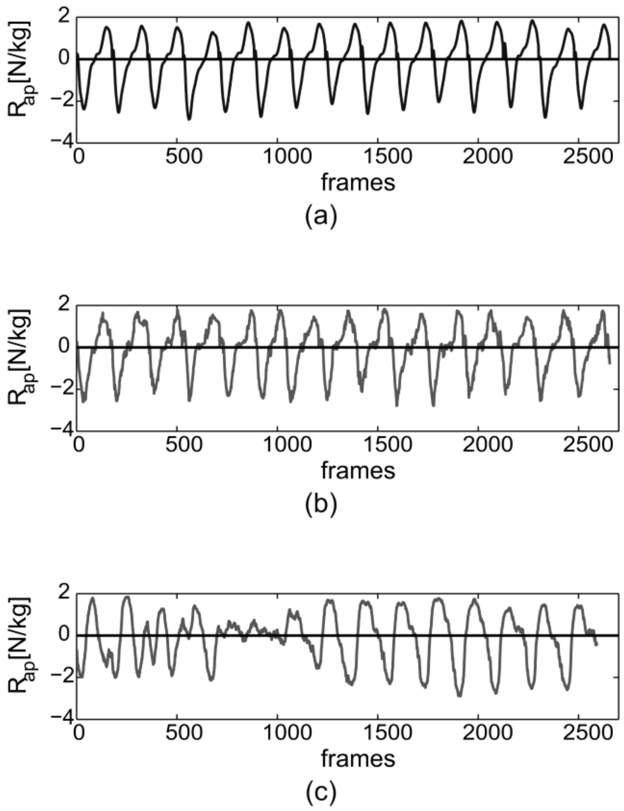



**Figure 3:** Example of the surrogation process, referring to an individual $R_{ap}$ time series. The original time series (a) can be compared to its surrogate forms, estimated by PPS (b) and by the iterative AAFT algorithm proposed by Schreiber and Schmitz (c). The surrogate in (c) has lost the original temporal geometry, while PPS surrogate maintained its overall temporal structure.

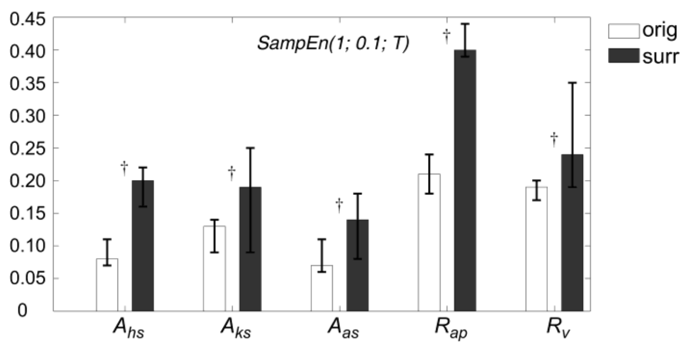



**Figure 4:** Comparison between *SampEn* in the original (white bars - $Y_i(t)$) and surrogate (dark bars - $\hat{Y}_i(t)$) time series data. Results concerning the 5 considered

variables are presented in terms of median values. Error bars depict interquartile ranges. (†) indicates that Wilcoxon tests evidenced statistically significant ($p < 0.05$) differences between groups.

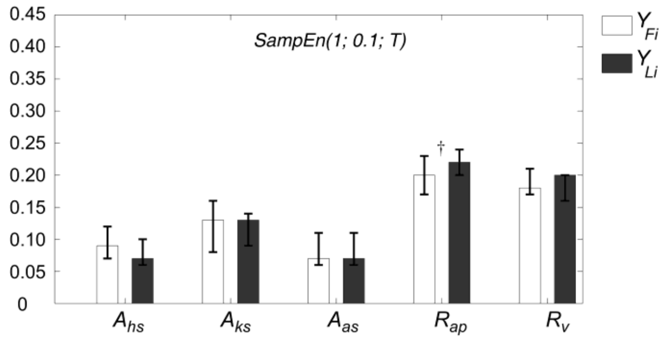



**Figure 5:** Comparison between *SampEn* in the first-half (white bars) and last-half (dark bars) trials of the experimental session. Results concerning the 5 considered variables are presented in terms of median values. Error bars depict interquartile ranges. (†) indicates that Wilcoxon tests evidenced statistically significant ($p < 0.05$) differences between groups.

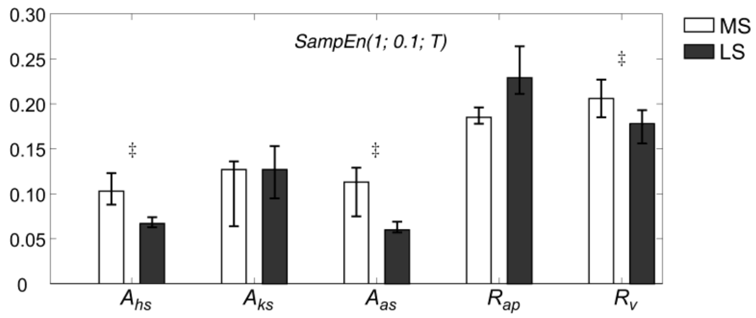



**Figure 6:** Comparison between *SampEn* in more (white bars) and less skilled (dark bars) race walkers. Results concerning the 5 considered variables are presented in terms of median values. Error bars depict interquartile ranges. (‡) indicates that Mann-Whitney tests evidenced statistically significant ($p < 0.05$) differences between groups.