Move it or lose it: Exploring the relation of defensive disruptiveness and team success

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Abstract

Due to the increasing number of tracking data available for official matches in different leagues there are new ways to capture the performance of teams. To not rely on notational data, we previously introduced the D-Def (Goes et. al, 2018), an aggregated variable to quantify passing solely based on tracking data. This value captures the change of organisation by a pass (defensive disruptiveness). In this study, we updated the D-Def by including an automated classifier for subunits, instead of using starting formations, and investigated the relation of the D-Def on team success. Position tracking data of all players and the ball collected during 88 Dutch Premier League matches was used. Alignment of subunits was automatically identified, using a K-Means classifier, for every pass. D-Def was calculated for every pass (N= 63601) as an aggregate in the change in movement as a result of the pass-based team- and line centroids of subunits and surface and spread of the defending team. Team success was evaluated via wins and losses. We excluded 21 matches because they resulted in a draw. The predictive value of the D-Def for success was calculated using logistic regression analysis. The regression model achieved a R² of 0.69, which is high in comparison to other key performance indicators in the literature. This shows that the approach previously introduced as a proof of concept is related to match outcome. Therefore, D-Def can be a useful tool to evaluate team performance. This study highlights that performance is predictable through spatio-temporal aggregates based on player tracking data and we do not need to rely on notational data anymore.

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1 Introduction

Performance analysis in soccer in general and tactical analysis, in particular, did take great strides in the last decade due to the availability of player position (tracking) data. The installment of optical tracking systems allows to capture game performance in different ways and opens up new opportunities for match analysis (Rein & Memmert, 2016). Previously, match analysis was only based on event data captured via notational analysis that evaluates performance via on-ball events of teams and players (Sarmento et al., 2014). However, tactical performance in team sports should not just be seen as a chain of events but rather as the management of space, time and individual actions (Garganta, 2009; Rein & Memmert, 2016). By just using event data that does not capture the interaction of players, that is focused on the player with the ball and gives no insight in the behavior of off ball players, a quantification of this management is close to impossible. Combining this with the unclear reliability of event data, several authors advocate for the use of player tracking data to investigate tactical team performance (Gudmundsson & Horton, 2016; Rein & Memmert, 2016)

The use of tracking data enables approaches to investigate this management process in order to evaluate match performance. One approach which takes these spatial-temporal constraints into account is the team centroid method (Folgado, Lemmink, Frencken, & Sampaio, 2014; Frencken, Lemmink, Delleman, & Visscher, 2011). Here the behavior of the team centroid, the geometric center of the positions of all players from one team (Cx,y), is used to analyze the behavior of the entire team. Results from this line of research indicate a strong coupling between team centroids during gameplay (Frencken et al., 2011) and key game events like goals and shots on goal (Frencken, de Poel, Visscher, & Lemmink, 2012).

Besides the team centroid, aggregates like the line centroid, stretch index, team surface area, team spread, or regions of dominance are also used frequently to capture the complex spatiotemporal dynamics of soccer from tracking data (Rein and Memmert 2016; Memmert et al. 2017). In general, these aggregates have proven to be valid measures of behavior in small-sided games, yet in their current form, the ability to capture the complex tactical dynamics of full-sized matches can be questioned.

In a previous study, we were able to combine several of those spatio-temporal features in an new approach to measure pass performance of soccer players (Goes, Kempe, Meerhoff, & Lemmink, 2018). The evaluation of passes is one of the most common ways to asses' tactical performance at individual and team levels in (scientific) performance analysis. Performing a "good" pass is a key skill for successful performance in team sports (Bush, Barnes, Archer, Hogg, & Bradley, 2015) and a main predictor for success in soccer (Liu et al. 2016). Multiple authors have already used tracking data in their analysis to model pass options (Spearman, Basye, Dick, Hotovy, & Pop, 2017), or objectively quantify pass effectiveness (Link, Lang, & Seidenschwarz, 2016; Rein, Raabe, & Memmert, 2017), that way increasing our insight into passing performance.

However, the aforementioned approaches are all biased in the same way as they overvalue passes that move the ball towards the goal or directly lead to goals or shots on goal. Our approach, in contrast, is based on the displacement of defending players (I-Mov) and the disruption of the organization of the defensive team (D-Def). Both performance indicators value passes higher if the induce a higher amount of total movement of defending players (I-Mov) or result in a larger change in defensive alignment and distance and space between team subunits (D-Def). In a validation study we could demonstrate that our measures are sensitive and valid in the differentiation between effective and less effective passes, as well as between the effective and less effective players (Goes et al., 2018). In addition, we could show in a second study that I-Mov relates to classic individual pass performance parameters like passing accuracy of key passes (passes that create goals or shots on goal) (Kempe, Goes, & Lemmink, 2018).

As we proved the relationship of our approach on an individual level, we are investigating its importance on a team level in this study. Therefore, we analyze if this approach is able to correctly predict wins and losses in official match play.

In addition, we addressed two major issues within our approach. In previous studies, we used a set time window of three seconds to evaluate passing performance. Although this time window yielded valid results, it is arbitrary and does not represent the variability of passes performed during a match. Therefore, we now calculate the effect of a pass on a normalized per second basis. The second issue we addressed, concerns the calculation of subunits and the allocation of players to those subunits. In both previous studies we used team starting formations to calculate subunits and in consequence intra-team distances and subunit centroids. However, in a fluid game like soccer, formations change often during a game. Furthermore, teams often implement different formations while attacking or defending. To tackle this problem, we used the idea to cluster players in formations based on tracking data that showed promising results in previous research (Bialkowski et al., 2016, 2015).

To sum up, this study tries to prove that game outcomes can be reliably predicted based on pass performance indicators derived from tracking data quantifying the disruptiveness of a pass.

2 Quantifying Defensive Disruptiveness

To quantify the effect of a pass, we implemented an updated versions of two previously proposed features that capture the disruption of the defensive organization as result of a pass (D-Def), and the movement of all opposing players in response to a pass (I-Mov). The theoretical rationale behind these features is based on the assumption that the attacking team tries to create space between the opposing lines through destabilization of the links between the opposing attacking, midfield, and defensive lines, as well as through forcing the opponent to move.

The disruption of the defensive organization as result of a pass was quantified using our previously published Defensive Disruptiveness (Def-D) feature (Goes et al., 2018). This feature is constructed based on the change in the average position of the attacking, midfield, and defensive line, the change in the average team position, and the change in team surface area and team spread. The D-Def measure is constructed out of three components that are derived from the scaled absolute change on all of the afore mentioned variables (eq. 1). The first component is related to disruption in the longitudinal direction of the field (PC1), the second component is related to disruption in the lateral direction of the field (PC2), and the third component is related to disruption of the team surface and spread area (PC3). The absolute scores on these three components then make up the total disruption (D-Def) score.

$$D\text{-}Def = |\,PC1\,| + |PC2\,| + |\,PC3\,| \tag{1}$$

In our previous publication, the different lines (attack, midfield, defensive line) were manually determined based on the starting formation of the team, and player roles were constant. However, for this analysis we improved our approach by using a K-Means clustering (n_clusters = 3) algorithm to automatically detect the defensive formation. Based on the defensive formation (i.e. [4, 3, 3]), we then automatically identified, for example, the defensive line based on the 4 last players (excluding the goalkeeper) in every timeframe, creating a much more robust and representative feature. For further details we refer to our previous publications (Goes et al., 2018; Kempe et al., 2018).

The movement of all opposing players in response to a pass was measured using our previously proposed individual movement (I-Mov) feature. This feature is constructed based on the sum of the absolute displacement along the longitudinal (I-Mov-X) and lateral (I-Mov-Y) axis off all opposing players in response to a pass (eq. 2). In our previous publication, we used the sum of the displacement of all players to make up the I-Mov feature for the team. However, for the current analysis we improved

this by using the mean I-Mov per player, as this method is much more reliable in case of possible missing or erroneous data that occur quite frequently in tracking datasets.

$$\text{I-Mov} = (\mid \text{Disp. } X_1 \mid + \mid \text{Disp. } Y_1 \mid + \dots + \mid \text{Disp. } X_n \mid + \mid \text{Disp. } Y_n \mid) / n \qquad (2)$$

We computed both the D-Def and I-Mov feature for every pass received by a teammate during the entire match. This was conducted by computing the change/displacement on all feature components during the pass window (between the moment of the pass and reception), and then dividing this value by the duration of the pass window in seconds. This resulted in standardized displacement/disruption scores/second. In our previous paper, we used a window of 3 seconds after a pass, as we assumed this should be adequate to detect both the effect of the pass, and prevent the inclusion of effects of the next pass. However, we experimentally determined that the standardized pass-window as implemented in the current study was a better fit and therefore improved our feature.

3 Modelling Team Success based on Pass Disruptiveness

To evaluate tactical performance and analyze the relationship between tactical performance and match outcome, we collected and processed position tracking data on both teams for matches played during 4 consecutive Dutch Eredivise seasons. Players were tracked with a semi-automatic optical tracking system (SportVU; STATS LLC, Chigago, IL) that captures the X and Y coordinates of all players and the ball at 10 Hz. Our dataset contained 118 matches in which 26 unique teams played each other. As we were only concerned with the differences between winning and losing teams, we excluded matches that ended in a draw. This resulted in a final dataset that consists of 25 teams that played in 89 matches that resulted in a win or a loss and contained 98.718 pass attempts of which 60.524 passes were successful.

The data of every single match were first pre-processed with ImoClient software (Inmotiotec GmbH, Austria). Pre-processing consisted of filtering the data with a weighted Gaussian algorithm (85% sensitivity) and automatic detection of ball possessions and ball events based on the tracking data. Both the tracking data and the ball event data were then imported as individual data frames in Python 3.6 and automatically processed on a match-by-match basis. We then computed the separate components of both the D-Def as well as the I-Mov feature for every pass during a match. All features were computed according to the methods as described in section 2.

Table 1 - Descriptive statistics winning and losing teams (*: p = .05 ⁑: p < .05, ⁂: p < .01)

	Wins (N = 89)	Losses (N = 89)	Mean Diff.	Effect Size (Cohen's d)
Individual Movement (I-Mov)				
I-Mov-X (Mean)	0.866m ± 0.673m	0.515m ± 0.675m	+68.1%	0.52⁂
I-Mov-Y (Mean)	0.772m ± 0.600m	0.451m ± 0.591m	+71.2%	0.54⁂
I-Mov (Mean)	1.638m ± 1.268m	0.966m ± 1.265m	+69.6%	0.53⁂
I-Mov-X (Total)	261.46m ± 222.14m	163.53m ± 219.69m	+59.9%	0.44⁑
I-Mov-Y (Total)	238.85m ± 213.81m	142.92m ± 191.86m	+67.1%	0.47⁂
I-Mov (Total)	500.31m ± 434.39m	306.45m ± 411.12m	+63.3%	0.46⁑
Defensive Disruptiveness (D-Def)				
PC1 (Mean)	0.018 ± 0.015	0.013 ± 0.022	+34.1%	0.24*
PC2 (Mean)	0.010 ± 0.013	0.014 ± 0.033	-23.6%	-0.13
PC3 (Mean)	-0.026 ± 0.022	-0.021 ± 0.022	-25.5%	-0.25*

D-Def (Mean)	0.474 ± 0.048	0.484 ± 0.072	-2.0%	-0.16
PC1 (Total)	4.88 ± 4.17	4.14 ± 3.57	+17.8%	0.19*
PC2 (Total)	2.99 ± 4.09	3.28 ± 4.55	-8.9%	-0.07
PC3 (Total)	-7.96 ± 6.85	-6.30 ± 6.65	-26.2%	-0.24⁑
D-Def (Total)	133.60 ± 54.33	130.50 ± 46.12	+2.4%	0.06

To compare performance between winning and losing teams, we aggregated all feature scores into mean (values per pass), and total (sum over a full match) scores. We then took the means and standard deviations of all winning and losing teams for a between-group comparison (Table 1). Effect sizes were determined based on the Cohen's *d* and between group differences were statistically tested using an independent t-test. For completeness, we not only displayed and tested the composite feature scores, but also the individual components, as this might provide additional information.

As a next step, we predicted match outcome based on the mean total movement feature (I-Mov$_{Mean}$, as it captures both the movement in longitudinal as well as lateral direction), mean longitudinal disruption feature (PC1$_{Mean}$), and mean surface disruption feature (PC3$_{Mean}$). We choose this combination of features based on their discriminative power and the fact that the combination of these features yielded the highest accuracy and lowest log loss scores. To do so we first split the data set in a training set that contained 80% of the data, and a test set that contained 20% of the data, stratified on match outcome. Furthermore, we scaled (Z-transformed) our features to the same scale using a Min-Max scaling algorithm. We then fitted a 5-fold cross-validated Logistic Regression model to our training dataset and predicted winning and losing probability for both teams in every match. Based only on the mean total movement per pass (I-Mov$_{Mean}$), the mean longitudinal disruption per pass (PC1$_{Mean}$), and the mean surface disruption per pass (PC3$_{Mean}$), we were able to predict binary match outcome with an accuracy of 69.4% and a log loss of 0.65, based on the following regression equation (3):

$$\text{Outcome} = -0.146 + 0.689 \text{ I-Mov}_{Mean} + 0.172 \text{ PC1}_{Mean} - 0.592 \text{ PC3}_{Mean} \qquad (3)$$

4   Discussion

The aim of this study was to further validate our approach of using changes in spatio-temporal features, derived of player tracking data, to evaluate (tactical) match performance. Our findings illustrate that this approach is capable to reliably distinguish between winning and losing teams. Therefore, we could prove that our approach is not just valid on an individual but also on a team level. In previous studies, we already showed that our performance indicators are able to evaluate players and passes (Goes et al., 2018), as well as relate to individual performance like passing accuracy and assists (Kempe et al., 2018).

Within this study, we now also showed that the I-Mov clearly differentiates between winning and losing teams with a difference of mean induced movement of pass of 69,6% in favor of the winning teams. D-Def, as the more complex performance indicator that registers the changes in defensive organization, could not differentiate in the same way as the I-Mov. However, two of its three factors (PC1 & PC3) did yield statistical differences between winning and losing teams. One can assume from those results that changes in the longitudinal organization of the defending team, creating larger distances between the different lines of defense, and the surface of the team organization, shape and spread of the lines and the team in general, represent changes in overall organization while change in horizontal organization just adds noise to the equation.

In general, it is understandable that the I-Mov is a more sensitive feature as teams are able to maintain their overall organization while moving. Therefore, changes in the D-Def caused by a pass are way smaller than in the I-Mov. Following this line of assumption, the I-Mov might be the better Key

performance Index to evaluate an overall or game performance whereas the D-Def might be more suitable to identifying the one or two key passes in a chain of events that led to a decrease in structural organization of the defending team. Therefore, the D-Def might rather be used to study passing or attacking sequences also referred to as "quality of possession" (Collet, 2013) and the I-Mov as a measure of overall team performance.

By combining the features of mean player movement (I-Mov), mean longitudinal disruption (PC1), and the mean surface disruption per pass (PC3) we are able to correctly predict the winning team in 69,4% of our test set. This results are especially promising as previous (pass) performance indicators just showed a weak relationship with success (Rein et al., 2017). By our knowledge, this is the first approach that is solely based on player tracking data that is able to predict game outcome better than pure chance with a prediction power better then previous models based on event data (Collet, 2013; Oberstone, 2009).

In order to achieve this prediction performance, we updated our previous model in two important ways. First, instead of a three second window, we now normalize the effect of a pass per second. In the previous model we undervalued longer passes as their effect might not be captured in total with the three second window. In a second step, we implemented a new way to register team formations which are the basis to calculate the changes in defensive organization. Therefore, we adapted the idea of Bialkowski et al. (2015 & 2016). They use a K-Nearst Neibhour like appraoch to cluster players in different palying positions and formations showing that this appraoch is able to predict palying formation with a maximal mean variation of 5.5 m. By applying this idea to our appraoch, although in a differnet form, instead of starting formations of a team, we now differnatiate between offensive and defensive formation and are able to elvaluate passes by taking the change of palying positions and formations into acoount. Both of those updates increase the validity of our appraoch by reflecting the high amount of variation in the game of soccer.

5 Conclusion

In this paper, we could further demonstrate that an approach solely based spatiotemporal variables is able to capture tactical game performance on a team level and is able to reliable predict game outcomes. One of our performance indicators (I-Mov) could further highly differentiate between winning and losing teams. Therefore, the I-Mov might serve a new tool to evaluate team performance instead of unreliable event data like pass accuracy, percentage of ball possession, or shots on goals.

Disclosure Statement

The authors of this paper reported no conflicts of interest

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