sciendo

Analysis of Successful Offensive Play Patterns
by the Spanish Soccer Team

by
Mario Amatria[1], Rubén Maneiro[1], M. Teresa Anguera[2]

Victory is the ultimate aim in soccer and therefore when a team wins an elite European or world championship, attempts will invariably be made to emulate the winning team's style of play. In this study, we performed an in-depth analysis of play by the Spanish soccer team during the 2012 UEFA European Championship, where it was crowned champion. Using observational methodology and T-pattern analysis, we identified hidden patterns of play that ended in a goal for the Spanish team. A generalizability coefficient (e2) of 0.986 demonstrated that the offensive patterns detected are robust and highly generalizable. These patterns were formed by technical actions consisting of ball control and pass, with alternations between short and long passes, in the central area of the rival pitch, with use of both wings to achieve width of play and prioritization of width over depth of play. We also found patterns showing that goals and shots at goal were made on a ball delivered from the opposite direction to the shot and were not preceded by a technical action.

Key words: *team sport, performance, game analysis, tactics.*

Introduction

When studying performance in soccer, one could assume that performance indicators recorded for successful or unsuccessful actions will reflect both individual and team performance. However, there is always an element of chance and unpredictability in team sports (Gronek et al., 2015; Kalinowski et al., 2019). Players, coaches, and fans largely agree that chance is sometimes important for understanding the result of a match.

The above argument, however, is not valid for the scientific community (Ramos et al., 2017). Empirically speaking, chance cannot be considered to be a conventional variable and we cannot apply it to practical situations or use it to draw inferences (Lames et al., 2010). In soccer, like in other team sports, every event (e.g., goal, shot, or sequence of actions), and everything that leads up to this event, can be measured, and as such can be computed by an algorithm. Nothing happens by chance.

But how can we measure these events objectively and empirically to guide decision-making in real-life situations? One way of reducing intangible aspects of play that remain hidden to the human eye could be to apply an empirical approach capable of uncovering the various structures and patterns that lie hidden within observable behaviors. T-pattern analysis, which involves the detection of temporal patterns of behavior (Magnusson, 2000, 2016) has proven to be a useful tool for this purpose.

T-pattern detection has enormous potential in applied research and interdisciplinary areas such as sport (Hristovski et al., 2017), where researchers are interested not only in quantifying performance indicators, such as goals, passes, or shots, but also in qualifying the steps that lead up to these actions. T-pattern analysis can detect the structures that trigger what can be termed a successful action in soccer. Numerous studies have used T-pattern analysis to identify these invisible structures that underlie all dimensions of soccer through algorithmic computations and have demonstrated that the results can have important

---

[1] - *Department of Physical Activity Sciences and Sports. Pontifical University of Salamanca, Spain.*
[2] - *Faculty of Psychology. Institute of Neurosciences. University of Barcelona, Spain.*

practical implications (Barlett et al., 2012).

Two noteworthy examples of studies that have analyzed interactions between a fixed number of players (mesostructure) are those by Sarmento et al. (2016), who deciphered patterns of direct attack in three top European clubs, and by Headrick et al. (2011), who described proximity-to-goal interactions between attackers and defenders.

Other authors, in turn, have applied T-pattern detection to investigate macropatterns, i.e., patterns within a match as a whole. Examples are Jonsson et al. (2006), who analyzed synergies of positional attack in FC Barcelona, and Barreira et al. (2014), who in an ambitious study applied T-pattern detection to identify optimal pitch areas in which to recover the ball and achieve a shot at goal in the 2010 FIFA World Cup.

Studies like this have provided some answers to the question: why does everything we see during a soccer match happen? Their results can help to empirically identify patterns underlying visible aspects of play and enable researchers not just to quantitatively decipher these formal aspects of the game, but also to delve into the functional and qualitative personality of the team and team play as a whole, ultimately favoring better decision-making in real-life situations.

The aim of this study was to analyze offensive play by a Spanish soccer team during the 2012 UEFA European Championship (UEFA Euro 2012) through the detection of T-patterns reflecting intrinsic patterns of play established during the spontaneous course of play.

Methods

Design

We used observational methodology and applied the observational design I/P/M, which stands for Idiographic/Point/Multidimensional. It was idiographic because we studied one team considered as a single unit, point because we studied a single competition (Anguera and Hernández-Mendo, 2013), albeit with an intrasessional follow-up, and multidimensional because we analyzed the multiple dimensions that constituted the *ad hoc* observation instrument used (Anguera et al., 2011). Observation was non-participatory and governed by scientific criteria, and the level of perceptibility was complete.

Participants

We used a convenience sample consisting of offensive actions by the Spanish national soccer team during its participation in UEFA Euro 2012. The study was approved by the ethics committee at the *Universidad Pontificia de Salamanca*. Intersessional consistency throughout the competition was ensured by the fact that all the matches observed were played by the same team (with the same players and jersey numbers) and on the same sized pitch divided into identical zones.

Observation instrument

The instrument used to observe the matches was designed by Maneiro and Amatria (2018). This instrument is a combination of a field format system and category systems (Anguera et al., 2007). The category systems are nested within the field format and contain exhaustive, mutually exclusive categories (Anguera and Hernández-Mendo, 2013).

Software tools

The data were recorded using the free software tool Lince (v. 1.2.1; Gabin et al., 2012).

The data quality control analyses were performed in GSEQ5 (Bakeman and Quera, 2011) and SAGT (Hernández-Mendo et al., 2016), and the T-pattern analysis was performed in Theme, v. Edu, which is a free version of THEME for academic use (Magnusson, 2000, 2016).

Procedure

The hierarchy of observation units, ranging from molecular to molar, is formed by event (technical actions, play interruptions, and interceptions), sequence of play, and match. A sequence of play, or move, was defined as the series of events that occur from the moment the team being observed gains possession of the ball to the moment it loses it. The sum of sequences constitutes a match.

The observation sample for the offensive actions by the Spanish national team during UEFA EURO 2012 contained 6861 events, corresponding to 5005 technical actions and 746 offensive sequences. Type IV data were collected, which means they are concurrent, time-based data.

Data quality analysis via interobserver agreement (Cohen's kappa) and generalizability theory

The reliability of the dataset was analyzed quantitatively by comparing the data recorded by the two observers who analyzed and annotated the

video recordings. The dataset created by the second observer contained at least 80% of the sequences of play recorded for the entire dataset (i.e., for all matches played by the Spanish team during the championship). The two observers were expert participants (Doctors in Physical Activity and Sports Sciences and certified national soccer coaches [level III]), and they both participated in a purpose-designed 30-hour training program (Anguera, 2003). This program included eight sessions in which the observers annotated data using the consensus agreement method (Arana et al., 2016), by which events are only annotated when both observers agree on the code.

Interobserver agreement for the categorical data recorded by the two observers was evaluated using Cohen's kappa statistic (Cohen, 1960), which is a statistical coefficient that corrects for chance agreement. It is expressed mathematically as $\kappa = \sum_{1}^{k} \frac{p_o - p_e}{1 - p_e} x100$ where k is the number of categories, p_o the observed percentage agreement, and p_e the percentage agreement expected by chance.

The calculations were performed in the free software program GSEQ5 following the recommendations of Bakeman and Quera (2011). The result was a kappa of 0.95, indicating satisfactory interobserver agreement (Fleiss et al., 2003).

Generalizability theory (Cronbach et al., 1972) was also applied to reduce error by controlling for sources of variation. The generalizability design was based on the work of Blanco-Villaseñor (1993). The analysis was performed in SAGT v. 10, a generalizability theory software package. The resulting generalizability coefficient was $e^2 = 0.986$, indicating that the results were highly generalizable and the data recorded in the different matches were consistent.

T-pattern analysis

Recent years have witnessed a growing interest in the detection of behavioral patterns hidden within data (Vilar et al., 2012) and numerous methodologies have been developed for this purpose. One of the most novel methods to emerge is T-pattern analysis, which searches for temporal patterns and is supported by a robust conceptual framework and a dedicated software application, THEME (Magnusson, 2000). The following are just some examples of studies that

have used T-pattern detection within THEME (Magnusson, 2000, 2016) and its latest developments (Amatria et al., 2017; Camerino et al., 2012; Castañer et al., 2017; Diana et al., 2017). For the current study, we used the free version of the program THEME, v. Edu.

We searched for T-patterns hidden within the full set of data corresponding to all the matches played by the Spanish national team at the 2012 UEFA European Championship.
We applied the following search variables:
- A minimum frequency of 5 occurrences.
- A significance level of $p < .05$.
- Validation of results by randomizing the data five times and only accepting patterns for which the probability of the randomized data coinciding with the real data was 0 or less.
- Application of a simulation filter available in THEME v. 5.0. This filter generates randomizations for each critical interval relationship defining the occurrence of a T-pattern before accepting it as such. The number of randomizations depends on the significance level (in our case, we set this number at 2000, -1/0.005 x 10-). The T-pattern is accepted if THEME v. 5.0 finds, among all the randomly generated relationships, n critical interval relations with (n/2000) < 0.005, with internal intervals that are the same size or smaller than those of the relationship tested.

Results

T-pattern detection

A total of 1465 T-patterns that met the search criteria were detected in the full dataset of offensive play by the Spanish national team during UEFA Euro 2012. There were 987 two-cluster patterns, 387 three-cluster patterns, 72 four-cluster patterns, 16 five-cluster patterns, and 3 six-cluster patterns.

The results presented below are those generated by the application of the automatic (quantitative) sort settings (Amatria et al., 2017) in THEME, v. Edu. They show the T-patterns with the highest number of occurrences, the highest number of clusters, and the longest duration (Table 1).

To aid in the interpretation of results, we created a figure showing an example of a T-pattern in a tree format, with images from the matches

illustrating the different clusters that made up the T-pattern (pattern L.1 [((((zi61,zf61,c1 zi61,zf61,c1)(zi61,zf71,c2 zi71,zf71,c2)) zi110,zf110,c1) zi110,zf110,ioc)].

In the next section, we present the T-patterns detected using the qualitative filters (Amatria et al., 2017) applied to answer the questions posed in this study. These were patterns related to both depth of play (i.e., movement of the ball from one sector of the pitch up to another one) and width of play (i.e., movement of the ball from one side of the pitch to the other). We used four qualitative filters, or levels of success, to analyze offensive performance in relation to depth of play. These levels of success, which are the equivalent of optimal targets (Hugues and Bartlett, 2002), were defined as follows: a) sequences of play ending in the definition sector (Level IV), b) sequences of play ending in a pass to the goal area (Level III), c) sequences of play ending in a shot at goal (Level II), and d) sequences of play ending in a goal (Level I), which is the ultimate measure of success (Kempe et al., 2014). These four success levels have an ordinal character from the least complex (Level IV) to the most complex (Level I).

It should be noted that only T-patterns that do not appear at lower levels are shown for a given level. For example, although patterns detected at level I are also present at levels II, III, and IV, they are shown only at the top level. This does not, however, occur the opposite way around.

Success level IV (L-IV) shows the T-patterns ending in the definition sector (zones 90, 100, 110, 120, and 130). This success level is relevant, because it shows progress while the team is building an attack. Just one T-pattern was detected in this case (Table 2).

Level III (L-III) contains T-patterns corresponding to sequences of play ending in a pass to zones 100, 110, and 130 (goal area). These patterns are obviously valuable, as they can show the actions that lead up to a ball being delivered to the immediate goal area. We detected 12 T-patterns at this level. Ten of these corresponded to sequences of play in the central areas of the pitch, and two to sequences in the lateral areas (Table 2).

Level II (L-II) shows T-patterns corresponding to sequences of play that contain at least one shot at goal, regardless of whether this was successful or not. Again, these patterns are important, as they reflect the occurrence of actions aimed at scoring a goal. The majority of T-patterns detected at level II occurred in zone 130, the rival goal area (Table 2).

Level I (L-I) shows T-patterns corresponding to sequences of play that end in a goal, the ultimate measure of success in soccer (Kempe et al., 2014). Five T-patterns were detected at this level (Table 2).

For the width-of-play analysis, THEME, v. Edu retrieved T-patterns that reflected the greatest width achieved in offensive play. Use of width is important when building an attack as it involves targeting areas of the pitch with the least density of defenders. We detected just two T-patterns in this analysis and they both started in zone 51, i.e., they both corresponded to sequences in which the ball was delivered from the left side of the pitch to the right. It is noteworthy that long passes were more common than short passes in these patterns (Table 2).

Discussion

The aim of this study was to apply T-pattern analysis to identify strings of events that occur intrinsically and spontaneously during the course of a soccer match, but remain invisible to the naked eye.

With respect to depth of play, like Camerino et al. (2012), we observed that most events occurred in the midfield area, particularly in the rival team's creation sector. Our findings regarding patterns leading up to a goal also coincide with those of Camerino et al. (2012), in that shots were taken in zone 100, to the left of the goal area. The areas in which the events leading up to these goals started also coincided with reports by Camerino et al. (2012). Patterns containing a pass into the goal area all started in the center of the rival team's creation sector. These findings, together with those for patterns containing events that occurred in the definition sector, coincide with those of Barreira et al. (2014).

Although our findings with respect to depth of play are not exactly novel and have been described for other elite soccer teams, they do reveal a clear level of technical complexity, with patterns consisting of 1 or 2 touches of the ball and alternations between team play and individual dribbling to move the ball up the pitch.

Table 1

T-patterns detected using the automatic sort settings in THEME, v. Edu.

| Setting	Code	String-like pattern	O / L / D	Mean (internal interval in frames)
Occurrences (O)	O.1	(zi61,zf61,c1 zi61,zf61,c1)	35 / 2 / 3388	95.80
Length (L)	L.1	((((zi61,zf61,c1 zi61,zf61,c1)(zi61,zf71,c2 zi71,zf71,c2)) zi110,zf110,c1) zi110,zf110,ioc)	3 / 6 / 1718	20.00 /103.67 /126.00 / 300.00 / 22.00
	L.2	((zi61,zf61,c1 zi61,zf61,c1)((zi61,zf71,c2 zi71,zf71,c2)(zi110,zf110,c1 zi110,zf110,c1)))	3 / 6 / 1707	20.00 / 103. 67 / 126.00 / 300.00 / 18.33
	L.3	(zi71,zf71,c2 ((((zi71,zf71,c1 zi71,zf71,c1) zi71,zf71,c2) zi71,zf120,c2) zi71,zf71,c2))	3 / 6 / 2984	65.67 / 47.67 / 158.33 / 265.67 / 456.33
Duration (D.)	D.1	(zi71,zf71,c2 (zi71,zf71,c1 zi71,zf61,c2))	10 / 3 / 4371	245.30 / 190.80
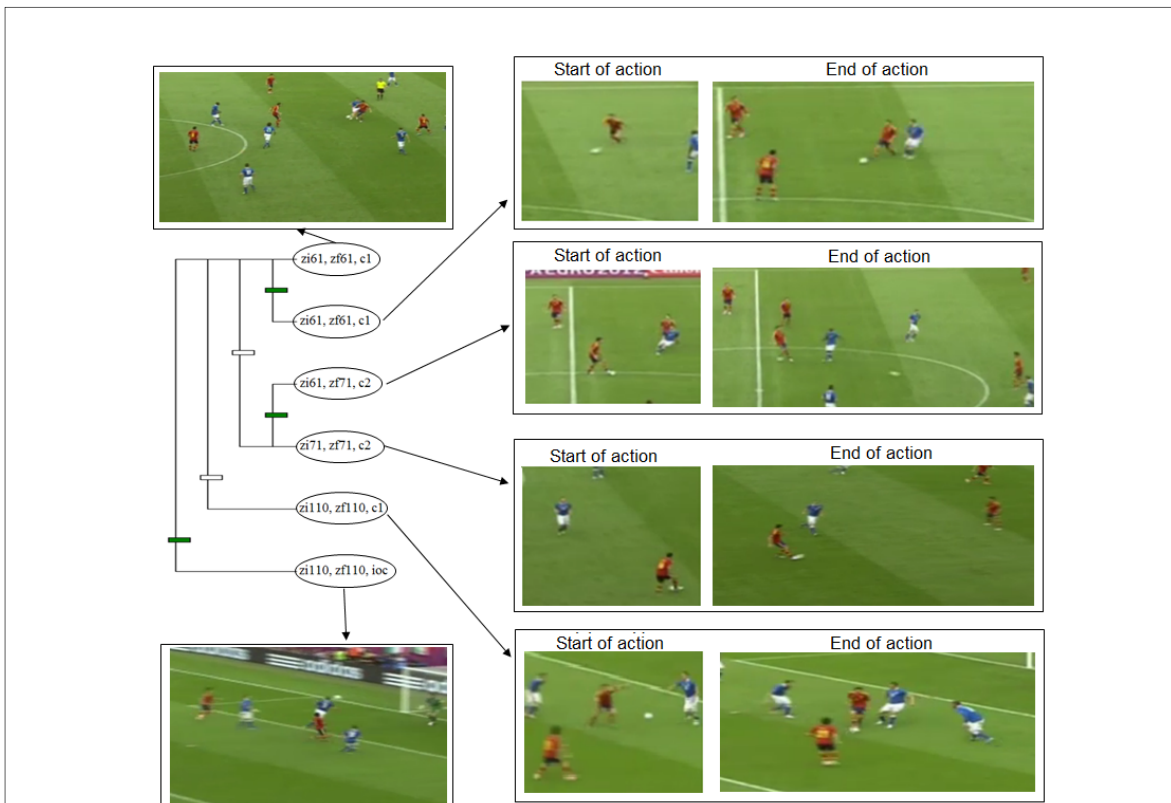
Figure 1

Example of a T-pattern in tree format with corresponding images from the championship. The T-pattern in question is pattern L.1, which is formed by ((((zi61,zf61,c1 zi61,zf61,c1)(zi61,zf71,c2 zi71,zf71,c2)) zi110,zf110,c1) zi110,zf110,ioc). The pattern starts with two contacts with the ball in zone 61; the player involved in the second contact controls the ball and passes it to zone 71. The receiving player controls the ball and passes it to culminate in a single contact in zone 110 and an IOC (occasional interception with continuation of play) in the same zone.

Table 2

T-patterns detected using qualitative options to reflect levels of success: Level IV (L-IV),
Level III (L-III), Level II (L-II), Level I (L-I) and width-of-play (C.O.).

Setting	Code	String-like pattern	O / L / D	Mean (internal interval in frames)
Level IV	L-IV.1	(zi61,zf90,c3 zi90,zf90,c2)	7 / 2 / 1052	149,29
Level III	L-III.1	(zi61,zf100,c3 zi100,zf100,p)	11 / 2 / 1561	140.91
	L-III.2	(zi120,zf120,ffse zi120,zf110,c1)	11 / 2 / 2025	1.27
	L-III.3	(zi61,zf61,c2 zi61,zf100,c3)	9 / 2 / 1491	164.67
	L-III.4	(zi61,zf100,c2 zi100,zf100,p)	8 / 2 / 807	99.88
	L-III.5	(zi61,zf61,c2 zi61,zf100,c2)	7 / 2 / 981	139.14
	L-III.6	(zi71,zf110,c3 zi110,zf110,p)	7 / 2 / 747	105.71
	L-III.7	(zi61,zf71,c2 zi71,zf110,c3)	7 / 2 / 1259	178.86
	L-III.8	(zi61,zf90,c2 zi100,zf100,p)	7 / 2/ 1937	275.71
	L-III.9	(zi70,zf61,c2 zi100,zf100,p)	7 / 2 / 2879	410.29
	L-III.10	(zi71,zf110,c3 zi110,zf110,c1)	7 / 2 / 634	89.57
	L-III.11	(zi71,zf71,c2 zi71,zf110,c3)	7 / 2 / 1176	167.00
	L-III.12	(zi120,zf120,ffse zi130,zf130,cfff)	7 / 2 / 886	125.57
Level II	L-II.1	(zi110,zf130,f zi130,zf130,cfff)	12 / 2 / 788	64.67
	L-II.2	(zi100,zf130,c1 zi100,zf130,f)	11 / 2/ 1944	3.00
	L-II.3	(zi110,zf130,c1 zi110,zf130,f)	9 / 2 / 2028	2.11
	L-II.4	(zi120,zf120,ffse zi110,zf130,f)	7 / 2 / 680	96.14
	L-II.5	(zi110,zf110,f zi110,zf110,ioc)	7 / 2 / 1968	8.71
	L-II.6	(zi110,zf130,f zi130,zf130,p)	7 / 2 / 136	18.43
	L-II.7	(zi61,zf71,c2 zi110,zf130,f)	7 / 2 / 1753	249.43
Level I	L-I.1	(zi100,zf130,f zi130,zf130,gf)	6 / 2 / 262	42.67
	L-I.2	(zi110,zf130,f zi130,zf130,gf)	6 / 2 / 149	23.83
	L-I.3	((zi100,zf130,c1 zi100,zf130,f) zi130,zf130,gf)	4 / 3 / 1999	1.25 / 22.50
	L-I.4	(zi61,zf61,r (zi100,zf130,f zi130,zf130,gf))	3 / 3 / 826	216.67 / 57.67
	L-I.5	(zi51,zf50,c1 zi130,zf130,gf)	3 / 2/ 1761	586.00
Width-of-play	CO.1	(zi51,zf51,c2 zi60,zf81,c2)	6 / 2 / 1716	285.00
	CO.2	(zi51,zf61,c3 zi81,zf71,c2)	4 / 2 / 944	235.00

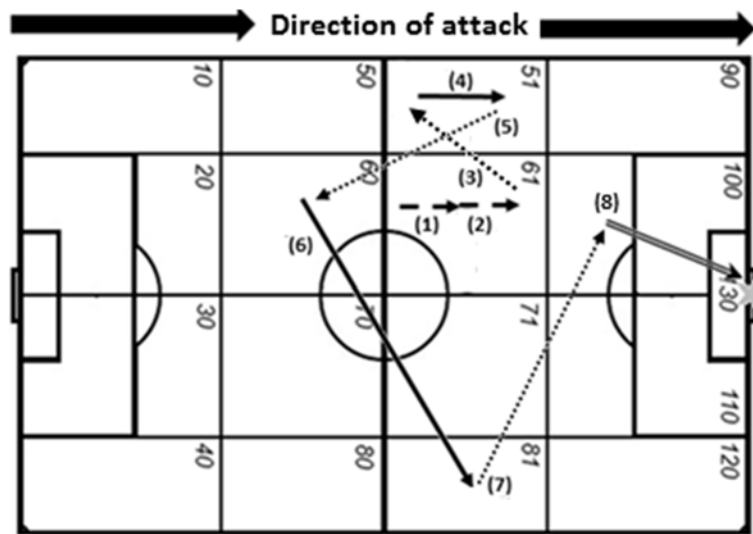**Figure 2**

Figure showing typical move by the Spanish national football team at UEFA Euro 2012, where No.= sequence order, ━ ➤ = C1, ➡ = C2, ⋯➤ = indeterminate action, ⇒ = shot, and ★ = goal.

In relation to the most frequent T-patterns corresponding to offensive sequences involving use of the two outer corridors, we observed that changes of direction were achieved by both passing and dribbling. Such strategies are designed to achieve a greater width of play, and crossing the ball from one side of the pitch to the other is not an easy task. Identifying T-patterns of this type is important, as they describe effective sequences of play in which the attacking team avoids the more crowded central corridor.

Finally, using the different algorithmic computations in THEME, we identified a sequence of play that could be considered representative of the Spanish team's attacking style (Figure 2). The sequence begins in the central areas of the rival's half of the pitch and includes changes of direction in which forwarders and midfielders take responsibility for concluding the sequence, using dummy moves and distractions to conceal their true tactical intentions.

The results of this study demonstrate that it is possible to use algorithmic computations to describe a team's particular style of play. In this case, we identified some of the secrets to the success of the champions of UEFA Euro 2012. The model applied is built on morphologically complex and sophisticated structures and is radically different to models used to date to study performance in elite soccer. Our findings, however, should not simply be accepted as they are, but scientifically tried and tested in real-life situations. For this to happen, our results should be transferred to the playing field, or more precisely to the training field, and be tested at two levels. From the perspective of defensive play, coaches should devise strategies to defend against the winning style we have described, while from the perspective of offensive play, they should try to replicate this model of success by designing training drills that will ultimately generate similar

patterns of play that can be transferred to competition situations.

Conclusions

We used T-pattern detection to identify and describe aspects of the successful attacking style of the champions of UEFA Euro 2012. Apart from shedding light on some of the secrets to the Spanish team's success, our results also serve to build on previous findings and contribute to a better understanding of what occurs within the deeper layers of a soccer match.

Our results can be summed up in six main points:

(1) To achieve a shot at goal and score, the Spanish national team simultaneously make good use of the width and depth of the pitch to create space through team and individual actions.

(2) The Spanish team prioritize width of play over depth of play to find space in which to build their attack and achieve a shot at goal or score.

(3) Both forwards and midfielders take responsibility for scoring. In doing so, they successfully trick their opponents into thinking they are going to do one thing, but then do another. Deception is a strategy used wisely by the Spanish team.

(4) The Spanish team effectively combines the use of frequent passes with long passes and changes of direction to avoid areas of the pitch with a high density of defenders.

(5) These hot zones, or areas of tactical creation, are the central areas of the rival's half of the pitch.

(6) The patterns detected throughout the championship were stable and robust, with little disruption from rival interactions, and in addition they were highly generalizable (e2 = 0.986).

The above conclusions provide valuable material that can be built on by coaches to help their teams mount more successful attacks and ultimately win more games. They also contain important lessons on defensive strategies to counter successful attacks.

References

Amatria M, Lapresa D, Arana J, Anguera MT, Garzón B. Optimization of game formats in U-10 soccer using logistic regression analysis. *J Hum Kinet*, 2016; 24: 163-171

Amatria M, Lapresa D, Arana J, Anguera MT, Jonsson GK. Detection and selection of behavioral patterns using Theme: a concrete example in grassroots soccer. *Sports*, 2017; 5: 20; doi:10.3390/sports5010020

Anguera MT. The Observation. In C. Moreno Rosset (Ed.), *Psychological evaluation. Concept, process, and application in the areas of development and intelligence* (pp. 271-308). Madrid: Sanz y Torres. Ciencia y Deporte., 1(1), 15-20; 2003

Anguera MT, Blanco-Villaseñor A, Hernández-Mendo A, Losada J. Observational designs: adjustment and application in sport psychology. *Cuad Psicol Deporte*, 2011; 11(2): 63-76

Anguera MT, Hernández-Mendo A. Observational methodology in the area of sport. *E-balonmano.com: Rev Cienc Deporte,* 2013; 9(3): 135-160

Anguera MT, Magnusson MS, Jonsson GK. Non-standard instruments. *Avances en Medición,* 2007; 5(1): 63-82

Arana J, Lapresa D, Anguera MT, Garzón B. *Ad hoc* procedure for optimizing agreement between observational records. *An Psicol,* 2016; 32(2): 589-595

Bakeman R, Quera V. *Sequential Analysis and Observational Methods for the Behavioral Sciences.* Cambridge: Cambridge University Press; 2011

Barlett R, Button C, Robins M, Dutt-Mazunder A, Kennedy G. Analysing team coordination patterns from player movement trajectories in soccer: Methodological considerations. *Int J Perf Anal Sport,* 2012; 12: 398-424

Barreira D, Garganta J, Guimaraes P, Machado J, Anguera MT. Ball recovery patterns as a performance indicator in elite soccer. *J Sport Eng Technol,* 2014; 228(1): 61-72

Blanco-Villaseñor A. Reliability, accuracy, validity, and generalizability of observational designs. In M.T. Anguera (Ed.), *Observational methodology in psychological research*. Barcelona: PPU., Vol. II., 151-261; 1993

Camerino O, Chaverri J, Anguera MT, Jonsson GK. Dynamics of the game in soccer: Detection of T-patterns. *Eur J Sport Sci,* 2012; 12(3): 216-224

Castañer M, Barreira D, Camerino O, Anguera MT, Fernandes T, Hileno R. Mastery in goal scoring, T-pattern detection and polar coordinate analysis of motor skills used by Lionel Messi and Cristiano Ronaldo. *Front Psychol,* 2017; 8: 741. doi: 10.3389/fpsyg.2017.00741

Cohen J. A coefficient of agreement for nominal scales. *Educ Psychol Meas,* 1960; 20: 37-46

Cronbach LJ, Gleser GC, Nanda H, Rajaratnam N. *The dependability of behavioral measurements: theory of generalizability for scores and profiles.* New York: Wiley; 1972

Diana B, Zurloni V, Elia M, Cavalera CM, Jonsson GK, Anguera MT. How game location affects soccer performance: T-pattern analysis of attack actions. *Front Psychol,* 2017; 8: 1415. DOI: 10.3389/fpsyg.2017.01415

Fleiss JL, Levin B, Paik MC. *Statistical methods for rates and proportions*, 3rd ed. Hoboken: John Wiley y Sons; 2003

Gabin B, Camerino O, Anguera MT, Castañer M. Lince: Multiplatform sport analysis software. *Procedia. Soc Behav Sci,* 2012; 46: 4692-4694

Gronek P, Wielinski D, Gronek J.Genetic and non-genetic determinants of aggression in combat sports. *Open Life Sci,* 2015; 10(1): 7-18

Headrick J, Davids K, Renshaw I, Araújo D, Passos P, Fernandes O. Proximity-to-goal as a constraint on patterns of behaviour in attacker–defender dyads in team games. *J Sport Sci,* 2011; 30(3): 247-253

Hernández-Mendo A, Blanco-Villaseñor A, Pastrana JL, Morales V, Ramos-Pérez FJ. SAGT: New Software For Generalizability Analysis. *Rev Iberoamericana Psicol Ejercicio y Deporte*, 2016; 11(1): 77-89

Hristovski R, Aceski A, Balague N, Seifert L, Tufekcievski A, Cecilia A. Structure and dynamics of European sports science textual contents: Analysis of ECSS abstracts (1996-2014). *Eur J Sport Sci,* 2017; 17: 19-29. DOI:10.1080/17461391.2016.1207709

Hughes M, Bartlett R. The use of performance indicators in performances analysis. *J Sport Sci*, 2002; 20(10): 739-754, DOI: 10.1080/026404102320675602

Jonsson GK, Anguera MT, Blanco-Villaseñor A, Losada JL, Hernández-Mendo A, Ardá T, Camerino O, Castellano J. Hidden patterns of play interaction in soccer using SOF-CODER. *Behav Res Methods*, 2006; 38(3): 372-381

Kalinowski P, Bojkowski Ł, Śliwowski R. Motor and psychological predispositions for playing football. *TRENDS Sport Sci*, 2019; 2(26): 51-56

Kempe M, Vogelbein M, Memmert D, Nopp S. Possesion vs. Direct play: evaluating tactical behavior in elite soccer. *Int J Sport Sci*, 2014; 4(6A): 35-41

Lames M, Erdmann J, Walter F. Oscillations in football – Order and disorder in spatial interactions between the two teams. *Int J Sport Psychol*, 2010; 41: 85–86

Magnusson MS. Discovering hidden time patterns in behavior: T-patterns and their detection. *Behav Res Meth Ins C*, 2000; 32(1): 93-110

Magnusson MS. Time and self-similar structure in behavior and interactions: From sequences to symmetry and fractals. In M. S. Magnusson, J. K. Burgoon, M. Casarrubea, & D. McNeill (Eds.), *Discovering hidden temporal patterns in behavior and interactions: T-Pattern detection and analysis with THEME* (pp. 3-35). New York: Springer; 2016

Maneiro R, Amatria M. Polar coordinate analysis of relationships with teammates, areas of the pitch, and dynamic play in soccer: A study of Xabi Alonso. *Front Psychol*, 2018; 9: 389. https://doi.org/10.3389/fpsyg.2018.00389

Ramos A, Coutinho P, Silva P, Davids K, Mesquita I. How players exploit variability and regularity of game actions in female volleyball teams. *Eur J Sport Sci*, 2017; 17(4): 473-481

Vilar L, Araújo D, Davids K, Bar-Yam Y. Science of winning soccer: Emergent pattern-forming dynamics in association football. *J Syst Sci Complex*, 2012; 26(1): 1-13

Corresponding author:

Mario Amatria, Phd
Department of Physical Activity Sciences and Sports,
Pontifical University of Salamanca.
Edificio Luis Vives. C/ Henry Collet 52-70Ulloa s/n.
37007. Salamanca. Salamanca - Spain
Phone: +34 923125027 ext 207
E-mail: mamatriji@upsa.es