

## GRAPH-BASED QUANTIFICATION OF BASKETBALL SPACING USING SPATIAL AND NETWORK METRICS

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### **Abstract**

*In modern basketball, adequate player spacing is crucial for maximizing offensive efficiency and improving shot quality. This paper proposes a novel approach to quantifying spacing using graph theory. Each player is represented as a node, and the pairwise Euclidean distances between them form the weighted edges of a complete graph. We compute several spatial and structural metrics, including total spacing, convex hull area, minimum spanning tree weight, and centrality measures. A case study on simulated tracking data illustrates the applicability of the framework, revealing key patterns associated with successful possessions. Results demonstrate that specific geometric and network-derived properties are strong indicators of tactical efficiency, providing actionable insights for coaches, analysts, and sports scientists.*

**Keywords:** *basketball analytics, graph theory, spacing, player tracking, network metrics*

### **INTRODUCTION**

In the modern era of basketball, offensive systems have evolved to prioritize floor spacing as a fundamental tactical principle. Proper spacing enables efficient ball movement, clear driving lanes, and higher-quality shot opportunities. As teams increasingly adopt data-driven strategies, the need for precise and quantitative assessments of spatial structure on the court has become more relevant than ever.

Despite the growing availability of player tracking data, existing studies often rely on heuristic or visual evaluations of spacing, lacking consistent metrics or formal models. Furthermore, much of the research is centered on outcome-focused analytics—such as shot success probabilities—without a rigorous examination of the spatial configurations that precede these events. Recent studies have begun to incorporate lineup-level network structures (CERVONE et al., 2016; LI et al., 2025) and role-aware modeling (LUCEY et. al., 2014), yet a consistent framework for quantifying spacing dynamics is still lacking.

In this paper, we introduce a novel graph-theoretic framework for representing and analyzing player spacing. Each player is represented as a node in a complete, undirected graph, with weighted edges corresponding to the pairwise Euclidean distances. From this structure, we extract a set of interpretable metrics—including total spacing, average pairwise distance, convex hull area, minimum spanning tree weight, and centrality measures—that capture both geometric dispersion and relational structure among players. Our approach facilitates frame-by-frame and possession-level analysis of team



spacing, enabling more profound insights into offensive behavior and tactical efficiency. By linking spatial structure to post-session outcomes, the proposed framework contributes a replicable and extensible tool for coaches, analysts, and sports scientists.

## RELATED LITERATURE

The proliferation of player tracking technologies has catalyzed a new generation of quantitative approaches to basketball analysis. Commercial systems such as SportVU and Second Spectrum have enabled frame-level positional data to be applied in evaluating players, analyzing ball movement, and predicting shot outcomes (RICO-GONZALEZ et al., 2021; SCOFANO et al., 2024). While these advances are significant, much of the literature has remained focused on isolated events—such as ball screens or shot attempts—rather than the continuous spatial dynamics that occur across entire possessions.

Several studies have attempted to quantify spacing using simple geometric constructs. Convex hulls, for instance, have been employed to estimate the area occupied by offensive players (SUPOLA et al., 2023) while entropy-based models have captured distributional spread in positioning (ZHOU et al., 2025). Although informative, such measures often neglect the relational structure of player interactions.

More recently, network-based methods have been introduced to capture tactical relationships in basketball. Pass networks model players as nodes and passes as directed edges, yielding insights into circulation patterns and centrality (RICO-GONZALEZ et al., 2021). However, these approaches typically emphasize on-ball actions and overlook off-ball spatial behavior, which is equally critical in creating offensive advantage. Extensions of network analysis have begun to examine lineup-level structures (FEWELL et al., 2012; MILLER et al., 2014; CERVONE et al., 2016), centric spatial density measures (BARRON et al., 2025; GUO et al., 2024), and role-aware predictive models (LUCEY et al., 2014), highlighting a growing recognition of the complexity of spacing and tactical interactions.

To our knowledge, there is still limited work that integrates geometric and graph-theoretic methods to explicitly model spacing among players. Our contribution addresses this gap by combining complete graph representations with spatial and structural metrics, delivering a comprehensive and interpretable framework for evaluating spacing quality in basketball.

## METHODOLOGY

### Graph Representation

We model each offensive unit as a complete undirected graph  $G = (V, E)$ , where each vertex  $v_i \in V$  represents a player on the court, and each edge  $e_{ij} \in E$  connects a pair of players  $(v_i, v_j)$ . The graph is constructed for every frame in which player tracking data is available. The Euclidean distance between players weights each edge:

$$w_{ij} = (x_i - x_j)^2 + (y_i - y_j)^2$$

Where  $(x_i, y_i)$  and  $(x_j, y_j)$  are the coordinates of players  $i$  and  $j$ , respectively. This formulation ensures that the graph captures the instantaneous spatial relationships among all five offensive players.



## Spacing Metrics

From the complete graph, we extract several spatial and structural metrics:

- **Total Spacing:** The sum of all edge weights in the graph, representing the cumulative spatial separation among all players.
- **Average Pairwise Distance:** The mean of the ten unique inter-player distances.
- **Convex Hull Area:** The area of the convex polygon formed by the five players' positions, indicating overall space occupation.
- **Minimum Spanning Tree (MST):** The minimal set of connections linking all players with the lowest total edge weight. A lower MST weight may indicate tighter formations, while a higher value reflects dispersion.
- **Centrality Measures:** We compute degree, closeness, and betweenness centrality for each player, reflecting their structural role in the spatial configuration.
- **Average Shortest Path Length:** The average of all shortest distances between node pairs in the weighted graph.

## Computational Pipeline

For each frame, the following steps are performed:

1. Parse player coordinates for the five offensive players.
2. Construct the complete graph and assign Euclidean distances as edge weights.
3. Compute all spacing metrics listed above.
4. Optionally, store metrics alongside contextual data (e.g., possession outcome, shot attempt, game clock).

This pipeline enables the development of scalable applications for large datasets (e.g., entire games or seasons) and supports both aggregate and possession-level analysis.

## Algorithm: Computation of Spacing Metrics

**Require:** Player coordinates  $\{(x_i, y_i)\}_5$  at frame

**Ensure:** Metrics vector  $m_t$

1. Construct complete graph  $G_t = (V, E)$  with  $|V| = 5$  and edge weights  $w_{ij} = x_i - x_j + y_i - y_j$
2. Total Spacing:  $S_t \leftarrow \sum_j w_{ij}$
3. Convex Hull Area:  $A_t \leftarrow \text{CONVEXHULLAREA}(\{(x_i, y_i)\})$
4. Minimum Spanning Tree (MST)  $\leftarrow \text{MST}_{\text{Weight}}(\text{compute MSTWeight}(G_t))$
5. Centrality: compute degree, closeness, betweenness for all  $v \in V$
6. Avg. Shortest Path:  $\ell_t \leftarrow \text{AVGSHORTESTPATHLENGTH}(G_t)$  on weighted  $G_t$
7. Output:  $m_t \leftarrow [S_t, \bar{d}_t, A_t, W_{MS}, \text{centralities}, \ell_t]$



## EXPERIMENTAL SETUP AND CASE STUDY

To demonstrate the applicability of our framework, we conducted a case study using simulated tracking data that emulates realistic offensive formations. Each frame consists of the (x,y) coordinates of five offensive players, sampled at a rate of 25 frames per second.

For each frame, we computed the complete set of spacing metrics described in Section 4. Metrics were analyzed both individually (e.g., variation in convex hull area over time) and in aggregate (e.g., mean total spacing per possession). To illustrate structural behavior, we visualized the player graph with annotated edge weights and centrality values.

A snapshot from a representative frame is shown in Figure 1, where players form a wide offensive alignment with above-average total spacing and high convex hull area. This configuration is indicative of a well-spaced possession.

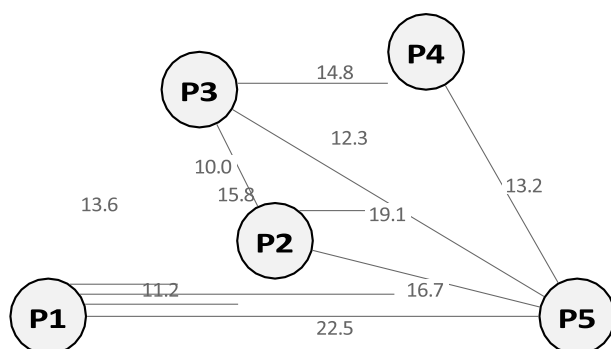


Figure 1: Graph representation of a single frame. Nodes denote players, while edge labels denote Euclidean distances (in feet, simulated data).

Additionally, we analyzed a sequence of 100 frames (4 seconds) from a mock possession. As shown in Figure 2, spacing metrics exhibit dynamic variation, with peaks occurring during moments of off-ball movement and corner spacing.

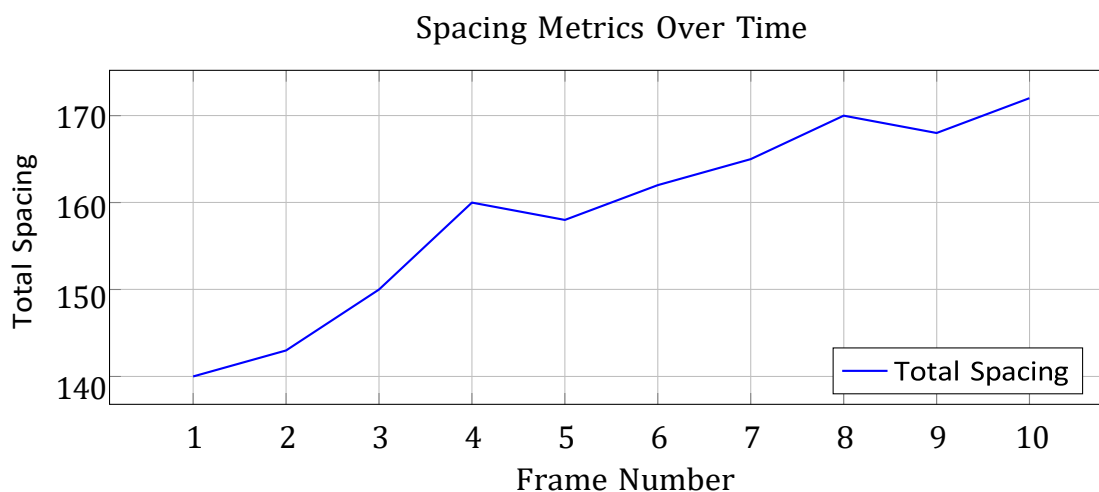


Figure 2: Evolution of total spacing over 10 frames (example data).

These results demonstrate the sensitivity of our metrics to tactical shifts and player positioning, suggesting their value in automated analysis and coaching feedback systems.

## DISCUSSION

The case study results underscore the expressive power and interpretability of graph-based spacing metrics. Geometric indicators, such as total spacing and convex hull area, consistently reflected the degree of offensive spread. At the same time, structural measures, including minimum spanning tree weight and centrality, revealed how players were interconnected within a formation. Together, these metrics offer complementary insights into the quality of spacing.

Well-spaced possessions were typically characterized by players occupying maximally distant positions while maintaining interconnectivity. Such configurations produced higher total spacing, expanded convex hull areas, and more balanced centrality distribution features that align with qualitative notions of tactical efficiency. These findings align with recent work on lineup-level networks (CERVONE et al., 2016) and density-based spatial measures (GUO et al., 2024), highlighting the potential of combining geometric and relational approaches.

An important strength of our framework is its ability to capture both instantaneous snapshots and temporal dynamics. Frame-by-frame computation enables us to track how spacing evolves during cuts, screens, and off-ball relocations, allowing for the identification of tactical events that may otherwise go unnoticed in traditional statistics. This dynamic perspective can support coaching applications by diagnosing breakdowns in spacing and reinforcing effective formations.

Despite these advantages, several limitations must be acknowledged. The current model operates in a purely spatial context, without integrating player roles, ball position, or defensive alignment. These factors are critical in shaping offensive efficiency and should be incorporated in future extensions (BOURGEAIS et al., 2025; LUCEY et al., 2014). Furthermore, the case study was based on simulated tracking data. While this choice facilitated methodological prototyping under controlled conditions, applying the framework to real-world datasets will require addressing challenges related to tracking noise, occlusions, and player identification.

In summary, the proposed approach demonstrates strong potential as a foundation for interpretable, data-driven analysis of basketball. By bridging geometric measures with network-based insights, it opens opportunities for scalable applications in coaching, scouting, and performance feedback, while also pointing toward rich avenues for future research.

## Limitations of The Study

While our framework provides a novel graph-based quantification of basketball spacing, several limitations must be acknowledged. First, the analysis was conducted using simulated tracking data rather than real game data. Although simulations enable methodological prototyping under controlled conditions, they limit adaptability to real, game-like situations where player behavior, defensive pressure, and contextual constraints vary.

Second, the current design does not explicitly integrate the position of the ball or the



tactical roles of individual players. Both contextual factors are crucial in shaping the quality of spacing and offensive efficiency. Future extensions of this work should therefore incorporate ball-centric metrics and role-aware attributes into the graph representation.

Finally, the study does not account for defensive positioning or tactical responses from the opposing team, which are key determinants of spacing effectiveness. Addressing these aspects with real-world tracking data will be essential to validate and generalize the proposed approach.

## **Practical Implications**

The proposed framework has several practical applications for various stakeholders in the basketball industry. For coaches, spacing metrics can serve as diagnostic tools during training sessions, helping to identify breakdowns in floor balance and to design drills that reinforce effective offensive structures. Performance analysts may integrate these measures into scouting reports to compare lineup efficiency or to quantify the impact of tactical adjustments on spacing dynamics across possessions.

Sports scientists can utilize this framework to explore the relationships between tactical behavior and physical demands, thereby bridging the technical and physiological aspects of performance. Finally, automated feedback and visualization systems could leverage these metrics in real time, enhancing both coaching support and spectator engagement.

## **Recommendations for Future Studies**

This study opens multiple avenues for further research. First, extending the framework to real-world tracking data will allow validation under authentic game conditions and across different competition levels (e.g., professional leagues, youth academies). Second, integrating the ball's trajectory, player roles, and defensive alignment will create a more context-aware model of offensive efficiency. Third, combining graph-based metrics with machine learning techniques could enable predictive models of possession outcomes or automated classification of tactical patterns. Lastly, expanding the framework to other invasion sports such as soccer or handball would test its generalizability and broaden its applicability in the field of sports analytics.

## **CONCLUSION**

This study introduced a novel graph-theoretic framework for modeling and quantifying player spacing in basketball. By representing offensive units as complete weighted graphs and extracting both geometric and structural metrics, we provide a systematic approach to analyzing spatial organization during possessions. The results of our case study suggest that spacing quality can be meaningfully captured through a combination of total inter-player distances, convex hull area, and network-based measures such as minimum spanning tree weight and centrality distributions. Beyond methodological contributions, the framework offers several practical implications. Coaches and performance analysts can use these metrics to monitor spacing dynamics over time,



identify suboptimal formations, and design drills that promote efficient offensive structures. Automated systems based on our approach could deliver real-time feedback during practices, highlighting moments of poor spacing or successful spacing creation. For sports scientists, the metrics provide interpretable indicators that bridge tactical concepts with quantitative evidence, facilitating communication between analysts and practitioners.

At the same time, the study highlights opportunities for future work. Integrating the ball's position, player roles, and defensive alignment will provide a more context-aware picture of offensive efficiency. Applying the framework to large-scale tracking datasets from professional competitions will further validate its robustness and establish normative baselines for optimal spacing under different tactical systems.

In conclusion, the proposed graph-based framework represents a step toward rigorous and interpretable quantification of basketball spacing. By linking spatial structure to tactical execution, it opens up pathways for data-driven decision-making in coaching, scouting, and player development. It offers a methodological foundation that can be extended to other invasion sports where space creation is central to success.



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