Fatigue in soccer: NEW APPROACHES AND CONCEPTS. SPAIN PERSPECTIVE

Carlos Lago-Peñas University of Vigo, SPAIN







Alicante (Spain), 16-18 November 2016

Today's talk

- Fatigue in soccer. Traditional concepts and approaches
- The influence of situational variables on distance covered in soccer
- The future of performance analysis
- Conclusions





Fatigue in soccer



Fatigue in soccer: A brief review

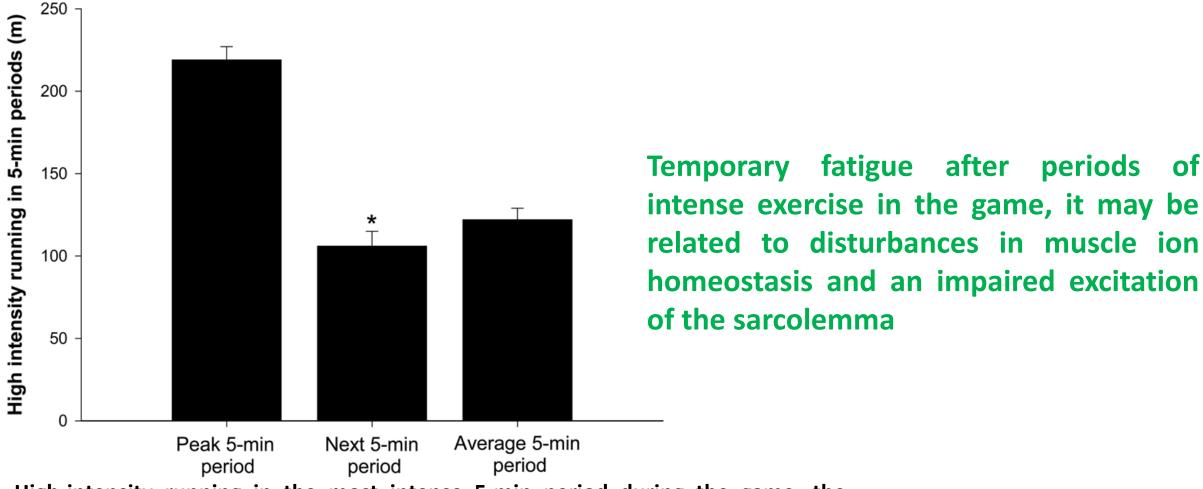
MAGNI MOHR, PETER KRUSTRUP, & JENS BANGSBO

Institute of Exercise and Sport Sciences, Department of Human Physiology, August Krogh Institute, University of Copenhagen, Copenhagen, Denmark

According to time – motion analyses and performance measures during match-play, fatigue or reduced performance seems to occur at three different stages in the game.

- after short-term intense periods in both halves;
- in the initial phase of the second half; and
- towards the end of the game.

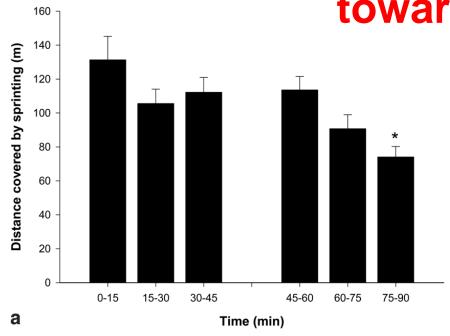
after short-term intense periods in both halves...

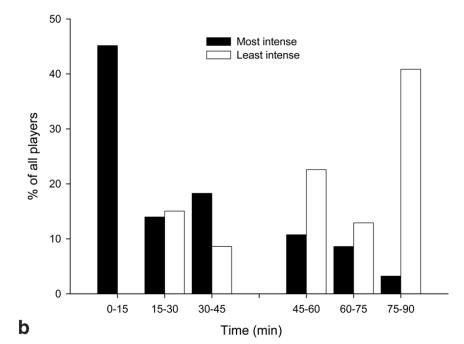


High-intensity running in the most intense 5-min period during the game, the following 5-min period as well as the game average for elite players during competitive matches (n = 18).

^{*} Significant difference between the 5-min period immediately after the most intense period during the game and the game average (data from Mohr et al., 2003a).

towards the end of the game.... 1/2

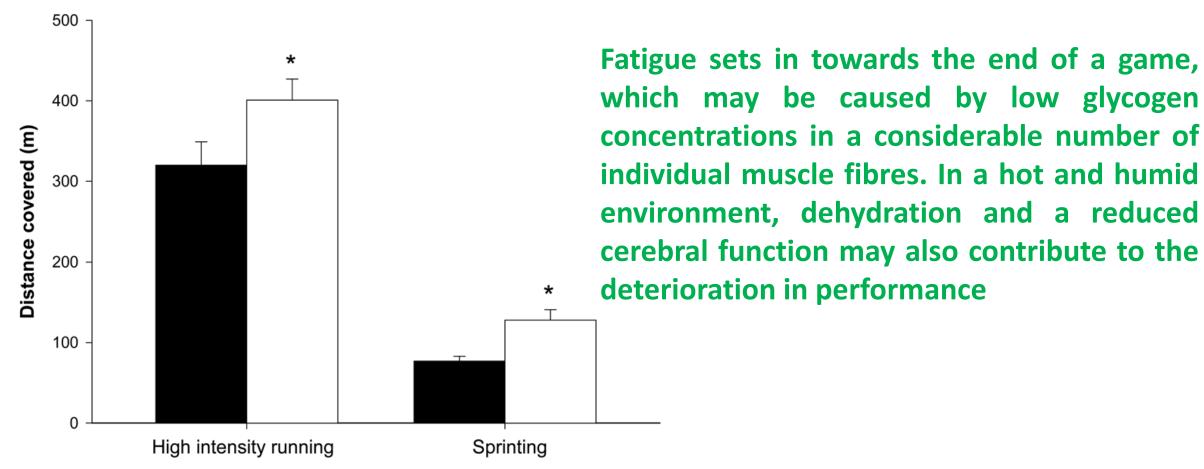




Distance covered by sprinting during 15-min periods throughout competitive soccer games at the highest international level (A, n = 18) and distribution of 15-min intervals with the most and least intense running for elite players during competitive matches (B, n = 93).

* Significant difference from the first four 15-min periods of the game (modified from Mohr et al., 2003a).

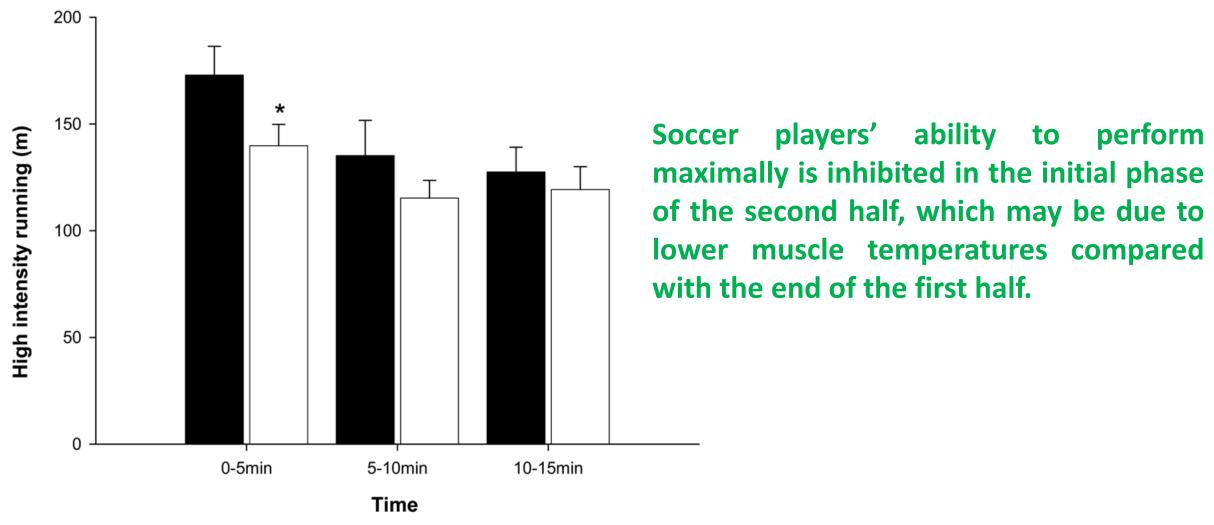
towards the end of the game.... 2/2



High-intensity running and sprinting during the final 15 min of a game by players participating in the entire game and substitutes only participating in the second half.

^{*}Significant difference between substitutes and players participating in the entire game (data from Mohr et al., 2003a).

in the initial phase of the second half...



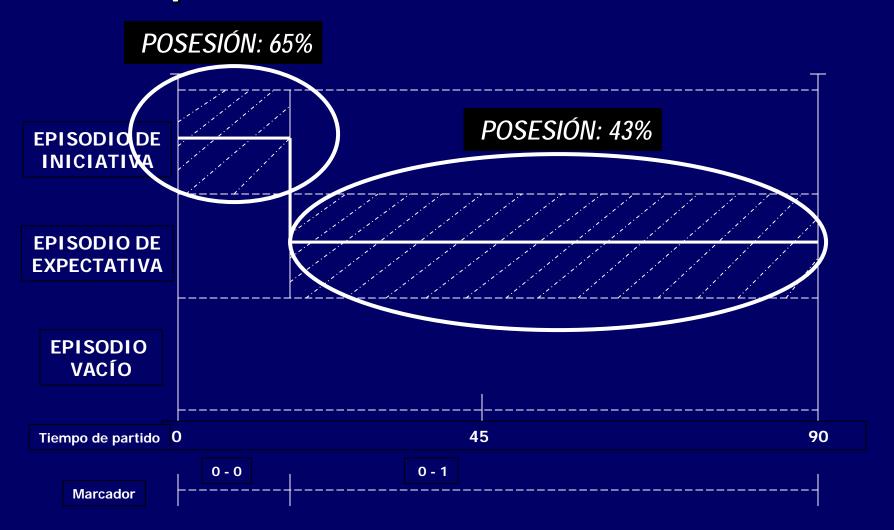
High-intensity running by elite soccer players during the initial phase of the first and second halves of competitive games (n = 42).

* Significant difference between the two halves .

Statistics Deportivo vs F.C. Barcelona Season 2004-2005

DEPORTIVO		F.C.
		BARCELONA
54%	Posesión del	46%
	balón	
3	Remates portería	5
14	Remates fuera	11
49	Centros al área	12
0	Goles	1

Performance Profile F.C. Barcelona Match Deportivo-F.C. Barcelona Season 2004-2005.



Performance Profile F.C. Barcelona INITITIATIVE ESPISODE Match Deportivo-F.C. Barcelona Season 2004-2005.

DEPORTIVO		F.C. BARCELONA
35%	Posesión del	65%
	balón	
0	Remates	3
	portería	
2	Remates fuera	4
2	Centros al área	2
0	Goles	1

Comparison of total distance covered by elite soccer players during the first and second halves of competitive match-play

Study	Nationality	System	Distance rui	n (m)		Difference
			Total	1 st half	2nd half	~ %
Bradley et al. [14]	English	ProZone	10714	5422	5292	-2.4
Bradley et al. [15]	English	ProZone	10842	5469	5372	-1.8
Carling et al. [16]	French	Amisco Pro	11126	5694	5432	-5.9
Castellano et al.[11]	Spanish	Amisco Pro	7829 *	3871 *	3958 *	+2.2
Di Salvo et al. [2]	European	Amisco Pro	11393	5709	5684	-0.4
Lago et al. [12]	Spanish	Amisco Pro	10943	5503	5440	-1.2
Rampinini et al. [7]	Italian	SICS	11828	5966	5862	-1.7
Zubillaga et al. [13]	English	Amisco Pro	10549	5297	5252	-0.9
	Spanish	Amisco Pro	10339	5121	5218	+1.9

^{*}Distance covered by players in each half during the effective playing time.

... non-conclusive ¡¡¡¡

Comparison of distance covered at maximal intensity by elite soccer players during the first and second halves of competitive match-play

Study	Category of movement	Nationa lity	System	Distance run (m)			Difference %
				total	1st	2 nd	_
					half	half	
Bradley et al. [15]	>25.1km.h ⁻¹	English	ProZone	255	123	132	+6.8
Carling et al. [16]	>22.0 km.h ⁻¹	French	Amisco Pro	337	165	172	+4.2
Castellano et al. [11]	>24.0 km.h ⁻¹	Spanish	Amisco Pro	223	116*	107*	-8.4
Di Salvo et al. [2]	>25.1km.h ⁻¹	English	ProZone	226	114	112	-1.8
Lago et al. [12]	>23.0 km.h ⁻¹	Spanish	Amisco Pro	284	137	147	+6.8
Zubillaga et al. [13]	>21.0 km.h ⁻¹	English	Amisco Pro	410	202	208	+2.9
		Spanish	Amisco Pro	460	194	266	+27.1

^{*}Distance covered by players in each half during the effective playing time.

... non-conclusive ¡¡¡¡

Analysis of physical activity profiles in elite soccer. The case of Real Madrid

One hundred and forty-nine matches including league, cup and UEFA Champions League played by the Real Madrid were monitored during the 2001-2002 to the 2006-2007 seasons (six seasons).

Data from both teams (Real Madrid and the opponent) were recorded. The players included in the study met two basic criteria: (1) completing the entire match (at least in three matches of the whole sample), and (2) because the physical loading of goalkeepers differs from that of field players, they were not included in the study.

Altogether, 2082 physical performance profiles were examined, 1052 from the Real Madrid and 1031 from the opposing team (Central Defenders (CD) = 536, External Defenders (ED) = 491, Central Midfielders (CM) = 544, External Midfielders (EM) = 233, and Forwards (F) = 278). km/h (Sprint), and the number of sprints (21.1-24.0 km/h and >24.0 km/h).

Analysis of physical activity profiles in elite soccer. The case of Real Madrid

Differences in the distance covered between Real Madrid and the opposing team in High-Intensity Running (21.1-24.0 km/h) depending on the player's position.

	Real Madrid	Opposing Team	η^2
Playing Position			
External Defenders (ED)	$340 (\pm 90)$	$341 (\pm 100)$.000
Central Defenders (CD)	$180 \uparrow (\pm 65)$	$192 (\pm 74)$.007
Central Midfielders (CM)	253 ‡ (± 87)	$284 (\pm 96)$.029
External Midfielders (EM)	$354 \ddagger (\pm 88)$	$382 (\pm 109)$.019
Forwards (F)	$269 \ddagger (\pm 86)$	$297 (\pm 103)$.022
Mean	$269^{\dagger} \ (\pm \ 104)$	285 (± 114)	.011

[‡]Significantly lower than the opposing team (p<0.01).

Players from Real Madrid covered lower distances (p<0.05) in HIR than players from the opposing team (Table 1). While ED did not show differences in their physical performance, CD (p<0.05), CM (p<0.01), EM (p<0.01) and F (p>0.01) from Real Madrid covered lower distances in HIR than their counterparts (180 v. 192, 257 v. 284, 354 v. 382 and 269 v. 297, respectively).

Miñano (2015)

[†]Significantly lower than the opposing team (p<0.05).

Analysis of physical activity profiles in elite soccer. The case of Real Madrid

Differences in the distance covered between Real Madrid and the opposing team in Sprint (>24.0 km/h) depending on the player's position.

	Real Madrid	Opposing Team	η^2
Playing Position			
External Defenders (ED)	374 ↑ (± 144)	$320 (\pm 143)$.034
Central Defenders (CD)	$161 \ (\pm 91)$	$164 (\pm 87)$.000
Central Midfielders (CM)	$179 (\pm 95)$	$196 (\pm 113)$.006
External Midfielders (EM)	$320 \uparrow (\pm 132)$	$361 (\pm 158)$.020
Forwards (F)	$235 \ddagger (\pm 99)$	$306 (\pm 138)$.081
Mean	$245^{\ddagger} (\pm 141)$	248 (± 145)	.004

[†] Significantly higher than the opposing team (p<0.05).

Players from Real Madrid players covered lower distances in Sprint (p<0.05) than players from the opposing team (Table 2). While CD and CM did not show differences in their physical performance, EM (p<0.05) and F (p>0.01) Real Madrid players covered lower distances in sprint than their counterparts (320 v. 361, 235 v. 306, respectively). However, ED from Real Madrid covered higher distances than their counterparts (374 v. 320, p<0.05).

Miñano (2015)

[‡]Significantly lower than the opposing team (p<0.01).

[†]Significantly lower than the opposing team (p<0.05).

Possible relationship between the true explanation and the estimated explanation

		True	Model
		$Y = \beta_1 + \beta_2 X_2 + \mu$	$Y = \beta_1 + \beta_2 X_2 + \beta_3 X_3 + \mu$
Estimated	$Y = b_1 + b_2 X_2$	Correct 1	Bias 2
d Model	$Y = b_1 + b_2 X_2 + b_3 X_3$	Inefficiency 3	Correct 4

DIAPOS SOBRE SESGO: King, keohane y verba

An Example of **BIAS**...

reg veloció	lsjcmjedad				
Source	55	df	MS		Number of obs $=$ 282
Model Residual	15.8426506 8.33686752	3 278	5.28088352 .029988732		F(3, 278) = 176.10 Prob > F = 0.0000 R-squared = 0.6552
Total	24.1795181	281	.086048107		Adj R-squared = 0.6515 Root MSE = .17317
velocid	Coef.	Std.	Err. t	P> t	[95% Conf. Interval]
sj cmj edad _cons	0081313 0207848 0698032 6.617306	. 0036 . 0035 . 0064 . 0934	6434 -5.87 917 -10.75	0.026 0.000 0.000 0.000	0152660009966 02776020138095 08258230570242 6.433328 6.801284



...this is the correct model

	xi: reg vel .puesto	ocid sj cmj_b _Ipuesto_					; _Ipuesto_1 o	mitted)					
ı	Source	SS	df		MS		Number of obs						
	Model Residual	17.5575844 6.41242564	9 269	1.95084271 .023838014				9 1.95084271 59 .023838014		1.95084271		F(9, 269) Prob > F R-squared Adj R-squared	= 0.0000 = 0.7325
	Total	23.97001	278	. 080	5223058		Root MSE	= .1544					
	velocid	Coef.	Std.	Err.	t	P> t	[95% Conf.	Interval]					
ı	sj	0067641	.0027	603	-2.45	0.015	0121988	0013295					
	cmj_b	022579	.0024		-9.09	0.000	0274702	0176878					
	talla	0066296	.0014	494	-4.57	0.000	0094833	003776					
	edad	0428683	.0072	433	-5.92	0.000	0571291	0286075					
	_Ipuesto_z	0869996	.0373	218	-2.33	0.020	1604795	0135197					
	_Ipuesto_3	0631956	.0365	571	-1.73	0.085	13517	.0087789					
	_Ipuesto_4	05833	.0361	893	-1.61	0.108	1295803	.0129204					
V	_Ipuesto_5	0956032	.0392	951	-2.43	0.016	1729682	0182381					
	Ipuesto_6	0956522	.0354	724	-2.70	0.007	165491	0258134					
	_cons	7.562476	.1973	691	38.32	0.000	7.173892	7.951061					

MATCH STATUS

Performance accomplishments are a powerful source of efficacy expectations and such expectations determine the task-related effort that has to be expended (Bandura, 1977). Match status may be viewed as a measure of performance accomplishments and hence may influence the effort made by a player (O'Donoghue and Tenga, 2001).

Match status is determined by whether a team or a player is winning, losing or drawing at the time a particular behaviour is recorded (Bloomfield et al., 2005a, 2005b; Jones et al., 2004; Taylor et al., 2008). According to Bloomfield et al. (2005a), Lago and Martin (2007) and Taylor et al. (2008), the importance of this situational variable is reflected in changes in team and player's strategies in response to the score-line. For low-scoring team sports like soccer or rugby, there are just three major levels of match status to be considered during analysis (team winning, losing or drawing).

Journal of Sports Sciences, 2001; 19(1): 25-26

BASES 2000: Back to the future

The effect of score-line on work rate in elite soccer

P.G. O'Donoghue¹ and A. Tenga²

¹School of Leisure and Tourism, The University of Ulster at Jordanstown, Newtownabbey, Co. Antrim BT37 0QB, UK and ²Norwegian University of Sports and Physical Education, Oslo, Norway

Table 1. Distribution of match time among different activities (mean $\pm s$)

	Group A	(n = 11)	Group B	Group B $(n = 10)$			
Activity	Level	Ahead	Level	Behind			
Stationary	10.8 ± 2.9	13.8 ± 5.4	11.0 ± 4.9	12.6 ± 3.3			
Walking	40.2 ± 7.8	42.7 ± 9.0	38.4 ± 5.3	41.1 ± 5.2			
Backing	7.8 ± 3.1	7.2 ± 3.2	8.1 ± 2.5	8.6 ± 2.2			
Jogging	28.2 ± 5.2	25.1 ± 6.1	28.1 ± 7.8	26.0 ± 6.7			
Running	3.4 ± 1.7	2.8 ± 1.3	3.5 ± 1.8	2.7 ± 1.5			
Shuffling	7.3 ± 2.5	6.2 ± 2.3	8.5 ± 1.9	6.5 ± 1.3			
Football	2.3 ± 0.8	2.3 ± 0.8	2.3 ± 1.2	2.4 ± 1.1			
High-intensity activity	13.0 ± 1.7	11.2 ± 1.7	14.3 ± 2.6	11.6 ± 2.0			

Players performed significantly less high-intensity activity when winning than when the score was level (z = 2.45, P < 0.05). Players also performed significantly less high intensity activity when losing than when the score was level (z = 2.70, P < 0.01). Players on teams that are winning relax their work-rate, allowing opponents back into the game, and that players on teams that are trailing may lose the motivation to maintain a sufficient work-rate.

The effects of situational variables on distance covered at various speeds in elite soccer

Variables			
	14.119 km/h	19.1 – 23 km/h	>23 Km/h
Playing positions			
Full Back	294 (55.3)**	189 (26.3)**	140 (24.0)**
Central Midfielder	459 (64.5)**	112 (24.5)**	-10.5 (16.4)
Wide Midfielder	482 (71.7)**	214 (45.7)**	147.1(34.4)**
Forward	122 (75.2)	190 (28.4)**	149.7 (24.1)**
Match status			
Drawing	0.40 (1.09)	-1.20 (0.45)**	-0.34 (0.41)
Winning	-0.05 (0.96)	-0.83 (0.42)*	-0.71 (0.30)*
Match location	-23.87 (47.1)	-27.7 (20.3)	-27.3 (16.5)
Quality of opponent	0.87 (4.94)	3.11 (2.18)	0.76 (1.69)
Intercept	1436 (87.8)**	485 (37.7)**	231.2 (30.7)**
Obervations	182	182	182
R^2	0.30	0.34	0.38

Notes: The values are the number of metres covered by players in a match. ** (P < 0.01) * (P < 0.05)



European Journal of Sport Science Fublication details, including instructions for authors and subscription information: http://www.informaworld.com/smpp/title~content=t714592354

The effects of situational variables on distance covered at various speeds in

Carlos Lago *; Luis Casais *; Eduardo Dominguez *; Jaime Sampaio b Facultad de CC da Educacion e o Deporte, Universidad de Vigo, Pontevedra, Spain b Department of Sport Sciences, University of Trás-os-Montes e Alto Douro, Vila Real, Portugal

Online publication date: 08 February 2010



European Journal of Sport Science

Publication details, including instructions for authors and subscription information: http://www.informaworld.com/smpp/title~content=t714502354

The effects of situational variables on distance covered at various speeds in elite soccer

Carlos Lago ⁵, Luis Casais ⁵, Eduardo Doninguez ⁵Jaime Sampaio ⁵

* Facultad de CC da Educacion e o Deporte, Universidad de Vigo, Pontevedra, Spain ⁵ Department of Sport Sciences, University of Tràs-os-Montes e Alto Douro, Vila Real, Portugal

Online publication date: 08 February 2010

Simulated distance covered (m) at different speeds depending on the match location, quality of opposition and match status

Match Status			Home matches					Away matches					
	Quality of opposition	Total	0-11 Km/h	11.1 - 14 km/h	14.1- 19 km/h	19.1- 23 km/h	>23 km/h	Total	0-11 km/h	11.1 - 14 km/h	14.1- 19 km/h	19.1- 23 km/h	>23 km/h
Winning 90 min	Strong	11140	7050	1744	1649	481	217	10856	6911	1584	1653	453	189
Winning 90 min	Weak	10824	6727	1662	1665	540	231	10540	6587	1501	1669	-512	204
Losing 90 min	Strong	10856	6853	1678	1653	555	281	10641	6713	1518	1629	527	253
Losing 90 min	Weak	10540	6529	1596	1669	614	295	10325	6390	1435	1646	586	268

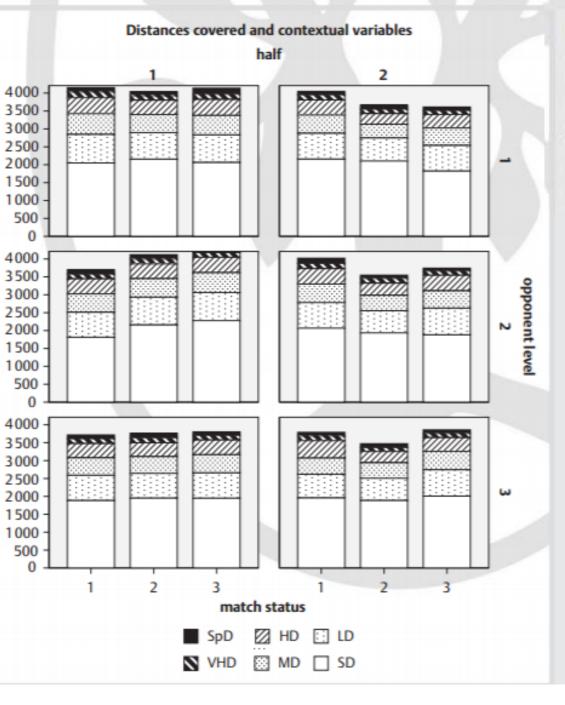


Fig. 1 Distances covered and contextual variables. Running intensities are: SD (0–11 Km · h⁻¹); LD (11.1–14 Km · h⁻¹); MD (14.1–17 Km · h⁻¹); HD (17.1–21 Km · h⁻¹); VHD (21.1–24 Km · h⁻¹); and SpD (> 24 Km · h⁻¹). Opponent level was Top (1), Medium (2) and Bottom (3). Halves were First (1) and Second (2). Match status was Lose (1), Draw (2) and Win (3).

Contextual Variables and Time-Motion Analysis in Soccer

ors J. Castellano', A. Blanco-Villaseñor², D. Álvarez³

Basque Country University, Physical Activity and Sport, Vitoria-Gasteiz, Spain

*Barcelona University Methodoloov of the Behavioural Sciences, Barcelona, Soai

Distances covered (Spd, VHD, HD and MD) by the reference team were greater when the result was adverse. This suggests that when losing, players try to reach their maximal physical capacity in order to draw or win the match. Accordingly, players clearly performed less low-intensity activity.

Match Status: concluding remarks

These results suggest that players **DO NOT ALWAYS USE THEIR** MAXIMAL PHYSICAL CAPACITY DURING THE MATCH. In fact, given that winning is a comfortable state for a team, it is possible that players assume a ball retention strategy, slowing down the game and resulting in lower speeds (Bloomfield et al., 2005b). On the other hand, when losing, players try to reach their maximal activity in order to win or draw the match. Other studies have considered match status in relation to the tactical aspects of performance. The influence of this factor is reflected in changes in team strategies and tactics as a response to match situations (Taylor et al., 2008). Teams often show a more defensive strategy when winning than when losing, and vice versa.



Journal of Sports Sciences

Publication details, including instructions for authors and subscription information: http://www.tandfonline.com/loi/risp20

The influence of match location, quality of opposition, and match status on possession strategies in professional association football

Carlos Lago ^a

Time spent in different zones of play by the ball depending on match location and match status.

		Playing at Home		Playing away			
Match status	Defensive third	Middle third	Attacking third	Defensive third	Middle third	Attacking third	
Winning	27.5	51.7	19.1	34.6	48.8	12.9	
Losing	17.2	57.0	25.5	24.3	54.1	21.6	
Drawing	20.2	56.1	23.2	27.3	53.2	19.3	

Overall, there was more play in the attacking zone when Espanyol was playing at home than playing away. Moreover, when behind, possession was less in the defensive zone and more in the attacking zone than when the team was winning or drawing

^a Facultad de CC da Educacíon e o Deporte , Universidad de Vigo , Pontevedra, Spain Published online: 15 Sep 2009.



Journal of Sports Sciences

Publication details, including instructions for authors and subscription information: http://www.tandfonline.com/loi/rjsp20

The influence of match location, quality of opposition, and match status on possession strategies in professional association football

Carlos Lago a

. Simulated possession for the team depending on match location, quality of opposition, and match status.

Playing at home			Playing away							
Opposition Status	Real Madrid (2nd)	Sevilla (5th)	Betis (9th)	Athletic (12th)	Real Sociedad (16th)	Real Madrid (2nd)	Sevilla (5th)	Betis (9th)	Athletic (12th)	Real Sociedad (16th)
Winning	39.0	39.5	40.3	40.9	41.6	33.0	35.3	38.3	40.5	42.4
Drawing	46.9	47.5	48.2	48.8	49.6	41.0	43.2	46.2	48.5	50.4
Losing	49.2	50.5	51.3	51.8	52.6	44.0	46.3	49.3	51.5	53.3

^a Facultad de CC da Educacíon e o Deporte , Universidad de Vigo , Pontevedra, Spain Published online: 15 Sep 2009.

QUALITY OF OPPOSITION

The opponent level has been considered from different methodological perspectives.

For example, teams and players have been categorized as 'successful' and 'unsuccessful' according to their standings within a particular tournament (Grant et al., 1999), or classified as 'strong' or 'weak' based on symmetric division of end-of-season classification (O'Donoghue et al., 2008; Taylor et al., 2008).

Lago et al. (2010) defined the quality of opposition as the differences in the end-of-season ranking between opposing teams.

Recently, team performance has been classified using cluster analysis procedures, which improve the classification by using more valid cut-off values (Sampaio et al., 2010a Marcelino et al., 2011).

Table 1. Total distance covered (m) and distance covered at several intensities by opposition level.

	Against 1st League (1 st)	Against 2nd League (2 nd)	Against amateurs (am)	Pairwise comparison
Total distance covered (m)	5395.3±588.6	5069.7±527.5	5407.9±597.3	
Distance covered at				
Low intensity (0.0–3.5 km · h ⁻¹)	422.2±67.0	436.9±67.2	399.8±91.1	
Moderate intensity (3.6-14.3 km · h ⁻¹)	3655.2±299.5	3615.1±332.3	3896.7±454.3	1 st <am*; 2<sup="">rtd<am*< td=""></am*<></am*;>
High intensity (14.4–19.7 km · h ⁻¹)	910.9±306.5	729.3±267.1	807.0±257.1	
Very high intensity (>19.8 km · h ⁻¹)	407.1±193.9	288.4±135.2	304.4±140.2	1 ¹⁶ >2 nd , am*

^{*} Significant differences at p<0.05. doi:10.1371/journal.pone.0097145.t001

Folgado H, Duarte R, Fernandes O, Sampaio J (2014) Competing with Lower Level Opponents Decreases Intra-Team Movement Synchronization and Time-Motion Demands during Pre-Season Soccer Matches. PLoS ONE 9(5): e97145. doi:10.1371/journal.pone.0097145 http://www.plosone.org/article/info:doi/10.1371/journal.pone.0097145



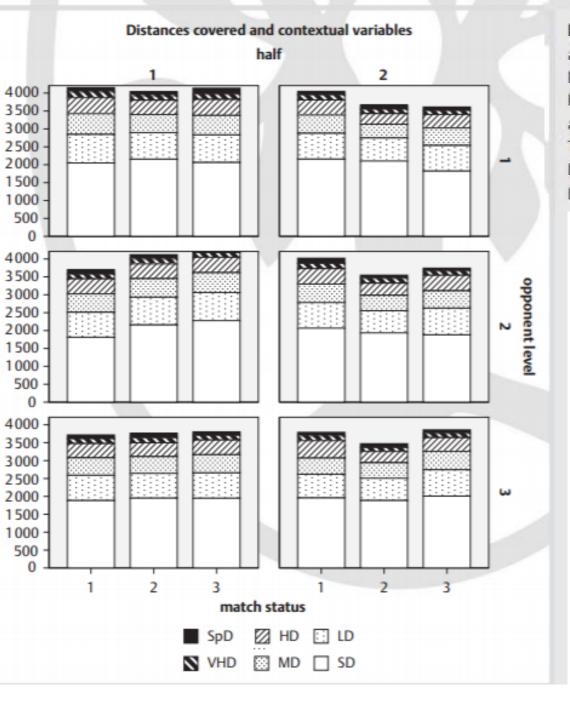


Fig. 1 Distances covered and contextual variables. Running intensities are: SD (0–11 Km · h⁻¹); LD (11.1–14 Km · h⁻¹); MD (14.1–17 Km · h⁻¹); HD (17.1–21 Km · h⁻¹); VHD (21.1–24 Km · h⁻¹); and SpD (> 24 Km · h⁻¹). Opponent level was Top (1), Medium (2) and Bottom (3). Halves were First (1) and Second (2). Match status was Lose (1), Draw (2) and Win (3).

Contextual Variables and Time-Motion Analysis in Soccer

J. Castellano¹, A. Blanco-Villaseñor², D. Álvarez³

Basque Country University, Physical Activity and Sport, Vitoria-Gasteiz, Spain

Bracelona University Methodolow of the Behavioural Sciences, Barcelona, Soai

With respect to the opponent level, the poorer the quality of the opponent, the shorter the distance covered by the reference team.

Int J Sports Med. 2007 Dec;28(12):1018-24. Epub 2007 May 11.

Variation in top level soccer match performance.

Rampinini E¹, Coutts AJ, Castagna C, Sassi R, Impellizzeri FM.

Author information

Abstract

This study examined the influence of the opposing team, seasonal variations and the influence of first half activity on match performance in top-level soccer players. Physical performance measures were collected using the ProZone match analysis system from 20 professional soccer players from the same team and their opponents (n = 188) during a season. Match activities (standing, walking, jogging, running, high-speed running and sprinting), distances (total distance [TD], high-intensity running [HIR] and very high-intensity running [VHIR]) and other measures including involvement with the ball and peak running speed were collected. The influence of opponent team, the level of opposition, first half physical activities on second half activities, and playing position were analysed. The main finding was that TD (r = 0.62, p < 0.05), HIR (r = 0.51, p < 0.05), and VHIR (r = 0.65, p < 0.05) of the reference team was influenced by the activity profile of the opponent teams. The TD and HIR was higher against Best opponent teams compared to Worst opponent teams (p < 0.05), and the TD, HIR and VHIR

travelled in the first half significantly influenced the distances covered in the second half. TD, HIR and VHIR were greater at the end of the season. These results may be used to interpret meaningful changes in match performance in top level soccer.

MATCH LOCATION

Several studies of the relationship between match location and work rate in soccer showed that home teams cover greater distances than away teams during low-intensity activity (Lago et al., 2010; Lago-Peñas et al., 2009; Zubillaga et al., 2007). Other studies suggest that the effect of this factor should be addressed in the interaction with other situational variables (e.g. playing at home and losing against a weak opponent) (Castellano et al., 2011).

INTERACTIVE EFFECTS

Existing notational analysis has provided preliminary information on the effects of situational variables such us match location, match status, and quality of the opponent on sports performance at a behavioural level. Most of previous research has examined situational variables independently not accounting for the possibility of higher-order interactions (e.g. playing at home and losing). However, the examination of situational variables in isolation would appear to provide limited insight into the complex nature of team sports performance (McGarry and Franks, 2003; Reed and O'Donoghue, 2005).

...what I'am working on right now...



LEADING ARTICLE

Current Approaches to Tactical Performance Analyses in Soccer Using Position Data

Daniel Memmert¹ · Koen A. P. M. Lemmink² · Jaime Sampaio³

Table 1 Candidate performance indicators for tactical performance analysis based on position data

Key performance index	Method	Description	References
Length, width, space	Distance	Measures the average expansion of a team in the direction of x and y or rather in both dimensions	Castellano et al. [19], Moura et al. [20]
Space control	Voronoi	Models space control with the help of a Voronoi diagram	Fujimura and Sugihara [21], Fonseca et al. [22], Taki and Hasegawa [23], Kang et al. [24], Horton et al. [25]
Event recognition	Rule-based, decision trees	Recognizes events from position data such as passes, goals, offside; rule- based system	Gudmundsson and Wolle [26], Wei et al. [27],
Route clustering	Clustering algorithms (Fréchet distance)	Filters subgroups from movement patterns of one or more players	Gudmundsson and Wolle [26], Hirano and Tsumoto [28]
Pass evaluation	Motion model and passable area	Calculates regions, such as the 'passable area', for every pass based on a motion model and evaluates passes according to difficulty or decision quality	Horton et al. [25], Gudmundsson and Wolle [29]
Distance from the team's centre	Euclidian metrics	Calculates the players' average, minimal and maximal distance from the team's centre	Sampaio and Maçãs [30], Bialkowski et al. [31]
Formation	Mean average, main component analysis	Calculates the average position and thus determines an actual tactical formation	Bialkowski et al. [32]





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Fig. 1 Team formation and predictability of distances between players and their positional-centroid. The results show the players' predictability in relation to their positional-centroid, as measured by the approximate entropy from the distance between each player and their positional-centroid. A cluster analysis automatically classified the predictabilities in three different groups (higher, medium and lower). The performance of the highly predictable players is also described with the average \pm standard deviation of the distance to positional-centroid. GK goalkeeper, CD central defender, LD left defender, RD right defender, CM central midfielder, LM left midfielder, RM right midfielder, FW forward, CF central forward, RF right forward, LF left forward, Cdef defensive centroid, Cmid midfield centroid, Cfw forward centroid

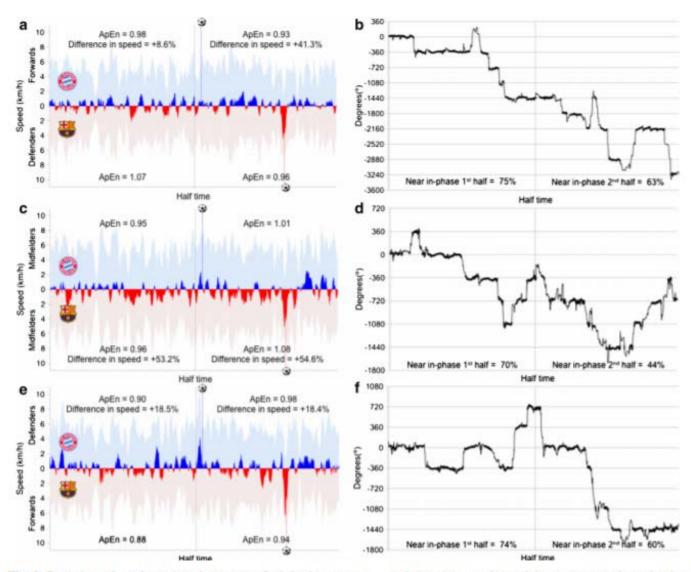


Fig. 2 Depiction of confrontations between a, b defenders versus opponents' forwards; c, d midfielders versus midfielders; and e, f forwards versus opponents' defenders. a, c and e show in lighter shading the average speed of the players of each team and, in darker shading, the difference between both teams. The approximate entropy (ApEN) shows the predictability from the speed time series and the percentage (%) shows the amount of time that players in one team were faster or slower than their opponents in each half of the match. b, d and f show how the speeds were synchronised during the match

(relative phase results) and the percentage of near-in-phase represents the amount of time that players were synchronised in each half of the match. The values close to 0° and 360° multiples refer to simultaneous patterns of synchronisation (i.e. in-phase, in which speeds are synchronised and both are increasing or both are decreasing), whereas values close to 180° and 360° multiples refers to asynchronous patterns of synchronisation (i.e. anti-phase, in which speeds are synchronised and present different trends, one increasing and the other one decreasing or vice-versa)

Sports Med DOI 10.1007/s40279-016-0562-5

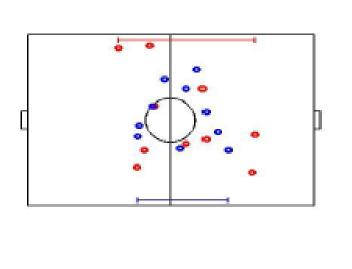


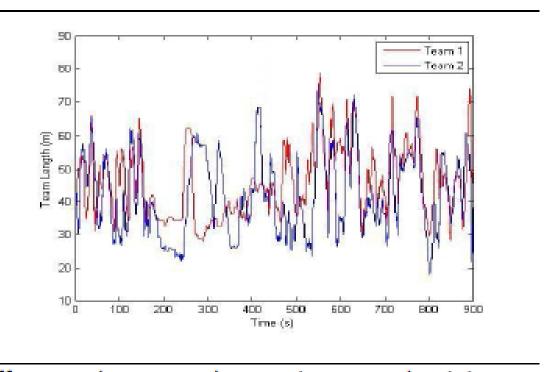
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Team length

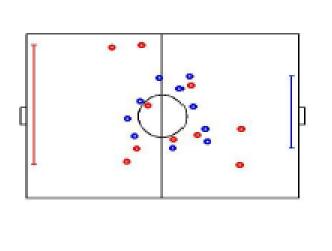


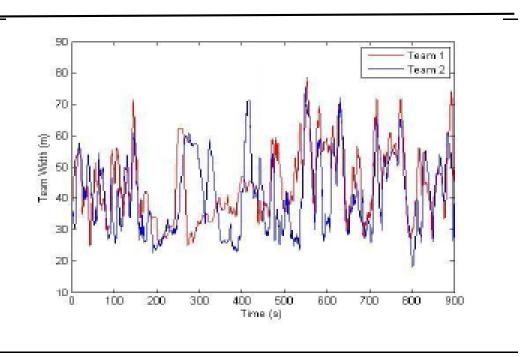


Computation details: calculated as the difference between the maximum and minimum positions of players in the field's longitudinal dimension in each time frame.

Meaning: This variable captures the compactness of the whole team and its variation as a function of changes in performance constraints. It can be used in the monitoring of specific reference values for team length, or to evaluate depth differences between teams.

Team width

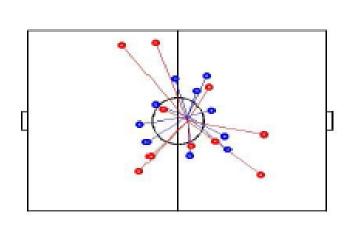


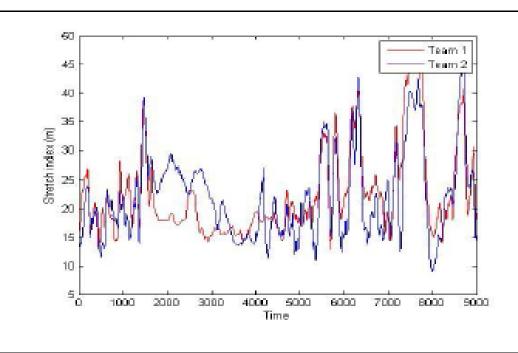


Computation details: calculated as the difference between the maximum and minimum positions of players in the field's lateral dimension in each time frame.

Meaning: When in defence, the width of a team may reveal the potential for the opponents to find inner or outer spaces to penetrate. When attacking, it may indicate the lateral spread of the team.

Stretch index

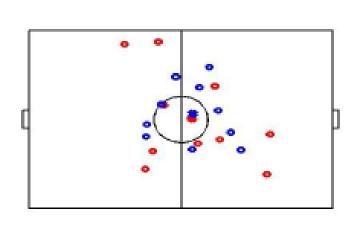


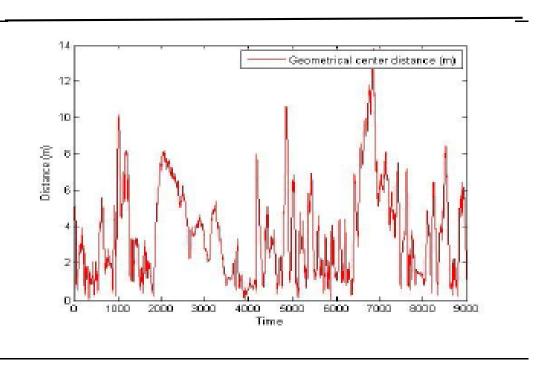


Computation details: computed as the average of the vectorial distance of each player to the corresponding team's centre [8] (it can be alternatively calculated decomposing positions in x- and y-axis of motion [9]).

Meaning: This compound variable captures the synergistic counter-phase relation of contraction and expansion behaviours of teams as a function of exchanges in ball possession ^[9]. First derivative of this measure may also evidence the speed at which teams stretch or shorten their dispersion on the field.

Team centre

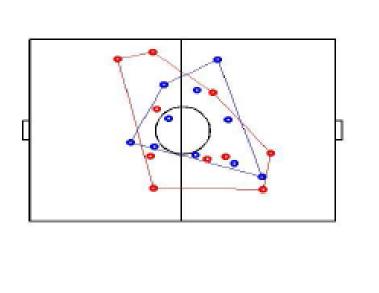


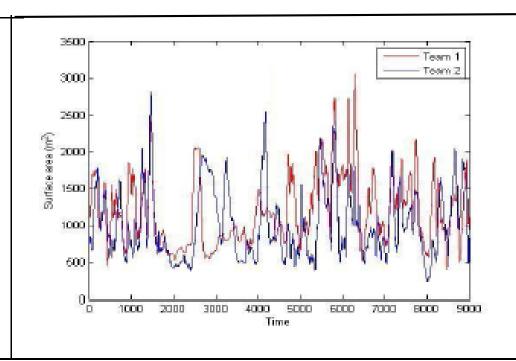


Computation details: calculated as the mean position of all team players over time in each axis of motion. Distance between team centres can also be measured (right panel).

Meaning: Based on the mean point or "centre of mass" of a team, this variable captures its global oscillatory movements such as movements towards or away from the goals or the sidelines. Distance between the team centres can also be used as an indicator of the closeness

Surface area

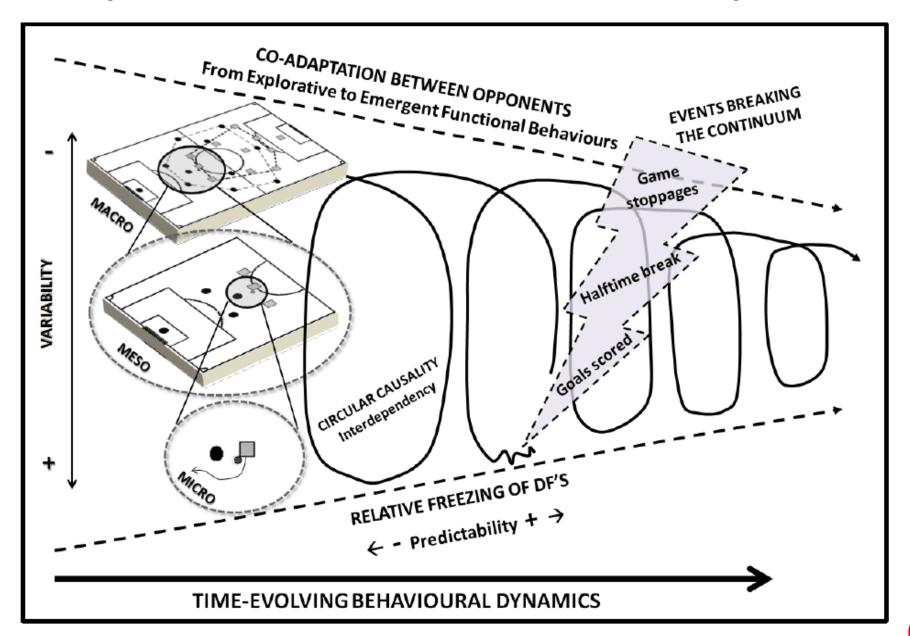




Computation details: calculated as the area of a polygon drawn by linking the externally positioned players in each team's formation. These values were computed using Matlab functions (convhull) employing the rule of a convex polygonal area (see left panel).

Meaning: This compound variable expresses the relation between the shapes and the occupied spaces of the two teams, and how they change over time. Overlapped areas can also be obtained.

A conceptual model of association football performance



A conceptual model of association football performance

The conceptual model captures the interdependence between the different levels of organization ranging from dyads to collectives (i.e., 1vs1, 3vs3 and 11vs11). This interdependence implies a circular causality which means that each individual performer reciprocally influences and are influenced by team's behavior. However, this cyclical and channelling flow is broken by some game events such as goals scored and halftime, and also stoppages in play for substitutions and injuries assistances.

Proc. Natl. Acad. Sci. USA Vol. 88, pp. 2297-2301, March 1991 Mathematics

Approximate entropy as a measure of system complexity

(statistic/stochastic processes/chaos/dimension)

STEVEN M. PINCUS

990 Moose Hill Road, Guilford, CT 06437

Communicated by Lawrence Shepp, December 7, 1990 (received for review Jane 19, 1990)

ABSTRACT Techniques to determine changing system complexity from data are evaluated. Convergence of a frequently used correlation dimension algorithm to a finite value does not necessarily imply an underlying deterministic model or chaos. Analysis of a recently developed family of formulas and statistics, approximate entropy (ApEn), suggests that ApEn can classify complex systems, given at least 1000 data values in diverse settings that include both deterministic chaotic and stochastic processes. The capability to discern changing complexity from such a relatively small amount of data holds promise for applications of ApEn in a variety of centexts.

In an effort to understand complex phenomena, investigators throughout science are considering chaos as a possible underlying model. Formulas have been developed to characterize chaotic behavior, in particular to encapsulate properties of strange attractors that represent long-term system dynamics. Recently it has become apparent that in many settings nonmathematicians are applying new "formulas" and algorithms to experimental time-series data prior to careful statistical examination. One sees numerous papers concluding the existence of deterministic chaos from data analysis

If one cannot hope to establish chaos, presumably one is trying to distinguish complex systems via parameter estimation. The parameters typically associated with chaos are measures of dimension, rate of information generated (entropy), and the Lyapunov spectrum. The classification of dynamical systems via entropy and the Lyapunov spectra stems from work of Kolmogorov (3), Sinai (4), and Oseledets (5), though these works rely on ergodic theorems, and the results are applicable to probabilistic settings. Dimension formulas are motivated by a construction in the entropy estculation and generally resemble Hausdorff dimension calculations. The theoretical work above was not intended as a means to effectively discriminate dynamical systems given finite, noisy data, or to certify a deterministic setting. For all these formulas and algorithms, the amount of data typically required to achieve convergence is impractically large. Wolf et al. (6) indicate between 10° and 30° points are needed to fill out a d-dimensional strange attractor, in the chaotic setting. Also, for many stochastic processes, sensible models for some physical systems, "complexity" appears to be changing with a control parameter, yet the aforementioned measures remain unchanged, often with value either 0 or =.

International Journal of Performance Analysis in Sport 2016, 16, 753-768.

Application of entropy measures to analysis of performance in team sports

Pedro Silva^{1,2}, Ricardo Duarte³, Pedro Esteves^{4,5}, Bruno Travassos^{5,6} and Luís Vila

Abstract

Over the last years, several researchers have been claiming that team ball sports may be viewed as dynamical systems and, thus, they should be thoroughly investigated using congruent concepts and tools. The study of variability in the sport performance domain has shown potential to contribute with valuable information about tactical behaviours related with space and time management within ever changing task constraints featuring team sports contests. Here we detail how different entropy measures have been applied to the study of performance variability to uncover the interactions underlying players and teams' performances. With that purpose, urging issues related with information entropy, approximate entropy and sample entropy applications are discussed as a mean to enrich the state of the art in team sport performance. In sum, measurements of entropy in team sports have shown great potential to assess the uncertainty of players' spatial distributions and dominant regions areas and of several collective team behaviours (e.g., team synchrony and team dispersion) throughout the course of a match. Entropy can also be used as a potential tool to identify expert performances and differentiate skilled from novice athletes. Future holds many other applications of this statistic in the context of performance analysis in sports, and the inclusion of new and more sophisticated entropy algorithms.

Keywords: variability, sports teams as complex systems, Shannon entropy, approximate entropy, sample entropy.

¹ FC Zenit, St. Petersburg, Russia

² Universidade do Porto, Faculdade de Desporto, Centre for Research, Educ Innovation and Intervention in Sport, Portugal

³ CIPER, Faculdade de Motricidade Humana, Universidade de Lisboa, Lisboa, Por

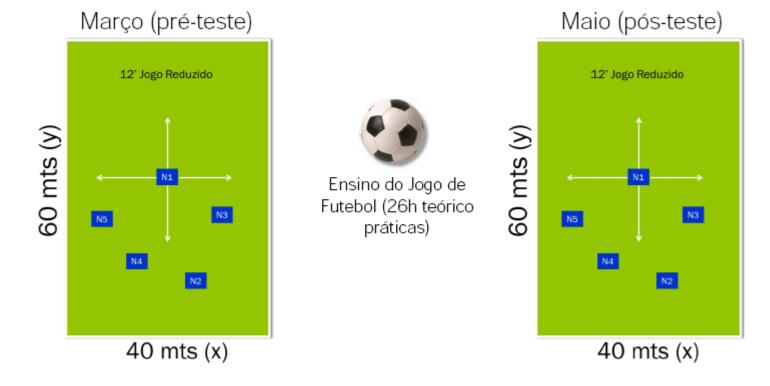
⁴ Polytechnic Institute of Guarda, Guarda, Portugal

⁵ CIDESD - Sports Sciences, Health Sciences and Human Development, Portugal

⁶ Universidade da Beira Interior, Department of Sport Sciences, Covilha, Portugal

⁷ Escola de Turismo, Desporto e Hospitalidade, Universidade Europeia, L Portugal

GPS - Posição dos jogadores (5 registos em cada segundo)



Measuring Football Tactical Behaviour

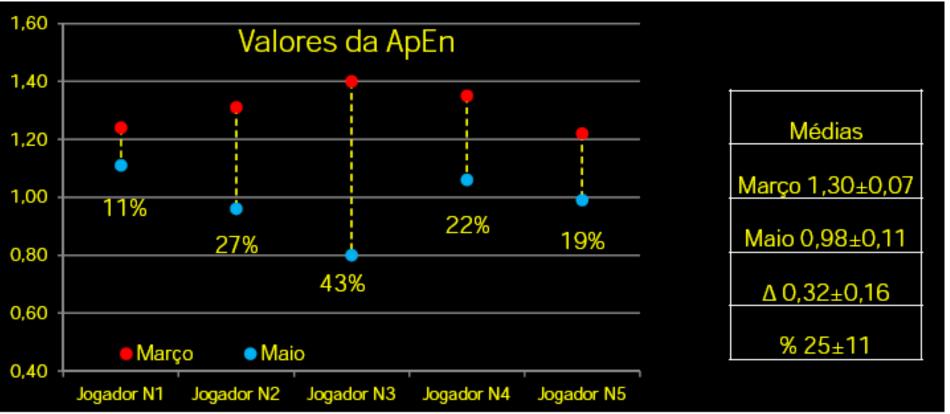
Measuring Football Tactical Behaviour

Authors

J. Sampalo¹, V. Maçās²

Affiliations

¹ Sports Science, Exercise and Health, University of Träs-os-Montes e Alto Douro, Vila Real, Portugal
² Research Center for Sports Sciences, Health and Human Development, University of Träs-os-Montes e Alto Douro, Vila Real, Portugal
² Research Center for Sports Sciences, Health and Human Development, University of Träs-os-Montes e Alto Douro, Vila Real, Portugal



Houve diminuição da imprevisibilidade no padrão de todos os jogadores... a dinâmica posicional é em Maio menos aleatória do que em Março...



Ensino do Jogo de Futebol (26h teórico práticas) Melhor performance táctica?

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Behavioural Science

Measuring Football Tactical Behaviour

Authors

J. Sampain', V. Maçin'

Sports Science, Sendie and Health, University of Taion-Afforder of Allo Duare, Vila Roal, Portugal

Records Center for Sports Science, Sendie and Health, University of Taion-Afforder of Allo Duare, Vila Roal, Portugal

Records Center for Sports Science, Sendie and Health, University of Taion-Afforder of Allo Duare, Vila Roal, Portugal

Records Center for Sports Science, Sendie and Health Duare, Vila Roal, Portugal

TAKE-HOME MESSAGES

Thanks for listening, any questions?