Editorial: Nonlinear dynamics and networks in sports

Javier M. Buldú [a,b,c,d], Miguel-Ángel Gómez [e], José Luis Herrera-Diestra [f], Johann H. Martínez [b,g,h]

[a] *Complex Systems Group, Universidad Rey Juan Carlos, Madrid, Spain*

[b] *Grupo Interdisciplinar de Sistemas Complejos (GISC), Spain*

[c] *Laboratory of Biological Networks, Center for Biomedical Technology, Universidad Politécnica de Madrid, Madrid, Spain*

[d] *Institute of Unmanned System and Center for OPTical IMagery Analysis and Learning (OPTIMAL), Northwestern Polytechnical University, Xi'an, China*

[e] *Faculty of Physical Activity and Sports Sciences, Universidad Politécnica de Madrid, Madrid, Spain*

[f] *CeSiMo, Facultad de Ingeniería, Universidad de Los Andes, Mérida, Venezuela*

[g] *Departamento de Ingeniería Biomédica, Universidad de los Andes, Colombia*

[h] *Instituto de Física Interdisciplinar y Sistemas Complejos, IFISC (CSIC-UIB) Campus Universitat de les Illes Balears E-07122, Palma de Mallorca, Spain*

Evolution, self-organization, synchronization, entropy, or chaos are traditionally related to statistical physics and applied mathematics. Although their early developments came up from systems exclusively of these branches of knowledge, the applications of the methodologies quantifying the appearance of such phenomena in other real systems are increasing from year to year. Among these, Sports Science is one of the beneficiaries of the high applicability of Complexity Sciences. This fact is becoming more evident due to the recent ability to capture a diversity of new variables thanks to new technological advances. In this way, it is possible to record the speed of a ball during a tennis match, the strokes' position, the distances ran by each player and the corresponding velocities. In team games, such as football, we can track the position of the twenty-two players and the ball at a resolution of 25 frames per second, which results in large datasets containing priceless information about each team (and player) style of playing. However, how to extract useful information from such large datasets? The answer is not simple and, on the contrary, it implies an analysis based on the complexity of the systems under study. Furthermore, it requires the effort of mathematicians, physicists, data-analysts and sports scientists united in a common framework in order to adapt classical (and not so classical) methodologies coming from nonlinear dynamics [1] or network science [2] to the analysis of sports. Despite there is a vast literature about nonlinear analysis of sports datasets, recent advances in such fields, such as multi- layer networks [3], chimera [4] or Bellerophon states [5], explosive synchronization [6] or controllability of networks [7] (to mention a few) make necessary a new revision of how sports science can benefit from them.

Specifically, the current Special Issue is focused on the use of nonlinear dynamics and networks models in order to improve the knowledge and practical applications about teams and ath- letes/players' performance during trainings and competitions.

The Special Issue opens with two papers about racket sports: Tennis and Badminton. Giménez-Egido et al. [8] compared two scaled competition formats for under-10 years (U-10) tennis players analyzing serving performances. Twenty players played 40 matches according to the International Tennis Federation's Tennis guide for U-10 players in the stage green (GC) and 40 matches in a modified competition (MC) decreasing net height (from 0.91 m to 0.80 m) and court size (from 23.77 m x 8.23 m to 18.00 m x 8.23 m) with green ball (lower compression ball). Their statistical approach showed a nonlinear trend between contexts with increased performance in first serve success (more aces and un-returned serves) in MC than GC. Authors suggest that nonlinear approaches should be considered during formative stages in youth tennis players where reducing net height and court-size improves the serve performance. On the other hand, Gómez et al. [9] showed how Network Science could be applied to identify the style of playing of badminton players. Specifically, the authors constructed badminton stroke networks, consisting of directed bipartite graphs whose nodes are spatial positions of the court connected through directed-weighted links accounting for the number of times the shuttlecock goes from one position to the other. The properties of the one-mode projections of the bipartite networks were analyzed and related to a player's specific style, showing that both the player and the rival must be considered in the analysis.

Basketball is another sport that has been traditionally analyzed under the scope of nonlinear dynamics and complexity sciences. Petersen et al. [10] proposed the use of a novel methodology to better capture the players' performance in an objective and unbiased viewpoint, which can be applied to different eras. The authors showed that, using a renormalization technique, it is possible to extract seasonal performance metrics. The method was applied to recovered data from Major League Baseball and National Basket- ball Association showing that the functional form of the distribution of career achievement is preserved at the season and career level. An appropriate renormalization of metrics that account for players' achievements can be used to compare players among several dimensions like season lengths, team strategies, as well as for different sports.

However, football is the sport that has benefited the most from this kind of approach, being the core of the Special Issue. Gómez et al. [11] and Li et al., [12] showed that team performance is more than just the performance of individual players. In particular, Gómez et al. [11] examined winning and losing teams' performances during the four different match-status periods that occur in close soccer matches' comebacks. Specifically, they used a non- linear analysis of the relative-phase obtained from the exchange of the ball possession between teams. Shots, passing effectiveness and ball possession performances were analyzed in 17 matches of the Spanish professional soccer league. Interestingly, the results revealed shifts from anti-phase to in-phase relations depending on variables such as the shot or passing effectiveness.

On the other hand, Li et al., [12] analyzed 1200 games from 2014-2018 Chinese Super League and applied a Linear Support Vector Classifier (LSVC) to the ranking of teams and exploitation of key performance features concerning match outcome. They analyzed different game outcomes (win vs. not-win) with LSVC and calculated a weight for different performance features. The weights showed that shots on target, pass success, saves, interceptions, clearances and tackles were important positive features. In contrast, opponent shots on target, passes, bad shot rate, crosses and red card were features that had a great negative impact. Finally, a team rank expressing the teams' performance was built.

The understanding and modeling of team and player dynamics have been the main focus of three papers of the Special Issue. López-Felip and Harrison [13] analyzed the dynamics of a player when keeping the ball possession and progressing with it. To do that, players of a team either keep passing the ball around or dribble it. The authors proposed a two-stage model to capture instances in which football players dribble the ball around the field. The model consisted of a "touch" event, an end-directed projectile launch, and a "go" phase, during which the ball follows its projectile course and the player performs locomotion toward the moving target of the ball. Adjusting parameter values, such as touch velocity, the model could be used to analyze how dribblings respond to the context of the game.

Marcelino et al. [14] went one step beyond by analyzing the coordination of players' dynamics. They analyzed the collective motion patterns exhibited by football players in order to under- stand the collective strategies associated with team performance. Authors identified collective dynamics that characterize winning and losing teams by analyzing pairwise relationships among all the players using spatiotemporal correlation functions. They also found different players' behaviors and interactions, allowing them to assign a unique behavioral pattern for each individual and team.

Furthermore, Clemente et al. [15] were concerned about the dynamics of players during training. They carried out a review about small-sided soccer games (SSGs), which are useful to reproduce specific collective dynamics with a small number of players, different formats, or pitch sizes to replicate certain dynamics of a real game. In this review paper, the authors provided new insights comparing different game factors. Specifically, authors focused on five topics related to tactical and collective behaviors: the effects of different game formats; the effects of different pitch sizes and con- figurations; the effects of task adjustments; the effects of age and competitive and expertise levels; and multidimensional effects.

Notwithstanding, Network Science and its application to football analysis have captured the most attention of scientists participating in this Special Issue. Last years have witnessed a diversity of papers showing how translating team dynamics into networks could lead to new insights about the performance of football players and teams [16]. Six papers of the Special Issue contributed to enlarge the state-of-art of this new approach.

Clemente et al. [17] used event datasets from the 2018 FIFA World Cup, built the corresponding player passing networks (where nodes are players and edges are passes between them), and analyzed the variations of the player centrality. Next, they investigated the interplay between centrality and the match outcome. Interestingly, the authors found different levels of correlations between prestige (amount of inbound passes) and the player's positions. Comparisons of passing network centrality levels between match outcomes were also reported. Thus, match outcome (and possibly scoring status during the match) was somewhat related to the passing centrality of various playing positions.

Wu et al. [18] studied the social network in football using player's positions and passing sequences. The results of this network approach showed that midfielders are the key position during the passing process, followed by central defending midfielders. This network analysis allowed obtaining the passing patterns related to playing positions and the success of passing sequences.

Sarmento et al. [19] studied the attacking phase of a football team by combining Network Science parameters and the opinion of two technical staff members: the head coach and a performance analyst. Two kinds of networks were analyzed: (i) pitch-networks, where nodes are different areas of the pitch (3x4) and (ii) player networks, where nodes are football players. Different network parameters were extracted to characterize the organization of the whole team but also to assess the importance of certain pitch regions and specific players. Finally, the opinion of the two members of the technical team allowed interpreting the results obtained and introduce some explanation about the role of the team's key players.

Herrera-Diestra et al. [20] investigated the particular organization of Guardiola's F.C. Barcelona (FCB) during season 2009/2010, using datasets from the Spanish National League "La Liga". They constructed and analyzed FCB's pitch networks, performing a multi-scale analysis focused on evaluating pitch networks' properties at different scales (i.e., at different partitions of the pitch). For each scale, a diversity of network parameters of FCB and its opponents were calculated. Results showed how, depending on the spatial scale, there are statistically significant differences between FCB and the rest of the Spanish league teams.

Ramos et al. [21] transformed the spatial coordinates of players into simplicial complexes [22], where links were created according to the proximity between a group of players. In this way, authors established sets of players forming different kinds of simplices representing n-ary spatial interactions. They demonstrated that the scaling properties in the frequency of occurrence of players' sets exhibit a Zipf-Mandelbrot regularity. This work also generalized how the sets Goalkeeper and Goal drove the exceptions of that regularity, unveiling some design in the players' configuration that could be associated with a match strategy.

Finally, Medina et al. [23] presented a method combining a simple regression model and complex network features to assess the probability of teams to win/loss/tie matches when playing home or away. They showed that the addition of both approaches could offer useful information in determining matches outcomes. To validate their conclusions, they used data from the Spanish national league "La Liga" during season 2012-2013 and observed that, in particular, betweenness centrality was the most informative parameter when evaluating performance during the tournament.

Given all contributions of this Special Issue, we are confident that the application of nonlinear dynamics and network science to analyze sports is an emerging field with promising perspectives that, in the years to come, will provide a complementary point of view to classical analysis about team and player/athlete performance.

Acknowledgements

We are grateful to the international journal Chaos, Solitons & Fractals, and especially to its Editor in Chief and its Publishers for having hosted this theme issue. We also want to thank all the contributors of the different papers and all the colleagues who assisted us in reviewing the papers. JMB is funded by MINECO, Spain (FIS2017-84151-P). JHM is funded by Colciencias call of projects 811.

References

[1] Strogatz SH. Nonlinear dynamics and chaos. New York: Perseus; 1994.

[2] Newman M. Networks: an introduction. Oxford University Press, Inc; 2010.

[3] Boccaletti S, Bianconi G, Criado R, Del Genio CI, Gómez-Gardenes J, Romance M, Sendiña Nadal I, Wang Z, Zanin M. The structure and dynamics of multilayer networks. Phys Rep 2014;544(1):1–122.

[4] Abrams DM, Strogatz SH. Chimera states for coupled oscillators. Phys Rev Lett 2004;93(17):174102.

[5] Qiu T, Boccaletti S, Bonamassa I, Zou Y, Zhou J, Liu Z, Guan S. Synchronization and bellerophon states in conformist and contrarian oscillators. Sci Rep 2016;6:36713.

[6] Leyva I, Sevilla-Escoboza R, Buldú JM, Sendina-Nadal I, Gómez-Gardeñes J, Arenas A, Moreno Y, Gómez S, Jaimes-Reátegui R, Boccaletti S. Explosive first-order transition to synchrony in networked chaotic oscillators. Phys Rev Lett 2012;108(16):168702.

[7] Wang LZ, Chen YZ, Wang WX, Lai YC. Physical controllability of complex networks. Sci Rep 2017;7:40198.

[8] Gimenez-Egido JM, Ortega-Toro E, Palao JM, Torres-Luque G. Effect of scaling equipment on u-10 players tennis serve during match-play: A nonlinear pedagogical approach. Chaos Soliton Frac 2020;139:110011.

[9] Gómez MA, Rivas F, Leicht AS, Buldú JM. Using network science to unveil badminton performance patterns. Chaos Soliton Frac 2020;135:109834.

[10] Petersen AM, Penner O. Renormalizing individual performance metrics for cultural heritage management of sports records. Chaos Soliton Frac 2020;136:109821.

[11] Gomez MA, Reus M, Parmar N, Travassos B. Exploring elite soccer teams? performances during different match-status periods of close matches? comebacks. Chaos Soliton Frac 2020;132:109566.

[12] Li Y, Ma R, Gonçalves B, Gong B, Cui Y, Shen Y. Data-driven team ranking and match performance analysis in chinese football super league. Chaos Solitons Frac

2020;141:110330.
[13] López-Felip MA, Harrison HS. The touch & go dribbling model. Chaos Soliton Frac 2020;140:110186.
[14] Marcelino R, Sampaio J, Amichay G, Gonçalves B, Couzin ID, Nagy M. Collec- tive movement analysis reveals coordination tactics of team players in football matches. Chaos Soliton Frac 2020;138:109831.
[15] Clemente FM, Afonso J, Castillo D, Los Arcos A, Silva AF, Sarmento H. The ef- fects of small-sided soccer games on tactical behavior and collective dynamics: a systematic review. Chaos Soliton Frac 2020;134:109710.
[16] Buldú JM, Busquets J, Martínez JH, Herrera-Diestra JL, Echegoyen I, Galeano J, et al. Using network science to analyse football passing networks: Dynamics, space, time, and the multilayer nature of the game. Front Psychol 2018;9:1900.
[17] Clemente FM, Sarmento H, Aquino R. Player position relationships with centrality in the passing network of world cup soccer teams: win/loss match comparisons. Chaos Solitons Fractals 2020;133:109625.
[18] Wu Y, Xia Z, Wu T, Yi Q, Yu R, Wang J. Characteristics and optimization of core local network: Big data analysis of football matches. Chaos Soliton Frac 2020;138:110136.
[19] Sarmento H, Clemente FM, Gonçalves E, Harper LD, Dias D, Figueiredo A. Analysis of the offensive process of AS Monaco professional soccer team: a mixed-method approach. Chaos Soliton Frac 2020;133:109676.
[20] Herrera-Diestra JL, Echegoyen I, Martínez JH, Garrido D, Busquets J, Seirul lo F, et al. Pitch networks reveal organizational and spatial patterns of Guardiola's FC Barcelona. Chaos Soliton Frac 2020;138:109934.
[21] Ramos JP, Lopes RJ, Araújo D. Interactions between soccer teams reveal both design and emergence: cooperation, competition and Zipf-Mandelbrot regularity. Chaos Soliton Frac 2020;137:109872.
[22] Battiston F, Cencetti G, Iacopini I, Latora V, Lucas M, Patania A, Young J-G, Petri G. Networks beyond pairwise interactions: structure and dynamics. Phys Rep 2020;874:1–92.
[23] Medina PA, Carrasco S, Rogan J, Montes F, Meisel JD, Lemoine P, Lago C, Valdivia JA. Is social network approach relevant on football results? Chaos Soliton Frac 2020:110369. In press

Published in Chaos, Solitons and Fractals
https://doi.org/10.1016/j.chaos.2020.110518