TEAM COORDINATION DYNAMICS OF WINNING NBA TEAMS

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INTRODUCTION

Predicting sports games outcomes is an endless pursuit shared by stakeholders ranging from fans to coaches to data scientists. Researchers commonly use regression and other data mining tools to attack this problem. For example, basketball game outcomes have been most often predicted using combinations of traditional box statistics [1]. That approach, however, limits understanding of team coordination to *post hoc* information about team performance. Recently, we have begun investigating the value of positional data recorded during basketball game play with the ultimate goal of predicting outcomes from team dynamics as they emerge. We approached this problem by analyzing the "shape" of team movements on the court. Specifically, we investigated whether team dynamics in NBA games mimicked long range correlated (LRC) patterns observed in other team contexts [2]. LRC implies that team structure is not random but structured over time. Two methods, Detrended Fluctuation Analysis (DFA) and Recurrence Quantification Analysis (RQA) were used assess team structure. We hypothesized that differences in team coordination dynamics captured by two time series methods may be related to game outcomes (i.e., winning or losing).

METHODS

We analyzed 622 NBA games from an archival data set obtained from Neil Seward's "nba-movement-data" GitHub repository. Player positions were tracked via SportVu (SportVu, Tel Aviv, Israel) software. SportVu is a camera system that collects data 25 times per second, following the ball and all players on the court. This resulted in 3D positional data captured for the 30 teams in the 2015-16 NBA season.

Data for each game was divided into "Team 1" and "Team 2" for each of the 622 recorded games. Player data was collected for the entire game. Player X and Y position coordinates were filtered, using the known court dimensions, to only contain players that were within the bounds of the court. The area of the polygon implied by the five players on each team was then calculated at each time point during the game. All area time series obtained for each of the four quarters, were subjected to RQA and DFA. In this context, a metric called percent determinism (DET; output from RQA) describes a team's tendency span given a spatial area on the court. When DET = 0, team structure is essentially random; when DET = 100, the team never varies in its structure. DFA measures correlation in a series over time and returns a value, α. An $\alpha \approx 1$ indicates positive time correlation. An $\alpha \approx 0$ indicates negative correlation, and an $\alpha \approx 0.5$ indicates no correlation. In the current context, this provides information about changing team structure. For example, $\alpha \approx 1$ suggests that large areas tend to follow by large areas and small areas tend to be small areas. Analyses were done in R (R Core Team (2022)).

RESULTS AND DISCUSSION

We fit a linear mixed effects model with normalized α and percent determinism, respectively, as the outcome variable and a fixed effect of win/loss and random team effects (i.e., random intercepts). A linear mixed-effects (LME) model was chosen to account for the non-independence due to teams playing multiple times over the course of a season. The α value was converted to a z-score to transform the units to standard deviations and ease interpretation. On average the winning team has an α value that is 0.24 standard deviations (a small effect by conventional standards) higher than the losing team and a percent determinism value that is 0.40 percent higher than the losing team (Table 1).

CONCLUSIONS

These preliminary results suggest that analyzing positional data using time series data may provide meaningful information relating to game outcomes and team coordination dynamics. These methods could be implemented in real time allowing a coach to alter team offensive and defensive formations, tactics as well as lineups to ultimately improve team performance. Future work will expand on these initial analysis methods using additional time series tools over additional time granularities with the aim to better understand team coordination and its role in, not only overall game outcomes, but also at the level of individual plays.

REFERENCES

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Table 1. Results from the linear mixed model for normalized alpha and percent determinism calculated using DFA and RQA, respectively. P-value interpretations were based on a significance level of 0.05.

	Normalized Alpha			**Percent Determinism**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.12	-0.22 – -0.03	**0.011**	95.25	95.05 – 95.44	**<0.001**
Win - Loss	0.24	0.13 – 0.36	**<0.001**	0.40	0.19 – 0.60	**<0.001**