VISUAL ANALYTICS TOOLS PROVIDING INSIGHTS INTO TENNIS MATCHES

by

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A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Computing and Information Systems

Charlotte

2016

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ABSTRACT

THOMAS EDWARD POLK. Visual analytics tools providing insights into tennis matches. (Under the direction of DR. JING YANG)

In this dissertation, I present a series of visual analytics tools designed to provide insights into tennis matches for the purpose of player improvement. These include analytic tools that can be divided into two basic categories: non-spatial-based, and spatial-based. The non-spatial-based tools acknowledge the difficulty in obtaining ball and player location tracking data and instead focus on tennis semantic data that is easier to collect, including scoring information, who is serving, and point outcomes (i.e., ace, double-fault, unforced error, forced error, and winner). Data collection techniques easily implementable by non-professional tennis players are outlined. This data is then combined using a set of novel, interactive visualizations whose utility is vetted through a preliminary user study. Spatial-based tools are then proposed that bring to light the potential insights available when we can get reliable player and ball tracking data integrated with domain-specific semantic data. Although spatial data is still typically hard to come by outside of all but the major professional tennis tournaments, the case will be made that spatial-based tracking systems are beginning to find their way into college tennis programs and even into private tennis clubs. Research tools and efforts are described that show how we can use visual analytics techniques to provide players and coaches with meaningful, strategic insights into players' strengths and weaknesses.

ACKNOWLEDGMENTS

Although my name is the only one that appears as the author of this work, it is clear that ideas don't grow and flourish in a vacuum - they require the perspective, inspiration, and motivation that only others can bring. First and foremost, I want to thank my advisor, Jing Yang. I came into her group ready to work on an entirely new project (unrelated to tennis), but when I offhandedly told her about my passion for tennis and some previous (albeit unsuccessful) work I did in this area, she encouraged me to continue with it. Not only did she encourage me in this effort, but she also challenged me to keep improving and honing my ideas, with the result being a solid paper being accepted to one of the top conference journals in our field. I also want to thank my co-graduate students, Hu Yueqi and Zhong Chong who engaged me with lively discussions and alternative ideas that helped me further refine and clarify my design ideas. I also want to thank Sandra Krause for her almost super-human efforts in helping me navigate through a changing degree program and going the extra mile to clear away the hurdles. Without her dedicated effort, I'm sure the date on this dissertation would be sometime in 2017 and not 2016! Finally, I want to thank two of my friends, MaryAlicia Johnson and Michelle Smith, both of whom acted as my cheerleader at times, convincing me I could finish this long journey.

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CHAPTER 1: MOTIVATION AND OVERVIEW

Sports analytics is a growing presence within the information visualization community, particularly now that large amounts of data are being collected across a variety of sports, including soccer, baseball, basketball, and tennis, as well as others. Professional sports teams are beginning to see the benefit of these analytical techniques in giving them a competitive edge. I have selected to focus my information visualization research efforts on analyzing tennis matches for several reasons. First, I am an avid tennis player and have a reasonably deep understanding and appreciation for the sport. This understanding allows me to combine my domain expertise with my visualization skills. Second, the highly structured nature of tennis matches lends itself to analysis. Matches can be analyzed anywhere from the selection of individual shots, up to points, games, or sets. Finally, much of the tennis-related research has been concerned with ball and player tracking with the intent of providing virtual replays or has focused on trying to automatically segment tennis matches into points, games. etc. Other tennis-related research, while focusing on player improvement, has been more concerned with stroke technique and less on strategy. The niche for my work is developing interactive visualizations aimed at identifying player strengths and weaknesses in actual tennis matches.

In this chapter, I introduce this dissertation and describe how it is organized. In the remaining sections in this chapter, I present my motivation for selecting tennis analytics as my area of focus and I then provide a basic overview of the rules and structure of tennis.

In chapter 2, I present an overview of the prior research most relevant to my work. In chapter 3, I present work stemming from my paper originally published in the 2014 InfoVis proceedings. In that paper, I developed and tested a tennis visual analytics system that was purposely constrained to only rely on non-spatial data. The driving force for this was the lack of this type of data for anything other than the biggest professional tennis tournaments. Even when this data is collected, it still requires an extensive, multi-camera system along with human analysts to provide score and other context information. Therefore, since a motivating goal is to create analytical tools to help non-professional players, the first set of visual analytics tools relied only on more easily collected data.

The remaining chapters focus on research efforts that include development of novel visualizations that more fully exploit spatio-temporal data. To be able to effectively work with spatio-temporal data, a great deal of data pre-processing is required. Therefore, in Chapter 4, I outline some of the key challenges in working with spatial data in a sports analytics context and then describe how I have addressed those challenges to create the semantically rich information that serves as the foundational basis for several novel visualizations. I then introduce the components of a tennis analytics system called *Spatial TenniVis* developed to assist tennis coaches and players in analyzing this information. This includes defining a set of design principles used to guide the development of the components. To further explain the utility of the Spatial TenniVis system and validate its usefulness by the targeted end users, I present a case study and the results of a user study in Chapter 6.

In chapter 7, I briefly summarize the contributions made in this dissertation and discuss additional research directions I expect to continue with after graduating. There is far more work fully mining the rich data available from tennis matches than can be encompassed in one dissertation.

CHAPTER 2: RELATED WORK

2.1 Introduction

This literature review is organized along the line of the visualization pipeline, with data collection at the front and the visualizations at the end. Section 2.2 reviews various types of sources providing sports data. Section 2.3 describes how data from these sources is turned into low-level features that can be used for further analysis. Section 2.4 then describes how domain knowledge is applied to turn the low-level features into semantically meaningful information ready to be used in visualizations. Section 2.5 categorizes how the semantic information is used to produce outputs that are of use to targeted users, such as sports fans, analysts, coaches, and players. Since the focus of my research is on generating custom tennis visualizations, section 2.6 reviews custom sports visualizations, with an emphasis on tennis. Other sports are included because many of the same techniques and approaches are valid in a tennis context as well. Finally, section 2.7 reviews other, miscellaneous areas with direct relation to my research efforts.

2.2 Data Collection

Effective information visualizations start with the collection of data a varying levels. This data is collected, filtered, modified, and synthesized with other data to develop higher level of information that can ultimately be transformed into meaningful visualizations aimed a specific audience to aid in answering specific types of questions. In this section, I review the most common sources of lower-level data used in sports analytics and visualizations. These include the following:

- **Video.** Many features of broadcast video and non-broadcast video can be exploited for information, particularly for player and ball tracking.

- **Audio.** Sounds from athletes, such as tennis balls being struck, baseballs being hit, etc., as well as crowd noise and announcers are useful, both alone and in concert with associated video.

- **Text.** On-screen text in graphics such as scores as well as closed-caption feeds can be mined for useful information.

- **Mobile Devices.** Mobile devices (smart phones in particular) have advanced features for recording location and orientation, as well as being a platform for popular, useful data collection apps like Twitter that can be utilized.

- **Wearable Sensors.** Basic biometric data like heart rate and respiratory rate, along with more advanced wearable sensors can provide more detailed, player-specific information that can be incorporated into visualizations.

- **Tracking Devices.** GPS devices and other positional devices can provide finer levels of location data to aid in understanding movement in sports.

- **Sports Statistics Service Providers.** A number of companies now provide large amounts of statistics and movement data for a variety of sports. These data have been the source of many compelling visualizations.

- **Data Collection Applications.** Publicly available and custom-made data collection applications are used for the collection of sports-specific data. Some of these applications collect data automatically, but many still have a human in the loop.

Each of these data sources will be briefly discussed in terms of the type of low-level data they provide.

2.2.1 Video

Video provides a rich source of raw material that can be mined for a variety of elements that serve as the foundation for much of the data upon which many sports visualizations are built. It serves not only as input to the visualization pipeline, but, once segmented and tagged, it can also serve as a key element in the visual output of a sports analytic system. Video is divided into two broad categories: broadcast-video and non-broadcast video. Each of these is discussed below.

Broadcast Video

Broadcast video comes from a (typically) live sports broadcast and is a combination of video feeds from multiple cameras placed around a sporting venue. These cameras may be stationary or moving and typically are capable of panning, tilting, and zooming (PTZ). Broadcast video, in contrast to non-broadcast video, typically has several characteristics that can be exploited for purposes of identifying key events. In a review of vision-based systems for soccer analysis, DOrazio and Leo [43] identified the following features extracted from video that are useful for sports analytics: dominant color, camera motion, motion intensity, histogram changes, and texture features. Yu and Farin [122] also identified dominant color, dominant texture, and motion vectors as key cinematic features to be exploited.

Non-broadcast Video

Although examples of sports video analysis abound for broadcast video, there are far fewer examples using non-broadcast video. However, several authors, including Wang et al. [111], Wang and Parameswaran [112], and Pingali et al. [89] have developed or adapted techniques for use with non-broadcast video sources. [111] developed techniques for use with a single, movable camera (i.e., panning, zooming, etc.) to analyze soccer matches, including the analysis of camera motion, ball tracking, and line and goal post detection. Wang and Parameswaran [112] developed ball tracking techniques using a single, fixed position camera. Pingali et al. [89] used synchronized video streams from eight cameras to develop a real-time, 3D ball and player tracking system for tennis. One advantage that non-broadcast cameras have is that the exact position and orientation of the camera(s) is often known and may be utilized.

2.2.2 Audio

Audio, typically from broadcast sporting events often contains useful, distinguishable content that can be used to categorize video segments or identify domain-specific events of interest, such as goals or touchdowns being scored or other highlights. This content includes crowd noises, discussion from commentators, changes in audio from commercials, and significant noises from the sport itself, such as striking a ball (i.e., with a bat, tennis racquet, or foot).

Duan et al. [44] looked at the performance of various audio features for their effectiveness at detecting potential events. For tennis, they evaluated applause, commentator speech, silence, and ball hits as a way to detect scoring a point, the interval between points, the interval during a point, and a serve, ace, or return, respectively. They also evaluated other audio features, including referee whistles, commentator speech, audience sounds, and basketball hitting backboard for soccer and basketball. Similarly, other researchers have also been able to exploit ball hits and applause to detect tennis events (Coldefy et al. [33], Kijak et al. [59]), as well as voice pitch, energy, and loudness for soccer matches (Coldefy et al. [32], Tjondronegoro et al. [106].

2.2.3 Text

Nearly all sports broadcasts include on-screen text that depicts the current state of the game being played. For tennis matches, this includes the names of the players and the current score. For American football, this includes the names of the teams, the score, the current quarter, and time remaining in the quarter. For soccer, this includes the names of the teams, the current score, and the match time. Tjondronegoro et al. [106] exploited the fact that, in soccer match broadcasts, important text often surrounded by a rectangular box during goal replays.

Another, more recent source of text related to broadcast sporting events comes from webcasts, an example of which is shown in Figure 1. This is a real-time text stream that is broadcast simultaneously with the event, allowing it to be used to detect and segment events in the video. Many sports broadcasts also include closed-caption text that can be mined for event detection. Two potential issues with this approach, however, is that sometimes the words are not translated properly to text and the lag time between the occurrence of an event and the time the text appears on-screen. For a good overview of video text extraction

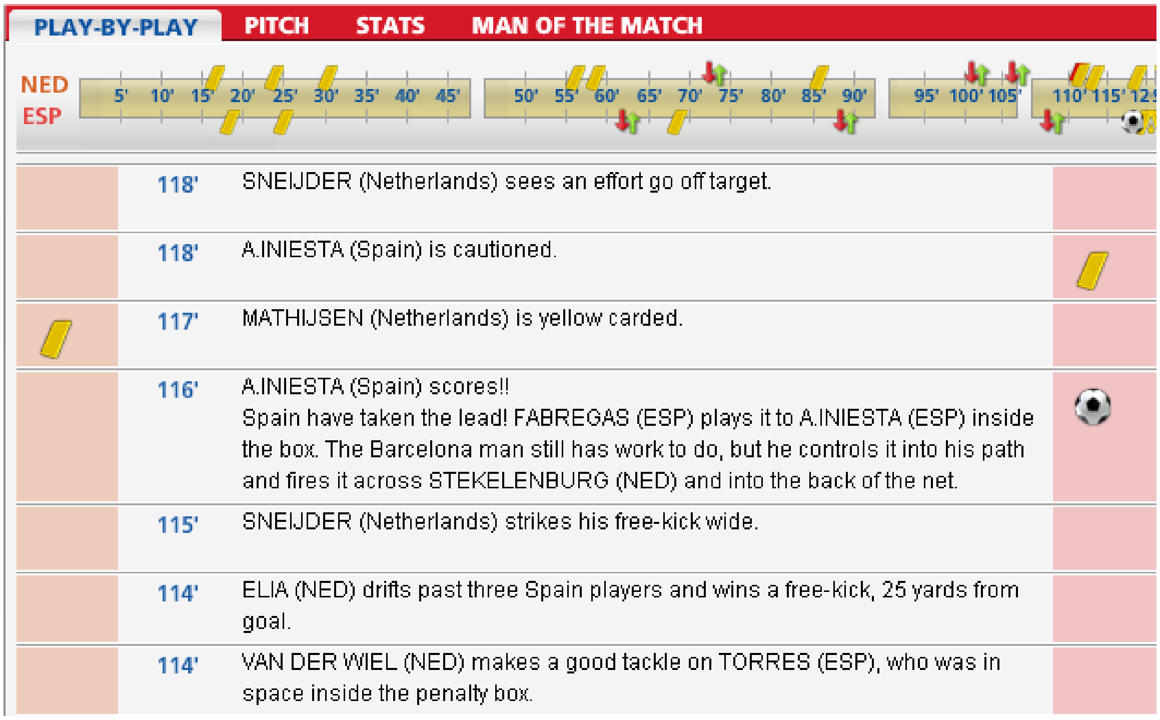


Figure 1: Example of webcast text for a soccer match (Chiu et al. [28]).

work, see Sumathi et al. [101] and Lu et al. [71].

2.2.4 Mobile Devices

Mobile devices, such as smart phones and tablet computers have built in features that can be readily utilized for data collection, including touch screen, camera, microphone, GPS, compass, accelerometer, and gyroscope. They also typically have a Bluetooth connection and plenty of internal memory storage to allow them to be networked with other devices and store data locally. They serve as a mobile platform for apps that can access and utilize these features.

One very ubiquitous app that researchers have used in mobile data collection is Twitter. Sports fans provide short, real-time text messages (tweets) during sporting events. Furthermore, these messages are often self-categorized using hashtags. Wongsuphasawat [120] collected tweets during a Champions League soccer match. He examined both the volume of tweets for specific hashtags as well as examining the text itself for keywords, such as *goal* or *offside*. Hoeber et al. [51] performed sentiment analysis on tweets collected during a Tour De France event.

McNab et al. [74] and Rowlands and James [92] examined the use of primarily the accelerometer feature of smart phones to accurately detect different parts of a pitch sequence in cricket as well as detecting when a person was jogging. Taylor et. al [104] indicated some difficulties in accurately categorizing different human behaviors, noting that some of these may be overcome if the phone is kept in the users hip pocket. Westin [115] used mobile devices connected to sensors to wirelessly transmit information about kayaking.

2.2.5 Wearable Sensors

Several researchers have investigated collecting data from wearable sensors to as an alternative to or as a compliment to collecting visual data. One reason for this is that wearable, wireless sensors do not have the same cost and complex infrastructure associated with camera arrays. Also, sensors do not suffer from some of the same occlusion problems that can occur in vision-based systems. One group of researchers at the Clarity Centre for Sensor Web Technologies in Ireland (Connaghan and O'Connor [39], Gaffney et al. [47], Connaghan et al. [37], Gaffney et al. [48], Kazmi et al. [57]) developed a Wireless Inertial Measurement Unit (WIMU) that was essentially a forearm-mounted accelerometer and gyroscope and used it in a variety of experiments with tennis players to successfully identify and classify tennis strokes (see Figure 2). Rowlands et al. [93] also advocated the use of inertial sensors since they are portable, cheap, and readily available. Other examples of sensors used for tennis analytics include a Foster Miller vest (the name of the company that developed the vest) used by Connaghan et. al [35] that recorded respiratory rate and temperature.

2.2.6 Tracking Devices

Spatial information plays a key role in many sports-based visualizations because the vast majority of sports involves movement, including movement of the players, as well as object movement, such as the ball or puck. In vehicle-based sports, such as cycling or auto racing, the movement of the object (i.e., vehicle) and the person are one and the same. Player movement data may be important for individual players (as in tennis singles) or for understanding the coordinated movements of groups of players (e.g., soccer, American football, basketball, etc.).

As discussed earlier, much of the research on player and object tracking has utilized computer vision techniques using multiple cameras to segment and track objects in 2D or 3D space. In this section, I briefly describe the use on other tracking devices, namely, Global Positioning System (GPS) devices as well as localization systems like Ubisense [11] used by a set of tennis researchers.

The location information initially provided by GPS technology lacked the precision needed to perform meaningful analysis on smaller sport platforms, such as tennis courts, basketball courts, or soccer pitches. However, Therón and Casares [105] indicated that recent upgrades in GPS systems, along with the advent of differential GPS, have lead to a considerable increase in location accuracy. This technology has been used not only in sporting events taking place over large areas, like auto racing (Milnes and Ford [75]), cy-

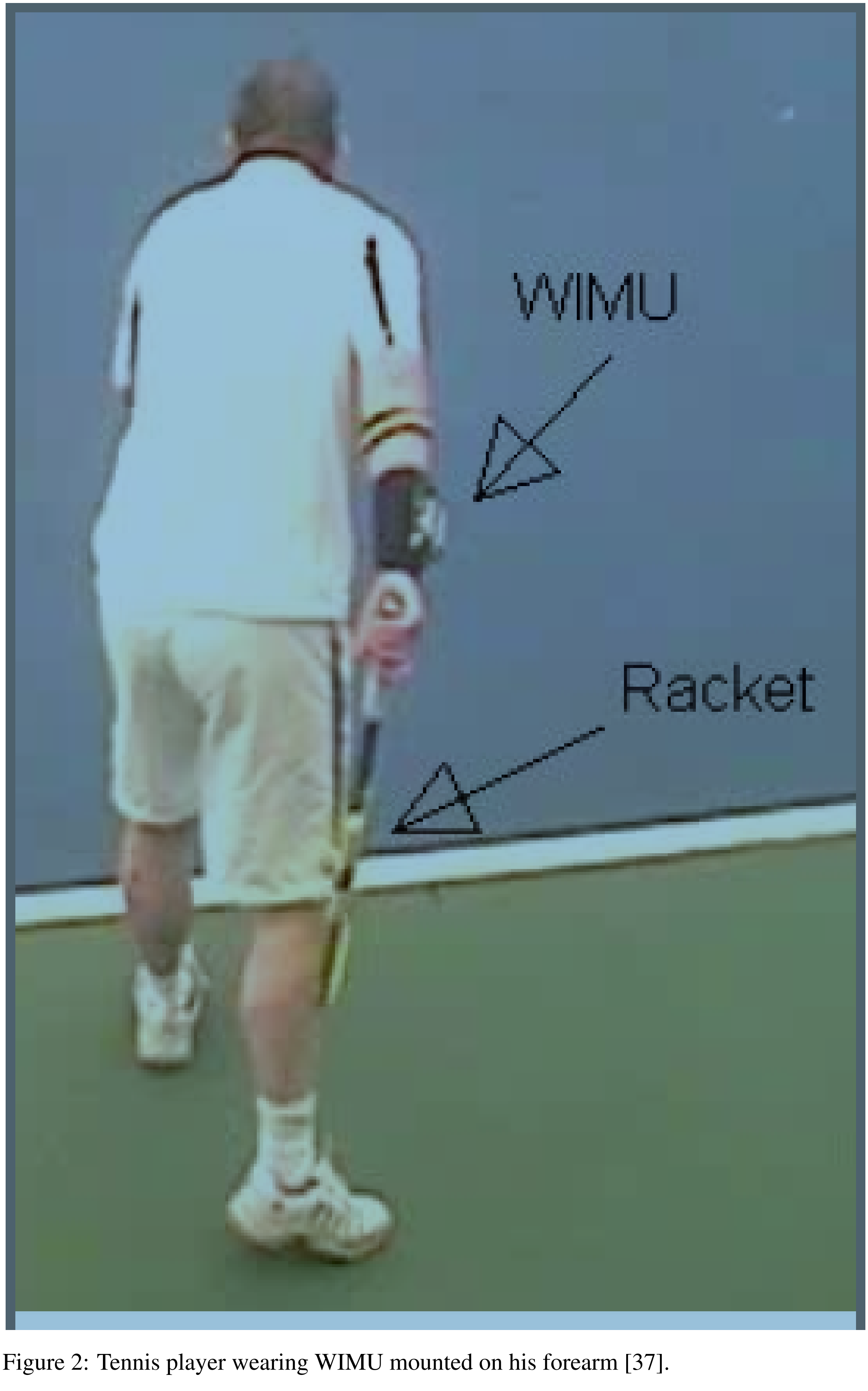


Figure 2: Tennis player wearing WIMU mounted on his forearm [37].

cling (Saupe et al. [95]), and skiing (Brodie et al. [22]), but has also been successfully demonstrated on much smaller playing areas, like basketball courts (Therón and Casares [105]). Localization technologies like Ubisense [11] are capable of providing 3D location of small wireless tags worn by the players with an accuracy of $\pm$ 15 cm (Connaghan et al. [35]). Several researchers have demonstrated the utility of this system in providing location information for tennis visualizations (Connaghan et al. [35], Conroy and Roantree [40]). Connaghan et al. [35] and Connaire et al. [34] used this system in conjunction with a vision-based system and body sensors as part of their TennisSense project that provided a rich set of interactive tennis visualizations. While this type of data collection can be very beneficial to coaches and players in terms of skills and technique improvement, the portability of such a system, plus the need for both players to agree to wear such devices (or carry wireless tags) limits its use in real competition settings.

These researchers, along with Conroy and Roantree [40] also utilized an UbiSense localization system that could locate players to within 15 cm of their true location through the use of tags worn in the players pocket. This system does not suffer from the same occlusion problems that can pose challenges to purely vision-based systems.

2.2.7 Sports Statistics Service Providers

Much of the visualization for professional sports has been made possible by sports statistics service providers. These private companies hire analysts to watch sporting events and log essential data. Many sporting arenas utilize Hawk-Eye [5] player and ball tracking systems to provide real-time, 3D tracking information. Companies such as Opta [6], ProZone [9], and SportVision [10] provide a wealth of detailed sports information. Researchers like

Perin et al. [81] and Janetzko et al. [53] have used this type of data to recently develop compelling, informative visualizations. There are several drawbacks to this data source for sports visualizations. First, many of the systems, such as Hawk-Eye require a lot of infrastructure and are expensive to install, with estimates of around $70K per court [12]. Second, much of the data collected by these organizations remains proprietary and may be owned by the tournament host, the company itself, or the sports franchise. Finally, these services are really only collecting data for major sporting events and therefore do not provide any benefit for amateur athletes.

2.2.8 Data Collection Applications

The final source of sports-specific data I review is data that comes from data collections applications. This includes both publicly available applications, such as Dartfish [4] and ProTracker Tennis [8] for collecting analyzing tennis data, as well as custom-made applications, such as TennisSense (Conaire et al. [34]) for tennis data and MatchPad (Legg et al. [65]) for rugby data. Perin et al. [82] also developed custom crowdsourcing apps that could be used by soccer fans to collect key event data, including positional data. For cycling, Beck et al. [18] used analytics software called *Training Peaks* [7] to collect location and biometric data on professional cyclists. For researchers looking to gather their own sports data to be analyzed, the solution may still be to develop their own system, potentially enhanced by a commercially available system as a component.

2.3 Low-Level Features

Low-level features serve as the building blocks used to form higher-level semantic data. As shown in Figure 3, low-level video features such as color and camera motion are ex-

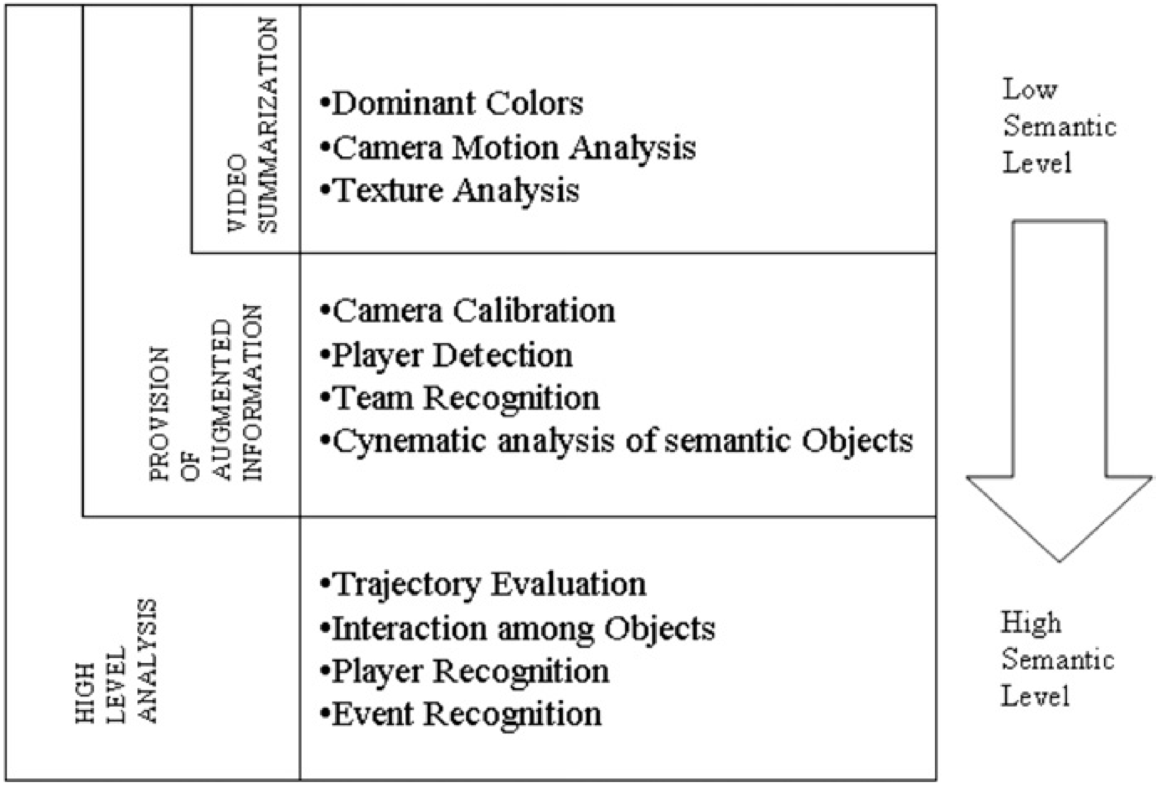


Figure 3: Low-level features from extracted data leading into higher-level semantics (DOrazio and Leo [43]).

tracted from raw video and then augmented with other data to form mid-level semantic features, which, when combined with domain knowledge (in this case, soccer) form higher-level semantics that form the basis of sports visualizations. These are features that can be directly extracted from raw captured video, audio, and various types of sensors. A variety of techniques have been developed to extract different kinds of features. The types of features typically collected and some of the techniques used are described. DOrazio and Leo [43] provide a good overview of features extracted from video for analysis of soccer matches. Hu et al. [52] also provide survey of low-level features used in video indexing and retrieval. The list below describes some of the highlights from this body of work.

- **Color.** Accurate characterization of color in sports video is a primary method for identifying and segmenting the playing field or court areas. The primary goal is to identify a dominant color in order to segment out a playing field or court. Dominant color is exploited as a way to differentiate the playing field or court from other camera shots, such as shots of the audience, and may also be useful for detecting team uniforms.

- **Line and Goal Detection.** These techniques involve the detection of lines defining the field of play or, in the case of soccer or basketball, the goal mouth. These techniques in conjunction with domain knowledge about regulation field and/or court dimensions provide useful information for camera calibration and identifying ball and player location.

- **Camera Motion.** In most sports video, particularly broadcast video, one or more cameras move to follow the action. Characterizing this movement can serve as another building block for identifying higher-level semantic data. In most cases, the intent is to distinguish movement due to camera motions from movements of objects within the video, such as players or the ball.

- **Camera Shot Changes.** A shot is a sequence of frames from one camera. Abrupt changes in the image correspond to changes in the video shot. These changes often correlate with higher-level, domain-specific concepts, such as the end of a point in tennis or the stoppage of play in soccer.

- **Sensor-Based Features.** Sensors worn by athletes can provide a rich, detailed data stream related to performance characteristics. For example, combining the outputs of an accelerometer, magnetometer, and gyroscope can be used to accurately measure inertia. Biometric data collection vests worn by athletes are typically unobtrusive and can typically measure heart rate, respiration rate, and skin temperature. These 3 distinct sets of raw data, when measured in tandem, can be used as a way to measure athlete performance and endurance, as well as serve as a monitoring system when certain thresholds are exceeded.

2.4 Mid-Level Semantic Data Derived from Low Level Features

Once the low-level feature building-blocks have been defined, they can be combined to derive higher level semantics. These semantics are heavily influenced by the specific sports domain being analyzed. In structured sports like tennis or baseball, score-based semantics such as points, games, and sets (tennis) or innings and outs (baseball) can be derived. In structured sports (e.g., tennis, baseball) and unstructured sports (e.g., soccer, basketball) alike, semantics centered on key play events are often defined, such as serves in tennis and foul shots in basketball. Listed below are some typical mid-level semantic data used in sports analytics and how they are derived from lower-level data. These data fall into broad categories: camera shot classification, object tracking, event detection, player performance metrics, and domain-specific statistics.

- **Camera Shot Classification.** Camera shot classification involves analyzing sequences of frames representing a single camera shot and categorizing it using domain-specific knowledge. Using low-level data, such as color, researchers such as Lao et al. [63] have been able to segement video sequences into semantically meaningful sequences, such as goals, fouls, substitutions, corner kicks, and attacks.

- **Object Tracking.** Object tracking provides researchers with a finer-grained level of domain-specific semantic detail than is possible for camera shot classification alone. Objects typically tracked include the ball (in ball sports) and players. Ball tracking techniques include ball segmentation and trajectory detection. Tennis ball segmentation techniques often exploit the known size and color characteristics of the ball to detect it in each frame (see Owens et al. [79] and Pingali et al. [88]).

- **Event Detection.** Sports can typically be broken down into a series of semantically meaningful *events*. In a structured game like tennis, events of importance include the following: points, serves and returns, rallies, baseline hits vs. volleys, forehands vs. backhands, and cross-court vs. down-the-line shots. These are all significant events in tennis matches and, when combined with each other as well as with other domain data can serve as inputs to higher-level visualizations for concepts such as momentum or tactics.

- **Player Performance Metrics.** Raw physiological data from sensors worn on athletes, such as heart rate, temperature, and respiratory rate can be combined and examined in relation to specific events as a way to form mid-level semantic concepts, such as endurance, fitness, and recovery time. They can also be used to monitor athletes in order to set alarm thresholds that warn, for example, when an athlete is heart rate exceeds a preset limit.

- **Domain-Specific Statistics.** Statistics are derived from observing and tracking basic events, such as number of base hits in baseball, number of successful vs. unsuccessful free throws in basketball, number of third down conversions in American football,

Table 1: References describing consumable outputs targeted to specific audiences

Consumable Outputs	**Target Audience**			
	Fans	**Analysts**	**Coaches**	**Players**
Auto-indexed video segments	[100, 77, 83, 45, 59, 70, 84, 33, 114, 122, 63, 68, 106, 107]	[100, 77, 83, 45, 59, 70, 84, 33, 114, 113]	[67, 34, 36, 113]	[34, 36, 113]
Virtual replays	[79, 89]	[42, 103]	[89, 42, 103]	[89, 42, 17]
Broadcast enhancements	[88, 114, 109, 60]	[118]	[114]	
Standard visualizations	[55, 41, 87, 80]	[41, 87]	[57, 87]	[16, 112, 98, 57, 87]
Custom visualizations	[24, 41, 51, 69, 76, 91, 99]	[19, 24, 26, 27, 30, 31, 29, 41, 50, 53, 56, 61, 69, 72, 76, 78, 81, 89, 91, 103, 102, 116, 117, 119, 121]	[19, 23, 26, 27, 30, 31, 29, 34, 39, 38, 50, 53, 56, 58, 72, 81, 89, 103, 102, 105]	[34, 39, 38]

and number of first serves that land in for tennis, to name a few. These events are then normalized to form relevant statistics. A few examples include batting average for baseball, field goal and free throw percentage for basketball, number of yards gained running and passing for football, and first serve percentage, number of aces, double-faults, winners, and unforced errors for tennis.

2.5 Consumable Results

Previous sections have focused on how low-level, data is collected and combined with sport domain-specific knowledge to generate higher-level semantic information. In this section, I review the relevant literature from the perspective of how this information is transformed into consumable outputs for a variety of end users. The end users are categorized as follows:

- **Fans.** Interested in getting richer information about select teams or players.
- **On-air announcers.** Looking for information to help them add commentary to live broadcasts.
- **Sports analysts.** Looking for graphics and tools to provide them deeper insights into sports for reporting purposes (private or public).
- **Coaches.** Want information (including real-time) to support strategic and tactical decision making and recruiting.
- **Trainers.** Need tools to help them train athletes in better techniques and enhance their performance.
- **Players.** Looking for insights into their own strengths and weaknesses as well as that of their opponents.

Consumable outputs resulting from utilizing high-level semantic information are broadly categorized as follows:

- **Automatically indexed/annotated video segments.** Video segments isolated and classified into semantically meaning categories.
- **Virtual replays.** Two- or three-dimensional replays of points or play segments.
- **Broadcast enhancements.** Graphics embedded in broadcast video to enhance viewer enjoyment.

- **Standard visualizations.** Simple visualizations such as bar charts, graphs, tables, etc., as well as more advanced but still standard visualizations, such as star charts, tree-maps, chord diagrams, parallel coordinates, etc. used to display semantically meaningful information.
- **Custom visualizations.** Custom-made, domain-specific graphical depictions of sports data for target audiences.

Table 1 displays a matrix of consumable outputs by target audience, with the cells containing references to papers related to this cross-section. Relevant portions of these papers are discussed within the context of each of the consumable output categories. Because the focus of the current research is on developing custom sports visualizations, this category will be discussed in more detail in the Custom Visualizations section.

2.5.1 Automatically Indexed/Annotated Video Segments

Much of the past research has focused on techniques to automatically segment videos and tag them with significant events using domain terminology. Much of this video comes from sports broadcasts and the need for this automatic segmentation is partly derived from the large amounts of sports video available and the widespread popularity of sporting events. The primary audiences for this output are fans, sports analysts, and coaches.

The basic idea is to take non-structured raw video and transform it into structured segments using image processing and computer vision techniques (Vijayakumar and Nedunchezian [110]). These segments are then annotated with semantically meaningful information to facilitate retrieval. The main objectives for video segmentation, in terms of creating a consumable output, are to distill lengthy videos by summarizing them based on key events and to index video segments with semantic information so they can be queried later.

The driving force behind creating video summaries is the sheer amount of data available. Sports highlight shows take hours and hours of sporting events and distill them down into exciting highlights as a way to quickly convey the essential part of sporting events. Hu et al. [52] list two broad strategies for video summarization: key frame-based static abstracts and dynamic video skimming. Key frame-based strategies involve extracting a single key frame to represent each specific significant video segment. These key frames then serve as a pictorial table of contents, storyboard, or video summary. Dynamic video skimming, on the other hand, seeks to create shortened videos that still maintain the temporal nature of the original, but with insignificant or uninteresting content removed. Ekin et al. [45] exploited cinematic features in broadcast video to develop play-break algorithms that successfully detected plays in basketball, goals in soccer, and shots in tennis. Coldefy et al. [33] automatically summarized tennis matches using audio and visual cues from broadcast video. Specifically, they identified winning serves and rallies. Wang et al. [114] segmented broadcast video to detect when a soccer team was on offense, goals scored, and percentage of possession.

In addition to summarizing lengthy videos into short highlight segments, other researchers had the objective of indexing semantically meaningful events to facilitate queries. Sudhir et al. [100] segmented broadcast video of tennis matches and indexed four types of semantically meaningful shot situations: baseline rallies, passing shots, serve-and-volleys, and net games. Miyamori and Iisaku [77] provided indexes into videos based on a combination of player location, ball location, and player behaviors and were able to successfully identify multiple play situations. Kijak et al. [59] used Hidden Markov Models with visual and audio cues from broadcast video to automatically classify scenes in tennis into one of four types: first missed serve, rally, replay, and break. Petkovic and Jonker [83] developed a user interface that allowed users to select object, spatial, and temporal information in order to retrieve semantically meaningful video segments. In each of these cases, the idea was to allow users instant access to domain-specific events of interest.

In a survey paper published in 2011, Hu et al. [52] identified six types of queries used to retrieve information from automatically indexed videos: 1) query by example, 2) query by sketch, 3) query by objects, 4) query by keywords, 5) query by natural language, and 6) combination-based query. Query by example involves starting with a target video, extracting key features, and then finding other videos with similar features. Query by sketch involves users drawing sketches, such as player trajectories, and then using these trajectories to find video segments with similar trajectories. With the query by objects approach, users select a specific object image and the video database returns all video clips with that object, including the objects location. Query by keywords is a rigid approach that involves users entering domain-specific keywords in order to obtain video clips that have been automatically tagged with those keywords. Query by natural language, on the other hand, uses semantic word similarity to provide a less-rigid, more flexible and natural way for users to retrieve video clips. Finally, combination-based queries involve combining two or more of the aforementioned query techniques as a way to select specific video clips.

While much of the emphasis has been on segmenting and indexing video for fan consumption or for use by sports analysts, other researchers have focused on providing tools to aid coaches. Connaghan et. al [36] used video from a nine camera array to automatically detect the following tennis events: stroke, rally, game, change of end, set, and match.

Wang et al. [113] developed techniques to identify shot patterns in tennis with the aim of providing a browsing interface to retrieve tennis clips matching specified patterns. Conaire et al. [34] developed a tennis coaching application called Tennissense that allowed coaches or players to query video clips based on rally length as well as by specifying spatial inputs.

2.5.2 Virtual Replays

Using player and ball tracking techniques from single or multiple cameras allows provides the spatio-temporal information needed to virtually replay single events or even entire matches or games. These types of visualizations are typically targeted at fans to give them a more immersive experience, but are also used by tennis referees to help make close line calls. Perhaps the best-known example of this is the HawkEye tennis system (Owens et al. [79]) used in professional tennis matches to replay points when players challenge a line call they believe is incorrect. This system uses an array of cameras to accurately track the 3D path of a tennis ball. In addition to providing an aid to the referee, it also adds excitement to the game for the fans. Pingali at al. [89] provided 2D player tracking for tennis matches. Tani et al. citetani2014sports created a strategy decision support system called SportsViz that they applied to American football that included 2D team tracking information useful to analysts and coaches. Dietrich et al. [42] developed techniques that allowed users to reconstruct entire baseball games and visually explore each play. Figure 4 shows a sample screen from their Baseball4D application that shows how the 3D trajectory data can be used to create a virtual replay. Bebie and Bieri [17] created an application called SoccerMan that allowed analysts to view 3D scenes from soccer matches at any angle.

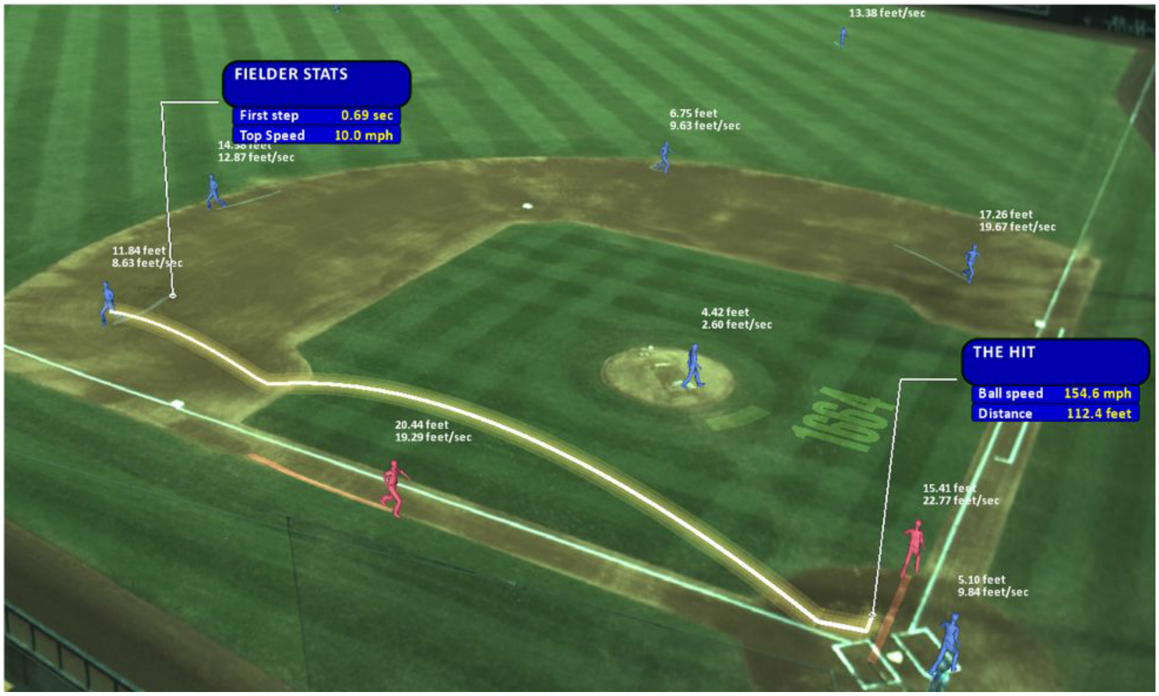


Figure 4: Sample screen from Baseball4D application by Dietrich et al. [42].

2.5.3 Broadcast Enhancement

There is a huge consumer demand for broadcast sporting events. To help satisfy this demand, broadcasters often look for additional ways to enhance their broadcasts. One typical way this is done is through the user of on-air commentary by sportscasters. Innovative graphics overlays to enhance a broadcast event and help consumers get a better understanding of a game are often employed. These graphic overlays can be roughly divided into three categories: score context text and graphics, embedded live broadcast informational overlays, and replay explanation graphics.

Score context text and graphical overlays are perhaps the most common and most familiar to sports broadcast viewers. These typically include textual information about the score of a game or match that are displayed at the periphery of the broadcast video image. Simplistic graphics providing well-understood information may also be included. Examples

Figure 5: Advertisements embedded in sideboards surrounding soccer pitch [1].

include graphics to indicate who is serving in a tennis match, which team is currently on offense, and the locations of runners on base in baseball. Embedded live broadcast informational overlays involve augmenting the raw video footage with added graphical content. One major application of this is to embed advertisements into the field of play or the areas surrounding the field. In many cases, these advertisements are displayed on sideboards surrounding a court or field, such as the advertisements displayed in soccer matches in the sideboards surrounding the pitch (see Figure 5. In other cases, the ads are placed directly on the field of play. One common example of this is to incorporate a company logo along with some other informational graphic overlay, such as the logo displayed next to the virtual line of scrimmage shown in Figure 6.

Other examples of informational graphics embedded in sports broadcasts include identification of the first-down line in American football, glowing “comet tails on moving hockey pucks and baseball pitches, graphical overlay of strike zones in baseball, and identification

Figure 6: Line of scrimmage and corporate logo embedded in broadcast video (Cavallaro et al. [25]).

of drivers in auto races (Cavallaro et al. [25]). These overlays are designed to enrich viewers experience by highlighting semantically meaningful information. As with text and simple graphic overlays, the design of embedded informational graphics tends to be very simplistic and easily understood by the average viewer.

An emerging area of embedding graphics in video for broadcast enhancement is augmented reality. The design goal is to give fans an immersive experience where they can see events from multiple, artificially generated viewpoints. Krevelen and Poelman [109] cited three key characteristics of augmented reality systems: 1) they combine real and virtual objects in a real environment; 2) they align real and virtual objects with each other; and 3) the run interactively in real time in 3D. In addition to providing an immersive experience for fans, augmented reality may also hold promise for player performance improvement. In his 2014 TED talk, Chris Klewe described a vision for how augmented reality could be built into players helmets to displays things such as outlined plays or provide warnings to the quarterback when an opposing player is approaching from the blind side [60].

The third category of broadcast enhancements involves graphical overlays used by sportscasters to explain replays of key events. These include simple drawing tools, such as a Telestrator [118], that allow the sportscaster to annotate a key frame from a video replay sequence to highlight the key elements of a play. More recently, more sophisticated systems like VizLibero [2] are being employed by sportscasters to provide richer detail on replays. Figure 7 displays a workflow diagram illustrating how graphics may be embedded into a sports broadcast.

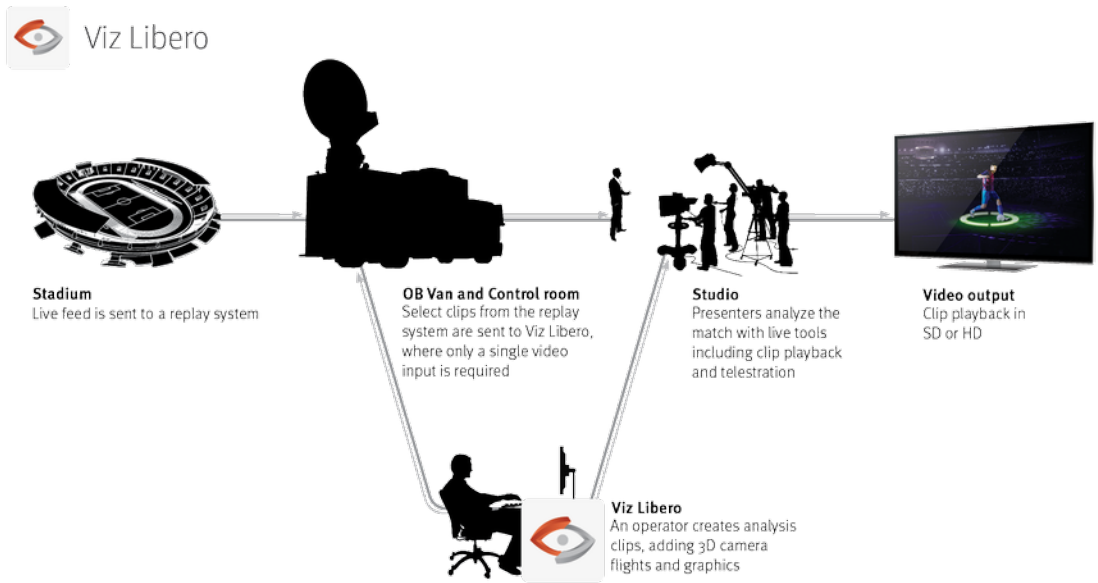


Figure 7: Workflow diagram explaining how VizLibero integrates graphics into a broadcast [2].

2.5.4 Standard Visualizations

Much of the research into visualizing sports have incorporated standard visualizations applied to sports data. These include very simplistic visualizations, such as bar charts, time series line graphs, and scatter plots, as well as more advanced visualizations, such as treemaps, sparklines, parallel coordinates, and heat maps. These visualizations are geared towards increasing fan understanding and assisting sports analysts, as well as providing feedback to coaches and players. Bar charts remain an effective, easily understood way to present discrete data. Cox et al. [41] created a baseline bar chart that encoded a baseball teams win/loss record for a season and included the run margin and the number of runs scored (see 8). Although simple, trends such as winning and losing streaks and how often a team loses close games can be readily seen. Adding data filtering also allows users to

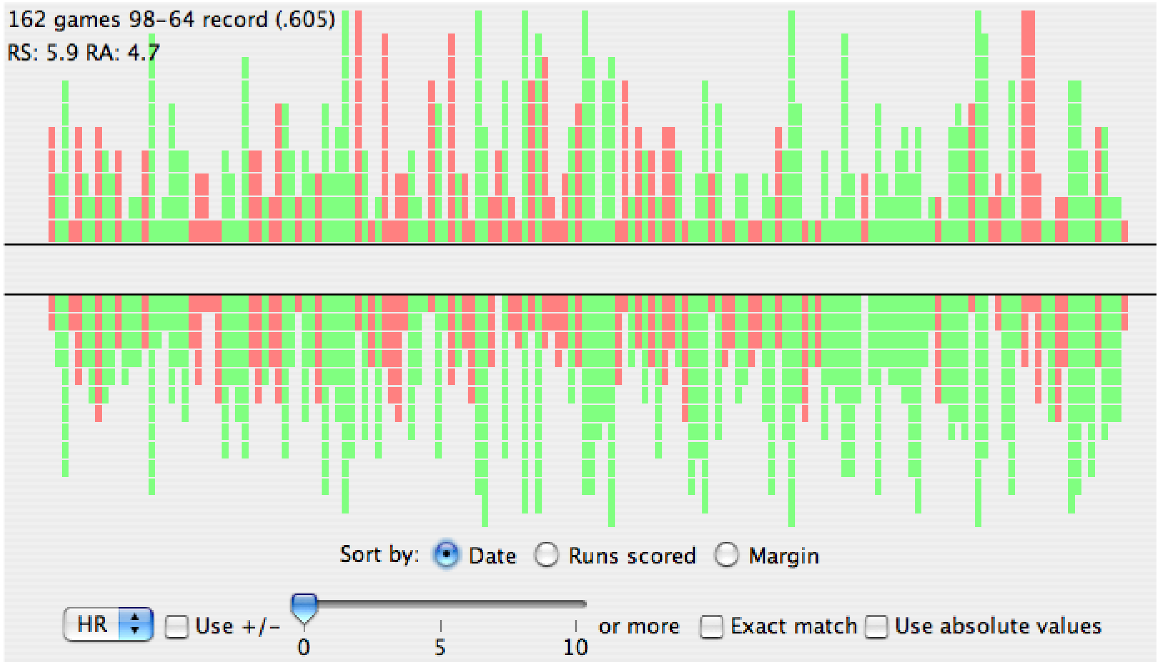


Figure 8: Baseline bar chart showing run margin above the baseline and number of runs scored by focus team below the baseline (Cox and Stasko, [41]). Green indicates the focus team won the game and red indicates they lost.

look for trends under certain, semantically meaningful conditions, such as when a specific pitcher is starting. Small multiple scatter plots, like the one shown in Figure 9 provide another example of a simple, yet effective visualization. In this case, each small multiple represents the number of points scored in NBA basketball games by the starting forward (x-axis) and by the starting guard (y-axis), showing the relative contribution by each.

Time series line graphs have typically been used to show either team performance or individual player performance over time. Kazmi et al. [57] used time series line graphs to display heart rate, respiration rate, and body temperature as a way to allow coaches to monitor the physiological condition of each player. The goal is to allow coaches to personalize training schedules for individual athletes and thus improve performance. Bavcic et al. [16] generated displacement and velocity time series as a way to identify forehand and

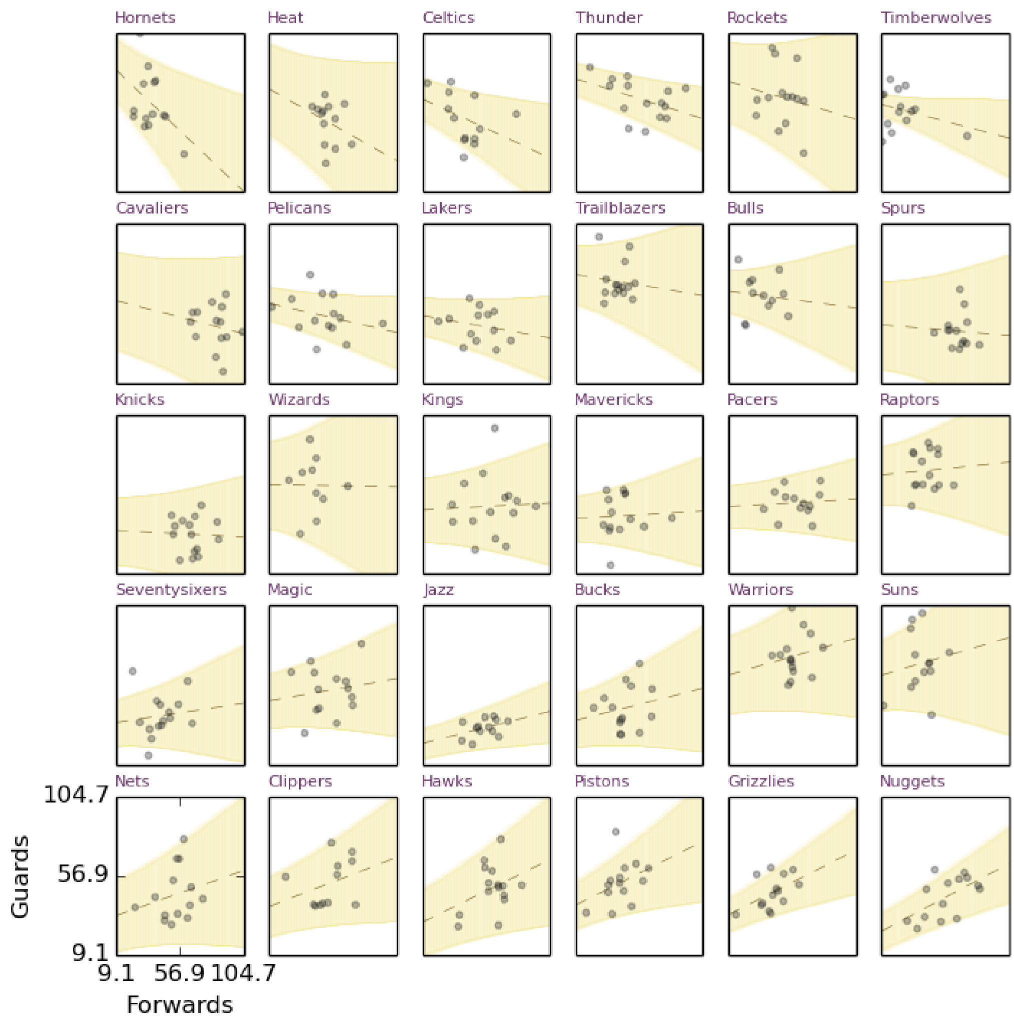


Figure 9: Small multiples scatter plots showing the relative point scoring contributions of NBA starting forwards vs. starting guards. Negative trends mean when forwards score a lot, guards don't. Positive trends mean that when forwards score a lot of points, so do the guards [3].

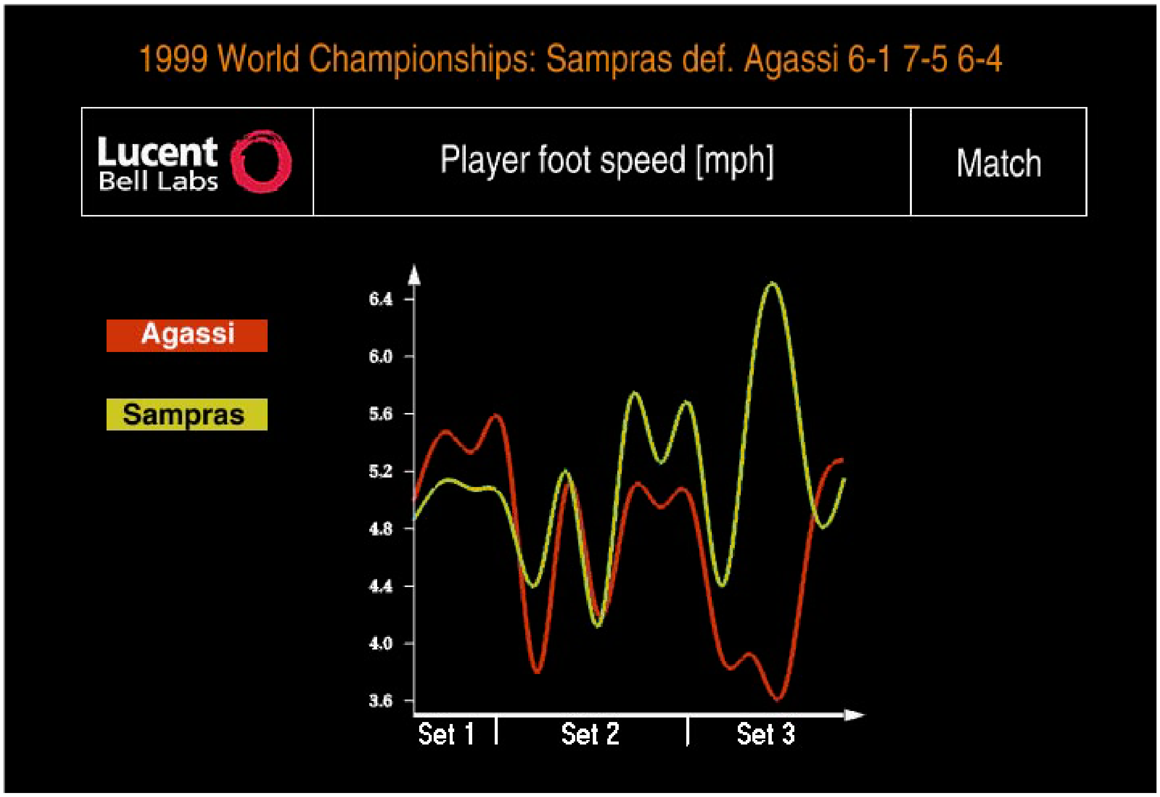


Figure 10: Average foot speed of two tennis players across a 3-set tennis match (Pingali et al. [87]).

backhand tennis strokes. Pingali et al. [87] developed a time series showing average foot speed of tennis players across each set of tennis match (see Figure 10).

Treemaps were used to display the sets, games, and points won by tennis players in a simulated tennis match (Jin et al. [55]) and to encode the number of times a baseball player was at bat and his performance (Cox and Stasko [41]). Owens et al. [80] used parallel coordinates to visualize the relationship between semantically meaningful dimensions for American football, such as number of rushing touchdowns, number of plays, etc. Mitchell and Moere [76] provided an example of how sparklines may be used to provide information about baseball team performance for an entire season.

2.5.5 Custom Visualizations

Custom visualizations represent a broad category of sports-related graphical visualizations that involve creating new informational graphics designed for a specific sports domain or context. Different sports have different sets of meaningful data. The challenge in making a good custom visualization is understanding what data is meaningful, who the target audience is, and how should that data be encoded in a way that can be understood by that audience? Because the focus of this dissertation is on developing custom visualizations to visualize tennis data, existing literature on custom sports visualizations will be discussed in a separate section, organized by sport.

2.6 Custom Sports Visualizations

In this section, I provide a brief overview of the literature for custom visualizations for specic sport domains, including tennis, soccer, basketball, American football, and baseball as well as a few examples from other sports domains. The intent is not to give an exhaustive review of this literature, but merely to discuss the current state of the art and focus in these areas of sports visualization.

2.6.1 Tennis

I start off by reviewing tennis visualization research since it is the main contribution area for my research. In this section, I will review some earlier work, including two well-cited papers by Jin et al. [54, 55] that used primarily domain data to develop a treemap-like match browser. I will then look at some of the key research by Pingali et al. [87, 89] that relied heavily on spatial data collected at professional tennis matches with the intention of providing additional visual analytics for tennis fans. I then move on to recent work where the focus shifts to collecting spatial data to develop custom visualizations for non-professional tennis players and their coaches (Conaire et al. [34], Kelly et al. [58], Connaghan et al. [38], Connaghan and O'Connor [39]).

Jin et al. [54, 55] built a treemap-like visualization of tennis matches called *TennisViewer* that exploited the hierarchical nature of tennis matches (see Figure 11). They envisioned tennis strokes at the lowest level, followed by points, then games, then sets, and finally, the match. It used a color-coding scheme to indicate points/games/sets/match won or lost and incorporated the use of stackable 'Magic Lenses that allowed users to see deeper levels of detail, including individual strokes (albeit, simulated).

Pingali et al. [87, 89] collected real ball and player tracking data from professional tennis matches using an array of cameras situated around a professional sports arena. With this data, they developed an interactive application that included two main visualizations: player trajectory heat maps and ball landing position plots (see Figure 12). They provided tennis-domain relevant filtering capabilities including the capability to select a specific set, game, or point, indicate who was serving, and also court location). The final visualizations also served as an index into the broadcast video and allowed users to select individual points to be replayed.

A group of researchers from Dublin City University (Ireland) published several papers from 2009 2013 focused on developing visualization-based coaching tools using a state-of-the-art tennis court facility that included a network of nine synchronized IP cameras (Conaire et al. [34], Kelly et al. [58], Connaghan et al. [38], Connaghan and O'Connor [39], see Figure 13). Using this network of cameras positioned around an indoor club court,

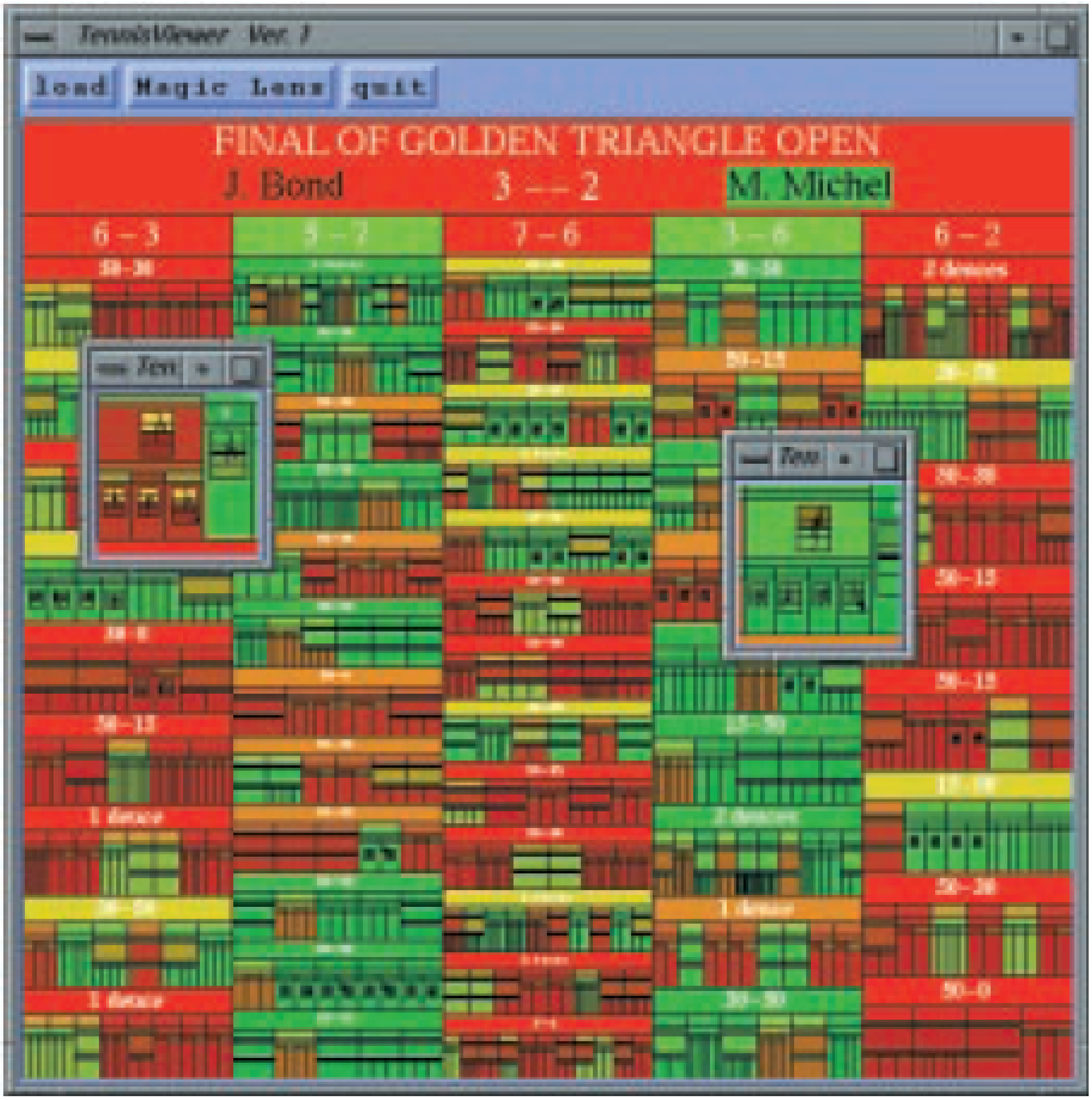


Figure 11: TennisViewer visualization showing results from a simulated tennis match (Jin et al. [55]).

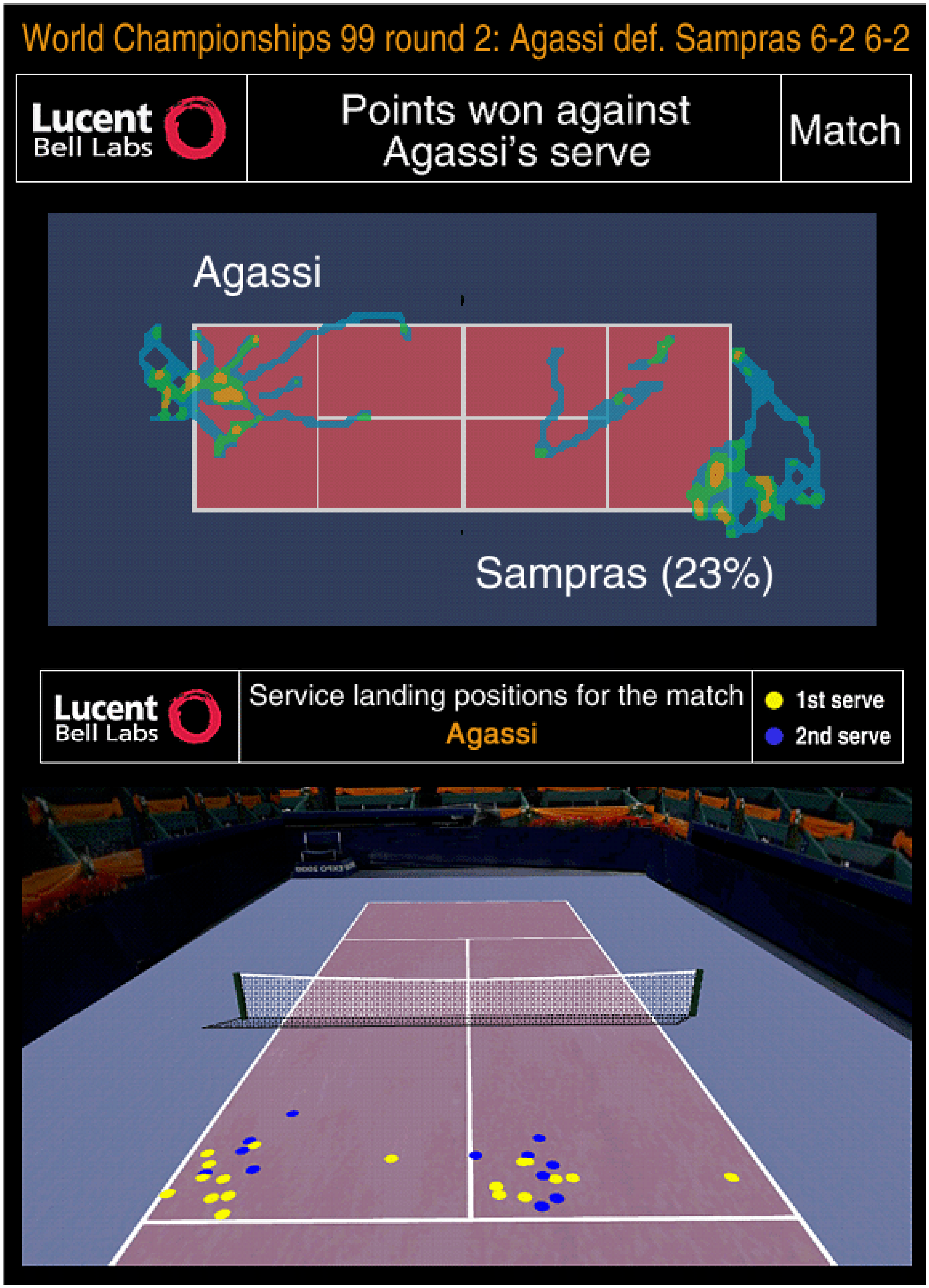


Figure 12: Sample visualization showing player trajectory heatmap (top) and service ball landing positions (bottom) by Pingali et al. [87].

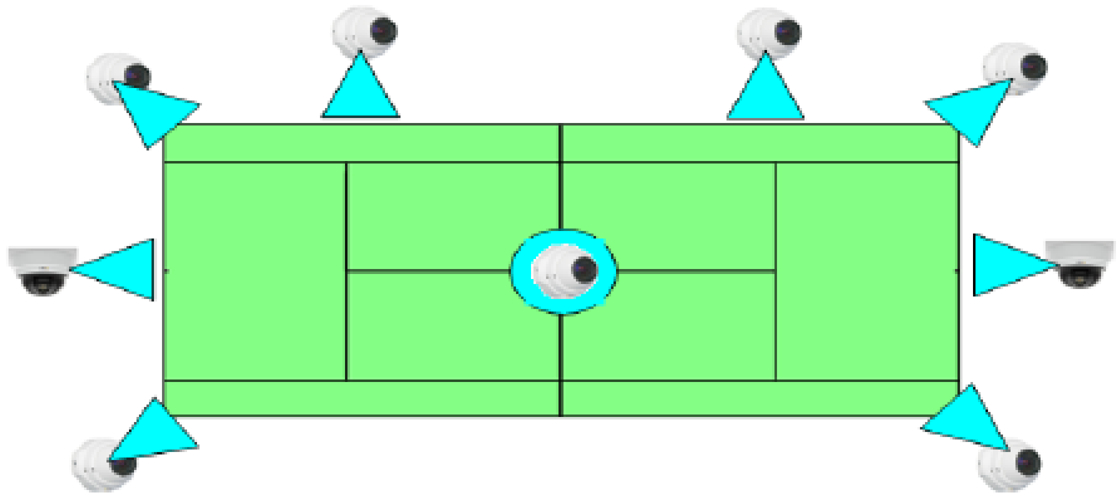


Figure 13: Layout of nine camera network to aid in player and ball tracking (Conaire et al. [34]).

researchers were able to segment the video footage to perform player and ball tracking in much the same way as done by Pingali et. al [87] at professional arenas. They validated their visual tracking system with an UbiSense tag-tracking system that required players to carry a small tag in their pocket. Using data provided from this system, they developed a number of coaching tools. One system called *Match Point* produced indexed videos from automatically detected tennis events and provided a rich set of filters based on domain semantics, such as serves, backhands, and forehands. They also provided an interactive court layout allowing users to specify spatial queries. Kelly et al. [58] enhanced the system by adding a visualization and annotation tool that allowed coaches or players to see 2D or 3D simulations using player and tracking data and provided a simple set of video annotation tools for coaches to convey key information to their players. Sample annotations are shown in Figure 14.

Figure 14: Sample tennis annotations from tennis coaching tool (Kelly et al. [58]).

2.6.2 Soccer

Soccer is perhaps the most widely viewed sport in the world. Revenues for Premier League soccer in England alone were 4.7 billion Euro in 2014 [119]. Broadcasters and sports analysts strive to provide deeper insights into the game to enrich the experience for the large body of enthusiastic fans. Coaches are looking for better analytical tools to help them shape strategies and more effectively recruit and train players. Companies such as Opta and Prozone employ loggers to collect stats for professional soccer matches that serve as input to sports analytics [19].

Using this type of analytical data, Perin et al. [81] developed a soccer visual analytics tool called SoccerStories that included a variety of linked visualization tools (see Figure 15). They validated the utility of these tools with a group of sports writers who used the tools to help generate content for their sports columns. The centerpiece of their tool was an outline of a soccer pitch where player and ball trajectories could be displayed, along with links to smaller related visualizations. In a similar fashion, Janetzko et al. [53] used a soccer pitch as the main visualization area, surrounded by a set of linked visualizations,

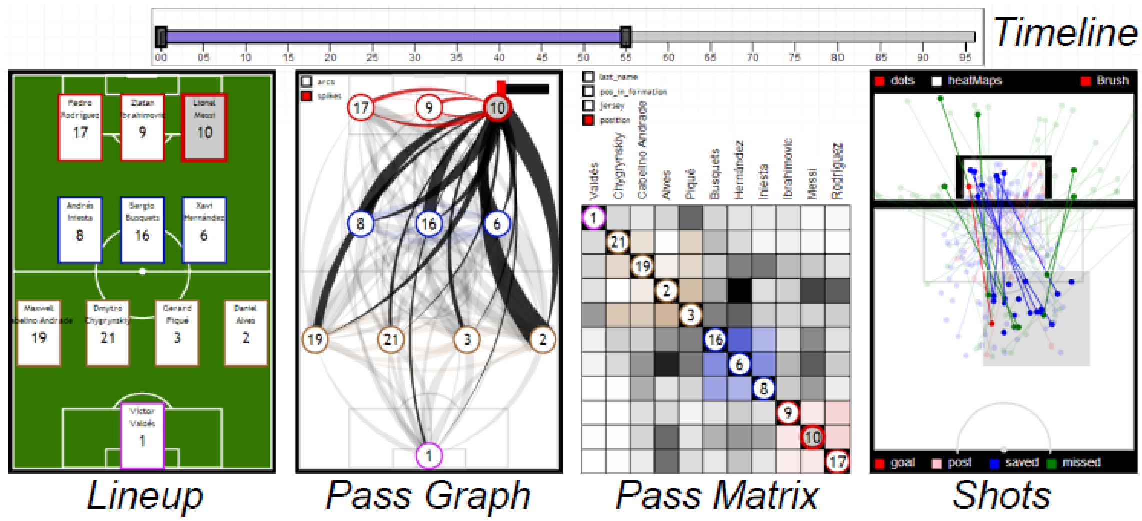


Figure 15: Linked soccer visualizations (Perin et al. [81]).

including parallel coordinates, horizon graphs, and small multiples.

Kameoka et al. [56] and Yamada et al. [121] also used a soccer pitch as the main area to display visualizations of filtered spatial data points. However, Yamada et al. [121] divided the pitch into 24 zones and developed a visualization showing the amount of activity (i.e. player movements) and ball possession within each zone (see Figure 16).

The soccer visualizations described so far have focused on visualization a single game. This would be considered the mid-level of analysis. Visualizations that summarize multiple games are at a higher level, while visualizations that focus on characteristics of individual players are at the lower level. For example, Cava and Freitas [24] created a matrix view of glyphs that encoded the following information: home vs. away, current championship qualification status, whether a game has been played yet or not, who won the game, and number of goals scored by each team. At the individual player level, Burns [23] developed a set of player-specific visualizations using soccer-inspired glyphs to indicate player characteristics such as execution mechanics, tactical utility, and precision.

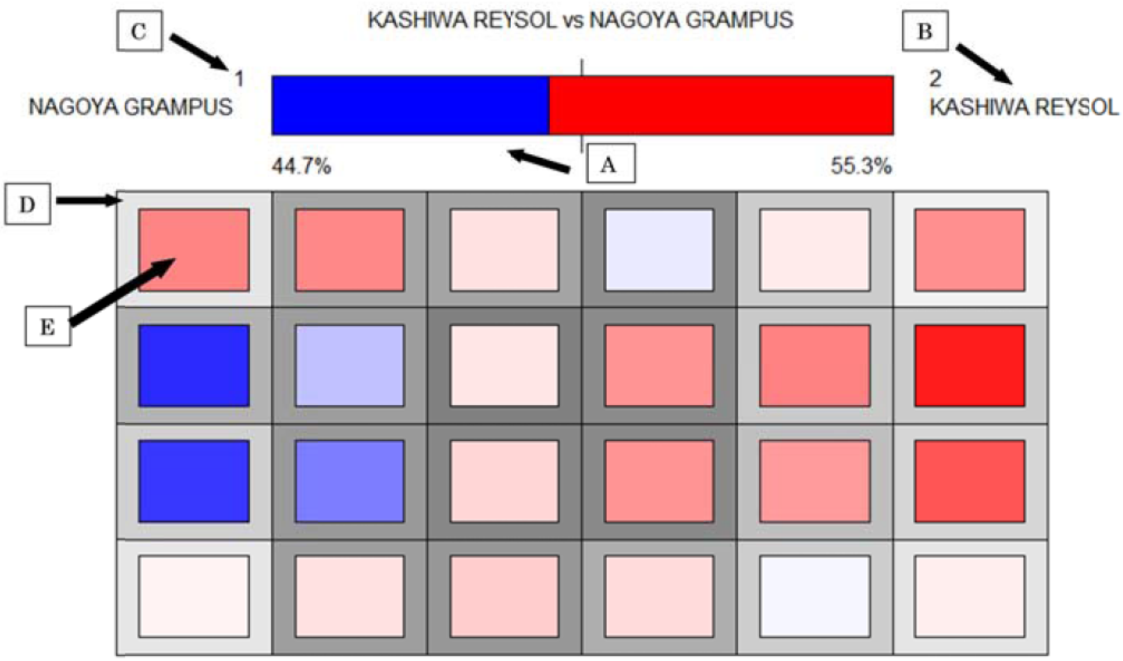


Figure 16: Soccer zones visualization by Yamada et al. [121]. (A) refers to overall team possession, (B) is the team name, (C) is the current score, (D) is the outer box for a zone indicating the amount of activity (pale is low, dark is high), (E) is the inner box for a zone indicating ball possession (red shades means home team possession, blue shades mean away).

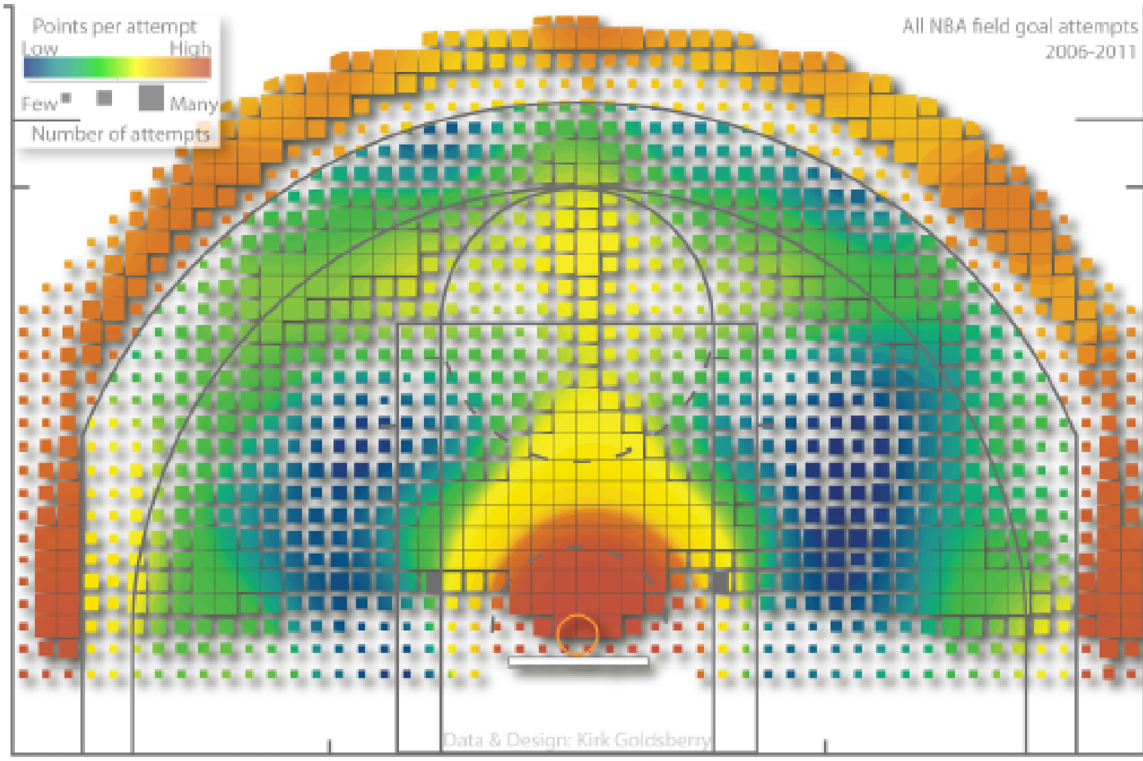


Figure 17: Basketball shooting heatmap encoding number of shot attempts (size of square) and points per attempt (color), created by Goldsberry [49].

2.6.3 Basketball

For basketball, much of the current visual analytics research centers around using player tracking data in combination with domain-specific semantics to evaluate the effectiveness of players, both offensively and defensively. Like soccer, basketball is a sport where the same players play on offense as well as defense. Goldsberry [49] argued that conventional basketball statistics, such as field goal percentage are not adequate differentiators of performance because they do not include a spatial component. He went on to develop composite shot heatmaps to identify key shot-making areas where the probabilities of making a shot are relatively higher (see Figure 17). Goldsberry [50] also developed a similar heatmap to assist in defining key areas of the court to defend (i.e., those areas where the field goal percentage is particularly high).

In addition to using the location of the shooter to determine different areas of shot effectiveness, Chang et al. [27] used the location of the nearest defender to the shooter when he shoots. With this information, they developed a heatmap that examined shot effectiveness in terms of distance to the basket as well as distance of the nearest defender. They defined two new metrics that incorporated this spatial data: Expected Shot Quality (ESQ) and used this metric to enhance the industry standard metric of Effective Field Goal percentage (EFG). Cervone et al. [26] utilized spatial data for all the players on a team and developed a visualization of Expected Possession Value that attempts to assign a point value for various decisions to shoot or pass the ball. Therón and Casares [105] used data provided from wrist-based GPS devices to develop visualizations depicting rhythm changes (changes of pace) in a basketball game.

Recognizing the dynamic nature of basketball games, where players may temporarily switch roles (e.g., from Point Guard to Shooting Guard), Lucey et. al [72] developed a role transition matrix for players on defense that identified confusing role-swaps that led to open shots for the opposing team.

2.6.4 American Football

Compared to some of the other sports being reviewed in this paper, there are relatively few papers on custom information visualizations for American football. However, there are two notable exceptions. First, Owens and Jankun-Kelly [80] developed an arc diagram (see Figure 18) that depicted yardage gains or losses and used color coding on the arcs to indicate play type, such as run, kick, pass, etc.).. Second, Tani et al. [102, 103] developed

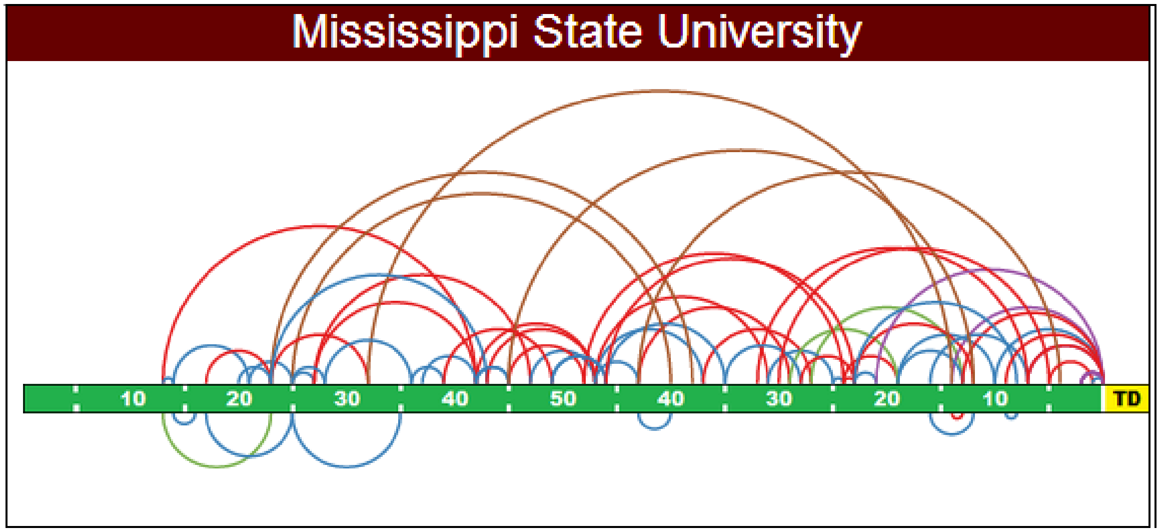


Figure 18: Arc diagram plays in a college football game (Owens and Jankun-Kelly [80]). Arcs below the horizon represent loss of yardage, while arcs on top represent yardage gains. Colors correspond to types of plays (e.g., run, pass, kick, etc.)

a football visualization system that clustered plays based on similarity and then allowed users to further apply domain-specific filters to retrieve specific types of plays for analysis. They used a two-dimensional football field to display results and provided links to the corresponding video segments.

2.6.5 Baseball

Baseball is perhaps the most statistics-heavy major sport. Wikipedia [116] lists over 100 traditional baseball statistics as well as several dozen more advanced statistics known as *sabermetrics* [117]. However, Losada et al. [69] noted that the widespread availability of baseball statistics had not yet resulted in many information visualization techniques. They developed an interactive visualization tool called *StatClub* that displayed heatmaps and other visualizations for a variety of statistics. Rao and Card [91] used their well-known *TableLens* application to effectively display very large amounts of batting data.

The two key focus areas in analyzing baseball are pitching and batting. Much of the

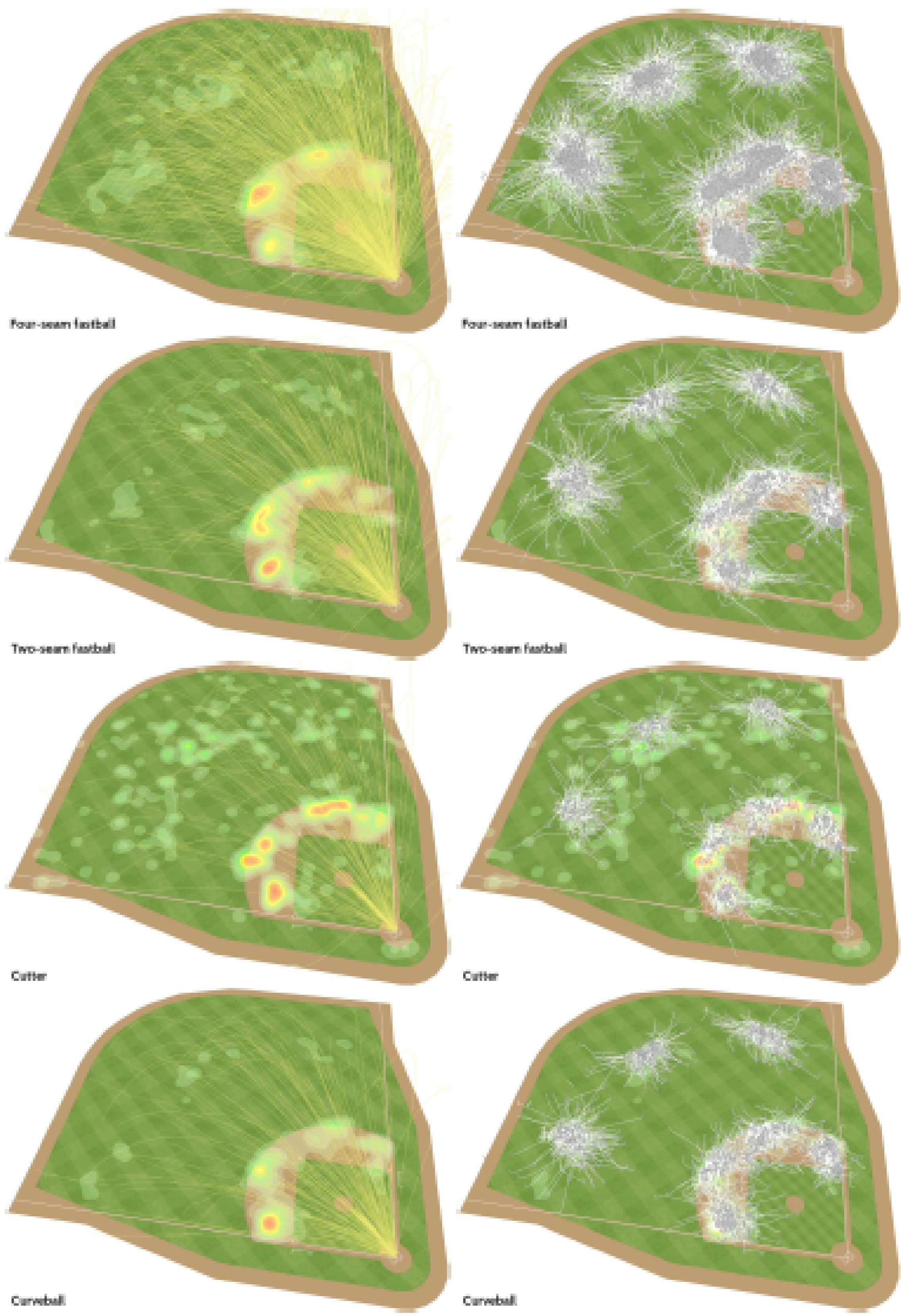


Figure 19: Ball and fielder heatmaps associated with different types of pitches (Dietrich et al. [42]).

key statistics revolve around pitchers trying to find the right types of pitches to minimize the probability of the batter getting a hit. To better understand the trajectories of pitches, Shum and Komura [98] developed a technique to extract three-dimensional pitch trajectory information from a single video sequence. Using this information, they developed a visualization showing these trajectories and superimposed them over a video frame. Moon and Brath [78] also focused on pitching and hitting data in their baseball visualization system. They also included filtering, linked views, glyphs, and heatmaps to provide flexibility in analyzing baseball matchups.

One of the most realistic-looking analysis systems was developed by Dietrich et al. [42] (see Figure 4). They used the results of recent technological advances in player and ball tracking to develop an interactive application that is able to reproduce entire baseball games. It allows users to visually explore individual plays from multiple angles and provides a series domain-relevant filters to assist in analysis. With this application, they also produced ball and fielder trajectory heat maps that demonstrated differences based on pitch types (see Figure 19).

2.6.6 Miscellaneous

In this section I review recent work that includes custom visualizations from a handful of other sports domains, including rugby, hockey, cycling, volleyball and auto racing. There is not the same depth of research in these areas as some of the sports covered earlier, but they are included to demonstrate the breadth of work in the sports analytics area.

Chung et al. [29, 30, 65, 31] published a number of papers centered around analyzing rugby matches. They developed an interactive, glyph-based system called *MatchPad* designed to run on tablet computers and demonstrated its utility with a professional rugby team. The interface, shown in figure 20 displayed glyph-based representations along with other event data in real-time from analyst inputs. The then developed additional visualization tools the relied heavily on interactive glyph sorting techniques to provide insights to analysts (Chung et al. [29]).

A recent example exemplifying the benefits of visualization in hockey analysis was provided by Pileggi et al. [85] in the *SnapShot* application. Using data provided by National Hockey League stat keepers, the developed an interactive visualization that included radial heatmaps showing where most shots were taken from, divided up by concentric rings centered around a hockey net (see Figure 21). Like the *MatchPad* application, this application also included data filtering capabilities to support analyst explorations and hypothesis testing.

For visual analytics in the sport of cycling, I briefly discuss recent research using two very different sources of data: data providers and fans. Beck et al. [18] used pedal power data from a data provider that also provided biometric, location, and environmental data including cyclist heart rate, current speed, pedal power, pedal cadence, traveled distance, altitude, and outside temperature. With this information, they developed a time-series visualization comparing two riders on the same track. Hoeber et al. [51] developed a system called *Vista* to provide visual Twitter analytics based on sentiment analyses performed on tweets. In this system, they encoded sentiment using color (green for positive, gray neutral, and red negative) and tested the system on tweets related to the 2013 Tour De France bicycle race. Figure 22 shows a screenshot of the Vista application that displays a timeline of tweet sentiments along with an overlay of several specific tweets. Users can apply data

Figure 20: MatchPad interface showing real-time rugby visualization (Legg et al. [65]).

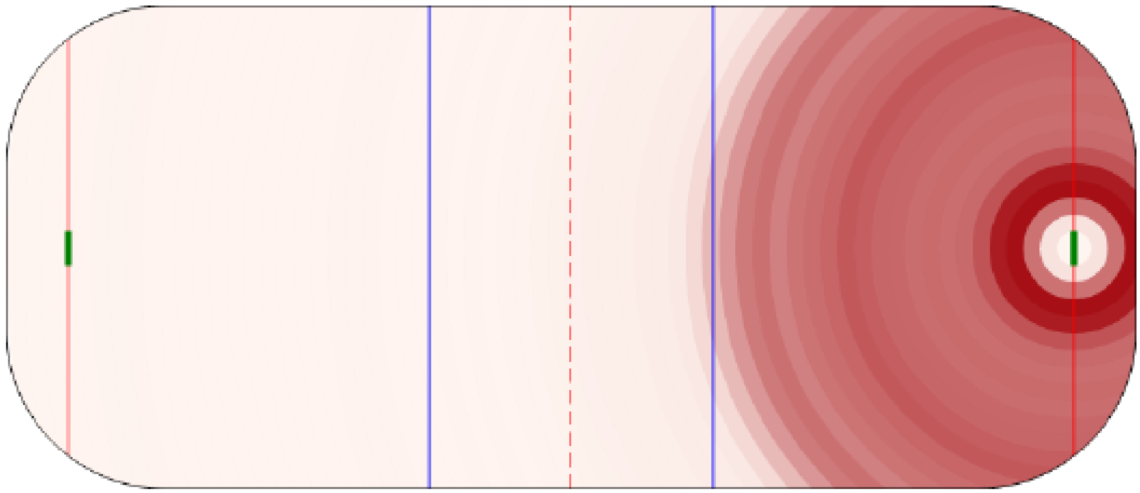


Figure 21: Sample radial heatmap generated by the Snapshot application showing where the most shots are taken from (Pileggi et al.[85].

filtering and temporal zooming to investigate the data further.

Using a single-camera setup to track players along with a custom-built data collection system, Koch and Tilp [61] analyzed 18 beach volleyball matches. They investigated probabilities of serve-reception, set-attacking, and reception-attacking. In their analysis results, they included an interesting 3-D bar chart superimposed on a volleyball court to indicate shot and smash patterns from set balls (see Figure 23).

Stoll et al. [99] took on the challenge of visualizing racecar position on a track with only sparse data collected at a few points along the racetrack route. Using interpolation techniques based on data collected from prior time trials from the same racecar or from similar participants, they developed a visualization allowing fans and analysts to have realistic simulation of the live race. As a visual aid to indicate positional uncertainty, the developed a gradient band where the opacity of the band indicated the level of uncertainty in the location accuracy (i.e., low opacity = low uncertainty, high opacity means high uncertainty). This is displayed in Figure 24.

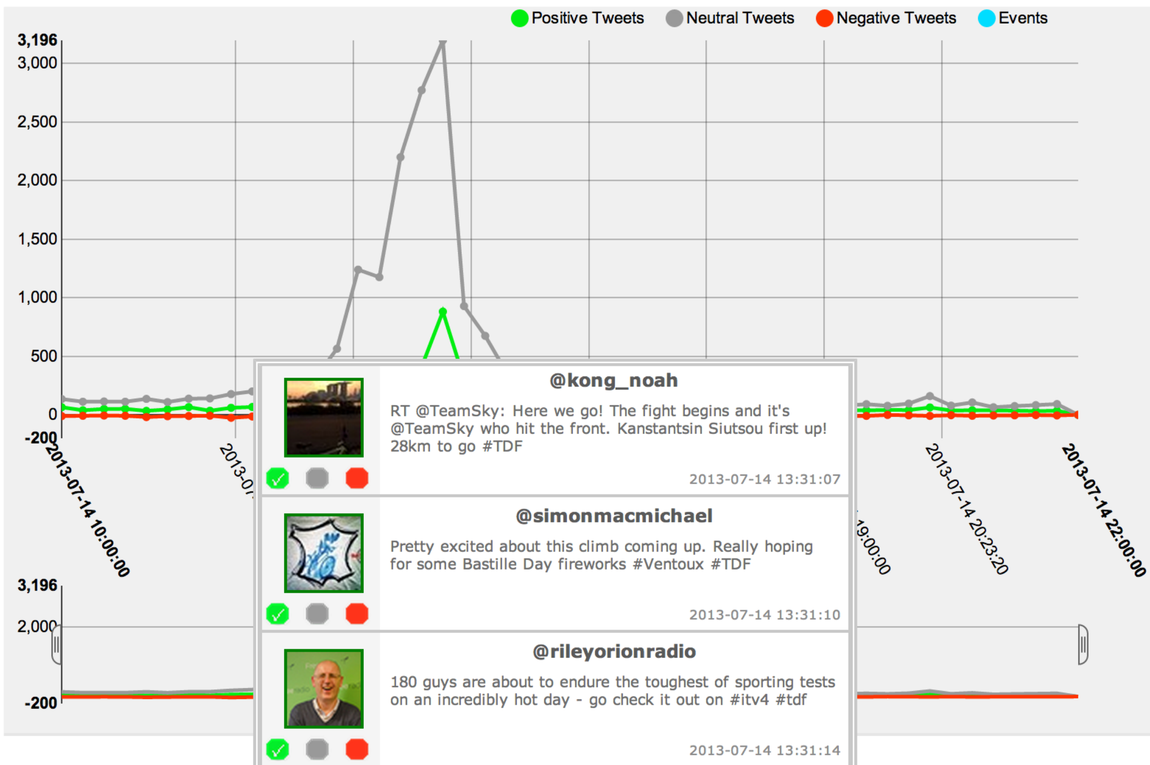


Figure 22: Timeline of tweet sentiments with 3 selected tweets overlaid on top (Hoeber et al. [51]).

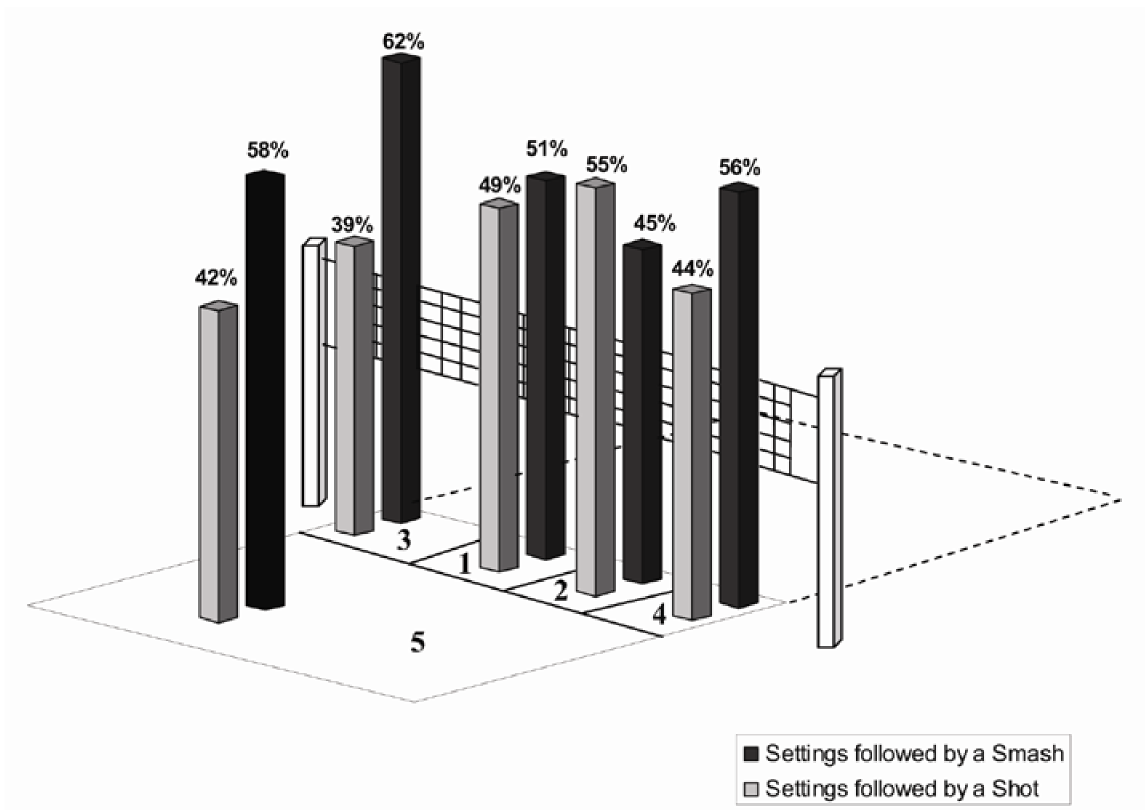


Figure 23: 3-D bar chart plot showing different attack techniques following perfect sets at various volleyball court locations (Koch and Tilp [61]).

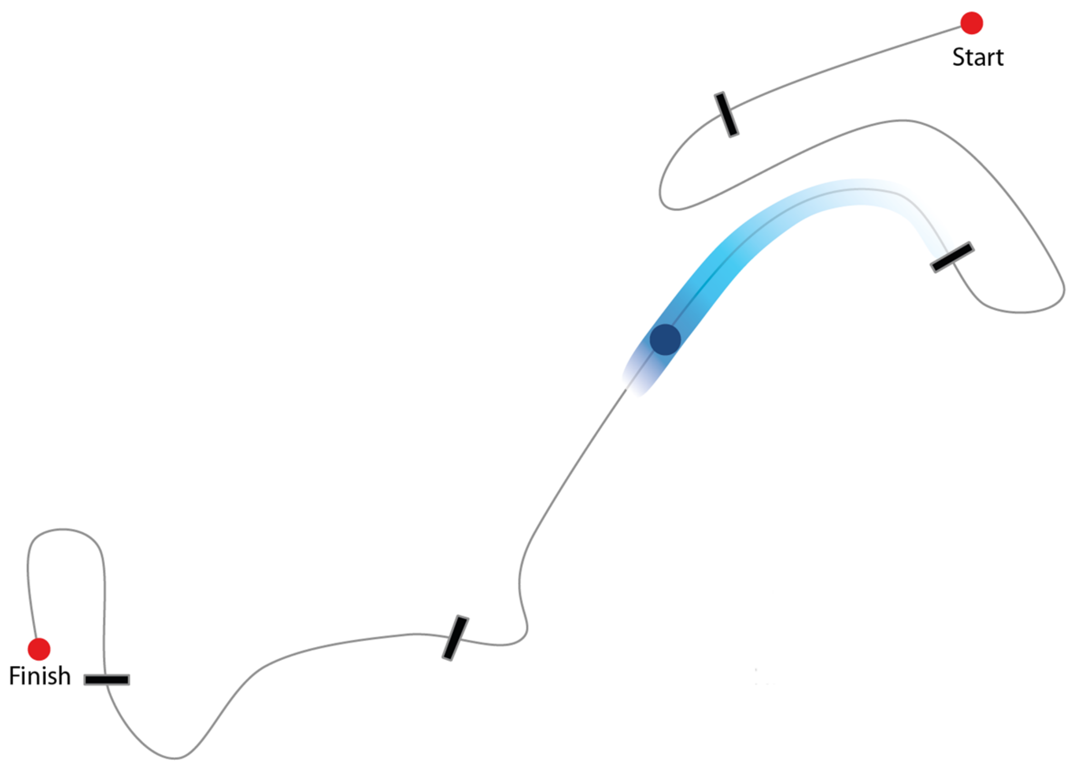


Figure 24: Racetrack outline with blue dot indicating approximate racecar location. The opacity of the surrounding blue band indicates location estimation uncertainty, where greater opacity = greater uncertainty (Stoll et al.[99]).

2.7 Key Design Considerations Related to My Focus Area

In this section I present brief reviews of research efforts in specific topic areas that are indirectly related to tennis visualization and analytics. These include the following:

- **Glyph Design.**Glyphs are relatively small, visual objects that encode multiple pieces of information using attributes such as size, shape, color, orientation, etc. There are multiple, potentially meaningful dimensions for points in tennis that may benefit from glyphs, such as who was serving, who won the point, how was the point won, etc. Therefore, a brief review of literature related to effective glyph design will be presented.

- **Spatio-Temporal Data.** Like most sports, tennis has a heavy spatio-temporal component and much of the existing research has focused on how to automatically collect spatial information about the players and the ball and to incorporate that information into useful information visualizations. Therefore, several papers discussing various important considerations needed when collecting and working with spatio-temporal data are presented.

- **Knowledge Generation Loop.** Analyzing data about a tennis match is analogous to conducting an investigation. Data is collected and presented to a user with domain expertise and that user sees potential patterns and forms hypotheses about that data the guides subsequent analysis. This process is captured well by the knowledge generation loop and therefore several papers discussing this topic are briefly presented to review some of the key concepts.

- **Storytelling.** Simply generating knowledge and insights for the coach or analyst is not sufficient. Those insights need to be shared with the player. This requires packaging up the insights into a convincing, rich, concise presentation readily understood by tennis players. Therefore, I will briefly review key concepts from storytelling as it applies to visualization design.

- **Design Studies.** It is not sufficient to simply encode information in some type of visual representation and present it to the end users. Effective visualizations should be well understood by key domain members that are not experts in visualization. The only way to verify this is to have actual end users from the target domain interact with a visualization to demonstrate its usability and effectiveness to generate meaningful insights. Therefore, guidelines for design studies are briefly reviewed.

2.7.1 Glyph Design

Glyphs are relatively small, graphical representations that visually encode multiple data dimensions. Borgo et al. [21] provide a basic definition of glyphs as small visual objects, discretely placed in a display space, that depict attributes of a single record or composition of multiple records. They are used as a form of data compression designed to maximize information transmission while minimizing display real estate. They accomplish this through multiple visual channels, including shape, color, texture, size, orientation, aspect ratio, and curvature (Borgo et al. [21]). They also outline 14 design guidelines in the following areas: design and usage, data mapping, glyph mapping, and rendering. They also discuss glyph interaction. From this list of 14 guidelines, the following appear to be the most relevant to my research topic:

- **Compromise Between Complexity and Density.** If a dense display of glyphs is needed, then each glyph should be relatively simple, representing only a few dimensions. If there will only be a small number of glyphs, then each glyph can depict a larger number of attributes.

- **Hybrid Visualizations.** If not too densely packed, glyphs can be incorporated into other visualizations where the space between the glyphs can be mapped to spatial dimensions.

- **Perceptually Uniform Glyph Properties.** When mapping data to a particular glyph property, care should be taken to ensure equal distances in space are perceived equally well. One notable negative example is mapping an attribute to the radius of a circle as opposed to the area of a circle, since a linear in the radius actually represents a quadratic increase in the area.

- **Redundant Mapping of Variables.** Including redundancy by mapping the same attribute to multiple glyph characteristics can reduce the risk of information loss.

- **Importance-Based Mapping.** Important variables should be mapped to more salient features of glyphs such that it guides the users focus of attention. More prominent visual stimuli, such as color, size, and opacity should be used.

- **Simplicity and Symmetry.** Simple, symmetric glyph shapes facilitate the perception of visual patterns.

Fuchs et al. [46] evaluated alternative glyph designs when used to depict time series data in a small multiple setting. They found that line glyphs performed well in tasks involving peak and trend detection, while radial encodings were better for reading values at specific temporal locations. They developed a set of recommendations that included the following:

- Use linear layout to improve value comparison.
- Position and length encodings are preferred over color encodings for values.
- Triangular shapes work better than rectangular shapes for color encoding.
- Dont use color to encode high density data.
- Circular layouts are better than linear ones for detecting temporal locations.

Glyphs have been successfully used in several sports visualizations. Legg et al. [65] and Chung. et al. [31] developed a set of glyphs used to depict key events in rugby matches (see Figure 25). Cava and Freitas [24] developed some simple, rectangular glyphs to visualize soccer match outcomes. These glyphs included concentric rings to depict goals scored by the winning team and goals scored by the losing team, with the area in-between visually representing the goal differential. Total number of goals scored was mapped to the diameter of the circle. Note that this last mapping violates the principle of perceptually uniform glyph properties proposed by Borgo et al. [21]. A better mapping may have been to map total number of goals to the area of the circle. For baseball, Moon and Brath [78] developed a series of glyphs that mapped color hue to pitch speed and glyph shape to pitch result (e.g., ball, called strike, swinging strike, etc.).

2.7.2 Spatio-Temporal Data

Nearly all sports involve movement of players and/or objects. Movement in individual sports like tennis singles often represents player tactics, such as running around a backhand

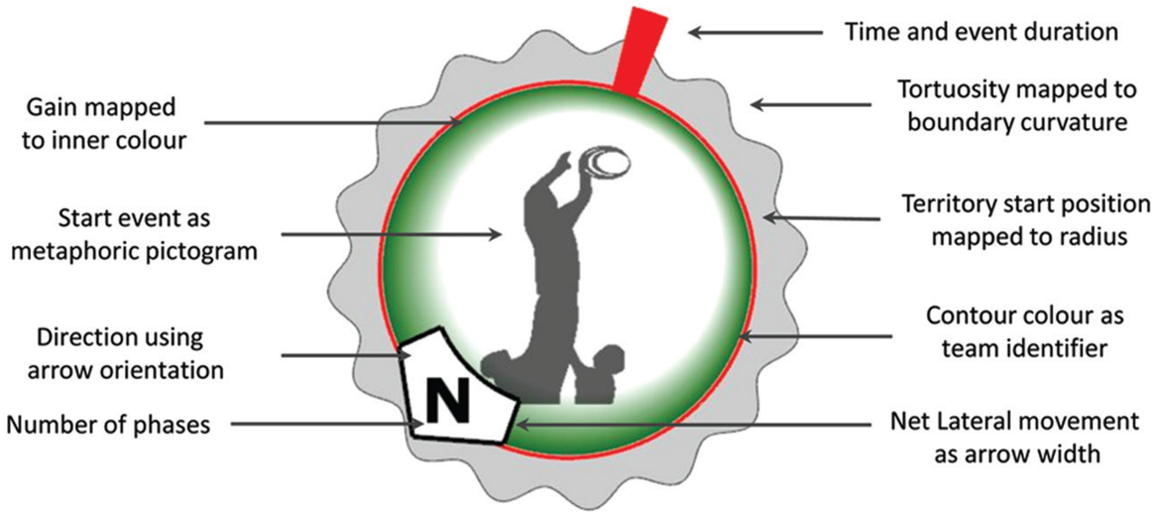


Figure 25: Rugby glyph with multiple dimensions mapped (Chung et al. [31]).

shot to hit a more powerful forehand shot. In team sports like soccer or basketball, it is often coordinated movement among teammates that is of primary importance. Much of the initial work in sports analytics has focused on how to accurately collect this movement data so it can be used for further analysis. However, knowing *how* to collect spatial data is only part of the challenge. The other parts include knowing *what* to collect, *how much* to collect, and *what to do with it* once you have it.

Determining what spatio-temporal data to collect is heavily dependent on the specific sport being studied and the kinds of questions analysts and other domain users want to answer. For tennis, the primary options are deciding whether to track the players or the ball or both. The ball, being a relatively small and uniform object can be treated as a single centroid. But, for players, the decision is whether to track the court location of the player or whether we need spatial information about specific body parts, such as arm and wrist locations when analyzing specific tennis strokes.

The question regarding how much data to collect comes down to one of figuring out the appropriate spatio-temporal resolution. Huge amounts of spatial data can be collected in short periods of time if the sampling rate is very high, particularly if multiple objects are being tracked. Andrienko and Andrienko [15] indicate that when the spatial and/or temporal resolution of the data is lower than needed for analysis, it can be generalized. For spatial data, this means compartmentalizing the data into larger unit areas. They stress that one must consider the goals of analysis when making these determinations.

These considerations also inform what to do with the data once you have collected it. That is, analysis goals form the basis for specific questions that in turn dictate how the spatio-temporal data is to be represented. In raw form, spatio-temporal data is a series of two or three dimensional point locations with corresponding timestamps and object identifiers. The visual representations of these points can change dramatically based on the questions being asked since these questions have implications for the spatial resolution required and the temporal time-scale desired. For example, for tennis player movement data, one question may be 'For the match as a whole, what are the movement characteristics of player A?". Implicit in this question is a spatial resolution that must map to locations on the tennis court at sufficient resolution to be able to indicate where a player has been. Therefore, a resolution of one inch by one inch, for example, seems to be unnecessarily fine grained, while a resolution of 10 feet by 10 feet seems too coarse and imprecise. Since the temporal timeframe is an entire match, then it seems that some type of court coverage heatmap seems appropriate.

2.7.3 Knowledge Generation Loop

When the goal of analysis enters the realm of player improvement, sports analytics becomes analogous to other analysis domains that have been well studied in the literature. Bier et al. [20] worked with intelligence analysts to model their data collection and sensemaking processes. In their process, analysts start by sifting through lots of data to then identify a subset of interest. They then review this subset, develop a set of hypotheses and then test these hypotheses. The result is generation of new knowledge that then guides further data gathering and exploration.

Sacha et. al [94] formalized this sensemaking process into a knowledge generation model for visual analytics, represented as a symbiotic relationship between human and computer where each plays a role best suited to their capabilities. The computer provides the data crunching and storage capacity needed, while the human provides the perception and cognitive reasoning needed to guide the process and interpret the results. Figure 26 shows the knowledge generation model. As it indicates, the computer holds the data, implements the model (calculations made with the data), and displays the visualizations. On the human side, activity takes place at various levels. Initial activities are focused on exploring the data to identify potential events or artifacts of interest. The next phase is one of forming and verifying or rejecting hypotheses. This phase then loops back into the exploration phase as new data are assembled based on the outcomes of the hypothesis testing. The third phase is the actual knowledge generation loop where new insights, supported by hypothesis testing, are generated.

When applied to a sports analytics context, the domain expert (i.e., coach, analyst, or

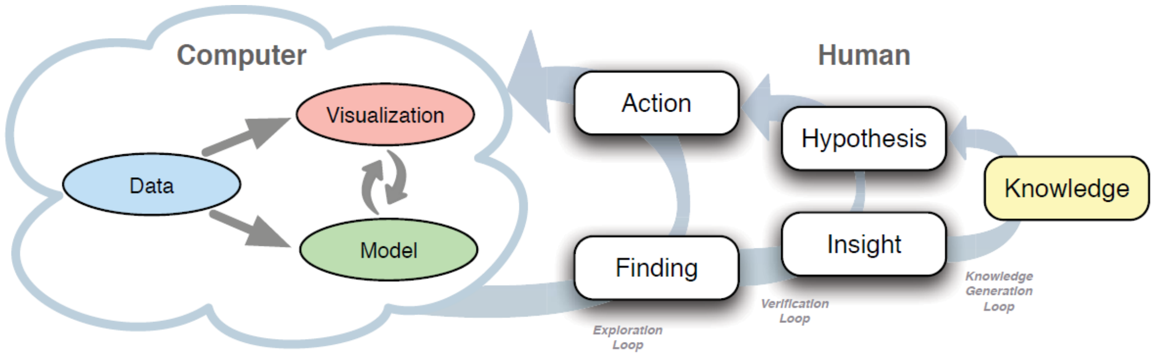


Figure 26: Knowledge generation model for visual analytics (Sacha et al. [94]).

player) interacts with a visualization by filtering and exploring data within a framework of their own understanding of the key events that are most likely to impact performance or an outcome. This forms the basis of their hypothesis generation. As these hypotheses are formulated and tested, they provide additional data points that, together with their own experience in the sport and knowledge of the players characteristics, help the user develop an explanation of the outcomes. For example, a tennis coach may have prior knowledge about a player's problems with their serve and therefore examine point outcome data for points starting with a first serve versus a second serve. If the coach's hypotheses are confirmed, this may then lead them to dig deeper into those points that start with a second (i.e. weaker) serve to try to pinpoint exactly why the player is losing these points. The end result is a reasoned explanation that accounts for the actual results. The final step then, is effectively communicating that explanation to the player. This concept is briefly reviewed in the next section *Storytelling*.

2.7.4 Storytelling

For sports analytic systems aimed at providing insights for player improvements, one additional key element in the knowledge generation loop is the ability to communicate the findings to the player. The coach or analyst needs the ability to collect the findings and place them in a format easily understood by the players. Recent approaches in visualization research has focused on incorporating concepts from the domain of *storytelling* as a way to effectively communicate findings and other insights.

Kosara and Mackinlay [62] make this point, indicating that presentation and communication of data have played a somewhat minor role in visualization research and that elements from storytelling should provide useful insights into how to effectively communicate results, particularly to end users not familiar with visual analytics. Some of these elements include transitions, building up views gradually, animation, and having a narrative structure.

In terms of visualization formats, Segel et al. [97] place interactive visualization stories along a spectrum with *author-driven* at one end and *reader-driven* at the other and describe three basic hybrid models: Martini Glass, Interactive Slideshow, and Drill-Down Story. Situated at the author-driven end of the spectrum, the Martini Glass model initially emphasizes an author-driven approach to drive the narrative and provide the insights (seen as the thin stem of the martini glass). Gradually, however, more and more control is handed to the end user, allowing them to drive further insights (the wide mouth of the martini glass). The Interactive Slideshow approach sits in the middle of the author-driven versus reader-driven spectrum in that the structure (i.e., the order and overall content of each slide in the slideshow) is controlled by the author, but each slide provides interactive tools allowing free exploration to the end user. At the reader-driven end of the spectrum lies the Drill-Down Story approach, where the visualization presents a general theme or overview and the user is given the freedom to drill down and explore areas of interest.

2.7.5 Design Studies

Sports visualizations designed with the express goal of player improvement must be usable and understandable by users outside the realm of visualization experts. They must be well-understood and usable by analysts, coaches, and the players themselves. Lee et al. [64] studied how novices make sense of unfamiliar visualizations and developed a model that described activities user engage in when encountering new visualizations and the kinds of issues they face when performing these activities. They conducted a user study and found that many of the subjects floundered when trying to understand some visualizations that are well-known to visualization experts (i.e., parallel coordinates, chord diagrams, and treemaps). Therefore, the usability and understandability of custom sports visualizations need to be validated with the actual end users. Perhaps the best way to do this is through one or more design studies, using actual members of the target audience as participants.

Sedlmair et al. [96] developed a nine-stage visualization design study methodology based on their own experiences and by reviewing existing visualization research. These stages fall into three categories: personal validation, inward-facing validation, and outward-facing validation. Personal validation implies the researcher has done due diligence in preparing to create a validation and collaborate with domain experts. Inward-facing validation involves validating the specific design concepts with domain experts. Outward-facing validation focuses on justifying the results of the design to the outside world (who are likely not domain experts).

Within each stage, they identify several potential pitfalls to avoid, including (among others) not having enough prior knowledge of visualization literature, not having the requisite data, exiting methods are already ‘good enough, and developing visualizations for problems that could be solved with automated algorithms. In a sports analytics context, building an effective visualization is facilitated by a reasonable depth of knowledge and/or experience in a sport and having ready access to other domain experts. Regarding data availability, the key problem does not appear to be the amount of data, but rather the proprietary hold stakeholders maintain over that data due to the competitive advantage this data may present. Compared to the field of information visualization overall, sports analytics still remains a fairly new area of focus and therefore is ripe for new techniques and visualizations. Tennis, in particular, is an excellent candidate for study due to its popularity and, therefore, the local availability of domain experts (i.e., tennis coaches and advanced players).

CHAPTER 3: ANALYZING TENNIS MATCHES USING SEMANTIC AND N0N-SPATIAL DATA

In this chapter, I present work involving the development and testing of an interactive visualization system designed to be used by tennis players and coaches to analyze tennis matches for the purpose of player improvement. The design of this visualization system was purposely constrained to only rely on non-spatial data. The driving force for this was the lack of this type of data for anything other than the biggest professional tennis tournaments. Even when this data is collected, it still requires an extensive, multi-camera system along with human analysts to provide score and other context information. Therefore, since a motivating goal is to create analytical tools to help non-professional players, the first set of visual analytics tools relied only on more easily collected data.

3.1 Introduction

Visualization has been an important means of match analysis in a variety of sports (Cox and Stasko [41], Goldsberry [49], Legg et al. [66], Perin et al. [81], Pileggi et al. [85]). For example, Perin et al. [81] demonstrated the usefulness of visualizations in helping tactics analysts find insights into soccer games they would not have otherwise been able to find. For tennis, much of the existing work utilizes ball and player tracking information to provide virtual replays of tennis matches (Pingali et al. [86]). This tracking information is also used to provide summary level information about player strategies such as player movement (Pingali et al. [87], Zhu et al. [123]). A major challenge facing these approaches

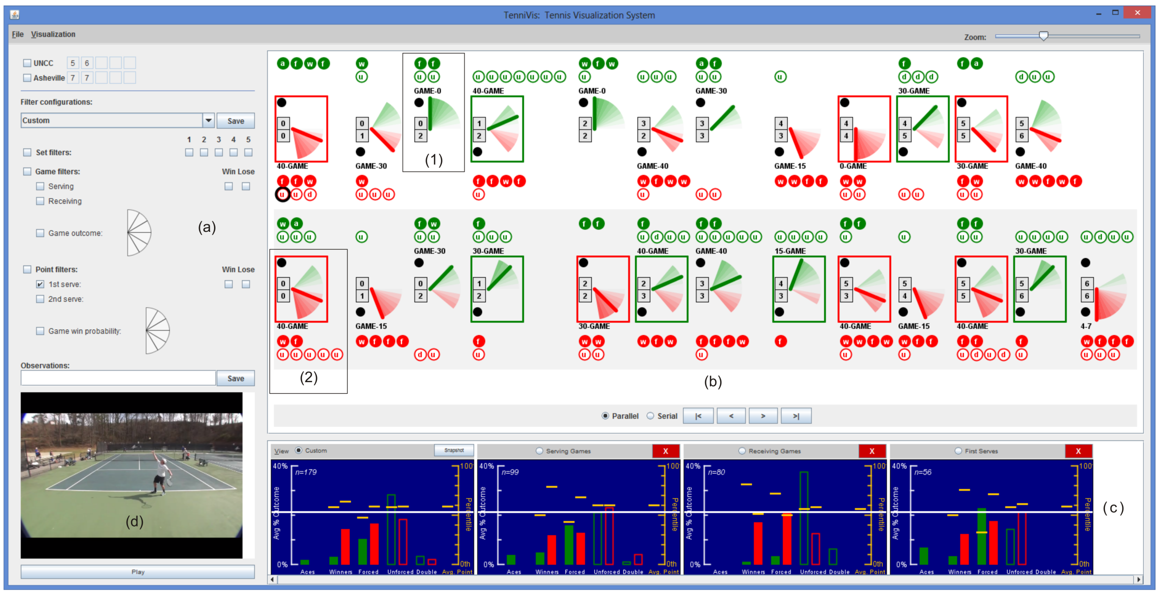


Figure 27: A college men's singles tennis match in TenniVis. (a) Match scores and filters. (b) Pie Meter view. Each Pie Meter represents a game. Balls above/below it represent points gained by player one/two. Solid/hollow balls represent good (ace, winner, forced error) /bad (double-fault, unforced error) points. The darker the green/red colors in the pie, the better the chance player one/two had to win the game. Needle color shows who won the game (green for player one, red for player two). Needle angle indicates the final score (the closer to East, the closer the score was). Red and green boxes identify service breaks. (1) A game won easily by player one. (2) A game won with difficulty by player two. (c) Bar charts of point outcome statistics in multiple filter configurations. (d) Video viewer playing a video clip of a point.

is that collecting the data typically requires an array of cameras and a system capable of handling the large amounts of video input in real time. While this might be reasonable for major, professional tennis tournaments, such a system is prohibitively expensive and impractical for the large body of non-professional tennis players at the college, high-school, and club levels.

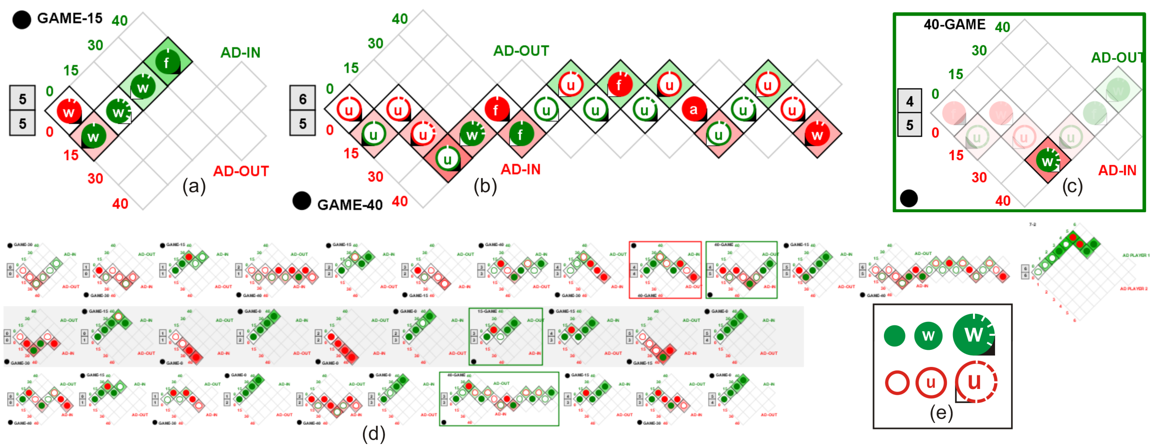


Figure 28: Fish Grid views of the Federer-Gonzalez match (won by Federer 7-6, 6-4, 6-4). (a)-(c) are captured from a zoomed-in view and (d) is a zoomed out view. Each Fish Grid is a score matrix rotated 45 degrees with point outcomes mapped on it as balls (green/red: point gained by Federer/Gonzalez; solid/hollow: good/bad shot). The horizontal order of the balls indicates the temporal order of the points. The vertical position of a ball indicate who was in lead before the point (above the horizontal, Federer is in the lead; below the horizontal, Gonzalez is in the lead). (a) A game won easily by Federer. (b) The longest game in the match (won by Gonzalez). (c) A game with a “choke” point for Gonzalez, identified using filters. (d) Fish Grids for the entire match. Although shown small here, they still convey trend information for each game. (e) Sample Point Outcome Glyphs (balls) at different zoom levels. At the maximum zoom level, tick marks represent point length in seconds and triangles represent service side (left/right) and first vs. second serve (solid/hollow).

Meanwhile, comparatively little work has been done on visualization of non-spatial data of tennis matches, such as score, point outcomes, point lengths and service information. Such data is easy to collect by non-professional players and carries both high level summaries and low level details about a match. Unfortunately, this data is usually analyzed in aggregated statistics and thus valuable insights about local details and trends are often missing.

The above observation inspired us to build a tennis visualization system for non-professional players based on non-spatial data. A system was thus developed with the following goals:

- To be economically and technologically feasible for non-professional tennis players. In other words, no expensive ball and player tracking equipment and analysis software will be required.

- To provide easy to learn visualizations and easy to use interactions. Therefore, tennis coaches and players will be able to use the system without the accompaniment of visualization experts.

- To support users quickly discovering patterns about players and matches; to facilitate them in ad hoc hypothesis generation and evaluation.

- To allow coaches and players to easily share insights gained from the visualizations.

Our new system, named **TenniVis**, provides the following features to meet the above goals:

- Easy-to-collect data input: TenniVis merely requires the following information as its inputs: (1) the match video captured by a single consumer-level video camera and (2) non-spatial data that can be easily collected by someone spectating a match (i.e., parent, coach, or teammate) in real time. It includes timestamps marking the start and end of each point, indication of second serve, and point outcome (i.e., ace, double-fault, winner, forced error, or unforced error). Other information, including score information, who is serving, service side (ad or deuce court), game length (i.e., number of points), point length, and service breaks, can be derived from the data and the inherent structure of a tennis match.

- Easily learnable visualizations: TenniVis provides two novel views that can be quickly learned and understood by novice users: the Pie Meter view and the Fish Grid view. The Pie Meter view (see Figure 27 (b)) provides a high-level overview of an entire match. It reveals who won a game and the degree to which the score in the game fluctuated in favor of one player. The Fish Grid view (see Figure 28) provides more details at the game level by displaying each point outcome as the game score progresses. The game length, trend, and critical points can be easily observed from this view.

- Ad hoc hypothesis generation and evaluation: A variety of player, set, game, and point level filters are provided, allowing users to generate hypotheses about point outcomes. Users can evaluate these hypotheses using the outcome bar chart snapshots (see Figure 27 (c)) as well as by reviewing the video associated with specific points.

- Result sharing: Users can annotate individual points with their observations from the associated video clips (see Figure 27 (d)). These points are highlighted in the visualizations for easy review. The annotated video clips are automatically assembled into an HTML report that can easily be shared with players or coaches.

Non-professional tennis players and coaches have participated and provided important input to the development of TenniVis. First, I have over 35 years of tennis playing experience. Second, a set of face-to-face meetings, phone interviews, and user studies have been conducted with non-professional tennis coaches. The coaches confirmed the feasibility of data collection for TenniVis. They also confirmed the usefulness of TenniVis in two pilot user studies where matches of their own players were analyzed.

The rest of this chapter is organized as follows: Section 3.2 provides background knowledge on tennis and discusses challenges facing non-professional players when analyzing tennis matches. Section 3.3 presents TenniVis and illustrates its features using the case of a professional tennis match between Roger Federer and Fernando Gonzalez from the 2007 Australian Open Finals, won by Federer in three sets (7-6, 6-4, 6-4). Section 3.4 presents two pilot user studies of college tennis matches, where the analysis was performed by the coaches themselves. Section 3.5 presents our conclusions and future work.

3.2 Background and Requirements Analysis

In this section, we introduce background knowledge of tennis, point out match information that is important for match analysis, and highlight the requirements it brings to tennis visualization systems in bold fonts. The important information and requirements were identified according to my own experience and intensive phone and face-to-face discussions with four club and college coaches.

Tennis lends itself to analysis due to its structured, hierarchical nature. A typical non-professional tennis match consists of the best two out of three sets, where each set is awarded to the player who gets six games first (with at least a two game margin). Each game is awarded to the player who gets four points first (with at least a two point margin). One player serves all the points in a game. Players alternate serving each game. They also change sides of the court after the first game and then after every two games. Serving is considered an advantage in tennis, so it is important to highlight games where the serving player loses the game. This is called a **service break**. **Who is serving and service breaks should be immediately noticeable to users.** If the game score within a set reaches six-six, a 12-point tiebreaker is played. In this tiebreaker one player serves one point and then each player takes turns serving two points. The player to get to seven points first with a margin of at least two points wins the tiebreaker and is awarded the set. If players get to six-six in the tiebreaker, they continue playing until one player gets a two point lead.

The scoring progression in a game is as follows: 0 (or love), 15, 30, 40, game. If, in a game, both players each get three points (called **deuce**), then play continues until one of the players gets a two point lead over the other player, thus winning the game. After a deuce point has been reached, when a player gets a point we say that player has the advantage. The score is usually reported from the server's viewpoint. In terms of risk, not all points within a game are equal. For example, a player serving at 40-0 in a game needs only to win one of the next three points to win the game. From the server's perspective, this is a far more comfortable position to be in relative to a score of 0-40 (known as a break point). **Visually encoding the risks associated with the points will help users understand the pressure on the players at each point.**

As with many sports, there is a psychological component to tennis that affects players differently. Some players ease off in their intensity after getting a lead just to see their lead slipping away (known as **choking**). Other players are able to step up and recover after being down in a match (known as **rallying back**). **Choking and rallying back should be easy to spot in visualizations because they may identify player patterns that need to**

be modified.

A tennis point begins with a serve by one of the players. The starting location of the serve is behind the baseline on either the right half of the court (called the deuce side) or the left half (called the ad side). See [13] for an explanation of the various parts of a tennis court. If the server misses the first serve (i.e., it does not land in the correct service box), this is called a **fault** and the player gets to try again. If the player misses the second serve, this is called a **double-fault** and the point is awarded to the receiving player.

When analyzing a tennis match, information about whether a point started off on a first versus a second serve is very important because a player's second serve is usually not as powerful or effective as their first serve (thereby giving the receiving player an easier opportunity to return the serve). If the server hits the ball in the opponent's service box and the opponent does not touch the ball, this is called an **ace** and the point is awarded to the serving player.

Tennis points can end one of three additional ways besides by double-fault or ace: winner, forced error, or unforced error. A **winner** is when a player hits a legal shot (other than a serve) to his or her opponent and the opponent does not touch the ball. A **forced error** is similar to a winner except that the opponent is able to touch the ball. Both winners and forced errors (as well as aces) are **"good" shots** attributed to the "good" shot made by a player. An **unforced error** is when a player, despite having enough time to get to the ball and execute a good shot, ends up instead hitting the ball out of bounds or into the net. An unforced error, like a double-fault, is considered a **"bad" shot** attributed to the player that made the error because it gives a point to the opponent.

In analyzing tennis matches, understanding how points end is vitally important to understanding why a player is winning or losing his or her matches. The coaches that I talked to during our pilot user studies indicated that unforced errors help them identify potential shots a player needs to work on. They also indicated that winners made by an opposing player are often the result of poor shot selection on previous shots by a player. Thus, examining winners helps identify areas where strategies may need to be improved. **Visually presenting point information, such as service information, good or bad shots, and point outcome types, can provide useful insights to coaches and players.**

In addition to having information about the outcome of a point (ace, winner, unforced error etc.) and the service information (first versus second serve), the score of a game at which a specific outcome occurs is also important. For example, some players may have a tendency to start off games slowly and get behind. Seeing this in the visualization, coaches can work with a player to change their tactics or teach them how to be more mentally prepared at the start of a game. Therefore, **it is very useful for visualization systems to visually present the point outcomes within the context of the score where they occur.**

While video analysis is fairly common in many sports, such as American football, this is not as common in tennis matches, due primarily to the expense of analyzing this data. Unlike team sports where there is one match in which all members of the team participate, team tennis matches involve multiple, separate matches being played simultaneously. In NCAA [14] tennis matches, teams play three doubles matches followed by six singles matches. A typical singles match may last two or more hours, leading to 12 hours of video (for just singles) to be analyzed per team match. Many teams play 2 or 3 matches per week, resulting in 36 hours of video per week. It is time consuming for the coaches to analyze such a large volume of video. Meanwhile, it is important for coaches and players to watch

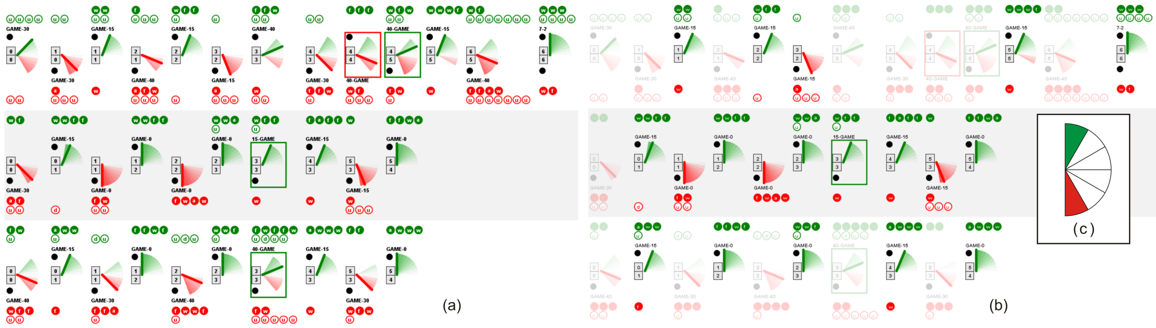


Figure 29: Pie Meter view of the Federer-Gonzalez match. (a) Before filtering. All games are displayed. (b) After filtering. Only games won easily by either player are displayed. (c) The Game Outcome Filter used for the filtering.

the video of interesting points. Thus **there is a dire need for visualization systems that can help coaches (or the players themselves) quickly identify points in a match that may lead to insights and watch the video clips associated with them, without having to sift through all of the raw video data.**

3.3 TenniVis

3.3.1 System Overview

In order to address the information needs discussed in Section 3.2, TenniVis employs visualizations that mimic real-life metaphors, such as dial meters, to make it easy for coaches and players to learn and interpret the visualizations. Consistent visual encoding schemes are used across the visualizations to facilitate learning and allow for easy transition between visualizations.

Figure 27 shows the main screen of TenniVis. On the left are a set of filters (top) and a video viewer (bottom). On the right are the main visualization window (top) and an outcome bar chart panel (bottom). Users can switch between the Pie Meter view and the Fish Grid view in the main visualization window. The currently displayed visualization can be zoomed in or out using the zoom slider located above it. TenniVis provides a multi-resolution approach to allow users to examine a match at multiple levels of detail. In particular, the Pie Meter view (see Figure 27 (b)) provides a match level overview where users can quickly examine the outcome of all sets and games, see how intensive each game is, and effectively compare the performance of the two players.

The Fish Grid view (see Figure 28) allows users to examine the match in a finer level of detail. Users can quickly see the progression of points within a game, each point outcome (ace, winner, unforced error, etc.) against a backdrop of the current game score. They can also instantly distinguish between very short games where one player wins easily and very long games where the players battle back and forth.

The finest level of detail TenniVis provides is the playback of match video of a user-selected point. When a point is selected, the video clip for that point immediately begins playing in the video viewer (see Figure 27 (d)). The user can also open up a larger, secondary window to view a full screen version of the video (particularly useful in a multiple-monitor environment).

A rich set of interactions are provided in TenniVis using a spectrum of filters (see Figure 27 (a)) that, in combination, allow users to select semantically meaningful sets of points. This allows them to examine the percent distribution, point length, and first serve percentage of point outcomes (ace, winners, unforced errors, etc.) in bar charts. In this way, users can create ad hoc hypotheses on why specific games or points were won or lost. Since users can easily drill-down to any point to watch the corresponding video clip, these hypotheses can be conveniently tested. To share the insights captured in the visual exploration, users are able to make notes on their insights and to generate reports that consist of written text and video clips that can be shared with the player or coaches.

In the following sections, I introduce the data collection, visualizations and interactions of TenniVis in full detail. The match between Roger Federer and Fernando Gonzalez in the 2007 Australian Open Men's Singles Final (won by Federer 7-6, 6-4, 6-4) is used as an example dataset since many readers are familiar with these players.

3.3.2 Data Collection

Match videos are desired in tennis analysis since all insights ultimately need to be evaluated through them. As one of the tennis coaches in our pilot studies commented, "they (the players) need to *see* it". TenniVis allows users to rapidly identify points of interest and conveniently watch their video clips. Since ball and player tracking data is not used in TenniVis, only one consumer-level video camera is needed for video capturing and no tedious manual tracking data collection is required.

The non-spatial data is manually collected on-the-fly by a person spectating a match. In order to support point-based selection of specific video clips, the start time and the end time of each point as well as who won the point, the type of outcome (i.e., ace, double-fault, winner, forced error, or unforced error), and service faults (i.e. missed serves) are recorded. This approach, while requiring the attention of the data collector throughout the match, can be easily collected using either a smart phone or smart watch app. The spectator only needs to synchronize the start time of the data collection app with the camera (before or after the match) and click a few buttons when a point starts and ends. There is ample time between points to perform this task. The data collection app can keep track of score and who is serving based on the rigid structure of a tennis match. Only one video per match is required. The TenniVis system simply indexes into specific points in the video based on the synchronized timestamps collected.

Data for historical matches can be collected in a similar way, with the only difference being that the spectator watches the match videos rather than the live matches. I asked several coaches about the feasibility of the players themselves collecting this data during a match (using a smart watch app) and they indicated this is not realistic. They noted, however, that they often have players who are not playing in a particular match who would be able to collect this data. The rigid structure of a tennis match allows a great deal of derived data to be collected from the trivial data items collected manually, including information such as score, who is serving, service breaks, break point opportunities, and point lengths (which is a surrogate measure for the number of shots in a rally).

3.3.3 Pie Meter View

Figure 29 (a) displays the Pie Meter view of the match between Federer and Gonzalez. It provides an overview of the match and also can be animated to present the dynamic process of the match. The visualization consists of multiple blocks. Each block visually presents a game. It contains a needle gauge-like glyph called a **Pie Meter** and rows of balls representing points called **Point Outcome Glyphs** (see Section 3.3.4). Games of the same set are placed in the same row, sorted from left to right by play order. The sets are ordered from top to bottom by play order. The score panels on the left of each Pie Meter show the game score within the set just prior to that game. A black ball shown at the top left of the Pie Meter indicates player one is serving, while a black ball on the bottom left indicates player two is serving. To highlight service breaks, games with a service break are surrounded by a red box (player two broke the serve of player one) or a green box (player one broke player two's serve).

Please note that in TenniVis, information about player 1 is always positioned in the top half of the visualization graphics and information about player 2 is always positioned in the bottom half of the visualization graphics, as exemplified by positioning of the black ball indicating who is serving. Similarly, green is always used to represent something good for player one and red is used to represent something good for player two. The highlight of service breaks is an example of this scheme. These encoding themes will be seen again and again in the rest of the dissertation. They are used in TenniVis since (1) A versus B is the most important information in tennis, an A versus B style sport; (2) According to Mackinlay [73], position and color hue are the most relevant encodings for perceptual tasks with nominal data. Thus they should be used for the most important information; and (3) Consistent visual encoding facilitates learning.

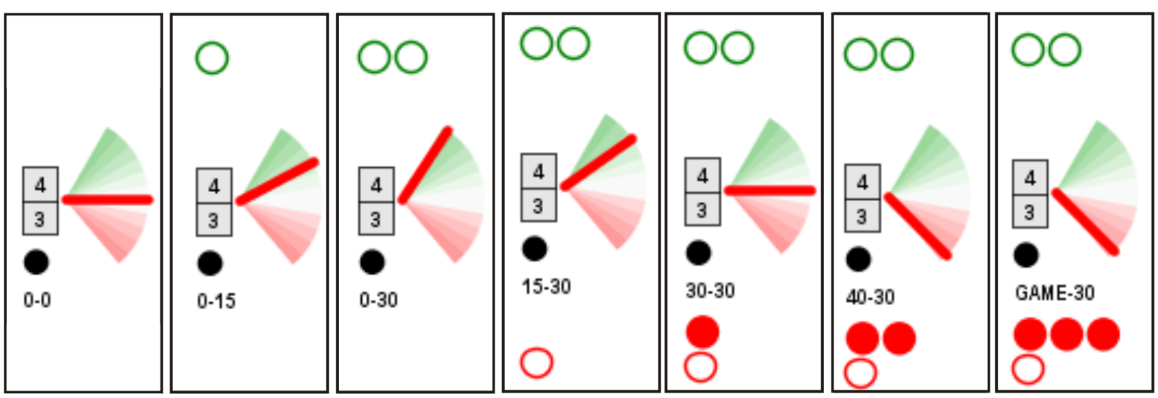


Figure 30: Succession of points from left to right and their corresponding needle angle changes in the Pie Meter for a game. Needle color shows that player 2 won. The green gradient colors indicate advantage for player 1 and the red gradient colors indicate advantage for player 2.

The needle gauge metaphor is employed in the Pie Meter since the rotation of a needle on a gauge is a familiar and natural way to reveal how a game progresses in favor of player one or player two. In our initial design, a full gauge covering 180 degrees is displayed and a needle dynamically traverses within the gauge as the game progresses. The position and the background color of the needle indicate whether the game is currently at a score in favor of player one or player two. After the initial prototype was implemented, I soon realized that the area traversed by the needle in a game reveals interesting information such as whether a game was dominated by one player or swung back and forth. Therefore, I revised the design and removed the part of a gauge not traversed by the needle in the game (so it looks like a pie). The details of the Pie Meter visual encoding is introduced below.

Following the color scheme, needle color shows who won the game (green for player one, red for player two). The gauge background (the pie) is divided into many sectors. Each of them is mapped to a range of conditional probabilities of player one winning the game (probabilities in short). The probabilities are encoded by colors of the sectors. Here again, green means player one has a better chance to win and red means player two has a better chance to win. The darker the color is, the higher the chance. The gauge is positioned vertically, with green sectors on the top half and red sectors on the bottom half.

All possible game scores are assigned a probability using a coin-flip simulation, assuming that players are equally skilled. When a game progresses, the needle is placed in the gauge according to the probability of the current score. When the game score is equal, the needle is placed at a white sector oriented to the East. When the score is more favorable to player one/two, the needle moves to the green/red sectors, indicating player one/two has a bigger chance to win. After removing the sectors not traversed by the needle in a game, the display only consists of sectors covering all possibilities happening in the game. Therefore, users can judge the intensity of a game by the color and angles of its Pie Meter. As Figure 29 demonstrates, even when the Pie Meters are relatively small, games where one player dominated are easily distinguishable from close games that swung back and forth.

The above simplistic approach assumes that players are equally skilled, which, of course, is often not the case. Better players are able to come back and win a game, even when they are behind in the score. However, this color coding scheme still makes it easy to distinguish situations that are more favorable to a player winning a game (shades of green) from those that are less favorable (shades of red).

The Pie Meter can be used in a static mode or an animation mode. In the static mode, the needle angle indicates how close the final game score was. There are eight possible final game scores: Game-40, Game-30, Game-15, Game-0, 0-Game, 15-Game, 30-Game, and 40-Game. These eight scores are mapped to needle angles ranging from +90 to -90 degrees (assuming East is considered 0 degrees). Once a game goes to deuce, the number of deuces is not considered: the score is mapped as Game-40. A similar approach is used for tie-break games.

A Pie Meter can be animated to step through the games (see Figure 30 for an example). When switching to the animation mode, all of the needles reset to a neutral, horizontal position (indicating neither player has an advantage). When player one wins a point, the needle angle moves up in a counter-clockwise direction and when player two wins a point, it moves down in a clockwise direction. Therefore, the angle of the needle indicates the current advantage (i.e., conditional probability of winning the game) one player has over the other and the final needle angle indicates how close the game was. In Figure 30 we can see that player one wins two points in a row, giving him a major advantage. Player two then rallies back, winning four points in a row to win the game.

Example 1 Figure 29 (a) reveals a few patterns about the match in which Federer (player one) won in straight sets (7-6, 6-4, 6-4). First, we see that Gonzalez (player two) broke Federer's serve first (indicated by the red box in the first set); but Federer broke right back. In sets two and three, there were only two service breaks (both by Federer) which gave him the match. The second pattern that emerges is that many of the games in the first and third sets involved swings from one player to another (indicated by Pie Meters with both red and green gradients displayed), while all games in set two were won fairly easily by one player or another.

3.3.4 Point Outcome Glyphs

According to the requirements analysis (see Section 3.2), the following information about point outcomes are desired, sorted by importance: (1) who won each point; (2) whether the outcome was due to a "good" shot by the player winning the point or a "bad" shot by her/his opponent; (3) the specific type of the point outcome; (4) at which score the point outcome was generated; (5) details about the point, such as how long the point was and service information. The Point Outcome Glyphs (the green and red balls in the Pie Meter and Fish Grids) are proposed to encode the above information for individual point outcomes.

Since there are many point outcomes in a game, the glyph representing an individual point outcome can't be too big. We select a ball-shaped glyph design (see Figure 28 (e) for an example) since (1) it is easy for users to associate a ball with a point outcome; (2) it provides a maximum amount of interior space in which to write the outcome letter (i.e., 'a' for ace, ‘w’ for winner, etc.); and (3) it allows us to use the stopwatch metaphor to encode time as tick marks. To be consistent with our color scheme, green balls indicate points awarded to player one since they are good for player one. Red balls are for points awarded to player two since they are in favor of player two. In addition, solid balls represent good shots (aces, winners, and forced errors). Hollow balls represent bad shots (double faults and unforced errors). Following our positioning scheme, points awarded to player one were placed above the Pie Meters and points awarded to player two were placed beneath the Pie Meters. In the Fish Grid View, the balls are placed at the game score (e.g., 30-15) at which the point outcome occurred.

To allow users to examine the point outcome information at multiple levels of detail, the Point Outcome Glyphs have three visual states based on the current zoom level. Additional semantic details are provided at greater zoom levels (see Figure 28 (e)). At the lowest semantic zoom level, the Point Outcome Glyphs only reveal who won the point and whether the point resulted from a good or a bad shot. At the medium semantic zoom level, we add the detail about the specific type of outcome using a single lower-case letter: (a)ce, (w)inner, (f)orced error, (u)nforced error, and (d)ouble fault. At the highest semantic zoom level, we encode point length and sevice information. Point length is encoded using white tick marks designed to look like five-second intervals on a stopwatch. For service information, we use a triangle to encode whether the point started on a first versus second serve (solid black versus hollow white triangle) and service side (deuce = right, ad = left).

Example 2 From Figure 29 (a), we can see a preponderance of bad shots (unforced errors), indicated by hollow balls, in the first set versus the second and third sets. In sets two and three there are more good shots (winners and forced errors), which are indicated by solid balls.

3.3.5 Fish Grid View

The Fish Grid view (see Figure 28(a-d)) provides detailed information about each point within the context of the whole match. A **Fish Grid** is essentially a 4X4 matrix where the row indices represent points won by player one and the column indices represent points won by player two. To be consistent with our positioning scheme, this matrix is rotated 45 degrees (resembling a fish) so that all the matrix cells located above the horizontal represent scores where player one is in the lead, cells below the horizontal represent a lead for player two, and cells on the horizontal represent even scores. This maintains the same visual metaphor established for the Pie Meters. Additional cells are added for deuce and ad points, making up the tail of the fish.

If a game goes beyond a single deuce, the tail of the Fish Grid grows to accommodate the extra points, thus making long games readily apparent. For example, in Figure 28 (b), we can see the longest game in the match (20 points). This occurred in the first set with Gonzalez (player 2) serving at 5 games to 6.

Each cell location in a Fish Grid represents a specific game score (e.g., 30-15). To help users navigate in a grid, a background color is assigned to each cell to indicate whether the score is in favor of player one or player two. In particular, a game win probability (from player one's perspective) for a given score is generated using the same coin-flip simulation discussed in Section 3.3.3. The probabilities are mapped to shades of green (win probabilities $>$50%), pure white (win probability = 50%), and shades of red (win probabilities $<$50%). Therefore, green cells represent scores in favor of player one while red cells represent scores in favor of player two.

In order to emphasize the scores that actually occurred in the game, only cells corresponding to those scores are colored. In this way, the Fish Grids essentially become sparklines [108], showing the basic temporal trend of each game, even when zoomed out. The vertical position of a Point Outcome Glyph indicates who is currently ahead in the game and its horizontal position encodes point sequence information. For example, Figure 28(a) shows that the game was led by Gonzalez at the very beginning as the result of a winning shot. But this was followed by four good shots in a row by Federer (three winners and a forced error), allowing him to win the game easily. We can also see from the point lengths encoded on the glyphs that both the 0-15 and 40-15 points started with a first serve and were very short. This indicates that Federer's serves on these points was probably effective. I verified this hypothesis by reviewing the video for these two points.

As with the Pie Meters, the current game score is shown to the left of each Fish Grid and the black ball indicates who is serving. The layout of the games is also the same as in the Pie Meter view.

Users can click on a Point Outcome Glyph in either a Fish Grid or a Pie Meter to play its corresponding match video clip in the video viewer (see Figure 27 (d)) or a standalone window. After watching a video clip, users can manually record their insights associated with the point through the text entry above the video viewer. Points with user observations are highlighted in yellow in both the Pie Meter and Fish Grid views (not shown in the figures). When a user hovers the mouse pointer over a highlighted point, their observations will be presented as a tooltip. When the users reload the video of a point by clicking on its Point Outcome Glyph, the observation will also be displayed in the text entry field above

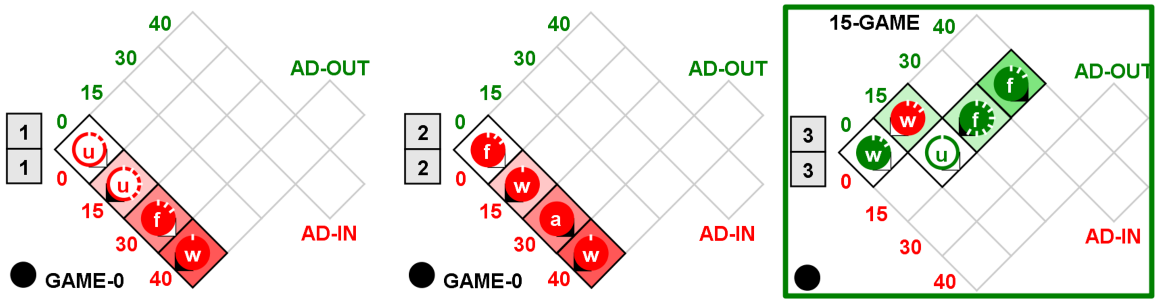


Figure 31: Fish Grids for games 3, 5, and 7 in the second set showing Gonzalez holding serve easily in games 3 and 5 but then getting broken easily by Federer in game 7.

the video viewer so that the user can edit the observation.

Example 3 In examining the second set, shown in Figure 28 (d), we see that in almost all the games, the serving player won easily. The glaring exception is the one and only service break where Federer won four of the five points on Gonzalez' serve. Using the zoom control, we take a closer look at games 3, 5, and 7 in the second set (shown in Figure 31). These show two service games won easily by Gonzalez followed by a service game in which Federer won by a large margin. To understand more closely why Gonzalez was able to win his two service games prior to the service break so easily and then lose the service break game so easily, we click on individual Point Outcome Glyphs in the Fish Grid (one at a time) to load them into the video viewer. In examining the videos of the 13 points for these three games, we saw that seven out of the nine points won by Gonzalez started with a serve to Federer's backhand and that all four points won by Federer started with a serve to his forehand.

3.3.6 Filters and Bar Charts

The filters (see Figure 32) allow users to interactively specific sets of points in support of hypothesis generation. These filters include the following:

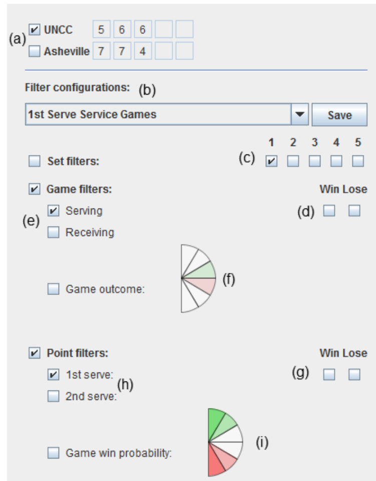


Figure 32: Filters providing multiple options to select subset of points ina a match. The following filter options are included: (a) player responsible for the outcome of a point; (b) user-created custom filter configurations; (c) toggle specific sets on and off; (games won or lost by player 1; (e) games where player 1 is serving or receiving; (f) magnitude of game outcome (i.e., easily won or lost or close games); (g) points won or lost by player 1; (h) points started by a first or second serve; and (i) points played at specific game winning probability.

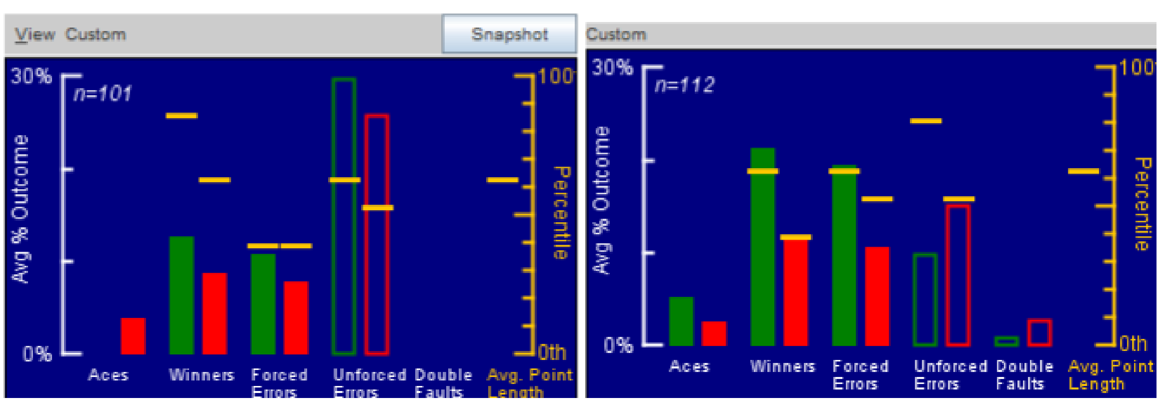


Figure 33: Bar charts comparing all points in the first set (left) to all points in sets two and three (right). The first set contains a lot of unforced errors and fewer winners and forced errors. Sets two and three have far fewer unforced errors and more winners and forced errors, particularly by Federer (the solid green bars).

- **Player shot filters (Figure 32 (a)).** Filters out points to display only those points where a specific player was responsible for the outcome, such as all good shots and bad shots by player 1.

- **Filter configurations (Figure 32 (b)).** This filter provides a list of common filter configurations coaches or players may be interested in. Users can also select any combination of the other filters and then click the Save Button to name and save that custom configuration. Doing so puts the custom configuration in the Drop-Down List Box, allowing users to switch easily between the configurations.

- **Set filters (Figure 32 (c)).** Displays only those points from selected sets. Makes it easier to see strategy and performance changes as the match evolves.

- **Game win/lose filters (Figure 32 (d)).** Filters points based on whether or not player 1 won the game or lost the game. Makes it easier to see performance and strategy differences in winning vs. losing games.

- **Serve/receive filters (Figure 32 (e)).** Filters to only show points where player 1 was serving or receiving. Serving is an advantage in tennis and being able to win while your opponent is serving is often the deciding factor in a match. This filter, when used in conjunction with the game win/lose filter, makes finding those situations easier.

- **Game outcome filter (Figure 32 (f)).** Based on Pie Meter design, this filter allows users to differentiate easily won games from close games. Each pie slice can be toggled on or off. This turns on or off those games where the Pie Meter needle angle came to rest in a specific angle range indicated by the pie slice.

- **Point win/lose filters (Figure 32 (g).** Filters points based on whether or not player 1 won the point or lost the point. Makes it easier to see performance and strategy differences. These differences can be verified by clicking on a point to see the corresponding video.

- **First or second serve filter (Figure 32 (h).** Filters points based on whether they started on a first or a second serve. Players tend to hit first serves harder and take more risk since they have a second serve if they miss. Second serves tend to be more conservative, since missing the second serve means losing the point. This filter makes it easy to see the impact of first vs. second serves on point outcomes.

- **Game win probability filter (Figure 32 (i).** Filters points based on the probability that player 1 will win or lose the game. At the start of a game, or when both players have the same number of points, the probability of either player winning the game is 50% (assuming players of equal skill). When there is a difference in the number of points each player has in a game, the odds tilt in favor of the player with more points. Using a Pie Meter as a selector, users can easily find game points where the score was close vs. game points where the score was more lopsided.

Filters can be turned on and off individually to provide basic insights or used in combination to support various investigative lines of inference. For example, coaches may want to look at all of their player's first serves. To focus on just these points, the coach would select the Serving game filter and the First Serve point filter. To facilitate efficient game analysis (particularly for novice users), a predefined set of common filter configurations is provided in the Filter Configurations Drop-Down. The set of predefined filters was added based on feedback from the coaches in our pilot studies. More advanced users can also create, name, and save their own filter configurations.

TenniVis provides a bar chart panel from which users can visually examine the aggregated statistics of outcomes of all points they selected using the filters. In the bar charts (see Figure 33 for examples), the relative percentage of each outcome type (aces, winners, unforced errors, etc.) is displayed. The same visual scheme used to encode information into the Point Outcome Glyphs is used in the design of the bars. Green bars are for points won by player one and red bars for points won by player two. Solid bars refer to good shots and hollow bars refer to bad shots. Users can see the actual number of each type of outcome by hovering the mouse pointer over a bar. A user-selectable secondary Y-axis can also be displayed on the bar charts. Users can choose to view average point lengths or first serve percentages. They can also toggle off this secondary axis completely.

The bar chart panel keeps one or more bar charts side-by-side (see Figure 27 (c)). The leftmost bar chart shows the statistics of the current selection and automatically updates whenever the filters are changed. The other bar charts are snapshots of previous filter configurations. To save a snapshot, users click a button to capture the snapshot for the current filter configuration before they modify the filters to a new configuration. They assign a name to it, which helps when recalling the meaning of the filter configuration. The snapshots enable users to compare a set of point outcomes for one filter configuration with those resulting from different filter configurations. When a new snapshot is created, the vertical scales of all existing bar charts are automatically adjusted to the same to enable comparison. Moreover, users can toggle on a horizontal ruler that spans across all snapshots to compare the bar charts more accurately.

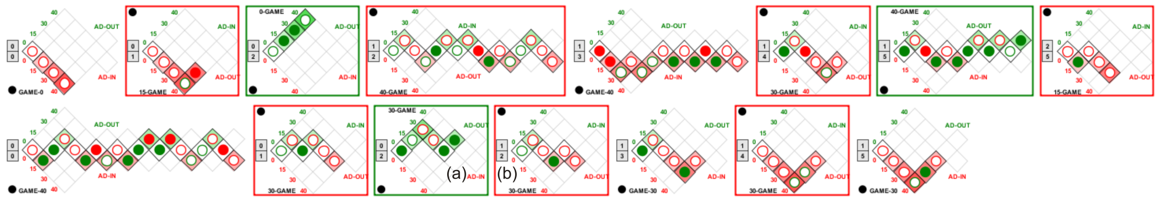


Figure 34: Fish Grids for a women's singles college match. The coach analyzing this match was particularly interested in games 3 and 4 of the second set (a,b).

Snapshots also serve for the purpose of insight management. First, clicking on the name of a snapshot brings the filters (and hence the Pie Meter and Fish Grid views) back to the status when the snapshot was captured. Second, observations related to a snapshot can be entered and saved with the snapshot. Third, the snapshot and its related observations are automatically added to the match report for sharing.

Example 4 In the Pie Meter view of the match (see Figure 29 (a)) we noticed a preponderance of bad shots in the first set versus sets two and three. We confirm this by making two bar chart snapshots: one for the first set and one for sets two and three combined (see Figure 33). Comparing these two bar chart snapshots, we see that most of the points in the first set were the result of unforced errors by the players (indicated by the hollow green and red bars). In sets two and three there were far fewer unforced errors and more good shots (winners and forced errors).

Example 5 The Pie Meters in Figure 29 (a) show that there appears to be a majority of short games in favor of Federer. This is easily verified using the Game Outcome Filter (Figure 29 (c)). By selecting the topmost and bottommost pie sectors, we can filter out the close games so we only see games won easily by one player or the other. In doing so, we see that, in Figure 29 (b), Federer won 15 games easily (including the first set tie breaker), while Gonzalez only won four games easily.

Example 6 To finish out our brief analysis of this match, we use the Game Win Probability filter in conjunction with the Game Win filter (see Figure 27 (a)) to identify any "choke" points by the players. A choke point is one where, despite a significant lead in a game by a player, the game is lost. Clicking on the lowest pie sector in the Game Win Probability filter will filter on just those points where Gonzalez was up 40-0 or 40-15. By also clicking on the Game Win filter to only show games won by player one (Federer), we are able to quickly isolate what is perhaps the most critical point in the match. This is shown in the selected point in a Fish Grid from the first set (Figure 28 (c)). This occurred in the first set where Gonzalez was serving at 40-15 with a chance to win the set. At this point in the match, he lost four points in a row, allowing Federer to break his serve. From a game psychology perspective, we see that Federer then won the next game easily on his serve while Gonzalez had to struggle through seven deuces to win his serve. This brought the match to a tie-breaker which was then won easily by Federer.

3.3.7 Insight Sharing and Report Generation

In the previous sections, we saw that users can record insights by annotating points and bar chart snapshots. Therefore, it is straightforward for a user to share his or her insights with others since the annotated video clips and bar chart snapshots are automatically added to a match report. At the present time, only a rudimentary match report is created that consists of a simple HTML page containing the text observations along with their corresponding bar chart snapshot images or links to the associated video clips. In the next iteration of TenniVis, I plan to expand and enhance the report generation capabilities by eliciting feedback from tennis coaches and players concerning what information to include and how to include it effectively.

3.4 Pilot User Studies

To test the effectiveness and usability of the visualizations presented in TenniVis, I conducted two pilot user studies: one with the women's tennis coach and one with the men's tennis coach at a local university. Since TenniVis was designed specifically to be used as an interactive tool for tennis coaches and players, it was important to demonstrate that it could be quickly learned by domain experts who don't necessarily have any expertise in visualizations. The goals of these studies were as follows: (1) assess the understandability of visualization graphics (i.e., Pie Meters, Fish Grids, and Bar Charts); (2) assess the perceived efficiency and effectiveness of TenniVis match analysis; and (3) elicit opinions on what type of information and features are needed in the match report (the report generation functions were not in the system during the studies).

3.4.1 Procedure

Using a two-monitor display (24 inch external monitor and a 15 inch laptop monitor), the TenniVis system was setup at the participant's work location in a meeting room. The main TenniVis application was displayed on the external monitor while the laptop monitor was used to display the pop-up video player window. Each pilot study was conducted in three parts: system demonstration, hands-on match analysis, and follow-up questionnaire. After a brief introduction in which the purpose and overview of the study were presented to the participant, the instructor spent 15 minutes demonstrating the various components of TenniVis using the Federer-Gonzalez match. Each of the visualizations and all of the controls were briefly explained to the participant and any questions were answered. The participant was then allowed 10 minutes to explore the system on their own using the same data set.

In the second part of the study, the instructor opened up one of two data sets. For the women's team coach, the data set consisted of a two set singles tennis match of the best singles player on her team recorded a few days earlier (shown in Figure 34). For the men's coach, the data set was a two-set tennis match for the best singles player on his team, also recorded a few days earlier. In both cases, the coaches were present at their respective players' live matches, although they were also watching five other matches simultaneously. The participant was asked to use the TenniVis system to evaluate their player's match and to "think out loud" as they performed this task. Participants then interacted directly with TenniVis as the instructor took notes about which visualizations and components the participants were using and the comments they were making. Since the primary goal of the pilot study was to assess the understandability and usefulness of the visualizations, (and not to assess TenniVis as a finished product) the instructor provided assistance as needed.

After approximately 30 minutes of self-directed interaction with TenniVis, the instructor presented the participant with a brief questionnaire. In this questionnaire, the participant assessed the usefulness and understandability of the overall TenniVis system, the Pie Meters, the Fish Grids, the Point Outcome Glyphs, the Bar Charts, and the video player. Assessments were indicated using Likert scale ratings where users were asked the degree to which they agreed or disagreed with various statements about the TenniVis system. They also had the opportunity to indicate what they liked most about the system, least about the system, and for additional features that would make it more useful. The results of each of these pilot studies are presented next.

3.4.2 Pilot Study 1 - Women's Tennis Coach

When analyzing the women's tennis match, the coach only spent a few minutes on the Pie Meter view (which is the default view when the application is started). She noticed the very high number of service breaks as indicated by the red and green boxes. She then switched to the Fish Grid view (see Figure 34). After scanning through all of the points in order in the Fish Grids, she stopped to more closely examine games three and four in the second set (Figure 34(a) and (b)).

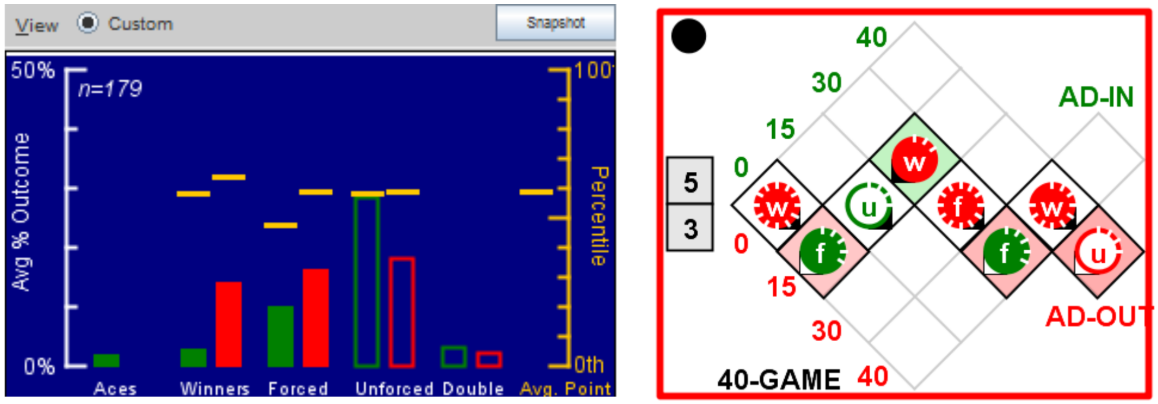
When zoomed into the second semantic zoom level, she was able to see the outcomes of each point in these games (represented by lower-case letters). In game three, she noticed from the Fish Grid how her player (player one) broke her opponent's serve with three solid shots (i.e., two forced errors and one winner) plus an unforced error made by her opponent. She then noted, however, that her player committed two double faults and two unforced errors in her next service game (game four).

Based on prior experience with her player, the participant suspected that her player may have committed the two unforced errors by trying to hit too many down-the-line shots (a potentially risky shot) versus going cross-court. She commented that "I've really been trying to work on her [the player] hitting the ball cross-court more because she goes down the line and then she either misses it or then they make her run cross-court…so I was immediately thinking 'How did she lose this point?"'. She loaded several points one-by-one into the video player and was able to find several examples that confirmed her hypothesis. She then decided to focus on serving and, using the zoom slider, further zoomed into game four to see more details such as first serves vs. second serves. From Figure 34(b), she noticed that five of the six points were from second serves (including two double-faults).

The results of the post-analysis questionnaire indicated that this participant did not fully understand the Pie Meters or the bar charts but found the Fish Grid and video player components very easy to use and understand. The participant commented that she liked the Fish Grid view since it was well organized. I attribute this to the fact that the Fish Grids display all points in the order they occurred and at the game score where they occurred. She indicated that having the supporting evidence provided by the video was useful because, “whenever I ask the girls, ‘How do you learn best? ’, they always say ‘By seeing it; by seeing what you are talking about”’. She said she liked the fact that TenniVis allowed her to directly access video clips for points of interest.

The participant described herself as somewhat averse to technology and indicated that as the primary reason she did not bother to use any of the filters or pay attention to the bar charts. She also had some initial confusion over interpreting the color coding used for the outcome balls, but indicated that having a key would probably solve this problem. Despite some of her issues with specific components of the system, she rated the system overall as easy to understand and use and strongly agreed that it provided her with useful insights that are not currently available to her.

The participant indicated that there is the need to generate simple, compelling reports that communicate her insights in a tangible way her players can readily grasp. She envisioned some type of electronic report that would include her observations along with the supporting video evidence.



(a) (b)

Figure 35: (a) Histogram of a men's singles college match. The coach noticed that, even though his player (player one) made fewer unforced errors (hollow red bar) than the opponent (hollow green bar), these were not enough to make up for the large number of winners and forced errors made by the opponent (red solid bars) versus his player (green solid bars). (b) Eighth game in the second set showing a critical point at 30-0 where the player setup his opponent for a winner.

3.4.3 Pilot Study 2 - Men's Tennis Coach

The men's tennis coach described himself as a data and statistics junkie with a firm belief in the power of statistics and analysis to be used as a tool to complement his training program. He was able to quickly grasp the meaning of the color coding used in the Pie Meters and for the Point Outcome Glyphs, commenting "the color coding is nice. . . the red and green is good because that's intuitive". In looking at the Pie Meters from the Federer-Gonzalez match, he commented "it looks like right off the bat he [Federer] was dictating play. . . because he has a lot of solid green points which means he's winning a lot of points" (as opposed to getting points due to bad shots from Gonzalez). Attention was then turned to the Fish Grid view where the participant commented that "you see kind of trends, up and down. . . and you see what the momentum looks like".

Once the data set for his own player was brought up, he immediately looked at the histogram (see Figure 35 (a)) coupled with the Pie Meter view to get an overall sense of the difference between the two players in terms of point outcomes. He commented that "overall, their guy hit certainly more winners. . . he also had more forced errors and our guy had less unforced errors. . . our guy doubled less and had a few more aces. . . but that looks a little negligible in terms of risk/reward". He then began using various filter combinations to create individual histogram snapshots for comparison, noticing that his player had a lot of points that started from his second serve.

Continuing his analysis after switching to the Fish Grid view, he noticed a key game in set two when his player was serving at five games to three (see Figure 35 (b)). He focused in on the point when his player was up 30-15 (only two points away from winning the set) and his opponent hit a winner (see Figure 35 (b)). The opponent then was able to regain the upper hand in the match and ultimately win it. He analyzed why his player lost this point by selecting it to view in the video player. He noticed that, although his player served his opponent with a tough serve out wide, he failed to capitalize on this advantage and gave his opponent an easy putaway shot at the net. This insight led the coach to indicate he would discuss shot selection with his player to avoid giving away the momentum in a match.

The results of the post-analysis questionnaire indicated the participant found the system to be very useful and easy to understand. He agreed strongly that it gave him useful match insights he is not currently able to get. He commented that, with the system, he can look at trends and get a visual sense of what was going on. The Pie Meter, Fish Grid, and video player components got very high marks for usefulness. The participant indicated that, while he liked the ability to animate the Pie Meter needles to "see what was going on", he preferred the Fish Grid over the Pie Meter because it was like a timeline that presented the ups and downs.

Both the Point Outcome Glyphs and the histograms got neutral usefulness ratings. The participant explained that the reason for the lower usefulness score for the Point Outcome Glyphs was that he really would like to see if the outcome was from a backhand or forehand. This issue can be addressed by collecting the backhand/forehand information in data collection and encoding it in the Point Outcome Glyphs.

He gave several useful suggestions on improving the usability of the histograms. First, he suggested allowing users to manually select games to be displayed in a histogram, rather than just relying on the filters. Second, he suggested a set of pre-defined filter configurations representing some of the standard statistics, such as service games, first serves, etc. Third, he recommended displaying actual numbers of outcomes instead of just percentages. These features were not in the system during the pilot user studies, but were added later based on this feedback. He indicated that giving his players actual numbers instead of just percentages would resonate more with them. Overall, the participant commented that he liked the fact that there are multiple ways to visualize the data in TenniVis.

The participant also confirmed the need for generating reports to communicate his insights to his players. He envisioned being able to use this system and then generate a report he could tape to a player's locker that provided specific insights that player needed to focus on.

3.5 Conclusion

In this chapter, I presented TenniVis, a novel tennis visualization system. It demonstrated how visualizations useful for tennis coaches and players can be generated using only the easily collected non-spatial game data and a video from a consumer level camera. Two new visual metaphors, namely the Pie Meter and the Fish Grid, were proposed and implemented in TenniVis. They convey summary and detailed information about a match in an organized way that is understandable by users with tennis domain expertise. The multi-resolution visualization pipeline, dynamic query capabilities, and ad hoc hypothesis development and testing capabilities provided by TenniVis make it an effective tool for tennis match analysis.

Through two pilot user studies, I verified that tennis coaches were quickly able to gain insights into their players' tennis matches through TenniVis and found the visualizations easy to use and understand. With only a minimal amount of training, coaches were able to interact with TenniVis to confirm suspicions they already had about a tennis match and to find new insights. They were excited about the prospect of having a tool to help them share their observations with their players. One of the coaches actually contacted us after the study to request a copy of the Fish Grid view for her player.

I acknowledge the insightful benefits provided by systems relying on tracking data and see our efforts as complementary to them. In the following chapters, I extend TenniVis for professional players by integrating the visual analytics of tracking data.

CHAPTER 4: SPATIAL DATA PREPROCESSING - TRANSFORMING RAW DATA INTO SEMANTICALLY MEANINGFUL INFORMATION

In this chapter, I outline some of the key challenges in working with spatial data in a sports analytics context and I lay out how I address those challenges to create the semantically rich information that underpins the analytic application described in the next chapter. These challenges include the following:

- **Excessive amounts of tracking data.** Ball and player tracking systems that utilize an array of cameras to provide 3-D tracking information for both players and the ball will result in a very large amount of location data in a relatively short period of time. Even at a relatively low rate of 30 frames-per-second, capturing the location of each player and the ball would generate approximately 648,000 individual data points (7,200 seconds * 30 observations per second * 3 observations = 648,000) for a two-hour tennis match.

- **Choosing the right coordinate system.** The raw spatial data coming from a tracking system will typically be in whatever arbitrary coordinate system is employed by the tracking system. This data needs to be normalized to a standard coordinate system so that data from multiple tennis matches can be compared.

- **Players changing court sides.** In tennis, like many other sports, players will alternate sides of the court they play from. We therefore need a process for standardizing the data so that similar shots can be tagged as such, regardless of which side of the court the player is playing from.

- **Sparse spatial data.** Depending on the spatial resolution of the tracking system, the landing positions of the ball as it bounces on the court will likely result in a relatively sparse matrix. For example, if a tracking system covers a 100 X 50 foot area and our tracking accuracy is one square foot, there will be 5,000 invidual bins in which a ball can land. In a tennis match with 200 points, if we assume that each point lasts an average of five shots, this would only be 1,000 data points. The situation gets far worse when you attempt to classify shots based on two locations (i.e., where the ball is hit from and where it bounces). In this situation, since the starting location will typically be on one half of the court and the ending location will be on the other half, this results in a total of 6,250,000 possible shot combinations (2,500 X 2,500 = 6,250,000).

- **Integrating meaning into raw data.** Raw spatial location data for the ball and players alone may be adequate if all you want to do is provide a virtual replay of all or part of a tennis match. However, to make this data useful for analysis, it needs to be infused with semantically meaningful context information.

In the remainder of this chapter, I will address steps taken to address these challenges.

4.1 Excessive Amounts of Tracking Data

Three-dimensional ball and player tracking systems are commonplace at major tennis tournaments and are used primarily for verifying line calls challenged by the players, as well as for providing virtual replays of points for tennis fans. These systems employ an array of cameras where each camera locates the ball and players within its field of view. By combining the ball and player locations from multiple viewpoints, calculating a reasonably accurate three-dimensional location of the ball and players is fairly straightforward. However, this also results in a large amount of tracking data, even if a relatively low-resolution 30 frames-per-second video feed is used. Therefore, an approach is needed that will dramatically reduce the amount of data actually stored.

The key to addressing this data overload issue is by focusing on what we want to do with the data and throwing away all but the actual data necessary to support the types of visualizations we want to develop. The key pieces of information we need to support our visualizations are the location of the ball and the two tennis players when the ball is being hit and when the ball lands. This presumes that we don't care too much about the specific three-dimensional trajectory of the ball or of the exact pathways players take when transitioning from one shot to the next. Although this additional information certainly has value, there is still a great deal that can be gleaned from just this minimal amount of data. Specifically, from just the key location data of the ball and player locations when the ball is being hit or bounces, we are able to characterize every shot in a tennis match. The timestamps associated with the location data can also be exploited to get a rough estimate of shot speed (not covered in this dissertation). As will be discussed in Section 4.5, this location data can also be used to automatically tag shots as backhands or forehands.

By utilizing only the spatio-temporal data for the ball and players at the key moments of the ball being hit or bouncing on the court, I am able to characterize each shot with only three pieces of data. In a 200 point match with an average of five shots per point, we need only 3000 individual spatio-temporal data points, not the 648,000 resulting from a three-dimensional tracking system. This represents a 99.5% reduction in the data footprint. Of course, this approach assumes we are able to accurately detect ball bounce and ball hit events. This is typically done by looking for sharp changes in direction of the ball trajectory. This line of research is beyond the scope of this dissertation.

For purposes of this research, I needed a data set from at least one tennis match and, since I did not have access to any tracking systems or data sets generated by such systems, I collected the tracking information manually. This involved stepping through a video of a professional men's tennis match (the Men's Final of the 2007 Australian Open between Roger Federer and Fernando Gonzales), frame-by-frame and then, whenever the ball bounced or was being hit by one of the players, recording the approximate two-dimensional location of the ball and the players on the tennis court surface. To aid in this process, I developed a data collection tool that displayed the video in one window and a tennis court schematic in another window. Location information was recorded by clicking on the tennis court schematic. Timestamp information was extracted from the video. This same data collection tool was also used to enter point outcome information, including which player won the point and whether the point ended as a result of a winner, unforced error, ace, or double-fault. Score information was derived by keeping track of the point outcomes in concert with understanding the scoring progression in a tennis match.

4.2 Choosing the Right Coordinate System

The spatial data collected for this research was done by clicking on a schematic of a tennis court, resulting in an x-y coordinate pair expressed as pixels based on the (0,0)

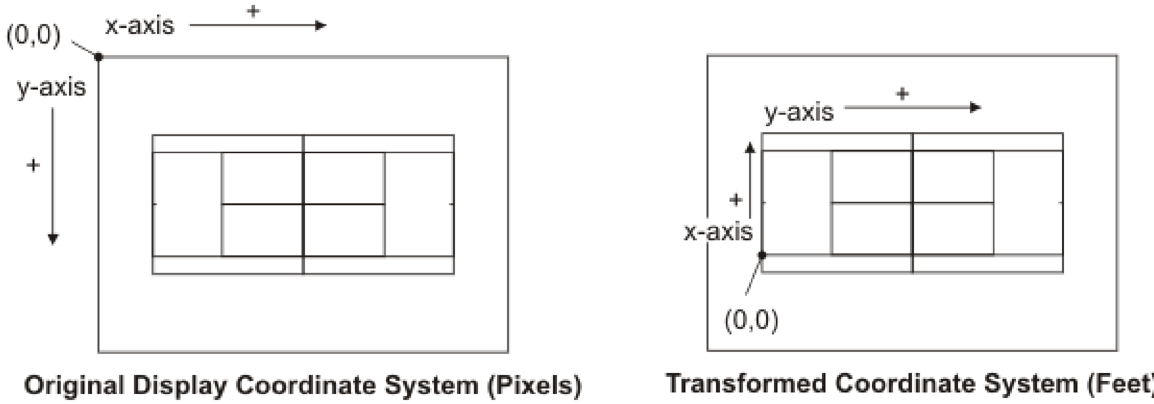


Figure 36: Original pixel-based coordinate system on the left is transformed into the feet-based system shown on the right. The origin is moved to the intersection of the baseline and the singles sideline on the deuce side of the court.

reference point located at the upper left of the schematic, as shown on the left side of Figure 36. This coordinate system was then transformed to locate the new origin at the intersection between the baseline and the singles sideline on the deuce side of the court. In addition, the x and y axes were flipped. The flipping of the axes happened early in the research project when the orientation of the tennis court was going to be portrait instead of landscape. However, for aesthetics and screen real-estate usage purposes, the orientation was changed. This occurred after the data had already been processed. The pixel-based coordinate system was replaced with a feet-based system in order to increase the readability of location data when performing debugging. Furthermore, pixel measurements will differ based on the resolution of the display on which the data is collected. Therefore, since distance expressed in feet is an absolute (as opposed to relative) measurement, it will ensure compatibility across data collection platforms.

4.3 Players Changing Court Sides

In a tennis match, players will change sides of the court after the first game and then subsequently after every two games. This is done to neutralize any advantages one player

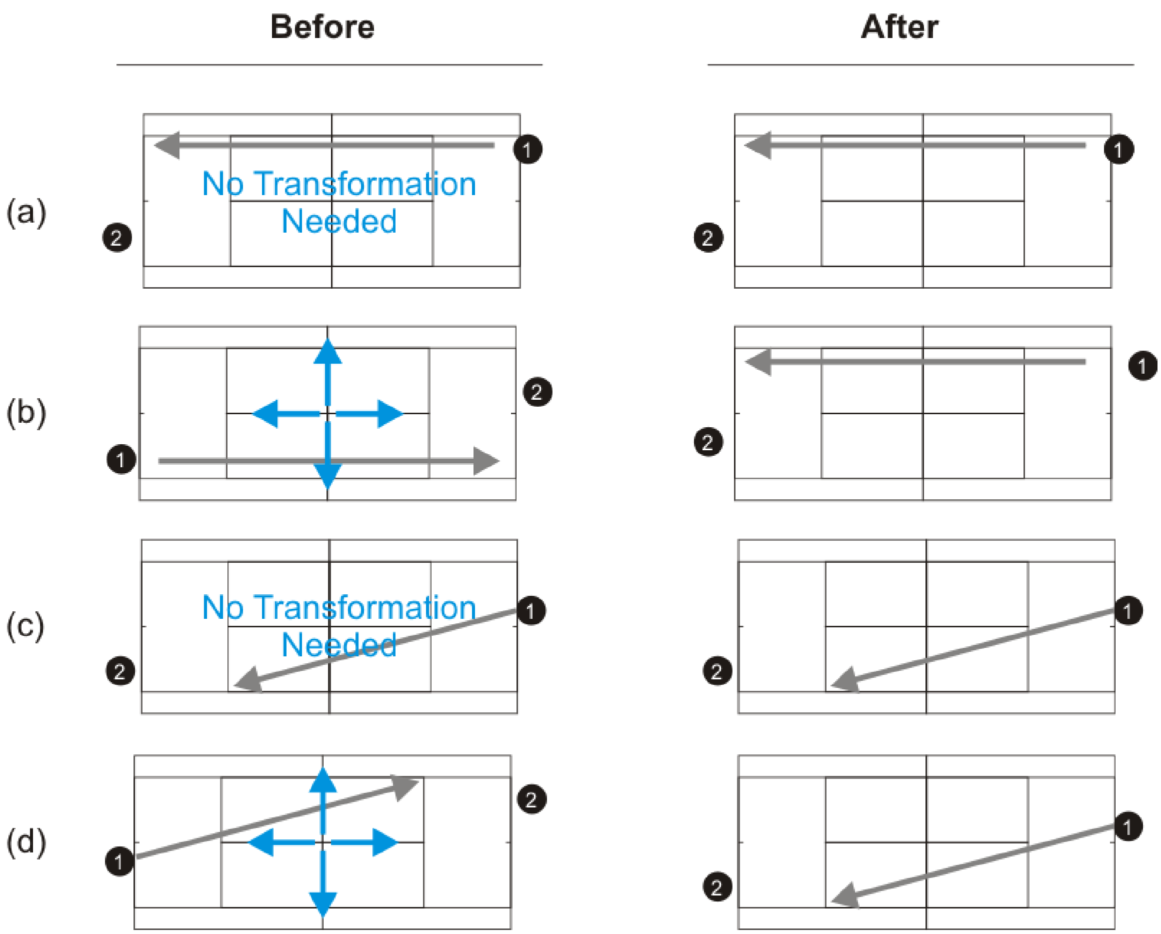


Figure 37: Demonstration of the problem associated with players changing sides of the tennis court they play from. Both (a) and (b) represent instances of the same shot (a deuce-side down the line forehand), yet player locations and shot trajectory are different. Similarly, (c) and (d) represent instances of a wide deuce court serve, yet also involve different player locations and ball trajectories. To solve this problem, shots when player one is on the left are transformed so that player one is always on the right.

may have over another due to environmental conditions, such as the location of the sun and wind conditions, as well as to neutralize any small differences there might be in the court surface itself. This poses challenges in data collection if we want to be able to aggregate data into semantically meaningful concepts such as shots. Figure 37 demonstrates the problem of cataloging similar shots when players play from both sides of the court. To address this issue, I have employed data mirroring techniques that will transform shots when player one is on playing from the left side of the court so that he is now alsway playing from the right side. This involves mirroring the both the x and y coordinates about the exact center of the court, as shown in Figure 37. This makes it easier to catalog two shots as being similar, even when they were actually made from different sides of the court.

4.4 Sparse Spatial Data

While high-resolution spatial data is useful for accurately representing and recreating shots, such as in creating a virtual replay of a tennis point), it can also result in a fairly sparse data set, since we have many more bins in which to locate ball and player locations. This sparsity makes it difficult when attempting to tag specific shots or ball landing locations as similar. One approach to handling this situation is to use clustering techniques to group close-by points into the same group. This has been employed by some researchers in an attempt to classify shots [112]. There are, however, several potential issues with this approach. First, many clustering algorithms, such as k-means clustering, require the *a priori* specification of the number of clusters. There may not be an obvious choice. Second, even with clustering algorithms such as DBSCAN that don't require *a priori* specification of the number of clusters, the clusters will certainly change from one dataset to the next.

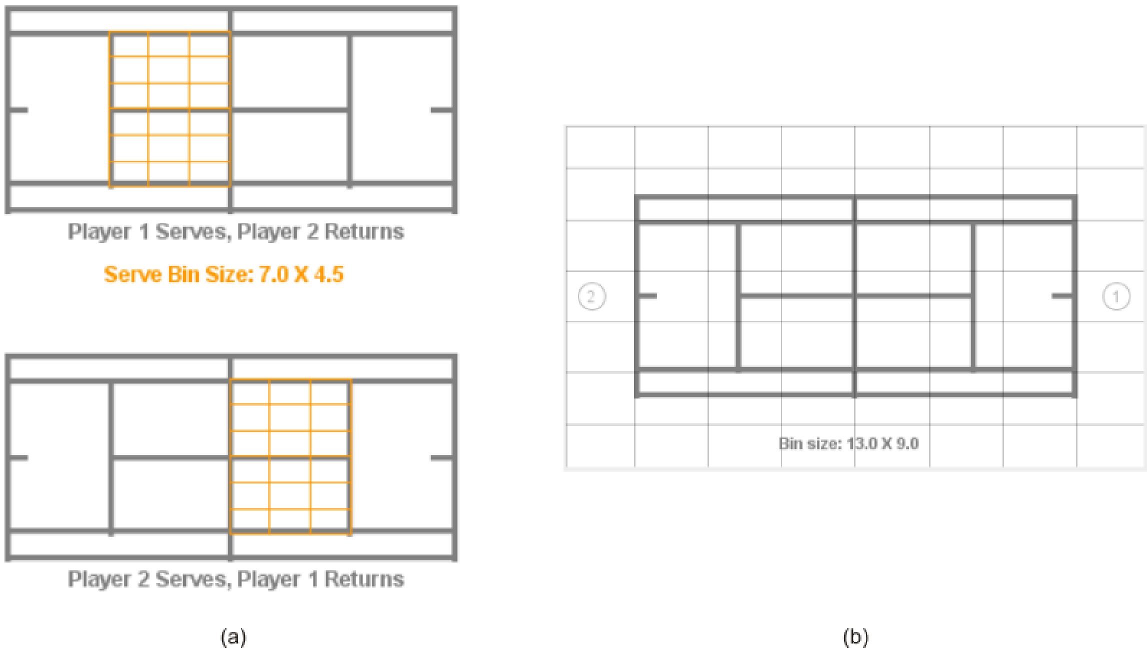


Figure 38: Smart bins used to define serve bins (a) and shot bins (b). The size of the grid boxes can be set via a set of x-axis and y-axis sliders. The sizes are selected such that the boxes will never cross the singles court boundary. They also do not cross over the net boundary.

Furthermore, these clusters may not conform to areas of the tennis court that are meaningful to a coach or analyst. For example, a clustering algorithms might group together locations that are out-of-bounds with locations that are in-bounds.

To address this issue, I have developed the concept of "smart bins". These are bins whose sizes are chosen in such a way as to divide up a tennis court into rectangular areas that take into account court dimensions and fit perfectly within these dimensions. An example of this concept, both for serve bins and shot bins is shown in Figure 38. As the figure shows, the bins are sized so they never cross the singles court boundary or the net boundary and the divide the court up symmetrically. For serve bins, there are six discrete x-axis interval sizes (in feet): 1.5, 2.7, 3.375, 4.5, 6.75, and 13.5. These divide a single serve box into 9, 5, 4, 3, 2, and 1 bins, respectively. The y-axis values for the serve bin sizes are 1.5, 3.0,

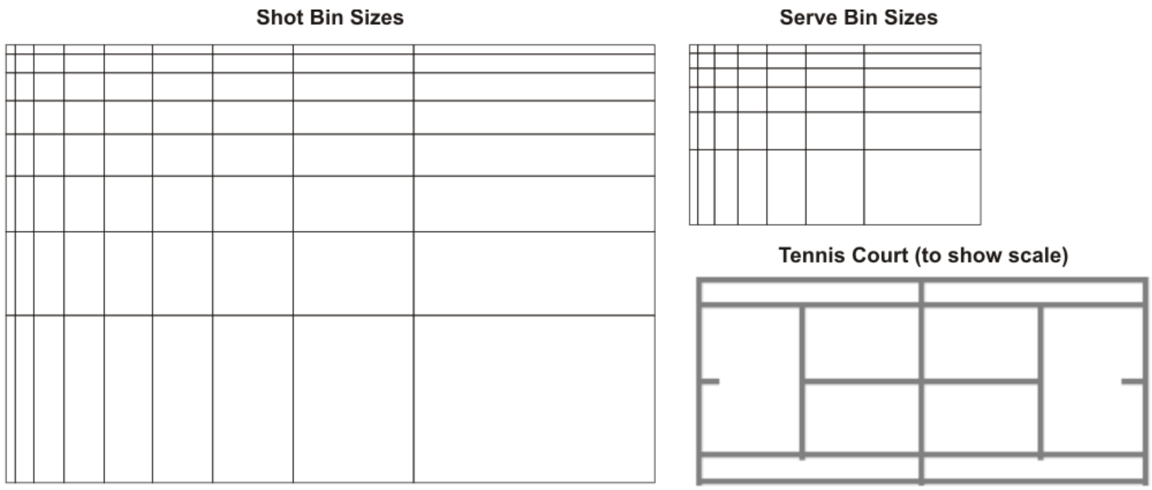


Figure 39: All combinations of shot bin sizes (left) and serve bin sizes (right), allowing coaches and analysts to divide up the court and service box into sections that support *ad hoc* analyses. A tennis court is shown to indicate scale.

4.2, 5.25, 7.0, 10.5, and 21, which divide the serve box up into 14, 7, 5,4,3,2,and 1 bins, respectively. Figure 39 displays all possible combinations of serve bin sizes and shot bin sizes. These support *ad hoc* analyses by coaches and analysts who can divide the court or service box up into grid sectors that support various lines of inquiry. For example, a coach may want to focus primarily on the left-right component of shots and therefore chooses a shot bin that is very long, but not very wide

The effect of these serve bin and shot bin sizes can be seen in Figure 40. Choosing fine-grained serve bins and shot bins shows individual serve landing locations and individual shot trajectories. Changing to coarse-grained bins serves to aggregate the data, emphasizing major patterns.

4.5 Integrating Meaning into Raw Data

As can be seen from the previous section, working with spatial data at multiple levels of resolution can result in a numerous ways of slicing up the data. This can be overwhelming

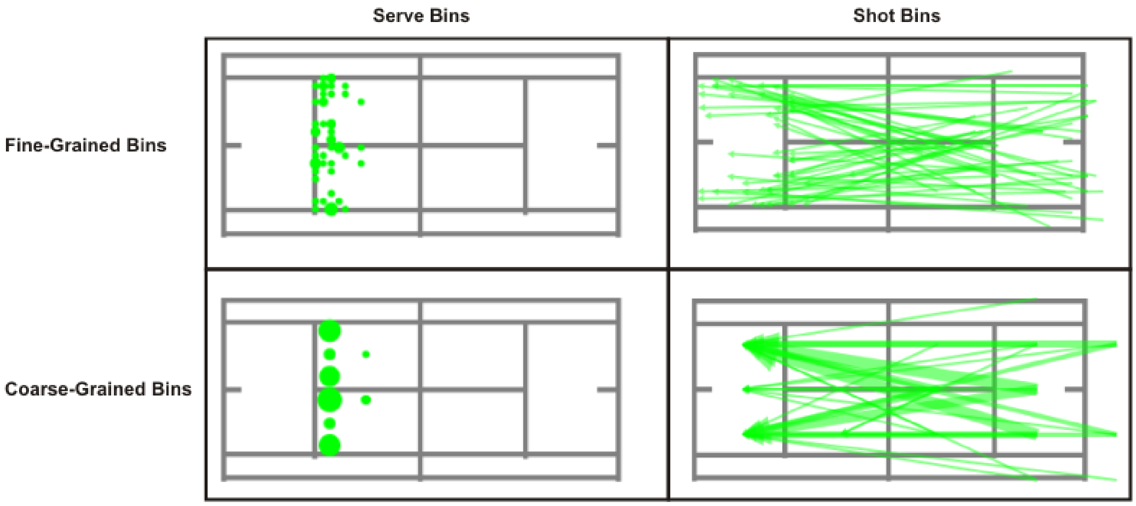


Figure 40: Demonstration of differences between fine-grained and coarse-grained bin sizes on serves and shots. Fine-grained bins show individual serve landing locations and shot trajectories. Coarse-grained bins aggregate the data to emphasize major patterns.

to users as they try to make sense of the data. The challenge, then, is to infuse the raw data with meaningful information that can assist users in finding pockets of insight. This is done in two primary ways: significance calculation and attribute tagging.

Significance calculation, done at the point level, calculates the percentage of points won by player one for every subset of points that has been predefined for the user as well as for *ad hoc* groupings selected by the user. This player one point winning percentage is then compared to the overall average of points won by player one. If the average for a specific group is significantly greater than or significantly less than the overall average, then this group of points is identified as significant. Significant, in this case, means that the specific outcome for the sample of points represented by a group of points, would have a less than 5% likelihood of occurring by chance. This is described in more detail in Section 5.11.

Several visualizations, described in the next chapter, utilize this significance calculation in how they represent specific sets of data. For example, circles in the Examination Activity Panels, described in Section 5.11.1, are color coded to indicate the level of significance for a specific set of points relative to the overall average. This significance is also utilized in the Significant Serve Filtering, described in Section 5.11.3, to only display serves that have been determined to be significant in terms of being associated with either a higher than expected or lower than expected point winning percentage for player one.

Attribute tagging is another way that meaning is infused into raw data to aid coaches and analysts in finding pockets of points that may provide insights into players' strengths and weaknesses. As each point is read from the database, it is "tagged" with certain attributes that are then used to support the interactive visualizations described in the next chapter. Some of these attributes include the following:

- **Point outcome.** Each point is tagged with how the point ended (i.e., ace, double-fault, winner, or unforced error) and which player is responsible for this outcome. This allows users to view specific sets of points based on outcome. It also allows this context information to be displayed for each point as it gets examined in the Video Player.

- **Match score.** Each point is tagged with the current score in the match when that point occurred. This is utilized, for example, by the Match Visualization Semantic Point Selector, described in Section 5.4.1, to layout points in a way that makes it easy for a user to see how individual games progressed.

- **Serving player and first vs. second serve.** Each point includes information about who is serving and whether or not the point started from a first or a second serve. This information is used in many of the Examination Activity Panels, described in Section 5.11.1, as a way to define pockets of points where a specific player was serving.

- **Point length.** The number of shots in each point is also encoded. One primary utilization of this information is seen in the Point Length Bar Chart, described in Section 5.5, that displays the number of points that lasted a specific number of shots. This allows users to distinguish between short points (indicating a strong influence of the serve) vs. long points (indicating a strategy of patiently looking for an opening to make a point ending shot).

Individual shots are also tagged with semantically meaningful information that are exploted by one or more visualizations:

- **Forehand vs. backhand.** Most tennis players have a more dominant stroke side, typically the forehand side. Each shot, excluding serves, is tagged as being a forehand or backhand shot and is derived by exploiting the location of the hitting player in relation to the ball, combined with knowledge of the player's handedness (i.e., left-handed or right-handed). This is utilized in some of the Examination Activity Panels (see Section 5.11.1 and is also displayed on the Video Point Selection Panels, described in Section 5.10.1, allowing users to quickly find points with a larger number of backhands vs, forehands, for example.

- **Volleys vs. ground strokes.** A volley is when a player hits a ball without letting it bounce. It is often associated with more aggressive play as a player is attempting to quickly end the point. Therefore, each non-serve shot is tagged as being either a ground stroke (i.e., the ball bounced before the shot) or a volley (the ball did not bounce).

Additional, more complex,semantically meaningful tags are also assigned to points as they are read from the database. These tags are based derived from multiple pieces of data about the shots in a point. For example, a point is tagged as a “serve and attack” point if the serving player progresses into the tennis court past a threshold distance after serving the ball. This is an indication they are attempting to serve-and-volley, an aggressive shot that attempts to surprise an opponent and that exploits an opponent’s weak return of serve. These tags can form the basis of an Examination Activity Panel that is designed to focus on a specific aspect of a tennis game. This approach is flexible enough to allow for future, semantically meaningful situations to be explored. For example, a coach or analysts may want to identify points where their player is playing points from inside the baseline vs. from behind the baseline.

4.6 Conclusion

In this chapter I identified several of the challenges associated with working with spatial data in a sports analytics context. I outlined how I addressed these challenges as part of the data pre-processing stage of the visual analytics pipeline. Multiple spatial resolution levels were defined in a way that acknowledged the domain-specific spatial constraints associated with the rules of tennis. I then described how points and shots were tagged with semantically meaningful attributes, thereby infusing the raw data with information that can be exploited by interactive visualizations to support the exploration process. These interactive visualizations will be described in detail in the next chapter.

CHAPTER 5: SPATIAL TENNIVIS: COMPONENTS FOR ANALYZING TENNIS MATCHES USING SPATIO-TEMPORAL DATA

In the previous chapter, I discussed the spatio-temporal data underpinning the analysis tools being developed, including the challenges in gathering this data and in re-characterizing it to facilitate analysis. In this chapter, I introduce the components of the tennis analytics system developed to assist tennis coaches and players in analyzing this data. To do this, I first establish a set of design principles that guide the development of an interactive visual analytics tool that integrates ball and player tracking data with domain-specific semantic information. This tool will not only be able to summarize *what* happened, but *why* it happened. I then describe each component in detail, focusing on the specific features that are tied to these underlying design principles.

5.1 Introduction

Analyzing tennis matches using spatial data is not new. Pingali et al. [88] demonstrated how player and ball tracking data can be used to enhance tennis broadcasts. Wang et al. [112] used tracking to identify and classify shot patterns. Conaire et al. [34] created a nine-camera tracking system that allowed coaches and players to view either virtual replay of points or replay of video from various camera angles. However, the common thread running through all of these approaches is that they tend to either emphasize the spatial data or the semantic data. In some cases (e.g., Pingali et al. [87, 89]), semantic-based query capabilities are provided and spatial data is used only to provide a virtual replay.

In other cases (e.g., Wang and Parameswaran [112], Conaire et al. [34]), spatial query capabilities are provided in the absence of semantic information, such as match score, and data is simply a collection of shots. While the former approach is a useful tool for seeing what happened at specific points in a match and the latter approach is good for examining players' shot execution skills and mechanics, what is needed is a tighter integration of semantic and spatio-temporal data in order to gain the synergistic insights this coupling can provide.

This tighter integration is achieved with the design of Spatial TenniVis, a visual analytics system that includes tools, such as the Match Visualization Semantic Point Selector, that help them see the "big picture" by providing an overview of the entire match, as well as tools, such as the Examination Activity Panels, that allow them to zoom into specific aspects of a tennis match. Part of the investigative analysis process also involves recording findings so they can be revisited later or communicated to players as part of a debriefing process. To support this activity, Video Findings Panels allowing users to annotate videos with comments will be described. Finally, as a way to help users cut through the complexity of the myriad tools provided, techniques for infusing various visualizations with significance color coding or filtering will be described. This demonstrates the symbiotic relationship between human and computer, where the computer provides quick calculations of significance and the human analyst integrates this information into their intuitive processes to more efficiently guide the investigation.

5.2 Design Principles and Related Features

Semantic data, such as who is serving, the game score, whether a point started on a first or second serve from the deuce or ad court, and how the point ended (i.e., ace, double-fault, winner, or unforced error) provides us with knowledge of *what* happened and serve as signposts leading the way to deeper investigation. Spatio-temporal data, including ball and player court location, helps us begin to answer the question of *why* the point ended the way it did. Are there certain strong shots by a player that lead to winning more points? Are there certain locations on the court a player makes more errors from? Are there certain types of serves that make it easier for a player to win a point? If, so, how do these serves evolve into winning shot patterns? To begin answering these questions, we need a visual analytics system that not only follows all of the well-established tenets of effective visualization design (e.g., overview first, detail-on-demand, linking and brushing, etc.), but also presents data in such a way as to facilitate understanding why points in tennis end the way they do. To this end, I have developed the following high-level principles to drive the design of this tennis visual analytics system:

- **Design Principle DP1: Organize around point outcomes.** Players win matches by winning sets, win sets by winning games, and win games by winning points. Points serve as the basic scoring units in tennis and result from players making a "good" shots (i.e., ace, winner, or forced error) or "bad" shots (i.e., double-fault or unforced error). Data should be organized by point outcome and visualizations should assist in seeing how players arrived at those outcomes.

- **Design Principle DP2: Visualize shots and shot combinations.** Points are won by making good shots or by making your opponent hit bad shots. Individual shots may end a point (e.g., ace, double-fault), but players also hit setup shots to get themselves into a winning position. Poor shot selection by one player may setup a winning shot by the opponent.

- **Design Principle DP3: Focus on serves, returns, and the last few shots in a point.** All points in tennis start from the serve. Points can be immediately won or lost on a serve (i.e., ace or double-fault) or may setup a winning situation. Second serves are typically less effective than first serves. Return of serve is also considered critical as a weak return may set up the opponent for an easy winner. Points may end quickly or may consist of many shots. In both cases, the last few shots by each player are the most critical, since these tend to setup the final shot.

- **Design Principle DP4: Support multiple levels of spatial resolution.** Specific shots may be considered in isolation or may be grouped more generally with other, similar shots. This supports analyzing shots based on tennis semantic concepts, such as down-the-line, cross-court, short shot, deep shot, etc.

- **Design Principle DP5: Facilitate easy visual comparison of different data slices.** Insights derive from setting up and testing hypotheses. Hypotheses are manifested as a selected slices of data that differ on one or more semantically meaningful dimensions. Visualization tools need to support easy comparison of these slices.

- **Design Principle DP6: Help users find what is meaningful.** Not all point outcomes are significant. Many are expected and can be ignored. Other, less obvious outcomes may be the desired "needles in the haystack" that lead to new insights. An effective visualization system will assist users in this investigative process. Even in a losing tennis match there are likely to be pockets of quality play that can help a player identify his or her strengths and build upon them.

- **Design Principle DP7: Provide quick access to the raw data.** The raw video footage will contain many more details than can be captured in any visualization. These include aspects such as player technique, footwork, and even emotion. Users may see something of interest in one or more visualizations and want to see the associated raw footage to learn more or confirm their hypotheses.

- **Design Principle DP8: Organize and save the results of analysis.** Users explore the data using various tools, develop hypotheses, and test those hypotheses to generate insights. Once they have done this, they need to be able to organize and save their results in the form of findings.

The proposed system, named **Spatial TenniVis**, will provide the following features to address the above design principles:

- **Point outcome-based data set selection.** Users will be able to select from four predefined data sets for visualization and analysis: good shots by player 1 (i.e., winners and forced errors), good shots by player 2, bad shots by player 1 (i.e., unforced errors), and bad shots by player 2. These can be displayed in user-selectable colors to facilitate comparison. **(Supports DP1 and DP5)**.

- **Point outcome visualization that also serves as data selector.** Borrowing point visualization concepts from *TenniVis* (discussed in the previous chapter), all point outcomes will be presented in such a way as to make it easy to see which sets, games, and points were won by each player and how each game unfolded. This visualization will not only present the outcomes, but will also serve as the basis for selecting subsets of points based on various criteria, such as who was serving, which set points come from, who won the game, etc. **(Supports DP1 and DP5)**.

- **Data fading and toggling.** Users can display up to all four data sets simultaneously. To help de-clutter the display and temporarily emphasize one or more data sets, users can use data faders (like the slider controls on mixing boards) to control the level of transparency of each data set independently. They can also choose two data sets and use a toggle fader that will transition between displaying each data set. By repeatedly toggle-fading between the data sets, areas of similarity and difference are readily discerned. **(Supports DP1 and DP5)**.

- **Differentiate points by point length.** Points can either end very quickly, in the case of double-faults or service winners, or they may last a long time, with both players hitting relatively safe shots in an attempt to look for a strategic opening to make a more aggressive shot. In addition, shorter points may indicate an effective or ineffective serve and/or return of serve game. The Point Length Bar Chart is also color-coded to indicate specific point length intervals that have a higher than expected or lower than expected win percentage for player one. **(Supports DP3 and DP6)**.

- **Serve/return display with spatial filtering.** Serves are perhaps the most important shot in tennis since they begin each point and often set the tone for how the point is played. Service returns are almost as important, because a weak return of serve often leads to a winning shot by the opponent, while a strong return can often take away the advantage that the serving player typically has. Users can view serve landing zones and returns of serve at various levels of spatial resolution. **(Supports DP1,DP2, DP3, DP4, and DP5)**.

- **Tennis court display with step animation and spatial filtering.** Users can display the last 3 shots by each player. While the Jellyfish plots show these as a reverse time series for individual dimensions, the tennis court display shows the 2D data for individual shots but provides controls allowing them to step backward or forward in time through these shots. As with the Jellyfish plots, shots are aggregated based on the selected spatial resolution. Users can also create spatial filters by drawing selection rectangles on this court to select specific shots, which update all other visualizations. Selected shots can also be displayed in the video player. Shots displayed are aggregated into "shot bins" based on the spatial resolution selected for each axis, making trends easier to see and making shots more sensitive to statistical testing (see Figure 40) . **(Supports DP1, DP2, DP3, DP4, DP5, and DP6)**.

- **Jellyfish reverse spatial time series plots.** Two-dimensional tennis shot data is separated into two single dimensions and then plotted as a reverse time series where up to the last three shots of each player are included for each point within the selected data set (see Figure 48). Aligning final shots for specific point outcomes and then looking back in time to see how those shots came about helps to see if there are specific patterns associated with point outcomes. **(Supports DP1, DP2, DP3, DP4,**

DP5, and DP6).

- **Spatial resolution sliders.** Users can select different levels of spatial resolution when displaying the underlying data. This applies to the Jellyfish plot as well as the tennis court plot. This will cause the endpoints of shots to align with the center points of the bins they are closest to. Separate resolutions may be selected for the x and y axes. Predefined resolution levels assure that bins always align to the tennis court edges (so no bin covers both an in-bounds and out-of-bounds portion of the tennis court). Coarser resolution levels also mean more shots per bin, making them more sensitive to statistical testing. **(Supports DP4 and DP5)**.

- **Video player.** Users can select specific shots and display them in a video panel. The video panel will allow for users to just play one shot, the last 3 shots in the point, or the entire point. Controls allow the user to play at different speeds and forward or reverse. Meta information about the point is displayed, such as the score and who is serving. Multiple video clips can be loaded into the video player and the user can jump between them to facilitate comparison. Viewing videos of specific points provides perhaps the richest set of information available to users in this application. This is where hypotheses can be confirmed and additional insights discovered. Users need the capability to record the insights found so they can return to them later. Therefore, I have added the capability for users to save a set of point videos, with comments, so they can review their findings later or compare findings from various scenarios. **(Supports DP2, DP3, DP5, DP7, and DP8)**.

- **Predefined query visualization.** While a robust, interactive visual analytics system needs to support *ad hoc* queries, it should also facilitate standard modes of analysis based on the specific domain. Therefore, a series of panels called Examination Activity Panels have been developed that provide simple, easily understandable visualizations of standard tennis queries. For example, winning games when one is serving is considered crucial in competitive tennis matches. Therefore, predefined queries centered around who is serving, which side of the court the server is serving from, and whether or not it is a first or second serve is likely to be of interest to a coach or analyst. Color coding can further be used to guide coaches and analysts to specific serve combinations that are associated with a higher than expected or lower than expected win percentage for player one. **(Supports DP3, DP5, and DP6)**.

- **Analysis snapshots.** Finding a specific set of points can take multiple steps. Not only do users have to select point outcomes and specific points within a match, they may also need to set specific spatial resolutions and select specific shot trajectories. Therefore, I have added the feature of taking an analysis "snapshot", which will allow users to name and save a specific configuration so they can quickly return to it. The configuration also includes color-coding based on the set of points it contains that will indicate if the points represent a higher than expected or lower than expected win percentage for player one. **(Supports DP1, DP4, DP5 and DP6)**.

- **Significant serve filtering.** Some serves in a tennis match are more significant than others because they are associated either with a higher than expected or lower than expected point winning percentage. The Serve/Return Display Panels allow the user to turn on significant serve filtering, which will only display serve landing positions that have a higher than expected or lower than expected win percentage for player one. The *expected* value is based on the overall point win/loss percentage for player one. Which serves that get filtered may change based on the spatial resolution selected as well as the point filters applied. This will help users find the insights and will support their hypothesis generation and testing process. **(Supports DP6)**.

In the remaining sections of this chapter, I describe the visual analytics components of the Spatial TenniVis system. These components include the Point Outcome Data Faders, the Point Comparison Toggle Fader, Match Visualization Semantic Point Selector, Point Length Bar Chart, Serve/Return Display Panel, Tennis Court Display Panel, Vertical Jellyfish Plot, Horizontal Jellyfish Plot, and the Video Player Panel. An important, novel contribution of this research is integrating statistics-based feedback to the user to help them focus in on situations where player one either wins more points than expected or fewer points than expected. To this end, I will discuss the following components and/or design features: Examination Activity Panels, Significant Serve Filtering, and Significant Shot Filtering.

5.3 Point Outcome Data Faders

The Point Outcome Data Faders, shown in Figure 41 allow the user to select from four possible data sets: player one winners, player one errors, player two winners, and/or player two errors. Using checkboxes, users can select these point data sets will cause the associated points to be shown in the "display" state on the Match Visualization Semantic Point Selector. The Serve/Return Display Panel will also show serve landing locations and return of shots associated with these points. The Tennis Court Display Panel and the two Jelly-

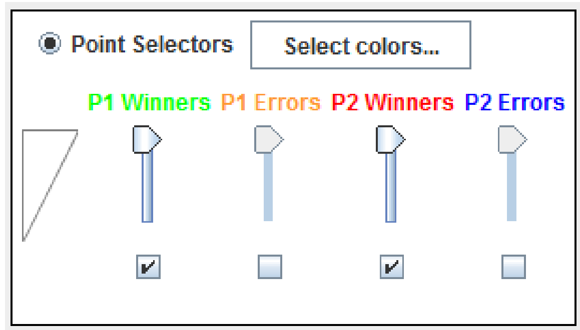


Figure 41: Point Outcome Data Faders. Allow users to select 1-4 point outcome data sets to display. Sliders adjust the transparency of each data set. Select Colors Button allows user to select from a color palette to set the colors of each data set.

fish Plots will also display shots for these point sets. Each point data set is displayed in a different default color. Users can select different colors by clicking on the Select Colors Button, which will bring up a dialog box with a palette of color options to choose from (not displayed). Users toggle each data set on and off using the checkboxes. The transparency level of each data set is set by the sliders, which impacts how shots from these data sets are displayed on the various display panels and Jellyfish Plots. This allows users to see through data sets when they overlap (much like an x-ray image). The transparency sliders don't affect the display state of points in the Match Visualization Semantic Point Selector, but the checkboxes do. Unchecking a checkbox causes the corresponding points in the Match Visualization Semantic Point Selector to be shown in the "filtered out" state (i.e., very faded). The selected point data sets are also reflected in the Point Length Bar Chart. That is, only points from the selected sets will be displayed in the Point Length Bar Charts component.

This design supports Design Principle DP1 (organize around point outcomes) because it provides individual datasets and controls for each of the four point outcomes. It also supports Design Principle DP5 (facilitate easy visual comparison of different data slices)

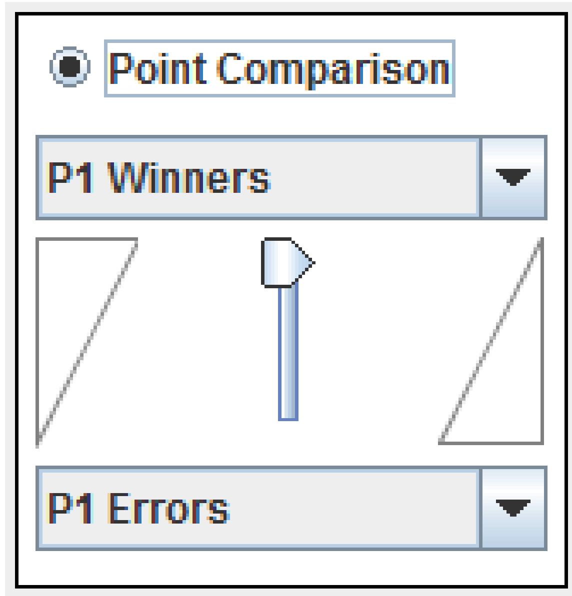


Figure 42: Point Comparison Toggle Fader. Allows users to select two of the four point outcome data sets to be displayed in the various panels and Jellyfish Plots and then simultaneously fade one out while the other fades in using the slider. By doing this continually, key differences between the shots associated with the selected data sets become readily apparent.

because individual data sets can either be toggled off completely, or have their transparency levels adjusted. This is true whether looking at shot data in the various display panels and Jellyfish Plots or at the display states of the points in the Match Visualization Semantic Point Selector. When used individually, it allows users to turn a specific point outcome data set on and see, on the Match Visualization Semantic Point Selector, where in the match these outcomes occurred to see if there are any patterns. For example, in the 49 winners made by player two in the match, only eight of them came during games where player one was serving, while 41 came from points when player two was serving. When used in combination, it allows users to compare the spatial patterns leading up to specific point outcomes to better generate insights.

5.4 Point Comparison Toggle Faders

The Point Comparison Toggle Fader allows users to select two different data sets and then, using a slider, simultaneously fade one data set out as the other fades in. By fading back and forth between the data sets, the shot differences between these two data sets become readily discernible on the Serve/Return Display Panel, Tennis Court Display Panel, and the Jellyfish Plots. Each Drop-Down List Box contains a list of all four point outcome data sets. Since exactly two data sets need to be displayed and since one slider is used to handle transparency levels for these two data sets, the Point Comparison Toggle Fader cannot be used at the same time as the Point Outcome Data Faders. This is accomplished by using Radio Buttons to make the user choose one component or the other. This component becomes particularly useful when combined with spatial filtering. For example, the user can select a specific part of the court player one made a shot from and then, using the Point Comparison Toggle Fader, toggle-fade back and forth see how different shot selections from that point differed in terms of trajectory and outcome.

This design supports Design Principle DP1 (organize around point outcomes) because it provides each of the four point outcome data sets to choose from. It also supports Design Principle DP5 (facilitate easy visual comparison of different data slices) because the simultaneous emphasizing and de-emphasizing of of data sets utilizes users' ability to visually detect changes in display areas they are focusing on.

5.4.1 Match Visualization Semantic Point Selector

The Match Visualization Semantic Point Selector, shown in Figure 43, displays all of the point outcomes in a match as an interactive point selection filter. Its design borrows from

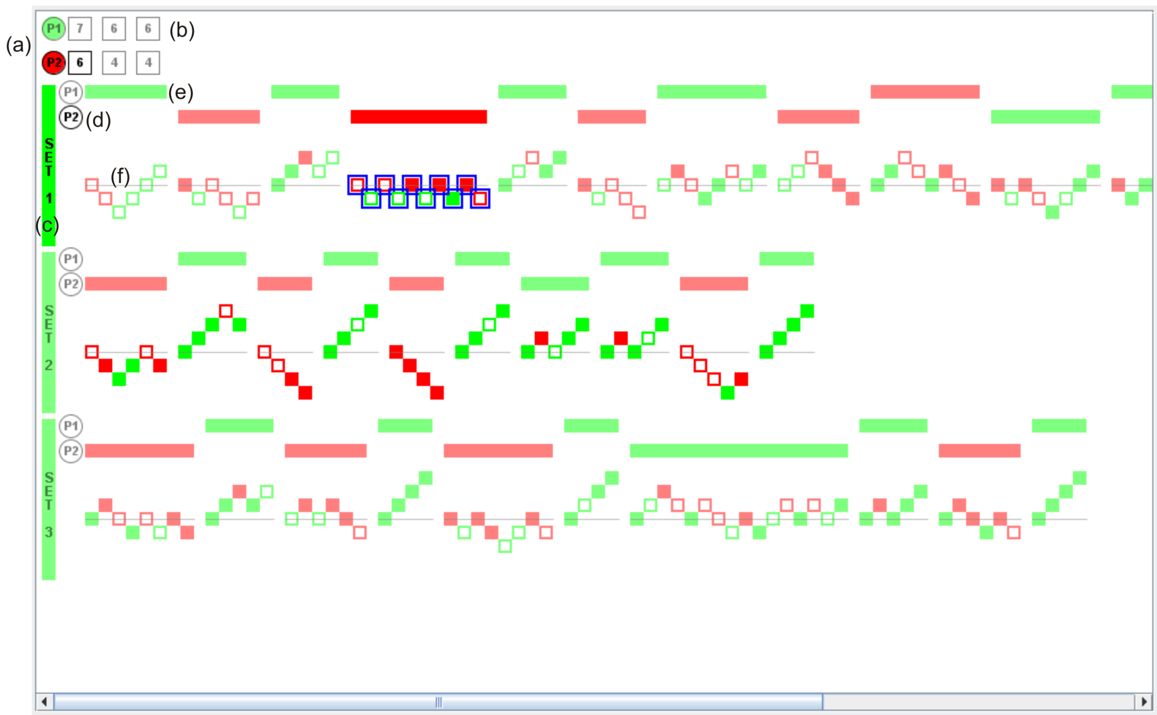


Figure 43: Match Visualization Semantic Point Selector. Displays all of the point outcomes in a match as an interactive point selection filter. (a) Green and red player winning games circles used to select winning games for each player. (b) Squares displaying games won in each set by each player and allowing player to select points for those games. (c) Set rectangles serve as labels for each set, are color coded to indicate who won the set, and are used to select points in that set. (d) Player serve circles indicate who is serving and allow users to select service game points for each player. (e) Game selection rectangles indicate who was serving (based on vertical position), who won the game, and allow users to select points for that game. (f) Point outcome squares indicate type of point outcome (solid green for good shots by player 1, hollow green for bad shots by player 2, solid red for good shots by player 2, and hollow red for bad shots by player 1) and allow user to select an individual point.

the Fish Grids discussed in the previous chapter. The overall match score is displayed at the top left. The green circle with P1 in it and the red circle with P2 in it (see Figure 43 (a)) are used both to label the games won for each player and to serve as point selectors. Clicking on a circle alternately selects/de-selects all of the games won by player 1 or player 2 (depending on which circle is clicked. Next to these are squares displaying games won in each set by each player (see Figure 43 (b)). Clicking a square alternately selects/de-selects the points associated with those games.

The rest of the visualization is divided into horizontal strips, where each strip represents data from a single set. Rectangles are used to label each set (see Figure 43 (c)) and are colored green if player 1 won the set and red if player 2 won the set, making it easy to see how the match unfolded. Clicking on the rectangle alternately selects/de-selects all the points in the set. For each set, white player circles are used to label games where each player was serving (see Figure 43 (d)). Clicking on a circle will alternately select/de-select points from games where a particular player was serving. Individual games are shown as rectangles (see Figure 43 (e)) and are color coded to indicate who won each game (green for player 1, red for player 2). The vertical location of the rectangle aligns with the player serving circles to indicate who was serving that game. The width of the rectangle is proportional to the number of points played in the game. This color and size coding scheme makes it easy to see service breaks (i.e., games where one player was serving but the other player won) and to distinguish short, easily won games, from long, heavily contested games. Clicking on the rectangle alternately selects/de-selects the points for that game. It should be noted that the red/green color scheme can easily be changed to alternate colors for users who have red/green color blindness.

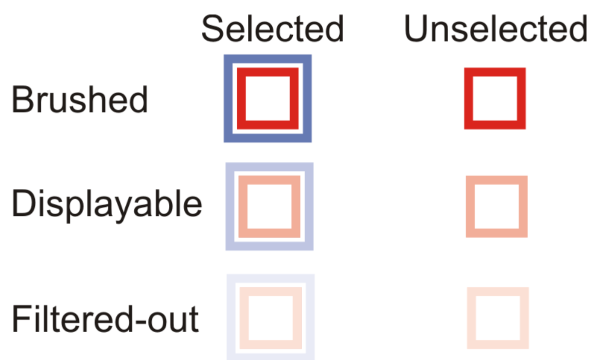


Figure 44: Six possible states for the Point Outcome Rectangles. Rectangles in the brushed state are the brightest (i.e., most color saturated). Rectangles in the displayable state are less-saturated. Rectangles in the filtered-out state have the least saturation, but are still visible. Selected rectangles have a blue border around them.

The individual points for each game are displayed below the game rectangles and aligned with them, making it easy to see which points come from which games (see Figure 43 (f)). These point outcome squares indicate who won each point and are color coded based on the four possible outcomes: solid green for good shots by player 1, hollow green for bad shots by player 2, solid red for good shots by player 2, and hollow red for bad shots by player 1. The vertical location of each square is based on the outcome of the previous point. When player 2 wins a point, the next square is displayed lower. When player 1 wins a point, it is displayed higher. The faint, horizontal lines are used to indicate when the score in a particular game is even. Rectangles displayed above the line indicate situations when player 1 was ahead in a game and squares below the line indicate situations where player 2 was ahead.

Each of the aforementioned graphics has three basic states, as shown in Figure 44: *displayable*, *filtered-out*, and *brushed*. The *displayable* state, indicated by a semi-faded graphic, means that the point or set of points represented by that graphic contain at least one point outcome that has been turned on in either the Point Outcome Data Faders or the Point Comparison Toggle Fader. The *filtered-out* state, indicated by a very faded-out graphic) indicates the point or set of points represented by that graphic do not contain any point outcomes that have been turned on in either the Point Outcome Data Faders or the Point Comparison Toggle Fader. The *brushed* state, indicated by vibrant, non-faded colors, is used to highlight graphics that are in a *displayable* state and have also been brushed by hovering the mouse pointer over the graphic. Any other graphic displays that contain points related to the brushed graphic are also displayed using vibrant, non-transparent colors. Separate from these three states is a selection state that only applies to the point outcome rectangles. A selected rectangle has a blue border around it while unselected rectangles have no such border. The color blue used follows the same color treatments as the other graphics, based on the state of the point. A point outcome rectangle can be selected or unselected, regardless of its state.

This design supports Design Principle DP1 (organize around point outcomes) because it displays the outcome for every point using an easy to understand coloring scheme. It also supports Design Principle DP5 (facilitate easy visual comparison of different data slices) because the visual states of the points change based on the specific data sets selected. For example, if only the "player 1 winners" data set is turned on, point outcome squares associated with the other three outcomes are all displayed in the *filtered-out* state, making it easy to see where, in the overall match, certain types of point outcomes were more prevalent.

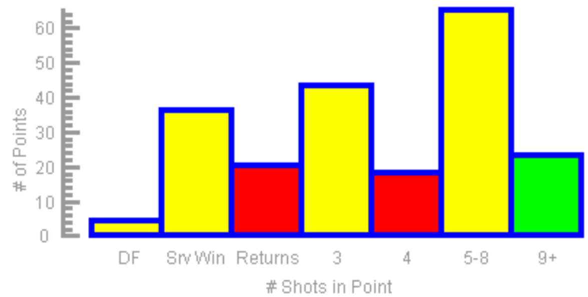


Figure 45: Point Length Bar Chart displaying the number of points lasting for specific numbers of shots. *DF* refers to points that ended by a double-fault. *Srv Win* refers to points ending via a service winner. *Returns* refers to points ending on the return of serve. *3* and *4* refer to pints ending in 3 or 4 shots, respectively. *5-8* refers to medium length points ending in the range of five to eight shots. *9+* refers to longer points that included nine or more shots. Color coding is used to indicate that a specific set of points lasting the specified number of shots is has a greater than expected player one winning percentage (green), lower than expected player one winning percentage (red), or where the player one winning percentage is not significantly different than expected (yellow). Each bar is clickable, causing the corresponding points to be selected or de-selected.

5.5 Point Length Bar Chart

The Point Length Bar Chart, shown in Figure 45, displays a series of bars that represent the number of points that lasted a specific number of shots. Based on interviews with tennis teaching pros, I defined the following discrete intervals to categorize points of different shot lengths. These include points ending by a double-fault, points ending via a service winner, points ending on a return of serve, points lasting three shots, four shots, five to eight shots, and nine or more shots. The reasoning for each of these intervals is as follows:

- **Double faults.** Double-faults result in an immediate loss of point to the opposing player. Coaches and analysts will want to know if there are specific situations where a player is more likely to double-fault, such as on a specific side of the court or perhaps in certain game situations, such as when a player is either way up or way down in a game.

- **Service winners.** Like double-faults, service winners also bring an immediate end to a point, but in favor of the serving player. Coaches and analysts will want to determine where the most effective serves are being hit and make sure the player maximizes his or her efforts to hit those locations.

- **Returns of serve.** Points ending via a return of serve point not only to high-quality play by the returning player, but may also be an indication of serve *ineffectiveness* by the serving player. Knowing an opponent's return of serve strengths allows the serving player to select serves that will minimize those strengths.

- **Three shot points.** Points that end in three shots usually indicate an effective serve that causes a weak return by the opponent that the serving player can then immediately take advantage of. Coaches can also focus on these points to assist a player in how to become a more effective service returner.

- **Four shot points.** Points ending in four points may be an indicator of an effective return and/or a weak serve. They represent points at the tail-end of what is considered a "short" point.

- **Five to eight shot points.** Points that last five to eight shots represent a range of points that indicate situations where a players may have to their knowledge of the opponents' strengths and weaknesses and setup a winning shot. Points that fall into this interval are ones where neither the serve nor the return of serve were effective enough to force an early outcome.

- **9+ shot points** This final interval represents all of the remaining points and are considered “long” points. This interval may be of interest to coaches who encourage their players not to take too many risks on shots, but rather try to force the opponent to make an unforced error by simply keeping the ball in play.

The Point Length Bar Chart uses dynamic scaling so that the tallest bar always reaches to the top of the y-axis. This was done because of the multiple scales at which a player may examine a set of points. For example, a player may want to see all the points in ther match to get a general idea of how many points fell into each interval. On the other end of the scale, a player may be focused on just a handful of points. Therefore, the dynamic scaling approach provides the most readability and maximizes the user of screen real estate. As with the Match Visualization Semantic Point Selector, the Point Length Bar Chart provides not only information, but also serve as interactive filters. Users can select all the bars or just look at specific bars to focus on specific categories of points, such as returns of serve. This filter will be reflected in the Match Visualization Semantic Point Selector, the Jellyfish Plots, the Tennis Court Display, and the Serve/Return Displays. The dynamic scaling of the bars ensures they are usually easily selectable by the user.

This design supports Design Principle DP3 (focus on serves, returns, and the last few shots in a point) by segmenting the data into discrete bins that points ending via double-faults, service winners, and on returns. It also allows users to select longer points so they can then focus their attention on points whose outcome is more likely due to decisions and actions taken within the last three shots of a point. It also supports Design Principle DP6 (help users find what is meaningful) by employing color-coding that indicates when points of a particular shot length have a higher than expected or lower than expected win percentage for player one.

5.6 Serve/Return Display Panel

The Serve/Return Display Panel, shown in Figure 46, displays serves and returns by both players for the point outcome data sets selected in the Point Outcome Data Faders or Point Comparison Toggle Fader. Only serves and returns for points that are not filtered-out are displayed. Using sliders, users can change the size of the serve bins used to spatially aggregate service landing positions. The spatial grid can be toggled on or off. Service returns can also be displayed. To avoid clutter, both the serve landing circles and service returns can be toggled on or off. Both the serves and returns are color-coded using the point outcome data set colors selected in the Point Outcome Data Faders. Users can brush individual serve landing zones, causing the corresponding points to be brushed in the Match Visualization Semantic Point Selector and the corresponding shots to be brushed in the Tennis Court Display Panel and the Jellyfish plots. Users can also draw bounding boxes around serve circles or the start or end points of return shots to spatially filter the data. This causes all of the other displays to be updated so that only points that pass the spatial filters are shown in the *displayable* state. This can be a powerful tool to help users see any possible trends, such as changes in serving strategy from one set to another. Selected serves and/or returns can be sent to the video player for more detailed comparison.

This design supports Design Principle DP1 (organize around point outcomes) because it displays each selected point outcome data set using the colors selected in the Point Outcome Data Faders. It supports Design Principle DP2 (visualize shots and shot combinations) because it visualizes service return shots. It supports Design Principle DP3 (focus on serves,

Figure 46: Serve/Return Display Panel. Displays serve landing positions and returns of serve, color coded by point outcome (i.e., player 1 winners, player 2 errors, etc.). Serve bin spatial resolution controlled by two sliders. Area of circles represent number of serves. Users can display either serve landing zones or service returns, or both. Users can select specific serves by drawing a bounding box around them. Returns of serve (not shown) can also be turned on or off and can also be selected using bounding boxes on the shot start or end locations. User can optionally choose to display only “significant” serves by checking a checkbox (described in more detail in Section 5.11.3).

returns, and the last few shots in a point) by displaying serves and returns. It supports Design Principle DP4 (support multiple levels of spatial resolution) by providing sliders to change the spatial resolution of serve landing zones. The spatial resolution for returns is set using the sliders provided in the Tennis Court Display Panel. It supports Design Principle DP5 (facilitate easy visual comparison of different data slices) by superimposing data sets on each other. Because these data sets are semi-transparent, multiple data sets can be seen (within reason).

5.7 Tennis Court Display Panel

The Tennis Court Display Panel, shown in Figure 47, displays shots made by one of the players. These will always be one of the last three shots made by a player. The idea is that these shots should contain the most fruitful data for analysis since they are so close to the end of a point. Only shots for points that are not filtered-out are displayed. Using sliders, users can change the size of the shot bins used to spatially aggregate shot starting and ending locations. The spatial grid can be toggled on or off. Shots are color-coded using the point outcome data set colors selected in the Point Outcome Data Faders. Users can brush shots, causing the corresponding points to be brushed in the Match Visualization Semantic Point Selector and the corresponding shots to be brushed in the Serve/Return Display Panel and the Jellyfish plots. Step animation controls allow users to step through the last 3 shots made by each player. Highlights are provided in the Jellyfish Plots to aid the user in determining which shots are currently being displayed. Users can also draw bounding boxes around the start or end points of shots to spatially filter the data. This causes all of the other displays to be updated so that only points that pass the spatial filters

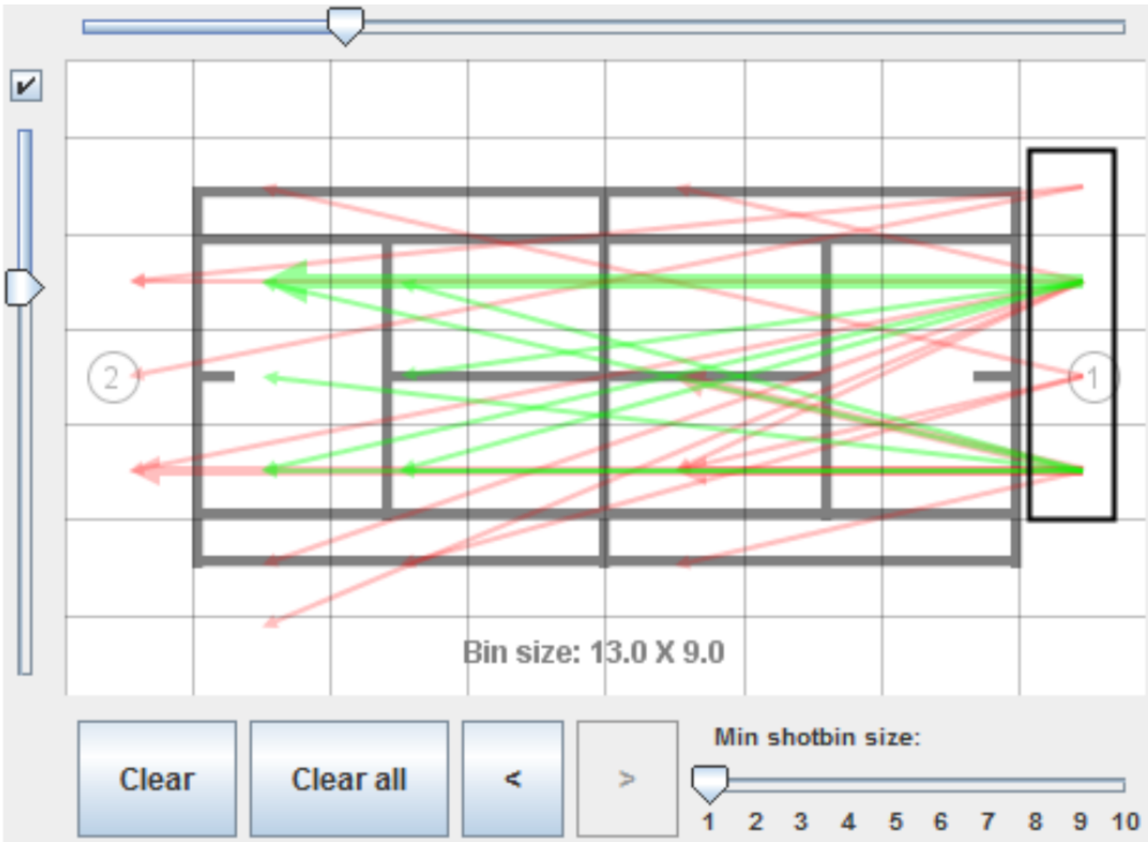


Figure 47: Tennis Court Display Panel. Displays shots made by each player (separately), shown as arrows indicating where the ball was hit from and where it landed. Shots are color coded by point outcome (i.e., player one winners, player two errors, etc.). Shot bin spatial resolution controlled by two sliders. Users can select specific shots by drawing a bounding box around the starting and/or ending locations. Step animation controls are provided to allow the user to step backward or forward in time through the last three shots made by each player (excluding serves and returns). Displayed here are the final shots made by player one for the player one winners data set (shown in green) and the player one errors data set (shown in orange).

are shown in the *displayable* state. This can be a powerful tool to help users see any possible trends, such as when in the match specific types of shots are made, such as winning shots being made more frequently when the player is serving. To avoid clutter and allow users to focus on finding shot patterns (as opposed to just individual shots), users can adjust a minimum shot bin size slider to only display shot bins that contain the selected minumum number of shots.

This design supports Design Principle DP1 (organize around point outcomes) because it displays each selected point outcome data set using the colors selected in the Point Outcome Data Faders. It support Design Principle DP3 (focus on serves, returns, and the last few shots in a point) by displaying the last three shots by each player. It supports Design Principle DP4 (support multiple levels of spatial resolution) by providing sliders to change the spatial resolution of shot start and end points. It supports Design Principle DP5 (facilitate easy visual comparison of different data slices) by superimposing data sets on each other. Because these data sets are semi-transparent, multiple data sets can be seen (within reason). Finally, it supports Design Principle DP6 (help users find what is meaningful) by allowing them to filter out the shot bins with only one or a few shots so they can focus on finding more common shot patterns.

5.8 Vertical Jellyfish Plot

The Vertical Jellyfish Plot, shown in Figure 48, shows the left-right dimension (x-axis) of the last three shots made by each player (excluding serves and returns) as a reverse spatial time series plot where the last shot is shown at the rightmost edge. This allows users to see how the final shots in a point came about. Shots are delimited by a series of

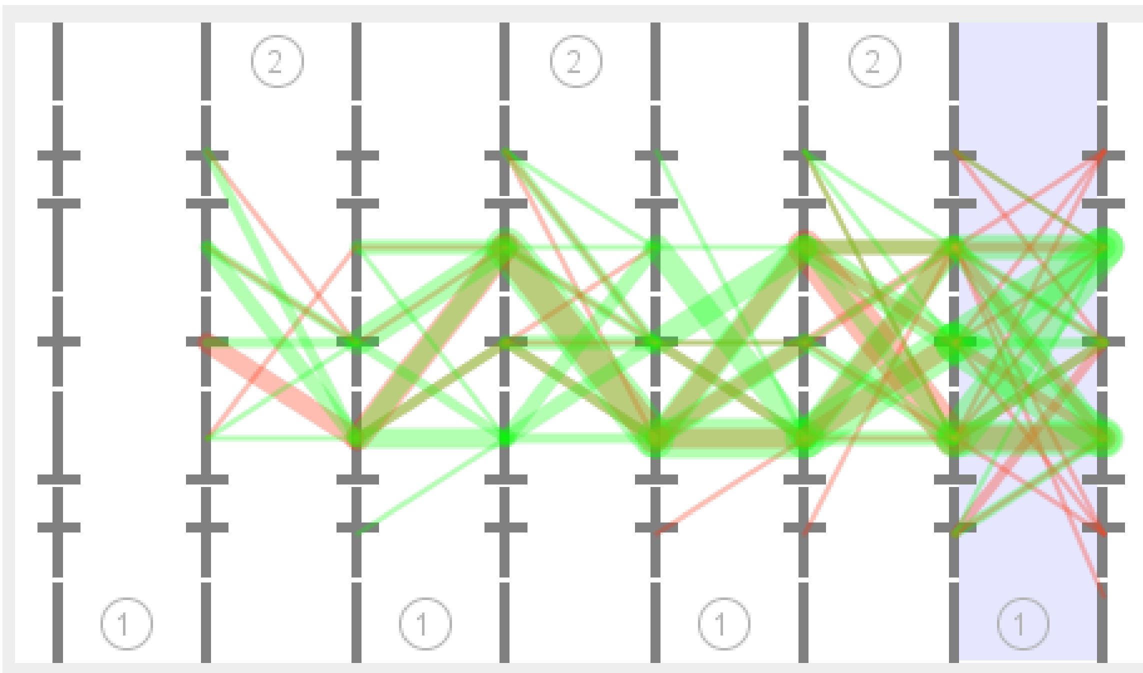


Figure 48: Vertical Jellyfish Plot. Displays the x-axis dimension of the last three shots made by each player (not including serves or returns). The x-axis is defined to run along the width of the tennis court (i.e., the shorter edge). This plot shows just the left-right dimension of shots. Reference lines are included to indicate where the doubles alley lines are located, as well as the center service line. White dashes help delineate shot bin sizes. Lines are color-coded based on point outcomes. Line thickness corresponds to the number of points associated with each shot bin. Time moves from left to right. The starting point of each line indicates where the ball was hit from and the ending location indicates where it bounced. The gray background indicates which shots are currently displayed in the Tennis Court Display Panel. Displayed here are shots made by both players for the player one winners data set (shown in green) and the player one errors data set (shown in orange).

vertical axis lines. These lines have dark, horizontal line segments that are aligned with the doubles alleys and center hash mark of the tennis court, to make it easier to see where a shot originated from and where the ball landed. The white dash marks embedded in the axis lines correspond to the shot bin grid boundaries, giving users a sense of the width of each shot bin. All shots within a specific shot bin are aligned to the center of that shot bin. Shots are plotted as lines going from one axis line to the next. The starting point of each line represents where the ball was hit from and the end point indicates where the ball bounced. Note that lines won't always connect, because the player may hit the ball from a different shot bin than where the ball bounced. Each line is color-coded based on the colors and transparency levels selected in the Point Outcome Data Faders. Line thickness corresponds to the number of points included in each shot bin. Users can brush lines, causing them to displayed in a fully-opaque version of their selected color. This includes not only the specific shot bin being brushed, but also to all shot bins leading to the selected shot bins and all subsequent shot bins propagating from them. Brushing also updates the display state of points in the Match Visualization Semantic Point Selector, shots in the Tennis Court Display Panel, serves and returns in the Serve/Return Display Panel, and shots in the Horizontal Jellyfish Plot. Labeling is included to indicate which player's shots are being displayed. As with the Tennis Display Panel, users can use the minimum shot bin size slider to hide shot bins with fewer than a threshold number of shots, thereby emphasizing the stronger shot patterns.

This design supports Design Principle DP1 (organize around point outcomes) because it displays each selected point outcome data set using the colors selected in the Point Outcome Data Faders. It supports Design Principle DP2 (visualize shots and shot combinations) because it shows not only individual shots, but also shot combinations since brushing shows this connectivity. It support Design Principle DP3 (focus on serves, returns, and the last few shots in a point) by displaying the last three shots by each player. It supports Design Principle DP4 (support multiple levels of spatial resolution) because it displays data at the resolution selected in the sliders located on the Tennis Court Display Panel. It supports Design Principle DP5 (facilitate easy visual comparison of different data slices) by superimposing data sets on each other. Because these data sets are semi-transparent, multiple data sets can be seen (within reason). Finally, it supports Design Principle DP6 (help users find what is meaningful) by allowing them to filter out the shot bins with only one or a few shots so they can focus on finding more common shot patterns.

5.9 Horizontal Jellyfish Plot

The Horizontal Jellyfish Plot, shown in Figure 49, shows the shot depth dimension (y-axis) of the last three shots made by each player (excluding serves and returns) as a reverse spatial time series plot where the last shot is shown at the bottommost edge. This allows users to see how the final shots in a point came about. Shots are delineated by a series of horizontal axis lines. These lines have dark, vertical line segments that are aligned with the baselines, service lines and net of the tennis court, to make it easier to see where a shot originated from and where the ball landed. The white dash marks embedded in the axis lines correspond to the shot bin grid boundaries, giving users a sense of the width of each shot bin. All shots within a specific shot bin are aligned to the center of that shot bin. Shots are plotted as lines going from one axis line to the next. The starting point of each line represents where the ball was hit from and the end point indicates where the ball bounced.

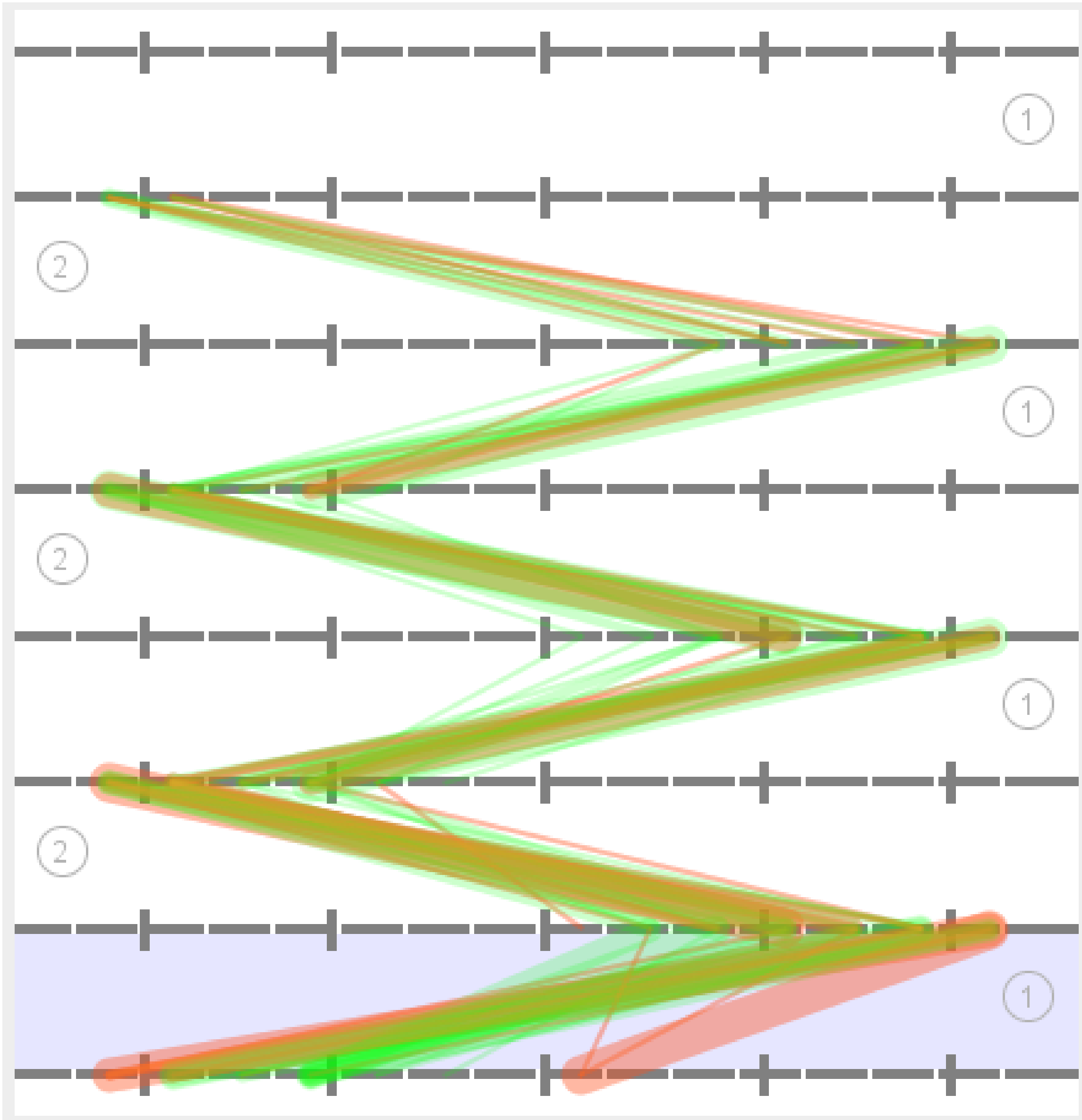


Figure 49: Horizontal Jellyfish Plot. Displays the y-axis dimension of the last three shots made by each player (not including serves or returns). The y-axis is defined to run along the length of the tennis court (i.e., the longer edge). This plot shows just the court depth dimension of shots. Reference lines are included to indicate where the baselines, service lines, and net are located. White dashes help delineate shot bin sizes. Lines are color-coded based on point outcomes. Line thickness corresponds to the number of points associated with each shot bin. Time moves from top to bottom. The starting point of each line indicates where the ball was hit from and the ending location indicates where it bounced. The gray background indicates which shots are currently displayed in the Tennis Court Display Panel. Displayed here are shots made by both players for the player one winners data set (shown in green) and the player one errors data set (shown in orange).

Note that lines won't always connect, because the player may hit the ball from a different shot bin than where the ball bounced. Each line is color-coded based on the colors and transparency levels selected in the Point Outcome Data Faders. Line thickness corresponds to the number of points included in each shot bin. Users can brush lines, causing them to displayed in a fully-opaque version of their selected color. This includes not only the specific shot bin being brushed, but also to all shot bins leading to the selected shot bins and all subsequent shot bins propagating from them. Brushing also updates the display state of points in the Match Visualization Semantic Point Selector, shots in the Tennis Court Display Panel, serves and returns in the Serve/Return Display Panel, and shots in the Vertical Jellyfish Plot. Labeling is included to indicate which player's shots are being displayed. As with the Tennis Display Panel, users can use the minimum shotbin size slider to hide shot bins with fewer than a threshold number of shots, thereby emphasizing the stronger shot patterns.

This design supports Design Principle DP1 (organize around point outcomes) because it displays each selected point outcome data set using the colors selected in the Point Outcome Data Faders. It supports Design Principle DP2 (visualize shots and shot combinations) because it shows not only individual shots, but also shot combinations since brushing shows this connectivity. It support Design Principle DP3 (focus on serves, returns, and the last few shots in a point) by displaying the last three shots by each player. It supports Design Principle DP4 (support multiple levels of spatial resolution) because it displays data at the resolution selected in the sliders located on the Tennis Court Display Panel. It supports Design Principle DP5 (facilitate easy visual comparison of different data slices) by superimposing data sets on each other. Because these data sets are semi-transparent, multiple

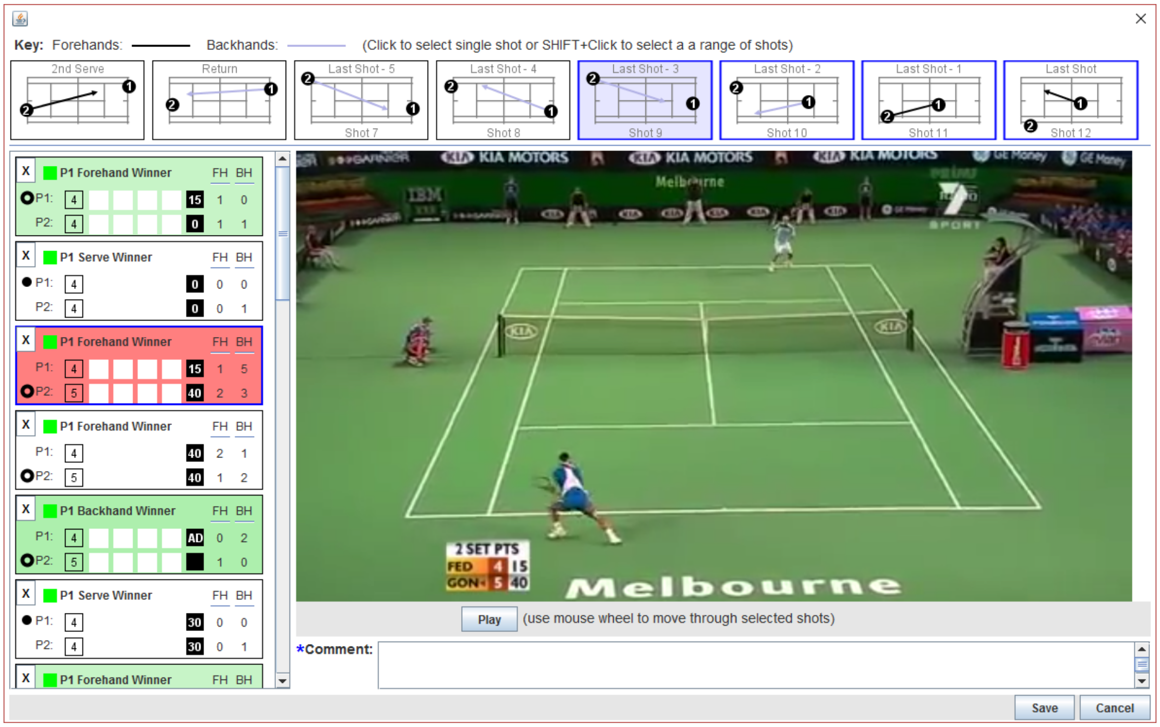


Figure 50: Video player dialog showing a list of points along the left and the shots from a selected point across the top, as well as a video playing in the main section for the selected point. Users can select to play the video of an entire point or a subsection of shots. Users can also play the video in slow-motion or pause the video and use the mouse wheel to scroll back and forth through the video clip. Users can annotate specific points with comments explaining what they find useful. They can also remove points that don't have any specific interest to them. They can then save the set of selected points (with comments) as a Video Finding that they can name and provide a description for.

data sets can be seen (within reason). Finally, it supports Design Principle DP6 (help users find what is meaningful) by allowing them to filter out the shot bins with only one or a few shots so they can focus on finding more common shot patterns.

5.10 Video Player Panel

The Video Player Dialog, shown in Figure 50 is a rich, interactive tool that allows users to view individual points in a tennis match or just a subset of the shots from specific points. Its primary purpose is to provide access to the raw video data so that users can see other characteristics of specific shots and points that may not be included in the main visualizations. This includes characteristics such as ball spin, ball height (i.e., lob vs. line drive), player footwork, player preparation, hitting technique, and possibly even emotion and body language. Using the main application tools, coaches and analysts can use semantic and spatial filtering capabilities to isolate a small subset of points they believe may contain some meaningful insights. Once they have isolated this subset, they can click the Launch Video Button on the main application to bring up the Video Player Dialog.

The main purpose of the Video Player Dialog is for users to identify points or specific shots that exemplify some insight or finding they have discovered. By viewing the raw video footage, they can either confirm or reject *ad hoc* hypotheses they have formed. When launched, all of the currently selected points will be available for display in the dialog. These can then be systematically whittled down to a small set of exemplary points that the user can annotate with text comments. The user is then able to save the entire package of video clips and associated comments as a “video finding”, providing a name for the finding as well as a text description. This video finding is then added to the main application and can be re-launched later. This ability to annotate points and save the video findings supports Design Principle DP8 (organize and save the results of analysis). The Video Player Dialog has three main components: the Video Point Selection Panels (displayed along the left-side of the dialog), Tennis Shot Display Panels (running along the top of the dialog), and the Main Video Player (shown in the middle of the dialog). Each of these components will be discussed individually in the following sections.

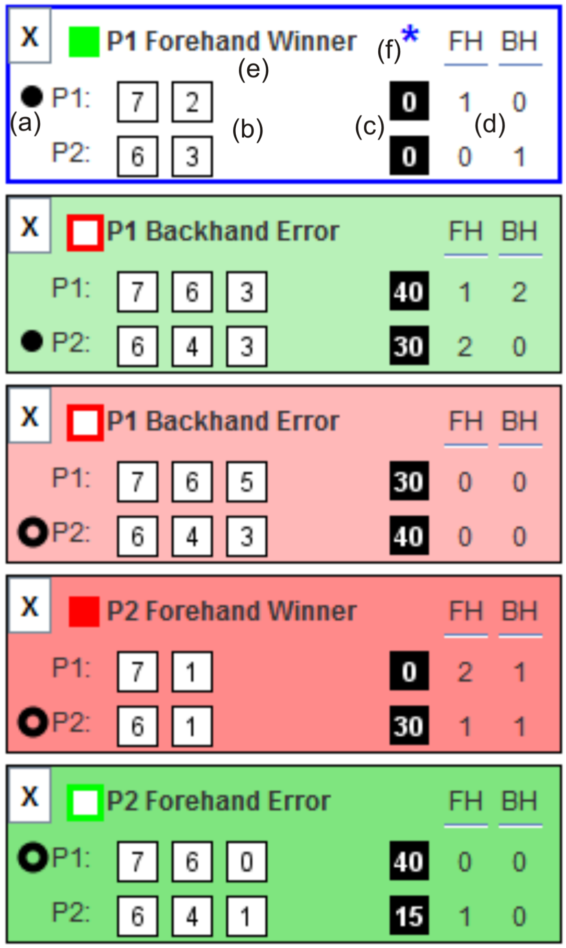


Figure 51: A sample of Video Point Selection Panels that allow users to select a specific point to view in the Main Video Player. Background color coding of the panels is based on game score (i.e., if player one is ahead, green shade will be used; if player two is ahead, red shade will be used; and score is even, background color is white). (a) Labels P1 and P2 indicating player one and player two. Which player is serving is indicated by a solid or hollow black circle. A solid circle indicates first serve and a hollow circle indicates second serve. (b) Boxes listing the current score (in terms of games won) within each set. (c) Game score within the current game. (d) Number of forehands and backhands in the point for each player. (e) Point outcome that indicates which player ended the point, how it was ended (i.e., via a winner or an error), and who won the point (i.e., green = player one, red = player two). (f) Blue comment asterisk indicating there is a comment annotation associated with this point. When point is selected, comment will be displayed in Comment Box below the Main Video Player.

5.10.1 Video Point Selection Panels

The Video Point Selection Panels (as shown in Figure 51) provide a mechanism for allowing users to select a specific point in the match to be viewed in the Main Video Player. The specific shots associated with the point also get displayed in the Tennis Shot Display Panels running across the top of the Video Player Dialog (see Figure 52). The Video Point Selection Panels also provide useful context information, including who is serving, whether the point started from a first or second serve, the current match score, the number of forehands and backhands in the point (and therefore also point length), who won the point, and whether the point was decided by a winner or an error. The same shading scheme used to indicate risk (as described in section 3.3.5) is used here to shade the background color of the panels. Shades of green indicate scores where player one is ahead. Shades of red indicate player two is ahead in the current game score. A white background is used when the score is even. If the user does not find anything interesting about a specific point, they can dismiss it by clicking the “x” button. If they do find something interesting, they can annotate the point with a comment using the Comment Box located below the Main Video Player. A blue asterisk will be displayed in the Video Point Selection panel, indicating there is an associated comment.

The Video Point Selection Panels support Design Principle DP5 (facilitate easy visual comparison of different data slices) because users can use these panels to quickly jump between points in order to view their differences or similarities in the Tennis Shot Display Panels or in the Main Video Player. The context information provided and color coding also facilitates this comparison. Design Principle DP7 (provide quick access to the raw

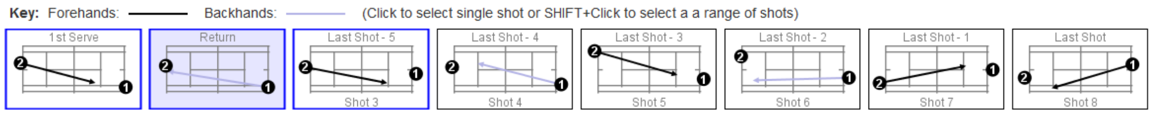


Figure 52: A series of Tennis Shot Display Panels displaying all of the shots in a specific point. Players are identified as white numbers in black circles. Shots are shown as directed arrows. Black arrows indicate forehand shots, while gray arrows indicate backhand shots. The serve and return are displayed first, followed by the last six shots in the point. A single shot or a contiguous range of shots may be selected for display in the Main Video Player (as indicated by the blue outline). When a specific shot is being shown in the video player, the corresponding Tennis Shot Display Panel will be highlighted with a light-gray background.

data) is also supported by providing one-click access to the raw video footage of a specific point.

5.10.2 Tennis Shot Display Panels

Tennis Shot Display Panels, shown in Figure 52, display the individual shots within a single tennis point, including the serve, return, and last six shots in the point. Each panel displays the location of each player when the ball is hit and shows the trajectory of where the ball bounces. Forehand shots are shown as black arrows and backhand shots are shown as gray arrows. Labels on the first (leftmost) panel indicates if the point started from a first or a second serve. This is followed by the return of serve panel. The remaining panels display up to the last six shots in the point, if applicable. Longer points with more than eight shots (including serve and return) will not have shots in the middle of the point displayed. This is because the most important shots are likely to happen at the end of the point rather than in the middle (since these shots ultimately lead to the point ending). Users are able to select individual shots or a contiguous range of shots to be displayed in the Main Video Player. When the video is playing, the corresponding Tennis Shot Display Panel will be highlighted, allowing users to see which shot is currently being viewed.

The Tennis Shot Display Panels support Design Principle DP2 (visualize shots and shot combinations) by displaying the individual shots in a match simultaneously. Users can “read” the shots in the point from left to right to distinguish any meaningful patterns. They also support Design Principle DP3 (focus on serves, returns, and the last few shots in a point) by only displaying the serves, returns, and the last three shots made by each player in a point. If the user just wants to focus on serves and returns, for example, they can just select these two shots and then have them looped over and over in the Main Video Player. The selected shots are maintained even when the user selects a different point to view. In this way, users can see the same shots (in terms of shot sequence) across different points, which supports Design Principle DP5 (facilitate easy visual comparison of different data slices). Design Principle DP7 (provide quick access to the raw data) is supported, since, by clicking on specific shots, users can immediately view just those shots of interest, without having to watch an entire point.

5.10.3 Main Video Player

The Main Video Player can be seen in Figure 50. It occupies the majority of screen real estate for the Video Player Panel and displays a video clip of either a point or a contiguous subset of shots within a point. Users can either play the video in normal speed or in slow motion. When the video reaches the last shot selected (or the end of the point), it automatically loops over again from the first shot selected in the sequence. Users can also pause the video. When a video is paused, users can use the mouse wheel to move the video forward or backward in time through the selected sequence of shots. To help keep the user oriented, the Tennis Shot Display Panel associated with the current shot being displayed in the video is highlighted. The Main Video Player supports Design Principle DP7 (provide quick access to the raw data) by displaying the actual raw video footage and providing tools allowing users to easily move back and forth through this data using various video controls.

5.11 Integrating Statistical Feedback into Visualizations

When investigating how novice users make sense of unfamiliar visualizations, Lee et al. [64] observed that novice users often end up floundering and are unable to understand a visualization. To help alleviate this problem, I have integrated visual statistical feedback into a series of visualizations as well as into the Analysis Snapshots capability. I have also added significance filtering to serves. This visual feedback can help guide users towards semantically meaningful situations that may warrant further investigation. The visual feedback mechanism is very simple, both in terms of calculation and in terms of understandability of results. I characterize a set of tennis points based solely on the outcome (i.e., which player wins the point). From this, then I generate a win percentage for player one. I then use the *overall* win percentage for player one for the *entire* match as the expected value and generate a binomial distribution around this expected value. I then compare the *actual* player one win percentage for a given sample to this expected value and calculate the probability that this outcome occurred by chance. If the probability is less than or equal to .05, then I say the result is statistically significant. That is, the actual player one win percentage is either significantly greater than or significantly less than the expected value. For the visualizations that incorporate visual statistical feedback, I represent the statistical significance using four different colors:

- **Green.** The player one win percentage is significantly *greater* than expected. Since this is good for player one, I use the color green.

- **Red.** The player one win percentage is significantly *less* than expected. Since this is bad for player one, I use the color red.

- **Yellow.** The player one win percentage is *not significantly different* than expected. Since this is not necessarily good or bad bad for player one, I use the color yellow.

- **Gray.** The sample size is not large enough to calculate significance. To determine this, I look at both possible extremes in the sample (i.e., player one wins all of the points or player one wines none of the points). If neither extreme would pass the p ¡ .05 threshold, then I use the color gray to indicate an insufficient sample size.

This coloring scheme is used in the Point Length Bar Chart (see Section 5.5) to indicate points with specific shot lengths that may be have a significantly higher than expected or lower than expected player one win percentage. It is also used in the design of the Examination Activity Panels, described in Section 5.11.1. This significance calculation is additionally used in the Significant Serve Bin Filter, described in Section 5.11.3, as a way to filter out all but the most significant serves.

5.11.1 Examination Activity Panels

To aid users in finding semantically meaningful sets of points that may hold insights into player strengths and weaknesses, I have developed Examination Activity Panels that are each centered around a specific aspect of a tennis match. These are essentially predefined queries that organize points from a tennis match into semantically meaningful groups. The percentage of points won by player one is calculated for each group and then the statistical

Figure 53: Examination Activity Panel for analyzing serves. The area of each pie circle is proportional to the number of points meeting a specific condition. The angle of the non-white pie slice (starting with 0 degrees at the top and going clockwise) indicates the percentage of points won by player one in that group of points. The actual number of points is displayed in in parentheses. Statistical color coding is used to identify point groups with a higher than expected (green), lower than expected percentage (red) or not significantly different that expected (yellow) percentage of points won by player one. If there is insufficient data to calculate significance, the color gray is used.

significance of this percentage is determined. Interviews were conducted with local area tennis teaching pros to determine a reasonable set of analysis configurations to serve as a starting point for analysis. Based on these interviews, I developed the following set of Examination Activity Panels:

- **Serve Analysis Panel.** Shown in Figure 53, this panel looks at points grouped by which player was serving (player one or player two), service side (deuce court or ad court), and serve number (first serve or second serve). This resulted in a total of 18 combinations.

- **Return of Serve Analysis Panel.** This panel looks at points grouped by which player was returning (player one or player two), service side (deuce court or ad court), serve number (first serve or second serve), and return stroke side (forehand or backhand). This resulted in a total of 54 combinations.

- **Volley Analysis Panel.** This panel includes points where one or both players hit a volley shot at least once during the point. A volley shot is when the player hits the ball before it bounces. Points were grouped by which player was volleying (player one or player two) and stroke side (forehand or backhand), resulting in six combinations.

- **Serve and Attack Analysis Panel.** This panel includes points when the serving player advances into the tennis court after serving past a specific threshhold. Based on interviews with local area tennis teaching pros, it was determined that this threshold should be halfway between the baseline and service line (i.e., nine feet from the baseline). Points were grouped by serving player (player one or player two), service side (deuce court or ad court), and serve number (first serve or second serve). This resulted in 18 combinations.

Point groups are represented by circles with a pie chart circumscribed within. The area of the circle is proportional to the number of points contained in a group. The angle of the non-white pie slice (starting with 0 degrees at the top and working clockwise) represents the percentage of points won by player one in that group. The significance color coding scheme described in the previous section is used to color each pie slice (red, green, yellow, or gray). The actual number of points in each group is displayed next to the circle. Using checkboxes, user can select one or more point groupings of interest. These will then be displayed in a list box underneath the corresponding Examination Activity category on the main application. An example of this is shown in Figure 54. Selecting a specific entry will serve to filter out all points not included in the group. This will be reflected in the Match Visualization Semantic Point Selector, the Serve/Return Display Panels, the Tennis Court Display Panel and the Jellyfish plots.

It should be noted that sometimes the *lack* of a significant player one winning percentage for a specific set of points may still be very much of interest to the coach or analyst. For example, at the professional level, players often win significantly more points when they are serving as compared to when they are receiving. This can be seen in Figure 53 by the large number of green circles in the column for when player one is serving and the large number or red circles on player two's side. What may stand out to a coach or analyst are the yellow circles associated with both players' second serves on the ad court side. This could be the starting point for a coach to see if there is anything in particular about the serve that

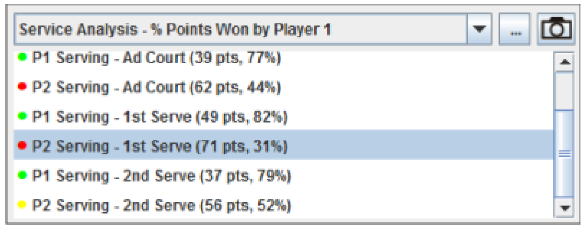


Figure 54: List box showing Serve Analysis Examination Activities selected by the user. Labels indicate a specific combination of attributes and also display the total number of points and player one winning percentage for that specific group. A colored circle indicates if the player one winning percentage is significantly greater than (green), significantly less than (red), or not significantly different from (yellow) the expected winning percentage. Clicking on a specific entry filters out all points that are not in the group.

can be improved.

The design of the Examination Activity Panels is data driven, thus providing flexibility to easily pre-define additional, semantically meaningful situations that will parse the points in a tennis match into useful categories for analysis. For example, one could search through all of the points looking for a specific shot (such as an inside-out forehand) and then create a new Examination Activity Panel to display the results. All that is required is to be able to pre-process points to tag those that pass this criterion.

The design of the Examination Activity Panels supports Design Principle DP3 (focus on serves, returns, and the last few shots in a point) because there are Examination Activity Panels dedicated to serves and returns. It supports Design Principle DP5 (facilitate easy visual comparison of different data slices) in two ways. First, on the Examination Activity Panels themselves, users can see differences in terms of the overall number of points (related to circle size) and in the percentage of points won by player one. Second, if the user has selected multiple examination activities to view in the drop-down list box on the main application, they can quickly switch from one view to the other to note differences in the other visualizations. The design also supports Design Principle DP6 (help users find what is meaningful) through its use of significance color coding that helps immediately distinguish pockets of points that are associated with a player one win percentage that is different from the overall average.

5.11.2 Analysis Snapshots

Isolating a specific set of points can take a meaningful amount of effort on the user's part. This may include selecting one or more of the four point outcome data sets, adjusting transparency levels using sliders, then selecting specific points in the Match Visualization Point Selector, and then further refining this set by clicking one or more of the bars in the Point Length Bar Chart. Once this basic set of points is selected, the user may want to focus on just those points from this subset included a wide serve to the ad side of the court. Finally, the spatial resolution sliders, both for serve locations as well as for shots, may be adjusted. The user may then want to look at an entirely different set of points with different setting for all of these controls. To make things more efficient, users are able to take an Analysis Snapshot by clicking on a button with a camera icon. This will then allow them to provide a short title to describe the specific configuration of points. This will then be displayed in a drop-down list box on the main display. The label will include a colored circle that uses the same significance coloring scheme described earlier, as well as displaying the total number of points in each configuration and the percentage of those points won by player one.

The ability to save snapshot point configurations supports Design Principle DP1 (organize around point outcomes) because it lets users define snapshots based on point outcomes. It supports Design Principle DP4 (support multiple levels of spatial resolution) because it

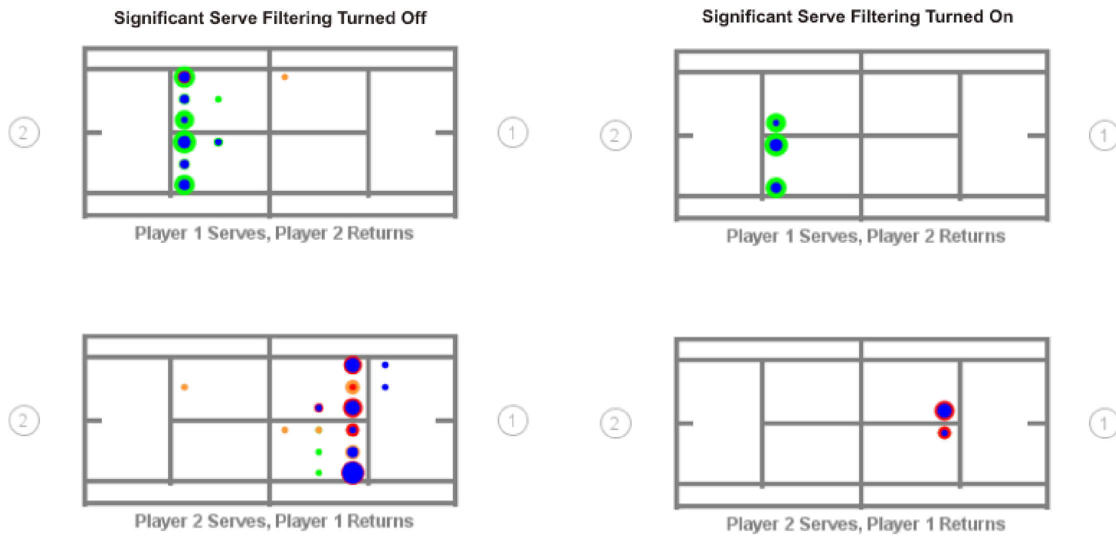


Figure 55: Significant serve filtering turned off (on the left) or on (on the right). When turned on, only those serve landing zones that are associated with a player one winning percentage that is either significantly greater than or less than expected will be displayed. Note that ALL serves for a given court location are included when making the significance calculation, not just those currently being displayed.

allows users to define snapshots based on different resolution levels. For example, some users may have some snapshots with very coarse-gained shot bins defined to get an idea of basic shot patterns while having snapshots with fine-grained resolution in order to see specific shot trajectories. Design Principle DP5 (facilitate easy visual comparison of different data slices) is well supported since the user can jump from snapshot to snapshot with a single mouse click. Finally, Design Principle DP6 (help users find what is meaningful) is supported through the user of significance color coding applied to the snapshots.

5.11.3 Significant Serve Filtering

Having an effective serve is an essential part of a winning strategy for a professional tennis player. This is evidenced by the importance placed on breaking your opponent's serve. Most professional players win more games when they are serving than whey they are receiving. Therefore, in addition to providing significance color coding for pockets of points in the Examination Activity Panels and the Point Length Bar Chart, the significance calculations are also applied to serves in the form of a filter that will only pass those serves that are associated with a greater than expected or lower than expected player one point winning percentage. Figure 55 shows the results of turning on significant serve filtering. On the left side of the figure, we see many different serve landing zones for serves by both players - this is with the significant serve filtering turned off. On the right hand side of the figure we see the result of turning on the significant serve filter. This indicates that player one's most effective serves were up the middle on the ad court and either up the middle or out wide on the deuce court. Player two's most effective serves came by hitting his serves up the middle on both the ad and deuce court sides.

The significance filter is calculated for all possible x and y spatial resolution combinations. Since we have six levels along the x-axis (i.e., the width of the service box) and seven levels along the y-axis (i.e., the length of the service box), there are 42 combinations of spatial resolution. Within each combination, there will be an array of serve bins. The result in a total of 1,176 individual serve bins (albeit, many of which will have zero serves). The significant serve bins are identified by looking at the point outcomes for all serves landing in a specific bin and calculating the winning percentage for player one. If this percentage is either significantly greater than or less than the overall player one point winning average, the serve bin is tagged as being significant.

The significant serve filtering supports Design Principle DP6 (help users find what is meaningful) because it isolates just those serving locations that are either the most effective (or least effective) for the serving player. This type of feedback is easy to interpret: players should try to maximize hitting their serves to locations with a high likelihood of winning the point and minimize serving to locations that are more likely to result in their opponent winning the point. Coaches or analysts can look at the video for these serves to help identify why these serves are so effective.

5.12 Conclusion

In this chapter I first established a set of design principles to serve as a foundation for building effective visual analytics tools specific to analyzing tennis matches. A series of features of the Spatial TenniVis system that exemplify these design principles were then outlined. I then described in detail a set of interactive visualizations that provide a concrete realization of the design principles and features. This resulted in a system that provides tennis coaches and analysts with a powerful set of visual analytics tools that can support the investigative process.

The degree to which the goals of this research in aiding coaches and analysts in quickly finding insights into tennis matches was successful will be demonstrated in the next chapter. This chapter will include a case study designed to highlight the potential uses of the various components of the Spatial Tennivis system followed by a user study that validates these components and demonstrates how members of the target user population actually use them in practice.

CHAPTER 6: CASE STUDIES AND USER STUDY FOR SPATIAL TENNIVIS

In this chapter, I first showcase the efficacy of the visual analytics components of the Spatial TenniVis system through a series of case studies. I then validate the utility of Spatial TenniVis through a user study involving local area tennis teaching pros. The case studies demonstrate a variety of analysis tasks the system can support and the kinds of insights each specific visualization component offers, particularly when combined with other components to offer a multifaceted assessment of various parts of a tennis match. The user study validates the usefulness of Spatial TenniVis in aiding coaches and/or analysts in finding insights into players' strengths and weaknesses.

6.1 Case Studies

In this section, I outline three case studies, each designed to showcase a variety of analysis tasks users can conduct with the Spatial TenniVis system. These case studies will involve an analysis of a professional men's tennis match: the 2007 Australian Open Finals between Roger Federer and Fernando Gonzalez. Although Federer won in three straight sets (7-6, 6-4, 6-4), the scores suggest a fairly close match within each set, with the match really being decided by a first set tiebreaker and only one break of serve in each of the second and third sets. This closeness of this match serves as a good testbed for the Spatial TenniVis system in that, if insights can be detected in such a close match, then they should be even easier to detect in more lopsided matches.

The first case study, called *Getting the Big Picture*, showcases the Point Outcome Data Faders, the Match Visualization Semantic Point Selector, and the Point Length Bar Chart. This analysis focuses on how these components can be used in tandem to quickly get a big picture overview of the match. The second case study, called *Serves and Returns: Analyzing the Short Points*, showcases the Serve Analysis Examination Activity Panel, the Serve/Return Display Panel, and the Video Player. It also demonstrates the usefulness of the Significant Serve Filter. The third and final case study, called *Setting up Winning Shots: Analyzing the Long Points*, showcases primarily the Jellyfish Plots, as well as the Point Comparison Toggle Fader.

6.1.1 Case Study 1: Getting the Big Picture

Case study 1 demonstrates how the system provides a high level overview of a tennis match and allows users to identify potentially significant situations that warrant deeper investigation. As shown in the Match Visualization Semantic Point Selector included in Figure 56 (a), the score boxes at the upper left show that the match was fairly close but that player one (Roger Federer) won all three sets. This is easily seen by the green coloring of all three Set Selection Rectangles. In scanning the Game Selection Rectangles in the first set, we see that both players were holding serve until player two broke player one's serve. This was followed, however, by player one immediately breaking player two's serve on the next game. It is also noted in the figure that player two was up 40-15 and just needed one more point to win the first set but then allowed player one to come back and break his serve. This was followed by an easy service game by player one and then a very difficult hold of serve by player two, requiring 20 points to finally win his serve. The tie-break game

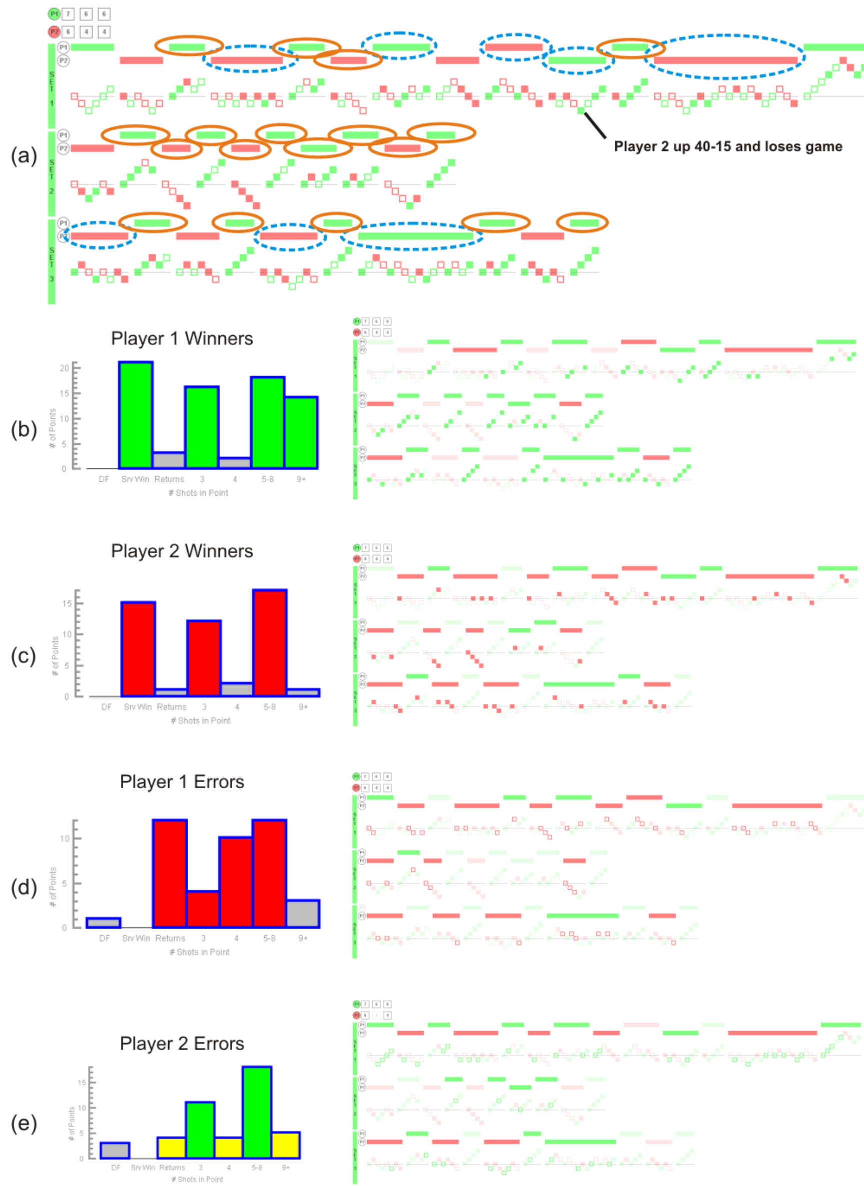


Figure 56: Components supporting Case Study 1. (a) Match Visualization Semantic Point Selector with the short game (circled in orange) and the long games (circled in blue with dotted lines). A key point in the match is also pointed out. (b) All the winning shots made by player one, as displayed by the Point Length Bar Chart and a smaller version of the Match Visualization Semantic Point Selector. Notice the higher percentage of winning shots in sets two and three vs. set one. (c) Winners made by player two in the match. More of these came from shorter points. Also note there are many fewer winners as compared with player one. (d) Errors made by player one in the match. Note that most of these came in the first set and many of them occurred on returns of serve. (e) Errors made by player two in the match. A large number of these came on points lasting 5-8 shots.

showed dominant play by player one, winning all but two of the nine points played.

The solid-line orange circles shown in Figure 56 (a) identify all of the short games in the match (i.e., games lasting four or five points). These represent games in which the winning player (usually the serving player) wins easily. The dotted-line blue circles identify all of the close games that went to deuce, indicating situations when the serving player is struggling to win his or her serve. An examination of these circled games reveals that, in the first set, both players had short games and both players struggled at times to hold serve, particularly in the 20 point game shown where player one broke player two's serve. Contrast this to the second set in which nearly all the games were short, including the only service break. In the third set, we see player one winning all of his service games easily while player two struggled nearly every time he served.

Finding 1: Player one won his serve easily while player two struggled to hold serve.

Furthering this case study, we look at how each player was winning or losing their points. We see in Figure 56 (b) that player one is winning on both the short points as well as the long points, and that most of the winners came in sets two and three. In Figure 56 (c) we see player two winning mostly on the shorter points and we note that, overall, player one has far more winners than player two. In Figure 56 (d) we see that player one made a lot more errors in set one as compared to sets two and three and that a considerable number of these came from returns of serve. Player two also had relatively more errors in the first set as compared to sets two and three, as shown in Figure 56 (e). It should be noted that both players made roughly the same number of errors.

Finding 2: Both players had similar numbers of errors, but player one had far more winners.

6.1.2 Case Study 2: Serves and Returns: Analyzing the Short Points

Case study 2 focuses on the serve and return games of both players and showcases the Serve Analysis and Return Analysis Examination Activity Panels, as well as the Serve/Return Display Panel (with the Significant Serve Filter turned on), as well as the Video Player. With the Significant Serve Filter Turned on, only those serve landing locations that have a significant higher than expected or lower than expected point winning percentage for player one are displayed. As Figure 57 (a) and (b) show, the most effective serve locations for both players was up the middle, although player one also had a lot of success serving out wide on the deuce side. This is useful feedback for both players who should focus on increasing their serves to these areas.

Finding 3: Player one should serve up the middle more, especially when serving to the ad court.

Looking at Figure 57 (c), we see that player one had a much higher percentage of winning points (i.e., 50% vs. 25%) when hitting a backhand return from the ad court. He also had almost three times as many backhand returns from this side as he did forehand returns.

Finding 4: Player two should have hit more serves to player one's forehand when serving to the ad court.

Figure 57 (d) shows that player one had more success on his second serves when he hit to player two's forehand instead of to his backhand. Despite this, player one hit three times more serves to the less-effective backhand side of player two than the forehand side. A quick examination of the nine points that featured these forehand side second serves (using the Video Player) revealed player two often being out of position and making weak returns that were easily exploited by player one. A screen shot of a particularly good second serve by player one up the middle on the ad side is shown in Figure 57 (e).

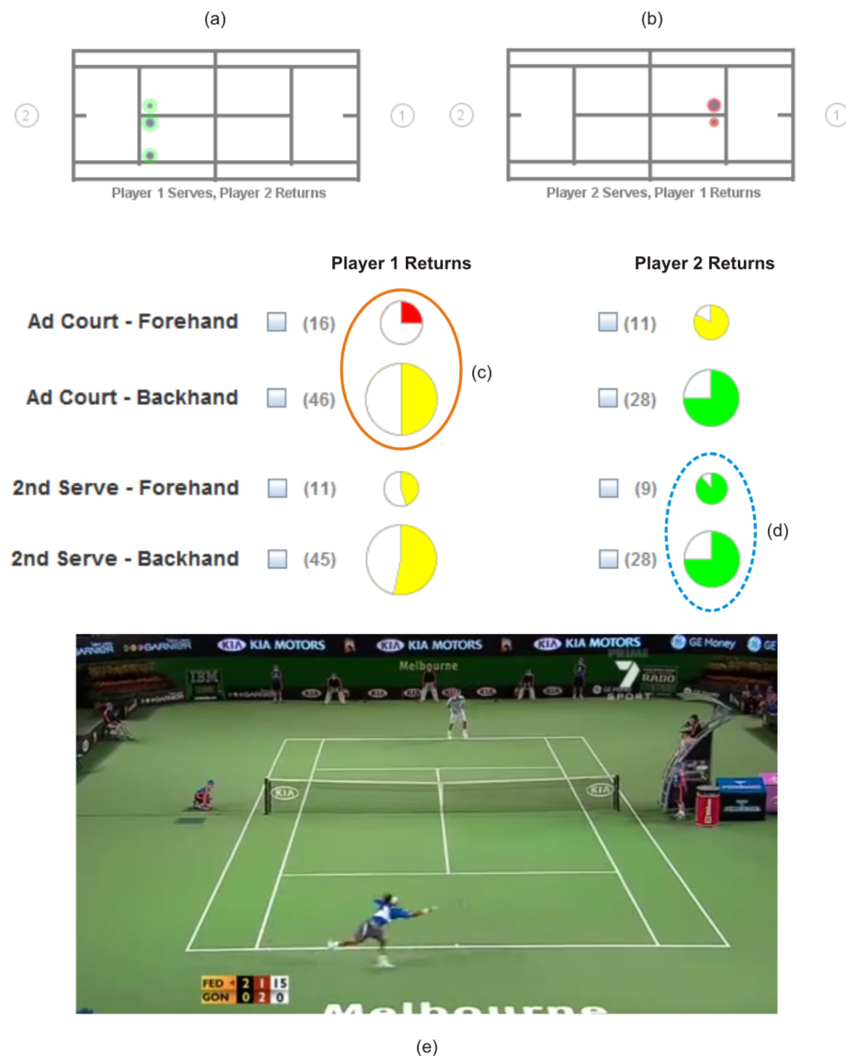


Figure 57: Components supporting Case Study 2. (a) Serve/Return Display Panel with the Significant Serve Filter turned on, showing player one's serves were most effective up the middle on both sides as well as out wide on the deuce side. (b) Serve/Return Display Panel with the Significant Serve Filter turned on, showing player two's serves were most effective up the middle on both sides, particularly on the ad side. (c) Solid-line orange circle indicating a much better backhand return of serve than forehand return of serve for player one on the ad court. The colored segment of the circles represent the percentage of points won by player one. (d) Dotted-line blue circle showing much more success for player one's second serves when he serves to his opponent's forehand side. (e) Screen shot from the Video Player showing an example of a good second serve by player one to player two's forehand.

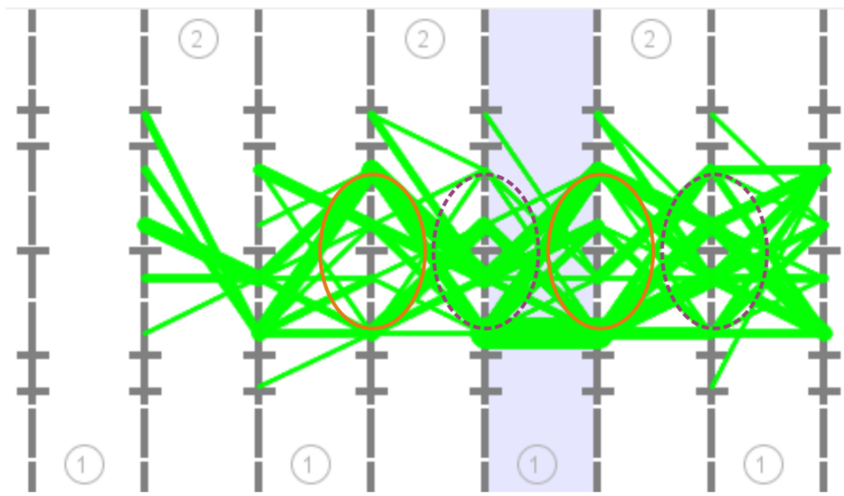
Finding 5: Player one should have served more second serves to player two's forehand.

6.1.3 Case Study 3: Setting up Winning Shots: Analyzing the Long Points

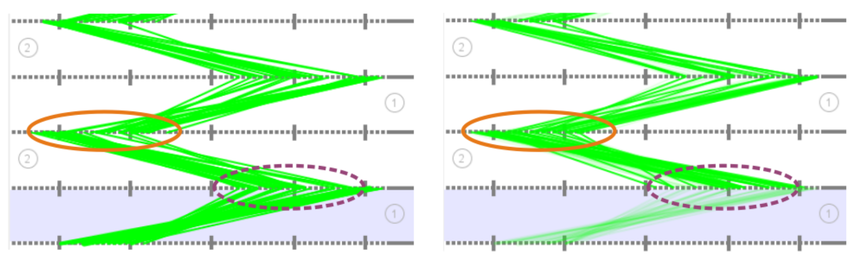
The third and final case study focuses on how players setup winning shot combinations on the longer points. It showcases primarily the Jellyfish Plots, as well as the spatial filtering capability of the Tennis Court Display Panel. Figure 58 (a) shows a Vertical Jellyfish Plot for all of the points won by plater one in the match that came from him hitting a winner. The last three shots by each player are displayed. One well-established pattern in tennis is to force your opponent wide and then hit to the open court. In this figure, we see player one's shots highlighted by the two solid-line orange circles and player two's shots highlighted by two dotted-line purple circles. One noticeable difference is that the solid-line orange circles are a lot less cluttered in the middle in comparison to the dotted-line purple circles, indicating that player one was hitting wider shots to his opponent while player two was hitting a lot more balls into the middle of the court.

Finding 6: Player one setup winning shots by forcing his opponent wide and making him hit balls into the middle.

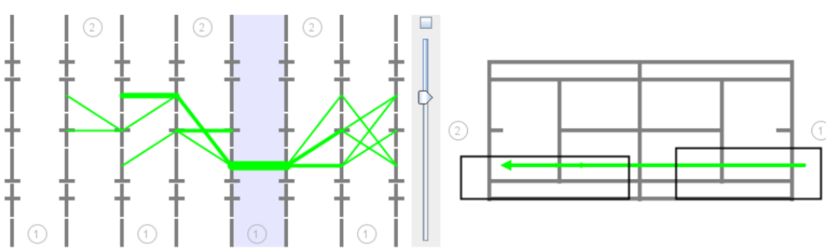
Figure 58 (b) attempts to demonstrate the utility of the Point Comparison Toggle Fader when looking at two sets of points in the Horizontal Jellyfish Plot (which shows the depth component of shots). In this case, winning shots by player one as well as winning shots by player two are BOTH displayed in green. The Point Comparison Toggle Fader allows a user to select two point outcomes (in this case, player one winners and player two winners) and the, using a slider toggle back and forth between these outcomes. The toggle fader will incrementally de-emphasize one set of points while simultaneously emphasizing the other. When done repeatedly, it gives the illusion of movement of the lines. The plot in the left



(a)



(b)



(c)

Figure 58: Components supporting Case Study 3. (a) Vertical Jellyfish Plot showing the left-right component of all the player one winning shots made during points lasting at least five shots. The last three shots by each player are displayed. The Solid-line orange circles show shots made by player one, most of which are hit fairly wide (i..e, not in the middle of the court). The dotted-line purple circles indicate shots made by player two, many of which were made to the center of the court. (b) Horizontal Jellyfish Plots depicting the depth component of the last three shots made by each player for points that were won via a winning shot by either player. The plot on the left represents just the player one winners while the plot on the right is the player two winners. Note that the average depth increases (i.e., moves to the right) for player two winners. (c) Example of using the Vertical Jellyfish Plot along with the Tennis Court Display Panel and spatial filtering to isolate a down-the-line shot by player one leading to making a winner on the next shot.

of Figure 58 (b) is emphasizing points won by player one, while the plot on the right-hand side emphasizes points won by player two. Using the toggle fader, it appears as though the lines are moving further to the right in the plot on the right hand side vs. the plot on the left hand (i.e., deeper into the court).

Finding 7: Short balls lead to winning shots by both players.

Figure 58 (c) showcases the use of the spatial filtering capability of the Tennis Court Display Panel used as a way to isolate points of interest found in the Vertical Jellyfish panel. In this case, I have isolated a set of five down-the-line shots made by player one that setup a point-ending winning shot on the next shot. In the entire match, there were 14 winners made by player one on points lasting nine or more shots (i.e., the long points). These five down-the-line shots occurred in just over a third of those winning points. Examining the video for these shots reveals that three of them are exemplary of player one's ability to run around his backhand and hit an "inside in" down the line shot that sets up the winner.

Finding 8: A down the line forehand from the backhand side is an effective way for player one to setup a winning shot.

6.2 User Study - Analyzing a Professional Men's Singles Match

The previous sections in this chapter showcased various components of the Spatial TenniVis system demonstrating their efficacy at discovering insights into a tennis match and generating meaningful findings. In this section I describe a user study involving six local-area tennis teaching pros using the Spatial TenniVis System to analyze a professional men's tennis match, the 2007 Australian Open Final between Roger Federer and Fernando Gonzales. Although Federer won this match in three straight sets, the first set was decided by a tie-breaker and the second and third sets were decided by a single service break.

6.2.1 Procedure

Six tennis teaching pros from the local area were recruited to participate in this user study. The criteria for inclusion was that they must be 18 years or older, have 20/20 vision or vision corrected to 20/20, have at least five years experience as a tennis coach or teaching professional, at least 10 years tennis playing experience, and have a USTA rating of 4.5 or higher. Using a 24 inch monitor, the Spatial TennisVis System was setup at the participant's work location (tennis clubhouse), except for one participant who agreed to come to the researcher's home office to conduct the study. After reading and signing an informed consent form that explained the user study, the participants were asked about their current practices in analyzing tennis matches. This was then followed by a 10-15 minute overview of the Spatial TenniVis components conducted by the researcher. During this overview, each component was explained and its use demonstrated. Following this, the participant was asked to analyze a professional men's tennis match (i.e., the 2007 Australian Open Final between Roger Federer and Fernando Gonzales).

Feedback from a pilot study using this system revealed that some of the components of the Spatial TenniVis system may be too complex to expect users to immediately grasp and "fly solo" using the system Therefore, a protocol in which the researcher provided guidance as needed in the operation of the system was adopted. This involved the researcher typically operating the system initially and then allowing the participant to operate it directly after seeing how the various tools work. In both cases, the participant drove the analysis and decided what specific lines of inquiry he or she wanted to pursue.

After 30-45 minutes of using the system to analyze the tennis match, participants were asked to read a series of statements centered around the usefulness and ease of understanding about various components of the system and asked to rate, using a five point Likert scale the degree to which they agreed or disagreed with each statement. A sixth choice of *Not Applicable* was also provided in cases where a participant may not had adequate interaction with a specific component in order to comment. Finally, participants were asked a series of open-ended questions asking them about which features of the system they like or disliked the most and how this system compares to their existing techniques for analyzing tennis matches. The results of the user study is presented next.

6.2.2 Results

Following the interaction with Spatial TenniVis, users were asked to evaluate several facets of the following Spatial TenniVis system:

- Examination Activity Panels
- Match Visualization Semantic Point Selector (called the Tennis Point Selector in the survey)
- Point Outcome Data Faders and Point Comparison Toggle Fader (called the Point Fader Controls and Toggle-Fader, respectively)
- Jellyfish Plots
- Serve/return and Tennis Court Display Panels
- Significant Serve Filter
- Point Length Bar Chart

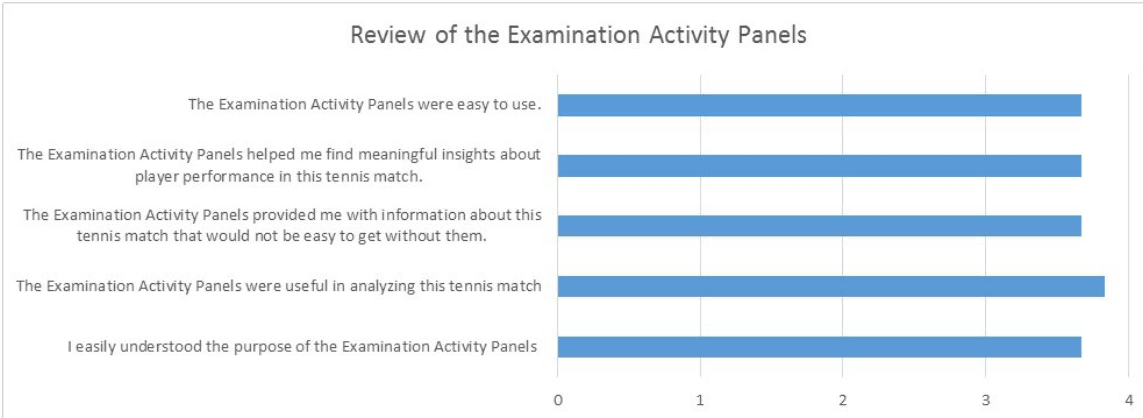


Figure 59: Results from the user review of the Examination Activity Panels. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

- Video Player

Results for each of these components will be summarized separately, followed by a summary that includes input from additional, open-ended questions as well as observations by the researcher.

6.2.2.1 Examination Activity Panels

Overall, participants rated the Examination Activity Panels as easy to use and understand and also rated them as useful in analyzing a tennis match. One participant indicated that they liked how it broke down the data in ways they were familiar with. Another indicated that the panel helped him see things visually. Although most of the participants looked at the information on this panel without using it to select points, one commented that they liked the pie charts because they were straightforward and simple and made selecting what they wanted to look at and compare much easier.

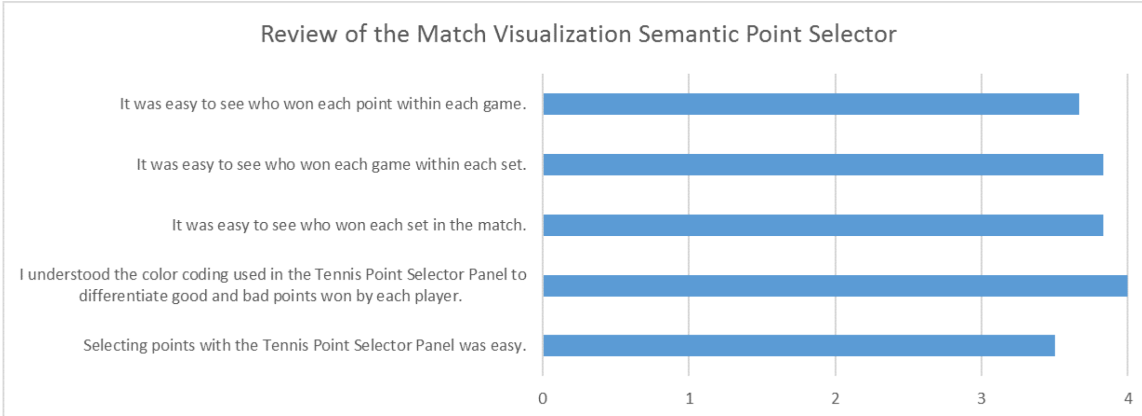


Figure 60: Results from the user review of the Match Visualization Semantic Point Selector. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

6.2.2.2 Match Visualization Semantic Point Selector

Overall, participants found the Match Visualization Semantic Point Selector easy to use and understand and rated it as useful in analyzing a tennis match. One participant indicated it helped them follow the momentum of the set while another commented they liked the color coding used. Several usage patterns seemed to emerge from observing how participants used this component. The first involved scanning the games and looking for anomalies, such as a service break or situations where one player is way up in a game and then allows the opponent to catch back up. Using this approach, participants skimmed over those situations that were expected (such as a player easily winning serve). The other approach was more linear in that participants looked at games and points in chronological order, trying to piece together a story of how the match evolved.

6.2.2.3 Point Outcome Data Faders and Point Comparison Toggle Fader

Both the Point Outcome Data Faders and the Point Comparison Toggle Fader were rated as useful by participants. One participant noted that they would probably need to use these

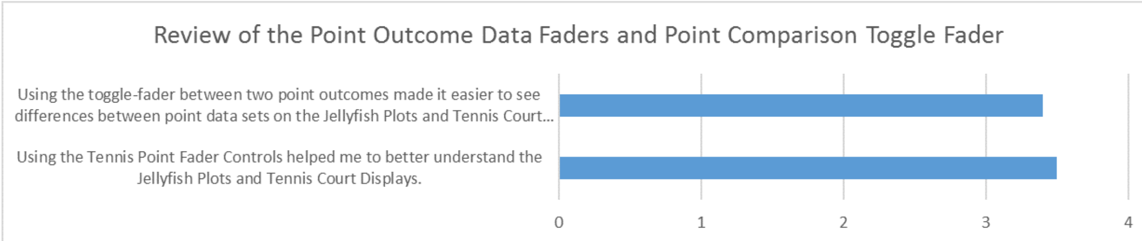


Figure 61: Results from the user review of the Point Outcome Data Faders and the Point Comparison Toggle Fader. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

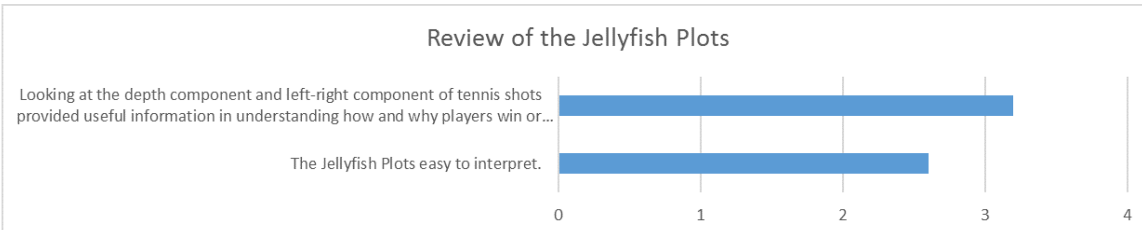


Figure 62: Results from the user review of the Jellyfish Plots. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

controls more to get more comfortable. It is noted that most participants did not use the fading capability very much and instead used the checkboxes to simply turn specific point outcome data sets on or off.

6.2.2.4 Jellyfish Plots

Compared to the other components, participants' comments and ratings indicated the Jellyfish Plots seemed to cause the most confusion. This was particularly true for the Vertical Jellyfish Plot, which displays the left-right component of shots. There are several likely explanations for this. First, unlike the Horizontal Jellyfish Plot, where the direction of the shot lines corresponds to the sides of the tennis court display, the shot lines on the Vertical Jellyfish Plot will, for player one's shots, actually be a mirror image of the corresponding shot when displayed on the Tennis Court Display Panel. This was necessary

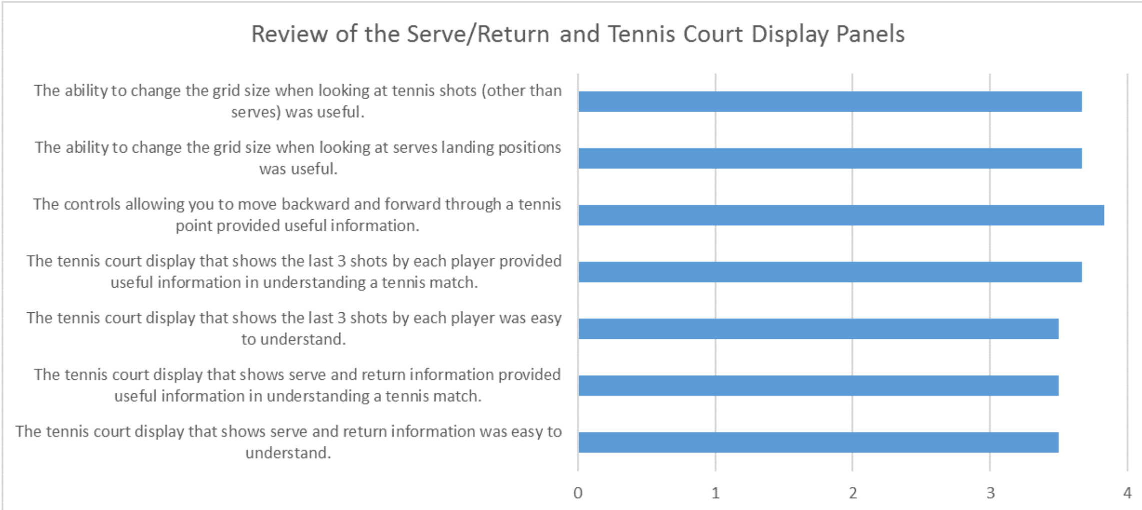


Figure 63: Results from the user review of the Serve/Return and Tennis Court Display Panels. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

in order to be able to connect the individual shots together. The second likely explanation for confusion over the Jellyfish Plots is the lack of experience using them. Several of the participants who gave the Jellyfish Plots low marks in terms of ease of interpretation also commented how being able to see this type of information (i.e., shots leading up to winners or error) would be useful. Another participant indicated that these plots may be more useful when looking at one point or one game at a time, rather than looking at all the data from an entire match all at once.

6.2.2.5 Serve/Return and Tennis Court Display Panels

Overall, participants rated the Serve/Return and Tennis Court Display Panels easy to understand and use and that they provided useful information. They also liked the idea that you can change spatial resolutions. One user commented that it allowed them to see correlations among shots while another indicated they liked being able to go from general patterns to then seeing the specific shot trajectories.

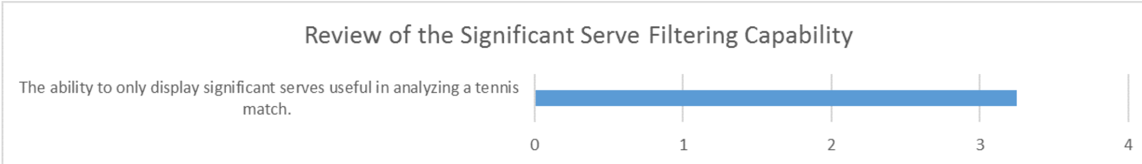


Figure 64: Results from the user review of the significant serve filtering capability. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

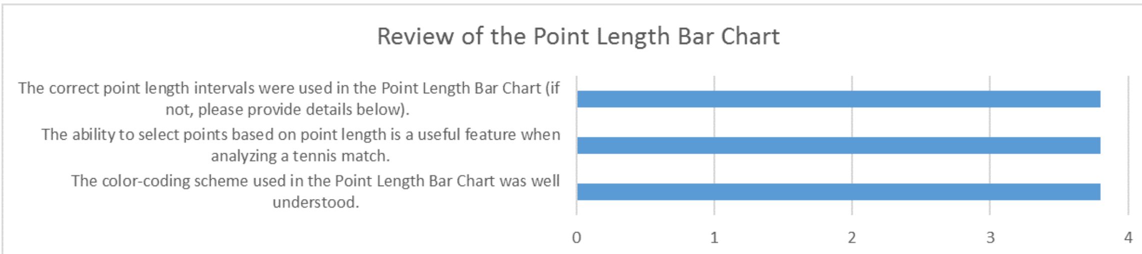


Figure 65: Results from the user review of the Point Length Bar Chart. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

6.2.2.6 Significant Serve Filtering

Although the overall rating for the significant serve filtering capability was generally pretty good (3.25 out of 4), one participant commented that it did not help them in their analysis. Another participant, found this capability to be interesting because they liked to see what leads to what.

6.2.2.7 Point Length Bar Chart

Participants indicated that the correct point-length intervals were used in the Point Length Bar Chart, the color-coding scheme was easy to understand, and the ability to filter points based on the number of shots was useful. Multiple participants commented that it was helpful in analyzing short points apart from longer points. This component was listed as one participant's most useful feature of the Spatial TenniVis System, indicating that it would

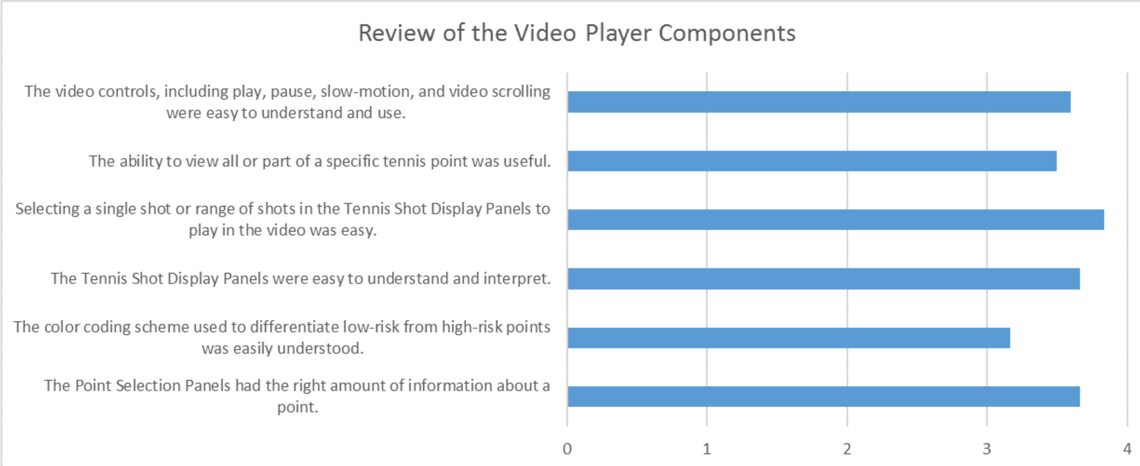


Figure 66: Results from the user review of the Video Player components, including the Point Selection Panels, Tennis Shot Display Panel, and the Video Player controls. The scale represents the degree to which participants agreed with each statement, ranging from Strongly Disagree (0) to Strongly Agree (4).

lead them to tell player one whether to be more aggressive or patient.

6.2.2.8 Video Player Components

Participants gave generally high ratings to all components of the Video Player, particularly the ability to select individual shots or a range of shots to view in the video player. The lowest marks (average = 3.17) were given to the color coding scheme used to set the background color of the Point Selection Panels. This may be due to the fact that the user had already selected a specific set of points to be viewed when launching the Video Player and therefore the main emphasis is in looking at all of them and not so much on needing additional visual analysis. The highest marks (average = 3.8) were given to the fairly straightforward video controls that included play, pause, slow-motion, and scrolling back and forth through a video sequence. One explanation for this may be that these controls were already very recognizable and well-understood by participants.

6.2.2.9 General Comments and Observations

Based on the follow-up questions and on observations of participants as they interacted with the Spatial TenniVis tool, there were a few general themes the emerged. First, half of the participants mentioned the Video Player as their most useful feature. This makes sense since this is where they can actually see confirmation of the insights they discovered while using the other visualization tools. One participant suggested adding a zoom feature allowing users to zoom in on a player to better see specifics in technique. Second, most of the participants rated the Vertical Jellyfish Plot (showing the left-right component of shots) as the least useful. I attribute this primarily to the alternating mirror image characteristic of the plot that made it difficult to map to the shots displayed in the Tennis Court Display Panel. Third, nearly all users rated this application as being superior to their existing match analysis methods, indicating that it gave them more detail and proving more specific facts. One participant thought this would be a good tool to help in evaluating players for recruiting purposes. Fourth, some of the improvements suggested included adding more on-the-spot statistics about selected points (such as showing percentage of points won, number of forehands and backhands, etc.) and also adding a score-based filter that would allow users to find specific game score situations, such as when a player is up 40-15.

Based on observing these participants interact with the system, it became clear different people take different approaches to analyzing matches. While most started with a high-level overview of the match using the Match Visualization Semantic Point Selector, how they proceeded from there differed from person to person. Some focused on specific aspects of the match, such as serving or returning, while others preferred just to look at the match game by game and point by point. Several interesting and memorable comments came out during the user study, including an observation by one participant that, with high level professional players, you are looking for what they did right (so you can encourage them to do it more often) while with lower level recreational players, your focus is more on seeing what they did wrong so you know what areas to work on. Another user commented that they have specific techniques they work on with their players and that they would be looking for evidence of how their players applied those techniques in actual matches. For example, a common complaint from many coaches is that their players sometimes go for too much, such as trying to hit the perfect down-the-line winner, and that having evidence to backup their claims that this strategy is not good would be beneficial.

6.2.3 Conclusions

The case study presented in this chapter showcased the visualization components of Spatial TenniVis and demonstrated how they can be used in a coordinated fashion to discover insights into a tennis match that would otherwise be difficult to get. Some of these, such as the Match Visualization Semantic Point Selector and the Examination Activity Panels presented results that were easy to learn and interpret, while others, such as the Jellyfish Plots, have a steeper learning curve and require additional experience to interpret.

The user study, conducted with six local area tennis teaching pros, verified the ability of Spatial TenniVis to provide rich insights into tennis matches that go beyond what is currently available from existing techniques. It also uncovered a few insights relevant to future enhancements of Spatial TenniVis. First, it is clear that different people like to analyze tennis matches in different ways. Therefore, the tool needs to be flexible enough to support multiple ways of approaching the data. This is particularly true when the analyst has personal knowledge of a player and therefore knows what to look for. Second, quick, easily interpretable summary statistics need to be readily available related to what the user is currently focused on. For example, in looking at a set of shots, having the ability to pop-up some basic statistics such as number of forehands vs. backhands, first vs. second serves, types of outcomes, etc. would be beneficial. Third, although the participants in this study did not actually create any Video Findings, when the capability to add notes to specific points in the Video Player and then name and save a collection of these annotated points so they can be brought up later, most of the participants indicated how valuable this would be in being able to share the information with their tennis players or in using it for recruiting purposes.

CHAPTER 7: SUMMARY AND FUTURE WORK

In this chapter, I summarize the research done as part of this dissertation and then briefly describe the future directions of my research into tennis analytics. This dissertation proposal described two main phases of research into analyzing tennis matches using visual analytic techniques. The first was to demonstrate the ability to gain meaningful insights into tennis matches using data feasible to collect by non-professional tennis players. Attention was then turned to gaining additional insights when spatial data *is* available. Although these approaches differed in terms of the types of insights they provide, the common thread is that both approaches are oriented toward the goal of player improvement by providing tools usable by teaching pros, tennis coaches, and the players themselves. Following this thread, future work will be aimed at providing more depth to the existing analytical tools developed in this dissertation as well as extending the breadth of the research to include coaching tools designed for the specific challenges of college tennis coaches.

For the depth component, three research trajectories are planned. The first involves adding additional analytical tools to the ones developed in this dissertation. Some of these have already been in the works, but were left out of the dissertation in order to keep the scope manageable. These include interactive visualizations focused on point length (i.e., the number of shots in a point), forehand vs. backhand analysis, and game score. In addition, tools aimed at better communicating the analysis results to players need to be developed. The second trajectory involves collaborating with other researchers in the field to integrate sensor-based data into the current analysis tools to get a more refined insight into stroke characteristics. Initial contact with several researchers has already been made. The third trajectory involves getting additional data sets and developing tools that look at a specific player's performance across multiple matches to identify key strengths and areas of improvement.

For the breadth component, I plan to work on tools designed to help college tennis coaches oversee inter-collegiate tennis matches. In NCAA college tennis matches, players will play six singles matches simultaneously. On a typical tennis team, there is one coach and an assistant coach. These coaches are allowed to provide instructions and feedback to their players during the match. This feedback can happen between points, but is typically given when players change sides every other game. The plan is to develop a set of tools that can be used in conjunction with the the tools developed as part of this dissertation and that provide a monitoring function designed to alert coaches when key player match characteristics fall above or below some predefined, player-specific thresholds. This would allow coaches to maximize their effectiveness by allowing them to concentrate their efforts on players that would benefit the most. In addition, I would also like to explore whether the visualizations in TenniVis can be applied to other sports such as table tennis and badminton, since they have structures similar to tennis.

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