UNIVERSITAT DE BARCELONA

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A complex systems approach

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Una aproximació des dels sistemes complexos

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Facultat d'Educació

INSTITUT NACIONAL D'EDUCACIÓ FÍSICA DE CATALUNYA (INEFC)

Centre de Barcelona

Programa de Doctorat EEES (HDK02)

Activitat física, educació física i esport

Línia d'investigació:

101103 Activitat física i salut

SPORTS MONITORING: A COMPLEX SYSTEMS APPROACH

La monitorització esportiva: Una aproximació des dels sistemes complexos

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Per optar al títol de doctor per la Universitat de Barcelona

Barcelona 2022

"Complex systems are everywhere. They're devilishly hard to capture in models and differential equations, but crucially important to understand" McCormick (2022).

Agraïments (*Acknowledgments*)

Aquesta tesi no és només meva, és de tothom que m'ha ajudat, i en especial de la Natàlia com a mare acadèmica. L'afany desinteressat de diners però sí de coneixement i d'aportar ciència innovadora a la societat que m'has trasmés sempre n'estaré agraït. A més, aquest petit camí no hagués començat, avançat ni acabat sense la teva constant ajuda i sabiesa. Una referent de valors que m'ha ensenyat molt en tots els aspectes de la vida, però sobretot a estimar i a promoure la ciència i l'educació.

I'm feeling very thankful to the other director of my thesis, Robert. You showed me the world from another perspective in which everything is somehow interrelated, and some basic but universal notions can explain either the politics' dynamics, the natural catastrophes or the micro-physiological processes. Your wisdom has marked my understanding and the international stay of my PhD in your town was a great experience. Blagodaram!

A l'Anna que m'ha ajudat immensament aquests dos últims anys en tots els aspectes personals i professionals, compartint dia a dia tots els dubtes i inquietuds d'una tesi doctoral. Al meu pare, Jordi, que des de ben petit m'ha inculcat l'estima pel coneixement, el pensament crític i el suport familiar. A tota la resta de la família, com el meu germà Jofre, la meva mare Marta, la meva àvia, la meva cosina Anna per ajudar a corregir l'anglès del primer article, i com no el meu tiet Xavi per acompanyar-me a fer el primer pas dins l'INEFC. També als avis que em van donar amor, però que ja no hi són. Per l'acompanyament constant, càlid i proper, d'en Baloo, el nostre gat que m'ha ajudat a relativitzar els problemes quotidians i sovint angoixants que ens generem els humans. També, a la Teresa i en Climent per abastir-nos de menjar i suport quan més falta a fet.

A tot el grup de recerca "Complex Systems in Sport", que a part de ser companys investigadors també han esdevingut amics. A en Jordi amb el que vam començar a encuriosir-nos sobre la ciència i anar als primers congressos quan just estàvem al segon any de carrera, ja que sense ell segurament no hauria començat aquest interès. A en Pablo per ser un referent proper que m'ha ajudat en aquest procés des del primer dia quasi com un tutor més, i conjuntament amb en Jordi i la Natàlia per tirar endavant un projecte com els podcasts "Linking Theory and Practice". A la Maricarmen, per ser companya aquesta última etapa de la tesi i pel seu caràcter crític, incansable i cooperatiu que m'ha fet millor professor i investigador. A la resta del grup, Carlota, Lluís, Óscar, Ángel, Sergi, Agne, Aleix, Kike, Mercè, Assumpta, etc., per tots els aprenentatges i col·laboracions. Els treballs innovadors d'aquest grup són la base i inspiració d'aquesta tesi.

To all scientists, as co-authors or reviewers, that helped me to improve parts of this thesis: Pedro, Joao, Andreas, Daniel, Josep Lluís, Casimiro, John. Thank you so much, I've learnt a lot from you!

A l'INEFC, en especial els companys de Barcelona, que m'han acompanyat en aquest viatge. Doctorands i companys des del primer dia, Joana, Aaron, Maria Ángeles, Carla i d'altres que s'han anat incorporant o marxant pel camí, així com tot el grup de "Cerveses INEFC", gràcies per fer d'aquesta feina força solitària una mica més agradable. Poder compartir inquietuds similars, i quan ha fet falta, lluitar per unes condicions laborals més dignes i justes pels doctorands. A l'àrea de recerca, per facilitar material i gestions burocràtiques, a l'Albert, la Míriam, la Maribel, el Joan, el Diego, i a l'oficina de projectes, Glòria i Carme, gràcies.

També a la resta de PDI i caps institucionals i departamentals, especialment a en Toni per empenyer-me a fer recerca als meus inicis, i a l'Edu pel seu suport i labor a la casa.

A EUSES (Universitat de Girona), en especial a l'Adrià i en Sergi, per oferir-me la possibilitat d'introduir-me al món acadèmic en la fase final de la tesi.

To the Swedish School of Sport and Health Sciences (GIH), especially to Eva, Sebastian and Daniel, for letting me introduce in the scientific world in 2018 when I was wandering around career opportunities. A en Sergi, el qual va dirigir el meu primer treball de recerca a Batxillerat, pels contactes que em van permetre tenir aquesta experiència.

A la Júlia pel fantàstic disseny de la portada.

Finalment, a tots els amics i companys d'entrenament, que tot i desconéixer en general el contingut d'aquesta tesi, els nostres debats multidisciplinars i experiències conjuntes han aportat molt a aquest resultat final: Èric, Joan, Oriol, Gerard, Roger, Martí, August, Javi, Pau, Guillemas, Dani, Tino. Díficil mencionar a tothom que d'alguna manera ha estat present durant aquesta tesi; tot l'entorn que m'ha acompanyat aquests últims anys n'és partícep.

Desitjo i espero que la pugueu gaudir i que sigui un treball que ajudi a millorar la manera d'entrendre i aproximar la monitorització esportiva i, conseqüentment, la promoció i regulació de la salut i el rendiment. *I wish and hope that you can enjoy this thesis, which may help improving the way to understand and approach sports monitoring and, consequently, the promotion and regulation of health and performance.*

Abstract

Sports monitoring, based on excessively simplistic theoretical assumptions and methodological techniques, has limitations for capturing and assessing athletes' behaviour. This thesis, conceptualizing athletes as complex adaptive systems (CAS), aims to propose methods and data analysis techniques for assessing CAS' properties, and approach sport-related phenomena accordingly. Four published research articles are included. They study the properties of hysteresis, variability and synergies in diverse phenomena: workload stress and tolerance, fatigue-induced exhaustion, exercising flow state, and the relation between intra- and interpersonal synergies in a dyadic task. The applied methods and techniques have shown their potential to capture: a) the psychobiological stress and exercise tolerance through the hysteresis area of heart rate and the rate of perceived exertion, b) the fatigue-induced exhaustion and the exercising flow state through the time-variability of acceleration, and c) the multilevel coordination of dyads through the analysis of synergies. These time series analysis techniques, taken at individual level, supposed an actionable and effective way to assess athlete's behaviour and improve the understanding of the studied phenomena. Therefore, this thesis proposes updating, on the basis of a complex systems approach, the current theoretical assumptions and methodological techniques of sports monitoring.

Resum

La monitorització esportiva, basada en supòsits teòrics i tècniques metodològiques excessivament simplistes, té limitacions per capturar i avaluar el comportament dels esportistes. Aquesta tesi, conceptualitzant els esportistes com a sistemes complexos, té per objectiu proposar mètodes i tècniques d'anàlisi de dades per avaluar les propietats dels sistemes complexos, i aproximar fenòmens esportius d'acord amb aquesta perspectiva. Quatre articles científics publicats són inclosos. Aquests estudien les propietats d'histèresi, variabilitat i sinèrgies en fenòmens diversos: estrès i tolerància a la càrrega, exhauriment induït per la fatiga, l'estat de flow en exercici, i la relació entre sinèrgies intra- i interpersonals en una tasca realitzada per parelles. Els mètodes i tècniques aplicats han mostrat el seu potencial per capturar: a) l'estrés i tolerància psicobiològica a l'exercici a través de l'àrea d'histèresi de la freqüència cardíaca i l'esforç percebut, b) l'exhauriment induït per la fatiga i l'estat de flow en exercici a través de la variabilitat temporal d'acceleracció, i c) la coordinació multinivell de parelles a través de l'anàlisi de sinèrgies. Aquestes tècniques d'anàlisi de sèries temporals, preses a nivell individual, han suposat una manera realista i efectiva per avaluar el comportament dels esportistes i millorar la comprensió dels fenòmens estudiats. Per tant, aquesta tesi proposa actualitzar els supòsits teòrics i les tècniques metodològiques actuals de la monitorització esportiva en base a una aproximació dels sistemes complexos.

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Abbreviations

ACWR – Acute: Chronic Workload Ratio

CAS – Complex Adaptive Systems

DFA – Detrended Fluctuation Analysis

DST – Dynamical System Theory

H exponent– Hurst Exponent

HR – Heart Rate

MFDFA – Multifractal Detrended Fluctuation Analysis

NPE – Network Physiology of Exercise

RPE – Rating of Perceived Exertion

TRIMP – Training Impulse

UCM – Uncontrolled Manifold

VO_{2max} – Maximal Oxygen Consumption

Chapter One

1. Introduction

1.1. State-of-the-art of sports monitoring

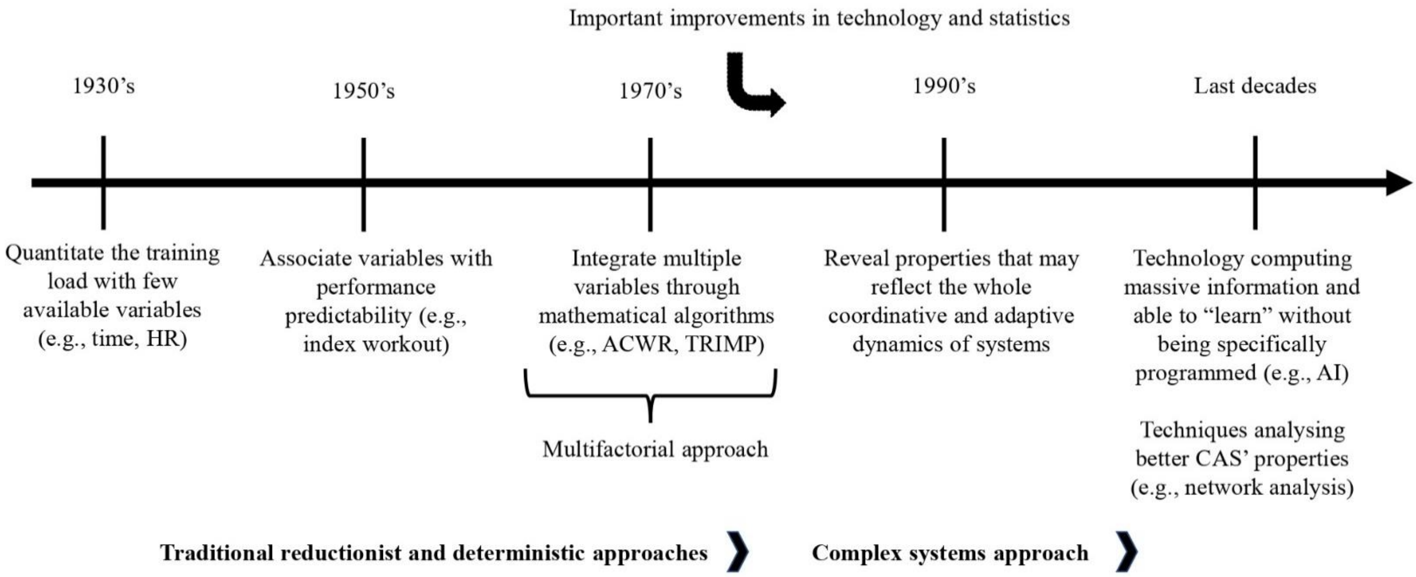
Monitoring is defined by the Merriman-Webster dictionary as ‘to watch, keep track of, or check’. In sporting contexts, the use of monitoring tools and physical activity trackers providing training and general health data has recently expanded dramatically. In 1954, Franz Stampfl, the Austrian coach who guided Roger Bannister through his final months of preparation before breaking the 4 min mile barrier, was considered unusual for hand-timing all of Bannisters runs (Foster et al., 2017). With improvements in technology beginning in the early 1980’s (radiotelemetric HR monitors, portable blood lactate analysers, rapidly responding respiratory gas analysers, reliable step counters, power meters, etc.), the scientific community has been able to provide new possibilities, which some years ago were inaccessible or difficult to access, relative to the analysis of internal and external loads (Foster et al., 2017). Today, new wireless technologies are expanding possibilities to provide simultaneous and continuous data related to biomechanical (e.g., acceleration, Delves et al., 2021), physiological (e.g., glucose, Moser et al., 2020) and performance variables (Herold et al., 2021). Such monitoring information is now widely considered a fundamental pillar for assessing sport training processes, for example, for revealing whether athletes are responding to training program, determining team selection, or helping to assess recovery (Bourdon et al., 2017; Halson, 2014).

Compiling and integrating multiple variables through a variety of mathematical algorithms (e.g., ACWR, Zouhal et al., 2021), and novel predictive analytics based on artificial intelligence (Claudino et al., 2019; Rein & Memmert, 2016; Seshadri et al., 2021) seems leading the current and next steps in sports monitoring. The tacit assumption that the collection of massive data is the key to provide integrative, pertinent and relevant information to promote athlete’s health and improve performance is extended (Bourdon et al., 2017; Fiscutean, 2021; Heidari et al., 2019; Tempelaar et al., 2020). Nevertheless, some authors have evidenced that none of the existing monitoring tools allows to accurately quantify or predict performance and prevent injuries (Bourdon et al., 2017; Halson, 2014; Impellizzeri et al., 2021; Impellizzeri, McCall, et al., 2020; Impellizzeri, Menaspà, et al., 2020; Seshadri et al., 2021). The proposed indexes and ratios seem insufficient, fragmented and often imprecise to dispense an effective performance and health promotion; specifically, when a conception of athletes/teams as complex adaptive systems (CAS) is taken into consideration (Balagué, Hristovski, Almarcha, et al., 2020). Despite the important technological advances, there is a general disconnect between the complexity underpinning human health and performance and the deterministic model through which athletic monitoring and assessment is conceptualised and constructed (Balagué, Hristovski, Almarcha, et al., 2020; Pol et al., 2020).

However, a dynamic complex systems perspective on sports monitoring, based on updated theoretical assumptions and methodological techniques, may improve sports monitoring adequacy, and subsequently, athletes and teams’ assessment.

Figure 1 illustrates the historical emergence of sports monitoring approaches to assess health and performance. Complex systems approaches are much less known and used compared to traditional, deterministic and multifactorial approaches, unable to adequately assess athletes and teams as CAS.

Figure 1. Summary of some relevant historical events in sports monitoring evolution (based on Foster et al., 2017).



Note. HR = heart rate; ACWR = acute:chronic workload ratio; TRIMP = training impulse; AI = artificial intelligence; CAS = complex adaptive systems.

1.2. How to monitor CAS?

Contemporary athletic monitoring philosophies perpetuate an archaic reductionist philosophical stance in sports training that envisions athletes and teams as linear, deterministic systems composed by multiple components. This monitoring information, expecting to guide coach decision-making processes in relation to athlete's health and performance promotion (Fiscutean, 2021), has a logic founded in an historically pervasive, but scientifically inaccurate, belief system. A belief system which interprets human biology as a collection of complicated, but inherently linear, deterministic cause-and-effect relationships. Such deterministic systems, when perturbed, respond to imposed stimuli with proportional and predictable adaptive responses.

Across the biological and neurological sciences, this conventional biomedical interpretation has been overthrown by the overwhelming evidence illustrating that human neurobiology is more appropriately conceptualized as a CAS: a system comprised of multiple embedded complex sub-systems which collaboratively and collectively share co-modulating information both vertically (e.g., genes, cells, tissues, organs, etc.) and horizontally (e.g., among molecules, cells, organs, etc.) to support the continued survival of the unified whole (Balagué et al., 2020; Ivanov et al., 2016). In turn, the organism itself functions as an integrated sub-system of a larger web of densely entangled complex systems interacting and self-organizing across multiple dimensions, scales and environmental networks. Table 1 contrasts the theoretical principles of athletes from traditional and complex systems-based approaches, respectively.

Table 1. Conception of athletes from traditional and complex systems-based approach. Adapted from Pol et al. (2020), with permission.

Properties of athletes	**Traditional approach**	**Complex systems-based approach**
Conception of organism	Machine	CAS
Control	Internal/external programs	Spontaneous synergies
Organization	Centrally regulated	Self-organized
Interaction with the environment	Multi-factorial additive, decontextualized	Non-additive, transactional
Relations	Linear, static, predictable	Nonlinear[1], dynamic, history-dependent, probabilistic[2]

[1] Nonlinear means nonproportional: although many complex adaptive systems (CAS) behaviours may for a long time perform in a linear regime (A as independent variable provokes a proportional effect on B over the time, i.e., small ΔA = small ΔB or big ΔA = big ΔB), for a certain small change of constraints their dynamics can also become nonproportional (small ΔA = big ΔB).
[2] Probabilistic character stems from the intrinsic noise of the CAS' behaviour (defined by a set of behavioural variables) and the fluctuations of the constraints that modify the stability of behavioural variables. Accordingly, CAS (even if stationary) cannot be predicted with certainty (100%) as it is in deterministic systems (e.g., classical mechanical systems). What can be predicted under similar constraints is only the probability distribution function of CAS' responses or patterns of behaviour (Fuchs & Jirsa, 2008; Hristovski et al., 2014; Kelso, 1995).

In contrast to complicated machines, CAS' behaviour cannot be accurately predicted from a particular variable or set of variables (Table 1). While machines behaviours emerge as a product of their individual deterministic component behaviours, in CAS, characterized by an interaction-dominant dynamics, their behaviour emerges as a product of the nonlinear integration of non-deterministically fluctuating personal and environmental influences acting across multiple levels and time scales (Balagué et al., 2017; Van Orden et al., 2003). A fundamental implication of this inherent and inescapable complexity is that, in the context of complex biological and/or medical contexts, fragmented metrics, or even the aggregation of multiple metrics, do not appear to provide meaningful predictive validity (Ching et al., 2018; Hu et al., 2016).

Therefore, some authors have questioned the logic underpinning contemporary trends in sports monitoring (Pol & Balagué, 2021). They point that the empirical assessment of surrogate measures of activity intensity, or isolated measures of physical function, even when blended using integrative algorithms or machine learning techniques, do not provide sufficiently reflective snapshots of current health status and/or performance potential. The prevailing fallacy of completing the puzzle through large quantities of multidimensional (e.g., biomechanical, behavioural, morphological, etc.) athlete-centered objective information lacks theoretical support in uncertain and complex scenarios (Sturmberg & Martin, 2021). Collecting isolated snapshots of a limited number of quantifiable measures, in the absence of a clearly defined and appropriately weighted relational hierarchy of performance priorities, promotes a distorted reality of CAS (Da Fontoura Costa & Silva, 2006; Gladyshev, 2017).

There are distinct properties of CAS independent of levels and timescales featuring their coordination and dynamics (Hristovski, 2013; Hristovski et al., 2014, 2019). From a mathematical point of view, the dynamical systems theory (DST) offers principles and concepts to study such properties (e.g., synergies, critical slowing down, variability, networks, etc.) in state variables[1]. They have been widely investigated in several scientific fields as physics, neurobiology, psychology, but also in sports science. For example, in decision making (Hristovski et al., 2006), injuries (Pol et al., 2019), intra- and interpersonal coordination (Ric et al., 2017; Vázquez et al., 2021), subjective experience dynamics (Balagué et al., 2015; Garcia et al., 2015) or motor creativity (Torrents et al., 2014). Such understanding has redefined, and is still redefining, the conception of athletes/teams and the training process itself, and subsequently, the usefulness and applications of monitoring tools as well (Balagué, Almarcha & Hristovski, 2020; Balagué, Hristovski, Almarcha, et al., 2020; Davids et al., 2003; Duarte et al., 2012; Hristovski et al., 2014; Pol et al., 2020).

From CAS' approach, subjective monitoring is dominantly promoted for continuously integrating multiple dimensions at different timescales, and thereby, capture the relevant changes of the organism-environment interactions (Balagué, Hristovski, Almarcha, et al., 2020; Pol et al., 2020). But also, objective monitoring connected to new techniques of analysis or old techniques applied to new phenomena are promoted to capture and inform better about CAS' properties (Balagué, Hristovski, Almarcha, et al., 2020; Weaving et al., 2017). Based on coordination dynamics, such methods aim gaining new insights into the changing relationships between groups of variables. Uncontrolled Manifold (UCM) to capture interpersonal synergies in sport (Passos et al., 2018), squared coherence to capture cardiorespiratory coupling on acute hypoxia (Uryumtsev et al., 2020), network analysis to capture multilevel organs' interactions (Ivanov et al., 2016, 2021), or Detrended Fluctuation Analysis (DFA) to capture physiological or kinematic variability of athletes in exhausting exercises (Gronwald et al., 2020; Vázquez et al., 2016) may stand as examples.

Table 2 contrasts the methodological hallmarks between traditional and CAS' approaches. Traditionally, isolated variables (in general from specific groups, e.g., trained young athletes, patients, etc.) are continuously monitored to extract only their mean or maximum values as a relevant health and performance information. Several authors question such approach and highlight the interest of analysing the idiosyncrasy of individual time series to detect the time-dependent variations of relevant state variables (Balagué, Hristovski, Almarcha et al., 2020; Molenaar, 2004; Nesselroade & Molenaar, 2010; Rose, 2016; Rose et al., 2013). The dynamics and individual variability profiles of state variables provide information about the coupling among system's components. These time series analyses, compared with mean or maximal values, seem to be more sensitive, detect qualitative changes[2] of athlete's behaviour and permit a better forecasting (Fonseca et al., 2020; Pol et al., 2019). For example, the cardiorespiratory coordination,

[1] Order parameters/collective variables, or more generally – state variables, represent the coherent and collective behaviour of the studied system (Haken, 1983).
[2] A qualitative change is a restructuring of the spatio-temporal order of the system. Phase transition is one possible way of attaining this change (Haken, 1983; Haken & Graham, 1971).

extracted by a principal component analysis approach, seem to be more sensitive than VO_{2max} or ventilatory thresholds to reveal specific training adaptations (Balagué et al., 2016; Garcia-Retortillo et al., 2019).

Table 2. Methodological hallmarks of monitoring from traditional and CAS' approach.

Methodological hallmarks	**Traditional approach**	**CAS' approach**
Variables	Isolated variables	State variables
Measures/data techniques	Means, thresholds and max values	Time series analyses
Evaluated changes	Quantitative	Quantitative and qualitative

Note. CAS = complex adaptive systems.

The applicability of this approach, together with the development of adequate technology, should enable in the future a more effective, integrative and realistic encapsulation of CAS' behaviours.

1.2.1. CAS' properties: Hysteresis, variability and synergies

CAS show instability and stability under multiple fast and slow-changing personal (from values to genetic expression) and environmental constraints (e.g., society, sport rules, opponents' actions, etc.) (Balagué et al., 2019). Instability leads to formation of previous and formation of new stable states and stability maintains the extant states. Due to the nonlinear organization of CAS, they usually do not have a single stable state, but may possess multistable states and hop between two or more states over time. This is, in fact, a universal property of complex neurobiological systems identified in vision, speech, motor or neural dynamics which evidences how adaptive systems are able to produce a large repertoire of coordinated behavioural patterns (see Kelso, 1995, 2012).

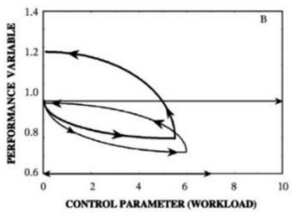
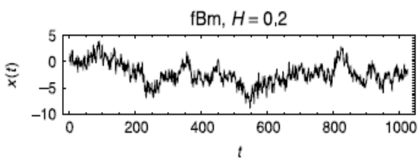
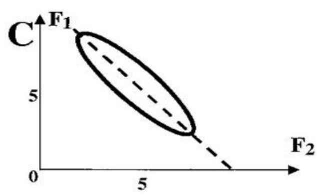
Hysteresis, variability and synergies- in an interrelated manner- inform about the stability properties of CAS. Hysteresis, a history-dependent property of complex systems, displays how after being perturbed systems recover their initial, relatively stable, state with a certain delay (Constant, 1929; Haken & Graham, 1971; Hristovski et al., 2010, 2014; Weiss, 1907). It may inform about the recovery efficiency of the studied system (Mayergoyz, 2003). On the other hand, variability reflects specifically the deviations of the system from its stable state (Kelso, 1995, 2012). This seems to be useful for detecting whether a neurobiological system is adapting to perturbation, which may be associated with healthy and performance states (Hristovski et al., 2013; Stergiou et al., 2006; Stergiou & Decker, 2011). Finally, synergies reflect the interactions which spontaneously emerge from the system's multiple components (i.e., elements), which act as a single functional unit compensating each other to maintain a relative stability of task goals (Black et al., 2007; Haken, 1987; Kelso, 2009). This becomes instrumental in studying how the goal-directed behaviours of humans are coordinated at different levels and timescales (Bernstein, 1967; Kugler & Turvey, 1987; Passos et al., 2016).

The study of such properties, entailing the dynamic and coordinative behaviour of athletes or teams, may permit a sensitive, and thus individualized, treatment of monitoring data.

But also, they may capture the performer-environment interaction, hardly detected through common monitoring systems. In fact, some sport-related phenomena linked tightly to the environment, such as the flow state or the proprioception, are particularly difficult to be conceptualized or even quantified (Montull, Vázquez, Rocas, et al., 2020; Montull et al., 2021). However, the study of hysteresis, variability or synergies may provide objective information about the history-dependency, fluctuations and components' interaction of the system in function the environment, respectively. Especially, in sporting context where this interaction is strong, such as in a slackline task requiring a constant co-adaptation (Paoletti & Mahadevan, 2012).

These CAS' properties can be objectively captured (see Table 3). Hysteresis area (Mayergoyz, 2003), fractal analyses (such as DFA and Multifractal Detrended Fluctuation Analysis 'MFDFA', Ihlen, 2012; Peng et al., 1994) and UCM (Black et al., 2007; Latash et al., 2001) can stand, respectively, as examples of data analysis techniques for approaching effectively and realistically diverse sport-related phenomena (see for example Delignières et al., 2011; Gronwald et al., 2020; Liu et al., 2014; Passos et al., 2018; Vázquez et al., 2021).

Table 3. Examples analysing hysteresis, variability and synergies.

Hysteresis	Variability	Synergies
The performance variable is analysed regarding its changing values for the same uploading and downloading control parameter (Hristovski et al., 2010).	The variance (autocorrelation) of the time series is analysed through H exponent. H = 0.2 indicates anti-persistent temporal variability structures because of deviations that tend to go on opposite directions (Tarnopolski, 2016).	The variance of two components (F1 and F2) are analysed through UCM for obtaining the synergies between them in relation with the performance variable (C) (Latash et al., 2001).
		

Note. H exponent = Hurst exponent; UCM = Uncontrolled Manifold.

1.2. Goals of the thesis

This thesis, conceptualizing athletes as CAS, aims to propose methods and data analysis techniques for assessing CAS' properties, and approach sport-related phenomena accordingly.

Four published research articles are included. They study the efficacy of data analysis techniques capturing the CAS' properties of hysteresis, variability and synergies to approach different sport-related phenomena. In particular (see also Table 4):

1- Hysteresis area of RPE and HR to approach workload stress and tolerance during cycling and running (Montull, Vázquez, Hristovski, et al., 2020).
2- MFDFA of time-variability properties of acceleration to approach exhaustion induced by acute fatigue effects during running and ski mountaineering (Montull et al., 2019).
3- DFA of time-variability properties of acceleration to approach exercising flow state during a slackline walking task (Montull, Vázquez, Rocas, et al., 2020).
4- UCM of acceleration time series to approach intra- and interpersonal synergies during a cooperative slackline dyadic task. Further, DFA of acceleration time series to approach the stabilizing roles within a dyadic task (Montull et al., 2021).

Table 4. Summary of the sport-related phenomena, type of exercise, monitored variables, data analysis techniques and CAS' properties studied in the research articles.

Research article	Sport-related phenomena	Exercises	Monitored variables	Data analysis techniques	CAS' properties
1	Workload stress and tolerance	Cycling, running	RPE, HR	Hysteresis area	Hysteresis
2	Fatigue-induced exhaustion	Running, ski mountaineering	Acceleration	MFDFA	Variability
3	Exercising flow state	Slackline (walking)	Acceleration	DFA	Variability
4	Intra- and interpersonal synergies of dyads	Slackline (balancing with dyads)	Acceleration	UCM DFA	Synergies Variability

Note. CAS = complex adaptive systems; RPE = rating of perceived exertion; HR = heart rate; MFDFA = Multifractal Detrended Fluctuation Analysis; DFA = Detrended Fluctuation Analysis; UCM = Uncontrolled Manifold.

Chapter Two

2. Assessing CAS' properties to approach sport-related phenomena

2.1. Research Article 1

HYSTERESIS BEHAVIOUR OF PSYCHOBIOLOGICAL VARIABLES DURING EXERCISE

Psychology of Sport & Exercise 48 (2020) 101647

Contents lists available at ScienceDirect

Psychology of Sport & Exercise

journal homepage: www.elsevier.com/locate/psychsport

Hysteresis behaviour of psychobiological variables during exercise

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ARTICLE INFO

Keywords:
History dependency
Psychobiological monitoring
Hysteresis area
Recovery during exercise
Exercise stress
Exercise tolerance

ABSTRACT

Objectives: The rating of perceived exertion (RPE) and the heart rate (HR) have been widely studied and monitored during exercise, but their hysteresis behaviour is still unexplored. Our aim was to study the hysteresis behaviour of RPE and HR in triathletes and non-athletes.
Design: Cross-sectional study.
Method: Eighteen triathletes at different competitive levels (elite $n = 9$, non-elite $n = 9$) and ten students were tested while cycling and running, using a pyramidal protocol (incremental/decremental workloads). The *hysteresis area*, considered positive when values of the dependent variables (RPE and HR) at the same workload were higher in the decremental phase than in the incremental phase, and vice versa for the negative areas, was calculated in all tests. The Wilcoxon matched-pairs test and Kruskal Wallis ANOVA were applied to detect intra- and inter-group differences, respectively, of RPE and HR values during the incremental and decremental phases, as well as between cycling and running.
Results: The following results were observed: a) an incoherent relationship of RPE with HR and workload, b) positive *hysteresis areas* of RPE and HR in all groups during cycling and running, c) a partial negative *hysteresis area* of RPE, but not of HR, in the triathlete groups, d) larger *hysteresis areas* of RPE and HR in students than in triathletes, and e) larger *hysteresis areas* in cycling than in running.
Conclusions: the study of the hysteresis behaviour of RPE and HR reveals the history dependency of both variables, highlights their incoherent or non-unique relationship during a pyramidal exercise, and questions their widely assumed linear association to workload intensity. The *hysteresis area* is proposed as a new non-invasive marker of exercise stress and tolerance that should be further investigated.

1. Introduction

The rating of perceived exertion (RPE) and the heart rate (HR) are quantitative measures of psychobiological stress that have been widely studied and monitored, during exercise (Borresen & Lambert, 2008; Eston, 2012; Foster, Rodriguez-Marroyo, & de Koning, 2017; Herman, Foster, Maher, Mikat, & Porcari, 2006). Current assumptions are that these variables display a proportional relationship to workload intensity and a positive association with each other. However, recent models of effort tolerance have suggested that both the relationship between these variables and their relationships to exercise intensity are more complex (Balagué, Hristovski, & García, 2019a; Glen, Eston, Loetscher, & Parfitt, 2017; Meckel, Zach, Eliakim, & Sindiani, 2018). Further, these models have not yet been tested using pyramidal exercises (i.e., alternating incremental/decremental workloads), which are a common form of workload distribution during training and competition. Such exercise protocols, involving different historical context dependency (applying and inverting the same dynamic sequence), may reveal incoherence or non-uniqueness in the responses of RPE and HR, and in the relationship of both variables to exercise intensity. They can also provide more precise information about the recovery of psychobiological variables during different types of exercise. In fact, this *recovery during exercise* has been the subject of far fewer studies than *post-exercise recovery*, usually tested in resting conditions. Moreover, these models may be used to study a hallmark of non-linear dynamic complex systems: the hysteresis phenomenon that explains the delay in a system's recovery of its initial state after a perturbation, evidencing history dependency (Hristovski, Balagué, & Schöllhorn, 2014; Hristovski, Venskaitytė, Vainoras, Balagué, & Vazquez, 2010).

Although linear associations between RPE, HR and exercise intensity have been reported during both constant and incremental workload exercise (Abrantes, Sampaio, Reis, & Sousa, 2012; Scherr et al., 2013), some authors have pointed out that this relationship depends on contextual factors, either between or within athletes, and the

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https://doi.org/10.1016/j.psychsport.2020.101647
Received 8 August 2019; Received in revised form 7 January 2020; Accepted 7 January 2020
Available online 15 January 2020
1469-0292/

need to distinguish between internal and external load. In turn, the validity of RPE and HR as internal load indicators is also dependent on the context (Impellizzeri, Marcora, & Coutts, 2018). The complex relationship between RPE and HR has recently been revealed, recording the variables at high sampling rates. A metastable coupling, i.e., intermittent coupling, decoupling and recoupling, between RPE and HR, has been described during constant exercise performed until exhaustion (Balagué et al., 2019a). This metastable behaviour, a result of the nonlinear interactions among components in complex dynamic systems, is necessary for adjusting the psychobiological processes to changes in personal and environmental constraints. In fact, it has also been detected at a phenomenological level in studies of the dynamics of other psychobiological variables, such as attention focus and pain (Aragonés, Balagué, Hristovski, Pol, & Tenenbaum, 2013; Balagué et al., 2015; Balagué, Hristovski, Aragonés, & Tenenbaum, 2012; Slapsinskaite, Hristovski, Razon, Balagué, & Tenenbaum, 2017). These non-proportional, i.e., non-linear, effects of sustained exertion on psychobiological variables have provided new insights for the study of endurance performance and behavioural exercise regulation (Balagué, Hristovski, Vázquez, & Slapsinskaite, 2014; García, Razon, Hristovski, Balagué, & Tenenbaum, 2015; Venhorst, Micklewright, & Noakes, 2018). Following in this vein, the study of hysteresis, a non-linear characteristic of complex systems, may provide novel information and contribute to improving our understanding of the behaviour of the most monitored psychobiological variables during exercise. It may help to reveal the limitations of the widely used linear and proportional models of exercise regulation, showing them to be founded on excessively simplified assumptions and artificially created contexts, such as those of exercise lab protocols.

Complex systems display history-dependent behaviour or a "memory effect" after a perturbation, which means that there is a delay before they recover their initial state. Such a memory effect arises because of a slow bidirectional variation of a control parameter. This phenomenon, known as hysteresis, has mainly been tested in studies of the efficiency of materials (Berthier, 2013; Bertotti, 1998; Mehdoui et al., 2013), but recently also applied to describe the behaviour of neurobiological systems. Previous work has studied hysteresis in brain activity (Sherrington, 2010), cardiovascular response (Liu, Yan, Yu, Zhang, & Poon, 2014; Swenne, 2015) and muscle/ligament/tendon properties (Butler, Grood, Noyes & Zerniche, 1978; Ramos, Lynch, Jones, & Degens, 2017; Woo & Adams, 1990), and some have proposed the study of hysteresis in disease diagnostics (Cabasson, Meste, Bailón, & Laguna, 2012; Cabasson, Meste, Blain, & Bermon, 2005; Meste, Blain, & Bermon, 2004). Although some of these studies incorporated exercise to investigate the hysteresis phenomenon, to the best of our knowledge, this is the first time that the hysteresis behaviour of psychobiological variables has been studied and is only the second study of the hysteresis effect in sports science (Trenchard, 2010). This author observed hysteresis in the behaviour of social systems, specifically, pelotons of cyclists during races, and related it to the resilience and robustness properties of these groups.

The hysteresis phenomenon may be quantified in biological systems using the *hysteresis area,* which reflects the amount of dissipated energy after the system's recovery (Mayergoyz, 2003). This amount of dissipated energy has been related to muscle fatigue because muscle activity economy depends on the amount of energy converted into heat (Ramos et al., 2017), and to cardiovascular pathologies (Liu et al., 2014). The latter authors use the *hysteresis area* to detect physiological differences between unhealthy (with cardiovascular pathologies) and healthy individuals. In sports science, the internal load reflects the amount of dissipated energy that an external load is provoking. Along these lines, Impellizzeri et al. (2018) proposed measuring the uncoupling of internal and external loads to identify how athletes cope with training programs. A lower internal load for the same external load may reflect increased fitness, and a higher internal load in the same situation may reflect a loss of fitness or fatigue accumulation. Moreover, the authors point out that the combination of psychological and physiological measures of internal load could suggest the kind of fatigue the athlete is suffering from. Accordingly, the *hysteresis area* of RPE and HR can be considered a non-invasive marker of exercise strain and tolerance.

The *hysteresis area* during exercise can be adequately evaluated applying pyramidal exercise protocols, where the same workload accrual is performed in reverse sequence (Meste et al., 2004). When the values of the dependent variable (i.e., RPE and HR) are higher during the decremental (downloading) phase than during the incremental (uploading) phase, the *hysteresis area* is considered positive; and when the values are lower, the *hysteresis area* is considered negative (Dotov, 2013; Frank, Profeta, & Harrison, 2015). In practice, the quantification of RPE and HR *hysteresis areas* during pyramidal exercises may assist practitioners to monitor fartlek type exercises and adequately adjust the external workloads to the internal ones (measured through RPE and HR).

It is worth noting that during pyramidal exercises, the decremental or recovery phase is active and progressive, in contrast with the classic post-exercise recovery, usually tested under resting or constant workload exercise conditions: i.e., so-called "active recovery". In this paper, we do not refer to "post-exercise recovery" or "active recovery" but specifically to "*recovery during exercise*", a much less explored concept in the literature.

Post-exercise recovery of RPE and HR follows an exponential curve and is faster, for a similar relative workload, in trained athlete populations (Dimkpa, 2009; Mann, Lamberts, Nummela, & Lambert, 2017; Otsuki et al., 2007). A stronger association between RPE and HR has been found in trained populations than in the untrained (Mann et al., 2017). In addition, it has been shown that the speed of HR recovery varies according to the type of exercise and training mode (McDonald, Grote, & Shoepe, 2014). In fact, cycling and running, the most common types of exercise, have different requirements that produce specific adaptations (Abrantes et al., 2012; Kriel, Askew, & Solomon, 2018; Millet, Vleck, & Bentley, 2009), and are thereby characterised by different perceptual sensations of effort[1] (Hutchinson & Tenenbaum, 2006). While the exercise and sports science literature has provided numerous findings related to the post-exercise and active recovery of HR (Dimkpa, 2009; Shetler et al., 2001), much less is known about the recovery of RPE, and particularly about the *recovery during exercise* of both variables. Pyramidal protocols provide the chance to investigate these under the framework of non-linear dynamics and to quantify them through the *hysteresis area*.

The aim of this research was to study the hysteresis behaviour of RPE and HR in triathletes and non-athletes during cycling and running, using a pyramidal exercise protocol. We hypothesised that this pyramidal exercise would produce a) a non-unique relation of RPE with HR, and of both with external workload, b) a positive *hysteresis area* of RPE and HR in all participants and in both types of exercise, and c) a smaller *hysteresis area* of both variables (RPE and HR) in athletes than in non-athletes. In addition, we aimed to explore potential differences between the *hysteresis areas* produced by running and cycling.

2. Methods

2.1. Participants

To determine the sample size for this study, a power analysis was conducted using G*Power 3.1 (Faul, Erdfelder, Lang, & Buchner, 2007). The total sample size finally recruited was 28, although 27 participants

[1] Perceived effort and perceived exertion are closely-related terms in scientific discussion (see Abbiss, Peiffer, Meeusen, & Skorski, 2015; Pageaux, 2016). As RPE (Borg, 1998) is the studied variable in this text, we refer to perceived exertion.

were needed to conduct intergroup comparisons for three groups using a moderate effect size of $f = 0.25$, $\alpha < 0.05$, power (1-β) = 0.90, with five relative load conditions, five repeated measures with 0.5 mean correlations and a non-centrality parameter λ of 16.87, $df = 4, 96$. Participants were voluntary male triathletes and students (22.45 ± 3.58 years). They were divided into three groups: elite triathletes (ET, $n = 9$), non-elite triathletes (NET, $n = 9$) and physical education students (PES, $n = 10$). Members of the ET group competed in triathlons at international level and the NET group at local level, while the PES group had no triathlon experience, but practiced between 3 and 5 h/week of aerobic activities. Prior to taking part in the study, all participants completed a questionnaire to confirm their health status. All experimental procedures were explained to participants before they gave their written consent to the experiment. The experiment was approved by the Local Research Ethics Committee (072015CEI-CEGC) and carried out according to the Helsinki Declaration.

2.2. Procedures

All participants performed pyramidal cycling and running exercises (see description below). They were familiarised with the testing procedures and used the 6 to 20 RPE scale (Borg, 1998) during incremental exercises, at least twice per week in the month prior to the experiment. Although the RPE scale is considered insufficient to capture the whole range of perceptual sensations during exercise (Hutchinson & Tenenbaum, 2006), we used it in this study due to its widespread monitoring use in practice and research. We asked the following question: "What is your perceived exertion at this moment?". Instructions had previously been provided on how to assess the RPE measurement, in accordance with Pageaux (2016): participants had the opportunity to ask questions, they had to differentiate exertion from other sensations, as a whole-body exercise experience, and had to consider maximal exertion on the basis of exercise-anchoring (not memory-anchoring). During the exercise, participants had a printed copy of Borg's 6-to-20 RPE scale placed in front of them to read before answering.

2.2.1. Pyramidal cycling and running exercises

Cycling and running exercises were performed on a cycle ergometer (Sport Excalibur 9295900) and treadmill (h/p Cosmos Pulsar 3p®), respectively. They consisted of a warm-up (5 min at 70 W or 6 km/h, respectively) followed by a pyramidal exercise during which participants reported their RPE (6–20). The incremental phase started at 100 W in the cycling exercise and 10 km/h (ET and NET groups) or 8 km/h (PES group) in the running one. Power was increased by 30 W/min and velocity by 1 km/h, until participants reported an RPE ≥18. At that moment, a decremental phase started, respectively reducing power or velocity, by the identical degrees (30 W/min or 1 km/h) until initial values were reached. RPE was verbally reported during the last 10 s of each power or velocity increment/decrement, and HR was continuously monitored (Polar Electro Oy, Finland) and recorded (Lode software, Lode, the Netherlands). The last registered values of each increment/decrement load (power or velocity) were considered for analysis.

2.3. Data analysis

Peak RPE and HR values obtained during the exercises were used to calculate the relative load as follows:

$$\% \text{ Relative load} = \text{Current load} \cdot 100 / \text{Peak load}$$

The mean RPE and HR values corresponding to relative loads over 50% were used to evaluate the hysteresis behaviour. Firstly, RPE and HR values corresponding to the same relative load in both incremental and decremental phases were compared within each group using Wilcoxon matched pairs test. Secondly, the mean *hysteresis areas* were calculated as differences between incremental and decremental phases at each workload for each group using the GeoGebra software for Windows (GeoGebra, Linz, Austria). Prior to calculation of the *hysteresis area*, data points were rescaled from 0 to 10, with 10 being the highest value in the group, in order to observe equivalent areas. Partial positive and negative areas were added together in each group as a total area. Kruskal-Wallis ANOVA was used to compare the differences between incremental and decremental phases at each workload among the three groups. Mann-Whitney U matched pairs test was applied in order to detect the differences between each group pair. Finally, the RPE and HR hysteresis areas for cycling and running exercises were compared through Wilcoxon matched pairs test. For all statistical tests, the significance level was set at $p < .05$. When reporting the within group analysis results, we used intervals of statistical values in order to summarize the statistics. Effect sizes were calculated (Fritz, Morris, & Richler, 2012; Lenhard & Lenhard, 2016) to demonstrate the magnitude of standardized mean differences: Cohen's d was performed for Wilcoxon and Mann-Whitney tests while Cohen's f and η^2 were performed for Kruskal-Wallis test.

3. Results

Table 1 shows the median and interquartile range (IQR) of the peak RPE and HR reached in the cycling and running exercises, and the differences between the values obtained during the incremental and decremental phases in each studied group.

3.1. Correspondence among RPE, HR and external workload

As shown in Figure 1 and 2, values of incremental and decremental phases of cycling and running exercises showed an incoherent relationship of RPE with HR and external workload.

Within group comparison between matched pairs in cycling revealed differences between incremental and decremental phases in RPE at high relative loads (80%–90%) in the ET group ($Z = 2.12–2.40$, $p = .03-.02$, $d = 1.26–2.10$), and at moderate-high workloads (60%–90%) in the PES group ($Z = 2.59–2.84$, $p = .01-.004$, $d = 1.24–3.94$). In contrast, differences between incremental and decremental phases of HR were found in all relative workloads in all groups: ET ($Z = 2.52–2.67$, $p = .01-.008$, $d = 0.88–1.23$), NET ($Z = 2.25–2.68$, $p = .02-.007$, $d = 0.70–1.10$ and PES ($Z = 2.80–2.81$, $p = .005$, $d = 0.72–1.87$).

On the other hand, the differences in running were found in RPE at low-moderate relative loads (50%–70%) in the ET group

Table 1
Peak Values and Differences (Median and IQR) between Incremental and Decremental Phases (50%–90% Relative Load) of RPE and HR for each Group both in Cycling and Running.

Cycling			Running		
Peak Values					
	RPE	HR		RPE	HR
ET	18 (1)	162 (17)	**ET**	18 (0)	179 (26)
NET	18 (1)	161 (17)	**NET**	18 (1)	178 (22)
PES	18 (2)	164 (24)	**PES**	19 (1)	187 (11)
Differences between Incremental and Decremental Phases					
	RPE	HR		RPE	HR
ET	0 (2)	12 (10)	**ET**	−2 (2)	6 (11)
NET	0 (3)	16 (13)	**NET**	0 (4)	17 (12)
PES	3 (2)	26 (11)	**PES**	2 (3)	21 (11)

Note. IQR = Interquartile range; RPE = Rating of Perceived Exertion; HR = Heart Rate; ET = Elite triathletes; NET = Non-elite triathletes; PES = Physical education students.

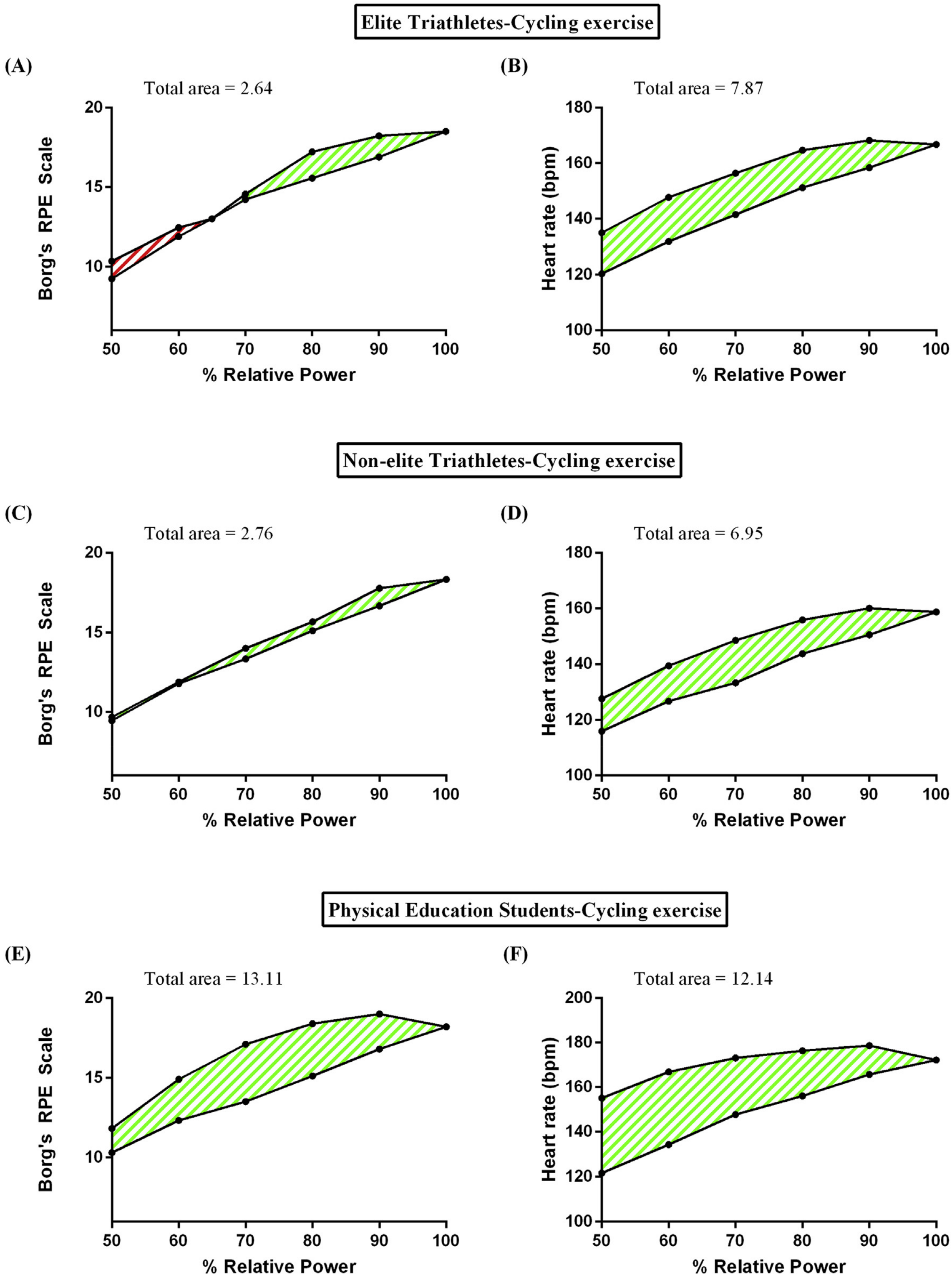

Fig. 1. Total Hysteresis Areas (Sum of Positive "Green" and Negative "Red" Areas) of Rating of Perceived Exertion (RPE) and Heart Rate for each Group, Corresponding to Workloads from 50% to 100% of the Relative Power in the Cycling Exercise.

(Z = 2.15–2.34, p = .03-.02, d = 1.37–1.85), and at low and high workloads (50%, 80%–90%) in the PES group (Z = 2.16–2.85, p = .03-.004, d = 0.88–1.91). In HR, differences between incremental and decremental phases were found in all relative loads and groups: ET (Z = 2.43–2.67, p = .01-.007, d = 0.42–0.52), NET (Z = 2.52–2.68, p = .01-.007, d = 0.60–1.13) and PES (Z = 2.80–2.81, p = .005, d = 1.43–2.76), except for 50%–60% relative loads in the ET group.

3.2. Comparison of hysteresis areas among groups

In cycling, the NET and PES groups presented only positive RPE and HR hysteresis (see Figure 1B, C, D, E, F). In contrast, the ET group presented a negative RPE hysteresis (60% and 70% relative workload, see Figure 1A). There were differences in the hysteresis areas among all the groups both for RPE: $H(140, 2) = 30.37, p < .001$ (Figure 3A), ES

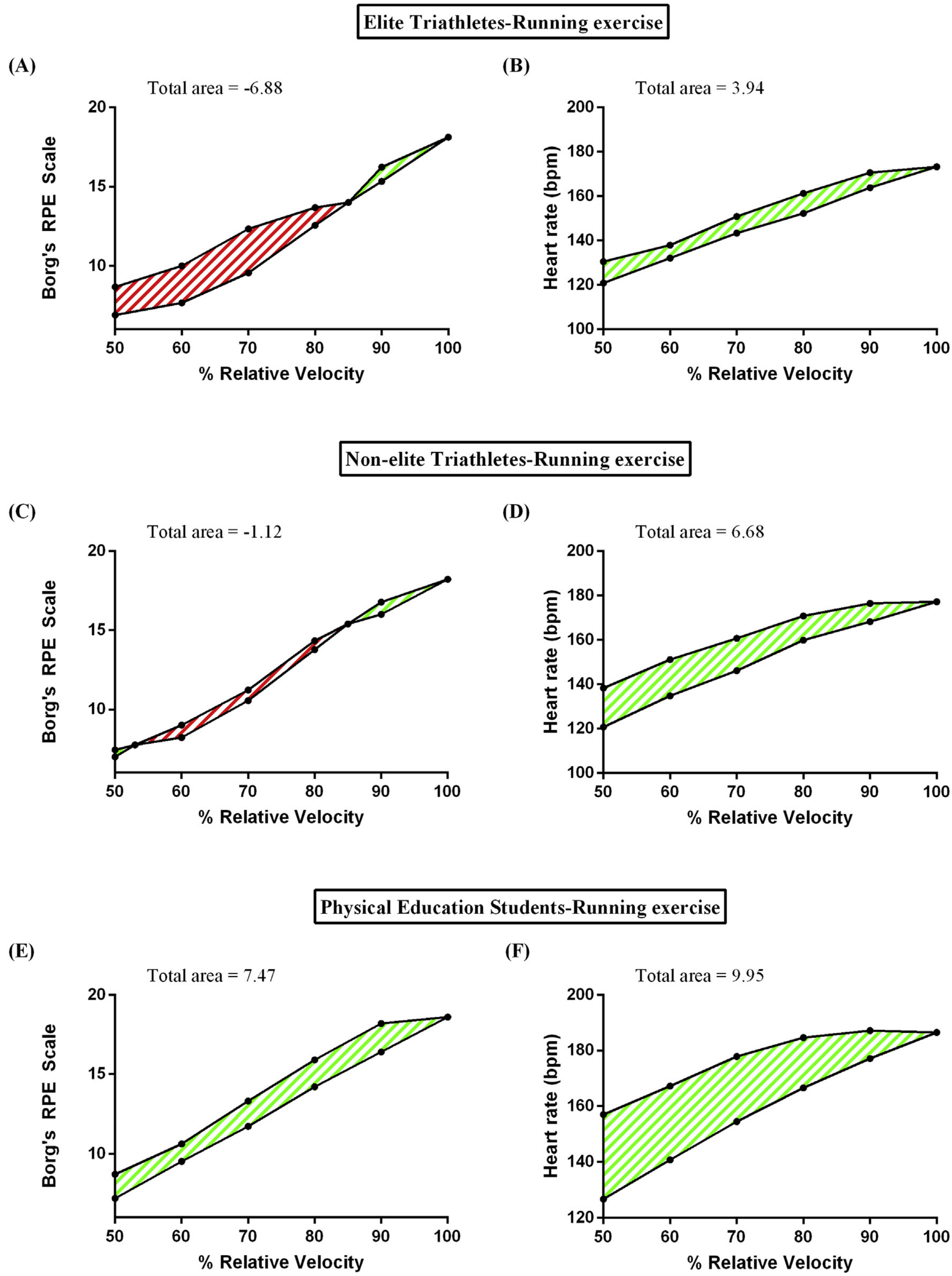

Fig. 2. Total Hysteresis Areas (Sum of Positive "Green" and Negative "Red" Areas) of Rating of Perceived Exertion (RPE) and Heart Rate for each Group, Corresponding to Workloads from 50% to 100% of the Relative Velocity in the Running Exercise.

(f = 0.51, η^2 = 0.21), and HR: $H(140, 2) = 35.41$, $p < .001$ (Figure 3B), ES (f = 0.57, η^2 = 0.24). As shown in Figure 1, the *hysteresis areas* of RPE and HR were only significantly larger in the PES group, compared with the ET (RPE: $U(95) = 444.50$, $p < .001$, $d = 1.22$; HR: $U(95) = 969.00$, $p < .001$, $d = 1.17$) and NET groups (RPE: $U(95) = 549.00$, $p < .001$, $d = 0.98$; HR: $U(95) = 421.00$, $p < .001$, $d = 1.28$).

In running, HR showed positive hysteresis in all groups (see Figure 2B, D, F) but negative RPE hysteresis between 80% and 90% relative velocity in the ET and NET groups (see Figure 2A, C). As shown in Figure 3C and 3D, intergroup comparison revealed differences both for RPE: $H(140, 2) = 35.97$, $p < .001$, ES (f = 0.57, η^2 = 0.24), and HR: $H(140, 2) = 42.35$, $p < .001$, ES (f = 0.65, η^2 = 0.30). Significant effects were found between the three groups in RPE (ET-NET: U

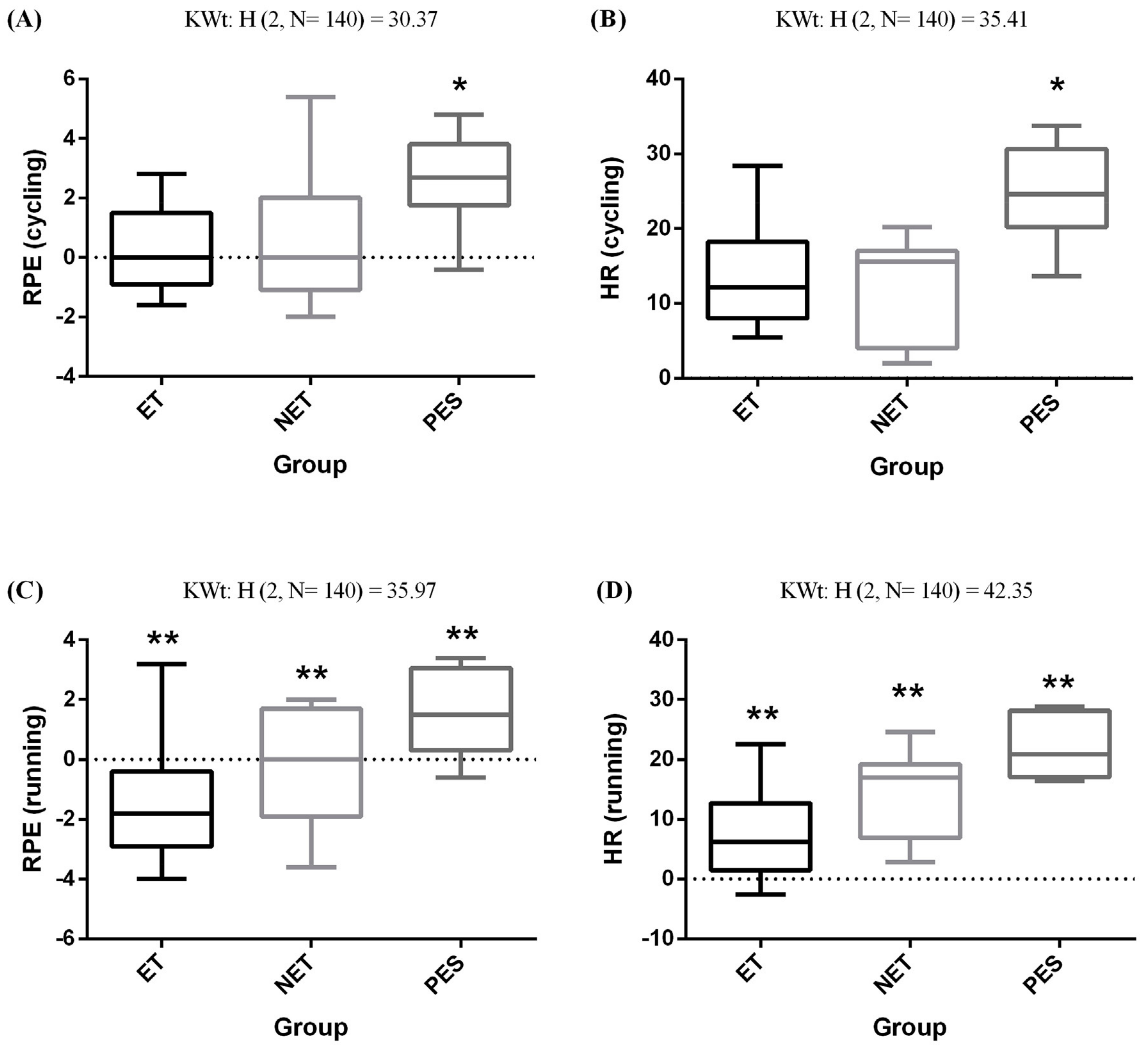

Fig. 3. Box and Whisker-plot comparisons of intergroup differences between incremental and decremental phases for RPE and HR in cycling and running. *Significant differences ($p < .001$) of PES Group with ET and NET groups. ** significant differences ($p < .001$) among all groups.

(90) = 674.50, $p = .006$, $d = 0.60$; ET-PES: $U(95) = 367.50$, $p < .001$, $d = 1.42$; NET-PES: $U(95) = 635.50$, $p < .001$, $d = 0.81$) and HR (ET-NET: $U(90) = 662.50$, $p = .004$, $d = 0.62$; ET-PES: $U(95) = 291.50$, $p < .001$, $d = 1.65$; NET-PES: $U(95) = 586.50$, $p < .001$, $d = 0.90$).

3.3. Comparison of RPE and HR hysteresis areas between cycling and running

RPE and HR hysteresis areas were larger in cycling than in running (see Figure 1 and 2); RPE (Z = 3.85, $p < .001$, $d = 0.69$) and HR (Z = 3.16, $p = .001$, $d = 0.55$).

4. Discussion

The main findings of the study of the hysteresis behaviour of RPE and HR during a pyramidal type of exercise by triathletes and non-athletes were: a) an incoherent relationship of RPE with HR and workload, b) a positive *hysteresis area* of RPE and HR across all groups, although they are non-significant for RPE in the NET group during cycling and running, c) a partial negative *hysteresis area* of RPE, but not HR, in the triathlete groups, d) larger *hysteresis areas* of RPE and HR for students than triathletes, and e) larger *hysteresis areas* in cycling than in running.

The incoherent relationship of RPE with HR and of both with external workload found in this study reinforces previous results, suggesting a complex association between RPE and HR, and questioning the assumed linear association between both variables and workload (Balagué et al., 2019a; Glen et al., 2017; Meckel et al., 2018). The metastable coupling dynamics found between RPE and HR (i.e., sometimes they are strongly coupled and sometimes decoupled), during exercise performed until exhaustion suggests that the behaviour of both variables is a product of complex mind-body-environment interactions. Formed by processes that take place over different timescales, the behaviour of RPE and HR cannot be reduced to respective psychological and physiological proportional responses to external workload (Balagué et al., 2019a). In that sense, the study of the hysteresis behaviour and, specifically, the quantification of the *hysteresis area,* supports the introduction of a new marker for evaluating the non-linear response of psychobiological variables to exercise. The applied pyramidal exercise revealed that the same external workload was performed with different internal loads, measured through RPE and HR values. This was due to a characteristic property of complex adaptive systems: degeneracy (Edelman & Gally, 2001). According to this property, different psychobiological synergies can satisfy the same objective. These synergies produce compensatory effects, reorganising according to the constantly changing personal (e.g., stress, fatigue) and environmental (e.g., external workload) constraints during exercise. As revealed by the applied pyramidal protocol, historical constraints play a fundamental role in the reorganisation of such psychobiological synergies. In accordance with Impellizzeri et al. (2018), the current results show that internal and external loads cannot be directly related, as is usually done when administering incremental exercise lab protocols. It can, therefore, be argued that the widely held linear relationship between RPE and HR and between both variables with external workloads is, at least in part, a consequence of excessively simplified and decontextualised assumptions, which are reflected in exercise lab protocols. Thus, the quantification of the *hysteresis area* seems a recommendable strategy to reveal the complex, dynamic and non-linear properties of biological systems during exercise and to provide information about their efficiency/economy (Mehdaoui et al., 2013; Ramos et al., 2017) and functional status.

Positive RPE and HR hysteresis behaviour in both cycling and running exercises was found in all participants at the highest achieved workload intensities (above 60%). However, a negative, non-hypothesised hysteresis response of RPE, but not of HR, was detected below such workloads, only in the triathlete groups. At the same external load, the higher values of RPE and HR obtained during the decremental phase, in all participants, reflected their lower efficiency due to workload accumulation. Comparing the groups' results, the smallest *hysteresis areas* in both cycling and running exercises corresponded to the ET group, whereas the largest corresponded to the PES group. This finding reflected a) the higher efficiency of triathletes compared to students when performing the pyramidal exercise, and b) the lower level of strain perceived by the former, due to their higher exercise tolerance. This was illustrated not only by the different values of the *hysteresis areas* achieved by the studied groups, but also by the different effect sizes between the incremental and decremental values of RPE and HR during the pyramidal exercise.

The results of the *recovery during exercise* of RPE and HR were not in agreement with the *post-exercise recovery* findings of Mann et al. (2017). While these authors reported a stronger association between RPE and HR during recovery in trained than in untrained populations, our results indicated the opposite. The PES group recovered their RPE more slowly and closer to their HR recovery, along the decremental phase, than the triathletes.

At intensities below 70% relative power and 90% relative achieved velocity, in cycling and running, respectively, the RPE values during the decremental phase were lower than during the incremental phase in the trained groups. This meant a faster recovery of RPE compared to HR, and reflected an incoherent psychobiological response, i.e., lack of unique correspondence between the variables. Distinguishing between mental and muscle fatigue, some authors suggest that RPE is more related to the former and HR to the latter (Impellizzeri et al., 2018; Marcora, Staiano, & Manning, 2009). However, this suggestion would not explain the differences observed between trained and untrained participants. The negative *hysteresis areas* of RPE, but not of HR, during cycling (ET group) and running (ET and NET groups) point to different memory effects and recovery during exercise. While at high workload intensities, the positive *hysteresis areas* found in all groups for both variables reflect their common *workload history dependency* (i.e., systemic "memory effect"), the negative *hysteresis areas* of RPE in the triathlete groups reflect a specific *training history dependency* of this variable. This means that RPE is not only affected by *workload history* but also by the *training history* (i.e., exercise habituation or tolerance) of individuals. Triathletes are more habituated to performing at high intensities, maintaining higher strain pedalling and running for prolonged periods of time than non-athletes. In fact, trained athletes and triathletes recover faster than non-athletes or non-elite athletes after a similar relative workload intensity (Barak et al., 2011; Klepochová et al., 2018; Park, Park, Kim, & Kwak, 2008). It is worth remarking that, in contrast to the absolute RPE and HR values usually monitored during exercise, the *hysteresis area* is a relative variable that offers information about a process of change. Thus, despite all participants obtaining the same maximal RPE value after the incremental phase, their *hysteresis areas* differed according their competition experience. This highlights the relevance of evaluation of the *hysteresis area* as a measure of the efficiency of adaptation to external workloads and fitness status. These findings are in line with some recent studies showing that physiological responses do not necessarily match psychological effects, nor the external workload (Balagué et al., 2015; Balagué et al., 2019a; Meckel et al., 2018). According to these authors, the subjective feeling of relief that participants (athletes and non-athletes) experience when reaching their goal may explain the lower values of RPE obtained in the decremental phase when compared to HR values.

The current findings are also consistent with previous studies showing differences in physiological and psychological variables between cycling and running, despite their similarities as endurance-type exercises (Borg, Van den Burg, & Hassmen, 1987). In those studies, higher peripheral strain and local pain (Slapsinskaite, Razon, Balagué, Hristovski, & Tenenbaum, 2015), higher lactate concentration and less uniform muscle distribution (Abrantes et al., 2012; Millet et al., 2009) have been more closely associated with cycling than with running. Each specialised training changes not only the physiological, but also the psychological response to exercise (Hassmén, 1990). Accordingly, in this study, the comparison between cycling and running revealed that *hysteresis areas* of RPE and HR were larger in cycling than in running. In addition, the intergroup comparison of incremental and decremental phases showed that while all groups differed in both RPE and HR in the running exercise, only the PES group differed significantly in the cycling exercise. This may reflect a lower habituation of non-specialised populations to this type of exercise and suggests that there are specific training adaptations to these exercise modalities.

4.1. Practical implications

Some practical implications related to monitoring and controlling training workloads can be extracted from the current results. During fartlek training, characterised by changes in workload intensity, it does not seem possible to directly associate internal workload (measured by RPE and HR values) to external workload. It is worth considering that this mismatch between external workload and RPE and HR values is more pronounced in non-athletes and when cycling as opposed to running. Additionally, the "psychobiological incoherence" found in the triathlete groups should also be considered. The different values of RPE and HR obtained for the same workload intensities during the incremental and decremental (recovery) phases show the high sensitivity of these variables to different history-dependent, and particularly, training history-dependent scenarios. Specifically, due to experienced subjectivity and underpinned by the perception-action coupling (Venhorst et al., 2018), RPE appears to be more sensitive to exercise tolerance in trained populations than is HR. In this sense, it can be a more suitable variable for monitoring training workloads in a healthy and trained population. The strong influence of previous physical and psycho-emotional loads, which influence the complex and non-unique relation of systemic response to external workloads, should concern practitioners when monitoring psychobiological variables for training purposes. Practitioners should interpret RPE and HR values from a history- and context-dependent perspective to prevent excessive or insufficient stimulation and avoid maladaptation or even overtraining. In this sense, they should consider the effects of multiple personal and environmental constraints, operating on different timescales, on perceived exertion (Balagué et al., 2019a; Balagué, Pol, Torrents, Ric, & Hristovski, 2019b). The evaluation of the hysteresis behaviour (area, curve, differences between incremental/decremental phases, etc.) while manipulating the external workload over different timescales (from a single exercise bout to a set of training sessions) may help to identify the efficiency of recovery processes and thus, prevent fatigue accumulation effects.

4.2. Study limitations and future directions

Concerning the study's limitations, the sample included only young males and should be understood in the framework of an exploratory research of complex properties and non-invasive markers of exercise strain and fatigue accumulation. Consequently, the present findings cannot be generalised to all populations and future studies should consider including females and other age groups. The use of *hysteresis areas* to represent the *recovery during exercise* of RPE and HR has not been described, to date, and the lack of information about the topic increases uncertainty in discussing the results. Specifically, the different responses of RPE and HR, reflected in negative *hysteresis areas*, illuminates *training history dependency* (i.e., training habituation), and should be carefully studied in future research to better explain the psychobiological incoherence. It would be interesting to investigate whether, in the general population, the greater habituation to running and therefore its stronger training-history effect, as compared to cycling, can explain the lower *hysteresis areas* produced. More research is needed to study the hysteresis behaviour in other sports or exercises (e.g., intermittent, strength type, etc.) but also in other exercise intensities (e.g., submaximal). Further, it is suggested that assessment of the *hysteresis area* may be transferable to other variables, extracted from micro, meso or macro levels, and not only evaluated over short timescales (e.g., single bouts of exercise or training sessions as well as in post-exercise) but also over longer timescales (e.g., sets of trainings or a whole season). Whether the current results can be useful to assess athlete's health status, fatigue status or adaptation to training should be further investigated. Finally, future applicability of hysteresis behaviour monitoring, such as software that could directly plot the *hysteresis area*, should facilitate the investigation and practical use of the proposed marker.

4.3. Conclusions

The study of RPE and HR dynamics through a pyramidal exercise protocol revealed the hysteresis behaviour of these variables. The quantification of such effects through the *hysteresis area* allowed us to distinguish the performance level of participants, the different *recovery during exercise* (through decremental workloads) of RPE and HR, and the higher psychobiological strain produced by cycling as compared to running. Besides questioning some assumed linear associations of RPE with HR and workload intensities, the results point towards the discovery of a new non-invasive marker of exercise stress and tolerance.

Funding

This work was supported by the Institut Nacional d'Educació Física de Catalunya (INEFC, Generalitat de Catalunya.

CRediT authorship contribution statement

Lluc Montull: Investigation, Data curation, Formal analysis, Funding acquisition, Methodology, Visualization, Writing - original draft. **Pablo Vázquez:** Investigation, Data curation, Formal analysis, Methodology, Writing - original draft. **Robert Hristovski:** Conceptualization, Methodology, Writing - review & editing. **Natàlia Balagué:** Conceptualization, Supervision, Writing - review & editing.

Declaration of competing interest

None.

Acknowledgment

We like to thank Andreas Venhorst for his constructive review and input to improve the manuscript.

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2.2. Research Article 2

MONITORING THE DYNAMICS OF EXHAUSTING EXERCISES: THE TIME-VARIABILITY OF ACCELERATION

Monitoring the dynamics of exhausting exercises: the time-variability of acceleration

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Received 31 August 2019; accepted 6 September 2019
DOI https://doi.org/10.21595/vp.2019.20980

Abstract. Fatigue has been related to changes in the time-variability properties of coordinative variables during an exhausting isometric exercise [1]. In this study we aimed to investigate the qualitative changes in acceleration (kinematic collective variable) during exhausting running ($n = 8$) and ski mountaineering (n males = 5, n females = 5) exercises. Time-variability of acceleration was calculated using the Multifractal Detrended Fluctuation Analysis (MFDFA). Initial and final time series of both exercises were compared through Wilcoxon test. A reduction of MFDFA spectrum was observed in the final period in both exercises while the participants approached exhaustion, except for the male group of ski mountaineers that increased their speed at the end of the exercise. In runners, those who approached the psychobiological exhaustion showed a higher reduction in the MFDFA spectrum compared to those who did not. Although more research is needed to model this dynamic behavior in front of different constraints, time-variability of acceleration throughout a multifractal application seems to provide a valid information about the system adaptation during exhausting dynamic exercises.

Keywords: multifractal analysis, self-organization, kinematic variability, fatigue, nonlinear dynamics.

1. Introduction

The study of the time-variability properties, widely used in scientific fields to investigate the complex systems behavior, has revealed changes in the structure of several collective variables during exercise [1-3]. The dynamic behavior of such collective variables informs about the temporal coupling of the system's components, and the ability of the system to control its behavior [1]. It has been investigated under different constraints (e.g., diseases, stress, etc.) to study phenomena as the self-organization and the interactions of processes across different levels and timescales: from micro- (e.g., cellular, etc.) to macro-timescales (e.g., psycho-emotional, etc.) [4-6]. Multifractal Detrended Fluctuation Analysis (MFDFA) has been used to identify the deviations in the fractal structures of the variability within time periods with large and small fluctuation, and thereby allowing to study this dynamic behavior [4, 5, 7].

A rapid and flexible control of the system's timescales has been demonstrated at kinematic level in high-skilled athletes, who are able to coordinate better their movements and have a higher effectivity and task performance [8-10]. On the contrary, a rigid and slower control of the component's interactions characterizes the less skilled and experienced performers, as well as less coordinated and efficient.

Taking fatigue as common constraint in exercise performance, it has shown how produces maladjustments of the timescales' dynamics [1-3, 11]. In that sense, it has been observed how participants lost their initial fine regulation and control during a quasi-isometric exercise (i.e., static task), disabling over time the task performance, as they approached exhaustion [1, 11]. However, the time-variability of kinematic variables during dynamic exercises performed until exhaustion has not been studied yet. This information can be useful in terms of training and health monitoring. Concretely, it can help to detect the coordinative changes and loss of control produced by the exercise induced fatigue and anticipate the exhaustion point. It is worth to point that although this type of analysis has been applied to evaluate physiological processes and diagnose diseases [5], its applications to monitor sport and exercise activities is still scarce.

Accordingly, this study, divided in two parts, aimed to investigate the qualitative changes of the time variability of a kinematic collective variable, such as the acceleration, during two competitive and maximal (exhausting) dynamic exercises in runners and ski mountaineers.

2. Methods

– Running exercise: Eight experienced runners (39.37 ± 6.19 y.o.) performed a Cooper Test covering the maximum distance in 12 min.

– Ski mountaineering exercise: Ten ski mountaineering athletes (5 males and 5 females; 25.8 ± 5.3 y.o.) competing at international level performed a trial vertical race (1980 m of distance and 415 m of positive gain). Following the federation's rules, the groups competed separately in function of the gender.

The athlete's acceleration was recorded using WIMU devices (Realtrack Systems SL, Almería, Spain) placed on L3 [12]. The sample frequency was 100 Hz. The time series of acceleration were analysed through MFDFA [7]. The first and last minute of exercise were compared in the runners, and the first and third portion of the time series were compared in the ski mountaineers. Each portion contained $N = 30000$ data points (males group), and $N = 41900$ data points (females group). Velocity was also calculated and recorded during these periods to compare the performance in both running and skiing exercises.

The differences between initial and final periods of the MFDFA spectrum were analysed with the Wilcoxon non-parametric test while it was also calculated the subtraction's differences between final and initial values of MFDFA spectrum and velocity. Heart Rate (HR) was continuously recorded in both exercises to assess the physiological stress and the Borg's RPE (CR-10) was monitored only at the end of the running exercise. Data analysis was conducted via Matlab© R2013b and SPSS.

3. Results

Both competitive exercises supposed a high psychobiological stress (HR running = 181.75 ± 9.31; RPE running = 8.38 ± 0.74; HR skiing = 187.23 ± 10.05) for the athletes. The results showed a reduction in the MFDFA spectrum of the acceleration time series (see example in Fig. 1) in both exercises as the effort accumulated, even though no significant differences were found between the first and the last period of exercise during running (z Wilcoxon = –1.402, $p = 0.161$) and ski mountaineering (z Wilcoxon = –1.38; $p = 0.17$).

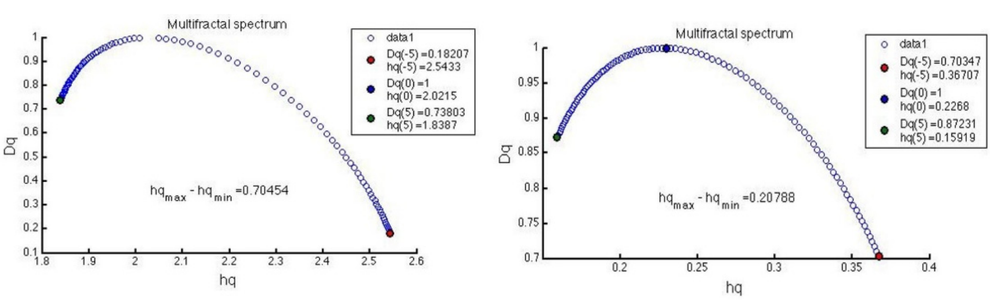

Fig. 1. Example of how the MFDFA of the acceleration spectrum was reduced from the initial to the final period of exercise

In the running study, those who approached exhaustion ($n = 4$; RPE ≥ 9; Average HR ≥ 180) showed higher reduction (0.28) in the MFDFA of the acceleration spectrum at the end of the exercise, compared with those who reached less psychobiological stress ($n = 4$; RPE < 9; Average HR < 180) with a reduction of 0.09. The loss of velocity between the initial and final period of the run matched with a reduction in the MFDFA of the acceleration spectrum (Table 1).

In the skiing exercise, gender groups followed different strategies during the race. While the female skiers group showed a reduction of the MFDFA of the acceleration spectrum and a velocity decrease at the end, the male group displayed a small increment of the MFDFA spectrum, probably due to a lower slope in the final part of the trial and reflected in an increase of the velocity (Table 1).

Table 1. Multifractal Detrended Fluctuation Analysis (MFDFA) spectrum of the acceleration and velocity of the first and last periods of the running and ski mountaineering exercises and their differences

	Runners ($n = 8$)	Male ski mountaineers ($n = 5$)	Female ski mountaineers ($n = 5$)
Initial MFDFA spectrum	0.37 ± 0.24	0.30 ± 0.06	0.49 ± 0.24
Initial Velocity (m/s)	4.10 ± 0.31	1.39 ± 0.04	1.22 ± 0.07
Final MFDFA spectrum	0.19 ± 0.05	0.53 ± 0.17	0.47 ± 0.10
Final Velocity (m/s)	3.79 ± 0.27	1.48 ± 0.07	1.12 ± 0.04
MFDFA spectrum differences	–0.18 ± 0.19	0.23 ± 0.11	–0.02 ± 0.14
Velocity differences	–0.31 ± 0.04	0.09 ± 0.03	–0.10 ± 0.03

These results are in accordance with previous studies during an isometric exercise [1, 11]. The reduction in the variability of the collective variable suggests a reduced adaptability to the task demands over time due to the accumulated effort and for hence a more difficult control of the task.

4. Conclusions

The time-variability of acceleration seems to provide a valid information about the system adaptation during exhausting dynamic exercises. More evidences are needed to model the way the collective variable changes its behaviour and how the system loses its control at different scales as a consequence of fatigue during exercise.

In future research, constraints that can affect the kinematic variability, such as the slope or the terrain, should be carefully controlled. The multifractal analysis of the acceleration time-variability points towards being a useful tool for monitoring and evaluating the adaptation to exercise. In this sense, it may complement the commonly used quantitative variables (e.g., HR or lactate values) in the control of training and competition. Such multifractal analysis may be applied as well to other variables with medical purposes.

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2.3. Research Article 3

FLOW AS AN EMBODIED STATE. INFORMED AWARENESS OF SLACKLINE WALKING

frontiers in Psychology

ORIGINAL RESEARCH
published: 10 January 2020
doi: 10.3389/fpsyg.2019.02993

Flow as an Embodied State. Informed Awareness of Slackline Walking

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Flow during exercise has been theorized and studied solely through subjective-retrospective methods as a "scull bound" construct. Recent advances of the radical embodied perspectives on conscious mind and cognition pose challenges to such understanding, particularly because flow during exercise is associated with properties of performer's movement behavior. In this paper we use the concept of informed awareness to reconceptualize flow experience as a property of the performer-environment coupling, and study it during a slackline walking task. To empirically check the possible relatedness of the behavior-experience complementary pair, two measures were considered. The experiential realm was quantified by the flow short scale and the behavioral realm by the Hurst (H) exponent obtained through accelerometry time series of the legs and the center of body mass (CoM). In order to obtain a coarse-grained insight about the degree of co-varying within the perception-action flow of performers, we conducted correlational and multiple regression analyses. Measures of behavioral variables (H exponents of the dominant, subdominant leg and the CoM, were treated as explanatory, and the flow scale and its subscale (fluency of movements and absorption) scores asresponse variables containing summarized information about perceptual experiences of performers. In order to check for possible mediating or confounding effects of training parameters on the action-perception variables' covariance, we included two additional variables which measured the degree of engagement of participants with the task. Results revealed that the temporal structure of fluctuations of the dominant leg, as measured by the Hurst exponent, was a strong mediator of effects of training variables and the subdominant leg fluctuations, on the flow scale and the subscale scores. The magnitude of Hurst exponents of both legs was informative about the degree of stability within the performer-environment system. The degree of critical slowing down, as measured by Hurst exponents, consistently co-varied with the flow scale and subscales. The experience of flow during the slackline walking task was dominantly saturated by the perceived fluency of movements and less so by the absorption experience. The stable co-variance of perception-action variables signified the embodied nature of the flow experience.

Keywords: radical embodiment, informed awareness, ecological dynamics, skill, stability, slackline

OPEN ACCESS

Edited by:
Duarte Araújo, University of Lisbon, Portugal

Reviewed by:
Maurizio Bertollo, Università degli Studi G. d'Annunzio Chieti e Pescara, Italy
Marek McGann, Mary Immaculate College, Ireland

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Specialty section:
This article was submitted to Movement Science and Sport Psychology, a section of the journal Frontiers in Psychology

Received: *01 June 2019*
Accepted: *17 December 2019*
Published: *10 January 2020*

Citation:
Montull L, Vázquez P, Rocas L, Hristovski R and Balagué N (2020) Flow as an Embodied State. Informed Awareness of Slackline Walking. Front. Psychol. 10:2993. doi: 10.3389/fpsyg.2019.02993

INTRODUCTION

Flow has been historically investigated in sport and exercise for its association with exceptional performance (Jackson et al., 2001; Swann et al., 2018). Commonly defined as a harmonious psychological state, intrinsically rewarding, involving intense focus and absorption in a specific activity (Csikszentmihalyi, 1975, 2002; Swann et al., 2018; Stoll, 2019), flow has been contextualized in a framework of challenge-skill balance, clear goals and sense of control (Jackson and Csikszentmihalyi, 1999; Nakamura and Csikszentmihalyi, 2002). Under this view, the state of flow has been traditionally measured solely by subjective methods (Jackson and Eklund, 2002, 2004) without attempts to relate it *empirically* to behavioral measures. This is curious because in physical activities the state of flow was theoretically connected to the fluency of movements (Rheinberg et al., 2003; Engeser and Rheinberg, 2008), which obviously has a behavioral, action content. In this paper we make the first empirical attempt to reconcile this methodological and theoretical gap.

Optimal psychological experiences, underlying the excellence in performance, have been mainly related to flow or clutch states, typically experienced in contexts of achievement and pressure (Swann et al., 2017a,b). In contrast, flow has been generally described in contexts of exploration and flexible outcomes as well as experiences of enjoyment during the activity and lower perceived effort (Swann et al., 2019). As such, the relationship of flow with performance in exercise has been widely reported in the literature (Dietrich, 2004; Engeser and Rheinberg, 2008; Schüler and Brunner, 2009; Fernández et al., 2015; Ufer, 2017). In this line, the basis of flow has been mostly settled on psychological (Swann et al., 2017a,b; Stoll, 2019), physiological (Dietrich, 2004; Keller et al., 2011; Tozman et al., 2015) and psychophysiological factors (Swann et al., 2012). This research has found evidences of brain inhibition of self-reflective introspection during tasks, self-awareness reduction, focused attention and automatic actions among other effects (Jackson and Csikszentmihalyi, 1999; Nakamura and Csikszentmihalyi, 2002; Goldberg et al., 2006; Harris et al., 2017). Flow state has been also described through sensations like lack of weight, lack of fatigue, movement efficiency, and more integratively, as fusion with the environment (Fuentes-Kahal and del Cerro, 2012; Bertollo et al., 2016). In this line, the ecological psychology, and more concretely the ecological dynamics, explains the conscious mind as the very physical relation which emerges at the level of performer-environment system (Araújo et al., 2017). Consequently, phenomenological experiences cannot be understood simply embracing an organism-centered view (Davids and Araújo, 2010).

Within the framework of ecological dynamics, the performer and the environment are continuously integrated as the action regulation unfolds. As the perceptions of affordances (opportunities of action) contingently regulate the actions, and hence cognitions, actions reciprocally create new perceptions for prospective (future) actions. This action-perception cycle is crucial for understanding how conscious experiences emerge. The *informed awareness* is the information about oneself (e.g., proprioception, interoception) *in relation* to the environmental information (Shaw and Kinsella-Shaw, 2007). In this paper, we assume that it is this informed awareness that can reach the state of flow. According to the flow short scale (FSS) (Rheinberg and Vollmeyer, 2003; Rheinberg et al., 2003; Engeser and Rheinberg, 2008; Peifer et al., 2014), we approach the flow experience as consisting of two dimensions: (a) fluency of movements, i.e., sense of control, and (b) state of absorption by the activity when demands of tasks and skills are in balance (Sheldon et al., 2015). The informed awareness in the state of flow hence would incorporate the self-information of fluent and flexible control of the body-environment coupling and dominantly task goal focused attention. The state of *non-flow* would then be experienced as non-fluent, non-flexible and hence effortful control of the body-environment coupling with dominantly internal focus of attention.

Several types of specifying information are constitutive of the informed awareness (Shaw and Kinsella-Shaw, 2007), such as: information of performer's needs, goals, effective means, the adaptiveness of enacting those means, as well as the progress toward the goal. These types of information are dynamically assembled in a form of a cycle consisting of continuous perception of and acting on affordances which have been defined as opportunities, invitations or solicitations for action (Gibson, 1979; Araújo et al., 2006; Withagen et al., 2012; Bruineberg and Rietveld, 2014), dwelling on many time scales. Every bodily action (performatory or exploratory) has a perceptual, and hence cognitive, role. Cognition is being constrained on-line by actions, and in this sense, bodily actions as well as the environment are constitutive to the cognition itself. In other words, informed awareness, as well as cognition as a part of it, is a distributed, embodied and thus, emergent property (Balagué et al., 2019) of the performer-environment system. In challenging[1], non-trivial tasks, demanding high skillfulness, the larger the adaptiveness of dynamic assembling of these types of information (i.e., attunement to affordances), the higher the flow is. The adaptiveness of the dynamic assembling would *behaviorally* correspond to the *fluency of movements*, which is one of the two subscales of the FSS. This means that the fluency of movements is a necesary (but possibly not sufficient) for the experience of flow. Hence, within the ecological dynamics framework the fluency of movements as important component of flow can be defined as a locally[2] optimal attunement (Bruineberg and Rietveld, 2014) to and acting on affordances during challenging tasks. That is, the behaviorally manifested fluency of movements would be a consequence of the attunement to the affordances. Consequently, the *subjective experience* of fluency of movements (sense of control), as a component of the informed awareness, would be a consequence of the attunement to affordances. This attunement to affordances would also stimulate the absorption component of the flow

[1]Degree of challenge can be defined as a relation between the nominal task difficulty and the skill level of the performer.

[2]Locally optimal – here means that there exist performer-environment configurations which temporarily and contingently enable the maximally possible fluency of perception – action cycle of the performer. This statement does not entail existence of mental representation with content in a form of e.g., pre-set optimal movement execution sequence.

experience by maintaining a task goal instead of internally proprioceptive focused attention due to the effortful control.

As the informed awareness is a conscious experience, it follows that it is reportable, i.e., subject to verbal reports. This means that although informed awareness, *itself*, is not a process involving propositional content, it can be nevertheless socio-linguistically contextualized (by experimenters who linguistically engage participants) in such a way so that the performer can provide verbal reports[3] *about* it. Hence, the data collected using the flow questionnaire can be defined as: judgment based time-delayed, coarse-grained verbal reports about the informed awareness experienced by performers during their engagement with the task. We use the word "coarse-grained" because while the informed awareness fluctuates at different time scales, the verbal reports must summarize that rich experience in a form of verbal statements. While the results of such questionnaires cannot be treated as a "gold standard" in determining behavioral or phenomenal experiential processes, it is also true that the concept of flow experience was and is still operationalized only in a form of questionnaire. In reaction to it, current literature is suggesting to offer more practical setting in collecting real-time data and capturing the dynamic nature of flow in exercise (Jackman et al., 2019).

Then, of particular interest for our purposes was considering a task emerging from a strong performer-environment coupling, in which the actions of the performer change the state of the environment and vice versa, and which co-regulating cycle exists at more than one characteristic timescale. Slackline walking is one of such challenging tasks which, besides the important visual coupling, relies on the tight mechanical coupling of the performer with the slackline (Paoletti and Mahadevan, 2012). The goal of the task is to keep balancing the body in upward position on the slackline positioned at some height from the ground, and walk successfully some distance. Dynamically, it is an unstable inverted pendulum system with extremely narrow support base, which has to be stabilized by continuous perceptions-action cycles. This process of stabilization of an unstable system generates fluctuations. The body-slackline coupling is so strong that the fluctuations of the contact feet (body) are kinematically indistinguishable from the fluctuations of the slackline (environment) itself. However, if the slackline has, for example, different tension these fluctuations will change their character and the rest of the cognitive engagement will have to change as well. The cognitive engagement of the performer extends out of the body including the environment. Hence, kinematic fluctuations are in fact fluctuations of the whole performer-environment system rather than merely fluctuations of the performer or environment alone (**Figure 1**). This mechanical contact deforms the feet tissues and provides tactile and proprioceptive information for the state of coupling between the performer and the environment. The specifying haptic information enables the feeling of the limb positions and their changes relative to each other, relative to the body, and relative to the environment. The deformation of feet tissues, as well as other bodily components and their immediate response, due to their elastic-mechanic properties is the first level of movement and posture control. This control involves the body as direct regulator (inhibitor or activator) of the rest of relevant cognitive engagements in accomplishing the task. In this sense the cognition is embodied (Van de Laar and Regt, 2009). The task requires a continuous perceptual coupling of the performer with the slackline, and the rest of the environment, in order to trace minute changes in slackline-body fluctuations. This is necessary in order to avoid the enhancement of fluctuations through a positive feedback which would inevitably bring about a loss of stability of the center of mass (CoM) and task disengagement. In other words, performers continuously strive to stabilize the perception of walk-on-ability affordance by continuous adaptation of their body movements and perceptual systems at different time scales. Any deviation from this locally optimal attunement to the walk-ability affordance induces a tension that has to be reduced by additional action. This tension reduction is equivalent to stabilizing their CoM. As the slackline-body coupling shapes the external – and self-information by continuously regulating the actions of performer, the coupled body-slackline dynamics becomes constitutive of the informed awareness. The adaptiveness of this dynamic information assembling is reflected in fluency of movements of limbs and the CoM of the body. In other words, the smaller and smoother the deviations from the locally optimal attunement and needs of their reduction, the higher the flow experience of performers would be. In this sense, flow experience as constituent of the informed awareness arises and is maintained through the shared information (defined as co-varying processes) within the locally optimal perception-action cycles of performers. In other words, the complementary pair of flow experience and behavior may be formulated as a dynamic product of these co-varying processes that create the locally optimal perception-action cycles. Verbal reports are just propositions about these co-varying processes constituent of the informed awareness.

Previous research has shown that stability during standing posture and human locomotion in unsteady conditions is produced through adjustments of motor control strategies' timing and compensatory synergies (Wang et al., 2014; Santuz et al., 2018). Particularly important study in this sense is Delignières et al. (2011) which convincingly argued about the velocity (and not position) dependent control of postural sway. These compensatory movements produce kinematic fluctuations around the task goal value, i.e., maintaining orthogonal (90°) and collinear to gravity force vector position of body with respect to the slackline support base, and maybe detected and classified according their stabilizing or destabilizing effects. Quickly suppressed deviations would tend to provide a better stabilizing control; in contrast, fluctuations that would positively add to the already extant deviation would tend, especially on longer time scales, to produce larger deviations from the task goal and a destabilizing effect. The temporal co-variation among the subsequent adjustments must be negative and produce

[3] Although uncommon, verbal reports have been used in ecological psychology. For example, the classical work of Warren (1984) used verbally reported judgments about affordances, i.e., informed awareness, in a stair-climbing task.

FIGURE 1 | Slacklining with accelerometers placed in both ankles and the Center of Mass. Written informed consent was obtained from the depicted individuals for the publication of these images.

anti-persistent or anti-correlated time variability. Otherwise, positively correlated adjustments or persistent properties would generate larger fluctuations from the task goal. That is, in anti-persistent fluctuations, deviations in one direction are statistically more likely followed by subsequent deviations in the opposite direction, and in persistent fluctuations deviations in one direction are statistically more likely to be followed by subsequent deviations in the same direction. Persistent fluctuations, signifying critical slowing down phenomenon and the impending instability (Scheffer et al., 2009), have been found in more rigid control during exercise, e.g., cases of extreme fatigue (Vázquez et al., 2016). On the other hand, anti-persistent fluctuations have been related to tighter, but rapid and flexible, control of kinematic variables (Terrier and Dériaz, 2012; Vázquez et al., 2016). Velocity-based control (with a transition from anti-persistence to persistence) have been shown in control of the postural sway (Boulet et al., 2010; Delignières et al., 2011). Moreover, some researchers have found relationships between experience, training, and skill levels with temporal co-variation of performance variables (Wijnants et al., 2009; Den Hartigh et al., 2015; Nourrit-Lucas et al., 2015). In particular, the postural and stride to stride control has been studied using the temporal variability of kinematic variables and quantified through Hurst (H) exponents (Balasubramaniam et al., 2000; Boulet et al., 2010; Delignières et al., 2011; Terrier and Dériaz, 2012; Vázquez et al., 2016).

Accordingly, based on what was discussed above, the aim of the current study was to capture the effects of the co-varying bi-directional process within the continuous perception-action cycle of a slackline walking task. Particularly, we were interested on how the dynamical stability of performance affects the embodied and extended information that shapes the flow experience in performers.

MATERIALS AND METHODS

Participants

Nineteen volunteer Spanish slacklining practitioners (17 males, 2 females, 25.3 ± 4.9 yo, 70.21 ± 8.79 kg, 1.79 ± 0.05 m) from a faculty of Sport Sciences and a Slackline Club participated in the study. To be included in the sample they had to be able to perform the proposed slackline walking task (see section "Procedures") and respond to the proposed flow scale questionnaire in English language (see section "Procedures"). Before starting, all participants completed a questionnaire to confirm their health status, their dominant/support leg (left, $n = 16$; right, $n = 3$) and subdominant leg, as well as an informed consent form. The experiment was approved by the local Research Ethics Committee.

Procedures

All participants performed a continuous slackline walking task (Gibbon Slackline TM, ID Sports, Stuttgart, Germany) at a freely chosen velocity, without shoes and without falling during 30 s on a band of 10 m long and 5 cm width. They were not exposed to changes in their visual or acoustic information during the trials. They had a maximum of three attempts, separated by a maximum of 5 min rest to accomplish the task. The tension (T) of the slackline's anchors (5.28 ± 0.65 kN), placed at 0.85 m from the ground, was calculated through the following formula:

$$T\,(kN) = [L\,(m) \times W\,(kg)]/[S\,(m) \times 400]$$

where W is the weight of the participants, L is the length of the slackline (10 m) and S is the sag under load (ensuring at least 0.5 m in the center) (Conley, 2006).

The dynamic stability of the performer-slackline coupling was measured through the temporal variability of the acceleration fluctuations of the ankles, the body segments closer to the slackline, and the CoM, reflecting the postural control during the task. To this end, accelerometer devices WIMU PRO^{TM} (Real Track Systems, Almería, Spain) were placed and fixed with supports on both dominant and subdominant ankles, on the outside part above the lateral malleolus (Mannini et al., 2013), and in the CoM, placing the accelerometer on the zone of L3 (Moe-Nilssen and Helbostad, 2004; Schütte et al., 2016; see **Figure 1**). The acceleration was recorded at a sample frequency of 100 Hz to ensure enough data (>1024) to analyze through Detrended Fluctuation Analysis (DFA) a task lasting 30 s.

The English version of the Flow Short Scale (FSS) (Rheinberg et al., 2003; Engeser and Rheinberg, 2008), validated and applied experimentally to other flow studies (Engeser et al., 2005; Schüler, 2007; Schüler and Brunner, 2009), was administrated at the end of the task. All participants were previously familiarized with the FSS questionnaire. The flow experience (F_{exp}) was measured in ten items (Cronbach's α = 0.81) that were divided in two different subscales: the fluency of movements scale (F_{mov}) including items 2, 4, 5, 7, 8, and 9, and the absorption by the activity scale (A) including items 1, 3, 6, and 10.

Data Analysis

Time series for the CoM, the dominant and subdominant leg which were subject to analysis were Euclidean metrics of the 3D Cartesian acceleration components. The Euclidean metrics were directly provided by the accelerometers. The DFA was performed on the data series of acceleration and the Hurst (H) exponent was calculated to assess the temporal structure and time variability properties of the kinematic behavior (N = 3072 data points). DFA was conducted as follows (according to Peng et al., 1994, 1995; Ihlen, 2012): first, the total length of the acceleration time series (N) was integrated by using the following equation:

$$Y(i) \equiv \sum_{k=1}^{i} [x_k - x]$$

Where $x_k$is the time series of acceleration and x is the average acceleration of the N data points. A quadratic polynomial function was then used to fit the time series to calculate the local trend (Ihlen, 2012). The resulting, i.e., velocity[4], time series were divided into different windows scales n of equal length, with the local trend being subtracted in each window. The maximum scale of 512 data points was chosen according to Kantelhardt et al. (2002). For each window the root mean square (RMS) fluctuation was calculated by using the following equation:

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[y(k) - y_n(k)\right]^2}$$

[4]Although original time series were acceleration time series, by integrating we obtained the velocity time series. Velocity time series' Hurst exponents (H_v) differ from the Hurst exponents of acceleration time series (H_a) by an additive constant: $H_v = H_a + 1$. Velocity time series, thus, belong to the Brownian motion type ($H_v > 1$) and acceleration time series to a noise type ($0 < H_a < 1$) of fluctuations (Delignières et al., 2011). However, because they differ only by additive constant, the meaning of the results is equivalent for acceleration and velocity profiles.

Where the $y(k)$ are the integrated (i.e., velocity) time series and the $y_n(k)$ is the local trend in each box. The H exponent, obtained as the slope value of the linear regression between the scale and local fluctuations on a log-log diffusion plot, was used to determine the temporal structure of the time series fluctuations.

H exponent values in the range $0 < H < 0.5$ were associated with anti-persistent character of velocity fluctuations, while $0.5 < H \leq 1$ values were associated with their persistent profile (Delignières et al., 2011; Ihlen, 2012).

Shared Information Between Flow Scores, Training Frequency/Age and Time-Variability of Kinematic Behavior

In order to detect the degree of shared information between the flow scores (F_{exp}, F_{mov}, and A), the training (ω and τ) variables and behavioral variables (H_{subdom}, H_{dom}, H_{CoM}), we conducted a Pearson correlation (r) and partial correlation analysis (ρ). Then, we performed a series of stepwise regression analyses in order to find out the best explanatory variable(s) responsible for the variance of flow experience scale F_{exp} and its subscales F_{mov} and A, which were treated as response variables.

Potential explanatory variables

ω = training frequency (hours per week): Mean = 2.29 ± 2.98; Min = 0.5; Max = 13
τ = training age (years of training): Mean = 3.05 ± 2.87; Min = 0.5; Max = 13
H_{subdom} = Hurst exponent of the subdominant leg
H_{dom} = Hurst exponent of the dominant leg
H_{CoM} = Hurst exponent of the center of the body mass

Response variables

F_{exp} = flow experience (full scale)
F_{mov} = fluency of movements (subscale)
A = absorption (subscale)

We checked the robustness of the stepwise regression results in three ways. First, we made series of standard simple and multiple regression procedures in order to control for possible confounding or mediating effects within the set of potential explanatory variables (Baron and Kenny, 1986). Second, we performed a series of forward and backward stepwise regression analysis and checked the level of congruence of results. Third, we applied a principal component analysis to highly correlated training variables (ω and τ), to construct a composite linear combination of both sets of standardized scores, in order to manipulate the number of degrees of freedom of the regression model, i.e., the number of potential explanatory variables. In the model including only directly measured variables, there were five potential explanatory variables, and in the model with the principal component there was one less, that is four potential explanatory variables. The variance explained by the explanatory variables was estimated by multiple coefficient of determination R^2. We reported coefficients of multiple coefficient of determination (R^2) adjusted to degrees of freedom of the model. Multiple regression effect sizes were expressed in Cohen's f^2. According to Cohen's (1988) guidelines, $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ represent small, medium, and large effect sizes, respectively. Significance level was set on $p < 0.05$. Data analysis was conducted via Matlab© R2013b and Statistica 7 software packages.

RESULTS

The F_{exp} was rated considerably high (5.06 ± 0.89), as its two subscales (F_{mov} = 5.1 ± 1.17; A = 5.01 ± 0.76). The DFA analysis showed a persistent temporal structure of velocity fluctuations in both ankles (H_{dom} = 0.68 ± 0.11; H_{subdom} = 0.71 ± 0.11) and a weakly anti-persistent fluctuations of the CoM (H_{CoM} = 0.49 ± 0.05). **Figure 2** shows two examples of individual time series with persistent and anti-persistent fluctuation dynamics, respectively. Cross-over of the slope, i.e., the Hurst exponent, was not detected (see **Figure 3**). The linear fit to diffusion plot data points in all 19 cases was statistically significant (p_{min} = 0.03, p_{max} = 0.001) and high (R^2 = 0.76 ± 0.02).

Correlation Analysis of Potential Explanatory and Response Variables

Correlation analysis revealed several important clusters of relationship. F_{exp} showed quite strong association with the subscale F_{mov} (r = 0.96; p = 0.000001) and strong relationship with subscale A (r = 0.73; p = 0.0009). Moreover, H_{subdom} and H_{dom} were highly positively correlated (r = 0.77; p = 0.0001) while showing no correlation with H_{CoM} (r = 0.24; $p < 0.235$, and r = 0.19; p = 0.436), respectively. Also, flow subscales F_{mov} and A were moderately related (r = 0.50; p = 0.03). Training variables ω and τ showed strong association (r = 0.71; p = 0.001).

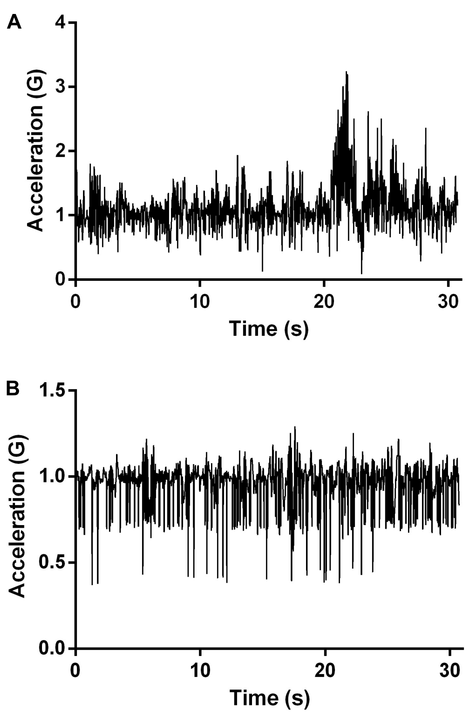

FIGURE 2 | Examples of individual time series with **(A)** persistent (H = 0.89) and **(B)** anti-persistent (H = 0.41) fluctuation dynamics.

Training frequency (ω) was also moderately associated to most of other variables: F_{exp} (r = 0.56; p = 0.012); F_{mov} (r = 0.56; p = 0.012); H_{subdom} (r = −0.51; p = 0.026) and H_{dom} (r = −0.57; p = 0.01), while training age (τ) had significant medium relationship only with H_{dom} (r = −0.49; p = 0.034).

H_{subdom} and H_{dom} showed moderate to high associations with flow scale F_{exp}: (r = −0.59; p = 0.008); (r = −0.72; p = 0.001), respectively, and its subscales F_{mov} (r = −0.55; p = 0.015); (r = −0.69; p = 0.001) and A (r = −0.46; p = 0.05); (r = −0.50; p = 0.029), respectively.

Controlling for joint effects of training variables ω and τ, the associations between the flow scale scores F_{exp} and its subscales F_{mov} (ρ = −0.93; p = 0.00001) and A (ρ = −0.69; p = 0.002) decreased. The association of flow scale F_{exp} and the F_{mov} subscale with the H_{dom} variable were maintained: ρ = −0.59; p = 0.013; ρ = −0.56; p = 0.019, respectively. Also, the statistically significant relationship between H_{dom} and H_{subdom} was maintained (ρ = 0.67; p = 0.03).

Controlling for H_{dom}, however, removed the statistically significant associations between training variable ω and the flow scale F_{exp} (ρ = 0.27; p = 0.284), as well as its subscales F_{mov} (ρ = −0.28; p = 0.265) and A (ρ = −0.1; p = 0.694).

Multiple Regression Analysis

In general, the results of the Baron and Kenny (1986) procedure revealed H_{dom} as a potential strong mediating variable. The results were sufficiently robust with respect to changes of the model seeking procedures (stepwise vs. backward) and the manipulation of the degrees of freedom of the model. The backward stepwise procedure revealed identical model to the one obtained by the forward stepwise procedure for the F_{exp} and F_{mov}, but not for A scores. The model degrees of freedom manipulation showed qualitatively the same results, but the statistical significance of the model fit was larger than in forward stepwise regression. However, this model had higher Durbin-Watson statistic and that was the reason to proceed with the interpretation of the original stepwise regression results. Further, we present the results from the forward stepwise regression results noting that the results for absorption scale A have to be taken with more care since they were more fragile with respect to the model used.

Multiple Regression Analysis of Flow-Scale Scores

Tolerance scores of explanatory variables that entered the forward stepwise regression equation, i.e., H_{dom} and ω, were at satisfactory level (T = 0.67, T = 0.67), respectively. Durbin-Watson statistic (DW = 2.60) revealed an independence of residual values. Residuals were also normally distributed (Shapiro-Wilk p = 0.294) and satisfied the criterion of homoscedasticity. Cooke's Distance statistic (D_{median} = 0.03; D_{max} = 0.27; D_{min} = 0.000001) showed that there were no influential cases potentially biasing the results.

Multiple correlation between the system of explanatory variables H_{dom}, ω and the F_{exp} scores was statistically significant and strong: R = 0.74; R^2 = 0.49; $F(2, 16)$ = 9.63; $p < 0.002$.

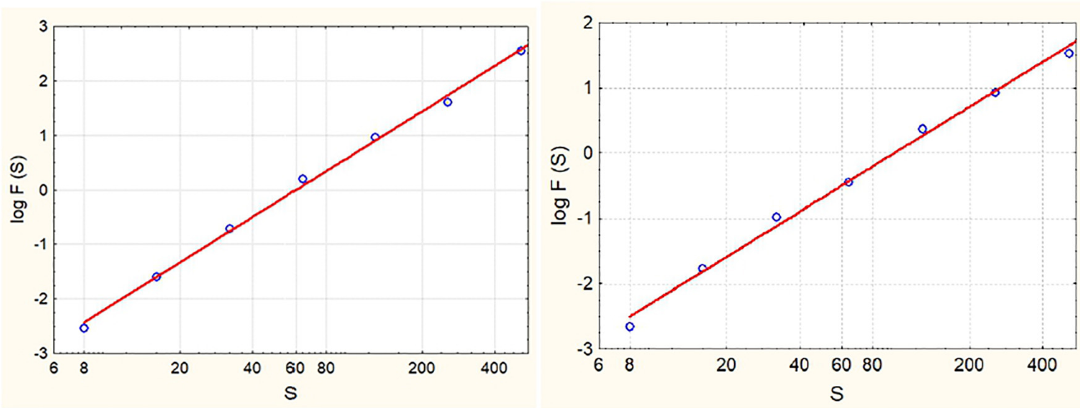

FIGURE 3 | Typical diffusion plots for two participants. F(S) is the magnitude of fluctuations as measured by the RMS (see Eq. 2), and S is the scale.

Cohen's $f^2 = 0.96$ revealed a very large effect size. Partial regression coefficient was significant only for H_{dom} ($\beta = -0.58$; $t(16) = -2.84$; $p < 0.01$), but for ω showed no statistically significance ($\beta = -0.23$; $t(16) = 1.11$; $p < 0.284$).

Multiple Regression Analysis of Fluency of Movements Subscale Scores

Tolerance scores of explanatory variables who entered the forward stepwise regression equation H_{dom} and ω were ($T = 0.67$, $T = 0.67$), respectively. Durbin-Watson statistic ($DW = 2.68$) revealed an independence of residual values. Residuals were also normally distributed (Shapiro-Wilk $p = 0.76$) and satisfied the criterion of homoscedasticity. Cooke's Distance statistic ($D_{median} = 0.03$; $D_{max} = 0.14$; $D_{min} = 0.002$) showed that there were no influential outliers potentially biasing the results.

Multiple correlation between the system of explanatory variables H_{dom}, ω and the F_{mov} scores as response variable was statistically significant and strong: $R = 0.72$; $R^2 = 0.46$; $F(2, 16) = 8.68$; $p < 0.003$; $f^2 = 0.85$ signified a very large effect size. However, partial regression was significant only for H_{dom} ($\beta = -0.553$; $t(16) = -2.61$; $p < 0.019$), and showed no statistical significance for ω ($\beta = -0.245$; $t(16) = 1.16$; $p < 0.26$).

Multiple Regression Analysis of Absorption Subscale Scores

Tolerance scores of explanatory variables which entered the regression equation: H_{dom} and H_{CoM} were ($T = 0.94$, $T = 0.94$), respectively. Durbin-Watson statistic ($DW = 2.07$) revealed the independence of residual values. Residuals were also normally distributed (Shapiro-Wilk $p = 0.28$) and satisfied the criterion of homoscedasticity. Cooke's Distance statistic ($D_{median} = 0.014$; $D_{max} = 0.86$; $D_{min} = 0.0002$) showed that there were no influential cases potentially biasing the results.

Multiple correlation between the system of explanatory variables H_{dom}, H_{CoM} and the A scores as response variable was statistically significant and of medium strength: $R = 0.58$; $R^2 = 0.25$; $F(2,16) = 4.00$; $p < 0.039$. Nevertheless, Cohen's test ($f^2 = 0.33$) revealed medium effect size. However, partial contributions of both variables were not significant, although H_{dom} was a borderline case: ($\beta = -0.43$; $t(16) = -2.05$; $p < 0.057$) and ($\beta = -0.297$; $t(16) = -1.41$; $p < 0.177$).

DISCUSSION

The aim of the current study was to capture the effects of correspondence within the bi-directional continuous perception-action cycle of a slackline walking task. The correlation analysis showed some intriguing relations between the treated variables. F_{exp} was dominantly associated to the fluency of movements subscale F_{mov} and less to absorption subscale A. After controlling for effects of training variables ω and τ and action variable H_{dom}, the differences of these associations increased. Moreover, controlling for training variables maintained the statistically significant association between the action variable H_{dom} with the flow scale F_{exp} and its fluency subscale F_{mov}, while controlling for H_{dom}, removed the significant associations between training variables ω and τ and the flow scale F_{exp} and its subscales F_{mov} and A. This may mean that it is the *information related to action* (i.e., the pragmatic information) which is the main constituent of the informed awareness of flow experience for this task. The regression analysis also consistently revealed H_{dom} as an explanatory[5] variable of the flow experience (the full scale and its subscales), although the absorption subscale A showed larger part of specific variance in comparison with the fluency of movements subscale F_{mov}. Absorption refers to a task engagement with minimal self-consciousness when demands and skills are in balance (Rheinberg and Vollmeyer, 2003; Peifer et al., 2014). The constraints of the slackline walking task may have not been able to induce such type of dominant outward focused attention in performers. It is probable that the slackline task is, to a certain degree, demanding of self-internally focused attention. Focusing on the body-slackline mechanical contact, i.e., enabling crisp self-information from tactile and

[5]For both subscales and the full scale the unexplained, i.e., flow unique variance, was probably due to individual history differences, unaccounted specific constraints impinging on the perception-action system (Balagué et al., 2019), as well as the error variance.

proprioceptive sources (Shaw and Kinsella-Shaw, 2007), may be crucial for accomplishing the task.

Indeed, slackline walk is commonly used as a meditative (mindfulness) practice (Curtis and Braga, 2018) which requires increased self-awareness. On the other hand, the flow experience, by its definition, requires reduced self-consciousness (Sheldon et al., 2015). It may be that there was a trade-off relation between these conflicting requirements for absorption, responsible for the results obtained in this specific task. This finding calls to attention to the possibility of varying degrees of involvement of movement fluency (sense of control) and absorption processes for the flow experience in different tasks.

Taking together these results with those of the correlation analysis, we can go a step further claiming that perception-action-environment processes, responsible for determining the values of H_{dom}, have a causal role in forming a flow experience, as constitutive of the informed awareness of participants. In this case H_{dom} would play a role of a nearly full mediator variable between the rest of explanatory variables and the response variables (flow scores). Neither training age nor frequency of training significantly predicted the flow scores (subscales and the full scale). Their effects, as well as the effect of H_{subdom} on the flow experience, were clearly mediated by the H_{dom} variable. The temporal structure of fluctuations of the whole coupled body-environment (i.e., slackline) system, as measured by H_{dom}, co-varies with and corresponds to the states of informed awareness (particularly the perception of fluency of movements). Note that these processes are not *only* neurologically regulated and even less they are skull bound. In other words, the changes in body-slackline coupling, i.e., the body-environment dynamics, as measured by H_{dom}, regulate the flow experience. Any deviation from the locally optimal attunement to the walk-on-ability-affordance creates a state that has to be stabilized by compensatory actions. Compensatory actions are a result of online explorations of stability. There is hardly a pre-set value, a mental representation of a "correct" action or action sequence that can be applied. A pre-set correct action simply cannot exist because there is an ever changing unpredictable flow of the performer-slackline interactions. What is important is to locally solve the perceptual attunement and action on the walk-on-ability affordance. Hence, all perceptual explorations and compensatory movements are made "on the fly" as a result of a successful contingent perception-action explorations. If these compensatory perception-action cycles come close to bring about instability in the performer-environment coupling they destroy the flow awareness and vice versa. Thus, flow and particularly the fluency of movements experience does not correspond to "*automaticity*"[6] of actions (see Harris et al., 2017 for opposite opinion), but to their functional flexibility, i.e., *adaptability*. Note again that the flow experience, as a part of the informed awareness *itself*, does not have to contain any propositional properties, but nonetheless can, to a degree, be captured by linguistically engaged performers, using propositional statements given in the questionnaire. In this sense, the flow experience *itself* can be defined not as merely skull bound mental state, but as embodied and extended active process of informed awareness emerging at the level of performer-environment system.

While the velocity fluctuations of the ankles showed persistent fluctuations, the velocity fluctuations of the CoM showed dominantly anti-persistent behavior. The persistent dynamics reflects a more balanced interaction of negative and positive feedback loops within the system, and the anti-persistent dynamics a dominance of the negative-stabilizing feedback (Cuomo et al., 2000; Vázquez et al., 2016). The persistent time variability structure of the ankle's velocity fluctuations reflected an exploratory and compensatory synergy of lower limbs to regulate the balance of the CoM on the webbing. In contrast, the anti-persistence of the CoM fluctuations signified its tightly controlled stability that has been enabled by different compensatory synergies reflected in ankle fluctuations (Latash et al., 2007; Singh et al., 2018). In general, it seems that the lower limbs explore possible coordination in order to form a negative feedback for the efficient positional control of the performer's CoM. This points to the possibility that performers experiencing low flow need larger movement explorations (leg excursions) to acquire a functional control of the body's CoM. On the contrary, high flow performers need less exploratory actions (less leg excursions) to attain the control. These differences signified variations in embodied cognitive strategies of performers while negotiating task constraints. The increased positive correlation of increments in the time series has been formally connected to the phenomenon of critical slowing down, i.e., the impending instability of the complex system, indicating the loss of system's resilience (Scheffer et al., 2012). Thus, higher H values meant that, on average, positive serial correlations were larger and thereby there was a more emphasized critical slowing in the system (Vázquez et al., 2016). This means that the performer-slackline system of participants with higher H values was less stable (i.e., increased the chances of critical transition, fall or task disengagement) than those with lower H values.

On the other hand, even a novice with several months of training may become well adapted to the constraints of the current task and release the attentional resources partly outward. One may hypothesize that a larger height or lower tension of the slackline, or both, would form a task with higher level of functional difficulty. Suitably modified task constraints may induce more direct effects of the training age and frequency of training on flow experience. Such task constraints may particularly affect effects of behavioral movement action variables such as H_{dom} on the absorption subscale scores due to larger salience of task internal related focus of attention in more challenging situations tasks of this type. These hypotheses warrant further investigation on a larger sample of performers.

The adaptability to environmental changes characterizes successful performers, because their system's stability is reflected in their capacity to negotiate the induced perturbations through stable but flexible coordinated movements (Davids et al., 2012; Santuz et al., 2018). Even good performers need compensatory movement variability (Davids et al., 2012). Such performance conditions involve a coordinated

[6] Automaticity, on the other hand, may be attained in stable, attentionally non-demanding environments. It does not require a strong action-related attention focus and may allocate the attention resources to task unrelated thoughts (e.g., Balagué et al., 2012).

action to integrate functionally the degrees of freedom of the performer-environment system (Davids et al., 2008). This integration is dynamically formed by the reciprocal interaction among the slower and shorter time-scale control loops of the performer-environment system (Hristovski and Balagué, 2010; Vázquez et al., 2016).

As slackline is not a regulated and competitive activity that performers practice regularly, the participants in this study could not be classified according their performance results, as was done in previous research (Den Hartigh et al., 2015). Regarding the retrospective self-report method used in this study, limitations should be also taken into account. Due to it, more research is warranted to confirm the current results. Moreover, a research based on bi- or multivariate time series of flow experience scores and behavioral quantities may provide in future more detailed and more realistic understanding of the continuous dynamic entanglement of processes which form the experience-behavior complementary pair.

In conclusion, as a first step toward the goals expressed in the previous passage, the stable co-variance of perception-action variables signified the embodied nature of the flow experience. The dynamic signatures of the whole performer-environment system, such as the critical slowing down, strongly affected the flow experience. In this sense, it is the ecological dynamics of the whole performer-environment system and the fluctuating dynamics of the continuous multi timescale perception-action cycles within it, that characterizes the experience of flow as a state of the informed awareness (Shaw and Kinsella-Shaw, 2007).

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Comité d'Ètica d'Investigacions Cliniques de l'Administració de Catalunya. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

NB, RH, LR, and LM conceived and designed the experiments. LM, LR, and NB performed the experiments. LM, PV, and RH analyzed the data. RH, LM, PV, and NB interpreting the results. LM, LR, PV, and NB contributed the reagents, materials, and analysis tools. LM, PV, NB, RH, and LR wrote the manuscript.

FUNDING

This study was supported by the Institut Nacional d'Educació Física de Catalunya (INEFC) and the Generalitat de Catalunya. LM is the recipient of a predoctoral fellowship from INEFC.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

2.4. Research Article 4

PROPRIOCEPTIVE DIALOGUE-INTERPERSONAL SYNERGIES DURING A COOPERATIVE SLACKLINE TASK

Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 25, No. 2, pp. 157-177.

Proprioceptive Dialogue - Interpersonal Synergies During a Cooperative Slackline Task

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Abstract: *Proprioceptive based interpersonal communication, playing a crucial role in cooperative motor tasks, needs further investigation. This study aimed to explore the interpersonal coordination of dyads cooperating to stand up in balance on a slackline through the study of inter and intrapersonal synergies. With this purpose, acceleration time series of the slackline as well as of both legs and the center of mass of slackliners were recorded. The Uncontrolled Manifold was used to evaluate inter and intrapersonal synergies, and afterwards, the Hierarchical Cluster Analysis was performed to detect hypothetical embedded organization of synergies. Furthermore, the kinematic variability of the synergetic elements was studied through the Detrended Fluctuation Analysis to find potential stabilizing roles among slackliners. Inter and intrapersonal synergies were identified with a higher hierarchical dominance of the former. Interpersonal stabilizing roles were demonstrated among slackliners, revealing greater kinematic control of free leg and the center of mass in those slackliners with more training experience and higher task performance. This exploratory study of interpersonal coordination found that there was an embedded organization between inter and intrapersonal synergies in which stabilizing roles emerged. Dyads established a dominantly proprioceptive dialogue to form a co-adaptive whole and cope with an unstable environment.*

Key Words: nonverbal communication, multilevel coordination, embedded organization, kinematic variability, stabilizing roles

INTRODUCTION

The recent explosion of interest in interpersonal coordination during competitive and cooperative motor tasks has led to a host of new and interesting questions about nonverbal communication (Passos, Davids, & Chow, 2016). In particular, haptic and proprioceptive communication that play a crucial role in

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cooperative motor tasks, requires further investigation.

Slacklining is a particularly challenging task that importantly relies on a tight physical coupling of the performer with the environment, represented dominantly by the slackline (Montull, Vázquez, Rocas, Hristovski, & Balagué, 2020; Paoletti & Mahadevan, 2012). The performer-slackline system is an unstable inverted pendulum system whose instability stems from the extremely narrow and non-rigid support base which is tensioned between two anchors (see Fig. 1). Due to the instability of the support base, standing up in balance on a slackline requires continuous fast adjustments of body movements and the consequent activation of perceptual systems operating at different timescales. Particularly, the haptic and proprioceptive information, enabling a fast perception of the limb positions and their changes in relation to the environment (represented by the slackline), is crucial. The performer-slackline coupling is so strong that the fluctuations of the feet in direct contact with the slackline are kinematically indistinguishable from the fluctuations of the slackline itself (Montull et al., 2020).

The performance of dyads standing up on the slackline requires a multilevel coordination among both slackliners interacting as a whole to reduce the slackline fluctuations. These fluctuations are produced by the co-adaptation between the interacting slackliners and the slackline itself (see Hristovski, Balagué, & Schöllhorn, 2013 for further clarification on such co-adapting processes). The enhancement of such fluctuations through a positive feedback (i.e., a circular causality of increasing slackliners' fluctuations) may bring inevitably to a loss of stability and the performers-slackline disengagement.

Synchronization, as an interpersonal coordination mode, has been widely studied in physics and biology, equating coupled individuals to oscillators (e.g., flashing of fireflies). However, even though many physiological systems exhibit oscillatory behaviours (e.g., firing neurons in the brain; Sulis, 2016), human behaviour is not oscillatory, and a significant part of human behaviour is cooperative. That is, individual behaviours may be distinct but collectively functional within the same temporal scale. The constant co-occurrence in time of individual behaviours that facilitate the collective (or dyadic) functionality, is a feature identified as synergistic behaviour.

Synergies, not restricted to muscles, but identified at many scales (from the cellular and neural to the cognitive and social) (Kelso, 2009a; Riley, Richardson, Shockley, & Ramenzoni, 2011), are temporary assemblages of elements, sensitive to the context, which act as a single functional unit to maintain a relative stability of task goals (Black, Riley, & McCord, 2007; Fusaroli, Raczaszek-Leonardi, & Tylén, 2014; Kelso, 2009a, 2009b). In Fig. 1, the task goal, represented by the stability of the slackline, is accomplished through the compensatory movements performed by the slackliners. In this way, the control of the dyadic system, continuously re-organized, is achieved through such reciprocal compensatory movements, rather than through the control of each slackliner as a single entity (Bernstein, 1967; Riley et al., 2011). That is, the individual elements adapt to form a collective behavioural pattern (synergy), and simultaneously the synergy governs the individual elements' behaviour through a circular causal relation (Haken, 1987; Kelso, 2017; Pol, Balagué, Ric, Torrents, Kiely, & Hristovski, 2020). Functional soft-assembled synergies spontaneously arise in the dyadic task due to a vast (nevertheless limited) set of combinations of degrees of freedom (DoF). This means that all DoF within a dyad may be involved in the formation of synergies, but some might have more participation than others. For instance, the free legs of both slackliners, in contrast to the support legs (in contact with the slackline). Moreover, due to contextual dependency, synergies may assume different functions using some of the same DoF, and the same function using different DoF (Edelman & Gally, 2001; Haken, 1987). Such pleiotropy and degeneracy properties enable the capacity of the dyad to switch between diverse coordinative states while maintaining metastable dynamics (Bovier & den Hollander, 2016).

The reciprocal dependency of the performers-slackline system brings consequentially the compression of DoF, and the behaviour of the system as a whole (Kelso, 2009a; Kelso & Engstrøm, 2006; Kugler & Turvey, 1987). Thus, a synergy has fewer DoF (possesses a lower dimensionality) than the set of elements from which it arises (Riley et al., 2011). Both features, the reciprocal compensation and the dimensional compression, are considered when evaluating synergies (Riley et al., 2011). Accordingly, the uncontrolled manifold (UCM) approach (Black et al., 2007) and the principal component analysis (PCA) (Ramenzoni, 2008) are two different methods to study the interpersonal coordination. However, one of the major critics on using PCA to address for the presence of synergies is that PCA cannot provide unequivocal evidence for the existence of synergies, because it does not directly measure reciprocal compensation (Latash, 2008; Riley et al., 2011). Black et al. (2007) identified that dimensional compression occurred due to a performance variable stabilized via reciprocal compensation among the task relevant elements. Thus, the UCM method can be viewed as a form of "interpretable" PCA, linking principal components to task variables (Schöner & Scholz, 2007, pp. 274).

UCM was originally created to explain how motor coordination was achieved due to a relation between task relevant elements that must be controlled with other task elements that must be left 'uncontrolled' to stabilize a performance goal (Scholz & Schöner, 1999; Schöner, 1995). Later, the UCM was related with synergetic analysis (Latash, 2010), which had recently identified the existence of interpersonal dyadic synergies in sports performance contexts (Passos, Lacasa, Milho, & Torrents, 2020; Passos, Milho, & Button, 2018). The UCM aims to characterize the structure of variance of the task elements within a subspace (i.e., a geometrical 'object' similar to an ellipsis) formed by all possible combinations of these elements to stabilize a performance goal (Black et al., 2007; Schöner & Scholz, 2007). Within that subspace (called itself the UCM) the task elements, which are reciprocally compensating, create two sorts of variance. The compensate variance which expresses task elements adjustments that contributes to stabilize the performance goal, and the uncompensated variance which is related with task elements adjustments that disturbs the performance goal stability

(Scholz & Schöner, 1999). The relation between the compensated and uncompensated variance enables to assess the presence and strength of synergies (Latash, 2010). Aiming to stabilize the same performance goal, synergies can be formed with different combinations of task elements.

As coordinative structures that make possible the multilevel coordination from micro (cellular processes) to macroscopic levels (dyadic behaviour), synergies tend to operate as embedded, i.e., nested, organizations (Kelso, 2009a; Pol et al., 2020; Richardson, Shockley, Fajen, Riley, & Turvey, 2008). Using UCM it is possible to observe which combination of task elements prevails over the others on synergy formation, and thus, identify the most relevant elements on synergies formation. However, complementary measures like Hierarchical cluster analysis are needed to detect the embedded organization of interpersonal synergies (García-Cossio, Broetz, Birbaumer, & Ramos-Murguialday, 2014; Murtagh & Contreras, 2012).

Continuous adjustments of both slackliners' movements to stand up in a dyadic balance on the slackline produce kinematic fluctuations on the task elements. The temporal variability structure of such postural fluctuations is based on velocity control and may provide information about the performance goal stability (Delignières, Torre, & Bernard, 2011; Montull et al., 2020). Detrended Fluctuation Analysis (DFA) may be particularly used for this proposal. Introduced by Peng, Buldyrev, Havlin, Simons, Stanley, & Goldberger (1994), DFA's outcome was initially represented by the exponent α, although the value of Hurst (H) exponent is conceptually equivalent (Bassingthwaighte & Raymond, 1994), as well as widely used with kinematic variables (Montull et al., 2020; Vázquez, Hristovski, & Balagué, 2016). Its results basically interpret two type of temporal structures: (a) the anti-persistent temporal variability structures (negative co-variation among subsequent adjustments), as a consequence of deviations that tend to go on opposite directions, have been found in tighter and faster control which is related with an adaptative behaviour (Cuomo, Lanfredi, Lapenna, Macchiato, Ragosta, & Telesca, 2000; Terrier & Dériaz, 2012; Vázquez et al., 2016); and (b) the persistent structures, in which subsequent deviations tend to follow the same direction, have been related to a more rigid kinematic control and the consequent impending instability (Scheffer, Bascompte, Brock, Brovkin, Carpenter, Dakos, Held, van Nes, Rietkerk, & Sugihara, 2009; Vázquez et al., 2016). However, particularly moderate persistent temporal structures (i.e., a more balanced interaction of negative and positive feedback loops) of velocity fluctuations were found in both ankles during a slackline walking task, reflecting an exploratory behaviour of lower limbs to regulate the balance of the body (Montull et al., 2020). As training experience influences the temporal variability structures of skill variables (Den Hartigh, Cox, Gernigon, Van Yperen, & Van Geert, 2015; Montull et al., 2020; Nourrit-Lucas, Tossa, Zélic, & Delignières, 2015; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009), they may inform of potential stabilizing roles within dyads.

The purpose of this study was to explore the proprioceptive based interpersonal coordination of dyads cooperating to stand up in balance on a slackline. With such purpose we aimed: (a) detecting and characterizing the inter and intrapersonal synergies that accomplished the task goal, (b) testing if interpersonal synergies were hierarchically dominant over intrapersonal synergies, and (c) identifying, on the basis of interpersonal synergies, roles of slackliners in relation with their training experience and task performance.

METHODS

Participants

Twelve experienced slackliners (S) (4 females, 8 males, 25.08 ± 3.03 yrs., 62.75 ± 5.82 kg, and 1.73 ± 0.07 m) voluntarily participated in the study. Their training frequency (hours/week) (ω) was 3.42 ± 3.12 and their training age (τ) was 3.08 ± 1.08. None of the participants had any previous experience performing the proposed dyadic task. They were randomly divided into 6 dyads (D), and each dyad had to perform five valid trials of the task. To determine the sample size of trials, a power analysis was conducted in G∗Power (Faul, Erdfelder, Lang, & Buchner, 2007). Using a large effect size (ρ = .5), α = 0.05, and power (1-β) = 0.8, the required sample size was 29. A total number of 30 trials were performed and analysed (6D x 5 trials). Experimental procedures were approved by the local research ethics committee.

Procedures

Dyads had to stand upright with one leg on the slackline, 'face to face' and holding hands, as long as possible (Fig.1). To consider a trial as 'valid' participants need to perform the task during at least 30 s. Thus, each dyad had to perform a total number of five trials lasting at least 30 s without putting the feet on the ground. Five-minute resting time was allowed between trials, and a maximum of five attempts were performed on each session to avoid fatigue accumulation. The tension (T) of the slackline's anchors (5.28 ± 0.65 kN), placed at 0.85 m from the ground, was calculated through the following formula:

$$T\text{ (kN)} = (L\text{ (m) x W (kg))}/\ (S\text{ (m) x }400)$$

where W is the sum of the weight of both participants, L is the length of the slackline (10 m) and S is the sag under load (ensuring at least 0.5 m in the central point of the slackline) (Conley, 2006).

Data Acquisition

Accelerometer devices WIMU PRO^{TM} (Real Track Systems, Almería, Spain) were placed: (a) on the external part of each participant's feet, above the lateral malleolus (Mannini, Intille, Rosenberger, Sabatini, & Haskell, 2013); (b) on the participants center of mass (CoM), at L3 zone (Moe-Nilssen & Helbostad, 2004; Schütte, Aeles, De Beéck, van der Zwaard, Venter, & Vanwanseele, 2016); and (c) on the slackline midpoint, at 0.15 m away from each participant (see Fig.1). Accordingly, the dataset was composed by seven time series used for further analysis: both slackliners free leg (Free), both slackliners support leg (Sup), both slackliners CoM, plus the slackline midpoint (Slack). Free and Sup were voluntarily chosen (right = 3; left = 3), with the condition that had to be the same for both slackliners of the dyad. The CoM time series characterized the postural control of the slackliner (intrapersonal coordination), while the Slack stability characterized the postural control of the dyad (interpersonal coordination) but also the embedded intrapersonal coordination of the slackliners. The time series data were recorded at a sample frequency of 100 Hz and exported with a frequency of 10 Hz for the synergies' assessment. That is, these accelerometer data were used to evaluate: (a) the synergies, and (b) the kinematic variability of dyads during the task (see next section).

Fig. 1. Slackline task. Accelerometers were placed on the support leg (Sup), the free leg (Free), the center of mass (CoM) and the slackline (Slack).

Data Analysis

Synergies Assessment

UCM was computed to evidence the presence and strength of both interpersonal (InterSyn) and intrapersonal synergies (IntraSyn) aiming to stabilize the Slack (performance variable) in each trial. While InterSyn could be formed by nine combinations of task elements between both slackliners (e.g., Sup of slackliner 1 x Free of slackliner 2), IntraSyn could only be formed by six combinations of task elements from each slackliner (e.g., Sup of slackliner 1 x Free of the slackliner 1).

The computational procedure for UCM

To compute synergies assessment based on UCM concept a Matlab© R2016b routine was created. For all the mathematical and statistical details associated with this computational procedure, see Passos et al. (2018).

To demonstrate the hypothesis that each combination of task elements stabilized the performance variable, a computational procedure based on the UCM calculated two types of variance produced by the task elements on each trial: (a) the compensated variance, which stabilizes the performance variable; (b) the uncompensated variance, which disturbs the performance variable stability. This computational procedure demands reference values for both, the performance variable and the task elements. For that purpose, the mean values of the data series of each trial was used as a reference value.

The system model used for the UCM was evaluated in time for each trial and multiple combinations of task elements, assuming linear approximations between small changes in magnitude of the task elements and the performance variable with respect to the reference configuration values. For this purpose, a Jacobian matrix of the system was evaluated at the reference configurations, describing how small changes in the output of the task elements were reflected in the magnitude of the performance variable and formalized as a matrix of partial derivatives of the performance variable with respect to the relevant task elements. However, no analytical kinematic model of the Jacobian matrix was available relating the performance variable and the task elements. Furthermore, the apparent output of the performance variable could not be independently tested for each task element to infer its contribution to the Jacobian. Consequently, the estimation of the Jacobian matrix was obtained using a linear multiple regression based on the methodology presented by Klous, Mikulic, & Latash (2011). This method assumes the following form:

$$(p^t - p^0) = K_1.\left(T_i^t - T_j^0\right) + K_2.\left(T_i^t - T_j^0\right)$$

where p = performance variable, T_i *and* T_j = two task elements for each possible combination (either for interpersonal $i, j = 1,...,9$ or intrapersonal $i, j = 1,...,6$), t : each discrete time point ($t = 1, \ldots, N$, corresponding to all the time points for each trial with dimension N), 0 : reference configuration, K_1 *and* K_2 : coefficients of the regression obtained for each trial, corresponding to the entries of the Jacobian matrix at the reference configuration.

The output of the computational procedure is an index ratio between the compensated and uncompensated variances, which compares the predominance of one over the other and enables to characterize the presence or absence of synergies as well as their strength. When UCM index > 1, then a synergy was considered. Moreover, the higher the UCM index value, the stronger the synergy (Black et al., 2007). On the contrary for UCM index < 1 then there was no synergy.

However, to validate each UCM index two statistical procedures were required. The first was an ANOVA test, performed to compare the means of every trial between compensated and uncompensated variances by all UCM ratios (setting the significance at $p < .05$). If there were no statistical differences between the compensated and uncompensated variances, then the trial could not be considered for analysis. The second procedure was the need to test the multicollinearity among task elements which could bias the UCM index values, and thus, lead to erroneous results. Multicollinearity was calculated with the Variance Inflation Factor (VIF) (Allison, 1999), where trials with a VIF > 5 were not considered for analysis (for further details concerning the VIF acceptable values please see Hair, Black, Babin, & Anderson, 2010).

Aiming to show the strength of synergies for all trials the mean UCM values of consistent InterSyn and IntraSyn were calculated. A synergy was 'consistent' when UCM > 1 in a minimum of four trials (e.g., Sup of slackliner 1 x Free of slackliner 2 achieved an UCM > 1 from trial 1 to trial 4).

Embedded Synergies

This study aimed to detect hypothetical embedded organization of synergies, that is, whether InterSyn dominated over IntraSyn. Hierarchical cluster analysis (Baker & Hubert, 1975) allows identifying the dominance of one type of synergy over the other. With this purpose, the consistent synergies were classified into clusters by their strength proximity (similarity): the higher proximity of InterSyn, the higher its dominance.

More than two consistent synergies were needed for evidencing different clusters, consequently, D4 and D6 were excluded because they had only two consistent synergies (see Table 1). The distance between synergies in the agglomerative clustering procedure was assessed by the (1 - *r*) measure; where *r* is the Pearson correlation coefficient. As a linkage method we used the nearest-neighbour (single-linkage) rule.

Evaluation of Kinematic Variability

The kinematic variability aimed to detect hypothetical stabilizing roles among slackliners (with different training experience and task performance) on interpersonal synergies formation (see statistics section). To analyse the kinematic variability, DFA (Ihlen, 2012; Peng et al., 1994; Peng, Havlin, Stanley, & Goldberger, 1995) was applied to the performance variable (i.e., Slack) and to the task elements (i.e., CoM, Sup, Free) of both slackliners within each dyad.

Firstly, an integration of the total length of the acceleration time series (N), which were varying from $N = 2048$ to $N = 8192$ data points, was performed as follows:

$$Y(i) \equiv \sum_{k=1}^{i} [x_k - \langle x \rangle]$$

where x_k = time series of acceleration, and $\langle x \rangle$ = average acceleration of the N data points.

Then, the local trend was computed to fit the time series of acceleration using a quadratic polynomial function (Ihlen, 2012), and thereby generating time series of velocity. Such time series were divided into different windows scales *n* of equal length, with the local trend being subtracted in each window: 7 scales were chosen according to Kantelhardt, Zschiegner, Koscielny-Bunde, Havlin, Bunde, and Stanley (2002) while a minimum scale of 8 was taken when analysing time series of $N = 2048$. The root mean square (RMS) fluctuation was calculated for each window by using the following equation:

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2}$$

where $y(k)$ = integrated time series, and $y_n(k)$ = local trend in each box.

The H exponent, obtained as the slope value of the linear regression between the scale and local fluctuations on a log-log diffusion plot, was used to determine the temporal structure of the time series fluctuations. H exponents were calculated from the Slack (H_{Slack}) data, as well as from the Sup (H_{Sup}), Free (H_{Free}) and CoM (H_{CoM}) data of each slackliner. Anti-persistent temporal structure of each time series was associated to H exponent values in the range $0 < H < 0.5$, and persistent temporal structure between $0.5 < H \leq 1$ (Delignières et al., 2011; Ihlen, 2012). Matlab© R2016b was used to perform the DFA.

Statistics

A Spearman correlation was performed to assess the relationship between (a) InterSyn and IntraSyn of all dyads through the numbers of task elements combinations that led to their formation, (b) the kinematic variability of slackliners (*H* exponent of Sup, Free and CoM) and their training experience variables (frequency and age) as well as task performance (time on task) of all dyads, and (c) the kinematic variability of slackliners and the UCM mean value of consistent InterSyn within each dyad. These analyses were conducted via SPSS v.15 (SPSS Inc., Chicago, USA), while the significance level was set at $p < .05$.

RESULTS

Inter and Intrapersonal Synergies

InterSyn and IntraSyn were detected for all dyads in all trials during the cooperative slackline task. The numbers of task elements combinations that led to InterSyn and IntraSyn was positively correlated (*rho* = .88; $p < .01$). The average strength of consistent synergies (i.e., combinations of task elements present at least in four trials, see Table 1), was higher in InterSyn (UCM = 17.15 ± 22.81) than IntraSyn (UCM = 12.36 ± 7.21). Synergies showed different strengths and Free was the task element that most prevailed on synergies formation; 33 out of 35 synergies were among Sup or CoM with Free.

Figures 2a and 2b illustrate the Hierarchical cluster analysis of dyads showing consistent InterSyn and IntraSyn (D1, D2, D3, D5, see Table 1). Synergies with high proximity ($r > 0.85$), creating close clusters, display a common feature: they are sustained by at least one InterSyn and contain the presence of Free. InterSyn showed stronger proximity than IntraSyn, being the dominant synergy in all dyads, while the task element Free strengthened its dominance as a relevant element. All dyads presented the same task element of one or both slackliners to form strong clusters of InterSyn and IntraSyn with mid-high proximity ($r > 0.74$).

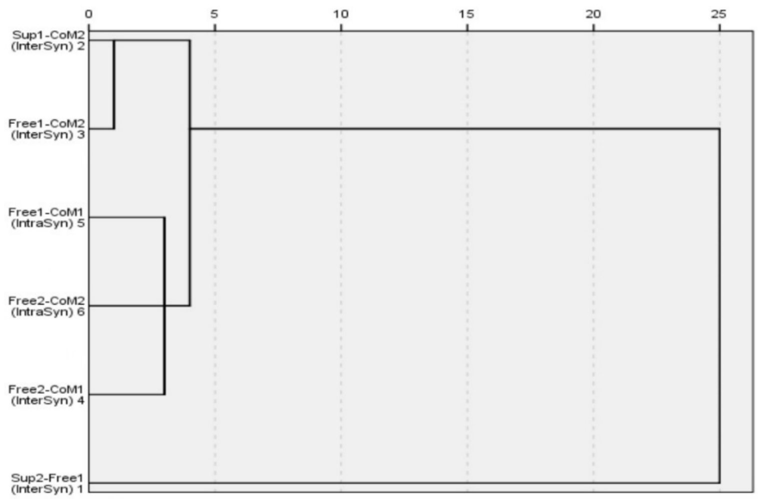
Table 1. Consistent Inter (InterSyn) and Intrapersonal Synergies (IntraSyn) of the Studied Dyads (D). Sup = Support Leg of Slackliners; Free = Free Leg of Slackliners; CoM = Center of Mass of Slackliners.

D1	*D2*	*D3*	*D4*	*D5*	*D6*
			InterSyn		
Free1-CoM2 Sup1-CoM2 Free2-CoM1 Sup2-Free1	Free3-CoM4 Free4-CoM3 Sup4-Free3	Sup6-Free5 Sup5-Free6 Sup5-CoM6	None	Sup10-Free9 Free9-CoM10 Free10-CoM9 Sup9-Free10	Free12-CoM11
			IntraSyn		
Free1-CoM1 Free2-CoM2	Free3-CoM3 Sup3-Free3 Free4-CoM4	Free6-CoM6 Free5-CoM5 Sup6-Free6	Sup7-Free7 Free7-CoM7	Free9-CoM9 Sup9-Free9 Sup10-Free10	Free12-CoM12

Kinematic Variability of the Slackline and Slackliners

Table 2 presents the kinematic variability of the Slack, and the CoM, Free and Sup of slackliners. The DFA analysis of Slack, used as the performance variable on interpersonal synergies formation, showed on average a weakly persistent structure of velocity fluctuations ($H_{Slack} = 0.53 \pm 0.20$). Respect the task elements used to stabilize the Slack, the CoM showed on average a moderate persistent temporal structure ($H_{CoM} = 0.64 \pm 0.17$), the Free revealed on average the highest persistent structure ($H_{Free} = 0.93 \pm 0.19$), and the Sup, directly in contact with Slack, displayed on average a weakly persistence ($H_{Sup} = 0.52 \pm 0.17$).

(D1)



(D2)

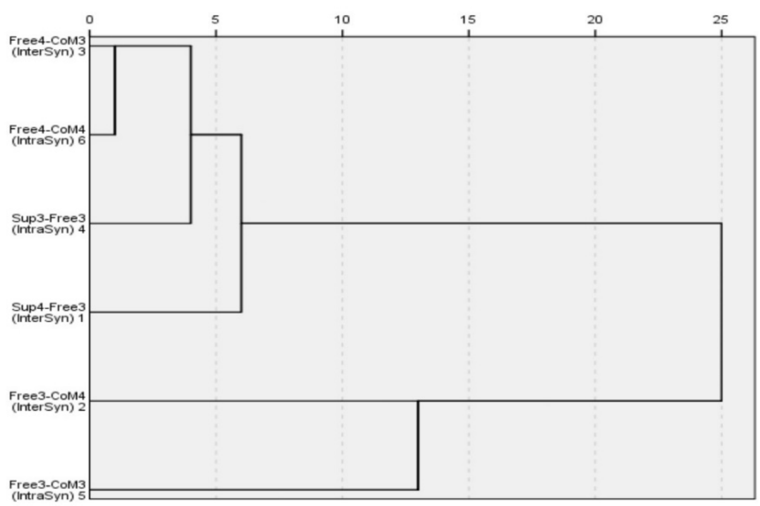


Fig. 2. Hierarchical cluster analysis of consistent inter (InterSyn) and intrapersonal synergies (IntraSyn) of (a) dyad D1 and D2; (Continued)

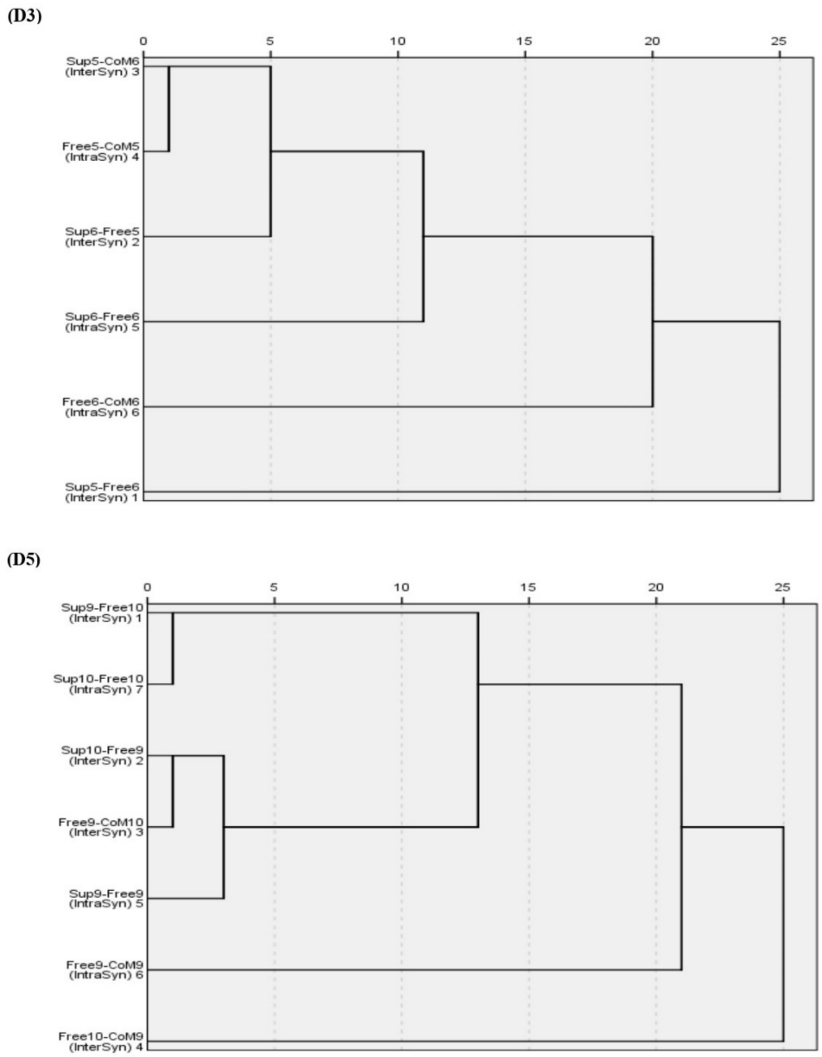


Fig. 2. (Continued)
Hierarchical cluster analysis of consistent inter (InterSyn) and intrapersonal synergies (IntraSyn) of (a) dyad D1 and D2; (b) D3 and D5. Stronger correlated clusters are closer to 0. Sup = support leg of slackliners; Free = free leg of slackliners; CoM = center of mass of slackliners.

Table 2. Kinematic Variability (Mean ± SD) of the Slackline and Slackliners (S) for Each Dyad (D). H_{Slack} = Hurst Exponent of the Slackline; H_{Sup} = Hurst Exponent of the Support Leg; H_{Free} = Hurst Exponent of the Free Leg; H_{CoM} = Hurst Exponent of the Center of Mass.

	D1		*D2*		*D3*	
H_{Slack}	0.84 ± 0.06		0.76 ± 0.08		0.43 ± 0.08	
	S1	*S2*	*S3*	*S4*	*S5*	*S6*
H_{Sup}	0.64 ± 0.21	0.59 ± 0.15	0.56 ± 0.13	0.67 ± 0.06	0.43 ± 0.03	0.66 ± 0.12
H_{Free}	0.89 ± 0.10	0.73 ± 0.21	0.71 ± 0.17	0.89 ± 0.14	1.04 ± 0.20	1.04 ± 0.18
H_{CoM}	0.81 ± 0.71	0.71 ± 0.09	0.41 ± 0.11	0.55 ± 0.08	0.75 ± 0.13	0.69 ± 0.19
	D4		*D5*		*D6*	
H_{Slack}	0.39 ± 0.03		0.38 ± 0.03		0.53 ± 0.20	
	S7	*S8*	*S9*	*S10*	*S11*	*S12*
H_{Sup}	0.47 ± 0.07	0.30 ± 0.05	0.50 ± 0.05	0.43 ± 0.05	0.69 ± 0.21	0.33 ± 0.08
H_{Free}	0.90 ± 0.21	0.94 ± 0.17	0.95 ± 0.10	0.89 ± 0.13	1.03 ± 0.17	1.19 ± 0.15
H_{CoM}	0.63 ± 0.20	0.52 ± 0.13	0.58 ± 0.10	0.61 ± 0.10	0.69 ± 0.13	0.76 ± 0.13

Correlation of Kinematic Variability of Slackliners with Training and Performance

A correlation of the kinematic variability of slackliners with their training experience and task performance was found. The H exponent of CoM and Free (featured by their moderate-high persistent structures), tended to decrease towards a weak-moderate persistence in slackliners with higher training frequency (ω) (*rho* = -.45; *p* = .01) and training age (τ) (*rho* = -.49; *p* = .01), respectively. These dyads also revealed a longer time on task, that is, a better task performance (H_{CoM}: *rho* = -.72; $p < .01$; H_{Free}: *rho* = -.72; $p < .01$; τ: *rho* = .49; *p* = .01) than those having higher *H* values (i.e., a higher persistent structure).

Kinematic variability and roles of slackliners

Stabilizing roles of individual slackliners were found in two dyads (D1 and D6). The stabilizing role was defined by a positive correlation between the kinematic variability of CoM and InterSyn' strength. No correlation was found between the other task elements (Free and Sup) and InterSyn. InterSyn were strengthened in slackliners displaying a lower persistence of H_{CoM} time series (S1: *rho* = -.90; *p* = .04; S11: *rho* = -.98; *p* = .01).

DISCUSSION

The study of interpersonal coordination of dyads cooperating to stand up in balance on a slackline revealed: a) inter and intrapersonal synergies of different strengths oriented to accomplish the task goal, b) an embedded organization of synergies with higher dominance of interpersonal compared to intrapersonal synergies, and c) stabilizing roles of slackliners within the dyad related to their training experience and task performance. Inter and intrapersonal synergies with non-unique strengths have been found in all dyads performing the slackline task. The number of combinations of task elements that contributed to synergies formation increased reciprocally at both levels, inter and intrapersonal, showing their co-emergence under the studied unsteady conditions, and the behaviour of dyads as a *co-adaptive whole*. Previous authors sustain that interpersonal synergies are generally weaker than intrapersonal (Black et al., 2007), however this research showed that interpersonal synergies were stronger than intrapersonal synergies. This is probably due to an inevitable interpersonal dependence (i.e., strong coupling) generated by a dyadic task in which slackliners had to hold their hands. These results highlight the fundamental contribution of interpersonal synergies to interpersonal coordination in cooperative movement systems in tight coupling with their environment (represented by the slackline) (Fusaroli et al., 2014; Passos et al., 2020).

In that regard, hierarchical cluster analysis showed more synergy proximities in inter than intra spaces, confirming that the *co-adaptive whole* was embedded and dominated by interpersonal synergies. These results are in agreement with previous research showing that social interpersonal relationships have a profound impact on individuals (Boren & Veksler, 2011). Additionally, slackliners shared the same task elements (Free, Sup and CoM) when inter and intrapersonal synergies showed proximity. This means that the embedded organization of interpersonal synergies presented a multilevel cooperation to accomplish the task goal.

The distribution similarities of interpersonal synergies reflected a fluent proprioceptive dialogue between the slackliners of the dyad, and showed that the slackline was the common ground for their complex dyadic cooperation, similarly as it happens during a friendly conversation (Abney, Paxton, Dale, & Kello, 2014; Fusaroli et al., 2014). The proprioceptive dialogue is explained through a continuous multiscale perception-action cycle (Montull et al., 2020; Solnik, Reschechtko, Wu, Zatsiorsky, & Latash, 2017), where the perception of affordances (opportunities of action) contingently regulated the actions of slackliners within the dyad and promoted the stabilizing roles that spontaneously emerged.

The UCM and the cluster analysis revealed that Free, co-stabilizing the dyad-slackline coupling through compensatory actions, was the dominant task element. However, these analyses could not reveal stabilizing roles among slack-liners. The kinematic variability analysis (represented by the H exponent), which was related with training experience and task performance, revealed potential stabilizing roles in two dyads. The Slack, as performance variable, was tightly controlled by fast and small movements of the Sup, featured by a weak persistence (i.e., close to negative-stabilizing feedback) (Cuomo et al., 2000; Vázquez et al., 2016). In contrast, CoM and especially Free, with more freedom of movements, showed on average the highest persistent temporal structures (i.e., larger positive serial correlations). Due to it, when the persistence of these task elements becomes excessively high (H values closer to 1), reflecting a rigid kinematic control, critical transition towards the task disengagement may occur (Montull et al., 2020; Vázquez et al., 2016; Scheffer et al., 2009). More experienced slackliners displayed a more moderate persistence of CoM and Free, and consequently, performed longer on the task. Particularly, the stabilizing roles revealed in two slackliners was a consequence of this moderate persistence of CoM.

Most dyads did not reveal stabilizing roles probably due to the considerably high variability of UCM values. Indeed, dyads searched stability through different synergetic strategies that were depending on how affordances and other non-evaluated organismic constraints, acting at different timescales (personality traits, psychobiological state, level of fatigue, motivation, etc.), constrained the roles at inter and intrapersonal levels (Balagué, Pol, Torrents, Ric, & Hristovski, 2019). The uniqueness of the dyad-environment interaction, and the lack of experience of the dyads with the task goal, could promote such diversity of task elements that led to interpersonal synergies, and may explain the lack of clear idiosyncratic patterns related to interpersonal synergies and individual roles. In fact, due to their lack of experience performing together, it can be considered that all dyads were immersed in an exploratory and familiarizing phase with respect to the task goal.

Methodological and Practical Implications

The dominantly proprioceptive dialogue of this study may have similarities with other nonverbal types of communication found in different micro and macro systems: from social interactions (Ferrer & Solé, 2001; Passos et al., 2016), neural systems (Lerner, Ye, & Deisseroth, 2016), cancer tissues (Solé, Valverde, Rodriguez-Caso, & Sardanyés, 2014) or viruses (Solé & Elena, 2018). That is, with an adequate adaptation, the data analysis applied here can be used to study other types of multilevel communication. Specifically, UCM demonstrated its potentiality to identify inter and intrapersonal synergies. It is worthwhile to highlight that testing multicollinearity in such UCM analysis represents a notably deviation from default statistical assumptions. Hierarchical cluster analysis was useful as a complementary measure to classify the cluster organization of synergies by their strength. It allowed the identification of the embedded structure of inter and intrapersonal synergies, one of the main contributions of the study. Finally, the evaluation of the kinematic variability through the DFA of the task elements allowed to detect stabilizing roles of slackliners, while training and performance variables enabled to contextualize it.

An attuned communication among processes acting at multiple levels is the basis to overcome big instabilities, and consequently, avoid undesired critical points (e.g., civil war, deadly disease, etc.; Solé & Elena, 2018). As in other cooperative social activities, the embeddedness of intrapersonal and interpersonal synergies seems crucial for long-lasting performance results (Balagué et al., 2019). Particularly, the dominance of the group over the individual dynamics should be taken into account in cooperative tasks when planning interventions. Although the group and the individuals that form it are related through circular causality, the larger stability of the group implies that interventions at group level may have larger efficacy than interventions at individual level (i.e., individuals are somehow subordinated by the dyad). Due to interpersonal synergies, individuals compensate their weaknesses when trying to reach a common goal. Scaled to different contexts and study areas, modulator elements which are dominantly forming the synergies due to their larger degrees of freedom and greater adaptive behaviour (such as Free in this task), may importantly inform about key compensating roles (e.g., when detecting a disease's formation).

As an expression of interpersonal coordination, synchronization is often measured without any reference to the synergies concept. An example is a study that aimed to analyse the influence of unintentional nonverbal synchrony between patient and therapist in the outcome of the psychotherapy session (Ramseyer & Tschacher, 2016). Despite the positive relation between the nonverbal synchrony and the session outcome, there was no reference to a dyadic synergy between the participants of the session. In this study it has been shown that interpersonal coordination emerges in dyadic interactions when there is a common goal and this interaction can be measured through multilevel synergies formation.

Without competing for a hierarchical control, a spontaneous and non-verbal emergency of roles may emerge. In this sense, in determined group contexts, a self-organized nonverbal cooperation may accomplish more satisfactorily task goals than pre-stablished roles imposed through verbal communication by commanded hierarchies (e.g., orders from a coach in sports teams, or business managers in companies). In addition, proprioceptive dialogues, either in individual or collective tasks, play a relevant role both in terms of injury prevention and performance (e.g., human castles, acrobatic gymnastics, trail running, etc.) (Han, Anson, Waddington, Adams, & Liu, 2015; Jeannerod, 2003). Finally, highlight that diversity, observed in the multilevel coordination of dyads, is a fundamental property to create learning opportunities in front of challenging tasks.

Limitations and Future Perspectives

As the proposed task is neither competitive nor widely practiced, participants could not be selected according to their performance results. Hence, more research is warranted to reproduce the current methodology in other motor activities such as acrobatic gymnastics. Furthermore, future research may consider enlarging the exposure time among participants for studying how collective coordinative behaviour is changing in function of having more information about the respective partner (i.e., how social memory affects the interpersonal perception-action cycle) (Gipson, Gorman, & Hessler, 2016).

As greater physiological synchronization might result from better team performance (Guastello, Marra, Peressini, Castro, & Gomez, 2018), it probably could be associated to better kinematic control as well. Neither physiological coordination nor intrapersonal sublevels of coordination such as intralimb coordination were not studied here. In fact, to our knowledge, physiological variables have not been studied yet using the UCM. The novel interest can hold in assessing a multilayer network of synergies (Kelso, 2009a) within inter and intrapersonal synergies using different systemic levels. Future research can consider including conceptual and practical frameworks of network physiology and network medicine to study the vehicles for communication behaviour and promote a mesoscopic approach focused on the functional integration (Bizzarri, Giuliani, Pensotti, Ratti, & Bertolaso, 2019; Ivanov, Liu, & Bartsch, 2016).

Finally, some authors have found that individuals learn and adapt under the subordination of more skilled partners, the so-called complexity matching effect (Almurad, Roume, Blain, & Delignières, 2018; Mahmoodi, West, & Grigolini, 2020). In this line, future research is warranted to deeply explore the emergence of dyadic roles proposed in this investigation.

CONCLUSIONS

This exploratory study of interpersonal coordination of dyads cooperating to stand up in balance on a slackline found an embedded organization between inter and intrapersonal synergies in which stabilizing roles emerged. Dyads established a dominantly proprioceptive dialogue to form a co-adaptive whole and cope with an unstable environment.

ACKNOWLEDGMENTS

This study was supported by the Institut Nacional d'Educació Física de Catalunya (INEFC) and the Generalitat de Catalunya. LM is the recipient of a predoctoral fellowship from INEFC.

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Chapter Three

3. Discussion

3.1. Results report

The main results of this thesis, which are used in the next section to discuss the benefits of assessing CAS' properties for approaching sport-related phenomena, are reported in Table 5.

Table 5. Main results of the research articles composing the thesis, according to the studied sport-related phenomena, data analysis techniques and monitored variables.

Research article	Sport-related phenomena	Data analysis techniques and monitored variables	Main results
1	Workload stress and tolerance	Hysteresis area of RPE and HR	Areas were lower in more experienced/trained athletes, showing faster recovery during pyramidal exercises. This recovery was harder in cycling compared with running.
2	Fatigue-induced exhaustion	MFDFA (time-variability) of acceleration	Athletes with higher psychobiological stress seem showing higher reduction in MFDFA spectrum of body fluctuations (i.e., less kinematic control) at the end of exhausting exercises.
3	Exercising flow state	DFA (time-variability) of acceleration	Performers who reported higher subjective flow experience while slacklining, displayed less persistence behaviour of body fluctuations (i.e., higher kinematic control).
4	Intra- and interpersonal synergies of dyads	UCM (synergies) and DFA (time-variability) of acceleration	Dyads showed embedded synergies while balancing on a slackline. The kinematic fluctuations of performers revealed their stabilizing roles within the dyad.

Note. RPE = rating of perceived exertion; HR = heart rate; MFDFA = Multifractal Detrended Fluctuation Analysis; DFA = Detrended Fluctuation Analysis; UCM = Uncontrolled Manifold.

3.2. Benefits of assessing CAS' properties to approach sport-related phenomena

Capturing how athletes are constantly self-organizing to adapt to multiple personal and environmental constraints is key to understand sport behaviour. Monitoring systems and data analysis techniques addressed to assess CAS' properties, and thereby, describe the dynamics of selected state variables are encouraged (Balagué, Hristovski, Almarcha, et al., 2020).

The research articles included in this thesis have applied data analysis techniques addressed to capture the hysteresis behaviour of psychobiological variables (Montull, Vázquez, Hristovski, et al., 2020), the structure of time variability of kinematic variables (Montull et al., 2019, 2021; Montull, Vázquez, Rocas, et al., 2020) and the synergies of kinematic variables (Montull et al., 2021), which enabled a better understanding of diverse phenomena like workload stress and tolerance, fatigue-induced exhaustion, exercising flow state, and the relation between intra- and interpersonal synergies in a dyadic task. In particular:

1- The hysteresis area of psychobiological variables points towards the discovery of a new non-invasive marker of workload stress and tolerance. It allows to overcome the limitations of assessment protocols capturing isolated and decontextualized values of psychobiological variables by plotting an area between the incremental and decremental values of the studied variable in function of the workload (control parameter). Results have been obtained monitoring RPE and HR during pyramidal running and cycling exercises, and more recently monitoring RPE, HR and muscle oxygen saturation during repeated exercises (Abenza et al., 2021). The hysteresis area may become instrumental to control the recovery efficiency of athletes after workload perturbations, and subsequently, to detect their adaptation to exercise requirements. For example, to detect the detraining effects of exercise programs (Martín-Guillaumes et al., 2021).
2- The time-variability of acceleration obtained throughout MFDFA seems to provide valid information about the system adaptation during exhausting exercises like running and ski mountaineering. The results give support to the potential of the time-variability structure analysis, either applied to kinematic or physiological variables, for revealing or early detecting acute fatigue (Gronwald et al., 2019; Vázquez et al., 2016). It is worth considering the difficulties of capturing the nonlinear response of athletes with workload accumulation using traditional measures.
3- The time-variability of acceleration throughout DFA was informative about the degree of stability of components during a slackline walking task and the co-variance of the perception-action cycle corresponding to a flow state experience. That is, the embodied fluctuating dynamics in relation to the environment. Thus, it may provide an objective and direct information of a psychobiological state, importantly associated with exceptional performance, that has been traditionally monitored through retrospective self-reported methods. The analysis of the time-variability of acceleration reinforces the capacity to detect adaptive responses during sport practice.
4- The UCM of acceleration time series is informative about the intra- and interpersonal synergies in a dyadic slackline cooperative task. A complementary hierarchical cluster analysis may serve to display the interdependency among synergy levels. In this case, showing how interpersonal dominated over intrapersonal synergies. Further, DFA in acceleration time series has been again useful, particularly, to detect the spontaneous and non-verbal stabilizing roles of the synergizing components. The analyses seem adequate for the study of coordination dynamics either in individual or collective sports, and in fact, supposes a challenge for current objective monitoring systems.

All these data analysis techniques, either applied to time series of psychobiological or kinematic variables, share similar possibilities: to reveal the coordination dynamics of

CAS, and thus, their stability properties, regardless of the individual characteristics, the type of exercise and the timescale of observation. In fact, despite further research is warranted to explore the applicability of such techniques to different continuous monitored variables, they have shown potential for capturing diverse sport-related phenomena. Furthermore, they inform about the nonlinear and environmental-dependent dynamics (see Table 6), usually despised or ignored by current theoretical assumptions, monitoring systems and test protocols. In this way, athletes' assessment may become more personalized as it is often claimed (Molenaar, 2004; Nesselroade & Molenaar, 2010; Rose, 2016; Rose et al., 2013).

Table 6. Nonlinear and environmental-dependent dynamics revealed by the research articles.

Research article	**Nonlinear and environmental-dependent dynamics**
Montull, Vázquez, Hristovski, et al. (2020)	Nonproportional relationship between RPE, HR and workload intensity in function of athletic expertise level.
Montull et al. (2019)	Nonlinear changes of acceleration with accumulated workload.
Montull, Vázquez, Rocas, et al. (2020)	Flow as a nonlinear embodied state spontaneously emerging from the performer-slackline interaction.
Montull et al. (2021)	Synergies and stabilizing roles of performers, interacting among themselves and with the slackline, changed over the trials and dyads.

These data analysis techniques, and others capturing CAS' properties as network analysis (Ivanov et al., 2016), connectivity (Balagué, Hristovski, Almarcha, et al., 2020; Uryumtsev et al., 2020), entropy (Busa & van Emmerik, 2016; Couceiro et al., 2014) or complexity matching (Fine et al., 2015), have shown the capacity to reveal information which cannot be obtained through current monitoring systems. Rather than providing isolated snapshots of single or multiple metrics, they provide insight into the changing relationships between measures; thereby creating opportunities to unravel qualitative changes to dynamically modulating and instantaneously emerging patterns (Ballester et al., 2016; Gershenson & Fernández, 2012; Van Orden et al., 2003).

Behavioural patterns emerge from the nonlinear and uncertain self-organization of embedded and embodied, experience-dependent and goal-directed performer-environment interactions. Hence, such techniques may drive the evolution of a more realistic and informative blending of monitored metrics and analytic methods, subsequently enhancing the relevance, efficacy and predictive capacity of monitoring protocols (Fonseca et al., 2020; Pol et al., 2019). For instance, the capacity of forecasting imminent transitions such as injury probability or task disengagement (Fonseca et al., 2020; Scheffer et al., 2009; Vázquez et al., 2016).

The evolution of a more insightful, reactive, and adaptive monitoring paradigms, providing instantaneously actionable information, would ultimately drive changes across the athletic preparation domain. A ready access to meaningful information would enable new means of managing the balance between load and recovery, a key aspect of athlete's health and performance. For instance, adapting multiple facets of athletic preparation, rehabilitation, exercise prescription and load regulation processes (Afonso, Bessa, et al., 2020; Afonso, Clemente, et al., 2020; Afonso et al., 2019; Kiely, 2018).

As the same dynamic concepts can be applied to different levels of analysis, in a future scenario, the techniques capturing CAS' properties may be complementary among them and be integrated in the same monitoring software. Anyway, choosing the most effective and efficient technique according to the monitoring goal and the studied phenomenon is of high relevance.

The coordination dynamic concepts used in this thesis may contribute to sport science integration by providing a common scientific language. A valid language for all levels of analysis (from molecular to social), and consequently, common to all scientific disciplines (biomechanics, nutrition, psychology, physiology, etc.) (Balagué et al., 2017; Nicolescu, 2002; Vázquez, 2017). For example, stable and state transition phases have been evidenced monitoring the dynamics of both kinematic and psychological variables (e.g., volition states, perceived exertion and attention focus) (Aragonés et al., 2013; Balagué et al., 2015; Garcia et al., 2015; Montull et al., 2019; Vázquez et al., 2016). This supposes potential benefits not only for understanding better sport phenomena but for intervening more efficiently in sport settings off. The common scientific language established on the basis of CAS' principles can be useful for the interdisciplinary collaboration necessary to promote athletic health and performance (Rothwell et al., 2020).

3.2.1. Practical considerations

According to Fonseca et al. (2020) four important steps are necessary for monitoring and assessing CAS' properties: a) define the time scale of the studied sport-related phenomena, b) define the state variable(s) that characterize the system in this context, c) establish protocols that capture the time evolution of the state variable(s) with a resolution sufficient to describe the dynamics of the system, and d) select those methods that enable to analyse the captured dynamics and forecast future states. In that sense, a theoretical understanding about CAS' principles and concepts is initially necessary to avoid ambiguity and confusion related with the type of questions, assumptions and research interpretations (Gershenson & Fernández, 2012). For example, the entropy measures, usually associated with the study of CAS, can be used to answer a very simple question about cause-effect relationships that has nothing to do with a complex perspective (Pol & Balagué, 2021). Secondly, this understanding also requires a methodological knowledge to decide not only which measure apply in function of the collected data and how it works (e.g., in applying fractal methods, Delignieres & Marmelat, 2012), but also how to interpret its results. For instance, time series of acceleration in a dynamic and outdoor exercise with a changing terrain (Montull et al., 2019) or in a static quasi-isometric exercise (Vázquez et al., 2016) require contextualizing and interpreting different types of noise. Finally, in terms of setting adequate state variables highlight that the monitored variables used in these research articles require further research to be considered as it.

3.3. Future perspectives and limitations

The advantages of the data analysis techniques used for detecting CAS' properties in this thesis should be taken into consideration when developing future monitoring systems. A continuous information about the dynamics of relevant state variables maybe crucial to assist performers during exercise. For example, wearable microchips detecting cardiorespiratory and muscle networks dynamics may alert about early signs of fatigue. The development of adequate technology of wearable devices, providing continuous and synchronous recordings for evaluating the physiological state seems of key importance. In turn, the development of data analysis techniques able to infer couplings among diverse variables with different dynamics, such as the time delay stability (Bashan et al., 2012), are the basis for future functional evaluation tools based on Network Physiology of Exercise (NPE) principles. Continuous recordings of behavioural variables (e.g., extracted from kinematic or phenomenological data), may also contain integrated information of different network levels and be used to detect modularity in vertical and horizontal integration of the network (Balagué, Hristovski, Almarcha, et al., 2020).

Despite developing technology in sports monitoring is fundamental, we cannot ignore that subjective outperforms any objective monitoring when integrating multidimensional, multiscale and environmental-dependent information is the purpose (Montull et al., in press). Subjective monitoring, dominantly promoted for an adequate monitoring of CAS, may provide a practical, efficient and effective means of acquiring high-level actionable information (Balagué, Hristovski, Almarcha, et al., 2020; Pol et al., 2019; Sturmberg et al., 2019). In this direction, it seems convenient to highlight its relevance for enhancing athletic awareness, a key aspect for an adequate health and performance regulation (Almarcha et al., 2021; Pol et al., 2020). Thus, objective monitoring should be repurposed as a tool to help enlarge, rather than replace, athletes' subjective monitoring (Montull et al., in press; Woods et al., 2021).

Chapter Four

4. Conclusions

This thesis shows that the used methods and time series analysis techniques, effective for capturing CAS' properties of hysteresis, variability and synergies, improve the understanding and assessment of different sport-related phenomena. In particular, it is the first time that:

a) The assessment of the hysteresis behaviour of psychobiological variables (HR, RPE) revealed their incoherent association with workload intensity, and proposed a new non-invasive marker of stress and tolerance sensitive to the performance level: the hysteresis area.
b) The time-variability of acceleration may inform about both, the athlete's adaptation to exhausting dynamic exercises and the exercising flow state, which has been defined as an embodied state emerging from the performer-environment system.
c) Synergies and variability analysis of acceleration time series allow to capture the interpersonal coordination and stabilizing roles of dyads co-adapting as a whole to cope with an unstable environment.

The applied methods and data analysis techniques, based on a complex systems approach, may be used to study different phenomena, regardless of the individual characteristics, the type of exercise and the timescale of observation. In view of this, future research is warranted to update theoretical assumptions and methodological techniques to improve current sports monitoring systems and assessment protocols.

4.1. Conclusions (català)

Aquesta tesi mostra que els mètodes i tècniques d'anàlisi de sèries temporals utilitzats, els quals són efectius capturant les propietats dels sistemes complexos d'histèresi, variabilitat i sinèrgies, milloren la comprensió i avaluació de diferents fenòmens esportius. En particular, és la primera vegada que:

a) El comportament d'histèresi de variables psicobiològiques, el qual revela una associació incoherent d'aquestes variables amb l'intensitat de treball, es proposa a través de l'àrea d'histèresi com un nou marcador no-invasiu d'estrès i tolerància, sensible al nivell esportiu.
b) La variabilitat temporal de l'acceleració pot informar tant sobre l'adaptació dels esportistes en exercicis dinàmics extenuants com sobre l'estat de flow en exercici, el qual s'ha definit com un estat corporitzat emergent del sistema esportista-entorn.
c) Les anàlisis de sinèrgies i variabilitat en sèries temporals d'acceleracció permeten capturar la coordinació interpersonal i els rols estabilitzadors de parelles co-adaptant-se com un tot per afrontar un entorn inestable.

Els mètodes i tècniques d'anàlisi de dades aplicats, basats en una aproximació des dels sistemes complexos, poden ser utilitzats per estudiar diferents fenòmens, independentment de les característiques individuals, el tipus d'exercici i l'escala temporal d'observació. En vista d'això, és necessari que la recerca futura actualitzi els supòsits teòrics i les tècniques metodològiques per tal de millorar els actuals sistemes de monitorització esportiva i protocols d'avaluació.

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