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Inspecting teammates' coverage during attacking plays in a football game: A case study

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Abstract

The tactical behaviour of football players is fundamental in sport teams. Despite this importance, the methods to measure such behaviour are very time-consuming for human operators. Therefore, the aim of this case study was to propose a set of collective technological metrics to evaluate the attacking coverage provided by teammates to the player in possession of the ball. For this case study data was collected from three official matches of the same professional team. Using the information about the Cartesian position of players in the field provided from a tracking method, it was possible to propose four different technological metrics and ratios: i) cover in support; ii) cover in vigilance; iii) attacking cover; and iv) depth mobility. Using those metrics it was possible to observe that on average the team observed use with higher regularity support in vigilance as well as depth mobility, thus suggesting a specific tactical behaviour. In summary, it was possible to apply all metrics to real data from three official matches, thus allowing a new technological method to improve the match analysis systems that use multiplayer tracking.

Keywords: Match analysis, tactics, metrics, football

1. Introduction

The football game is a complex team sport that depends from coordination processes within and between players during match (Davids, Araújo, & Shuttleworth, 2005). As such, it is important to propose and develop match analysis methods that may allow to inspect the interpersonal coordination dynamics within playing patterns emerging from each different sub-phase (e.g., 1v1, 2v2). When developing such methods one should keep in mind the synchronization of all collective behaviours (Gréhaigne, Bouthier, & David, 1997; McGarry, Anderson, Wallace, Hughes, & Franks, 2002). This synchronization and dynamic behaviour depend from a spatiotemporal relationship that emerges during the match (Bourbousson, Sève, & McGarry, 2010).

In the last few years, the scientific community have paid an increased attention to such synchronization and dynamic behaviour, with the main purpose of providing useful methods to analyse the coordination patterns between players in team sports (Bourbousson, et al., 2010; Clemente, Couceiro, Martins, Dias, & Mendes, 2013a). The first studies around this topic, such as Passos et al (2009) and Clemente et al (2013a), were carried out by considering each sub-phase of the game separately (1v1), thus inspecting the dynamics behind the attacker-defender dyad in a spatiotemporal way. Nevertheless, the study of interpersonal distances, speed or acceleration synchronization was only considered as the starting point of the necessary match analysis metrics. From the 1v1 perspective, Bourbousson et al (2010) and Frencken, Lemmink, Delleman and Visscher (2011) developed a set of collective metrics (e.g., *centroid*, *stretch index* and *surface area*) to inspect the synchronization dynamics between teammates using the space and time as reference. Later, Clemente, Couceiro, Martins, Mendes and Figueiredo (2013c) developed an updated version of these metrics and introduced a new concept called *effective area of play* that considers a tactical parameter based on the defensive and attacking triangulations.

In sum, the study of teammates' synchronization have been based on the distance between players. Nevertheless, the football game is a team sport that depends from a set of collective rules to increase the coordination possibilities between teammates. These rules are described as tactical principles (Costa, Garganta, Greco, Mesquita, & Seabra, 2010). These tactical principles are rules that deal with the spatiotemporal relationships as well as behaviours. From many and various theoretical considerations of those principles, there is a consensus about their importance for attacking and defensive situations (Costa, et al., 2010; Gréhaigne, Richard, & Griffin, 2005). Despite the great importance of defensive situations, the main aim of a football match is to score. Therefore, following is a discussion of the tactical attacking principles.

The tactical attacking principles aim to give fundamental information to players, allowing an improvement of collective behaviour (Clemente, Couceiro, Martins, & Mendes, 2013b). These tactical principles provide some behaviour rules for organizing and attuning players' behaviour to the main goal of the team, thus creating successful opportunities to score. Thus, tactical principles are fundamental guidelines, allowing an improvement of collective behaviour in order to disrupt the defensive organization of the opponents' team. The five fundamental attacking principles in football are (Costa, et al., 2010): *i*) penetration; *ii*) attacking cover; *iii*) depth mobility; *iv*) width and length;

and *v*) attacking unit. From those principles it is possible to identify that attacking cover and depth mobility are the two that most require an inter-players' perception to support those teammates in possession of the ball.

The coverage principle is characterized by the supporting action provided by a teammate to the player with ball possession. Thus, this support provided by the teammates to the player with ball possession is fundamental to the attacking phase, providing him with many options to conclude the process with efficacy (Costa, Garganta, Greco, & Mesquita, 2009). To benefit from this principle, the attacker with ball possession needs to simplify his/her action, opting for safe passes or actions. Furthermore, it is fundamental that teammates move towards or away from with possession of the ball depending on the position of opponents and the ball.

Depth mobility is characterized by optimal teammates' movements to receive the ball from the player in possession (Costa, et al., 2009). These movements can be done away from the player with the ball (i.e. break movements) or near to them (i.e. support movements). The guidelines for this principle are the variability of actions depending on the position of the ball and the opponents, as well as movements' speed trying to unbalance the defensive organization. All of the mobility processes should be made with meaning, i.e., giving valid solutions for a successful conclusion to the attacking phase (Worthington, 1974). Thus, it is fundamental that teammates understand the dynamic processes, allowing the quality of their play to improve during the attacking phase.

Despite them being of great importance for football coaches, the analysis of these principles are so far based on a manual observational process. As a result, this process takes a lot of time and human resources. Nevertheless, using the new technologies of computational tracking of players it is now possible to develop an automatic system (automatic data processing) to identify tactical principles. Therefore, the aim of this study is to propose a set of computational tactical metrics based on Cartesian information provided from tracking systems. These tactical metrics will be developed based on manual observation indicators in order to continue the research performed until now and to give new opportunities for football match analysis.

2. Methods

2.1. Sample

Three official home matches of a professional team from the *Portuguese Professional Premier League* were analysed. The team used the same strategic distribution in the field (1-4-3-3) throughout all games. At each match the final score was different, i.e., win (match 3), lose (match 2), and draw (match 1). Thus, the final score of each match was considered. From those three matches were collected 9218 moments. All of the collected data complies to the APA ethical standards for the treatment of human or animal subjects.

2.2. Data Collecting

Teams' actions were captured using a digital camera (*GoPro Hero* with 1280× 960 resolution), with the capacity to process images at 30 Hz (i.e. 30 frames per second). The camera was placed on an elevated surface above the ground in a way that would capture the whole field. The field dimensions were 104×68 metres. After recording the football match, the physical space was calibrated using direct linear transformation (DLT), which amends the position of the elements (i.e. players and ball) in pixels to the metric space (Abdel-Aziz & Karara, 1971). In order to ensure the reliability of such conversion, experimental trials were carried out by considering random points on the field were initially collected, metrically assessed and then mapped into real coordinates.

The manual tracking of players was accomplished after calibration, thus returning the position of the players and the ball over time in Cartesian coordinates (see Figure 1). A graphical user interface was developed so as to visualize the match by controlling the framerate with a sampling time of one second. During each frame, the operator was requested to identify the location of all players and the ball, following the typical point-and-click approach. That identification corresponded to one point in the centre of each players' feet and the centre of the ball. The whole process associated with this approach (i.e. detection and identification of players' trajectories, space transformation and metrics computation), was performed using the high-level calculation tool *MatLab* (Couceiro, Clemente, & Martins, 2013).

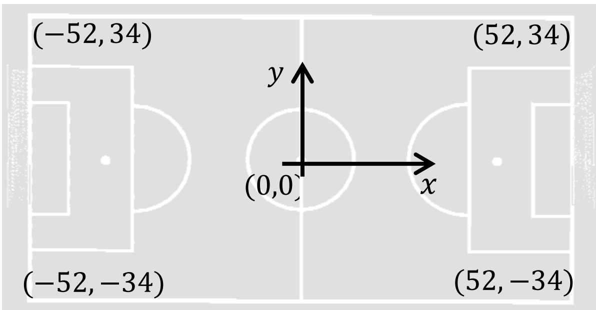


Figure 1. Football referential field

As a matter of efficiency, only played time was considered, excluding all moments in which the ball was not in the field (i.e. ball out of bounds). Since the methodology proposed herein involves some computational complexity, each second will correspond to an analysed instant of each player and the ball.

2.3. Computing the Tactical Attacking Principles

The first concept that must be developed is the attacking definition zone (ADZ). This concept comes from Costa et al (2009) and consists of the development of a circumference of 5-metre radius around the ball (Figure 1). Using this circumference (centre-of-game) a set of tactical metrics will be developed that will identify the effectiveness of the tactical principles performed by the team.

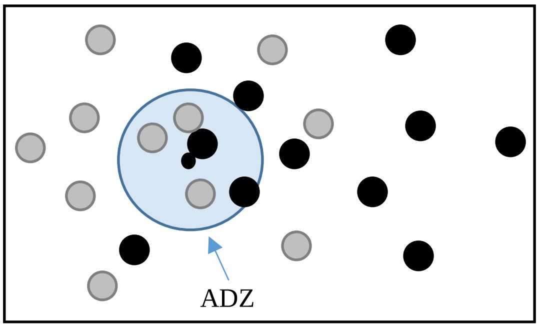


Figure 2. Attacking Definition Zone (ADZ): Centre-of-game representation

From the Cartesian position of all players and the ball the circumference (centre-of-game) around the ball at each second of match is developed.

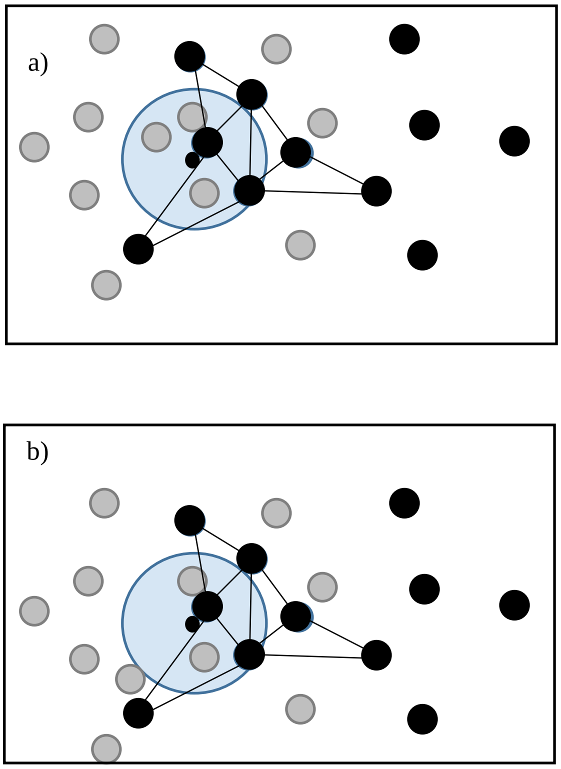
Using the centre-of-game it is possible to identify the players closest to and farthest from the ball and zone of definition. From all this information can be computed a set of metrics based on the indicators that characterize the effectiveness of the attacking principles of play. All metrics herein described were computed, at each second, whenever the team had the possession of the ball. Considering those instants, the average of each attacking play was considered, *i.e.*, starting at the beginning of attacking play (instant 1) until the moment that ball was lost (last instant). Each metric varies over time throughout the play efficacy.

a) Attacking Cover

The attacking cover can be classified as: *i*) in support (teammates who support the player in possession of the ball in the centre-of-game); and *ii*) in vigilance (teammates who support the player in possession outside of the centre-of-game). Therefore, each kind of cover must have a specific criteria to be classified as effective:

a. Cover in support: inside the ADZ there must be at least two players of the team in possession of the ball and a numeric equality or superiority against the opposite team must be observed;
b. Cover in vigilance: outside the ADZ there must be teammates making up an effective triangulation with one of the players inside the ADZ.

The effective triangulation comes from Clemente, Couceiro, Martins, Mendes, & Figueiredo (2013c). Such classification depends from metric interaction between attacking and defensive triangulations. In the moments in which the team possesses the ball (attacking), the effective triangulation will only be considered if the overlapping defensive triangulation has a perimeter higher than 36 meters, or if no defensive triangulation at all overlaps the attacking triangulation. On the other hand, the non-effective attacking triangulation will be considered if the attacking and defensive triangulations are overlapped and if the defensive have a perimeters lower than 36 meters.



There is no coverage in support (due to a numeric disadvantage of the black team with ball possession) but there is cover in vigilance (effective triangulation performed by 5 teammates outside the ADZ).

There is cover in support (due to numeric equality) and there is coverage in vigilance (effective triangulation performed by 5 teammates outside the ADZ).

Figure 3. Examples of coverage in support and in vigilance

By identifying the effective cover in support and in vigilance three main ratios can be analysed: *i*) ratio of effective cover in support; *ii*) ratio of effective cover in vigilance; and *iii*) ratio of effective attacking cover.

The ratio of effective cover in support (ECS) counts the number of times that the support complied with the requirements previously explained over the total number of ADZ. For this metric (ECS), the effectiveness of one kind of coverage (in support or in vigilance) is required, at least, per each second of play. Such metric it is a relative metric and is obtained from:

$$ECS_r = \frac{Number\ of\ effective\ covers\ in\ support}{Number\ of\ ADZ}. \tag{2}$$

A similar ratio defined using the effective cover in vigilance performed by teammates outside of the centre-of-game is a relative metric and is obtained from:

$$ECV_r = \frac{Number\ of\ effective\ covers\ in\ vigilance}{Number\ of\ ADZ}. \tag{3}$$

From the accomplishment of at least one kind of cover (support or vigilance) in each ADZ can be computed the ratio of attacking cover is a relative metric and is obtained from:

$$EC_r = \frac{Number\ of\ effective\ covers}{Number\ of\ ADZ}. \quad (4)$$

All these ratios allow the analysis of how teammates interact in order to provide a useful opportunity to the player in possession of the ball. This is also very important for identifying whether this cover is performed more in proximity (i.e. in support) or in further way (i.e. in vigilance). These three metrics can be computed second-by-second, varying the cumulative results throughout an attacking play (starting at the moment the team possesses the ball until the moment that the ball is lost). When the attacking play is interrupted, the average of the ratio throughout the play is computed and then attributed to this specific attacking play. When another attacking play starts, the process of computing begins again as previously described.

b) Attacking Depth Mobility

The attacking depth mobility will be considered based on a simple indicator: Always when one teammate offers a line of pass in proximity to the last opposition defender this will be considered as effective attacking depth mobility. This proximity will be considered as the 5 metres behind the line of last opposition defender (considering the x-axis).

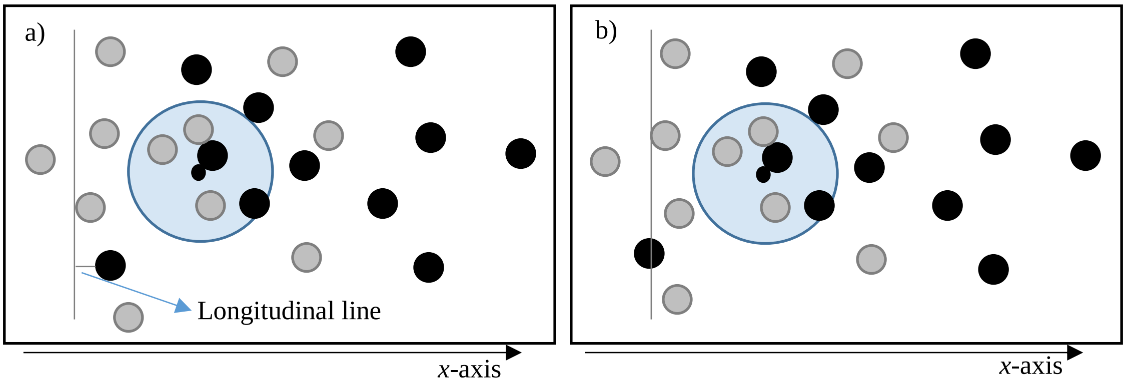


Figure 4. Depth mobility examples: a) effective depth mobility (inside the proximity of 5 metres to the last defender line); b) non-effective due to being offside

Using this relative metric it is possible to define the depth mobility ratio (DM) as follows:

$$DM_r = \frac{Number\ of\ depth\ mobility}{Number\ of\ ADZ}. \quad (5)$$

The depth mobility metric allows the identification of whether the longitudinal line (distance between the last opponent defender and the forward player in the x-axis) is being explored by the forward players in order to provide a possible different way to play and to press the opponents' defenders.

Once again, this metric can be computed second-by-second, varying the cumulative results throughout an attacking play. When the attacking play is interrupted, the average of the ratio throughout the play is computed and then attributed to this specific attacking play. When another attacking play starts, the process of computing begins again as previously described.

2.4. Statistical Procedures

Descriptive statistics was used to inspect the results from the four tactical principles. The three case study matches were organized by each half of the game and score, thus resulting in six variables: Draw1H1 (draw, match 1 and half 1), Draw1H2, Lose2H1, Lose2H2, Win3H1, Win3H2. Moreover, for each tactical principle, a boxplot was computed to support the graphical representation of the results. The final scores per match were draw (match 1), lose (match 2) and win (match 3).

For the descriptive analysis the mean value, the standard deviation, the minimum and maximum value and the coefficient of variation were determined. The classification of dispersion using the coefficient of variation was performed using the following scale (Pestana & Gageiro, 2008): *i*) low dispersion [0; 15% of CV[; *ii*) moderate dispersion [15; 30% of CV[; and *iii*) great dispersion ≥ 30% of CV.
All statistical procedures were computed using the SPSS statistics software (version 21).

3. Results

From the obtained results, it was possible to retrieve the descriptive tables of attacking coverage ratio (table 1 and figure 5), coverage in support (table 2 and figure 6), coverage in vigilance (table 3 and figure 7) and depth mobility (table 4 and figure 8).

Table 1. Descriptive statistics of attacking coverage ratio

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
Draw1H1	0.78	0.22	27.49	0.28	1
Draw1H2	0.81	0.22	27.04	0.29	1
Lose2H1	0.81	0.22	27.06	0.3	1
Lose2H2	0.71	0.22	30.91	0.17	1
Win3H1	0.81	0.20	25.18	0.35	1
Win3H2	0.78	0.25	31.36	0.14	1
Total	0.78	0.22	28.49	0.14	1

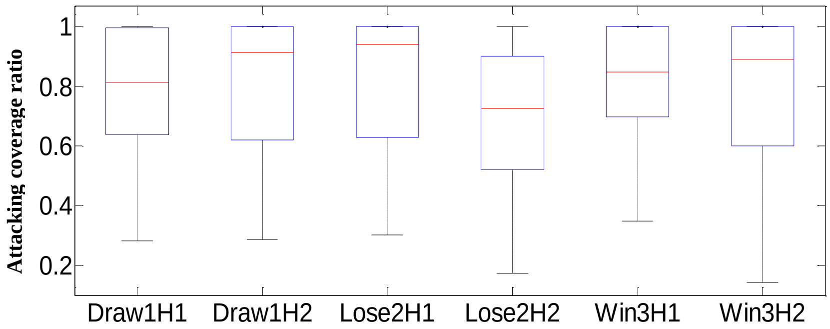


Figure 5. Box plots of attacking coverage ratio

It is possible to observe that the attacking coverage was accomplished with great regularity. The mean value of 0.78 suggests that at least one in-support or in-vigilance cover are performed during attacking play, thus improving the lines of pass. The lowest value was 0.14 and the maximal value was 1. The coefficient of variation for all matches was around 28%, thus suggesting a moderate dispersion from play to play.

The first quartiles of box plots (Figure 5) are bigger in the majority of cases. This can result from the higher value of the second quartile (median), thus reducing the possibility of increasing. The highest value of the cover ratio is 1, thus the tendency is for the third quartile to be smaller.

Table 2. Descriptive statistics of coverage in support ratio

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
Draw1H1	0.22	0.12	54.97	0.04	1
Draw1H2	0.34	0.27	79.24	0.05	1
Lose2H1	0.34	0.27	79.24	0.05	1
Lose2H2	0.31	0.16	52.82	0.08	1
Win3H1	0.45	0.35	76.45	0.05	1
Win3H2	0.40	0.16	40.74	0.05	1
Total	0.35	0.24	69.83	0.04	1

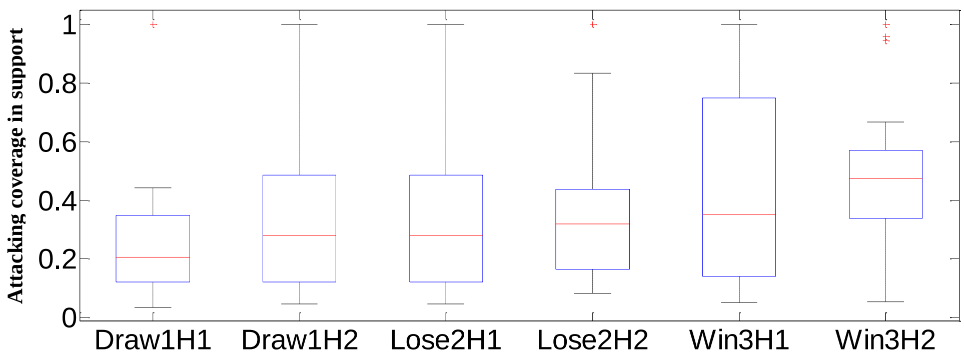


Figure 6. Box plots of coverage in support

The mean of cover in support is 0.38. This lower value can be explained by the team's own characteristics of increasing the lines of passes far away from the ball position. It is also possible to analyse that the coefficient of variation is great, achieving values of 79%. In the mean, the coefficient of variation is around 70%, suggesting a great variability of this principle from move to move.

In this case, the bigger quartiles are the thirds (Figure 6). This can be explained by the proximity of the second quartile (median) to the lower ratio value. In all matches it is possible to observe that the median is higher in the second half, thus suggesting a greater proximity to building the attack.

Table 3. Descriptive statistics of cover in vigilance ratio

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
Draw1H1	0.77	0.21	27.61	0.28	1
Draw1H2	0.82	0.22	27.29	0.29	1
Lose2H1	0.79	0.23	28.91	0.22	1
Lose2H2	0.70	0.24	33.63	0.17	1
Win3H1	0.79	0.20	25.06	0.35	1
Win3H2	0.76	0.25	32.64	0.14	1
Total	0.77	0.23	29.51	0.14	1

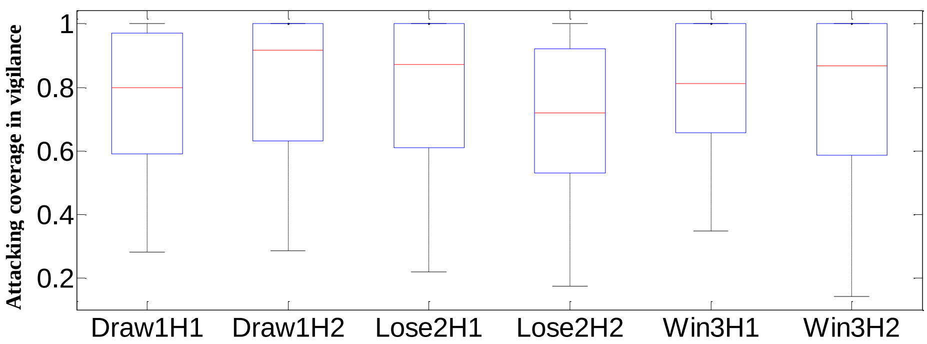


Figure 7. Box plots of coverage in vigilance

The cover in vigilance is performed more than cover in support. It is possible to observe that the mean of the ratio for all matches is 0.77. This result suggests that teams have more options for the player with ball possession in spaces outside of the centre-of-game. The mean coefficient of variation is 29.5%, thus the variability is lower than in the case of cover in support but still has a moderate dispersion.

From the box plots (Figure 7) it is possible to observe that the first quartiles are bigger than the third. This can be explained by the higher proximity to the maximal value of ratio. In two of the three matches it was possible to observe that the median of ratio was higher.

Table 4. Descriptive statistics of depth mobility ratio

	Mean	Std. Deviation	%Coefficient of variation	Minimum	Maximum
Draw1H1	0.89	0.15	17.13	0.42	1
Draw1H2	0.82	0.24	29.85	0.2	1
Lose2H1	0.91	0.12	13.18	0.57	1
Lose2H2	0.96	0.06	6.27	0.75	1
Win3H1	0.94	0.1	10.81	0.61	1
Win3H2	0.89	0.19	21.01	0.35	1
Total	0.90	0.16	18.06	0.2	1

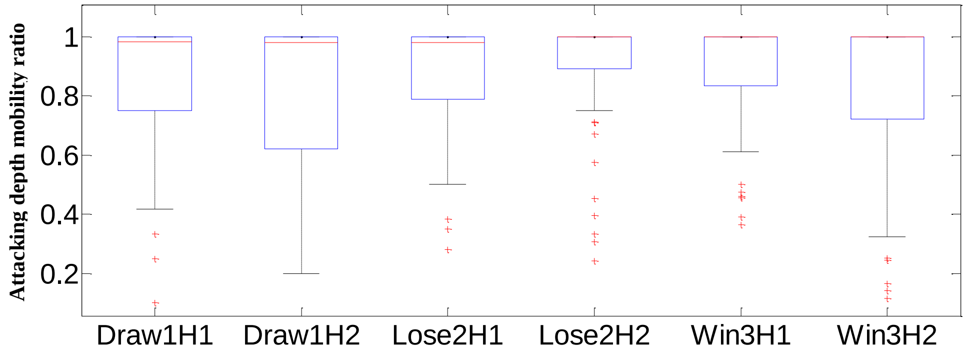


Figure 8. Box plots of depth mobility

The mean value of depth mobility is around 0.90. This greater value suggests that there is regularly one striker closer to the opponents' defenders. The coefficient of variation is around 18%, thus suggesting a low dispersion from play to play.

The box plots (Figure 8) allow a higher median closer to maximal value (1) to be observed. All first quartiles are bigger than the third. These results can be explained by the greater value of the median.

3.1. Variation of tactical metrics coefficients throughout matches

The mean per each attacking play coefficient was computed and then used in a temporal series throughout a match. Hence, the temporal analysis is not the real time but the sequence of all attacking plays. A fitting smoothing spline was considered in order to ensure at least a coefficient of determination (*R*-square) of 0.70. The values of the *R*-square and the Root Mean Squared error per each match and tactical metric can be observed in table 5.

Table 5. Data of *R*-square and root mean squared error per each tactical metric

Data set	Fitting method	*R*-square	Root Mean Squared Error
Draw1 coverage	Smoothing spline	0.6986	0.1851
Draw1coverage in support	Smoothing spline	0.7505	0.2323
Draw1 coverage in vigilance	Smoothing spline	0.7184	0.1803
Draw1 depth mobility	Smoothing spline	0.7503	0.1946
Lose2 coverage	Smoothing spline	0.7047	0.1927
Lose2 coverage in support	Smoothing spline	0.7480	0.1848
Lose2 coverage in vigilance	Smoothing spline	0.7536	0.1987
Lose2 depth mobility	Smoothing spline	0.7295	0.1581
Win3 coverage	Smoothing spline	0.7694	0.1850
Win3 coverage in support	Smoothing spline	0.8988	0.2135
Win3 coverage in vigilance	Smoothing spline	0.7137	0.1876
Win3 depth mobility	Smoothing spline	0.7521	0.1779

It is possible to observe in Figure 9 a variation of coefficient throughout the attacking plays. Nevertheless, such variability seems to be regular mainly in the attacking coverage and the coverage in vigilance, with values greater than 0.4. The coverage in support tends to be reduced during attacking instants.

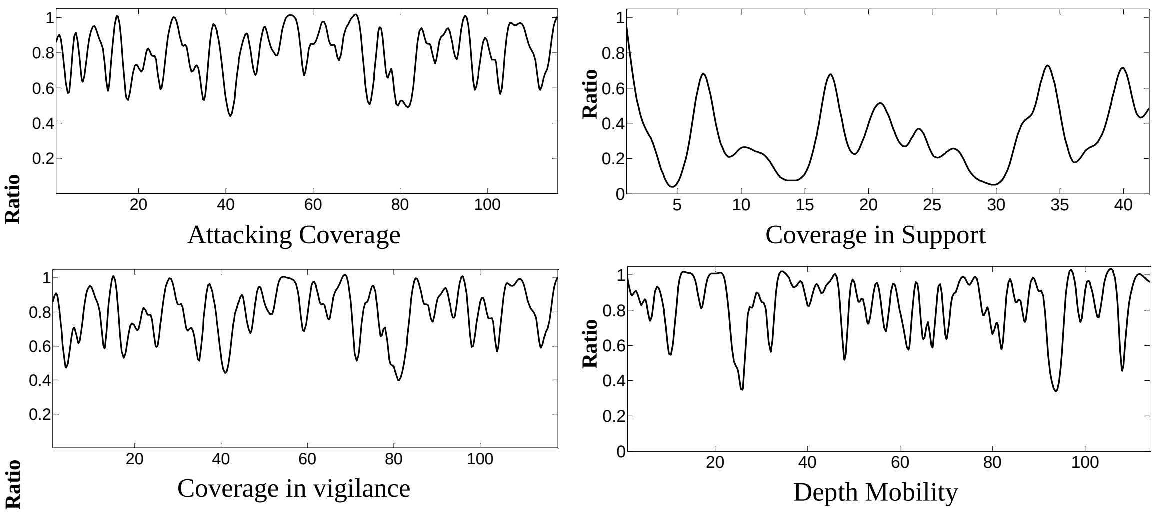


Figure 9. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout first match (score – draw)

In the second match (lose) (Figure 10), it was possible to observe similar patterns of variability throughout the match when compared to the first match. The coverage in support still presents lower value but, in this case, the wave seems to be more regular that in match 1 (draw).

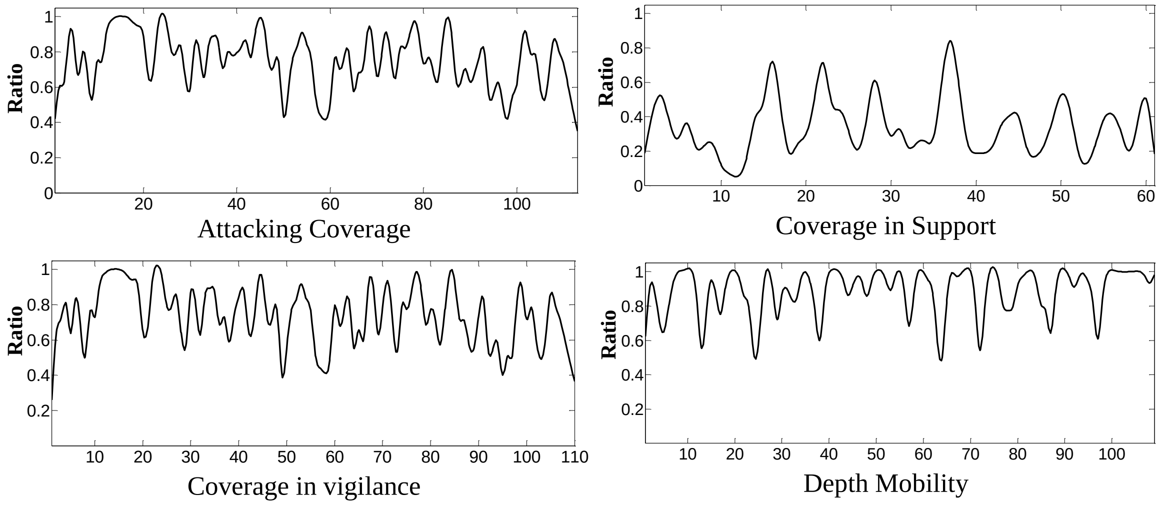


Figure 10. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout second match (score – lose)

In the third match (win) (Figure 11), it is possible to observe the highest values of coverage in support coefficients throughout the temporal series. The waves of attacking in coverage and coverage in vigilance are very similar and this can be justified by the fact that the team opts to play using long passes, thus reducing the possibilities of short passes.

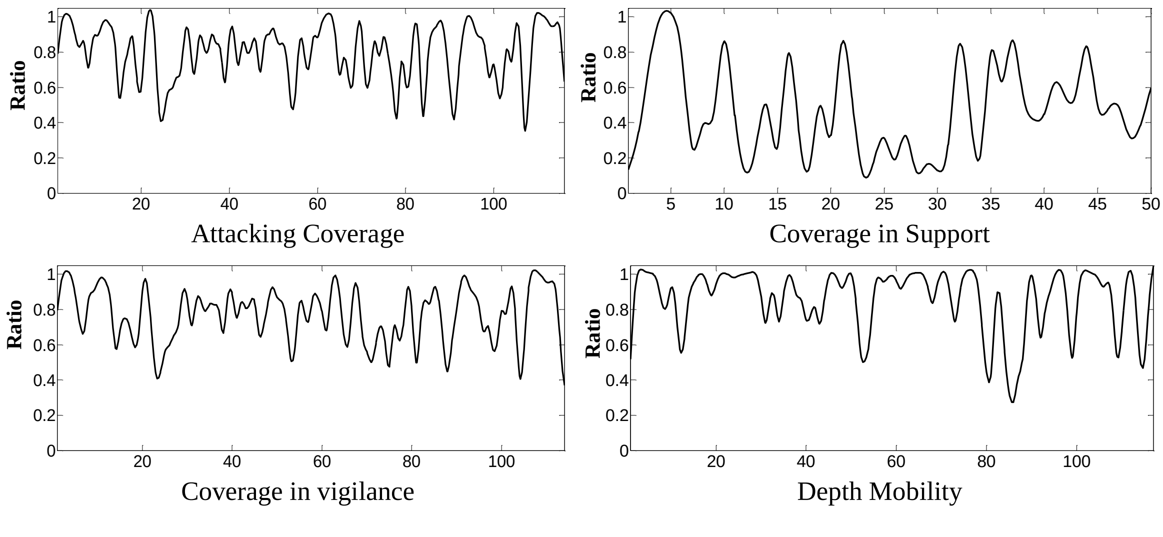


Figure 11. Temporal-series of tactical metrics coefficient [range between 0 and 1] throughout third match (score – win)

From these temporal-series, it was possible to observe values of Root Mean Squared Error between 0.2323 and 0.1581.

4. Discussion

The new possibilities that come from new technological advances allow the development of new metrics to evaluate human performance (Clemente, et al., 2013c). In the particular case of team sports it is important to understand how players cooperate and synchronize their spatiotemporal relationships in organizing themselves to achieve the main goal (Duarte, Araújo, Correia, & Davids, 2012). Therefore, the study of teammates' synchronization represents an important step forward to improve sports training, organizing sessions using the information collected from the matches or even the collective performance during training sessions.

Therefore, the aim of this study was to propose a set of automatic collective metrics (automatic data processing) to estimate how teammates cooperate and synchronize their spatiotemporal relationship during the attacking process to support each other. In such behaviour designated as cover it is very important to provide the player in possession of the ball some different solutions to ensure success in the building of the attack (Trapattoni, 1999; Dooley & Titz, 2011). Taking this into consideration four different metrics (attacking coverage; attacking coverage in support; attacking coverage in vigilance; depth mobility) with an individual ratio were developed in order to provide information about how a team provides such coverage.

The principle of cover can be performed in two main ways: *i*) in vigilance; and *ii*) in support. In support mean the great proximity of teammates to the player with ball possession, providing him with a short line of passes. In the case of cover in vigilance, this mean teammates perform some movements to create a line of passes in a peripheral position from the ball's location (Castelo, 1996).

Using both ratios of cover in support and vigilance it was possible to observe that in this case study the teammates ensured a higher level of cover in vigilance (0.7 in mean) than in support (0.3 in mean). Such results can be explained by the way the measure was developed. To ensure coverage in support it is necessary to have at least two players in the attacking definition zone and a numerical equality or superiority with opponents as well. Therefore, both conditions decrease the possibilities of ensuring such a principle in every move. Moreover, the closer to the opponents' defensive area, the greater the number of opponents' players inside the centre-of-game. In that sense, in order to overcome this problem, the cover in vigilance is very important for providing the player in possession with some possibilities to take off the ball from the zone with pressing. Consequently, the higher value ratio in the case of cover in vigilance is understandable given the previous discussion.

The option to provide a greater level of coverage in vigilance can be associated with the space covered by the team. In fact, the attacking process is characterized by all the team covering a large space (Clemente, et al., 2013c). Consequently, inter-players' distances increase, thus reducing the proximity to the player in possession of the ball and increasing the possibilities to generate long lines of passes. Such hypothesis must be inspected in further studies in order to better understand how both facts are connected.

From both types of cover, measuring the attacking cover was also proposed in this study. To accomplish such a principle at each play, one in support or in vigilance cover must be performed. The mean ratio of 0.78 suggested a higher regularity of performing such a principle at each offensive play. Moreover, the level of dispersion was moderate, thus reinforcing the accomplishment of this principle throughout the match. In fact, the cover action is one of the main actions to be performed during the match. In 'invasion' sports, such as football, the player with the ball must have the greatest possible number of options to ensure the success of their action. Even in the defensive phase cover is important to support the first teammate that tries to recover the ball. In that sense, these cover principles should be one of the main indicators to measure tactical behaviour in sports teams. It would be interesting in further studies to combine some spatiotemporal metrics such as the stretch index or the effective area of play with these principles of cover. With such an analysis it will be possible to understand whether the distance between teammates contributes to a better accomplishment of cover principles.

The last ratio proposed in this study was the depth mobility. This principle allows the analysis of how forward players provide solutions closer to the opponents' defenders. Depth mobility is very important for many teams who opt to play in a counter-attack style or that use many long and deep passes. In this case study it was possible to observe a ratio closer to maximal value (0.90). This value can be explained by the option to ensure that at least one player stays closer to the last opponents' defender, providing a forward option for the teammate with the ball.

In this case study it was possible to analyse that the team opted to perform attacking coverage using the farthest players from the ball. The greater values of success ratio were in the cover in vigilance and depth mobility, thus suggesting that this specific team play a specific type of game. As a case study, there still remain many issues to be solved in the future. One of them is to explore such tactical principles in a bigger sample with different teams that have different styles. It would also be interesting, as discussed above, to combine the information from the principles of play with other spatiotemporal metrics (e.g., Bourbousson, et al., 2010; Clemente et al., 2013c) to identify some specific properties and how those relationships improve the quality of tactical behaviour measured using these ratios.

In another perspective, it would be interesting to use these tactical metrics to inspect the variability of teammates' synchronization throughout the football game. Moreover, it may be possible to inspect possible variations of playing patterns between different periods of the match. It can also be possible to use those metrics to compare the performance of the collective behaviour between top-level and amateurs teams or between novice and expert players.

5. Conclusion

The aim of this case study was to propose four different tactical metrics to inspect the behaviour of football teams. The results showed that the team opted to use, with higher regularity and success, cover in vigilance and the depth mobility, suggesting a tendency to play in a larger space. From the results, it is expected that these metrics will help coaches to analyse the regularity of how their players provide cover throughout the matches, even during the training sessions. Using this information, it is possible to organize the training sessions and tasks to improve such playing principles. Moreover, these ratios can complement by a match analysis software that considers multiplayer tracking in a real or post-match way. Such metrics are only dependent from the Cartesian information of players' positions in the field, thus reducing the time expended by operators to perform such manual analysis.

6. References

Abdel-Aziz, Y., & Karara, H. (1971). Direct linear transformation from comparator coordinates into object space coordinates in close-range photogrammetry. ASP symposium on close-range photogrammetry (pp. 1-18). Falls Church, VA: American Society of Photogrammetry.

Bourbousson, J., Sève, C., & McGarry, T. (2010). Space–time coordination dynamics in basketball: Part 2. The interaction between the two teams. **Journal of Sports Sciences**, 28(3), 349-358.

Castelo, J. (1996). Futebol a organização do jogo: como entender a organização dinâmica de uma equipa de futebol e a partir desta compreensão como melhorar o rendimento e a direcção dos jogadores e da equipa. S.I.: Jorge Castelo.

Clemente, F. M., Couceiro, M. S., Martins, F. M., Dias, G., & Mendes, R. (2013a). Interpersonal Dynamics: 1v1 Sub-Phase at Sub-18 Football Players. **Journal of Human Kinetics**, 36, 181-191.

Clemente, F. M., Couceiro, M. S., Martins, F. M., & Mendes, R. (2013b). An Online Tactical Metrics Applied to Football Game. **Research Journal of Applied Sciences, Engineering and Technology**, 5(5), 1700-1719.

Clemente, F. M., Couceiro, M. S., Martins, F. M., Mendes, R., & Figueiredo, A. J. (2013c). Measuring tactical behaviour using technological metrics: Case study of a football game. **International Journal of Sports Science & Coaching**, 8(4), 723-739.

Couceiro, M. S., Clemente, F. M., & Martins, F. M. (2013). Analysis of football player's motion in view of fractional calculus. **Central European Journal of Physics**, 11(6), 714-723.

Costa, I. T., Garganta, J. M., Greco, P. J., & Mesquita, I. (2009). Princípios Táticos do Jogo de Futebol: conceitos e aplicação. **Motriz**, 15(3), 657-668.

Costa, I. T., Garganta, J., Greco, P. J., Mesquita, I., & Seabra, A. (2010). Influence of Relative Age Effects and Quality of Tactical Behaviour in the Performance of Youth Football Players. **International Journal of Performance Analysis in Sport**, 10(2), 82-97.

Davids, K., Araújo, D., & Shuttleworth, R. (2005). Applications of Dynamical Systems Theory to Football. Em T. Reilly, J. Cabri, & D. Araújo, **Science and Football V** (pp. 556-569). Oxon: Routledge Taylor & Francis Group.

Dooley, T., & Titz, C. (2011). **Football – The 4-4-2 System**. Germany: Meyer & Meyer Sport.

Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sports Teams as Superorganisms: Implications of Sociobiological Models of Behaviour for

Research and Practice in Team Sports Performance Analysis. **Sports Medicine**, 42(8), 633-642.

Frencken, W., Lemmink, K., Delleman, N., & Visscher, C. (2011). Oscillations of centroid position and surface area of football teams in small-sided games. **European Journal of Sport Science**, 11(4), 215-223.

Gréhaigne, J. F., Bouthier, D., & David, B. (1997). Dynamic-system analysis of opponent relationship in collective actions in football. **Journal of Sports Sciences**, 15(2), 137-149.

Gréhaigne, J. F., Richard, J. F., & Griffin, L. (2005). **Teaching and learning team sports and games**. New York: Routledge Falmar.

McGarry, T., Anderson, D., Wallace, S., Hughes, M., & Franks, I. (2002). Sport competition as a dynamical self-organizing system. **Journal of Sports Sciences**, 20(10), 771-781.

Passos, P., Araújo, D., Davids, K., Gouveia, L., Serpa, S., Milho, J., & Fonseca, S. (2009). Interpersonal pattern dynamics and adaptive behavior in multi-agent neurobiological systems: A conceptual model and data. **Journal of Motor Behavior**, 41, 445-459.

Passos, P., Milho, J., Fonseca, S., Borges, J., Araújo, D., & Davids, K. (2011). Interpersonal distance regulates functional grouping tendencies of agents in team sports. **Journal of Motor Behaviour**, 43(2), 155–163.

Pestana, M. H., & Gageiro, J. N. (2008). Análise de Dados para Ciências Sociais: A complementaridade do SPSS. Lisboa, Portugal: Edições Sílabo.

Trapattoni, G. (1999). **Coaching High Performance Football**. Spring City, Pensylvania: Reedswain Inc.

Worthington, E. (1974). **Learning & teaching football skills**. California: Hal Leighton Printing Company.

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