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Movement variability and skills monitoring in sports

KEYWORDS

Biomechanics, experimental methods, injury, performance, reliability

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TITLE

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ABSTRACT

The aim of this paper is to present a review on the role that movement variability plays in the analysis of sports movement and in the monitoring of the athlete’s skills. Movement variability has been traditionally considered an unwanted noise to be reduced, but recent studies have re-evaluated its role and have tried to understand whether it may contain important information about the neuro-musculo-skeletal organisation. Issues concerning both views of movement variability, different approaches for analysing it and future perspectives are discussed.

Information regarding the nature of the movement variability is vital in the analysis of sports movements/motor skills, and the way in which these movements are analysed and the movement variability subsequently quantified is dependent on the movement in question and the issues the researcher is trying to address. In dealing with a number of issues regarding movement variability, this paper has also raised a number of questions which are still to be addressed.

INTRODUCTION

Movement variability is pervasive throughout the multiple levels of movement organization and occurs not only between but also within individuals (Bartlett, Wheat, & Robins, 2007; Bartlett, 1997; Bates, 1996; Hatze, 1986; James, 2004; Müller & Sternad, 2004; Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006). Every time we replicate the same movement a certain amount of change may be recorded between its subsequent repetitions, regardless of how good or familiar we are in performing it (

**** Figure 1 about here ****

The study of movement variability has been gaining increasing interest in the sports biomechanics community and recent conference papers and lectures in the sports biomechanics community (Bartlett, 2005; Bates, 2010; Hamill, 2006; Bartlett, 2004; Hamill, Haddad, & Van Emmerik, 2005; Preatoni, 2010; Wilson, 2009) have demonstrated the importance of movement variability (MV) and coordination variability (CV) in the analysis of sports movements.

Sports biomechanics possesses distinctive peculiarities compared with other branches of the study of human motion such as clinical biomechanics or ergonomics. While clinical biomechanics is generally devoted to describing average behaviours and to comparing pathological patterns to a physiological range, the sports context should not be centred on the idea of average subject and normality. Rather, sports biomechanics usually aims at enhancing the individual capabilities, in terms of performance, technique proficiency and consistency of results. At the same time, it should also pursue injury prevention and wellness, given the increased (in some cases maximal) and repetitive biomechanical demands the athlete receives.

Details concerning movement organisation and performance may be fundamental in sports, and the higher the level of performance the greater their importance. Elite athletes possess an outstanding mastery of their movements and their motor outcomes often appear very repeatable and stereotyped. However subtle differences may distinguish one from another, or small changes may develop over time as a consequence of environmental changes, training procedures, learning phenomena, latent pathologies or incomplete recoveries. These underlying factors may be easily masked by the presence of variability.

Therefore the study of movement variability in sports deserves particular attention. It should not be addressed only in terms of reliability and appropriate experimental procedures, which are still essential, but it should also be considered as a potential source of information in the process of analysing and monitoring the athlete's biomechanical qualities.

Despite the efforts of researchers, many issues concerning the variability of human motion are still to be thoroughly addressed and/or are waiting for comprehensive explanations. These issues include: the magnitude of movement variability and the subsequent need for appropriate experimental design and data processing; the meaning of MV; the information MV may provide and the possible relationship between MV and performance, MV and the acquisition/development of motor skills, and/or MV and injury factors. Furthermore, MV needs to be considered during the selection of the experimental design and may influence the validity of the obtained results. Currently, however, there are no universally agreed guidelines for practitioners regarding the treatment of variability within experiments. The lack of such information becomes more serious when the focus of investigations is shifted from basic movements such as walking or running to the multiplicity of more complex sports movements.

Therefore, the aim of this paper is to present a review of the role and the potential that movement variability and coordination variability may have in the process of monitoring the athlete's motor patterns. The review will endeavour to address (i) how much MV is present in sports movements, (ii) how the human system copes with MV and (iii) the purpose of MV. We will report practical indications about how MV should be treated, present the different approaches that may be used to study MV in sports and we will emphasise their limits and potential applications. In addition, we will report possible developments and ideas for future research in MV.

SPORTS SKILLS AND THE DUAL NATURE OF MOVEMENT VARIABILITY

Motor skills represent the ability of obtaining a predetermined outcome with a high degree of certainty and maximum proficiency (Newell & Ranganathan, 2009; Schmidt & Lee, 2005). Hence, the process of learning or improving sports skills involves the capability of producing a stable performance under different conditions: only repeated motor performance reflects mastery in carrying out a desired task.

The process of monitoring the athlete's capabilities may be schematised like a feedback loop (Preatoni, 2007; Preatoni, La Torre, Santambrogio, & Rodano, 2010b) (

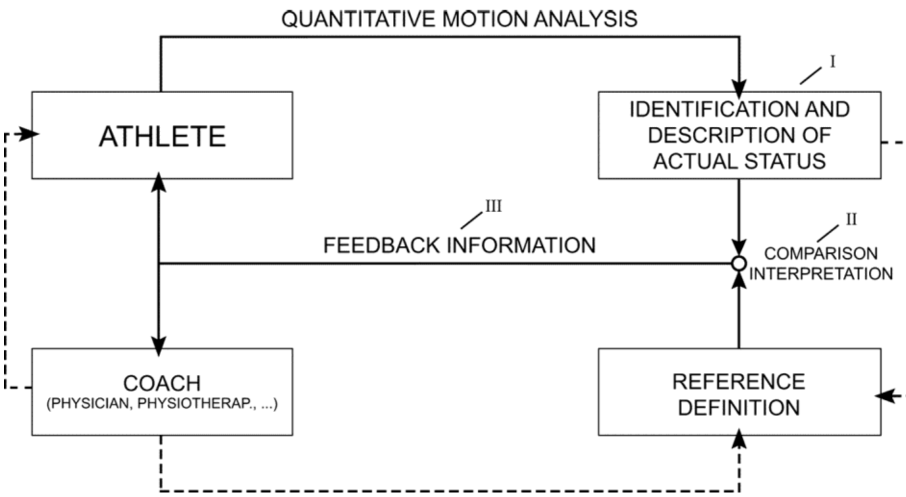


Figure 2), where the starting point is the athlete executing a motor task and the end point is the same athlete who gets back information concerning his/her performance directly or through the coach's mediation.

**** Figure 2 about here ****

Three intermediate phases are identifiable. Phase I addresses the issue of motor performance depiction. Phase II deals with the definition of references that provide the criterion to which measures from Phase I are compared and through which the individual skills are assessed. The interpretation of biomechanical data and the determination of references may be carried out on multiple levels, like, for example: using coaches' anecdotal indications, creating a record of individual changes over time, modelling optimal behaviour through a purely theoretical approach and/or simulation. Phase III involves the need for returning data to the athlete/coach, after translating biomechanical observations into information that is suitable for both the end users' needs and their know-how. This cyclic flow of information provides athletes and coaches with a tool to monitor motor skill trends, to check on possible anomalies, to plan and control training programs and rehabilitative procedures.

In light of the framework presented in

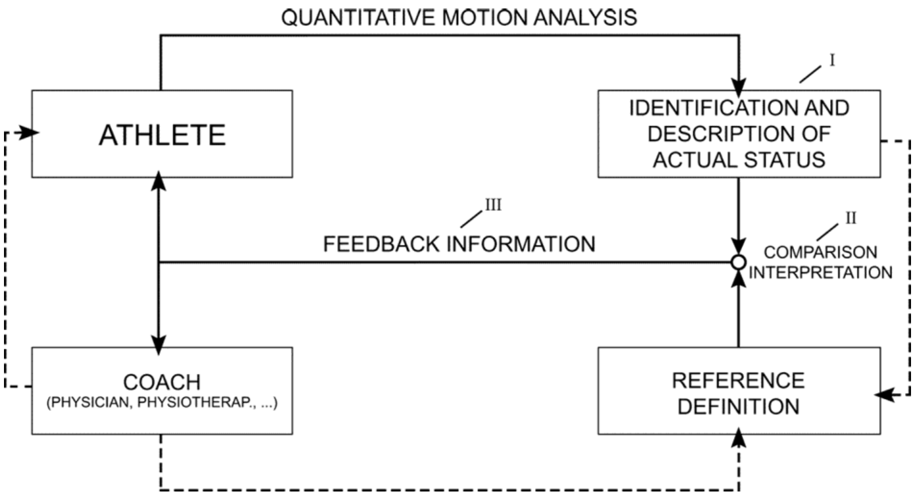


Figure 2, MV may emerge as an unwanted source of error that should be eliminated or reduced (Fitts, 1954; Fitts & Posner, 1967; Harris & Wolpert, 1998; Schmidt, Zelaznik, Hawkins, Frank, & Quinn Jr, 1979; Van Beers, Baraduc, & Wolpert, 2002). When trying to capture the biomechanics of individual technique, research should depict the core strategy that governs the movement, regardless of the variations that emerge across repetitions.

However, MV always occurs when the same action is repeated and even the elite athlete cannot reproduce identical motor patterns (Bartlett, et al., 2007). MV is inherently present in motor performance and may be associated with the extreme complexity of the neuro-musculo-skeletal system and with the redundancy of its degrees of freedom (e.g. Bartlett, et al., 2007; Bernstein, 1967; Hamill, et al., 2005; James, 2004; Newell, et al., 2006; Riley & Turvey, 2002). While MV has been associated with a reduction in performance due to a lack of consistency (Dierks & Davis, 2007; Knudson & Blackwell, 2005; Salo & Grimshaw, 1998), it may not correspond only to randomness but also to functional changes whose investigation might unveil information about the system health, about its evolutions, and about its flexibility and adaptability to variable external conditions (Bartlett, et al., 2007; Glazier & Davids, 2009; Hamill, Van Emmerik, Heiderscheit, & Li, 1999).

Therefore MV may possess a dual connotation. (1) It is an unwanted error which impedes a simple description of the actual individual status through standard approaches. Moreover, it hinders the detection of the small inter-individual differences or intra-individual changes that often characterise the sports domain. At the same time, (2) MV reflects the inherent functional features of the neuromuscular system and may contain important information that should not be neglected.

THE TRADITIONAL APPROACH: MOVEMENT VARIABILITY AS NOISE

There is a growing need to develop methodologies that enable investigators to capture and effectively analyse individual motor skills and their change over time independent of the variability that emerges with repetition of the same movement. Many studies have revealed changes inherent to human motion and have suggested, whenever possible, the use of experimental protocol in which multiple trials are recorded for the subject (Chau, Young, & Redekop, 2005; Fleisig, Chu, Weber, & Andrews, 2009; Hamill & McNiven, 1990; James, 2004; Preatoni, 2007; Preatoni, et al., 2010b; Rodano & Squadrone, 2002; Winter, 1984) given that the analysis of a single trial can often lead to erroneous conclusion (Bates, Dufek, & Davis, 1992) particularly in the study of individual motor skills. Variability in motor skills stabilises within certain ranges (James, 2004) and this may be dependent on the subject, the variable and on the experimental procedures for data collection.

According to the conventional control theory approach, movement variability is made equal to noise (Equation [1]) that prevents the final output from matching the planned program (Bartlett, et al., 2007; Bays & Wolpert, 2007; Fitts, 1954; Harris & Wolpert, 1998; James, 2004; Müller & Sternad, 2004; Newell, et al., 2006; Van Beers, et al., 2002). In this approach, outcome variability (i.e. variability in ‘what’ has been achieved) and performance variability (i.e. variability in ‘how’ it has been obtained) are equally read as poor achievement: both of them come from noise that may corrupt the different levels of motor organisation (V_{eb}, i.e. errors in the sensory information and in the motor output commands) and may be caused by the changeable environmental conditions (V_{ee}) or by measuring and data processing procedures (V_{em}).

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

This view of MV has important implications for the investigation of sports skills and highlights the need for proper experimental designs and data reduction procedures (Bartlett, et al., 2007; Comyns, Harrison, Hennessy, & Jensen, 2007; Dona, Preatoni, Cobelli, Rodano, & Harrison, 2009; Preatoni, 2007; Preatoni, et al., 2010b). The quantification, synthesis and meaning of MV are very important in depicting the athlete's status and can influence the practical decisions made in sport.

In the investigation of sports skills a crucial element is a consistent description of the actual motor skills of the athlete. This may involve the extraction of either discrete or continuous variables which describe the athlete's kinematic and kinetic patterns.

Discrete Measures of Variability

Quantitative biomechanical analysis often involves the extraction of parameters from kinematic and kinetic curves. The assessment of discrete measures is commonly used to understand the characteristics of a particular motor task and to outline the differences between different populations. In addition, discrete parameters have been used for performance evaluation (Bartlett, 2005; Vamos & Dowling, 1993) or enhancement and injury prevention (Granata, Marras, & Davis, 1999; James, Dufek, & Bates, 2000; Nigg & Bobbert, 1990).

While several researchers have investigated the reliability of normal walking variables (Benedetti, Catani, Leardini, Pignotti, & Giannini, 1998; Chau, et al., 2005; Dingwell & Cavanagh, 2001; Growney, Meglan, Johnson, Cahalan, & An, 1997; Kadaba, Ramakrishnan, & Wootten, 1990; Kadaba, Ramakrishnan, Wootten, Gainey, Gorton, & Cochran, 1989; Steinwender, Saraph, Scheiber, Zwick, Uitz, & Hackl, 2000; Stolze, Kuhtz-Buschbeck, Mondwurf, Jöhnk, & Friege, 1998; Winter, 1984), relatively few studies have been conducted to assess the variability of kinematic and kinetic variables during sports movements. This lack of research is compounded further by the wide variety of motor tasks that are performed by athletes in many different sports disciplines. Jumping (James, et al., 2000; Rodano & Squadrone, 2002) and running (Bates, Osternig, Sawhill, & James, 1983; Devita & Bates, 1988; Diss, 2001; Ferber, Mcclay Davis, Williams, & Laughton, 2002; Lees & Bouracier, 1994; Queen, Gross, & Liu, 2006) are the most frequently studied movements and more recently the sprint start (Bradshaw, Maulder, & Keogh, 2007) and race walking (Preatoni, 2007; Preatoni, et al., 2010b) and baseball pitching (Fleisig, et al., 2009) have been investigated.

When analysing any sporting movement we need to be careful not to confuse variability present within 'global parameters' (parameters which define the output of the whole system) with variability that is present within kinetic and kinematic (technique parameters). Low variability in the outcome measure does not necessarily indicate a low variability in technique parameters describing the movement. This has previously been demonstrated in reaching movements whereby variability in discrete kinematic variables did not correspond to the endpoint variability (Messier & Kalaska, 1999). In gait analysis, Karamanidis, Arampatzis, & Bruggemann (2003) reported that variability within kinematic data is primarily determined by the specific parameter under investigation. Further to this, Van Emmerik et al. (1999) reported lower levels of variability in segmental kinematics between individuals with Parkinson's disease and healthy controls but not for basic gait parameters. They concluded that variability of stride characteristics offers a less sensitive measure of differences between groups than does variability of segmental coordination. Additionally, Preatoni (2007) and Preatoni et al. (Preatoni, et al., 2010b) showed that skilled race walkers produced intra-individual coefficient of variation that were very low (less than 3%) for ‘global parameters’ such stance duration, step length and progression speed, but may become fairly high (greater than 10%) for kinematic/kinetic parameters related to movement execution and technique.

Many different methods have been proposed for estimating the variability within kinematic and kinetic parameters. The use of standard deviation (Fleisig, et al., 2009; Kao, Ringenbach, & Martin, 2003; Owings & Grabiner, 2004) and coefficient of variation (Bradshaw, et al., 2007; Queen, et al., 2006) as spread estimators is common within quantitative motion analysis. However, the use of these methods relies on the assumption that the data being analysed are normally distributed and this is not always the case or may be not easily assessed.

Non-parametric measures, such as the inter-quartile range (IQR) or the median absolute deviation (MAD) have been indicated as more robust estimates of variability (Chau & Parker, 2004; Chau, et al., 2005). In support of this view, Preatoni (Preatoni, 2007) and Preatoni et al. (Preatoni, et al., 2010b) analysed race walking data and concluded that summarising the variability of discrete variables should not be addressed using parametric estimates indiscriminately. The use of either standard deviation or coefficient of variation could inflate variability assessment thus diminishing the chances of detecting significant differences when they do in fact exist (Chau, et al., 2005). However, MAD and IQR also manifested statistically significant changes due to contaminants in nearly 50% of the considered kinetic/kinematic parameters (Preatoni, 2007). Therefore, the use of non-parametric estimators of spread, combined with the collection of a “proper” number of trials and the identification and elimination of atypical occurrences appear to be the most advisable solution (Chau, et al., 2005).

Unfortunately, the identification of how many repetitions may be considered appropriate is not straightforward, due to multiple causes. Universally recognised references are not always available, or are available for a limited number of sports movements, and no proposed standards exist on how this estimation should be made, especially when more than one single measure is included in the analysis.

The sequential estimation procedure (Hamill & McNiven, 1990) is a technique used to determine the number of consecutive trials that are necessary to obtain a stable mean for each considered variable, subject and movement, whereby a value is generated for the cumulative mean by adding one trial at a time. Stability is recognised when the successive mean deviations fall within a range around the overall average. The specific criterion to obtain a stable mean (i.e. the bandwidth) is based on the need to obtain a stable result while attempting to keep the total of trials as low as possible (Hamill & McNiven, 1990). The number of trials required to depict a stable performance is therefore a consequence of the activity, the subject and the variable under investigation (Preatoni, 2007; Preatoni, et al., 2010b). In the analysis of running, the number of trials required to provide reliable estimates of the ground reaction force (GRF) data variables has been identified to be as few as 8 (Bates, et al., 1983) and as many as 25 (Devita & Bates, 1988). In walking, the minimum number of trials required has been shown to be 10 (Hamill & McNiven, 1990). When looking at joint kinetic data (moments and powers) during vertical jumping, Rodano & Squadrone (2002) concluded that a 12-trial protocol was needed to obtain a stable estimate. Preatoni et al. (2010b) observed a number of kinematic parameters depicting race walking technique in a group of elite athletes, and suggested that as many as 15 trials were necessary to obtain stability of average values.

In order to be able to determine how to successfully treat movement variability and the conclusions that can be drawn when investigating a wide variety of sports skills it is necessary to create a database of what has previously been identified.

Continuous Measures of Variability

The use of discrete variables in the analysis of human movement is powerful but may not be sufficient to provide an exhaustive description of the observed movement. When a single measurement is extracted from a continuous variable, a large amount of data are discarded and potentially useful information may be unaccounted for (Queen, et al., 2006; Ryan, Harrison, & Hayes, 2006; Sutherland, Kaufman, Campbell, Ambrosini, & Wyatt, 1996). Indeed, the shape of kinematic/kinetic curves is often a good indicator of "how" a motor task is accomplished and may help either physicians in classifying the patient's behaviour as physiological or pathological, or coaches in identifying the athlete's characteristics and their change over time. When repeating the same movement many times, an individual does not generate kinematic/kinetic patterns that perfectly overlap, but produces a family of curves that may differ from each other in magnitudes and timings.

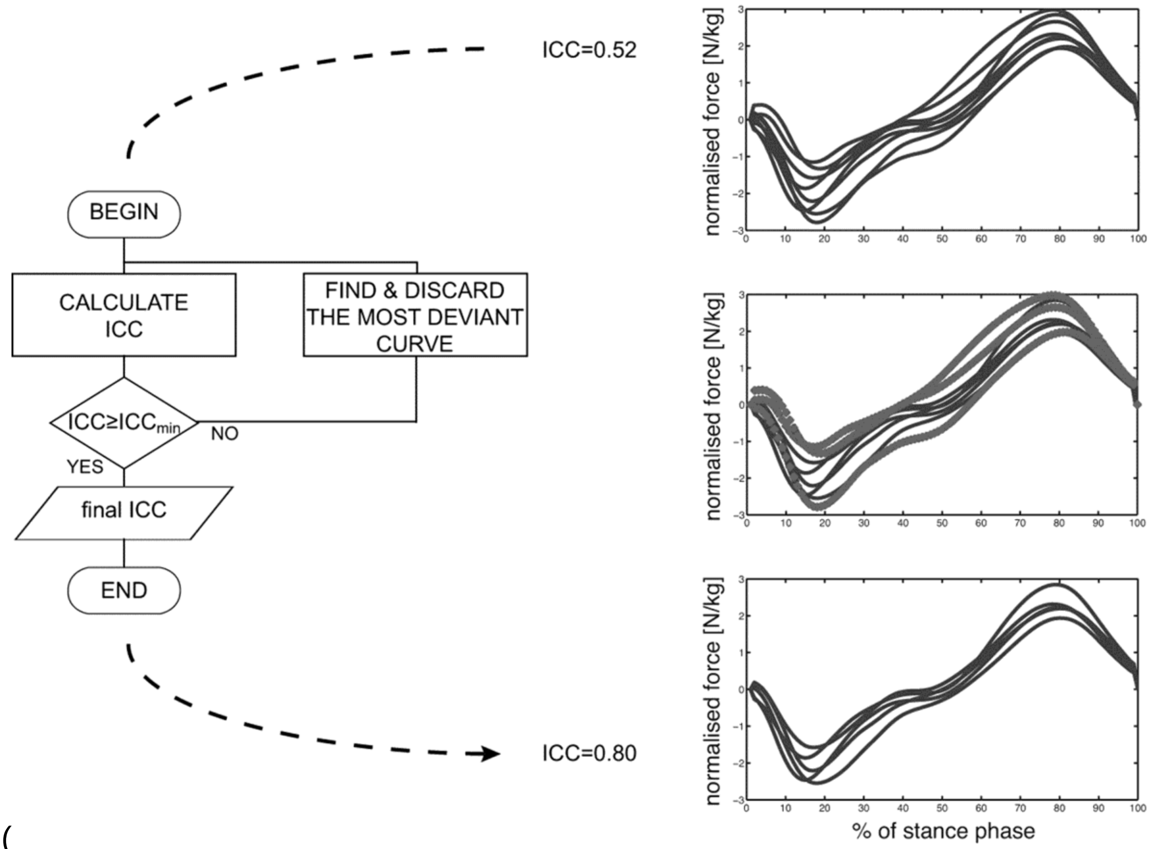
The issue of variability across curves is considered by practitioners when attempting to depict the individual motor patterns, but the analysis typically stops at summarising the general characteristics of a group of curves through the estimation of confidence bands (e.g. mean curves ± a multiple of the standard deviation). Previous research on the variability within continuous variables is even less prevalent than research on discrete parameters. Some authors have investigated the reproducibility of gait variables but have generally focussed on the influence of methodological factors on data repeatability (Growney, et al., 1997; Kadaba, et al., 1989) or on the differences between normal and pathological subjects (Steinwender, et al., 2000).

The two estimators that have been commonly used to assess repeatability in continuous variables are the coefficient of multiple correlation (CMC) (Kadaba, et al., 1989) and the intra-class correlation coefficient (ICC) (Duhamel, Bourriez, Devos, Krystkowiak, Destée, Derambure, & Defebvre, 2004; Ferber, et al., 2002). Both indices may range between 0, for extremely poor repeatability, and 1, for perfect reproducibility. The CMC requires experimental designs with multiple testing sessions, even if intra-session variability is the only aim of the analysis. For example, Growney et al. (Growney, et al., 1997) used 3 trials collected on each of 3 separate days; Queen et al. (Queen, et al., 2006) adopted two separate testing sessions with as many as six trials each. Alternatively, the ICC can be calculated when data from a single testing session are available, and may be considered as the “proportion of variance due to the time-to-time variability in the total variance” (Duhamel, et al., 2004).

Within-day, between-day and overall variability of continuous variables have mainly been assessed during walking (Growney, et al., 1997; Kadaba, et al., 1989; Steinwender, et al., 2000) and running activities (Queen, et al., 2006). Results showed that lower limb kinematics and kinetics have better reproducibility in the sagittal plane, while reliability on secondary planes of motion is less effective. Hence, the authors concluded that repeatability for sagittal plane variables is good enough for their use in clinical examinations, provided that operators are very careful with marker placement and in the control of experimental settings (Growney, et al., 1997; Kadaba, et al., 1989; Queen, et al., 2006; Steinwender, et al., 2000).

Unfortunately, and similarly to what has been reported in the previous section on discrete measures variability, there are neither standard guidelines to be followed, nor agreement about what should be set as a threshold for good reliability in continuous measures. Shrout (1998) proposed categories of agreement based on ICC of discrete variables, and set “substantial” reliability for values greater than 0.80. However, other authors (Atkinson & Nevill, 1998; Duhamel, et al., 2004) have underpinned the need for more research to identify appropriate reference values and argued that each motion variable, experimental objective and population may involve different limits above which repeatability can be considered good.

Moreover, there is lack of such investigations in sports movements, and in cohorts of high-level athletes in particular. Preatoni (Preatoni, 2007) analysed 15 continuous variables in a group of very skilled race walkers, including joint angles, moments and powers, and ground reaction forces. Results concurred with previous findings, reporting better reliability for ground reaction forces and angles in the sagittal plane, but also showed that the values of ICCs were lower than the ones reported for walking (Duhamel, et al., 2004), and that the level of intra-individual variability was substantially subject- and variable-dependent. Preatoni also suggested an iterative procedure



(Figure 3) based on the calculation of the ICC, which may be used to iteratively identify and discard the most unrepresentative curves of a subject, until the remaining ones have a repeatability that is equal or greater than a pre-determined threshold.

**** Figure 3 about here ****

However, much more effort is required to define standard guidelines for addressing continuous measures of variability in sports and to create reference databases that could help in the analysis of data on performance and on its consistency and evolution over time. The list of open issues that still deserve attention is long and would also include, for instance: (i) the selection of the best statistical methods for summarising and comparing families of intra-individual curves (Chau, et al., 2005; Duhamel, et al., 2004; Lenhoff, Santner, Otis, Peterson, Williams, & Backus, 1999; Olshen, Biden, Wyatt, & Sutherland, 1989; Sutherland, et al., 1996), especially when the aim of the study is the detection of the subtle individual changes of the athlete (Hopkins, 2000; Hopkins, Hawley, & Burke, 1999), and not a patient's classification that should be free from type II errors (Olshen, et al., 1989; Sutherland, et al., 1996); (ii) the definition of proper experimental protocols and selection of a representative number of trials, based on continuous measures of variability; (iii) sensitivity analysis about the effect of time-normalisation of curves and the possible need for curve registration (Chau, et al., 2005; Sadeghi, Allard, Shafie, Mathieu, Sadeghi, Prince, & Ramsay, 2000; Sadeghi, Mathieu, Sadeghi, & Labelle, 2003).

As already stated, movement variability has traditionally been considered to be noise and therefore an aspect of human motion that we are trying to eliminate. However, this is not possible and therefore it must be taken into consideration when investigating sports movements. Within sports biomechanics we have the additional constraint of often being limited by the number of trials we are able to collect, especially if collected within a competition setting. Furthermore, the additional factors encountered during competition in comparison to training may also influence both the movement itself and the variability present and this therefore also needs to be taken into consideration.

MOVEMENT VARIABILITY AS INFORMATION: NEW APPROACHES

Recent investigations and experimental evidence have shown that outcome and performance variability should not be read in the same way. While outcome variability is by definition an unwanted deviation from the pursued objective, performance variability is not necessarily bad. Several researchers have supported the idea that inter-trial variability (V_{tot}) does not correspond to noise only but is a combination (Equation [2]) of artefact of noise in the neuro-musculo-skeletal system (i.e. V_e in Equation [1]) and functional changes that may be associated with its nonlinear properties (V_{nl}) (Bartlett, et al., 2007; Glazier & Davids, 2009; Hamill, et al., 1999; James, 2004):

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

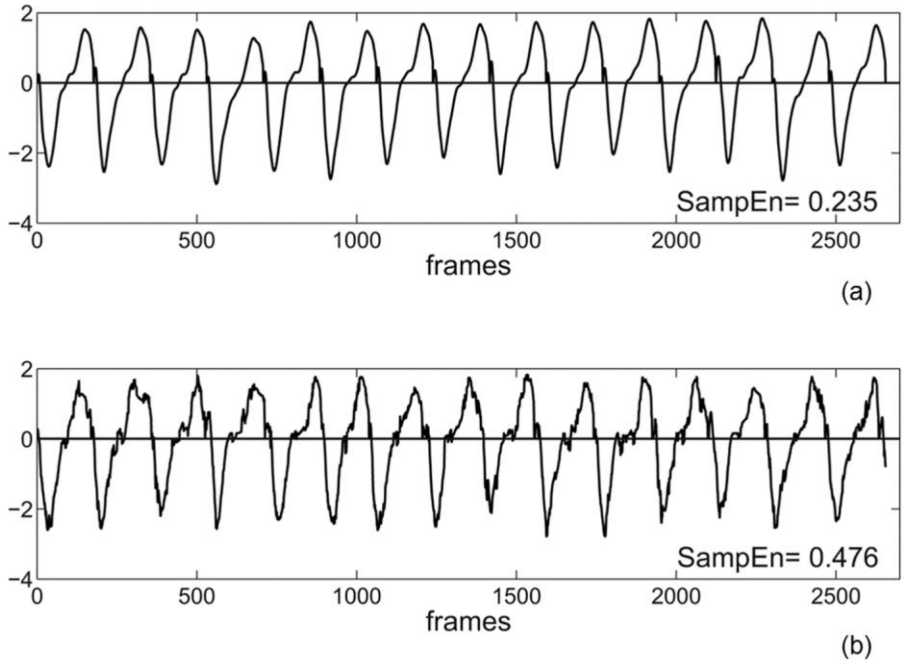
V_{nl} is an integral part of the biological signal and may be interpreted as the flexibility of the system to explore different strategies to find the most effective one among the many available. This adaptability allows for learning a new movement or adjusting the already known one by gradually selecting the most appropriate pattern for the actual task (Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Deutsch & Newell, 2003; Dingwell & Cusumano, 2000; Dingwell, Cusumano, Cavanagh, & Sternad, 2001; Dingwell, Cusumano, Sternad, & Cavanagh, 2000; Hamill, et al., 2005; Harbourne & Stergiou, 2003; Hausdorff, 2005; James, 2004; Müller & Sternad, 2004; Newell, Broderick, Deutsch, & Slifkin, 2003; Newell, Challis, & Morrison, 2000; Newell, et al., 2006; Riley & Turvey, 2002). The subject is thus able to gradually release the degrees of freedom that have been initially frozen to achieve a greater control over an unfamiliar situation. Changes in the contributions of V_e and V_{nl} to the total variability may be related to changes in motor strategies and may thus reveal the effects of adaptations, pathologies and skills learning (e.g. Bartlett, et al., 2007; Dingwell, et al., 2001; Wilson, Simpson, Van Emmerik, & Hamill, 2008). It should be noted here that what we are referring to in this paper is biological variability, which is not noise resulting from measuring and data processing procedures, but is internal to the movement signal and cannot be removed from the signal. Non-biological noise (V_{ee} and V_{em} in Equation [1]) on the other hand is a high frequency component which can be attenuated by data conditioning (Kantz & Schreiber, 1997).

The conventional approaches to MV can only quantify the overall variability, and they rely on assumptions and procedures that do not allow examination of its features and structure. They cannot, for example, assess the extent to which V_e (or, more specifically, V_{eb}) and V_{nl} participate in the generation of MV, and therefore they are not effective in evaluating the possible information MV conveys. The use of nonlinear dynamics tools (e.g. entropy measures), the analysis of coordinative features (e.g. continuous relative phase) or the use of functional data analysis represent alternative instruments to explore the nature of motion variability and its relation with performances, skills development or injury factors. Only recently and only few authors have used these methods to investigate MV in sports and in elite athletes in particular.

An Example of Nonlinear Methods: Entropy Measures

A number of nonlinear methods, such as the Lyapunov exponent (Abarbanel, Brown, Sidorowich, & Tsimring, 1993), and entropy measures (Pincus, 1995; Pincus, 1991; Richman & Moorman, 2000), have been proposed as tools for investigating the nature of variability in biological systems. Nonlinear methods do not consider the subsequent repetitions of the same motor task as a number of similar but independent events that need to be summarised through statistics (e.g. average pattern and confidence band). Rather, they look at the repeated cycles of the movement as a continuous pseudo-periodic time-series and try to evaluate the dynamics that govern the changes occurring between the cycles. Some authors have recently applied nonlinear analysis in the study of neuro-motor pathologies (Dingwell & Cusumano, 2000; Dingwell, et al., 2000; Morrison & Newell, 2000; Newell, et al., 2006; Smith, Stergiou, & Ulrich, 2010; Vaillancourt & Newell, 2000; Vaillancourt, Slifkin, & Newell, 2001) or in the characterisation of movement development, posture and locomotion (Buzzi, et al., 2003; Dingwell, et al., 2001; Harbourne & Stergiou, 2003; Lamoth & Van Heuvelen, 2012; Newell, et al., 2003; Newell, et al., 2000; Newell, et al., 2006), but the number of studies concerning sports movements is extremely limited (Preatoni, Ferrario, Dona, Hamill, & Rodano, 2010a). This lack of research may be mainly due to the computational procedures of these techniques, which require a relatively large amount of data (i.e. number of data points = number of trials x duration x sampling frequency), and which consequently make the experimental procedure be difficult to be implemented in a sports context where typically a limited number of repetitions can be collected.

Among the different nonlinear methods, entropy measures such as Approximate Entropy (*ApEn*) (Pincus, 1995; Pincus, 1991) or Sample Entropy (*SampEn*) (Richman & Moorman, 2000) can be considered particularly appropriate for the study of sports movements, where variability is likely to have both a deterministic and a stochastic origin, and where data set are typically small and may be affected by outliers (Preatoni, et al., 2010a; Stergiou, Buzzi, Kurz, & Heidel, 2004). Entropy indices quantify the regularity of a time-series (e.g. a kinematic or kinetic measure) that contains a sequence of repetitions of the same movement



(Figure 4a). *ApEn* and *SampEn* measure the probability that similar sequences of *m* points in the time-series, remain similar within a tolerance level (*r*) when a point is added to the sequence (*m*+1 sequences) (Pincus, 1995; Richman & Moorman, 2000). That is, in more simplistic terms, a count of how many similar patches of *m* points are replicated in the time-series, carried out for each sequence of *m* points in the signal, and divided by the same count carried out for a patch *m*+1 points long. *ApEn* and *SampEn* range from 0, for regular or periodical time series, to positive values, for which the higher the entropy, the less regular and predictable the time series (Pincus, 1995; Richman & Moorman, 2000). Since regularity is related to the complexity of the system that produces the signal (Pincus, 1995), an increase in regularity may indicate a loss of complexity of the system and has often been associated to pathological conditions (Vaillancourt & Newell, 2000; Vaillancourt, et al., 2001). Furthermore, differences in the predictability of movement patterns may also reflect underlying changes in motor strategies whereby the effects of adaptations, and skills learning may be revealed (Bartlett, et al., 2007), which may be particularly beneficial in sports movement analysis when subtle changes in performance are hidden by the magnitude of MV.

**** Figure 4 about here ****

Preatoni (Preatoni, 2007) and Preatoni et al. (Preatoni, et al., 2010a) studied the nature of MV in sports by measuring sample entropy in kinematic and kinetic variables during race walking. They analysed the influence of the different sources of variability (i.e. V_e and V_{nl} in Equation [2]) over movement repeatability by comparing entropy values of the original time-series (made up of 20 gait cycles) with the ones of their surrogate counterparts. Surrogation is a method for generating new time-series, which maintains original data and its large-scale behaviour (periodicity, mean, variance and spectrum) but eliminates its possible small-scale structure (chaotic, linear/nonlinear-deterministic)

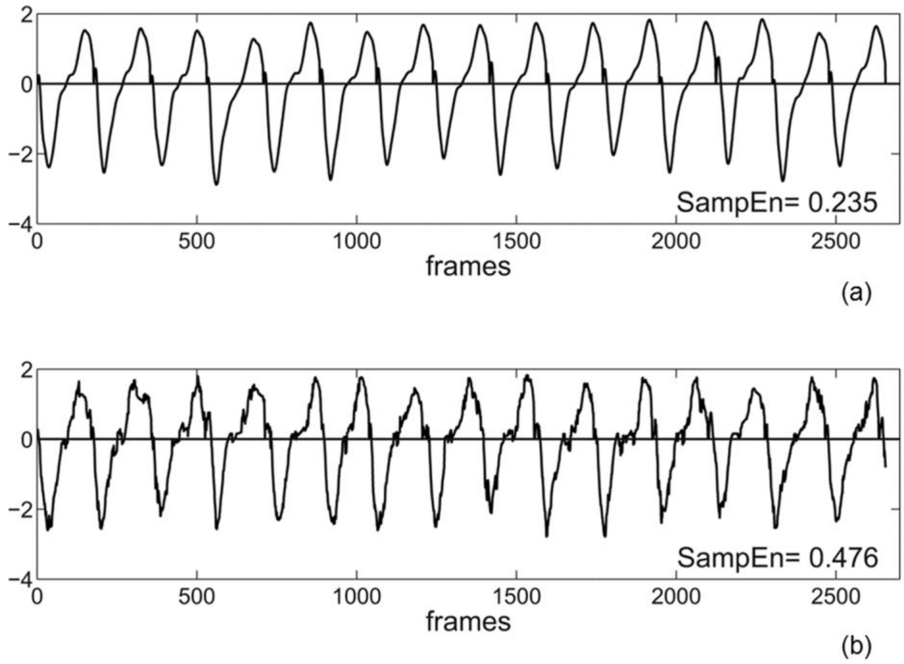


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Figure 4b). Therefore, if *SampEn* significantly increases after surrogation, then it is very likely that the variability between trials (periods) is not, or not only, the outcome of random processes. The study of race walking reported a significant increase of *SampEn* after surrogation in the range between 16% and 59%, depending on the analysed variable. Their results confirmed that MV is not only noise but also contains functional information concerning the organisation of the neuro-musculo-skeletal system. Results comparing entropy content in the first and last half of trials also suggested that the structure of variability appears invariant and no adaptation effects emerge when a proper experimental protocol is followed.

Finally, the same authors showed how entropy measure might have a potential for a fine discrimination between skill levels. While traditional analysis had failed in distinguishing between good athletes and elite ones in a group of apparently similar individuals, *SampEn* evidenced significant differences, with less skilled race walkers showing increased regularity and therefore an increased control over those joints that in race walking mainly compensate for the locked position of the knee. Conversely, in line with the interpretation that higher values of entropy may be read as a better flexibility and adaptability to unpredictable environmental changes (Newell, et al., 2006; Vaillancourt, et al., 2001) subjects with an outstanding ability reported a less rigid control over their body's degrees of freedom.

Dynamical Systems Theory Approach

Non-linear tools such as entropy measures are computing-intensive procedures that give a concise and powerful measure/assessment of the nature of movement variability and of the extent of its being functional. However, they are not particularly effective in depicting how MV can be functional because they address multiple movement cycles as a whole, they do not look into its constitutive phases, and typically they do not observe the relationships between the multiple elements that concur in coordination and movement execution.

In a dynamical system with multiple degrees of freedom, variability in performance is a necessary condition for optimality and adaptability. Variability patterns in gait parameters such as stride length and stride frequency, therefore, may not reflect variability patterns in segmental coordination. This has been demonstrated in studies on Parkinson's disease (Van Emmerik, et al., 1999). In biomechanical research on running injuries, several studies have now demonstrated an association between reduced coordination variability and orthopaedic disorders (Hamill, 2006; Hamill, Haddad, Heiderscheit, Van Emmerik, & Li, 2006).

Coordination variability can be defined as the range of coordinative patterns the organism exhibits while performing a movement. It is often quantified as the between trial (i.e. between gait cycle) standard deviation of the movement trials. Multiple studies have reported that a certain amount of variability appears to be a signature of healthy, pain-free movement (e.g. Hamill, et al., 1999; Heiderscheit, Hamill, & Van Emmerik, 2002; Miller, Meardon, Derrick, & Gillette, 2008). These authors suggest that this finding is indicative of a narrow range of coordination patterns that allowed for pain-free running. However, since all of these studies were retrospective in nature, a causal relationship between variability and pathology could not be ascertained. Prospective studies on coordination variability and injury development are needed to assess this relationship.

From a dynamical systems perspective, variability is not inherently good or bad, but indicates the range of coordination patterns that can be used to complete the motor task. This offers a different view in comparison to the more traditional 'variability is bad' perspective. In contrast, dynamical systems theory suggests that there is a functional role for variability that expresses the range of possible patterns and transitions between patterns of movement that a system can accomplish. It should be noted that abnormally low or high levels of variability may be detrimental to the system.

In a dynamical systems approach, the reconstruction of the so-called state space is essential in identifying the important features of the behaviour of a system. The state space is a representation of the relevant variables that help identify the key features of the system. Two methods for representing the state space of a system are typically used: 1) the angle-angle plot; and 2) position-velocity plot. An ‘angle-angle’ (e.g. sagittal plane knee angle versus ankle angle) plot can reveal regions were coordination changes take place as well as parts of the gait cycle where there is relative invariance in coordination patterns. These coordinative changes in the angle-angle plots can be further quantified by vector coding techniques (see Heiderscheit, et al., 2002). The other form of state space is where the position and velocity of a joint or segment are plotted relative to each other. This state space representation is also often referred to as the phase plane. The phase plane representation is a first and critical step in the quantification of coordination using continuous relative phase techniques (see Hamill, et al., 1999).

The relative motion between the angular time series of two joints or segments has been used to distinguish changes in coordination in sport as a function of expertise (see Wheat & Glazier, 2006). Various techniques have been developed over time to quantify the relative motion patterns and variability in angle-angle diagrams. These methods include chain encoding method developed by Freeman (see Whiting & Zernicke, 1982) and vector coding (Tepavac, 2001). In a modified version of vector coding (Heiderscheit, et al., 2002), the relative motion between the two segments is quantified by a coupling angle, an angle subtended from a vector adjoining two successive time points relative to the right horizontal. Since these angles are directional and obtained from polar distributions (0-360°), taking the arithmetic mean of a series of angles can result in errors in the average value not representing the true orientation of the vectors. Therefore, mean coupling and standard deviation of the angles must be computed using circular statistics (Batschelet, 1981; Fisher, 1996).

The vector coding analysis can also provide a measure of coordination variability. Coordination variability measures can be obtained as averages across the gait cycle of between-cycle variation (a global variability measure), or more locally at key points or intervals across the cycle (such as early stance, mid stance, swing, etc.).

Continuous relative phase (CRP) is often considered a higher order measure of the coordination between two segments or two joints

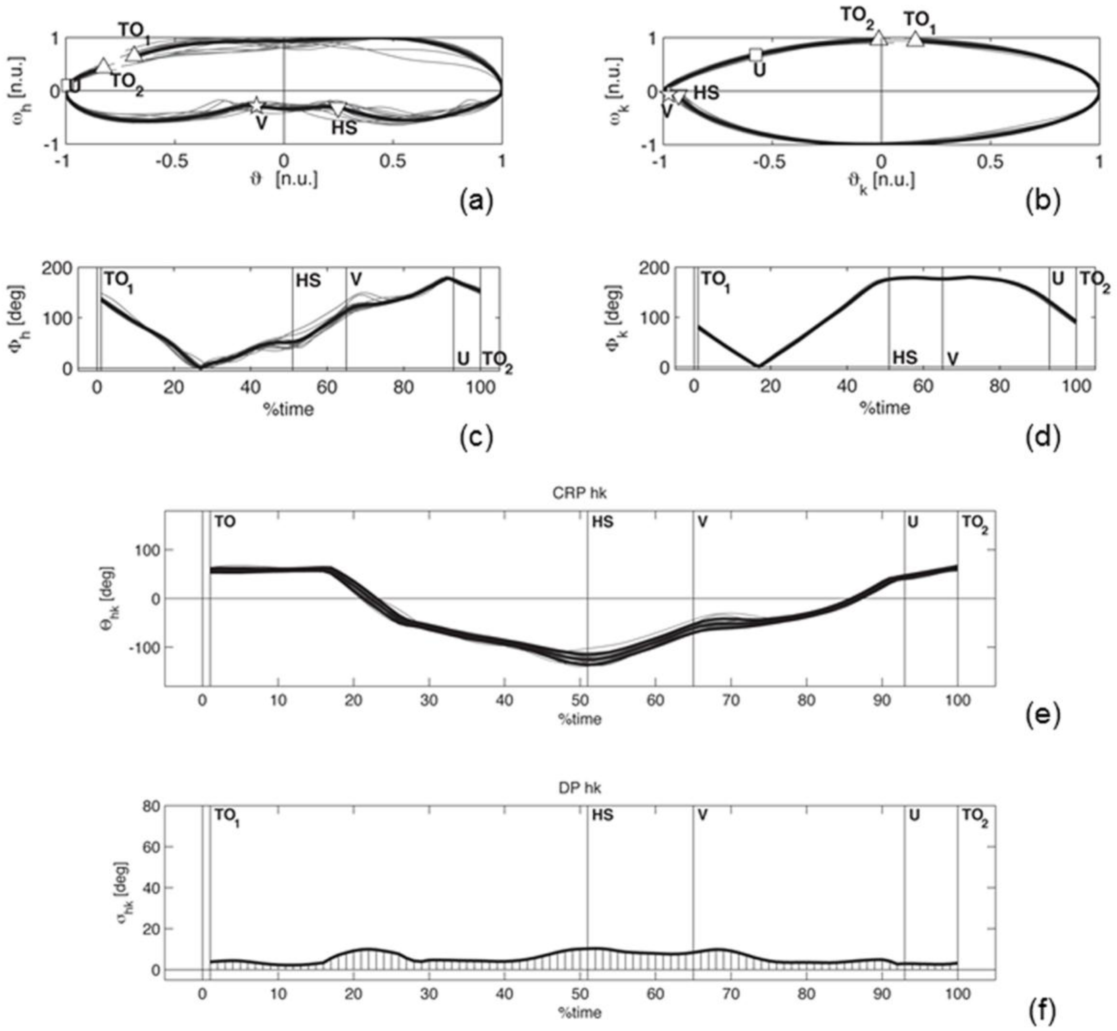


Figure 5. This higher order emerges from the derivation of CRP from the movement dynamics in the phase plane of the two joints or segments. CRP analysis has been used to characterize joint or segmental coordination during gait (Hamill, et al., 1999; Van Emmerik, et al., 1999). While CRP may seem to be relatively easy to implement, there are several key concepts regarding the methodology and the interpretation that must be addressed. First, CRP is not a higher resolution form of discrete relative phase (DRP) (Peters, Haddad, Heiderscheit, Van Emmerik, & Hamill, 2003). CRP

quantifies the coordination between two oscillators based on the difference in their phase plane angles. It should be understood that the motion of the segments and joints are not physical oscillators but are modelled behaviourally as oscillators.

**** Figure 5 about here ****

A particularly important step in the CRP procedure involves normalizing the angular position and angular velocity profiles. Normalization of the two signals (i.e. position and velocity) that make up the phase plane is necessary to account for the amplitude and frequency differences in the signals. For a complete description of the necessity of normalizing these signals see (Peters, et al., 2003). The phase plane is constructed by plotting the angular position versus angular velocity for each of the oscillators (i.e. joints or segments). For each of the oscillators, the phase angle is obtained by calculating the four-quadrant arctangent angle relative to the right horizontal at each instant in the cycle. To determine the CRP angle, the phase angle for one oscillator is subtracted from the other and then scaled to the range 0-180^o. When the CRP(i) angle is 0^o, the two oscillators are perfectly in-phase. A CRP(*i*) angle of 180^o indicates that the oscillators are perfectly anti-phase. Any CRP(*i*) angle between 0^o and 180^o indicates that the oscillators are out-of phase, but could be relatively in-phase (closer to 0^o) or anti-phase (closer to 180^o). It is often tempting to use the CRP angle to discuss which oscillator is leading and which is lagging relative to the other oscillator. Since the phase angle of one oscillator is subtracted from the phase angle of another, the lead-lag interpretation is often assumed. However, the calculation of CRP described above does not allow for such an interpretation.

The CRP time series can also be used to obtain a measure of coordination variability. For a proper assessment of coordination variability, the following two key aspects need to be addressed: (1) average variability measures should not be obtained directly from CRP time series that vary systematically throughout the movement (stride) cycle, and (2) variability measures can only be obtained from data that do not contain discontinuities. To obtain a measure of variability, we typically calculate the standard deviation with respect to the average CRP in the data.

Principal Component Analysis and Functional Principal Component Analysis

Principal Component Analysis (PCA) is a statistical technique, which is ideally suited to dimension reduction and examination of the modes of variation in experimental data. Traditionally PCA has been used to examine and interpret data sets that are discrete in nature, rather than continuous time series or curves. PCA reduces the dimensionality of an experimental problem by converting a large number of measures into a smaller number of uncorrelated, independent variables called principal components (PCs) that explain the modes of variation in the experimental data.

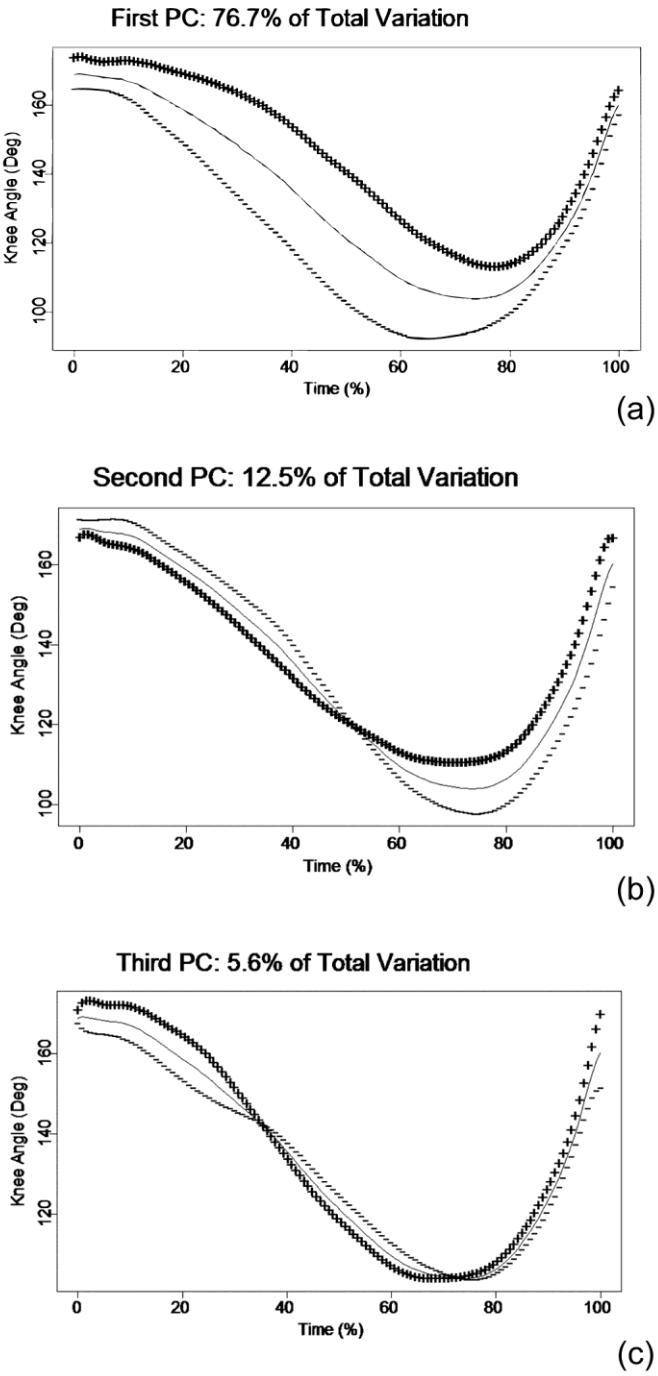
More recently PCA techniques have been adapted and used in biomechanics research to analyse temporal waveform data in various applications including gait (Landry, Mckean, Hubley-Kozey, Stanish, & Deluzio, 2007; Muniz & Nadal, 2009), balance (Pinter, Van Swigchem, Van Soest, & Rozendaal, 2008) ergonomics (Wrigley, Albert, Deluzio, & Stevenson, 2006), and surface electromyography (Hubley-Kozey, Deluzio, Landry, Mcnutt, & Stanish, 2006; Perez & Nussbaum, 2003). Currently two distinct approaches have been used to apply PCA to the analysis of biomechanical data sets where the data appear as families of curves or waveforms. These approaches are: PCA of waveforms (Deluzio & Astephen, 2007; Deluzio, Wyss, Costigan, Sorbie, & Zee, 1999) or functional PCA (f-PCA) which is generally categorised as part of a larger analysis process, and functional data analysis (FDA) originally introduced by (Ramsay & Dalzell, 1991).

In PCA of waveforms, the original curves are re-sampled to ensure equal numbers of records on every waveform and then entered into a large matrix where a Principal Component Score (PC) is derived for each data point on the waveform. While this procedure is relatively easy to implement using proprietary software applications such as IBM® SPSS® (IBM, New York, USA) or Minitab (Pennsylvania, USA), it has some deficiencies. Firstly, creating data sets of equal length may result in distortion of the time series. Secondly the smoothing and calculation of derivatives is carried out separately from PCA procedures resulting in unknown and potentially unwanted sources of variation entering the PCA. Thirdly and most importantly, in PCA of waveforms, the data points on the curve are assumed to be independent of each other, but in reality we know that any point on a curve is correlated to the data points that precede and follow that point. As a result of these deficiencies it may be difficult to relate the waveforms described by each PC to specific subjects in the experimental population.

FDA and f-PCA were devised by Ramsey and Dalzell (Ramsay & Dalzell, 1991) in an attempt to rectify some of the limitations of other approaches. The distinctive feature of functional data analysis (FDA) is that the entire sequence of data points for a measurement are considered as a single entity or function rather than a series of individual data points (Ryan, et al., 2006). The term *functional* in FDA and f-PCA refers to the intrinsic nature of measurements we frequently obtain in biomechanics experiments. While biomechanical data are obtained at various regularly spaced time points, these measurements can be assumed to be generated by some underlying function which we can denote as the function: $x(t)$. A further characteristic of the functional data is that of smoothness. In practise, the smoothing and derivation of functions are generally linked processes and the decision on the choice of appropriate basis functions is dependent on the nature of the data being analysed. For example, if the observed data are periodic, then a Fourier basis may be appropriate. Alternatively, if the observed functions are locally smooth and non-periodic, then B-splines may be appropriate; if the observed data are noisy but contain informative "spikes" that need to avoid the effect of severe smoothing, then a wavelet basis may be appropriate. The final choice of basic functions should provide the best approximation using a relatively small number of functions.

B-splines have been shown to be useful basis functions for smoothing kinematic data because their structure is designed to provide the smooth function with the capacity to accommodate changing local behaviour (Coffey, Harrison, Donoghue, & Hayes, 2011). B-splines consist of polynomial pieces joined at certain values of x (t), called knots. (Eilers & Marx, 1996) outlined the general properties of a B-spline basis. Once the knots are known it is relatively easy to compute the B-splines using the recursive algorithm of de Boor (De Boor, 2001).

The functional form of a PCA (f-PCA) has previously been used to distinguish differences in kinematic jumping patterns and coordination in groups of children at various stages of development (Harrison, Ryan, & Hayes, 2007; Ryan, et al., 2006). The analysis of these data showed that at the early stages of development in the vertical jump, most subjects' movement patterns were characterised by the first f-PC



in Figure 6 and therefore displayed higher levels of variability than found in the later stages of development. The high scorers in f-PC3 were typically described as more mature performers and these were subjects who displayed a smoother and quicker counter-movement which is typical of a more effective stretch-shortening cycle performance.

**** Figure 6 about here ****

Dona et al. (Dona, et al., 2009) applied f-PCA bilaterally to sagittal knee angle and net moment data in race-walkers of national and international level and found that scatterplots of f-PC scores provided evidence of technical differences and asymmetries between the subjects even when traditional analysis (mean ±s curves) was not effective. They concluded that f-PCA was sensitive enough to detect potentially important technical differences between higher and lower skilled athletes and therefore f-PCA might represent a useful and sensitive aid for the analysis of sports movements, if consistently applied to performance monitoring. f-PCA was also used by Donoghue et al. (Donoghue, Harrison, Coffey, & Hayes, 2008) to examine the effects of in-shoe orthoses on the kinematics of the lower limb in subjects with previous Achilles tendon injury compared to uninjured controls. Donoghue et al. (Donoghue, et al., 2008) provided evidence using f-PCA that in-shoe orthoses appeared to constrain some movement patterns but restored some aspects of variability in other movements. Coffey et al. (Coffey, et al., 2011) took this analysis further using an extension of f-PCA which they called Common f-PCA. This technique is better suited to analysis of families of curves where repeated measures designs are used. Using Common f-PCA, Coffey et al. (Coffey, et al., 2011) provided evidence that control subjects had greater levels of variability in lower limb movement patterns than injured subjects.

All of the above studies highlight the importance of treating variability in the data as a real, biological phenomenon that has a structure which can be separated from the noise or error information generated by data acquisition. In this respect f-PCA appears to be a very useful to aid the investigation of biological variability in biomechanical studies.

CONCLUSION

This paper has briefly examined the “dual” role that motion variability plays in the analysis of sports movement, being concurrently a limitation, both in terms of its function and the way we deal with it, as well as a potentiality. Regardless of the point of view from which we consider MV, more research is needed to gain a thorough insight into this issue. For example, there is still lack of: (i) reference values and database, that could help in the interpretation of movement and coordination variability in sports; (ii) knowledge of the relationship between causes (e.g. detrimental behaviours, motor learning) and effects (e.g. changes in the analysed variables or indices) (Bartlett, et al., 2007; Hamill, et al., 2005; Preatoni, 2007; Preatoni, et al., 2010a); (iii) integration of the outcomes of the different methods of investigation; and, (iv) ability in translating complex approaches and results into suitable information that may be easily read as feedback and thus applied on the field.

Previous studies investigating MV have looked at functional motor skills such as walking (e.g. Chau, et al., 2005), whilst other authors have focused their attention on injury factors (e.g. Hamill, et al., 2005; Hamill, et al., 1999) or on coordinative patterns (e.g. Seay, Haddad, Van Emmerik, & Hamill, 2006), by studying the variability in phasing relationships between different elements of the locomotor system (body segments or joints). Fewer works have concentrated their attention on the relation between sports skills and MV/CV, with practical implications for performance monitoring and training purposes. Wilson, et al. (2008) studied how coordination variability changes in relation with skills development in the triple jump. Preatoni (2007) and Preatoni, et al. (2010a) reported different levels of entropy, in selected variables, between elite and high-level race walkers. Furthermore, Preatoni (2007, 2010), Preatoni et al. (2010a) and Donà et al. (2009) presented evidence relating to how advanced methodologies may be an important means for finely investigating individual peculiarities – e.g. subtle changes over time that may be due to underlying pathologies

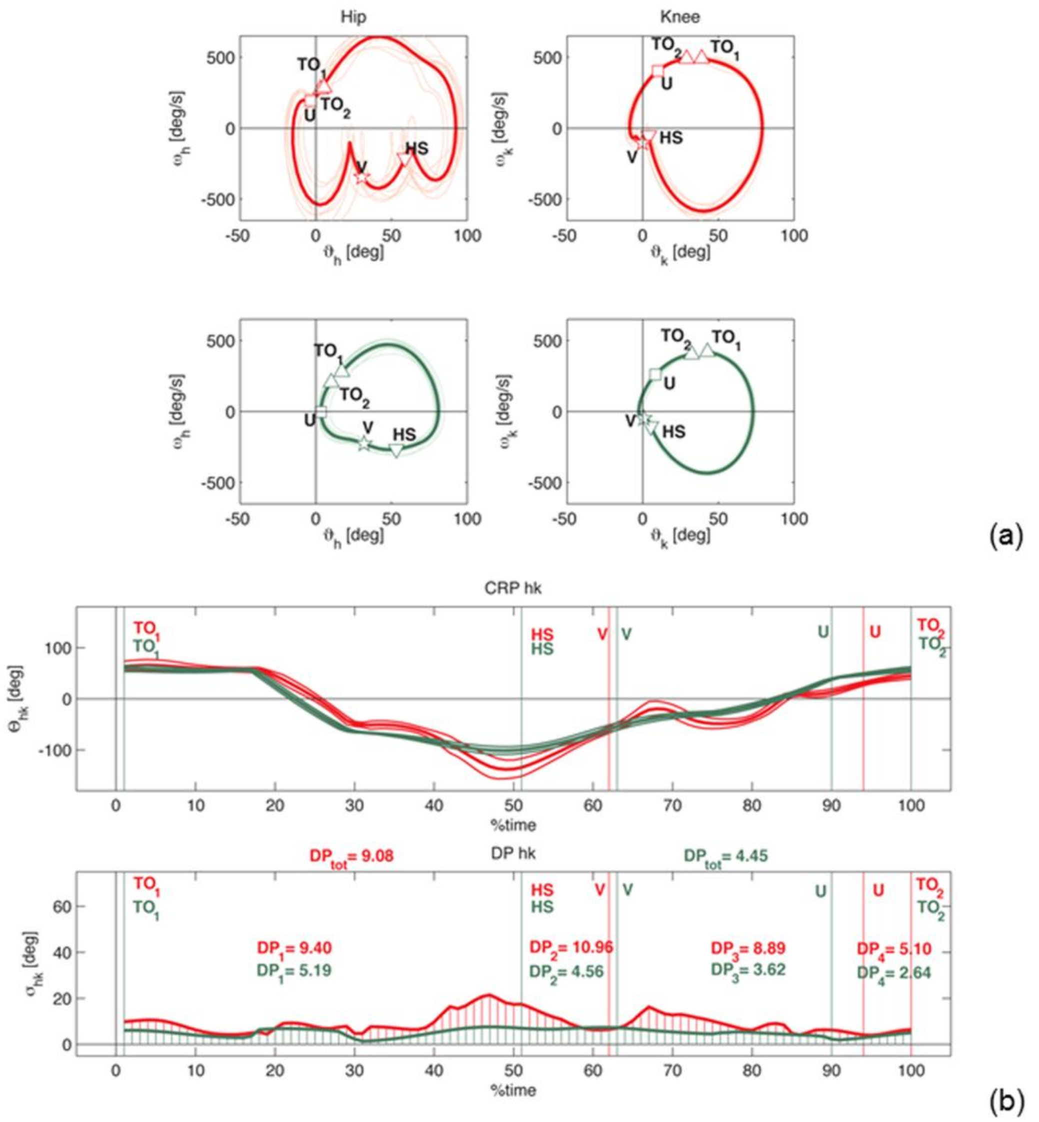


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Figure 7) – when no apparent changes occur at a macroscopic level.

**** Figure 7 about here ****

This paper has considered five methods of analysis of sport movements which are able to address MV. Discrete and continuous measures of variability have traditionally viewed variability as an unwanted source of error which is detrimental to performance. These measures allow the quantification of MV in a way which is not computationally complex and which does not rely on a very large sample size. In addition these measures provide information which is easy to interpret and understand by the end user (athlete or coach). However, similar performances in sporting events are often the result of different motor strategies, both within and between individuals and these subtle discrepancies are typically less detectable than the ones that emerge in clinical studies, and are often concealed by the presence of invariance. Hence, the conventional use of discrete variables or continuous curves may be ineffective and the potential of more advanced methodologies may be exploited (Table 1).

**** Table 1 about here ****

When a movement is performed repetitively, the motions of the body's segments will exhibit some variability, even for a cyclical motion like running. A common assumption in many locomotion studies is that increased variability in gait parameters such as stride length and stride frequency is associated with instability. Although increased variability in these spatio-temporal patterns of footfalls may indicate potential gait problems, an understanding regarding the mechanisms underlying instability requires insight into the dynamics of segmental coordination in the upper and lower body. DST provides an approach to quantifying variability which considers a higher order measure of coordinative variability and therefore allows the potential

for analysing subtle differences between individuals/performances and the possibility of analysing across functional phases of the movement in question. Unfortunately DST requires the use of large numbers of trials and, maybe as a result of this, there is currently a lack of research applied to the analysis of sports skills. Entropy has many of the benefits and drawbacks of DST but unlike DST cannot provide information regarding the way through which movement variability is functional. However what entropy can add is the potential for analysing the content or nature of the MV present in the system and therefore potentially the ability for fine discrimination between skills. Finally, f-PCA supplements DST and entropy by creating a function that describes the complete movement, and by giving a tool both for data reduction and for the interpretation of performance and skills learning factors.
The considerations which need to be taken when quantifying and treating MV have been discussed in addition to what conclusions we can draw when investigating sports skills. How a particular movement or motor skill is analysed and the MV quantified is dependent on the movement in question and the issues the researcher is trying to address.

The implications of the issues discussed in this paper are wide reaching. Movement variability should not simply be treated as noise which needs be eliminated. Equally it should not be viewed as a solely function element of human movement. Practitioners need to consider the presence of movement variability in motor skills and adopt appropriate methodologies which are able to deal with and quantify it.

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TABLES

Table 1. Summary of the new approaches to movement variability presented in this review paper, including their potential/benefits for sports biomechanics and the drawbacks in their application.

Method	Use/Potential/Benefits	Drawbacks
Entropy Measures	- Characterises the nature of movement variability (deterministic/functional vs. stochastic/error) - Allows fine discrimination between skill levels - Has potential for the identification of injury risk/factors - Does not need data normalisation	- Computationally complex and intensive - Is applicable at one variable at a time; - It does not directly provide information about how variability may be functional; - It does not allow for insight into the different phases of the movement.
DST – CRP	- Assesses coordination across entire stride or movement cycle - Includes higher order phase plane dynamics - May be more sensitive in detecting performance changes	- Limited to sinusoidal signal - Requires normalisation to address frequency and amplitude differences between signals - Results are difficult to reflect back to a spatial joint/segment motion interpretation only
DST – DRP	- Relatively simple to implement - No reconstruction of higher dimensional state space is required	- Coordination assessment is based on single event in time series

		- Is less reliable and applicable when peaks in time series are not well defined or change
DST – Vector Coding	- Is applicable to sinusoidal and non-sinusoidal data - Requires less stringent normalization - Is easier to use in clinical applications and interpretations	- The loss of higher order information compared to CRP may reduce sensitivity
PCA/f-PCA	- Analyses modes of variation in data sets that present as curves or groups of curves - Allows dimension reduction without discarding important information - Presents the Functional Principal Components (f-PCs) in the same domain as the original functions - Time normalisation or landmark registration is optional - Allows fine discrimination between skill or ability levels - f-PCA can be applied to simple time series curves or more complex representations of coordination - f-PCs can be directly related to real	- f-PCA is not readily available using proprietary software packages - Computation of f-PC is complex - PCA of waveforms and f-PCA are fundamentally different but often confused as the same process. - f-PCs of complex curve data sets (phase-plane plots and angle – angle diagrams) are difficult to interpret.

subjects in the analysis

- f-PCs can be analysed using Hypothesis testing or Discriminant Analysis

FIGURE CAPTIONS

Figure 1. Example of the outcoming variability in a well mastered motor task like writing. Repeatedly fast-writing the same word generates traces that do not perfectly overlap.

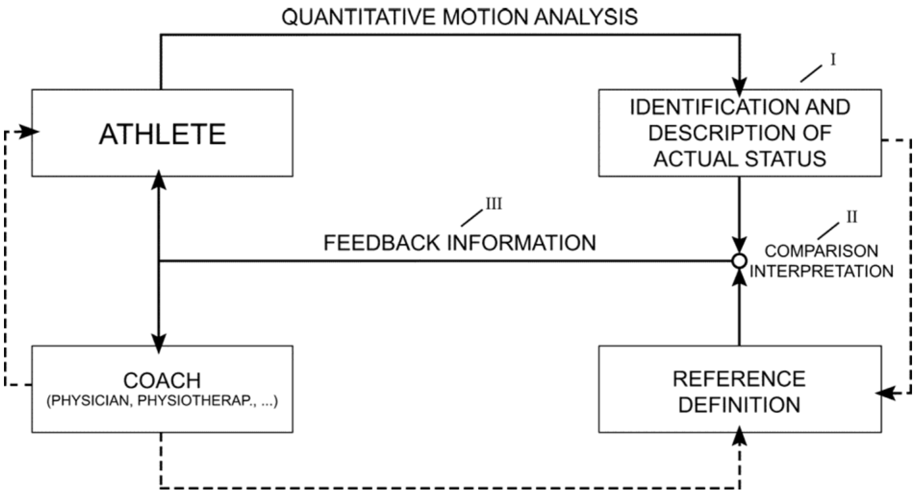

Figure 2. The athlete’s monitoring scheme. Three key issues may be identified in the monitoring process: (I) the robust description of motor characteristics; (II) the interpretation of biomechanical measures; (III) the translation of complex biomechanical analyses into readily comprehensible information for application on the field.

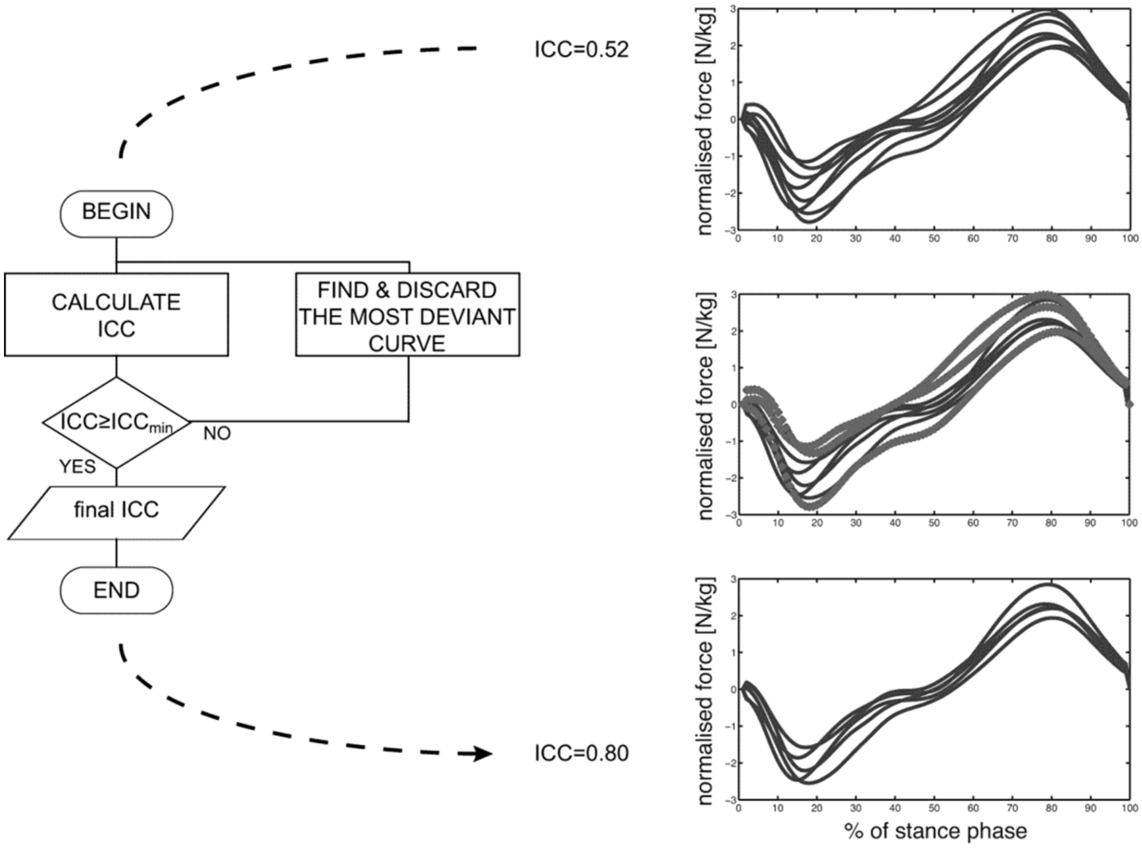

Figure 3. Algorithm for the iterative identification and discard of unrepresentative curves through the use of ICC (left) and an example of its application (right) when multiple repetitions of race walking stance are taken into account and the threshold for good repeatability is set at ICC_{min}= 0.80.

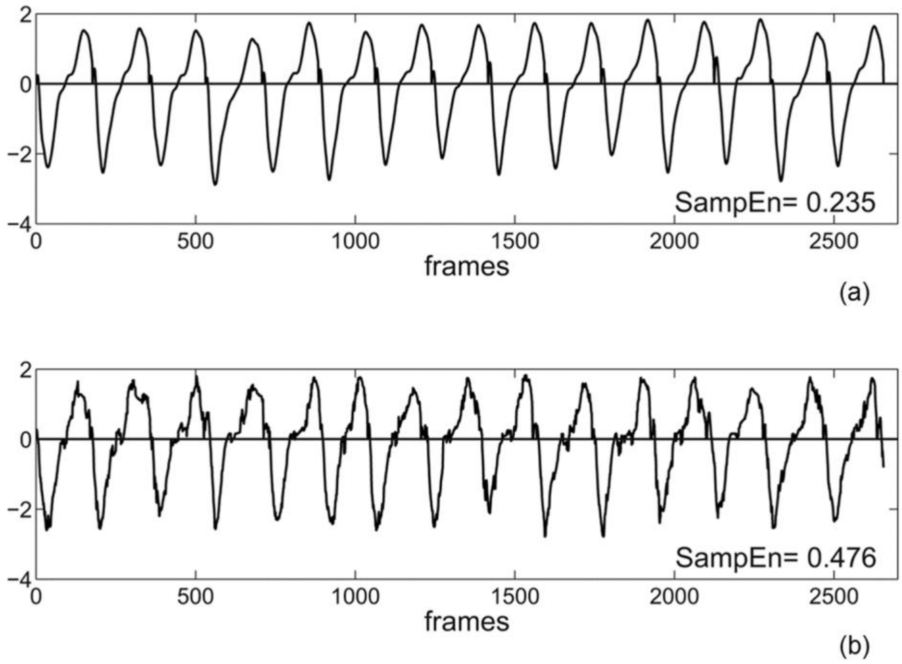

Figure 4. Example of a time-series made up of multiple repetitions of the same tasks (a) and its corresponding surrogate counterpart (b). Surrogation was here carried out by applying the pseudo-periodic surrogate algorithm (Miller, Stergiou, & Kurz, 2006; Small, Yu, & Harrison, 2001).

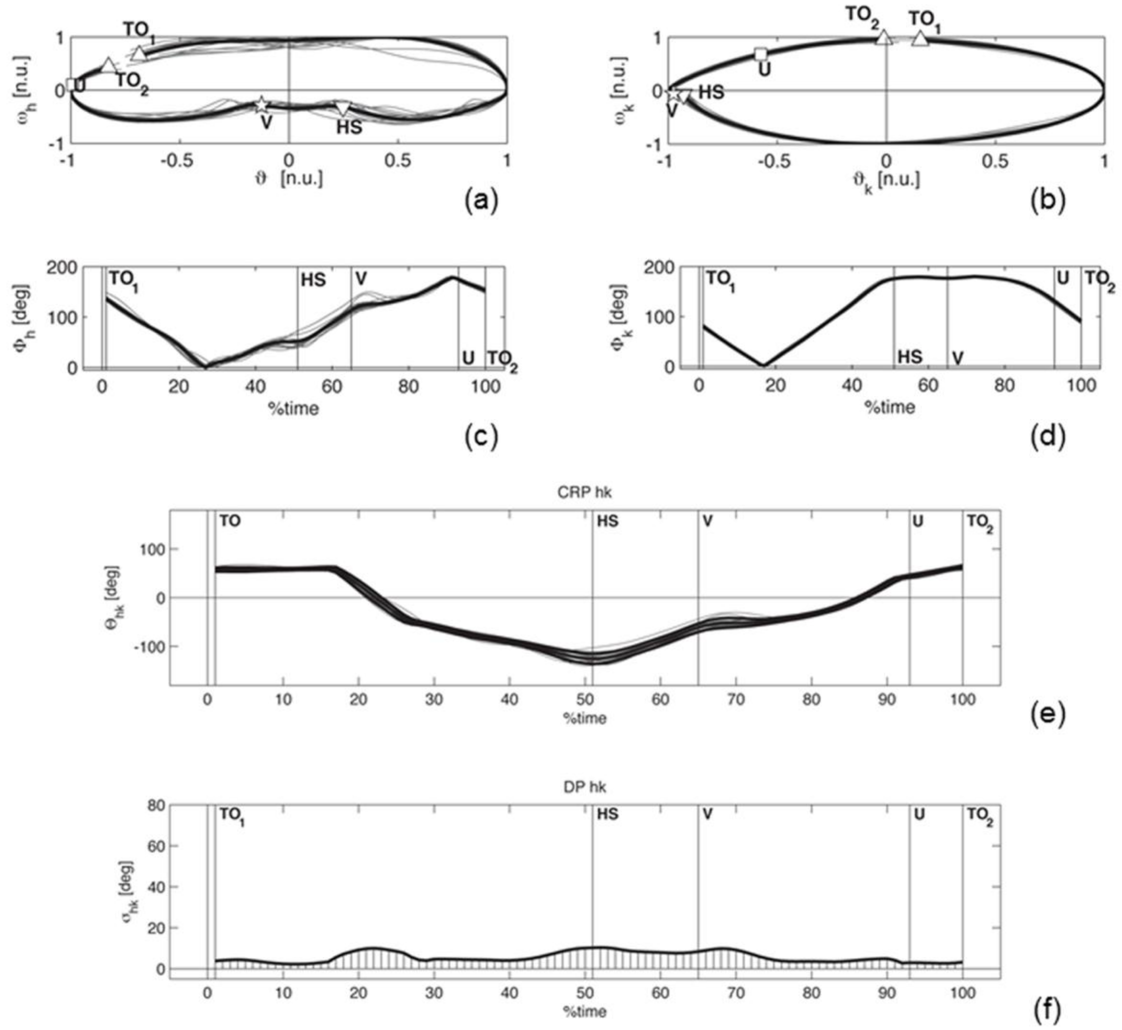

Figure 5. Example of CRP calculation based on data from a race walker's hip and knee joint motion. Normalised (Hamill, et al., 1999) phase plane plots concerning the hip (a) and the knee (b) angles are used to calculate the respective phase patterns (c and d). (d) is then subtracted from (c) to obtain the CRP plot (e). The deviation phase (time-to-time standard deviation of the CRP) is reported in (f). Data are normalised to 100 points, with gait cycles identified by two subsequent toe-offs (TO_1 and TO_2). HS= heel-strike; V= instant when the support leg passes through the projection of the centre of mass; U= instant when the knee is unlocked. Bold lines represent mean and standard deviation.

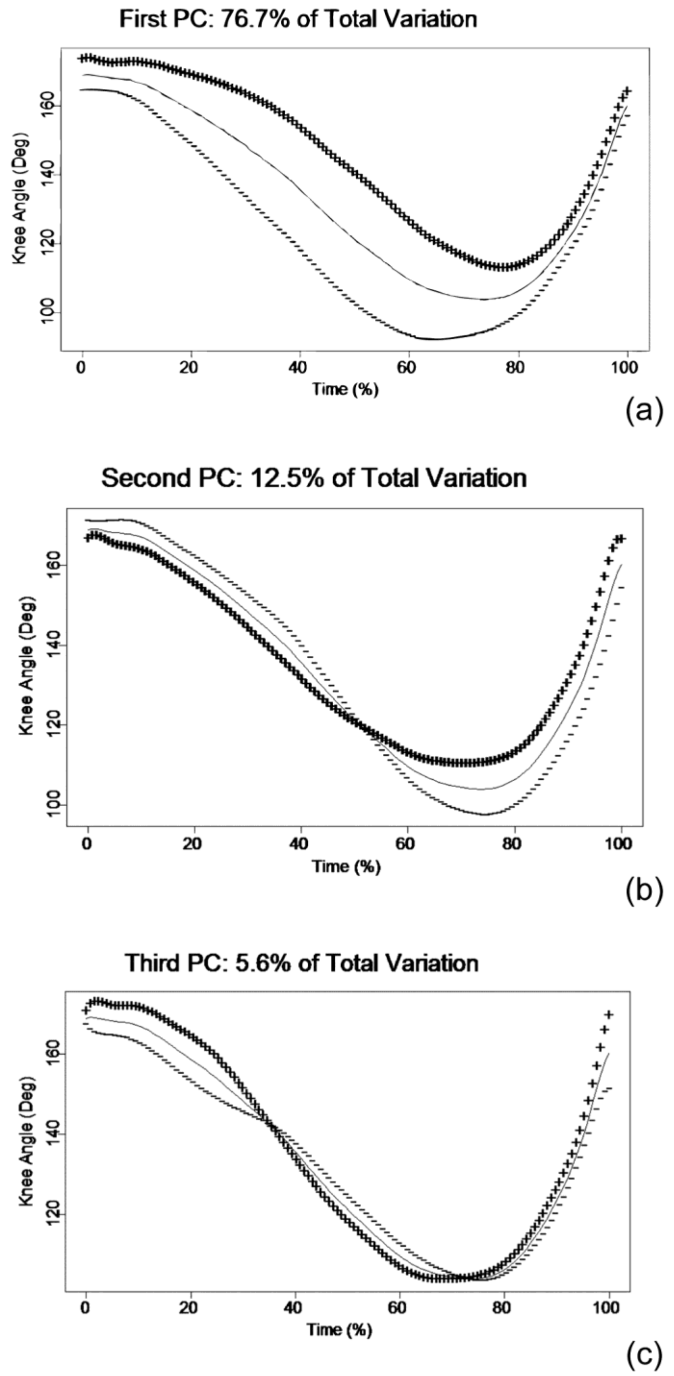

Figure 6. The first three Functional Principal Components (f-PCs) on unregistered data for knee joint function during vertical jump in children The graphs show mean ensemble curve with the high scorers for each f-PC being represented by +signs and the low scorers for the f-PC represented by – signs.

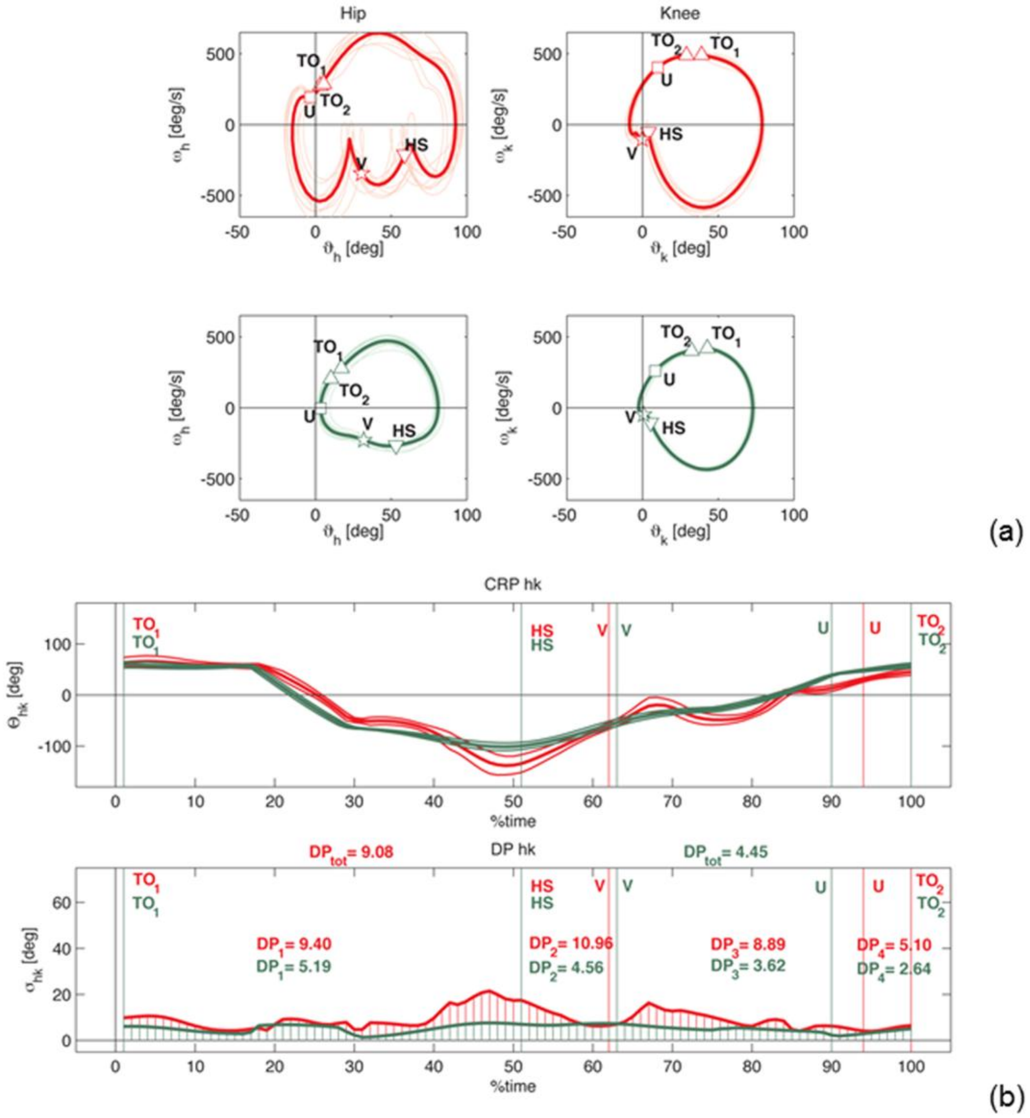

Figure 7. Example showing the potential of advanced studies of movement and coordination variability in evidencing underlying changes due to injury. The phase plane plots of the hip (a-left) and knee (a-right) joints concerning multiple race walking gait cycles pre- (red) and post-injury (green) are here reported, together with

the outcoming CRP variables (b) (see

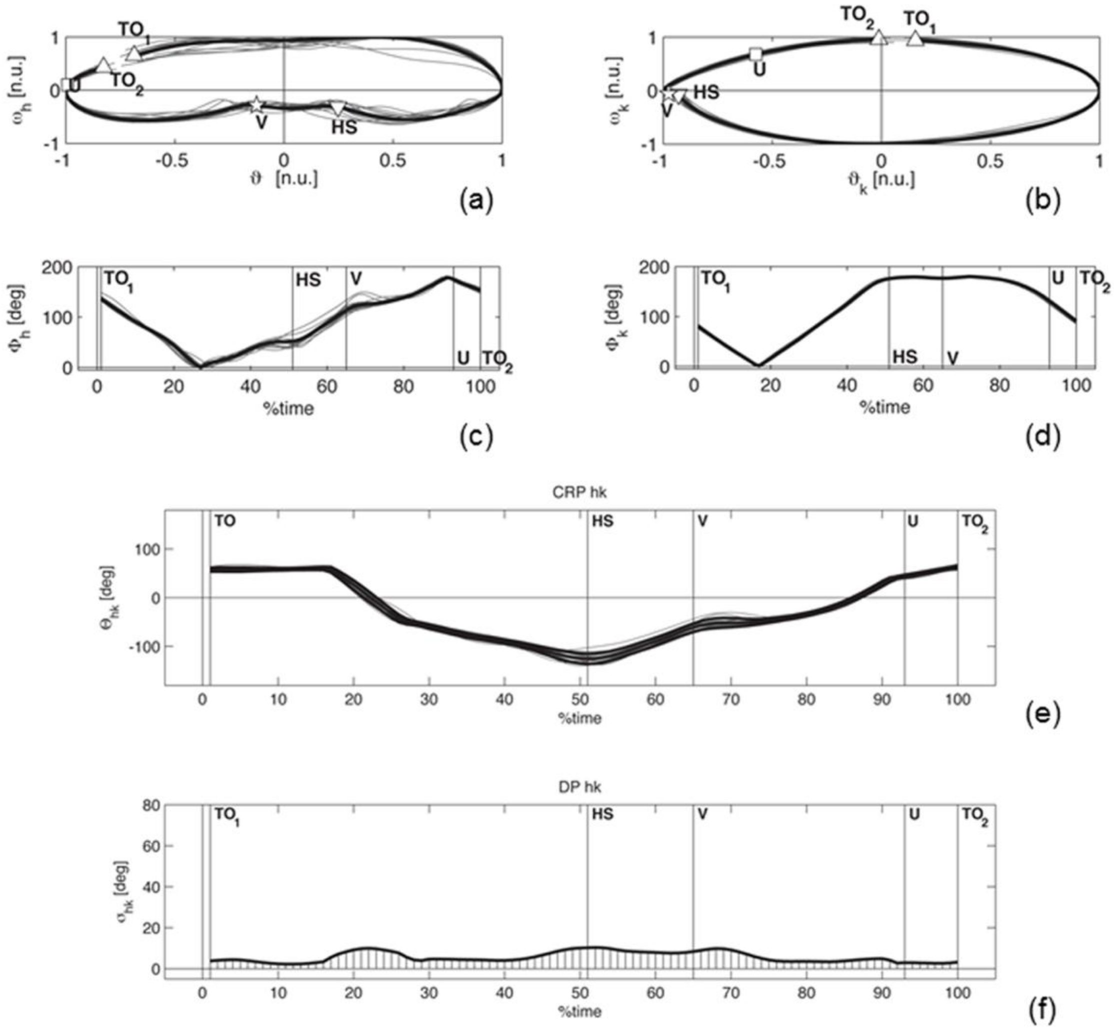

Figure 5 for annotations). The athlete was considered clinically recovered and reported no significant changes in terms of: duration of the movement, speed, step length, antero-posterior and vertical ground reaction force. However, both entropy measures and phasing relations between joint angles manifested a decrease of regularity/variability between the two testing session, evidencing that something had changed in the neuro-muscular organisation of movements. Only the availability of proper reference values may help in interpreting whether the increased variability in the pre-injury test was a detrimental factor or whether the higher regularity in the post-injury test was a sign of excessive control resulting from the pathology.