Chapter 1
Brief Review About Computational Metrics Used in Team Sports

Abstract The purpose of this chapter is to analyze how position data have been used in the aim of match analysis. A brief related work will present the main measures and results that come from soccer analysis based on georeferencing. Individual measures that characterize the time-motion profile, tactical behavior, predictability, stability and spatial exploration of players will be discussed. Collective measures that represent the Geometrical Center and team's dispersion will be also presented during this chapter. The main evidences that resulted from these measures will be briefly discussed.

Keywords Position data · Georeferencing · Match analysis · Measures · Tactics · Soccer

1.1 Using the Dots to Characterize Individual Behavior: Related Work

Tracking systems have been used to follow the instantaneous positions of soccer players in both training and game situations [6]. These tracking systems determine the position of a player in a Cartesian coordinate system [35, 41], representing each player as a dot. Multicamera semi-automatic systems, local position measurement technology and global positioning system technology are the most used options to quickly record and process the data of players' positions on a pitch [3].

The wide use of these tracking systems provided new possibilities of analysis in the case of soccer. New applications and techniques are now used to determine and estimate individual and collective performance of players and teams [20]. Sports sciences are now capable of using the knowledge from scientific areas such as mathematics, physics, computer science and engineering to objectively measure performance, adjust training plans and make better decisions during a match [10].

The most common application of position data to support the daily practice of coaches and sport scientists is the calculus of time-motion profiles of players during training sessions and matches [5]. By using time-motion profiles, it is possible to

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determinate the external load of players during their activities, namely measuring walking, jogging, running, striding and sprinting distances and characterizing the high-intensity activities as accelerations and decelerations [31]. Individualization of these data provides immediate and significant information regarding training loads and the impact on each player [33]. Moreover, motion-analysis also allows to determine the extent of fatigue experienced by players during competitions and identify the variance of performance during the season [6].

Position data have also been used to analyze the behavior of players [16, 39, 41]. Players and the ball were tracked in a single match as a case-study [41]. In that study, it was observed that all players, except the goalkeeper, follow the movements of the ball more closely in the longitudinal axis than in the lateral one [41]. However, in the same study it was found that the ball changed direction in the lateral axis with more frequency than in longitudinal one.

The variability of movements has also been analyzed through the use of Kolmogorov Entropy, Sample Entropy or Approximate Entropy [24]. Such approach allows for the identification of positional variability of a player in a time-series and to understand the regularity of their movements during the game [39]. The information of a position in a histogram can also be measured in its variability by using the Shannon Entropy [17].

In a single-match case study it was found that the higher values of Approximate Entropy and Shannon Entropy were found in midfielders [17]. In an alternative application, it was found that increasing the pitch size (as a task constraint) would result in a decrease of variability, thus the individual player zone was smaller [39].

The exploration of the pitch can be another interesting use of position data in soccer. In a study that analyzed the influence of pitch area-restrictions on tactical behavior, it was found that the Spatial Exploration Index can be higher under free-spacing conditions [29].

As possible to identify, position data provide a lot of possibilities to analyze the motion of players and characterize the behaviors in different scenarios. The use of such approaches may provide information to adjust Small Sided Games (SSGs) (smaller versions of soccer games) [14] and to add specific task constraints that may help in the re-adjustment of individual tactical behavior [19]. The use of position data to characterize individual behavior is growing and for that reason the major applications have not been published, so far.

However, not only individual behavior can be measured by using position data. The synchronization with an individual opponent (dyad), with teammates (cooperation) or with the opponents (opposition) is another possibility, used to objectively measure and determine patterns of interaction. Based on that, Sect. 1.2 will briefly present the related work about the use of position data to characterize the collective behavior of players during the games.

1.2 Measuring the Collective Behavior Based on Data-Position: Related Work

Interaction between teammates can be interpreted and measured in many different ways [20]. Traditional and new approaches to the match analysis provide new insight about the information that can be used to characterize the teams and their process of cooperation and opposition with other teams [40]. For that reason, the analysis can be done on an intra-level, to characterize the networking of a team, or on an inter-level, to identify the "rapport de forces" (balance of strengths) [30].

Collective organization can be understood as a dynamic process that emerges from the context based on the constraints of the match [34]. The interactions among teammates may be measured with a position data analysis [10]. In a spatio-temporal analysis we may identify the synchronization of teammates and the shapes of the team in different playing scenarios [2].

Some measures based on position data have been proposed to classify the collective behavior of teams and to identify the synchronization with the opponents [20, 40]. The classification of the measures can be based on their aim [1]: (i) team center; (ii) team dispersion; (iii) team synchronization; and (iv) division of labor within teams.

Measures that analyze the team center aim at identifying the Geometrical Center of a set of dots (in this case, the players of a team) [9]. Three different approaches have been conducted to compute the Geometrical Center of a team: (i) the centroid, that represents the exact Geometrical Center of the dots (players), excluding the goalkeeper [27]; (ii) the weighted centroid, which considers all players but requires the position of the ball to attribute weights to the position of each player in order to compute the centroid [7]; and (iii) the centroid considering the middle of the two farthest players [32]. The team center has been used to identify the variance of the middle point of a team during the match, to analyze the in-phase relationships between centroids of both teams and to identify the oscillations of centroids in critical moments (e.g., shots, goals) [2, 13, 27, 38].

The purpose of team dispersion is to objectively measure the expansion of a team and the areas covered by the players [28]. Usually, the dispersion of the teammates depends both on the match and ball possession statuses [18]. A higher dispersion of teammates can be observed in attacking moments than in defensive ones [36]. Different measures based on position data have been proposed: (i) Stretch Index, which can be described as the mean dispersion of the players, considering the Geometrical Center [21, 41]; (ii) weighted Stretch Index, which considers the dispersion of the players to the weighted centroid [7]; (iii) team's spread, which also considers the overall dispersion of all players [36]; (iv) Surface Area, which represents the area of a polygon constituted by all teammates [22, 27]; (v) effective area of play, which only considers the effective triangulations made by teammates [13]; (vi) playing area, which represents the area of maximum width and length of a team, in each instant [26]; (vii) team length and width, which measures the dispersion in both axes [23]; and (viii) defensive play area and triangulations, which measures the area covered by each sector of a team during defensive moments [12].

The main results of team's dispersion revealed that teams occupy a bigger area while in possession of the ball than in defensive moments [11]. Moreover, some studies found that bigger areas occupied in defensive moments are associated with critical moments such as suffered shots or goals [36]. The analysis of the synchronization about the covered areas of both teams revealed a tendency to an in-phase relationship, with the exception of short periods of anti-phase [37]. These exceptions of anti-phase were associated with critical moments (e.g., shots and goals) [37].

The analysis of variability of these covered areas also revealed a tendency to be more regular throughout the match, with a higher variability in the first minutes of the game [22]. The comparison with performance variables suggests that teams cover greater areas against weaker teams [4] and that areas are bigger in drawing matches than in losing or winning matches [11]. Finally, the triangulations made between midfielders occupy a greater area than those between the other playing roles [15].

Different measures based on position data have been proposed to identify the properties of teams and the behaviors of players. The major ranges have been used to classify the division of labor among players [41]. The main evidences suggest that defenders increase the individual covered area in attacking moments and that forwards increase the areas in defending moments [20]. Voronoi diagrams have also been used to characterize the spatial behavior of players and teams [25].

The axes "drawn" by the defensive, midfield and forward sectors were also analyzed by a specific measure [8]. The Sectorial Lines measure represents the line of a set of dots (players) in a specific region of a team. The synchronization of these three lines (defensive, midfield and forward) was small, thus suggesting an independent angular positioning between sectors during attacking and defensive moments [8].

As possible to identify, all these collective measures provide an interesting approach to the analysis of the match and may reveal some patterns of interaction between teammates and between teams, which can be determinant to optimize the training process and to make informed decisions about the strategy to adopt in a game.

The following sections will discuss the usability of these measures in match analysis and how to compute them in a dedicated software called Ultimate Performance Analysis Tool (uPATO).

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