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https://doi.org/10.1007/s12650-020-00687-2

REGULAR PAPER

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# A survey of competitive sports data visualization and visual analysis

Received: 22 July 2018 / Revised: 24 March 2020 / Accepted: 6 May 2020


**Abstract** Competitive sports data visualization is an increasingly important research direction in the field of information visualization. It is also an important basis for studying human behavioral pattern and activity habits. In this paper, we provide a taxonomy of sports data visualization and summarize the state-of-the-art research from four aspects of data types, main tasks and visualization techniques and visual analysis. Specifically, we first put sports data into two categories: spatiotemporal information and statistical information. Then, we propose three main tasks for competitive sports data visualization: feature presentation, feature comparison and feature prediction. Furthermore, we classify competitive sports data visualization techniques based on data characteristics into five categories: high-dimensional data visualization, time-series visualization, graph (network) visualization, glyph visualization and other visualization, and we analyze the relationship between major tasks and visualization techniques. We also introduce visual analysis research work of competitive sports, propose the features and limitations of competitive sports data, summarize multimedia visualization in competitive sports and finally discuss visual analysis evaluation. In this survey, we attempt to help readers to find appropriate techniques for different data types and different tasks. Our paper also intends to provide guidelines and references for future researchers when they study human behavior and moving patterns.

**Keywords** Competitive sports · Data visualization · Visual analysis

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Published online: 18 August 2020

## 1 Introduction

The main goal of competitive sports is to produce superior sporting performance, ultimately assisting the winning of competitions. At the very core of competitive sports data are the athlete and their behavior. In sports, not only do athletes themselves have physical self-behavioral activity, behavioral activities between athletes also exist in which spatiotemporal, described and counted behavior data can be logged. Therefore, the rise of competitive sports data has given impetus to the development of research in competitive sports and also has simultaneously provided a basis for the study of the law of human life and the habits of human beings. Many researchers made use of the large quantity of online open-source competitive sports data to analyze and develop software and tools (Legg et al. 2012; Losada et al. 2016; Perin et al. 2013; Polk et al. 2014). This data analysis work would be helpful for professional analytics, allowing effective behavior-based decision-making during games, improving the effects of teams' training and performance in competitions (Janetzko et al. 2014; Legg et al. 2012, 2013; Rusu et al. 2010). Therefore, competitive sports data analysis is necessary in this field and has received extensive attention by researchers. However, the problem is that competitive sports data include athletes' behaviors and various pieces of statistical information, so that generally data are relatively large in quantity and also include many behavioral patterns unseen to the naked eye, thus presenting challenges to data analysis. Specifically, an analysis of sports statistics can effectively identify athletes' behavioral patterns (Goldsberry 2012; Losada et al. 2016), including their individual contribution and degree of activity. However, competitive sports data contain multiple dimensions such as space and time and others. Sports analysts cannot intuitively perceive the data, and relying purely on numbers cannot fully represent the data analysis results.

Regarding the above problem, with the increasing requirements of data analysis, user interfaces based on visualization and visual analytics have become widely used (Lei et al. 2015). In recent years, researchers in the field of visual analytics have proposed many useful methods and tools that assist analysts and coaches in finding behavioral patterns, solving particular difficulties that arise during the analysis process. Thus, competitive sports data visualization and visual analysis are becoming a hot topic in the research field. The purpose of this paper is to first analyze the characteristics of competitive sports data, classify and sum up the possibility of visualization of the data, also summarize the latest techniques in this field and then provide research guidelines for future research. Finally, we identify the challenges involved in visual analytics in the competitive sporting realm.

### 1.1 Related surveys

Current research in the field of competitive sports is comprehensive. For example, Stein et al. analyzed team sport data from several aspects including acquisition, modeling and research. They also mentioned visual techniques in their methodology section (Stein et al. 2017). Wang and Parameswaran reviewed the research of sports video analysis and discussed research issues and potential applications in this field (Wang and Parameswaran 2004). Villar et al. reviewed the demand of sports events in terms of attendance (Villar et al. 2009). Other researchers have studied how emotion affects players' performance in competitive sports (Lazarus 2000), including discrimination in professional sporting (Kahn 1991). These researches presented their statistical data in a tabular form which is difficult for readers to intuitively understand and is hard to perceive important information quickly. When analyzing data, analysts often need to spend a large amount of time identifying behavioral patterns of athletes. In order to make perception more intuitive, many researchers use visualization of competitive sports data to allow for easier and faster understanding.

Previous research in the field of sports data visualization has been classified in terms of spatiotemporal data. Some studies used user-centered classification, while other studies summarized the application of sports video visualization. Some studies summarized the basic methods used in the sports data visualization research, also summarizing the basic ideas of visual data analysis. However, there are some insufficiencies apparent in these studies. Gudmundsson and Horton simply classified sports spatiotemporal data from object trajectories and event records without having summarized the description and subdivision of data features (Gudmundsson and Horton 2017). Perin et al. proposed three main data categories: box-score data, tracking data and meta-data. Their classifications for sports visualization are based on the data categories. But they did not analyze the visualization techniques (Perin et al. 2018). Page and Moere analyzed team sports visualization and divided them into three categories: player-centered, audience-centered and referee-centered visualization (Page and Moere 2006). Yet, from the perspective of users, their study did not provide a description or analysis on the main tasks of sports visualization. Borgo et al. focused on video sports visualization and summarized a few representative papers (Borgo et al. 2011). The work of Lei et al. is relatively comprehensive, having not only classified sports data into attribute statistical data, attributes and spatiotemporal attributes, but also outlining additional papers, classifying existing work into sports data news and sports data majors. Moreover, they reviewed the classification of sports data visualization work based on data features (Lei et al. 2015). However, they did not summarize the main objective of competitive sports data visualization, and the classification view discussed is also different from what we discuss in this paper. One additional difference is that visualization and visual analysis techniques classified vary depending on the research subject conducted upon.

In this paper, an analysis of the characteristics of the data is provided, including the classification and discussion of the data type. We also present a summary of the main research tasks and collect related publications, then analyze and discuss the research topics. We classify visualization research work based on the techniques and sum up the current application and research of different techniques. Our study focuses on academics. Some online software and tools for visualization will not be discussed in this paper. This paper contributes by providing basis for the future on competitive sports data visualization, which can fill in the blank spaces in the competitive sporting realm.

### 1.2 Taxonomy of the survey

In this paper, we study on the classification of competitive sports data, the main tasks and the key techniques of competitive sports data visualization.

- Competitive sports data category. The characteristics of competitive sports data include the original acquired spatial information and time information, as well as various types of statistical information calculated by analysts. Therefore, in Sect. 2, we classified competitive sports data into spatiotemporal information data and statistical information data, where each type includes two subcategories. Also, we also discuss the research status of each category in competitive sports visualization.
- The main tasks in competitive sports data visualization. The main purpose of research work in competitive sports is to present various pieces of sports information and data characteristics, to compare the behavioral pattern for players and their performance and contribution to competitions, and to provide sports analysts and coaches with game tactics and team lineup decisions. Therefore, in Sect. 3, we classify the main task of competitive sports data visualization into three categories and review the current research work for each category. Three categories include presentation, comparison and prediction.
- Key techniques of competitive sport data visualization. Competitive sports data generally include various attributes. Therefore, in Sect. 4, we summarize three common visualization techniques based on the above data features, which are high-dimensional data visualization, time-series data visualization, graph (network) data visualization and glyph data visualization. We also review how the existing research work combined with multiple visualization and interaction techniques to solve problems in competitive sports data visualization and visual analysis.
- The relationship among competitive sport data, tasks and techniques. In Sect. 5, we collect current research publications and summarize their data, tasks and visualization techniques and then generate two tables to show the relationships among them. These two tables present the using preference of visualization techniques for certain data types or specific tasks and also give the reference to researchers in their future studies.

## 2 Competitive sports data category

### 2.1 Spatiotemporal information

Competitive sports data visualization can be classified according to different sports categories. Common categories include net-separated confrontation (playing through a net), swap offensive (offensive and defensive exchange), indirect confrontation (playing with different balls), direct confrontation (playing with the same ball) and speed and power, as shown in Table 1. However, sports such as chess and cards games, hits (shooting darts), endurance (walking, running, swimming, skiing), fighting (martial arts, fencing, boxing, wrestling, etc.), racing (windsurfing, sailing, etc.) and rock climbing (mountain climbing, etc.) are

**Table 1** Categories in competitive sports and visualization research in each category

| Competitive sports category | Current visualization research |
|---|---|
| Net-separated confrontation | Table tennis (Wang et al. 2019; Wu et al. 2018a) |
| | Tennis (Pingali et al. 2001; Polk et al. 2014) |
| Swap offensive | Baseball (Cox and Stasko 2006; Dietrich et al. 2014; Lage et al. 2016) |
| Indirect confrontation | Billiards (Höferlin et al. 2010; Parry et al. 2011) |
| Direct confrontation | Soccer (Albinsson and Andersson 2008; Andrienko et al. 2017; Bialkowski et al. 2016; Cava and Freitas 2013; Janetzko et al. 2014, 2016; Perin et al. 2013, 2016; Sacha et al. 2017; Stein et al. 2015, 2016b, a, 2018; Rusu et al. 2010, 2011; Vuillemot and Perin 2016; Wongsuphasawat 2013; Wongsuphasawat and Gotz 2012; Wu et al. 2018b) |
| | American football (Owens and Jankun-Kelly 2013; Tani et al. 2015) |
| | Basketball (Chen et al. 2016; Goldman and Rao 2013; Goldsberry 2012; Larsen et al. 2008; Losada et al. 2016; Maheswaran et al. 2012; Okamoto 2011; Sisneros and Van Moer 2013) |
| | Hockey (Pileggi et al. 2012) |
| | Handball (Hervieu et al. 2009) |
| | Rugby (Chung et al. 2013, 2016; Legg et al. 2012, 2013) |
| Speed and power | Cycling (Wood 2015) |

This research is classified depending on different ball games

Competitive Sports Data
- Spatio-temporal Information
  - Absolute Spatio-temporal Information
    - Spatio-temporal Information for Ball
    - Spatio-temporal Information for Player
  - Relative Spatio-temporal Information
    - Possession Information
    - Shooting Information
    - Battle Array Information
    - Tactical Information
- Statistics Information
  - Event Statistics Information
    - Moment Event
    - Period Event
  - Staff Statistics Information
    - Player's Personal Information
    - Comparative Information among Players
    - Team Information

**Fig. 1** Competitive sports data category. Treemap shows the structure and the relationship for different pieces of information

not yet involved in the area of competitive sports data visualization; therefore, they will not be discussed in this paper.

Current visualization research focuses on confrontational sports, and ball sports visualization is more comprehensive. In a ball game, although the rules of the game are different, the data collected are similar. For example, ball and players' space-time trajectory data are often recorded for basketball by SportUV (LLC 2014). Similar information is also recorded for sports such as soccer, American football, rugby, badminton and table tennis. Most data provide overarching information, including details, stadium information, player information and game information of the entire sports game. In this paper, we classified sports data by a multitude of attributes, shown as Fig. 1, and take basketball, soccer and other ball data as examples for discussion.

Spatiotemporal information refers to the information collected in spatial and time coordination. It includes trajectory information, possession trajectory, possession time, distance traveled, and so on. Spatiotemporal information is captured and recorded by various sensors. Analysts can study the dynamic behavior of players and sports teams and analyze the tactical decisions and the connections among players to predict further behavior. Thus, researchers usually design novel visual views to show the performance of players and teams from different perspectives (Losada et al. 2016; Rusu et al. 2010). In this paper, we have put together a classification system for spatiotemporal information in the context of the absolute static space and divide it into absolute spatiotemporal information and relative spatiotemporal information.

*Absolute spatiotemporal information* We classify absolute spatiotemporal information as the spatiotemporal information for both the ball and the players according to different objects on the court. It uses the court as a reference system and is stationary compared to absolute static space. In the research of competitive sport data visualization, absolute spatiotemporal information is captured and recorded by sensors (LLC 2014) and is also the basis for other spatiotemporal information and statistical information. In basketball and soccer, absolute spatiotemporal information of a ball refers to the ball's trajectory information, including the ball's vertical and horizontal coordinates on a court, for example, a basketball's bounce height and the corresponding time it takes. Absolute spatiotemporal information refers to a players' trajectory information, including the vertical and horizontal coordinates of players on the court and the corresponding time. Both information types are often visualized simultaneously in one visualization image (Dietrich et al. 2014; Hervieu et al. 2009; Janetzko et al. 2016; Lage et al. 2016; Pingali et al. 2001; Sacha et al. 2017; Stein et al. 2018; Tani et al. 2015). Other derived spatiotemporal information and statistical information such as the relative position between the basket or goal from the players, the speed and acceleration of players can be calculated from absolute spatiotemporal information.

*Relative spatiotemporal information* Unlike absolute spatiotemporal information, relative spatiotemporal information uses a reference system, the ball and the players that exist move relative to absolute static space. In this paper, we divide spatiotemporal information into four information subcategories: possession, shooting, battle array and tactical. In basketball or soccer, possession information uses a ball or a player as a reference and calculates its relative position; this includes the relative distance between the ball and the player, and the possession time for each player. Shooting information uses a basket or goal as a reference. It calculates the distance between the player and the basket or goal, the distance between the ball and the basket or goal, and the change in each parameter over time. Possession information and shooting information are widely used in the analysis of a player's performance, helping to evaluate a player's efficiency and their contribution to the game (Goldman and Rao 2012; Losada et al. 2016; Maheswaran et al. 2012; Moon and Brath 2013; Perin et al. 2013; Pileggi et al. 2012; Stein et al. 2015; Wu et al. 2018b). Battle array information mainly takes humans as a reference and calculates the relative positioning relationship between players: for example, in a basketball or soccer game, the relative position among players in the same team or their relative position among the players in different teams and the change in each parameter over time. In the research of confrontational sports, battle array information is often used to analyze the performance of the offensive and the defensive players (Cava and Freitas 2013; Goldman and Rao 2013), changing roles of the players (Stein et al. 2015), changing of battle array (Bialkowski et al. 2016; Wu et al. 2018b) and tactical strategies (Cox and Stasko 2006; Höferlin et al. 2010; Ishikawa and fujishiro 2018; Sisneros and Van Moer 2013; Stein et al. 2016a; Wu et al. 2018a). Tactical information involves the data of multiple team members. It usually takes the entire team as a reference to calculate movements among the team: for example, in basketball or a soccer game, the number, and duration of a team's offensive and defensive, the defensive status and location of an offensive team member, the changes in the formation of two teams, and so on. Tactical information is an important criterion for judging a team's performance in a game, and it is also the foundation for training players and studying game decision-making.

## 2.2 Statistical information

Statistical information does not have temporal and spatial characteristics, as it focuses more on personal information of players or competitors, or the players' decision of behaviors and movement on the field. Statistics information includes scores, shooting times, free throws, and so on. Statistical information is not only easy to record in a game, but can also reflect the teams' performance in a game. It can offer an overarching analysis for entire games and can also offer a detailed analysis based on a specific event or specific object. The two main research topics in statistical sports data visualization are how to present data in an intuitive readable way and how to interact and explore with the data. In our paper, we classify statistical sports data into two forms: event statistics and personnel statistics.

*Event statistic information* Event statistic information focuses on the players' behavior decision on the sports field. We define the events that occur at each discrete time point as time-series events, and a series of time-series events are defined as period events. A single event that happens in a single time series has multiple data dimensions, including time, coordinates, players, event types, event descriptions, team information, score information, and so on. In sports such as basketball or soccer, hitting and missing events during shooting are called time-series events. The act of a player when shooting at a certain time series in a certain coordinate position is also called a time-series event. Other time-series events include mistakes, free throws or misses, fouls, assists, steals, player substitutions and off-court incidents. Many researchers study the performance of players over some time and calculate player's efficiency as a way to evaluate whether players have improved on scoring or reduced the opposition's score while defending. Therefore, time-series events are another form of measurement for player's performance and contribution in games. This important indicator is also the basis for analyzing player's behavioral patterns and has become the focus of most sports data visualization research (Goldman and Rao 2012; Janetzko et al. 2016; Losada et al. 2016; Maheswaran et al. 2012; Pileggi et al. 2012; Perin et al. 2013; Wang et al. 2019). Compared to a time-series event, a period event has similar attributes; however, a period event is a combination of multiple time-series events so that it could be described as the event that happened during a period. Therefore, the time attribute includes a start time and an end time. Also, during the period, the players and the ball interact with each other; thus, a period event may consist of multiple players. For example, in a basketball game, an attack is a behavioral pattern that is coordinated by all players of an entire team. During the attack, several time-series events happen by a player including the passing and shooting of a ball. A period event in a basketball game can also include fast breaks, winning balls, offensive climaxes, etc. Period events in a soccer game include continuous passes, shot steals, defensive counterattacks and positional attacks. A period event is often used to analyze game tactics and team contributions (Cox and Stasko 2006; Höferlin et al. 2010; Sisneros and Van Moer 2013; Stein et al. 2016a; Wu et al. 2018a). It is also important for showing the relationship between team contribution and competition results in data visualization for competitive sporting (Chen et al. 2016; Jin and Banks 1996, 1997; Perin et al. 2016; Polk et al. 2014; Saito et al. 2004; Tan et al. 2007; Wongsuphasawat and Gotz 2012).

*Staff statistics information* Staff statistical information focuses on the players' personal information. We classify it into three information categories: the players' personal, players' comparative and the teams'. A player's personal information includes the player's name, ID, jersey number, height, weight, speed, acceleration, hit rate, error rate, possession times, and so on. In the research of competitive sports visualization, the display of a player's personal information is indispensable. However, being a simple data type, it is not a hot research topic in the field of data visualization. Comparisons among players include speed, score and efficiency. This information tends to be interesting for coaches and sports analysts. Through its analysis, they can find the differences in player's performance for different players at the same given time, the differences in player's performance for the same player at different time series in time. It is of great value to evaluate a players' quality, ability, efficiency and contribution in a game and is also of concern to researchers in the field of data visualization (Chung et al. 2013, 2016; Goldman and Rao 2013; Goldsberry 2012; Janetzko et al. 2014; Legg et al. 2012; Losada et al. 2016; Okamoto 2011; Rusu et al. 2011; Stein et al. 2015; Wood 2015). Team information includes shooting times, free throws, errors and other quantitative information for team performance and efficiency. In competitive sports data visualization research, team information often relates to battle array and tactical information. It is commonly used for comparison and contribution evaluations among teams (Bialkowski et al. 2016; Cox and Stasko 2006; Stein et al. 2016a).

## 3 Main tasks of data visualization

The objects of competitive sports visualization include audiences, players, coaches, referees, sports analysts, sponsors, and so on. Different objects have different desires for competitive sports data. For example, the audience wants to understand the score of a game and the best player. The players pay attention to player's performance on the field. The coach needs to understand the mutual coordination of players and battle array tactics. The referee needs to understand the special events in a game and the behavior of players. Sports analysts pay attention to all kinds of information about players and games, while sponsors care about the most promising players and teams. The main goals of visualization are different for different stakeholders and objects. Therefore, we divide the main tasks of competitive sports visualization into three main categories: feature presentation, feature comparison and feature prediction.

Feature presentation is the display of basic information and various characteristics of players' behavior. The purpose of feature presentation is to compare the present features and the relationship among various types of data. Comparisons of different features for one player and the comparison of the same features among different players are both possible. Feature prediction first analyzes the data and uses existing information to predict the characteristics of various types of data. It then presents the results, such as a team's battle array or a game's tactical analysis and prediction. This paper aims to present three different visualization methodologies, discuss their objectives and main tasks and also summarize the current research work.

### 3.1 Feature presentation task

The most common task is to display and present data. This could include the presentation of a player's performance on the field, track information, special events and the data for an entire game. We subdivide the task of presenting and summarizing the current research work based on the above topics.

*Presentation for trajectory information* Trajectory information data mainly include a player's position on the sports field as well as information associated with possession, shooting, battle array and tactics. For intuitive understanding and perception of the spatiotemporal data, researchers usually insert the trajectory information into developed visual software. The study on presenting trajectory information for baseball data includes Dietrich's work (Dietrich et al. 2014) and Lage's work (Lage et al. 2016). Also, Pingali worked on tennis data (Pingali et al. 2001) and Stein worked on soccer games (Stein et al. 2018). Both of them studied on video data visualization. Similar soccer research has also been completed by Perin et al. (Perin et al. 2013) and Sacha et al. (Sacha et al. 2017).

*Presentation for player's performance* In the research of competitive sports data analysis, player's performance on the sports field is an attractive topic. The hit rate, turnover rate, foul rate, total number of scores and various other sporting indicators, such as speed and acceleration, can all be used to measure a players' performance. This is statistical information. Current research on players' performance mainly includes basketball visualization by Losada (Losada et al. 2016), soccer visualization by Rusu (Rusu et al. 2010) and Janetzko (Janetzko et al. 2016). Losada focused on the past and current player's performance, while Rusu focused on the comparison among players; especially, Janetzko focused on the solution for multiplayer presentations without overlap in visualization.

*Presentation for special events* Various special sporting events are also attractive research topics in statistical data research and competitive sports data visualization, and data could include the shooting and passing at the event. Special events not only enable users to understand popular information but also enable users to understand the tactics of a team in a game. Therefore, many researchers pay to maintain a high interest in it. In a basketball data study, Goldman and Rao (Goldman and Rao 2012) and Maheswaran et al. (Maheswaran et al. 2012) focused on the offensive rebound rate of a home team and visitor team, but they use different visualization techniques. Losada et al. also studied basketball data and presented information about shooting events and passing events (Losada et al. 2016). Also, there are more researchers who present special events in rugby (Legg et al. 2013), baseball (Moon and Brath 2013), snooker (Parry et al. 2011), soccer (Janetzko et al. 2016; Perin et al. 2013; Stein et al. 2016b) and hockey data (Pileggi et al. 2012).

*Presentation for game information* In addition to the above, the presentation for entire sports games is also an indispensable task in competitive sports data visualization. The earliest work in this field presented basketball game (Turo (1994)) and tennis game (Jin and Banks 1996, 1997). After that, Chen and Tan et al. also showed basketball data game (Chen et al. 2016; Tan et al. 2007). The difference in basketball researches is that they used different visualization techniques. In recent years, the demonstration of data from tennis games was done by Polk et al. (Polk et al. 2014). Also, both Saito et al. and Wongsuphasawat visualized the scenic information for soccer games and also provided an overview of the games (Saito et al. 2004; Wongsuphasawat 2013). Wongsuphasawat also showed the details of each game.

*Presentation for other information* In addition to the above spatiotemporal information and statistical information, Larsen et al. presented the effect of racial prejudice on betting results, game scores, and the chance of winning (Larsen et al. 2008). Andrienko et al. showed the pressure of opposing players and the spatial distribution of players in the field (Andrienko et al. 2017). This information is also related to basketball games and athletes and can be used on a wider range of competitive sports.

### 3.2 Feature comparison task

Researchers of data visualization have a great interest in the comparison of competitive sports data, mainly in performance and ability of different players on the field, comparison of different players' roles, performance comparison of different players and event comparison in competitions. In this paper, we divide feature comparison tasks in competitive sports data visualization into subcategories and discuss the current research in these areas.

*Player's performance comparison* For many competitive sports, there is more than one player or two teams participating in a game. Therefore, one of the important ways to evaluate a player's contribution is to compare different players in the same team or compare players with the same roles on different teams. In many feature comparison studies of different players' abilities, Legg et al. (Legg et al. 2012) and Chung et al. (Chung et al. 2013, 2016) studied on rugby games. The difference is that Legg et al. only worked on players' performance while Chung et al. worked on both players' and teams' contributions. For basketball data, Goldsberry worked on players' performance Goldsberry (2012), while Goldman and Rao worked on teams' performance (Goldman and Rao 2013). Only Wood compared cycling players' performance (Wood 2015). Both Cava and Freitas (Cava and Freitas 2013) and Rusu et al. (Rusu et al. 2011) studied on soccer game visualization and separately compared game results for different teams and goalkeepers' performance.

*Behavior events comparison* The comparison of player's behavioral patterns and the characteristics of sports events is also a common topic in the competitive sports visual research field. Owens and Jankun–Kelly visualized data from US college football matches and compared player behavioral patterns (Owens and Jankun-Kelly 2013), while Janetzko's work was a comparison of the patterns of multiple soccer players (Janetzko et al. 2014, 2016).

*Game information comparison* Except for the comparison of players' abilities and performance at behavioral events, researchers also compared the features of a game. Albinsson and Andersson were the earliest researchers to compare feature data who studied on football game data (Albinsson and Andersson 2008). For soccer game information, Cava and Freitas compared shooting results by different teams (Cava and Freitas 2013), while in Stein's work (Stein et al. 2015), they compared the text information of a game. Also, Perin et al. also compared ranking information and score information for soccer games (Perin et al. 2016).

### 3.3 Feature prediction task

In addition to feature presentation and feature comparison tasks, another significant area of study in this research field is whether it is possible to make decisions on sports behavior by visual analysis. This would allow the improving of game tactics and strategies and predicting of information such as results of a game. In competitive sports, it is often difficult for sports analysts and coaches to obtain accurate information about all decisions, as decisions may be influenced by irrational factors. These subjective factors include the environment, psychology and emotions that lead to deviations in decision-making. Some researchers have used visual analysis techniques in the study of competitive sports decision-making, accurately and intuitively presenting data to analysts and coaches, and helping them analyze the underlying characteristics and pinpointing sports behavioral patterns. Their work provides a more comprehensive reference for data analysis and provides decision-making support, reducing and avoiding inefficient data representation from subjective factors that would interfere with decisions made by analysts and coaches. This paper divides the common decision-making tasks into several subcategories, including the estimation of game results, battle array decision-making, sports event prediction and tactical game decision-making.

*Game result estimation* Research on prediction and estimation of the result of sporting games mainly comes from the visualization of soccer and basketball data. For example, Vuillemot and Perin developed a sports events prediction system for the Union of European Football Association (UEFA) Europa League (Vuillemot and Perin 2016). Okamoto estimated the relative probability of winning and losing by calculating player's performance in different situations (Okamoto 2011).

*Battle array decision* Currently, less work has been done for this task. Bialkowski et al. clustered proportions of common arrays in a soccer game and compared the initial battle array plan by visualization to help coaches make decisions for the battle array structures (Bialkowski et al. 2016). Also, Wu et al. designed a ForVizor system for explorations of team formation information in soccer games (Wu et al. 2018b).

*Sports event prediction* Stein et al. analyzed and predicted dangerous situations and warning signs in soccer games (Stein et al. 2016b). Wongsuphasawat and Gotz (Wongsuphasawat and Gotz 2012) also visually analyzed the path of moving events in soccer games to predict future events using different visualization methods. Stein et al. used animation while Wongsuphasawat and Gotz used time-series visualization methods.

*Game tactics decision-making* Sports game's tactical strategy is one of the most attractive topics concerning sports coaches and analysts. The trajectories of the ball and the player are important resources for constructing and checking strategies (Tani et al. 2015). Current research is also increasingly shifting focus onto this topic. For example, the earliest tactical strategy research was a baseball visualization system from Cox and Stasko, which helped media reports and team officials make decisions and predict future scores (Cox and Stasko 2006). Afterward, Höferlin et al. designed a snooker visualization system to improve game tactics and players' training (Höferlin et al. 2010). Sisneros and Van Moer applied visualization to help baseball coaches coordinate players and make game tactics (Sisneros and Van Moer 2013). Stein et al. provided soccer experts with a visual interactive system that enables experts to coordinate players and make game-related decisions (Stein et al. 2016a). Ishikawa and fujishiro visually analyzed the tactics in rugby games to understand changing trends (Ishikawa and fujishiro 2018). In recent years, the visualization system for table tennis developed by Wu et al. helped analysts find strategic models that make better decisions (Wu et al. 2018a). The latest research was done by Wang et al. who developed a visual analytics system for table tennis which provided player and tactic navigation (Wang et al. 2019).

## 4 Competitive sports data visualization techniques

In this section, we discuss the current research on competitive sports data visualization based on data visualization techniques. We analyze relevant papers for competitive sports data visualization and extract the main visualization techniques in each research paper. Then, we classify them into four categories according to the calculated statistics, namely high-dimensional data visualization, time-series visualization, network (map) visualization, glyph visualization and other types of visualization. Our work provides researchers with a better understanding of the future work that needs to be done, and those visualization techniques can be used for specific data types. It also provides a basis for the visualization techniques that can be expanded and combined for specific goals.

### 4.1 High-dimensional data visualization

Competitive sports data usually have many different attributes and belong to high-dimensional data variables. Therefore, high-dimensional data visualization is widely used to explore the distribution and distribution patterns in competitive sports research, as it reveals the implicit relationships and influences in multiple dimensions. The basic methods for high-dimensional data visualization include icon-based, pixel-based, geometric-based, hierarchical-based, graph-based and hybrid methods (Keim and Kriegel 1996). In recent years, the graph-based methods have become the main research direction and one of the most common techniques in sports data visualization research.

In high-dimensional data visualization, scatter plot, star chart or radar chart, parallel coordinate and heat map are the most widely used. Due to dimensional constraints, scatter plot is often not applied to situations where all dimensions need to be displayed simultaneously; however, it can only be visualized for a limited number of more important dimensions. The star diagram shows the characteristics of different attributes in the form of radiation. Parallel coordinates are widely used in large-scale applications but are prone to problems such as dense lines and overlapping coverage. It is necessary to use clustering methods for feature processing. Heat maps highlight the distribution of characteristics data and are often applied to analyze the spatial distribution of ball shooting rates and the player's shooting positioning. Besides, the projection can reflect the distribution of attributes for each parameter and can also display the relationships among multiple dimensions. It is one of the visualization methods that can simultaneously display high-dimensional data attributes (Ren et al. 2014). However, according to our study, less research work is presented for the application of the projection methods used to visualize the competitive sports data. The unique data structure and characteristics of competitive sports are a possible reason.

*Scatter plot* Okamoto compared and demonstrated the winning and losing in basketball games by scatter plot (Okamoto 2011). In addition to presenting winning and losing data, Goldman and Rao also applied scatter plot to analyze the influence of three pointers in a basketball game (Goldman and Rao 2013). Lage et al. designed scatter plot for baseball data (Lage et al. 2016), as shown in Fig. 2a. From their research, it can be seen that the scatter plot can show team performance and compare team behaviors, giving an oversight of the influence of team performance.

*Star plot (radar chart)* Player's performance is a criterion for player contribution measurement in competitive sports. Losada and Rusu et al. studied the performance of athletes. Losada et al. used radar chart to present player's performance in a basketball game (Losada et al. 2016), as shown in Fig. 2b. However, Rusu et al. designed concentric circles instead of traditional star chart to express the performance of each soccer player (Rusu et al. 2010).

*Parallel coordinates plot* Legg et al. used parallel coordinates to visualize the correspondence of similar metrics based on rugby games video (Legg et al. 2013). Chung et al. used parallel coordinates to visualize rugby data and help users to understand the effects of model parameters and sorted events (Chung et al. 2013), as shown in Fig. 2c. Then, they used different ranking models to analyze team and player's performance (Chung et al. 2016). For basketball game data, Chen et al. presented score data based on parallel coordinates (Chen et al. 2016). Except for rugby and basketball data, Stein et al. designed a visualization method similar to parallel coordinates to show the ranking of semantically meaningful features in soccer games (Stein et al. 2015). Janetzko et al. presented an extension for parallel coordinate tackling the overplotting problem for soccer matches (Janetzko et al. 2016). From the above work, parallel coordinates are helpful when they come to representing relationships between multiple variables.

*Heat map* Location and geographical distribution is a much-debated topic in competitive sports data visualization. Goldsberry, Losada and Maheswaran et al. used heat maps to visualize the geographic distribution in basketball data. Goldsberry et al. showed the complex dynamic spatial information for players and teams (Goldsberry 2012). Losada et al. presented player-shooting positions (Losada et al. 2016), as shown in Fig. 2d. Studies by Maheswaran et al. presented offensive rebounding rates (Maheswaran et al. 2012). In soccer data visualization, Perin and Stein et al. used heat maps to separately show the behavioral patterns of corner events and cross-movements (Perin et al. 2013), and the passing frequency in each area (Stein et al. 2016b). For baseball data, Dietrich and Lage et al. used heat maps to display spatial distribution. Dietrich et al. showed all the hitting positions and putting positions (Dietrich et al. 2014). Lage et al. visualized all the trajectories in many baseball games (Lage et al. 2016). Also, Pileggi et al. proposed a new

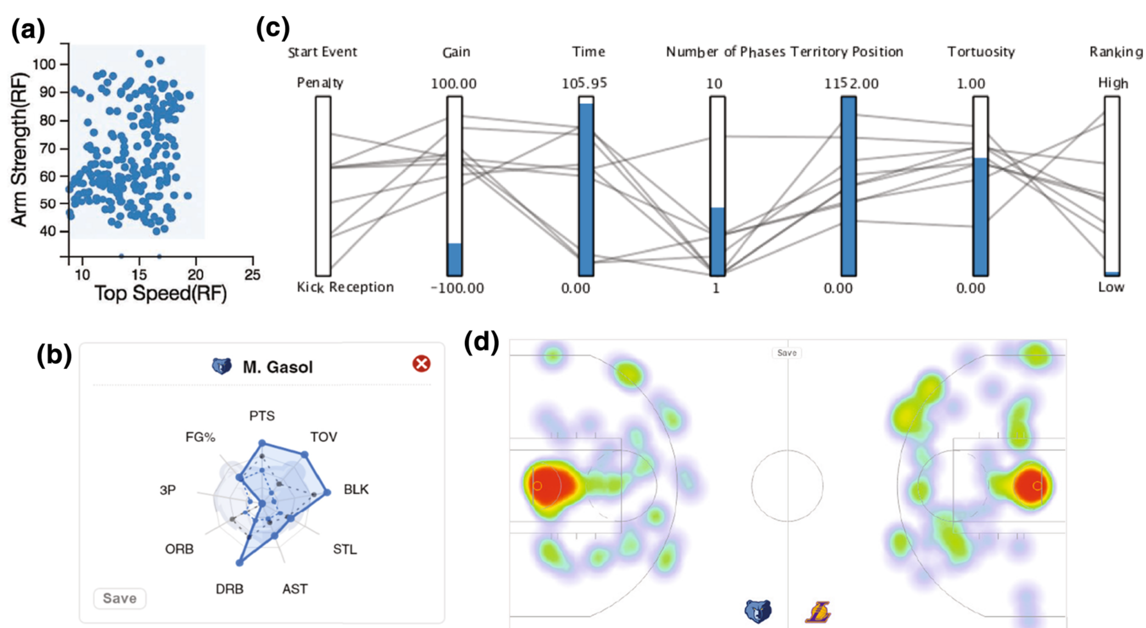


**Fig. 2** High-dimensional data visualization in competitive sports: **a** Scatter plot shows the correlation between arm strength and top running speed in all baseball gameplays with the light-blue rectangle as a filter (Lage et al. 2016). **b** Radar chart for the description of player's performance (Losada et al. 2016), including player-shooting tendency in previous games, the average performance of all games and the performance in the current game. **c** Parallel Coordinates for a better understanding of model parameters and sort events (Chung et al. 2016). **d** Heat map for presenting the shooting position distribution in NBA games (Losada et al. 2016). Images courtesy of the original papers, used with authors' permission

approach that produced radial heat maps to the short length and shooting frequency in a hockey game (Pileggi et al. 2012). By summarizing the related work in heat maps, it can be seen that heat maps are widely used to display information related to spatial distribution in sports data visualization. Such data included shooting and hitting distribution, the distribution of ball passing and its frequency, moving trajectories and dynamic space information.

### 4.2 Time-series visualization

Time-series visualization is often combined with geographic cartography, allowing for the display of dimensions of spatiotemporal information and various related information patterns. It reflects the behavioral patterns of information objects over time. The trajectory is not only high-dimensional data but also real-time data. It is spatiotemporal data with geographic location information using a time tag. Therefore, time-series visualization is suitable for showing the moving trajectory. In addition to traditional statistical charts, such as a line chart, histogram, bar chart, etc., there are other techniques in time-series visualization including flow maps which are based on two-dimensional space and space-time cubes which is based on three-dimensional space. Although trajectory data are mostly time-series data, they have not been widely applied by the researchers in the existing visualization work, with fewer applications using traditional statistical charts. Line chart and histogram are common visualization tools for time-series data. Line chart shows the development of changing trends of the research object through rising and falling curves. It is often applied to player characteristics and game-changing information. Histograms are formed by rectangles with different heights. It is used to represent data distribution. It is also common in the statistical analysis articles but is less used in data visualization systems.

*Line chart* Many researchers used line chart in their work. For example, Perin et al. designed an overlap-free chart for the soccer scores based on line chart (Perin et al. 2016), as shown in Fig. 3a. Janetzko et al. used line chart to show the changing player attributes when analyzing a single soccer player (Janetzko et al. 2014). For basketball games, Goldman and Rao used line chart to show the estimated offensive rebound rate (Goldman and Rao 2012), while Larsen et al. showed the impact of self-racial bias on betting results, game results and surpluses (Larsen et al. 2008).

*Histogram* Histogram visualization is currently only used for soccer, basketball and snooker data analysis. Albinsson and Andersson used histograms to present soccer data attributes and the relationship among attributes (Albinsson and Andersson 2008). Andrienko et al. showed the pressure between the ball and opposing soccer player (Andrienko et al. 2017), as shown in Fig. 3b. Sisneros and Van Moer designed the PluMP visualization based on scatter plot and histogram for the score statistics of basketball teams (Sisneros and Van Moer 2013). Parry et al. analyzed the importance of various events for snooker video data by histograms (Parry et al. 2011).

*Other methods* In other time-series works, Bialkowski analyzed the role of soccer players at different time series and displayed the results on a timeline (Bialkowski et al. 2016). Wongsuphasawat and Gotz used time-series visualization to analyze the progression path and related attributes of the events in the soccer data (Wongsuphasawat and Gotz 2012). Then, they presented a game summary by a visualization that

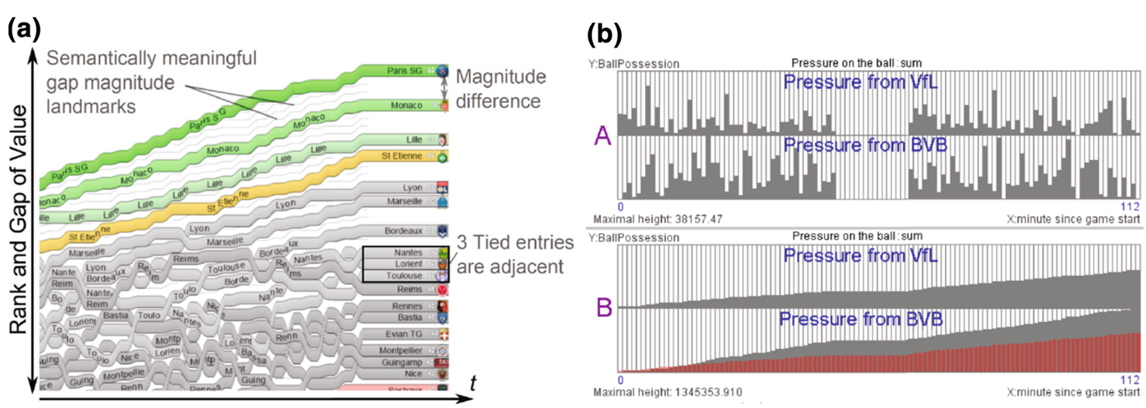


**Fig. 3** Time-series visualization in competitive sports: **a** Visualization of time-varying ranking information and game score information in soccer data based on line chart visualization (Perin et al. 2016). **b** Time histogram for presenting the pressure for soccer and the opponent players (Andrienko et al. 2017). Images courtesy of the original papers, used with authors' permission

combines timeline-based and tree-based techniques (Wongsuphasawat 2013). Sacha et al. showed soccer players' trajectories by using time-series visualization (Sacha et al. 2017). Ishikawa and fujishiro used a time-series visualization to analyze the transition of tactile situations in a rugby game (Ishikawa and fujishiro 2018). Also, Chen et al. designed time-series visualization to show game results and team information for basketball games (Chen et al. 2016). Du et al. focused on sonification, designed time-series visualization and generated sounds to enhance users' understanding of team offensive and defensive behaviors (Du et al. 2018).

### 4.3 Network (graph) visualization

Network visualization is also called graph visualization. For hierarchical data, data with network nodes and links topologic in structure, researchers in the field of big data often use network visualization to directly represent the potential for different attributes in relationships and the different influence patterns they may carry. Due to the time-varying feature of the data, network data visualization can not only be displayed statically but must also be displayed dynamically. Common network data visualization includes node-based graphs, space-filling graphs, large-scale dense graphs based on edge binding and large-scale graphs based on hierarchical clustering (Ren et al. 2014). However, competitive sports data belong to spatiotemporal data and the timing dimension is an indispensable attribute of the data. Based on network visualization, it is difficult to characterize the time dimension. Therefore, network visualization is used minimally in competitive sports. In a variety of network visualization, treemaps are a node-based graph. It conveys relationships by deposing data into branches and is commonly used to present hierarchical data. The adjacency matrix shows how nodes are connected by the intersections of the corresponding rows and columns. Treemaps and matrices are the most commonly used visualization methods in network visualization.

*Treemap* According to our study, Tan et al. and Turo used treemaps to analyze basketball data (Tan et al. 2007; Turo 1994). Moreover, Tan et al. designed a novel tree-shaped visual structure to provide a better overview of the data and present potential complex relationships among the data, as shown in Fig. 4. Jin and Banks used a competition tree to organize information in tennis matches (Jin and Banks 1996). They also integrated game routines and the tree structure of the game (Jin and Banks 1997). Cox and Stasko designed treemap to show the number of baseball players in various areas (Cox and Stasko 2006).

*Matrix* Matrices were used for soccer and basketball data. Bialkowski et al. explored the cluster proportion of common formations of defensive players, midfielders and offensive players and used glyph matrix visualization to display the clustering results (Bialkowski et al. 2016). Perin et al. used an adjacency matrix to display passing frequency and passing time in soccer games (Perin et al. 2013). Cava and Chen used the

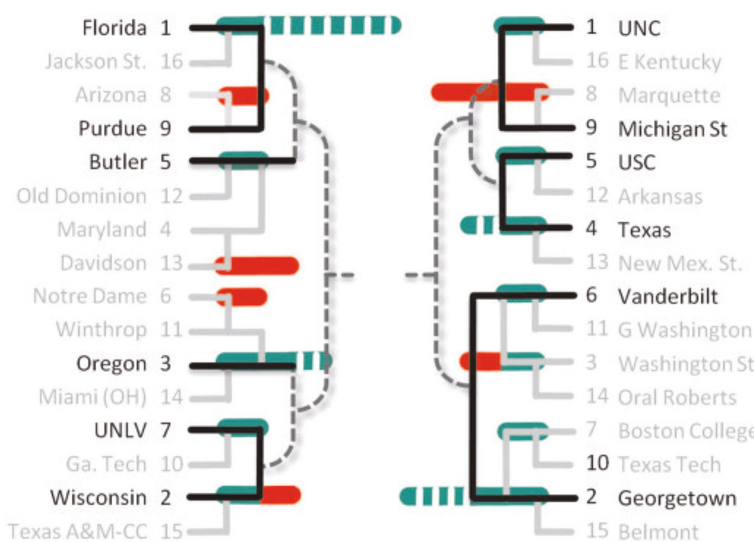


**Fig. 4** Treemap as network (graph) visualization in competitive sports: The tree-shaped visualization structure visualizes the predictive and the real-world outcomes of each stage in a basketball game and shows the correctness and potential complex relationships between the data with colored bars (Tan et al. 2007). Image courtesy of the original paper, used with authors' permission

adjacency matrix to separately show the results of soccer and basketball games (Cava and Freitas 2013; Chen et al. 2016). However, Cava and Freitas compared the results of different games.

*Other methods* Some researchers studied other types of graph visualization. For example, Perin et al. designed node-based graph and hive plot based on graph visualizations. Node-based graphs showed the frequency of the player attendance in a passing event, the spatial position of moving action and the time sequence of the events. The hive plot showed the spatial information of the passing sequence (Perin et al. 2013).

### 4.4 Glyph visualization

Glyph visualization is also one of the widely used visualization techniques. It visually describes the data by using graphical entities and conveys several data features through shape, size, color, position and other encoding channels. Therefore, it is usually only suitable for displaying multivariate datasets. Glyph visualization is used to display player's performance in competitive sports, and data would include the time interval of ball possession, the difference in the number of goals scored and the result of scoring events.

Research for presenting soccer player's performance by Rusu et al. is the earliest work in glyph visualization (Rusu et al. 2010). Legg et al. used player-shaped glyph to describe events in rugby data, as shown in Fig. 5a. They also solved the issue of real-time moving performance analysis (Legg et al. 2012) and displayed rugby game event data (Legg et al. 2013) based on glyph layout algorithms. Other researchers also studied events information presentation by glyph visualization. Chung et al. also displayed the scored events in rugby game by glyph visualization in a visual analysis system (Chung et al. 2013, 2016). Also, Polk et al. used ball-shaped glyph visualization for score information in tennis matches (Polk et al. 2014), as shown in Fig. 5b.

Other-based glyph visualization is also designed for shooting information, ball possession intervals, game event data filtering and tactical information. For example, Cava and Freitas combined an adjacency matrix with glyph visualization to provide an overview of the championship results (Cava and Freitas 2013), as shown in Fig. 5c. A study on multivariate glyph visualization for baseball shooting information has been completed by Moon and Brath (Moon and Brath 2013). For presenting ball possession intervals information in soccer games, Stein et al. designed other-based glyph visualization (Stein et al. 2015). After that, they proposed a visual interaction system providing an event filter based on glyph visualization (Stein et al. 2016b). Wu et al. designed tennis tactic views based on glyph visualization to display the attributes of each stroke (Wu et al. 2018a).

### 4.5 Other visualizations

Except for the high-dimensional data visualization, time-series visualization, network (graph) visualization and glyph visualization, there are other methods for displaying different data attributes, such as arc diagrams and tag clouds which have also been used by researchers for the visualization of competitive sports data. Some researchers also have designed novel visualization methods based on their own research goals.

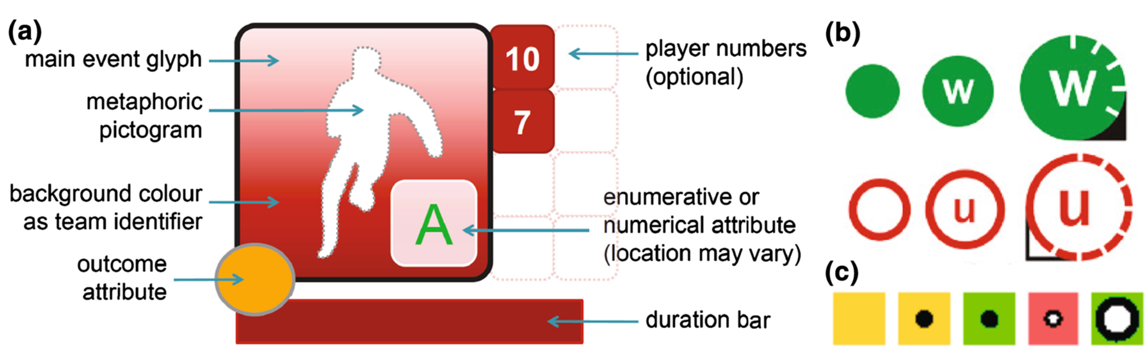


**Fig. 5** Glyph visualizations in competitive sports: **a** Player-shaped glyph visualization describes events information in rugby data (Legg et al. 2012). **b** Ball-shaped glyph visualization for different zoom levels in tennis data (Polk et al. 2014). **c** Other-shaped glyph visualization for presenting map matches attributes in soccer data (Cava and Freitas 2013). Images courtesy of the original papers, used with authors' permission

*Arc diagram* Researchers have used arc diagrams in recent years for competitive sports data visualization. Losada et al. used arc chart to display information including order, frequency and time of ball passing (Losada et al. 2016). Also, Owens and Jankun–Kelly presented player's behavior types and different pieces of game information by arc diagrams for American college football games (Owens and Jankun-Kelly 2013).

*Tag cloud* To visualize textual information, Perin et al. display player names in a soccer visualization system by tag cloud method to reflecting the frequency and position of players (Perin et al. 2013). This method is not common in competitive sports data visualization.

#### *4.5.1 Self-designed visualization*

Many researchers have designed new visualization methods; one of the earliest designs was for baseball data. Cox and Stasko designed a baseline visual and a treemap which showed team performance and player number in various areas (Cox and Stasko 2006). In recent years, researchers have also designed data visualizations for tennis, bicycles, table tennis and basketball. Polk et al. designed Fish Grid and Pie Meter to analyzed single-player information in tennis games (Polk et al. 2014). Pingali et al. showed players' performance, style and strategy in their designed visualization system (Pingali et al. 2001). Wood proposed an automatic-construction profile and created a spline-based visualization for bicycle racing (Wood 2015). For table tennis data, Wu et al. designed an interactive visualization system to provide visualization for game information, including time orientation, statistical and tactical information (Wu et al. 2018a). Wang et al. also designed several views combined with donut chart and the pie chart for table tennis data (Wang et al. 2019). Also, Du et al. designed a time-series visualization to study basketball data sonification (Du et al. 2018).

Soccer data visualization is the widest research. Rusu et al. used a metaphor-based visual analysis method to measure the goalkeeper's performance (Rusu et al. 2011). Vuillemot and Perin also developed a predictive sports events system for the Union of European Football Associations (UEFA) Europa League (Vuillemot and Perin 2016). Janetzko et al. designed horizon graphs to compare the attributes of multiple players and the characteristics of events (Janetzko et al. 2014). Stein et al. used the Tyson polygon method to subdivide the stadium into unit areas with the same area for the presentation of free-kick information (Stein et al. 2016a). They also designed a grid-based free space visualization (Stein et al. 2016b). Wu et al. designed formation flow for visualizing changes in formation patterns and display continuous formations of spatial flows (Wu et al. 2018b).

## 5 The relationships among data, tasks and techniques

In this section, we collect current research publications and find the inner link among competitive sports data, main tasks and visualization techniques. From the two tables we summarized, researchers can not only know which technique was used for a given data category, or choose the perfect visualization technique according to the data category, but also understand which technique was used for a given visualization task, or select the appropriate visualization technique based on the main tasks and goals. Further expansion and combination will be the reference for future research work.

### 5.1 The relationship between data and visualization techniques

We discuss the statistics of 41 papers and extract one or more data categories and visualization techniques from each paper and then summarize their relationship as shown in Table 2. According to Sect. 2 and Sect. 4, there are 11 data subcategories and 14 technique subcategories. In Table 2, different colors represent the different main categories. The color saturation represents the different subcategories in the same main category. For example, bluish violet, blue, light orange and pink separately represent four data categories, such as absolute spatiotemporal information, relative spatiotemporal information, statistics information, staff statistics information. Two bluish-violet colors from light to dark represent two different subcategories, namely spatiotemporal information for ball and spatiotemporal information for player. The rest color can be narrated in the same manner.

**Table 2** Relationship between data and techniques in competitive sports data visualization: summary of 14 techniques and 11 data categories, extracting from each paper

| Category | | | High-dimensional Data Visualization | | | | Time-series Visualization | | | Network (Graph) Visualization | | | Glyph Visualization | Other Visualizations | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Scatter Plot | Star Plot/Radar Chart | Parallel Coordinates | Heatmap | Line Chart | Histogram | Other Methods | Treemap | Matrix | Other Methods | Glyph | Arc Diagram | Tag Cloud | Self-designed |
| Spatio-temporal Information | Absolute Spatio-temporal Information | Spatio-temporal Informtaion for Ball | | | [Janetzko et al. (2016)] | [Dietrich et al. (2014); Lage et al. (2016)] | | | [Hervieu et al. (2009); Sacha et al. (2017); Stein et al. (2018)] | | | | | | | [Pingali et al. (2001); Tani et al. (2015)] |
| | | Spatio-temporal Informtaion for Player | | | | | | | | | | | | | | |
| | Relative Spatio-temporal Information | Possession Information | | [Wu et al. (2018b)] | | | [Goldman and Rao (2012)] | | [Stein et al. (2015)] | | [Perin et al. (2013)] | [Perin et al. (2013)] | [Stein et al. (2015); Wu et al. (2018b)] | | [Perin et al. (2013)] | |
| | | Shooting Information | | | | [Maheswaran et al. (2012); Pileggi et al. (2012); Moon and Brath (2013); Perin et al. (2013); Losada et al. (2016] | | | [Losada et al. (2016)] | | | | [Moon and Brath (2013)] | | | |
| | | Battle Array Information | [Goldman and Rao (2013)] | | [Stein et al. (2015)] | | | | [Bialkowski et al. (2016)] | | [Cava and Freitas (2013); Bialkowski et al. (2016)] | | [Cava and Freitas (2013); Wu et al. (2018b)] | | | [Wu et al. (2018b)] |
| | | Tactical Information | | | | | | [Sisneros and Van Moer (2013)] | [Ishikawa and fujishiro (2018)] | [Cox and Stasko (2006)] | | | [Wu et al. (2018a)] | | | [Stein et al. (2016a); Wu et al. (2018a)] |
| Statistical Information | Event Statistic Information | Moment Event | | | [Janetzko et al. (2016)] | [Maheswaran et al. (2012); Pileggi et al. (2012)] | [Goldman and Rao (2012)] | | [Perin et al. (2013); Losada et al. (2016)] | | | | | | | [Wang et al. (2019)] |
| | | Period Event | | | | | [Perin et al. (2016)] | [Sisneros and Van Moer (2013)] | [Wongsuphasawat and Gotz (2012); Chen et al. (2016)] | [Jin and Banks (1996, 1997); Tan et al. (2007)] | [Wu et al. (2018a)] | | | | | [Cox and Stasko (2006); Polk et al. (2014); Stein et al. (2016a)] |
| | Staff Statistics Information | Players' Personal Information | | | | | | | | | | | | | | |
| | | Comparative Information among Players | [Goldman and Rao (2013)] | [Losada et al. (2016)] | [Chung et al. (2013, 2016); Stein et al. (2015)] | [Goldsberry (2012)] | | | | | | | [Legg et al. (2012); Chung et al. (2013, 2016); Stein et al. (2015)] | | | [Rusu et al. (2011); Okamoto (2011); Janetzko et al. (2014); Wood (2015)] |
| | | Team Information | | | | | | | [Wongsuphasawat (2013); Bialkowski et al. (2016)] | | [Bialkowski et al. (2016)] | | | | | [Cox and Stasko (2006); Bialkowski et al. (2016); Stein et al. (2016a)] |

From Table 2, it can be seen that the player's personal information is necessary but the data type is too simple to be a hot research topic in the field of data visualization. Absolute spatiotemporal information for ball and player was often visualized simultaneously. In relative spatiotemporal information, possession and shooting information were also visualized together sometimes. All visualization techniques were applied by relative spatiotemporal information. Absolute spatiotemporal information and event statistic information were not visualized by glyph visualization. Also, for possession and shooting information, researchers were more inclined to existing visualization techniques instead of self-design visualization.

Among these common visualization techniques, arc diagram was not used in any data categories. The least applied visualization is the tag cloud, only for presenting possession information, while time-series visualization is the most used technique. Except for the player's personal information, high-dimensional data visualization was not applied to tactical information and team information, but the frequency of using parallel coordinates and heat map is higher than that of scatter plot and star plot (radar chart). Also, time-series visualization was not used for comparative information among players. Furthermore, network (graph) visualization and glyph visualization were not applied for moment event. Generally speaking, researchers like to visualize different data categories by using high-dimensional data visualization and time-series visualization.

## 5.2 The relationship between main tasks and visualization techniques

We summarize 52 papers for the relationship between tasks and visualization techniques as shown in Table 3. Similar to Table 2, there are 12 subcategories of visualization tasks and 14 subcategories of visualization techniques.

**Table 3** Relationship between main tasks and techniques in competitive sports data visualization: summary of 14 techniques used for 12 visualization tasks, extracting from each paper

| Category | | High-dimensional Data Visualization | | | | Time-series Visualization | | | Network (Graph) Visualization | | | Glyph Visualization | Other Visualizations | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scatter Plot | Star Plot/Radar Chart | Parallel Coordinates | Heatmap | Line Chart | Histogram | Other Methods | Treemap | Matrix | Other Methods | Glyph | Arc Diagram | Tag Cloud | Self-designed |
| Feature Presentation Task | Presentation for Trajectory Information | | | | [Dietrich et al. (2014), Lage et al. (2016)] | | | [Sacha et al. (2017)] | | | | | | [Perin et al. (2013)] | |
| | Presentation for Player Performance | | [Rusu et al. (2010)] | [Janetzko et al. (2016)] | [Losada et al. (2016)] | | | | | | | [Rusu et al. (2010)] | [Losada et al. (2016)] | | [Pingali et al. (2001)] |
| | Presentation for Special Events | | [Losada et al. (2016)] | [Legg et al. (2013); Janetzko et al. (2016)] | [Maheswaran et al. (2012); Pileggi et al. (2012); Perin et al. (2013)] | [Goldman and Rao (2012)] | [Parry et al. (2011)] | | | [Perin et al. (2013)] | [Perin et al. (2013)] | [Legg et al. (2012); Moon and Brath (2013); Stein et al. (2016b)] | | | |
| | Presentation for Game Information | | | [Chen et al. (2016)] | | | | [Wongsuphasawat (2013); Chen et al. (2016)] | [Turo (1994); Jin and Banks (1996, 1997); Tan et al. (2007)] | [Chen et al. (2016)] | | | | | [Polk et al. (2014)] |
| | Presentation for Other Information | | | | | [Larsen et al. (2008)] | [Andrienko et al. (2017)] | | | | | | | | |
| Feature Comparison Task | Player Performance Comparison | [Goldman and Rao (2013)] | | [Chung et al. (2013, 2016)] | [Goldsberry (2012)] | | | | | | | [Chung et al. (2013, 2016); Legg et al. (2013)] | | | [Rusu et al. (2011); Wood (2015)] |
| | Behavioral Events Comparison | | | [Janetzko et al. (2016)] | | [Janetzko et al. (2014)] | | | | | | | [Owens and Jankun-Kelly (2013)] | | [Janetzko et al. (2014)] |
| | Game Information Comparison | | | [Stein et al. (2015)] | | [Perin et al. (2016)] | [Albinsson and Andersson (2008)] | | | [Cava and Freitas (2013)] | | [Cava and Freitas (2013); Stein et al. (2015)] | | | |
| Feature Prediction Task | Game Results Estimation | [Okamoto (2011)] | | | | | | | | | | | | | [Vuillemot and Perin (2016)] |
| | Battle Array Decision | | | | | | | [Bialkowski et al. (2016); Du et al. (2018)] | | [Bialkowski et al. (2016)] | | | | | [Du et al. (2018); Wu et al. (2018b)] |
| | Sports Event Prediction | | | | [Stein et al. (2016b)] | | | [Wongsuphasawat and Gotz (2012)] | | | | | | | [Stein et al. (2016b)] |
| | Game Tactics Decision-making | | | | | | [Sisneros and Van Moer (2013)] | [Ishikawa and fujishiro (2018)] | [Cox and Stasko (2006)] | | | [Wu et al. (2018a)] | | | [Cox and Stasko (2006); Stein et al. (2016a); Wu et al. (2018a); Wang et al. (2019)] |

Comparing the feature presentations and feature comparisons, in the work on feature prediction task, researchers always design their visualization. In addition to visualization techniques, many researchers designed their own data visualization for data analysis. Researchers paid relatively little attention to trajectory and other information presentation, behavioral event comparison, game result estimation and game event prediction. The most immediate task in the feature presentation task is usually special events presentation. Four common visualization techniques were used. For player's performance presentation and comparison, and game results estimation, researchers did not use time-series visualization and network (graph) visualization in these two subcategories. Also, the trajectory data include time-varying attributes, but researchers did not use time-series visualization. For feature prediction task, high-dimensional data visualization was used only in two papers.

Among the common visualization techniques, the least used visualization is the tag cloud technique, while heat maps, parallel coordinates and glyph visualization are the most used. In high-dimensional data visualization, scatter plot was not used for feature presentation tasks, but instead, star plot or radar chart was used for it. Parallel coordinates were not applied for feature prediction tasks, and instead, heat maps were applied for all major task categories. In time-series visualization, line chart was not used for feature prediction tasks, while histograms were used for all major task categories. Treemap in the network (graph) visualization was only applied for game statistics presentation and game tactics decision-making, while matrices were applied for all major task categories. Although glyph visualization was used more often, there was only one paper in which glyph was applied. Arc diagrams were not applied for feature prediction tasks. The tag cloud was only applied to the trajectory presentations. In general, researchers were more inclined to design their visualizations for analyzing specific tasks.

## 6 Competitive sports data visual analysis

In Sect. 4, we mainly discuss four visualization techniques common in competitive sports data visualization. In this section, we discuss the workflow and interactions of competitive sports visualization analysis and analyze heterogeneous data of competitive sports.

### 6.1 Competitive sports data visual analysis research

Many researchers worked on soccer data visual analytics and proposed relevant streamline techniques. Janetzko et al. studied semiautomatic detection and proposed streamline work procedures for analyzing a single soccer player, and then established a procedure for analyzing similar events based on the machine learning method (Janetzko et al. 2014). Stein et al. made improvements based on the work of Janetzko et al. and proposed a novel visual analysis procedure for soccer data (Stein et al. 2015). After that, Stein et al. proposed a typical streamline analysis (Stein et al. 2016a). Also to workflows for different objects and different events, Vuillemot and Perin studied the results prediction flow of a soccer game (Vuillemot and Perin 2016). Sacha et al. developed a novel visual analytics system for soccer data providing several interactions (Sacha et al. 2017). Besides, Wu et al. designed and developed a visual analytics system for soccer data (Wu et al. 2018b). From the above work, we summarize that the workflow involves three aspects: different objects, different events and result prediction. The interactions only include several simple operations such as filtering, highlighting, clicking, dragging, and so on.

In the research of rugby data visualization, Legg et al. developed the MatchPad system for rugby data which includes four key stages (Legg et al. 2012). Subsequently, they also proposed an iterative analysis process (Legg et al. 2013). Also, Chung et al. developed a visual analysis system for rugby events data and proposed a system procedure (Chung et al. 2013). In subsequent studies, they continued to propose a knowledge-assisted ranking framework (Chung et al. 2016). These studies focus on event analysis. The difference is that Legg et al. studied on event-based video search, while Chung et al. studied on event-based sorting. Their work did not involve analysis for different objects. The purpose of the interaction is mostly searching and ranking.

Researchers also proposed different procedures in their study of other competitive sports data. Pileggi et al. proposed a series of procedures from the viewpoint of hockey analysts (Pileggi et al. 2012). Dietrich et al. designed the structure of the baseball visualization system including three data streams: player position, ball position and game event (Dietrich et al. 2014). Tani et al. proposed the procedures for the American football data visualization system (Tani et al. 2015). Wu et al. developed a visual analytics system for tactical analysis in table tennis with three components: data processing, model and visualization (Wang et al. 2019).

### 6.2 Heterogeneous data visual analysis in competitive sports

We summarize heterogeneous data visual analysis in competitive sports from three aspects. First of all, the same field sports competitions include multiple players and the same player has multiple attributes. This information involves the combination of multiple objects, including the movement of space and time and the player's performance. It provides a variety of perspectives for analyzing player's behavioral patterns in competitive sports. Second, through the additional data presented, player's sports data can be enriched. To better understand and analyze player's behavioral patterns, researchers may need to add more information. For example, the additional information includes textual information that describes competition conditions and sports events. This is important data that cannot be ignored to further identify the semantics of movement. Finally, the study of competitive sports can be incorporated into an array of multidisciplinary studies. Competitive sports involve people's behaviors and activities. Therefore, it is associated with many behavioral disciplines. Also, since a player's mental state can determine physical conditions in a game, consequently, to a certain extent affecting their performance and affecting the final results of a game, space-time and statistical data can be used in association with psychology and life sciences. Cross-combinations in various fields can help coaches in competitive sports to make better tactical decisions, bringing considerable value to many business areas.

## 7 Discussion

There are some special problems and challenges in competitive sports data visualization and visual analysis. In this section, we first introduce the features and limitations of competitive sports data, then discuss multimedia data visualization work and summarize the existing work. At last, we discuss competitive sports data visualization evaluation.

### 7.1 Features and limitations of competitive sports data

Competitive sports data are mostly used for the display and comparison of trajectory and personal statistical data and are also used for trajectory information extraction and special events detection. Although competitive sports data provide an abundant pool of resources, some problems and limitations still exist during their study.

First of all, collecting data. Researchers paid more attention to direct confrontational competitive sports. Soccer and basketball are the most prominent. However, there are few studies on other competitive sports data, and many fields are still blank. Difficulties in collecting data are one of the reasons for the lack of research work. With the advanced data collection techniques, such as GPS devices and mobile phones, various types of trajectory data are increasingly complementing (Liao et al. 2015). In the future research work, researchers can obtain data through different ways to conduct visualization research, find out commonalities and differences and make the research work in this field richer and more complete.

Secondly, processing data. Researchers usually need to conduct data processing for the use of data. The frequency of common sensor-based sample data is very high so that the amount of data is large. It takes a lot of time and labor costs for data processing. The accuracy of the data processor determines the data quality. Therefore, researchers should pay attention to research distribution, scope and deviation. When selecting data, it is necessary to further consider the errors and uncertainties caused by inaccurate data.

Thirdly, visualizing data. At present, competitive sports data visualization involves three tasks which are presentation, comparison and prediction. However, the visualization techniques used in the research work are basic and single. Traditional visualization cannot meet the needs of visualization research. Many researchers have designed novel visualization. This is the future research trend in this field. In short, solving problems that arise in the process of competitive sports data visualization and visual analysis is both a challenge and an opportunity.

### 7.2 Multimedia visualization and visual analysis

Most multimedia data in competitive sports are video. Video visualization reveals important features and special events in the video. Users can explore feature event data through video visualization. Therefore, video processing is an important part of competitive sports data analysis, but it has not yet been fully investigated by visual analysts. In this paper, we summarize the current major techniques in order to provide a reference for future research work.

Researchers combined video data processing with feature extraction and event detection. Researchers who began to visualize competitive sports video data were Pingali and Saito. Saito et al. studied the soccer player's trajectory by tracking techniques from multicamera videos (Saito et al. 2004). Pingali et al. developed the tennis visualization system to collect players and trajectory from videos in real time (Pingali et al. 2001). Recently, Stein et al. proposed a visual analysis system for soccer data that combined team-moving specifications and trajectory visualization based on video data (Stein et al. 2018). Also, Höferlin and Parry began studying snooker video data. Höferlin et al. studied how to convert video into spatiotemporal attributes to help snooker players train (Höferlin et al. 2010), while Parry et al. studied the summarizing method for snooker video events and proposed a hierarchical event representation framework (Parry et al. 2011). The research work on rugby videos has been done by Legg et al., who developed a system based on a sketch-based video (Legg et al. 2013). Besides, Wu et al. collected soccer videos, tracked the positions of players for each frame and also provided a video button to display the game video for users in their system (Wu et al. 2018b). The above work only studied video data. However, Hervieu et al. studied both video and audio data (Hervieu et al. 2009).

In the research of video visual analysis, Saito et al. proposed to use a camera for tracking player trajectory on the soccer field (Saito et al. 2004). Pingali et al. processed real-time videos and used eight cameras to track the ball and player trajectory on the tennis court and proposed a visualization based on real-time tracking of moving trajectories (Pingali et al. 2001). Also, Höferlin et al. studied the trajectory of the ball in a snooker match and designed a video processing procedure (Höferlin et al. 2010).

### 7.3 Competitive sports data visualization evaluation

Most of the researches have been able to verify the methods they have proposed and been able to evaluate the contribution of their research work. Many verifications and evaluation tasks are studied by presenting case studies. However, there are rare universal evaluation rules and guidelines for competitive sports visual analysis. By summarizing the existing work, we propose the key features for a novel competitive sports visual analysis tool. First of all, the researcher should explicitly confirm who the users are. They include the audience, players, coaches, referees, sports analysts, sponsors, etc. The needs of different users are different. Second, according to different needs, different measurements would need to be focused on including patterns, features or events. Third, the provided methods or tools are supposed to be extendable and support different sizes of data sets. The above key features can help researchers determine the scope, advantages and disadvantages of proposed methods or tools in future research.

## 8 Conclusion and future work

In this paper, we first introduce the classification of competitive sports data and summarize the data features and current visualization application. Then, we classify the main tasks of competitive sports data visualization. Also, we summarize visualization techniques based on the existing research. Finally, we discuss the characteristics and limitations of using multimedia data in visualization and problems arisen during visual analysis research and evaluation of visual analysis. By comprehensively reviewing and summarizing the existing research, we can construct a structure of classification for competitive sports data visualization and guide possible future research trends.

From the results of analysis and discussion, it can be seen that with improving techniques, data collection has created increasingly abstract data features in recent years. Feature extraction and analysis based on statistical analysis and machine learning carry great potential and are a valued direction in the field of competitive sports data visualization research. Methods on how to choose appropriate visualization techniques for different data types, data attributes and derived features, how to better mix different data attributes to present data visualization and visual analysis results and how to establish significant assessment frameworks are three urgent problems that need to be discussed in future research.

**Acknowledgements** This work is supported by the National Key Research and Development Program of China (2016QY02D0304). We appreciate all the authors who gave us permission to reuse their images in this research. We would also like to thank all researchers for their contributions in competitive sports visualization field and the editors of this journal and the anonymous reviewers for their valuable suggestions and comments.

## References

Albinsson PA, Andersson D (2008) Extending the attribute explorer to support professional team-sport analysis. Inf Vis 7(2):163–169

Andrienko G, Andrienko N, Budziak G, Dykes J, Fuchs G, von Landesberger T, Weber H (2017) Visual analysis of pressure in football. Data Min Knowl Discov 31(6):1793–1839

Bialkowski A, Lucey P, Carr P, Matthews I, Sridharan S, Fookes C (2016) Discovering team structures in soccer from spatiotemporal data. IEEE Trans Knowl Data Eng 28(10):2596–2605

Borgo R, Chen M, Daubney B, Grundy E, Heidemann G, Höferlin B, Höferlin M, Jänicke H, Weiskopf D, Xie X (2011) A survey on video-based graphics and video visualization. In: Eurographics (STARs), pp 1–23

Cava R, Freitas CDS (2013) Glyphs in matrix representation of graphs for displaying soccer games results. In: SportVIS-workshop on sports data visualization. Atlanta, Georgia, USA: IEEE VIS

Chen W, Lao T, Xia J, Huang X, Zhu B, Hu W, Guan H (2016) Gameflow: narrative visualization of NBA basketball games. IEEE Trans Multimed 18(11):2247–2256

Chung DH, Legg P, Parry M, Griffiths I, Brown R, Laramee R, Chen M (2013) Visual analytics for multivariate sorting of sport event data. In: Workshop on sports data visualization, vol 3

Chung DH, Parry ML, Griffiths IW, Laramee RS, Bown R, Legg PA, Chen M (2016) Knowledge-assisted ranking: a visual analytic application for sports event data. IEEE Comput Graph Appl 36(3):72–82

Cox A, Stasko J (2006) Sportsvis: discovering meaning in sports statistics through information visualization. In: Compendium of symposium on information visualization, pp 114–115

Dietrich C, Koop D, Vo HT, Silva CT (2014) Baseball4d: A tool for baseball game reconstruction & visualization. In: 2014 IEEE conference on visual analytics science and technology (VAST), IEEE, pp 23–32
Du M, Chou JK, Ma C, Chandrasegaran S, Ma KL (2018) Exploring the role of sound in augmenting visualization to enhance user engagement. In: Pacific visualization symposium (PacificVis), IEEE
Goldman M, Rao JM (2012) Effort vs. concentration: the asymmetric impact of pressure on nba performance. In: Proceedings of the MIT sloan sports analytics conference, pp 1–10
Goldman M, Rao JM (2013) Live by the three, die by the three? The price of risk in the NBA. In: Submission to the MIT sloan sports analytics conference
Goldsberry K (2012) Courtvision: new visual and spatial analytics for the NBA. In: 2012 MIT sloan sports analytics conference
Gudmundsson J, Horton M (2017) Spatio-temporal analysis of team sports. ACM Comput Surv (CSUR) 50(2):22
Hervieu A, Bouthemy P, Cadre JPL (2009) Trajectory-based handball video understanding. In: Proceedings of the ACM international conference on image and video retrieval, ACM, p 43
Höferlin M, Grundy E, Borgo R, Weiskopf D, Chen M, Griffiths IW, Griffiths W (2010) Video visualization for snooker skill training. In: Computer graphics forum, Wiley Online Library, vol 29, pp 1053–1062
Ishikawa Y, Fujishiro I (2018) Tidegrapher: visual analytics of tactical situations for rugby matches. Vis Inform 2(1):60–70. https://doi.org/10.1016/j.visinf.2018.04.007
Janetzko H, Sacha D, Stein M, Schreck T, Keim DA, Deussen O, et al. (2014) Feature-driven visual analytics of soccer data. In: 2014 IEEE conference on visual analytics science and technology (VAST), IEEE, pp 13–22
Janetzko H, Stein M, Sacha D, Schreck T (2016) Enhancing parallel coordinates: statistical visualizations for analyzing soccer data. Electron Imaging 1:1–8
Jin L, Banks DC (1996) Visualizing a tennis match. In: Proceedings IEEE symposium on information visualization'96, IEEE, pp 108–114
Jin L, Banks DC (1997) Tennisviewer: a browser for competition trees. IEEE Comput Graph Appl 17(4):63–65
Kahn LM (1991) Discrimination in professional sports: a survey of the literature. ILR Rev 44(3):395–418
Keim DA, Kriegel HP (1996) Visualization techniques for mining large databases: a comparison. IEEE Trans Knowl Data Eng 8(6):923–938
Lage M, Ono JP, Cervone D, Chiang J, Dietrich C, Silva CT (2016) Statcast dashboard: exploration of spatiotemporal baseball data. IEEE Comput Graph Appl 36(5):28–37
Larsen T, Price J, Wolfers J (2008) Racial bias in the NBA: implications in betting markets. J Quant Anal Sports 4(2):7
Lazarus RS (2000) How emotions influence performance in competitive sports. Sport Psychol 14(3):229–252
Legg PA, Chung DH, Parry ML, Jones MW, Long R, Griffiths IW, Chen M (2012) Matchpad: Interactive glyph-based visualization for real-time sports performance analysis. In: Computer graphics forum, Wiley Online Library, vol 31, pp 1255–1264
Legg PA, Chung DH, Parry ML, Bown R, Jones MW, Griffiths IW, Chen M (2013) Transformation of an uncertain video search pipeline to a sketch-based visual analytics loop. IEEE Trans Vis Comput Graph 19(12):2109–2118
Lei H, Lao T, Liu Z, Zuo W, Chen W (2015) Sports data visualization survey. J Comput Aided Des Comput Graph 9(27):1605–1616
Liao Z, Li Y, Peng Y, Zhao Y, Zhou F, Liao Z, Dudley S, Ghavami M (2015) A semantic-enhanced trajectory visual analytics for digital forensic. J Vis 18(2):173–184
LLC S (2014) SportVu data visualization suite. http://www.sportvu.com/. Accessed 16 April 2018
Losada AG, Therón R, Benito A (2016) Bkviz: a basketball visual analysis tool. IEEE Comput Graph Appl 36(6):58–68
Maheswaran R, Chang YH, Henehan A, Danesis S (2012) Deconstructing the rebound with optical tracking data. In: Proceedings of the 6th annual MIT SLOAN sports analytics conference
Moon B, Brath R (2013) Bloomberg sports visualization for pitch analysis. In: Workshop on sports data visualization
Okamoto DM (2011) Stratified odds ratios for evaluating NBA players based on their plus/minus statistics. J Quant Anal Sports 7(2):5
Owens SG, Jankun-Kelly T (2013) Visualizations for exploration of American football season and play data. In: The 1st workshop on sports data visualization. IEEE
Page M, Moere AV (2006) Towards classifying visualization in team sports. In: 2006 International conference on computer graphics, imaging and visualisation, IEEE, pp 24–29
Parry ML, Legg PA, Chung DH, Griffiths IW, Chen M (2011) Hierarchical event selection for video storyboards with a case study on snooker video visualization. IEEE Trans Vis Comput Graph 17(12):1747–1756
Perin C, Vuillemot R, Fekete JD (2013) Soccerstories: a kick-off for visual soccer analysis. IEEE Trans Vis Comput Graph 19(12):2506–2515
Perin C, Boy J, Vernier F (2016) Using gap charts to visualize the temporal evolution of ranks and scores. IEEE Comput Graph Appl 36(5):38–49
Perin C, Vuillemot R, Stolper CD, Stasko JT, Wood J, Carpendale S (2018) State of the art of sports data visualization. In: Computer graphics forum, Wiley Online Library, vol 37, pp 663–686
Pileggi H, Stolper CD, Boyle JM, Stasko JT (2012) Snapshot: visualization to propel ice hockey analytics. IEEE Trans Vis Comput Graph 18(12):2819–2828
Pingali G, Opalach A, Jean Y, Carlbom I (2001) Visualization of sports using motion trajectories: providing insights into performance, style, and strategy. In: Proceedings of the conference on Visualization'01, IEEE Computer Society, pp 75–82
Polk T, Yang J, Hu Y, Zhao Y (2014) Tennivis: visualization for tennis match analysis. IEEE Trans Vis Comput Graph 20(12):2339–2348
Ren L, Du Y, Ma S, Zhang X, Dai G et al (2014) Visual analytics towards big data. J Softw 25(9):1909–1936
Rusu A, Stoica D, Burns E, Hample B, McGarry K, Russell R (2010) Dynamic visualizations for soccer statistical analysis. In: 2010 14th International conference on information visualisation (IV), IEEE, pp 207–212

Rusu A, Stoica D, Burns E (2011) Analyzing soccer goalkeeper performance using a metaphor-based visualization. In: 2011 15th International conference on information visualisation (IV), IEEE, pp 194–199

Sacha D, Al-Masoudi F, Stein M, Schreck T, Keim DA, Andrienko G, Janetzko H (2017) Dynamic visual abstraction of soccer movement. In: Computer graphics forum, Wiley Online Library, vol 36, pp 305–315

Saito H, Inamoto N, Iwase S (2004) Sports scene analysis and visualization from multiple-view video. In: IEEE international conference on multimedia and expo, 2004. ICME'04. IEEE, vol 2, pp 1395–1398

Sisneros R, Van Moer M (2013) Expanding plus-minus for visual and statistical analysis of NBA box-score data. In: The 1st workshop on sports data visualization. IEEE

Stein M, Häußler J, Jäckle D, Janetzko H, Schreck T, Keim DA (2015) Visual soccer analytics: understanding the characteristics of collective team movement based on feature-driven analysis and abstraction. ISPRS Int J Geo-Inf 4(4):2159–2184

Stein M, Janetzko H, Breitkreutz T, Seebacher D, Schreck T, Grossniklaus M, Couzin ID, Keim DA (2016a) Director's cut: analysis and annotation of soccer matches. IEEE Comput Graph Appl 36(5):50–60

Stein M, Janetzko H, Lamprecht A, Seebacher D, Schreck T, Keim D, Grossniklaus M (2016b) From game events to team tactics: visual analysis of dangerous situations in multi-match data. In: International conference on technology and innovation in sports, health and wellbeing (TISHW), IEEE, pp 1–9

Stein M, Janetzko H, Seebacher D, Jäger A, Nagel M, Hölsch J, Kosub S, Schreck T, Keim D, Grossniklaus M (2017) How to make sense of team sport data: from acquisition to data modeling and research aspects. Data 2(1):2

Stein M, Janetzko H, Lamprecht A, Breitkreutz T, Zimmermann P, Goldlücke B, Schreck T, Andrienko G, Grossniklaus M, Keim DA (2018) Bring it to the pitch: combining video and movement data to enhance team sport analysis. IEEE Trans Vis Comput Graph 24(1):13–22

Tan D, Smith G, Lee B, Robertson G (2007) Adaptivitree: adaptive tree visualization for tournament-style brackets. IEEE Trans Vis Comput Graph 13(6):1113–1120

Tani T, Huang H, Kawagoe K (2015) Sports play visualization system for American football. In: Proceedings of the international multiconference of engineers and computer scientists, vol 1

Turo D (1994) Hierarchical visualization with treemaps: making sense of pro basketball data. In: Conference companion on Human factors in computing systems, ACM, pp 441–442

Villar JG, Guerrero PR et al (2009) Sports attendance: a survey of the literature 1973–2007. Rivista di Diritto e di Economia dello Sport 5(2):112–151

Vuillemot R, Perin C (2016) Sports tournament predictions using direct manipulation. IEEE Comput Graph Appl 36(5):62–71

Wang J, Zhao K, Deng D, Cao A, Xie X, Zhou Z, Zhang H, Wu Y (2019) Tac-simur: tactic-based simulative visual analytics of table tennis. IEEE Trans Vis Comput Graph 26:407–417

Wang JR, Parameswaran N (2004) Survey of sports video analysis: research issues and applications. In: Proceedings of the Pan-Sydney area workshop on Visual information processing, Australian Computer Society, Inc., pp 87–90

Wongsuphasawat K (2013) A narrative display for sports tournament recap. In: Workshop on sports data visualization in conjunction with IEEE VIS

Wongsuphasawat K, Gotz D (2012) Exploring flow, factors, and outcomes of temporal event sequences with the outflow visualization. IEEE Trans Vis Comput Graph 18(12):2659–2668

Wood J (2015) Visualizing personal progress in participatory sports cycling events. IEEE Comput Graph Appl 35(4):73–81

Wu Y, Lan J, Shu X, Ji C, Zhao K, Wang J, Zhang H (2018a) ittvis: interactive visualization of table tennis data. IEEE Trans Vis Comput Graph 24(1):709–718

Wu Y, Xie X, Wang J, Deng D, Liang H, Zhang H, Cheng S, Chen W (2018b) Forvizor: visualizing spatio-temporal team formations in soccer. IEEE Trans Vis Comput Graph 25(1):65–75

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