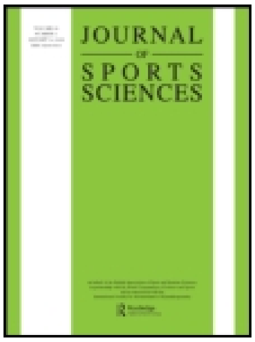

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Motor variability in sports: A non-linear analysis of race walking

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Abstract

This aim of this study was to analyse the nature of movement variability and to assess whether entropy measures may represent a valuable synthetic index of neuromuscular organization. The regularity of kinematic/kinetic time series during race walking, the changes in the structure of intra-individual variability over the test 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 non-linear features in movement variability. SampEn was statistically lower in the original data than in surrogates. In contrast, the regularity of time series did not change significantly throughout the subsequent intra-individual repetitions. Hip and ankle joint angles and vertical ground reaction force manifested increased entropy for skilled athletes. Results suggest 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 provide some indications about neuromuscular control of the lower limb joints during race walking gait, and about the differences between more and less skilled individuals.

Keywords: *Sample entropy, surrogate time series, biomechanics, locomotion, motor skills*

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 an individual repeats a movement, a certain number of changes is registered between the successive trials. Motor variability is inherently present throughout the multiple levels of movement organization and occurs not only between but also within individuals (e.g. Bartlett, Wheat, & Robins, 2007; Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006; Preatoni, 2007; Preatoni, Squadrone, & Rodano, 2005). Motor variability results from the extreme complexity of the neuro-musculo-skeletal system and from the redundancy of its degrees of freedom. The neuro-musculo-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 control theory, movement variability is considered a negative property of the motor system that is not able to organize the multiple degrees of freedom and to make the final output match the planned program. Motor variability is thus reduced to the concept of error (Bartlett et al., 2007). In contrast with this view, new interpretations of motor variability 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, Van Emmerik, Heiderscheit, & Li, 1999):

$$V_{tot} = V_e + V_{nl} \tag{1}$$

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

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and data-processing errors (V_{em}); (iii) other external sources of variation (V_{ee}) that may arise from changes in the environment or in goal settings.

$$V_e = V_{eb} + V_{em} + V_{ee} \tag{2}$$

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 person 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, Haddad, & Van Emmerik, 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 ageing effects (e.g. Dingwell, Cusumano, Sternad, & Cavanagh, 2000).

Therefore, the most challenging issues are not only the quantification of motor variability, but also the insight into its origin and meaning (Bartlett et al., 2007). Unlike conventional statistics (e.g. standard deviation, coefficient of variation, intra-class correlation coefficient), which only quantify the overall variability, non-linear dynamics tools may also help in evaluating the information motor variability conveys. Among them, entropy measures, such as approximate entropy, *ApEn* (Pincus, 1995; Pincus et al., 1991), 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 non-linear dynamics to investigate movement variability, and to associate non-linear 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, Broderick, Deutsch, & Slifkin, 2003; Newell et al., 2006).

Moreover, few research publications have applied non-linear tools to the study of motor variability in sports and with elite athletes in particular. Non-linear tools may be very useful in sports, because some extraneous factors that influence variability are easily masked by the overall motor variability. 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 non-linear origin (i.e. V_{nl} in equation 1) may reveal important information for understanding how motor variability might affect performance, for the design and monitoring of training programmes, 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 motor variability (Bartlett et al., 2007; Newell et al., 2006).

Among the huge variety of sports disciplines, race walking 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, 2008). Race walking 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 to running (Cavagna & Kaneko, 1977). The specific constraints that the race walking 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, race walking is the motor task that most resembles normal walking, thus giving us the chance to make a direct comparison with one of the most studied movements in the literature.

Thus 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 laboratory could affect motor variability throughout the acquisitions; (3) to demonstrate how non-linear 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 (mean age 19.7 years, $s = 2.1$; height 1.75 m, $s = 0.10$; mass 58.3 kg, $s = 8.3$) of national and international standard participated in this study. Detailed data on competitive results is reported in Table I. From the data in Table I and information provided by coaches, it emerged that the race walking velocity of the participants ranged from

Table I. Athletes' season best over the most common distances of race walking competitions (5, 10. and 20 km events).

Participant	Sex	5 km	10 km	20 km
1	M	0:20:06.61 (4.14)	0:42:59.95 (3.88)	–
2	M	0:21:03.68 (3.96)	0:42:22.59 (3.93)	–
3	F	0:23:25.60 (3.56)	0:48:34.43 (3.43)	1:39:47.0 (3.34)
4	F	0:24:04.61 (3.46)	–	–
5	M	0:19:58.00 (4.17)	0:40:56.74 (4.07)	1:25:39.0 (3.89)
6	F	0:22:55.20 (3.64)	0:46:38.53 (3.57)	–
7	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
s (speed)		0.28	0.24	0.28

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

3.34 to 4.17 $m \cdot s^{-1}$ during competitions and from approximately 2.75 to 5.0 $m \cdot s^{-1}$ during training. All participants trained for 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.

The study received approval from the local institutional review board and all participants were informed of the aims of the research, test procedures, anonymity of personal data, and the right to withdraw from the experiment at any time. The participants provided written informed consent before testing began.

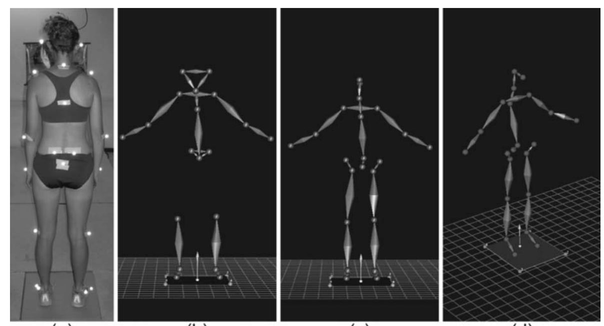

Figure 1. Example of athlete prepared with the SAFLo marker set and the corresponding body model. (a) Anatomical landmarks where markers were glued: lower prominence of the sacrum, posterior superior iliac spines, lateral femoral condyles, lateral malleoli, and fifth metatarsal heads (for the pelvis 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) Technical markers reconstruction. (c, d) Two different views of the stick diagram built on estimated joint centres.

Instrumentation

The kinematics of race walking were investigated using an eight TV-camera optoelectronic system (ELITE2002, BTS, Milan, Italy) to capture the three-dimensional coordinates of anatomical landmarks. The sampling rate was fixed at 100 Hz. The TV cameras were positioned and set so that their field of view covered the acquisition volume and so that markers on both sides of the participant were 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 $8 \times 2 \times 4$ m). A maximum mean error of 1.0 mm for the distance between markers was obtained. Ground reaction forces 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 participants move naturally.

The participants were prepared by gluing 19 retro-reflective hemispherical markers (15 mm diameter), with a 1 cm pin support, on to selected anatomical landmarks (Figure 1a). 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 min warm-up, and an average of 10–15 trials to familiarize him or her 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 allow the participants to 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, to allow 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 (James, Herman, Dufek, & Bates, 2007; Preatoni, 2007; Rodano & Squadrone, 2002), 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 1c, d), joint angles and their derivatives (Pedotti & Frigo, 1992). Data were filtered following the procedures proposed by D'Amico and Ferrigno (1990), which are especially suitable for sports movements and allow measurement noise to be reduced without losing possible useful information from the neuro-musculo-skeletal system (D'Amico & Ferrigno, 1990; D'Amico, Ferrigno, & Rodano, 1989). The power spectrum of each raw signal was estimated by adopting an autoregressive model of order 9. The denoising filter was constructed as a low-pass filter. As automatic motion analysers 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 the signal-to-noise ratio falls below 50%. The frequency f_2 that bounds 99.5% of the signal power and the frequency f_3 bounding 99% of the signal power were also assessed, to verify the consistency of the estimation. The filtering procedure is important for a reliable evaluation of parameters. In general, it is recommended that the signal-to-noise ratio is optimal before proceeding with the investigation of variability, otherwise measures of motor variability 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; Preatoni, 2007; Queen, Gross, & Liu, 2006).

Only the stance phase of each acquisition was used. Therefore, the analysed movement was defined as the interval (Δt) between heel strike, when $R_v(t)$ overcomes a 5 N threshold, and toe-off, when $R_v(t)$ returns to baseline. Since movement variability had to be investigated both extensively and finely, high accuracy in determining the beginning and the end of the movement was necessary.

Non-normalized curves were used for non-linear analyses of motion variability. No time normalization procedures were performed 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 participant/side, and t for the time points) were created by aligning the 20 available curves (Figure 2), so that they comprised a sequence of similar events (stance phases) with an overall length that was consistently longer than the natural time scale 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.

A strictly continuous time series could have been obtained only by collecting data from consecutive strides performed on a treadmill. However, the use of a treadmill was not considered because: (1) it would

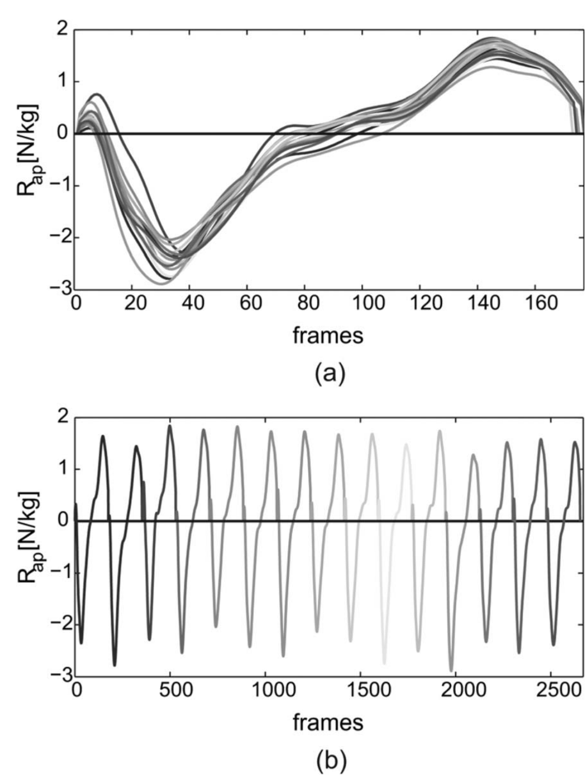

Figure 2. Example of an individual pseudo-periodic time series. The original curves concerning the stance phase (a) were aligned to form a continuous sequence of similar events (b). The reported variable was R_{ap} for the left limb of participant 2.

not have allowed the estimation of ground reaction forces, and (2) it might have altered the natural movement of race walkers and might have influenced movement variability, which were the most relevant topics of this research (e.g. Alton, Baldey, Caplan, & Morrissey, 1998; Dingwell et al., 2001; Wank, Frick, & Schmidtbleicher, 1998; Wheat, Baltzopoulos, Milner, Bartlett, & Tsaopoulos, 2005).

The regularity of each sequence of data was assessed using sample entropy (*SampEn*) (Richman & Moorman, 2000). *SampEn*, similar to the better 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 ($t = 1, \ldots, T$), *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 the 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 of 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 high regularity, m was set to 1 and r to $0.1 \cdot \mathrm{SD}$ (where SD is the overall standard deviation of the time series) (Richman & Moorman, 2000).

Different levels of analysis regarding the regularity of time series were performed. 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 non-linear features in motor variability 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/non-linear 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 (Miller, Stergiou, & Kurz, 2006; Small et al., 2001). The pseudo-periodic surrogate method provides a robust means 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 non-linear structure that characterizes 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 individual is not only the outcome of random processes. Figure 3 shows an example of surrogation performed by PPS. PPS is compared with 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 participant. First, *SampEn* of $Y_i(t)$ was calculated. Ten surrogates of the original signal were created 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 as absolute values but

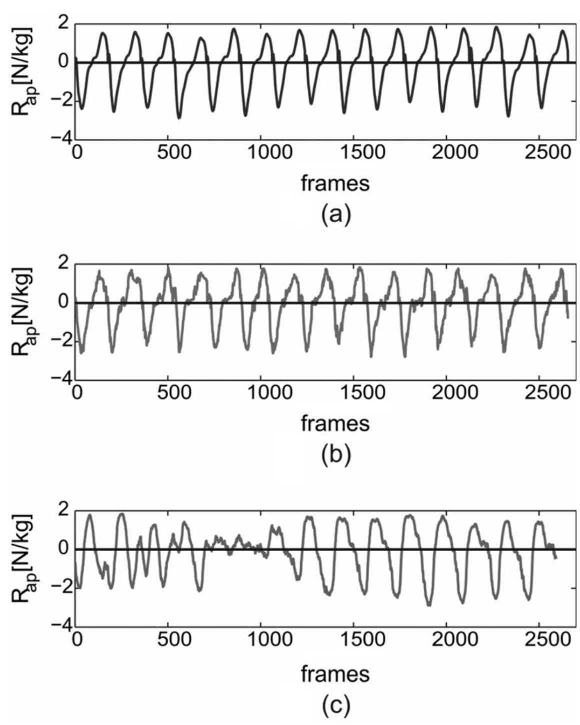

Figure 3. Example of the surrogation process, referring to an individual R_{ap} time series. The original time series (a) can be compared with its surrogate forms, estimated by PPS (b) and by the iterative AAFT algorithm proposed by Schreiber and Schmitz (2000) (c). The surrogate in (c) has lost the original temporal geometry, whereas the PPS surrogate maintained its overall temporal structure.

also as the percentage variation produced by surrogation. Differences in the magnitude of *SampEn* among the five variables analysed were assessed using Kruskal-Wallis statistics ($\alpha = 0.05$) and Bonferroni *post-hoc* comparisons.

Second, the 40 trials performed by each participant 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 motor variability from the first 50% of the trials for each participant was compared to the regularity from the last 50%, so that eventual changes in the variability structure over the test session could be detected. *SampEn* was calculated, for each variable and participant, 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 trials ($Y_{Li}(t)$). The significance of differences between the entropy content of $Y_{Fi}(t)$ and of $Y_{Li}(t)$ was assessed by applying Wilcoxon tests ($\alpha = 0.05$).

Finally, we compared the motor variability of more and less skilled athletes by assessing the regularity of the kinematic and kinetic waveforms they produced. The hypothesis was that sample entropy represents a synthetic index of neuromuscular organization, and that it is useful for gauging and distinguishing performance proficiency and ability, even in a population of national and international athletes. Race walkers were assigned to two groups based on skill. This was determined by combining competition results (Table I) with the evaluation of an expert coach who judged their technical ability. Participants 2, 5, and 6, who were international athletes, formed the more skilled group; participants 1, 3, 4, and 7, who competed at a national level, constituted the less skilled group. Mann-Whitney tests ($\alpha = 0.05$) were used to assess between-group differences in *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, 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 Δt. The overall v of the population was $2.72 \pm 0.23\ \text{m} \cdot \text{s}^{-1}$, comparable to a training pace. Intra-individual coefficients of variation (CV) revealed very low levels of variability with the distribution of intra-individual CV at a 95th 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, revealing 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}) for original time series, and from 0.14 (A_{as}) to 0.40 (R_{ap}) for surrogates. Antero-posterior ground reaction force was the variable that 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 hip angle in the sagittal plane.

Kruskal-Wallis tests revealed 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 ($P = 0.03$).

No changes in regularity were observed throughout the test session. Results generally showed stable values of *SampEn* between the first and second half of trials that each participant performed (Figure 5). *SampEn* changed significantly only for R_{ap}: median values increased from 0.20 ($Y_{Fi}(t)$) to 0.22 ($Y_{Li}(t)$).

The more and less skilled groups manifested statistically different values of entropy for three of the five variables considered (Figure 6): A_{hs}, A_{as}, and R_v showed a significant increase of *SampEn* in the more skilled compared with the less skilled group (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 $d = 1.430$ respectively. *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

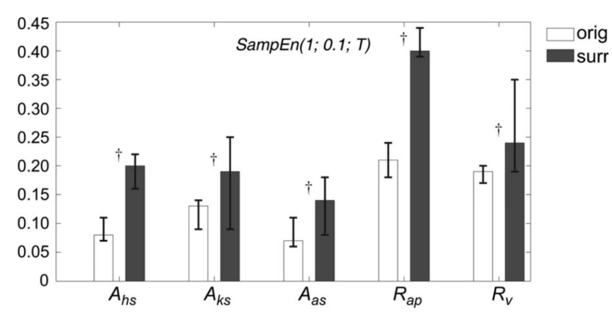

Figure 4. Comparison between *SampEn* in the original (white bars, $Y_i(t)$) and surrogate (dark bars, $\hat{Y}_i(t)$) time series data. Results for the five variables considered are presented in terms of median values. Error bars depict inter-quartile ranges. †Statistically significant ($P < 0.05$) differences between groups (Wilcoxon test).

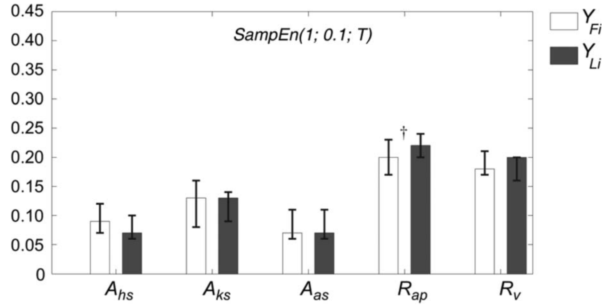

Figure 5. Comparison between *SampEn* in the first half (white bars) and second half (dark bars) of trials of the experimental session. Results for the five variables considered are presented in terms of median values. Error bars depict inter-quartile ranges. †Statistically significant ($P < 0.05$) differences between groups (Wilcoxon test).

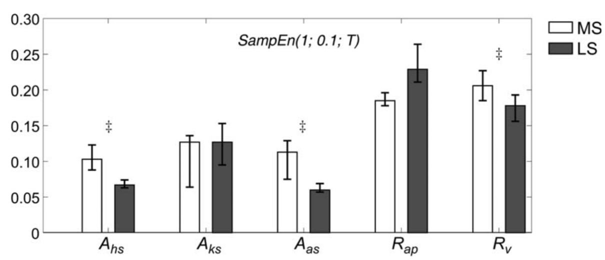

Figure 6. Comparison between *SampEn* in more skilled (white bars) and less skilled (dark bars) race walkers. Results for the five variables considered are presented in terms of median values. Error bars depict inter-quartile ranges. ‡Statistically significant ($P < 0.05$) differences between groups (Mann-Whitney test).

waveforms evidenced a comparable level of predictability: 0.13 (0.07) vs. 0.13 (0.06).

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 motor variability and was undertaken to determine whether the fluctuation that occurred over many repetitions of the same task were the outcome of noisy processes or were induced by non-linear properties of the neuromotor dynamics (Newell et al., 2006). The *SampEn* of the measured waveforms was estimated and compared with the entropy of their PPS surrogates. *SampEn* values (Figure 4) were low (Richman & Moorman, 2000) and close to zero for every variable considered. 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 kinematic and kinetic measures studied. The meaningfulness of statistical tests was supported by the large effect sizes. The percentage decrease of regularity after the original data had undergone surrogation was considerable and ranged 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 had a non-linear structure that surrogation had eliminated. Therefore, in line with other authors' findings (e.g. Bartlett et al., 2007; Dingwell et al., 2001; Hamill et al., 2005; Müller & Sternad, 2004; Newell et al., 2003, 2006; Riley & Turvey, 2002), motor variability might possess functional information about the organization of the neuro-musculoskeletal 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.

Race walking 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 race walking rules, which impose an unnatural pattern on knee flexion–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 (Cairns, Burdett, Pisciotta, & Simon, 1986; Murray, Guten, Mollinger, & Gardner, 1983; 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 an individual's motor variability might change during the test session was also addressed. To our knowledge, there are no published studies of intra-session changes in movement variability. A comparison between first and final trials executed over a single test session was made to determine 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 allowed the race walkers to be acquainted with the test procedures from the beginning.

The third level of this study was to show how the information motor variability conveys might be used practically. Non-linear 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 based on skill, *SampEn* differences between more and less skilled groups were evaluated. Less skilled individuals showed significant differences compared with more skilled ones. Due to the limited number of participants in both the more and less skilled groups, a problem of low statistical power may arise. The limited sample sizes was due to the participants being high-level athletes. 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 the less skilled than in the high skilled group, suggesting that the less skilled athletes needed to control those joints more to compensate for the extended knee and to maintain a correct technique. These findings concur with those of researchers who mostly investigated the influence of pathologies or ageing effects (Newell et al., 2006; Vaillancourt et al., 2001). Greater entropy may be interpreted as better flexibility and adaptability to unpredictable environmental changes. That is, individuals with better coordination 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. race walking rules about knee locking), and time series regularity was comparable in the two groups. Force variables manifested an increased magnitude of *SampEn* compared with the kinematic variables. Ground reaction forces 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 motor variability. Motor variability 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 organization of the neuromuscular system. These influences are subtle and not easily detectable using traditional analyses (Preatoni, 2007). Nevertheless, motor variability 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 allowed theoretical interpretations of motor variability: although variability may appear as a negative property of the neuro-musculo-skeletal systems, it is not exclusively the outcome of random, noisy processes, but 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 the intra-individual regularity of patterns does not change over the acquisition process. Third, it characterized athletic ability by differentiating the performance of more and less skilled athletes.

Our results illustrate 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 described and applied has the merit of being a synthetic index of the neuromuscular organization. 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, non-linear analysis might be included in longitudinal monitoring of athletes to quantitatively support coaches' decisions and training procedures.

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Appendix

Pincus (1995) and Pincus et al. (1991) 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 comparison of patterns of length m.

Given N data points $\{u(i)\}$ with $i = 1, \ldots, N$, 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:

$$C_i^m(r) = N^{-1}\{\text{number of } x_m(j) \text{ such that } \mathrm{d}[x_m(i),\, x_m(j) \leq r]\} \tag{A1}$$

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 with 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 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 a probability measure the ratio of the logarithmic sums, but they compute directly the logarithm of conditional probability).

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

$$\mathrm{A}_i^m(r) = (N - m - 1)^{-1}\{\text{number of } x_{m+1}(j) \text{ so that } d[x_{m+1}(i), x_{m+1}(j)] \leq r,\ i \neq j\} \quad \text{(A2)}$$

$$\mathrm{B}_i^m(r) = (N - m - 1)^{-1}\{\text{number of } x_m(j) \text{ so that } d[x_m(i), x_m(j)] \leq r,\ i \neq j\} \quad \text{(A3)}$$

$$\mathrm{A}^m(r) = (N - m)^{-1}\sum_{i=1}^{N-m} \mathrm{A}_i^m(r) \quad \text{(A4)}$$

$$\mathrm{B}^m(r) = (N - m)^{-1}\sum_{i=1}^{N-m} \mathrm{B}_i^m(r) \quad \text{(A5)}$$

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