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USING COLLECTIVE METRICS TO INSPECT SPATIO-TEMPORAL RELATIONSHIPS BETWEEN FOOTBALL PLAYERS

Filipe M. CLEMENTE[1,2,3], Micael S. COUCEIRO[4,5], Fernando M. L. MARTINS[1,2,6], Rui S. MENDES[1,2] & António J. FIGUEIREDO[3,7]
[1]Polytechnic Institute of Coimbra, ESEC, Department of Education, Coimbra, Portugal
[2]Polytechnic Institute of Coimbra, RoboCorp, ASSERT, Coimbra, Portugal
[3]Faculty of Sport Sciences and Physical Education, University of Coimbra, Coimbra, Portugal
[4]Artificial Perception for Intelligent Systems and Robotics (AP4ISR), Institute of Systems and Robotics (ISR), University of Coimbra, Polo II, Coimbra, Portugal
[5]Ingeniarius, Lda., Mealhada, Portugal
[6]Institute of Telecommunications (Instituto de Telecomunicações), Covilhã, Portugal
[7]CIDAF, Faculty of Sport Sciences and Physical Education, University of Coimbra, Coimbra Portugal

ABSTRACT

The aim of this study was to analyse the influence of score status on the spatio-temporal relationships between team mates. Four collective metrics (weighted Centroid, weighted Stretch Index, Surface Area and Effective Area of Play) were computed based on the location of the players at each second of a match. Three matches of a team were analysed and 9218 position instants of 22 players and the ball were collected. Statistically significant differences with small effects were discovered in three possible scores in all dependent variables: Weighted Centroid y ($F_{(2, 9215)}=236.627$; $p<0.001$; $\eta^2=0.049$; Power=1.00); Weighted Centroid x ($F_{(2, 9215)}=126.985$; $p<0.001$; $\eta^2=0.027$; Power=1.00); weighted stretch index ($F_{(2, 9215)}=190.005$; $p<0.001$; $\eta^2=0.040$; Power=1.00); Surface Area ($F_{(2, 9215)}=322.809$; $p<0.001$; $\eta^2=0.065$; Power=1.00); and Effective Area of Play ($F_{(2, 9215)}=139.352$; $p<0.001$; $\eta^2=0.029$; Power=1.00). The present study showed that score status influenced the collective organisation. This is in line with previous findings which, after performing notational analysis, suggest that a team's strategies are also influenced by the score status.

Key words: Collective behaviour; Match analysis; Metrics; Football Tactics.

INTRODUCTION

Special attention has been given to the analysis of collective behaviour in team sport in recent years (Duarte *et al*., 2012). One explanation for this can be the holistic viewpoint on the complex behaviour supported by chaos theory and dynamical systems (Kauffmann, 1993; Kelso, 1995; Davids *et al*., 2005). In addition, recent advances in technology allow for a more thorough analysis of the information about the players' position on the field (Carling *et al*., 2008). This information makes is possible to develop and apply a set of individual and collective metrics which would improve the understanding about player, and thus, team behaviour. Until now several metrics have been proposed in order to build a systemic understanding about the collective behaviour of teams (Bourbousson *et al*., 2010b; Frencken *et al*., 2011). The main metrics proposed in the literature until now are: (a) Centroid (Yue *et al*., 2008); (b) Stretch Index (Bourbousson *et al*., 2010b; Moura *et al*., 2012); (c) Surface Area (Okihara *et al*., 2004; Frencken *et al*., 2011); (d) Effective Area of Play (Clemente *et al*., 2013); (e) Territorial Domain (Vilar *et al*., 2013); (f) Networks (Bourbousson *et al*., 2010a); and (g) Dominant Region (Taki *et al*., 1996).

The complexity of team sports promotes a high interest in their comprehension. Thus, match analysis is one of the most important areas to have been improved recently in scientific sport fields in order to assist with improvement of team performance (Reilly & Gilbourne, 2003). Recently, the action range has been increasing from the individual notational analysis to the tactical analysis, crossing the kinematic analysis (Yue *et al*., 2008). Nevertheless, due to their technological complexity, the tactical and collective behaviours have been under explored until now (Passos *et al*., 2011). Thus, there remains much to explore and understand about the way collective behaviour influences sport performance.

In professional team sport the main objective is the final score. Thus, during the match many strategies are performed to achieve the best possible score. Strategies are different depending on the team's score status (losing, winning or drawing). Most teams usually have a higher attacking intensity during unfavourable events (drawing or losing), in order to reverse their score status. Nevertheless, the collective behaviour of the team has not been studied thoroughly enough based on the team's score status. The collective behaviour value variation should in fact be further examined in order to improve the understanding about a teams' interaction. Inspecting different behaviours in relation to the score status makes it possible to characterise the team's process, thus helping to improve the players' interaction within their own team or to explore the opposing team's weaknesses.

PURPOSE OF THE STUDY

The aim of this study was to analyse the team's collective behaviour in the three possible match scores (winning, drawing and losing), in order to identify the differences in the collective behaviour related to score status. Score status was defined as the period of time that a given team had one of three possible scores during the match, thus score status can change during the match. A professional football team from the official Portuguese first league championship was analysed during different home matches. Statistically significant differences were expected in the collective behaviour among the three different score statuses.

METHODOLOGY

Sample

Three home matches of a professional team were analysed. Each match had a different final score (winning, losing or drawing). Thus, 1 match was considered for each final score. Overall, 9218 instances of time were considered and obtained from the 3 matches. All of the collected data complies with the American Psychological Association ethical standards for treatment of human or animal subjects.

Data collected

The teams' actions were captured using a digital camera (*GoPro Hero* with 1280 x 960 resolution), with the capacity to process images at 30Hz (30 frames per second). The camera was placed on an elevated position above the ground (from 10m to the field lateral line and in an elevation of 15m) in order to capture the whole field. The field dimensions were 104 x 68m. The field was calibrated using special markers allowing recognition of them on the images.

The first step in the collection of the data was to record the players' behaviour using the digital camera as described. The camera was placed facing the middle line of the field. Considering that this digital camera can record with 180º, it was possible not to move the digital camera, thus ensuring the same marker positions were captured on the digital image. The field was calibrated using 19 markers positioned on the referential field lines. These markers were metrically identified from point zero, which was the inferior vertex of the field (Figure 1).

***FIGURE 1*: INITIAL CALIBRATION TO EXTRACT THE DIRECT LINEAR TRANSFORMATION**

***TABLE 1*: POSITIONING OF MARKERS IN LONGITUDINAL AND LATERAL AXES FOR INITIAL CALIBRATION**

Space	**#1**	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
x (m)	0	52	104	104	104	104	104	104	52	0
y (m)	0	0	0	13.9	30.4	37.9	54.4	68	68	68

Space	**#11**	**#12**	**#13**	**#14**	**#15**	**#16**	**#17**	**#18**	**#19**
x (m)	0	0	0	0	87.7	87.7	16.3	16.3	52
y (m)	54.4	37.9	30.4	13.9	13.9	54.4	54.4	13.9	34

x= Marker longitudinal axis (metres) y= Marker lateral axis (metres) #= Marker

After capturing the football match, the physical space was calibrated using Direct Linear Transformation (DLT), which transforms the elements' position (players and ball) in pixels to the metric space (Abdel-Aziz & Karara, 1971). This method consists of a proportional equivalence of virtual space on real physical space. This calibration is based on the identification of field markers (real coordinates) on virtual images (virtual coordinates) (Fernandes *et al*., 2010). This procedure was performed using the software MATLAB.

First, a calibration based on the first frame of each half of each match was performed. The initial calibration aimed to extract the DLT coefficients provided from 19 bi-dimensional markers on virtual space (pixels) for the real physical space (metres), following the correspondence between Figure 1 and Table 1.

A graphical interface allowing for the visualisation of 1 frame of the match per second was developed. During each frame the operator was requested to identify the locations of all players and the ball following the typical approach point and click. That identification corresponded to 1 point in the centre of the player's feet. Each point on the virtual space (pixels) of the image was converted using an algorithm[1] based on the relationship between virtual coordinates and real coordinates defined by Figure 1 and Table 1.

In order to ensure that the reliability of such a conversion was defined, experimental tests with random points on the field collected previously were mapped with real coordinates and the space measured metrically. On the toolbox developed through MATLAB, those points and the results were identified to allow for the identification of the higher standard deviation that was 5cm in relation to the real coordinates. This border was considered viable to perform the study because it did not compromise the main goal of study, which was to identify the spatio-temporal relationship between players. For a detailed description of this tracking process (DLT) consult Woltring and Huiskes (1990).

For the purpose of efficiency, only play moments were used, that is all moments in which the ball was not in the field (ball out of play) were excluded from the analysis. The methodology herein proposed has a computational complexity inherent to it, meaning each second will correspond to each analysed instant.

Computing the tactical behaviour

Five collective metrics were computed for the match analysis: (a) Weighted Centroid; (b) Weighted Stretch Index; (c) Surface Area; and (d) Effective Area of Play. A summary explanation about each metric will be presented below.

Weighted Centroid (wC)

The Centroid is the geometric centre calculation of the team. The usefulness of the team's centroid may be the potential to compute the in-phase relation between the 2 opposing teams in longitudinal and lateral directions (Bourbousson *et al*., 2010b). Moreover, it can be a useful metric to analyse the equilibrium point of the team, with regards to their distribution.

[1] The script that allow the remapping of virtual coordinates in real coordinates having as input the DLT coefficients can be seen at http://isbweb.org/software/movanal/reconfu2.m

The Centroid calculation has been proposed without considering the ball and the player's proximity to it. Nevertheless, the proximity to the ball is an important indicator that should be considered. The approach of Clemente *et al*. (2013) was used, considering that the proximity of the players to the ball would assign different weights to the centroid position. The relevance of each player to the team's Centroid, w_i weight, was based on the Euclidean distance of each player to the ball,

$$w_i=1-\frac{\sqrt{(x_i-x_b)^2+\left(y_i-y_b\right)^2}}{d_{max}} \quad (1)$$

where (x_b, y_b) corresponds to the position of the ball and d_{max} is the Euclidean distance of the farthest player to the ball at each iteration (Clemente *et al*., 2013).

Weighted Stretch Index (wSI):
The Stretch Index measures the space expansion or contraction of the team on the longitudinal and lateral directions (Bouboussonson *et al*., 2010a). The Stretch Index is measured based on the centroid position, thus it is the sum of each player's dispersion on both axes. Similarly to the team's Centroid, a Weighted Stretch Index metric for the team may then be calculated as (Clemente *et al*., 2013),

$$s_{ind}=\frac{\sum_{i=1}^{N} w_i d_i}{\sum_{i=1}^{N} w_i} \quad (2)$$

where d_i is the Euclidean distance between player i and the team's Centroid.

$$d_i=\sqrt{(x_i-\overline{x})^2+\left(y_i-\overline{y}\right)^2} \quad (3)$$

Within this context, the Stretch Index can be obtained by computing the mean of the distances between each player and the Centroid of the team.

Surface Area (SA)
The Surface Area is based on the calculation of the entire area covered and the sum of triangulations emerging from the match (Frencken *et al*., 2011). Therefore, the sum of emerging triangulations is the value of all possible triangular combinations of N players, in which N is the total number of players within a team (Clemente *et al*., 2013). In the particular case of football, a maximum of 11 players (for each team) could be on the field at the same time. Hence, all possible combinations of 3 out of 11 players, is a total of 165 cumulatively formed triangles (Clemente *et al*., 2013). Consequently, the sum and area of the triangulations are computed at every instant.

Effective Area of Play (EAP)
The Effective Area of Play metric is based on the Surface Area. It is one more parameter related to ball possession. This parameter is used to analyse the overlapping occurring between opposite triangulations. When a defensive triangulation has an area of more than 36m, the offensive triangulation will be considered instead of the defensive one (Clemente *et*

al., 2013). A greater amount of open space between the defensive players decreases the difficulty for the offensive players to overcome the opposition (Dooley & Titz, 2011).

Statistical procedures

The one-way ANOVA was used to analyse the statistically significant differences between teams with and without ball possession. The assumption of normality distribution of one-way ANOVA in the 2 conditions (with or without ball possession) was assessed using the correction of the Kolmogorov-Smirnov test by Lilliefors. Although the distributions are not normal in the dependent variable, (since n>30), and because of the use of the Central Limit Theorem, normality was assumed (Maroco, 2010). The analysis of homogeneity was carried out using the Levene test. It was found that there is no uniformity of practice under the previously mentioned conditions. However, despite the lack of homogeneity, the F-test (ANOVA) is robust to homogeneity violations when the number of observations in each group is equal or approximately equal (Pallant, 2011), which was the case in this study. The violation of the assumption of normality does not radically change the F-value (Pallant, 2011). The classification of the size effect (measure of the proportion of the total variation in the dependent variable explained by the independent variable), and the power of the test were done according to Hopkins *et al*. (1996). The statistical analyses were performed using IBM SPSS Statistics (version 21) with a significance level of 5%.

RESULTS

***TABLE 2*: DESCRIPTIVE STATISTICS FOR EACH DEPENDENT VARIABLE DURING THE SCORE STATUS**

Variables		**Mean**	**Std. Deviation**
Centroid *y*	Loss	37.31	10.32
	Draw	33.36	9.14
	Win	32.09	10.35
	Total	34.38	10.22
Centroid *x*	Loss	49.81	13.82
	Draw	47.77	13.54
	Win	44.25	14.20
	Total	47.39	14.04
Weighted Stretch Index [m]	Loss	15.85	3.76
	Draw	17.44	3.48
	Win	15.91	3.54
	Total	16.38	3.68
Surface Area [m^2]	Loss	14403.85	5707.70
	Draw	17356.31	5119.86
	Win	14401.03	4684.26
	Total	15350.38	5389.11
Effective Area of Play [m^2]	Loss	7445.19	6071.68
	Draw	9674.15	6634.92
	Win	7292.82	5837.39
	Total	8111.91	6278.68

The collective behaviour was examined considering the team's score status (Table 1). From this analysis it was possible to identify that teams increase their average longitudinal (*x*-axis) position when the score status is unfavourable. Moreover, when teams have a losing score, they increase their average lateral position (*y*-axis) turning to the left side of the field. The dispersion metrics (Stretch Index and Surface Area) increase their values during score status of drawing a match. A similar situation can be observed in the effective area metric.

The *one-way* ANOVA was performed to inspect the collective behaviour variance between the 3 different score statuses during the matches. Statistically significant differences with small effects were found between the 3 possible score statuses in all dependent variables:

Weighted Centroid *y* ($F_{(2, 9215)}$=236.627; $p<0.001$; η^2=0.049; Power=1.00);
Weighted Centroid *x* ($F_{(2, 9215)}$=126.985; $p<0.001$; η^2=0.027; Power=1.00);
Weighted Stretch Index ($F_{(2, 9215)}$=190.005; $p<0.001$; η^2=0.040; Power=1.00);
Surface Area ($F_{(2, 9215)}$=322.809; $p< 0.001$; η^2=0.065; Power=1.00); and
Effective Area of Play ($F_{(2, 9215)}$=139.352; $p<0.001$; η^2=0.029; Power=1.00).

In order to inspect the differences between the 3 possible score statuses, the Tukey's HD post hoc test was applied (Table 3).

***TABLE 3*: MEAN DIFFERENCE BETWEEN THREE SCORE STATUSES FOR ALL DEPENDENT VARIABLES**

Dependent variables	**Match**	Losing	Drawing	Winning
Centroid *y*	Losing	-	3.946*	5.221*
	Drawing		-	1.275*
	Winning			-
Centroid *x*	Losing	-	2.035*	5.555*
	Drawing		-	3.520*
	Winning			-
Weighted Stretch Index	Losing	-	–1.594*	–0.057
	Drawing		-	1.537*
	Winning			-
Surface Area	Losing	-	–2952.469*	2.810
	Drawing		-	2955.279*
	Winning			-
Effective Area of Play	Losing	-	–2228.956*	152.369
	Drawing		-	2381.325*
	Winning			-

*Mean difference is significant at the 0.01 level

It can be observed that only between the losing and winning statuses no differences for the Weighted Stretch Index, Surface Area and Effective Area of Play metrics were detected. For all remaining situations there were statistically significant differences.

DISCUSSION

The importance of the synchronisation among players is unquestionable (Travassos *et al*., 2012). This inter-player relationship should be analysed in order to understand if it really depends on the score status. The inter-player relationships in football follow some fundamental rules that are general for all teams (Gréhaigne *et al*., 2005). They are usually depicted as fundamental tactical principles of play (Costa *et al*., 2010). Despite these natural and useful principles, several changes become evident in the team's organisation during the game. The score status of a team is usually one of the main factors for increasing the emergence of new organisations and collective adjustments. Therefore, four collective metrics were applied during three different matches of a team where the score status varied during the match.

The Weighted Centroid metric was applied to measure the team's central point in the course of the match. In previous studies it was observed that the centroids of both teams are in-phase (synchronised) during the majority of the match, mainly on the longitudinal axis (Bourbousson *et al*., 2010b). It was also found that the majority of goals scored in open play resulted from an imbalance in the centroids, where the attacking team's Centroid overcame the opponent defensive team (Bourbousson *et al*., 2010b; Bartlett *et al*., 2012). In the present study the Weighted Centroid on the longitudinal axis was closer to the opponent's goal in the moments of disadvantage in the score (losing and drawing). This collective adjustment was statistically significant. This can be explained by the team's strategy to increase the opportunities to score (Bate, 1988). Thus, players increased their dispersion on the field with a higher frequency in order to invert the unfavourable situation. This advance in the field can be related to more ball possession and continuous attacks in order to increase the chance of scoring (Bate, 1988). In fact, previous studies suggested that there is a connection between the losing status and the increase in ball possession (Lago, 2009).

A significant decrease in the centroid location was observed during the winning status. These results are related to the strategy of the team to reduce their defensive pressure to the first third of the field in order to protect their own goal and revert to the disadvantage against the opponent's pressure to score. Thus, players in advantage opted to protect their goal, thus increasing the number of defensive players and at the same time they also tried to counter-attack in order to interrupt the opponent's advance (Lago, 2009). This strategy makes it possible to explore the possible ways to unbalance the opponent in the transition phase (the moment the opponent loses ball possession). This kind of behaviour was observed in previous studies which identified that ball possession was greater in the losing moments than it was in the winning ones (Lago-Peñas & Dellal, 2010).

Regarding the Weighted Centroid y, statistically significant differences depending on the score status were found. When a team is losing the match, they direct their exploration to the left side of the field, approaching the wing and away from the centre of the field. This can be associated with a greater tendency to attack continuously. During offensive playtime one of the most important tactical principles is to explore the width and length of the field (Costa *et al*., 2010). Therefore, it is expected that when a team increases their continued attack they mainly explore from the wings. On the other hand, a team reduces its distribution on the field during winning status, trying to explore more ways to counter-attack (Lago, 2009). This option reduces the exploitation of the field wings, thus maintaining a higher centralisation on the field. This is logical since the direct play style and counter-attack explore more the central zone and the space behind opponent defenders.

Despite the important information obtained from the Weighted Centroid, it is not possible to fully understand the way players cover the field and move away from the team's central point (Clemente *et al*., 2013). Therefore, the Weighted Stretch Index and Surface Area are used to provide information about players' dispersion (Bourbousson *et al*., 2010b). It was possible to establish that the dispersion was significantly higher during the drawing status. Moreover, no significant differences were observed between losing and winning moments. Both observations can be discussed and implemented in the team's strategy in order to improve their approach to obtaining the main goal. During the winning and losing moments there are two different kinds of defensive and offensive strategies.

For instance, while losing, a team tries to increase their ball possession, thus increasing their dispersion on the field in order to come closer to the opponent's goal (Lago, 2009). Their defensive pressure is higher in order to recover the ball as soon as possible so as to counter the disadvantage and build offensive plays. While winning, a team tries to protect their own goal by increasing the number of players in defensive positions and counter-attacking with a smaller number of players, thus ensuring the compactness of the defensive moments (Clemente *et al*., 2012). In both cases (losing and winning moments), the teams exhibit a great compactness. This compactness results from the small distance between team mates, therefore, their dispersion is lower than in drawing moments. During drawing moments a team tries to retain the defensive security while attempting to score a goal to win the game. Therefore, a team's compactness is lower due to the necessity of exploring the offensive moments by width and length. In defensive moments a team may disperse more due to the need to cover wide spaces in order to counter the opponent's exploration, except for the forward players who need to maintain their position for continued attacks.

The team mates' triangulations were analysed considering the Effective Area of Play metric (Clemente *et al*., 2013). The importance of these triangulations lies in that they secure the support in both offensive and defensive moments. In defensive moments the triangulation is generated based on the proximity between team mates. This closeness decreases the opponent team's opportunity to penetrate their defence (Trapattoni, 1999). In offensive moments, triangulations secure certain attacking strategies by providing support to the player with ball possession (Dooley & Titz, 2011). Similar to dispersion metrics, Effective Area of Play is significantly higher during drawing moments. This metric has a high positive correlation with both Weighted Stretch Index and Surface Area (Clemente *et al*., 2013), thus these results are in line with previous findings. In defensive moments, the effective triangulation is determined by the proximity between team mates. Therefore, the compactness formed during the losing and winning statuses decreases the effective area covered. Regarding the drawing status, the width and length are better explored, thus increasing the triangulations area in defensive and offensive moments.

Using collective metrics made it possible to understand the importance of score status in order to change teams' strategy and organisation. The collective adjustment depends on many factors, however, mainly on the score status (Lago-Peñas & Dellal, 2010). Different relationships between team mates were observed depending on the score status, thus suggesting the existence of changes in team mates' synchronisation during the match. These findings may have important practical implementations in football match analysis. For instance, a team's properties can be detected by observing certain changes in the team's Centroid, dispersion values and triangulations formed during the match. These observations can be used by coaches to improve the synchronisation of team mates by adjusting certain relationships. At the same time, the opponent coach can detect certain weak and strong points about the spatio-temporal relationships of the other team's players, hence taking advantage of this information for the benefit of his or her team.

This study would be improved by using some notational information, such as the ball possession, shots performed or the type of passes used in each score status. This information could promote the discussion, complementing some players' spatio-temporal relationships analysed from the collective metrics. The present study showed that score status influences collective organisation. This is in line with previous findings where the use of notational analysis suggested that a team's strategies are influenced by score status, thus changing a team's play style during the match (Jones *et al*., 2004; Bloomfield *et al*., 2005; Lago & Martín, 2007). In further studies the information obtained from the collective metrics and notational analysis should be used to increase the team's understanding process and improve the football match analysis.

CONCLUSION

The interrelationships among football team mates depend on many contextual factors. One of the most important is the score status during the match. Therefore, the spatio-temporal relationships between team mates were analysed in three possible score statuses. The results showed that the losing status increased the longitudinal dispersion of the players in the field in order to advance towards the opponent's goal. The losing status reduced the space between team mates, thus increasing the compactness. The winning status significantly reduced the central point of the team, thus keeping it closer to the team's own goal. During the winning moments, a team's compactness was similar to the one exhibited during the losing status. During the drawing moments the dispersion of team mates in the field was higher. Different score statuses constrain the collective behaviour, thus becoming an indicator for some adjustments in the team's organisation.

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Dr Filipe Manuel CLEMENTE: Faculty of Sport Sciences and Physical Education, University of Coimbra, Estádio Universitário de Coimbra, Pavilhão 3, 3040-156 Coimbra, Portugal. Tel.: + 351 239 802770, Fax.: + 351 239 802779, E-mail: Filipe.clemente5@gmail.com

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