Exploring the Dynamics of Ice Hockey Strategies Using YOLOv8 and Gephi in Sports Education

Boyang Zhang, Wapice, Finland
Tommy Löwendahl, Wapice, Finland

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Abstract
In modern fixed-field team sports, computer vision techniques have been commonly applied in analyzing team strategies and tactics. This research presents a combination approach using object detection, multi-object tracking, and social network analysis (SNA) to investigate the dynamics of ice hockey strategies. Specifically, we utilize YOLOv8 object detection algorithm to detect players and ByteTrack to track their movements. The passing information between players is used to construct a network representation of the team's strategy. By using weighted-edges and modularity network community detection, this research demonstrates the team roles of each player in community analysis and captures the impact of team strategies. The goal of this research is to promote teamwork, strategic analysis, and the development of innovative knowledge of sports rules and strategies in sports education.

Keywords: Object Detection, Social Network Analysis, Community Analysis

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Introduction

With the development of science and technology, the field of sports' analytics has made remarkable progress in recent years. Particularly in group fixed-field team sports, such as football, basketball, ice hockey, badminton which are characterized by teams that play in a fixed-field with a specific set of regulations. Analyzing these sports has traditionally been challenging because of the complexity of interactions between players (Jana & Hemalatha 2021; Weber et al. 2022).

With using the latest computer vision techniques and social network analysis (SNA), this research provides new opportunities for analyzing fixed field team sports in weighted edges and modularity network community analysis. In this chapter, we will explore the concepts of fixed-field sports, YOLOv8, and SNA in computer vision.

Group fixed-field sports are sports which are played on a field or court with fixed boundaries and a set of rules, with more than two players. With these fields, group fixed-field sports are characterized by the interactions between players and their movements across the playing fields. Nowadays, there are multiple popular group fixed-field sports, for instance soccer; American football; basketball; ice hockey (Figure 1 indicates the size of ice hockey rink); and volleyball. The unique character of the group fixed-field sports is with multiple players participate in it that takes place on a static or unchanging field of playing area. Analyzing group fixed-field sports is challenging due to complex player interactions, the fast-paced nature of the games, limited observability of player movements, large volumes of data, and contextual factors (Raabe, Nabben, & Memmert 2022). However, advances in computer vision and SNA have made it possible to analyze these sports in a new and exciting way.

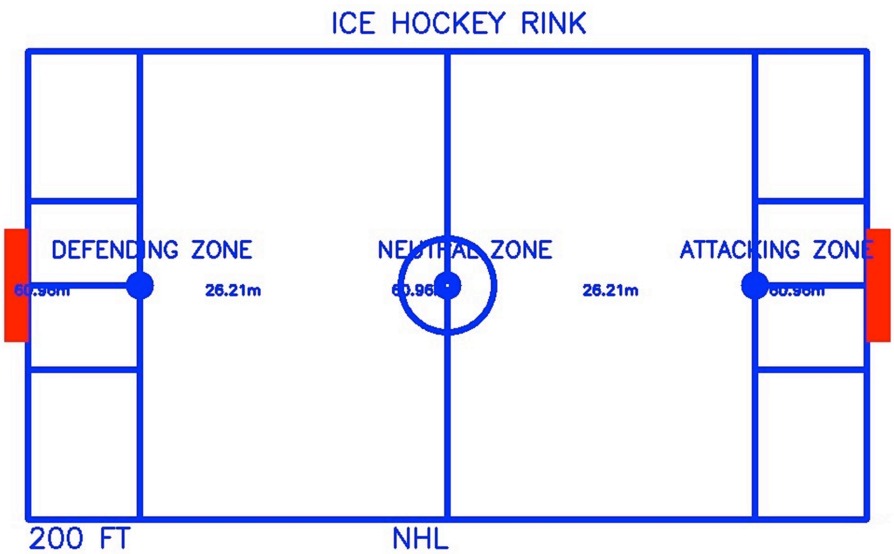

Figure 1: Ice Hockey Rink

YOLOv8 (You Only Look Once version 8) is a stage-of-the-art object detection model used in computer vision tasks (Jocher, G., Chaurasia, A., & Qiu, J, 2023), such as instance segmentation, classification, post estimation. It is designed to detect objects in images and video streams. YOLOv8 is particularly useful for analyzing group fixed-field sports as it can accurately detect players on the playing field.

After the detection of plays, ByteTrack is used to track the historical movement, ByteTrack is a multi-object tracking (MOT) algorithm which developed to estimate the and optimize bounding boxes selection (Zhang et al. 2022). ByteTrack aims to overcome the limitations of traditional MOT methods by introducing a simple and strong tracking approach. ByteTrack is designed to track objects in challenging conditions such as occlusion, scale variation, and fast motion. The combination of YOLOv8 and ByteTrack provides a powerful tool for analyzing player movements.

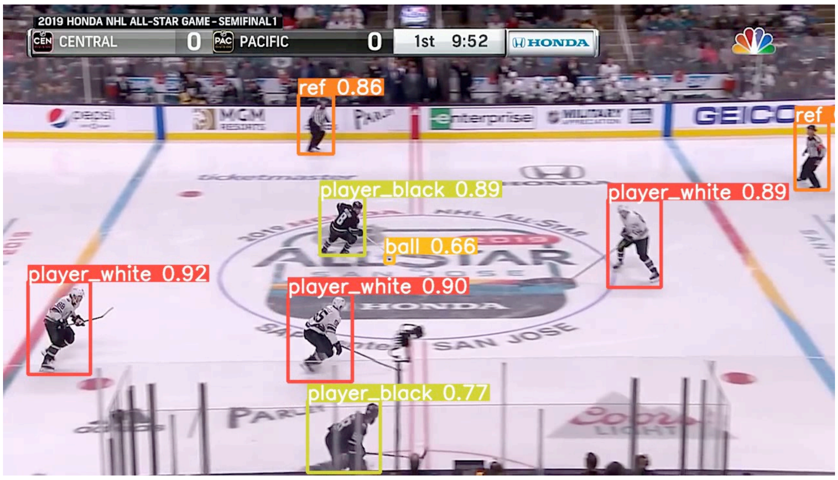

Figure 2: YOLOv8 object detection

Social network analysis (SNA) is a method for studying social structures by analyzing the relationships between individuals or groups (Abbasi, Altmann, & Hossain 2011; Grandjean 2016; Otte & Rousseau 2002). In modern sports analytics, SNA can be used to analyze the interactions between players on a team or between teams in a league. By using SNA, coaches can identify the key players on a team and how they interact with each other (Zhang et al. 2017). They can also analyze the strategies used by teams and how they change over time (Wäsche et al. 2017).

Overall, the use of YOLOv8 and ByteTrack provides accurate players detection and tracking, SNA is built based on the object detection and passing information. SNA can be used to analyze team strategies and tactics.

Theoretical Background

Social network analysis (SNA) can be a valuable tool for analyzing the structure and dynamics of sports teams (Clemente, Martins, & Mendes 2016; Serrat 2017; Wäsche et al. 2017), such as in ice hockey team strategies. By applying various measures and techniques, coaches can gain insights into the network relationship and interaction between players (Fransen et al. 2015). The SNA can be used to understand the factors that influence team performance (Yang & Tang 2004), and to identify potential leaders or influencers not only within a team, but also in between other teams. Overall, social network analysis can provide a unique perspective on sports teams and can help coaches to make decisions about team selection, training, and strategy, particularly in group fixed-field team sports (Fransen et al. 2015; Vick, Nagano, & Popadiuk 2015; Yang & Tang 2004).

Weighted edges are a concept that to assign numerical values to the edges of a certain network in graph theory (Liu et al. 2014), which can be in the form of directed or undirected edges to represent relevant measures (Háznagy et al. 2015) such as capacity, distance, passing information. In ice hockey, the passing direction frequency between players can provide valuable insights into team strategies and tactics. The weight of the edge represents the direction of the pass with frequencies. The factor of weighted degree centrality measures the weights of edges connected to a node. Nodes with high weighted degree centrality are those that receive or make accurate and direct passes more often than other players.

Community detection defines clusters that aim to identify communities of nodes in a network that are more densely connected to each other than to the rest of the network (De Meo et al. 2011; Fortunato & Barthélemy 2007; Liu et al. 2014). In ice hockey, community detection can be used to identify groups of players that tend to pass to each other more often than to other players. The modularity algorithm, as introduced by De Meo et al. (De Meo et al. 2011), has proven to be a practical and widely adopted approach for community detection. Among the various methods available, the Louvain method stands out as the most utilized one. The modularity algorithm maximizes the modularity score by assigning nodes to communities that are more densely connected within the community than expected by chance, while considering the directionality of the edges (De Meo et al. 2011). The directed modularity score can range from -1 to 1, with higher values indicating a better community structure (De Meo et al. 2011).

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

Figure 3: The modularity formula identifies cohesive communities in a network by measuring the deviation of observed edges

In the formula (Figure 3), *Q* represents the modularity of the partition in Figure 3, which measures how a given partition of a network graph in which captures its inherent community structure by comparing the actual number of edges within communities to the expected number of edges (De Meo et al. 2011). And, *m* denotes the total number of edges in the network, reflecting the size of the network. A_{ij} stands for the weight of the edge between nodes *i* and *j*, representing the strength of the connection between two nodes in the network. K_i corresponds to the degree of node *i*, which is the number of edges that connect to it. The c_i signifies the community to which node *i* belongs, where a community is a subset of nodes that are densely connected to each other but sparsely connected to nodes in other communities. $\delta(ci, cj)$ is the Kronecker delta function, serving to return 1 if nodes *i* and *j* belong to the same community (Murniyati et al. 2023).

Methodology

In this chapter, the dataset collation and annotation method are discussed. The McGill Hockey Player Tracking Dataset (MHPTD) is used to perform object detection (Zhao, Li, and Chen 2020). The dataset contains 25 NHL ice hockey video clips, and it follows the format of the MOT challenges (Multiple Object Tracking) which is a widely used benchmark dataset for evaluating computer vision algorithms for player tracking, which is available at https://github.com/grant81/hockeyTrackingDataset.

The MHPTD dataset has been annotated by an open-source image and video annotation tool called Computer Vision Annotation Tool (CVAT) to facilitate analysis. This tool enables users to label and tag specific objects within a video clip to create a comprehensive and annotated dataset for further analysis. From this data, we set up 6 different classes which are available in below Table 1:

Class	Description
player_color1	Represents a player on the team with color1.
goalie_color1	Represents the goalkeeper of the team with color1.
player_color2	Represents a player on the team with color2.
goalie_color2	Represents the goalkeeper of the team with color2.
ref	Represents the referee or officials in the video frames.
ball	Represents the hockey ball

Table 1: Object Classes and Description in Ice Hockey

In the next step, we convert the CVAT annotation which is XML format in to corresponding yolo format. The yolo format is comprised of a text file for each image, containing one row for each object detected in the image. Each row comprises of the object's class label and normalized coordinates of the object's bounding box in the image. The converted YOLO format files are utilized to train a YOLOv8 object detection model using YOLOv8x frameworks. We split the dataset into training, validation, and testing datasets. After the training, we chose the best model based on the evaluation results using mAP (mean average precision) and confusion matrix. And after that, we fine-tune the model by adjusting hyper-parameters to improve its performance. In the next stage, we extract the detection results of video clips. After the detection, a directed network is built based on that nodes represent individual players and edges represent interactions between them (the pass from player A to player B).

To create the network using the MHPTD dataset, it is vitally significant to identify the nodes and edges. The nodes are the individual players, and the edges are the passes made between players during games. In object detection, there are 6 different classes, in the class of "ref" was not included in building the network. The player_color1 teams are divided into 2 groups, which includes defensemen and forward. There are 6 players in each team, which are defined as, for example in team A, A_goalie, A_forward1, A_forward2, A_forward3, A_defencemen1, A_defencemen2; in team B, there are B_goalie, B_forward1, B_forward2, B_forward3, B_defencemen1, B_defencemen2. A directed network is created between all the players and the ball.

The use of the MHPTD dataset provides a rich dataset that allows for the creation of a detailed network of player interactions in ice hockey. By using this dataset and applying SNA techniques, we can gain insights into the network structure of ice hockey, also the roles of individual players within the network, and how the network changes over time. The software Gephi is used for network building.

Findings and Discussion

This chapter delves into the findings from the analysis of weighted edges and community detection. This chapter aims to shed the light on the significance of player interaction in the social network analysis perspective, and the overall game play dynamics.

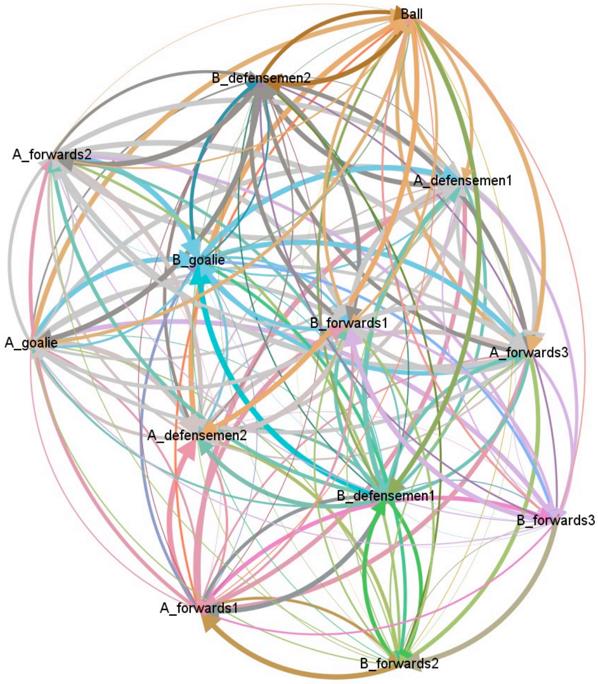

Figure 4: Over-all of the Weighted Network of One Match

In object detection, YOLOv8 performs player detection towards the MHPTD dataset. Individual players are detected with a specific classID, and because of the class are divided by two colors, for example. After the detection of individual plays in different teams and the ball detection, the ball possessor is defined as which player is in the possession of the ball by comparing the proximity of each player to the ball's distance. If the ball is within the proximity range of a player longer than a specific time range, not too short of time in some passing cases, the one player with unique classID is the ball possessor. In the next step, the ball passing is defined as a ball moving from one possessor to another possessor with different classID, which can be in the same team or different team.

After extracting the passing information, a Gephi network is built based on the direction of passing in one match. As shown in Figure 4, it is an example of the over-all weighted network of one match, colors represent different weights in passing. Nodes indicate the position of the players. Moreover, we can set different edge weight selection for further analysis, for example, in below Figure 5, we select the edge weight filter between 221 to 298, to analysis different passing frequencies.

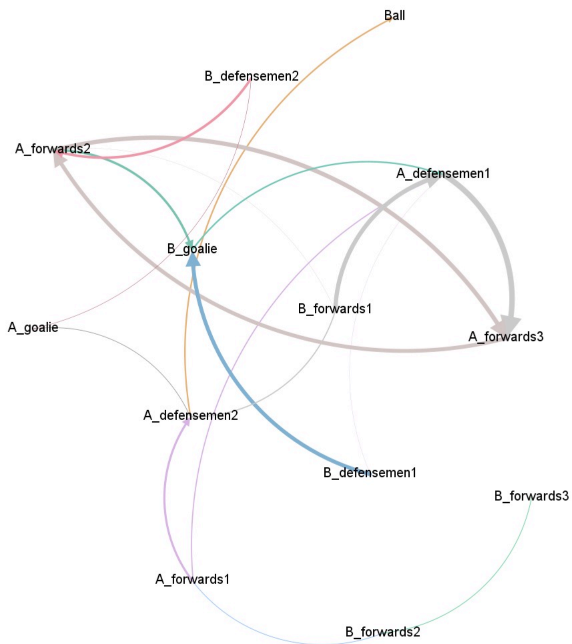

Figure 5: Different Weighted Edges Setting Selection

By exploring the distribution of weighted edges' values across the team, coaches can gain insights into the dynamics of player interactions and identify key players responsible for orchestrating offensive plays. For example, in Figure 5, the connection between B goalie and B_defensemen1 has a strong tie which means that the defensive strategies work well between the two players. On the other hand, A_forwards2 and A_forwards3 have a strong tie for offensive strategies. With more in-depth analysis, coaches can identify players who are particularly important for facilitating the flow of playing in building up both defensive and offensive strategies. Furthermore, the changes in weighted edges over time can provide insights into team strategies and play performance, because of the changing of players in the same position.

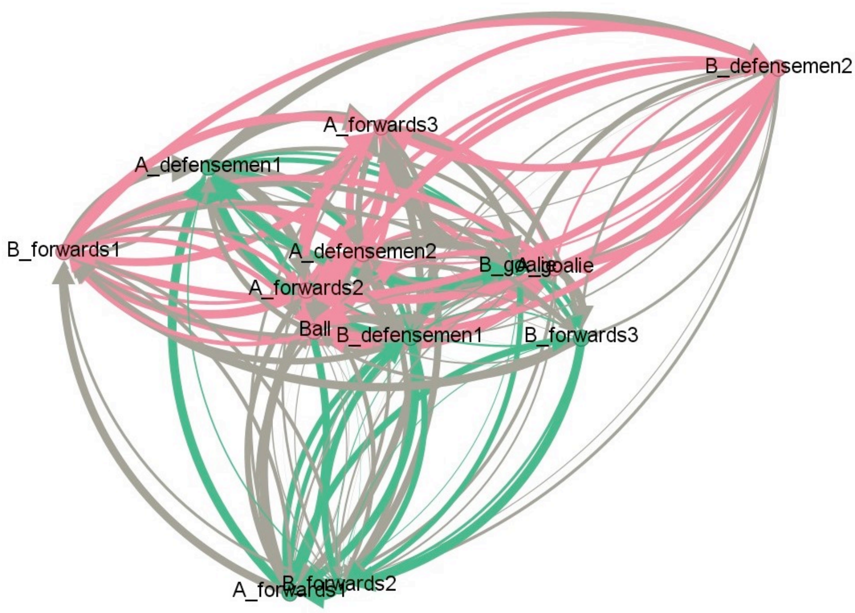

Figure 6: Community Detection by Louvain Method in the Context of Ice Hockey

By using Louvain's modularity algorithms (Blondel et al. 2008), the communities can be detected as the passing patterns and strategies which are available in Figure 6, different colours represent different detected communities. The Louvain algorithm identifies clusters of nodes that have more edges within the cluster with directions (Murniyati et al. 2023). In the context of ice hockey, community detection can be used to identify groups of players who tend to pass to each other more often than others from. Moreover, players with strong connections in both the same team and same community perform better defensive strategies. From the perspective of offensive, the players in different teams but placed within same community demonstrate noteworthy in the gameplay dynamics. Because it is in the passing network, weak ties can be utilized to locate novelty (Aral 2016; Granovetter 1973) which might be the points for fluid offensive transitions, or breakpoints to launch rapid attacks.

One advantage of utilizing modularity for community detection is that it provides a quantitative measure of the quality towards the detected communities, in the game of ice hockey, it indicates the players who pass more actively to the others and form the passing community structure. Interpretation of the communities' structure can help coaches to deeply understand the team strategies and tactics, also with concerns of the community structure changes to the tactic changes over time.

Conclusion and Future Research

Computer vision techniques have become increasingly prevalent for investigating team strategies and tactics of group fixed-field sports. This paper presents a novel combination of YOLOv8, ByteTrack, SNA, and community detection. The social network is built based on the players' on-ice interactions, which helps coaches to interpret team strategies by weighted edges and modularity. The overarching goal of this research is to foster teamwork, promote strategic analysis, and advance knowledge of sports rules and strategies in sports education. By employing cutting-edge computer vision techniques and social network analysis, this study contributes significantly to the understanding of ice hockey strategies, offering valuable insights for coaches, analysts, and players seeking to optimize team performance.

Future research can be conducted in multiple perspectives. From the network-based approach, not only weighted edges, and community detection, but also other factors. Such as, degree centrality and betweenness centrality for players' passing connections and key offensive players identification; clustering coefficient for team coordination with competitor team; PageRank analysis for identifying influential players; directionality for progression and evolution of the games; node attributes for player positions and shooting abilities; cluster analysis for goalkeepers' role. By exploring various network-based approaches, coaches can gain insights into the team strategies with understanding from passing network perspectives, and more approaches can be investigated in the passing network. From the object detection perspective, player re-identification can be used to research individual player's performance like passing accuracy, offensive and defensive role; motion capture and movement tracking can offer valuable understanding of player behavior, like shooting position, offensive position; our research is using video clips, the multiple camera fusion can help to explore motion capture and re-identification with more accurate result.

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