CourtTime: Generating Actionable Insights into Tennis Matches Using Visual Analytics

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Abstract—Tennis players and coaches of all proficiency levels seek to understand and improve their play. Summary statistics alone are inadequate to provide the insights players need to improve their games. Spatio-temporal data capturing player and ball movements is likely to provide the actionable insights needed to identify player strengths, weaknesses, and strategies. To fully utilize this spatio-temporal data, we need to integrate it with domain-relevant context meta-data. In this paper, we propose CourtTime, a novel approach to perform data-driven visual analysis of individual tennis matches. Our visual approach introduces a novel visual metaphor, namely 1-D Space-Time Charts that enable the analysis of single points at a glance based on small multiples. We also employ user-driven sorting and clustering techniques and a layout technique that aligns the last few shots in a point to facilitate shot pattern discovery. We discuss the usefulness of CourtTime via an extensive case study and report on feedback from an amateur tennis player and three tennis coaches.

Index Terms—Visual analytics, tennis analysis, sports analytics, spatio-temporal analysis.

1 INTRODUCTION

The increasing availability of spatial data in sports analytics applications has provided analysts, coaches, players, and even fans with insights. For tennis in particular, 3D ball and player tracking has become commonplace at the larger professional tennis tournaments. This technology is also appearing at non-professional venues in the form of “smart courts” that provide players with instant feedback about shot statistics and point replays [1]. However, as noted by Kovalchik et al. [18], the sport of tennis has been slow in taking full advantage of the analytics offered by these technologies. Where these technologies are in place, they are often used as training devices where the focus is on developing and improving specific shots and to provide summary-level statistics over a wide range of shots. The shot-level data collected is often analyzed in relative isolation from other match-specific metadata, such as the current game score, who is serving, serve side, etc. To provide more effective, match-specific feedback to players and coaches about the players’ strengths and weaknesses and to identify strategies that work or strategies that need improvement, we believe a tighter integration between spatio-temporal ball and player tracking data and match metadata will yield deeper insights. For example, during the expert review, one of the tennis coaches we interviewed scanned through the depth-based 1-D Space-Time Charts looking for how many times each player came to the net and how effective they were. She commented that, if this was one of her players, she could see if her player was missing opportunities to come into the net or coming in when she shouldn’t and then coach her accordingly.

We propose CourtTime, a novel visual analytics approach that integrates spatial data with match context data, including score, service information, and point outcomes. Matches are won by winning games. Games are won by winning points. And points are won by hitting effective shots or patterns of shots or by making your opponent hit ineffective shots. Raw spatial data tracking ball and player movements are transformed into tennis shots, which are then classified into meaningful archetypes such as cross-court, down-the-line, or short ball. Using
a small multiple approach combined with agglomerative clustering techniques and user-defined similarity measures, we present novel, interactive visualizations designed to help players and coaches quickly find playing patterns that can provide insights into tennis matches not possible with traditional summary statistics techniques.

In particular, we make two contributions: First, a data extraction pipeline to integrate spatial data with match context information. We describe video annotation techniques designed to efficiently integrate match context information, like point outcome and score information with ball and player movement data. On this basis, we aggregate tracking data into tennis shots and then classify those shots into a set of shot archetypes used to generate meaningful features. Our second contribution is a visual, multi-faceted, multi-level approach for the analysis of annotated spatio-temporal tennis data. We propose a visual analytics system to help players and coaches efficiently find meaningful point and shot patterns that lead to specific outcomes (winning or losing a point) and produce actionable results. Our approach employs overview-and-detail coupled with small multiples, as well as filtering and aggregation techniques. For the visual representation of spatio-temporal point outcomes, we introduce 1-D Space-Time Charts, a minimalist aggregated view on depth and left/right movements of players on the tennis court.

We demonstrate the utility of key features of the system through a detailed use case where we analyze a professional men’s tennis match, finding actionable insights not possible with summary statistics alone. We also gather feedback from an amateur tennis player using one of his recent tennis matches and from an expert tennis teaching pro.

2 Related Work

CourtTime integrates raw spatial data with match context data for generating actionable insights into amateur tennis matches using visual analytics. Spatial data has been utilized in various sporting contexts, including basketball [8], soccer [2, 10, 14, 21, 39, 40], hockey [22], baseball [7, 19], American football [30], table tennis [38], and tennis [4, 5, 20, 24, 28, 34–37]. For tennis, the primary source of this data has come from ball and player tracking systems, such as HawkEye [20], LucentVision [24], and TennisSense [4, 5]. Recent research has exploited this data to provide insights into tennis matches. Following, we briefly discuss related work from tennis match analysis in general, including the data gathering and analysis process.

Before tennis data was collected at large, only summary information was available. However, researchers understood the tremendous potential of collecting ball and player movements to better understand and appreciate the sport. For example, Pingali et al. [23, 25] collected ball and player tracking data from professional tennis matches and introduced an interactive application with two main visualizations: player trajectory heat maps and ball landing position plots. Furthermore, they provided filtering capabilities for sets, games, and points. The final visualizations also served as an index into the broadcast video and allowed users to select individual points to be replayed.

Going one step further, Conaire et al. [4, 5] equipped an indoor club court with a network of cameras that enabled researchers to segment the video footage to perform player and ball tracking similar to the approach used by Pingali et al. [23] at professional arenas. Conaire et al. developed an interactive system, called TennisSense, to automatically extract key events from the match videos. 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, such as Match Point, which provided indexed videos, a rich set of filters, and enabled user-defined queries on an interactive court layout. Kelly et al. [16] enhanced the TennisSense system by adding a visualization and annotation tool that allowed coaches and 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. Notably missing from these filters, however, were any that were score-based, making this more of a training-oriented system.

In contrast, HawkEye data from professional tennis matches has recently been made available to a handful of researchers to analyze different aspects of tennis matches. For instance, Wei et al. [32, 33] used three years worth of tracking data to predict the likelihood of serves and discover player movement patterns. Wei et al. [34–36], furthermore, used data from just one grand slam tournament to predict the next shot based on characteristics of the incoming shot, such as speed, location and angle. Roulit et al. [28] used HawkEye data collected from 84 professional tennis tournaments from 2003-2008 to analyze serve performance. Whiteside and Reid [37] also used HawkEye data to analyze serves using data about impact location, speed, projection angles, landing location and relative player locations. While this research has provided several insights into player tendencies and shot prediction, its focus has been primarily on mining the spatial data while integration with non-spatial data has been of secondary importance.

Unlike spatial-driven analysis of tennis matches, research has also focused exclusively on non-spatial, context data to segment videos into meaningful units or to provide insights. Jin et al. [11, 12] proposed a treemap-like visualization of tennis matches called TennisViewer that exploited the hierarchical nature of tennis matches. Kijak et. al [17] and Coldhey et al. [3] used audio cues and/or visual cues to segment tennis videos into semantically meaningful chunks. More recently, Polk et al. [26] developed a system called TenniVis that relied on video captured from one consumer grade camera along with a simple data collection system that collected timestamps, score, and point outcome information. Using this information, they were able to develop a set of informationally rich glyphs to depict a tennis match and that also served as indexes into the corresponding video footage.

One common thread running through much of the existing tennis analytics research is the lack of tight integration of non-spatial, context data with the player and ball spatio-temporal data. Focus has typically been on using the detailed spatio-temporal data provided by tracking systems to generate insights into specific tennis shots, such as serves or in-point play in relative isolation from the context information. Recent work by Reno et al. [27] attempts to bridge this gap through the automatic annotation of context information, such as score, from the spatio-temporal data. However, the authors acknowledge the system is not perfect and cannot be reliably counted on to keep an accurate score. Furthermore, in amateur matches, players typically make their own line calls and occasionally make mistakes. These mistaken calls, however, are still counted; so even a “perfect” system may not be able to keep score consistently. Moreover, such an automated system is also not able to make judgments about point outcomes, such as whether a specific shot was a forced error or an unforced error. This leads to our approach that includes manual intervention in the data collection process to accurately record the score and make judgments about point outcomes. As for our visual analytics approach, we make use of small multiples [31], which allow us to encode time-specific situations on a per-point basis as well as at the shot level.

3 Design Requirements

In this paper, we propose CourtTime, a visual analytics system that we developed in close collaboration with tennis players and coaches. In this section, we outline the driving requirements behind the design choices we made in our visual analytics application. We developed these requirements through discussions with local area tennis teaching pros and coaches as part of our ongoing research in this area. Some of the key feedback we received included the tendency of coaches to want to start with familiar statistics to get a general picture of a match before moving into specific areas. When looking at one of their player’s matches, they sought out confirmation of what they already believed about the player’s strengths and weaknesses. They also appreciated the ability to see the underlying video, indicating a “seeing is believing” attitude. We derived the following list of requirements:

R1: Familiar overview first, details later. Following Schneiderman’s mantra of overview first, zoom and filter, then details on demand [29], users should start at an overview level that provides familiar statistics as a way to identify points of potential interest. Once they have identified these points, they should be able to drill-down into the detailed spatial data.
R2: Support multi-faceted, multi-level search. Coaches and analysts are often familiar with the specific strengths, weaknesses, and strategies of players. They need the capability to approach the data from a variety of viewpoints to look for specific situations or to support or confirm hypotheses. This is consistent with Keim's analysis first - show the important - zoom, filter, and analyze further - details on demand approach [15].

R3: Focus on point outcomes. Points are the building blocks from which players win matches. Players win points by hitting good shots (winners) or by their opponent making bad shots (errors). Therefore, the common thread running through the visualizations is that each incorporates point outcome.

R4: Facilitate finding patterns. Once users have drilled down to a specific set of points, they want to figure out the hows and why's to explain those points. The system should facilitate this process through visual cues and interaction techniques designed to make spatial patterns in the data more salient.

R5: Keep the human in the analysis loop. Users are not just passive consumers of the results provided. They want to be active participants in the knowledge discovery process by introducing their own assumptions and beliefs into the analysis loop to confirm or reject hypotheses.

R6: Provide ready access to the raw data. The various visualizations and interactions can provide substantial evidence to users that can explain how and why various points ended the way they did. However, a picture (or in this case, a video) is worth a thousand convincing visualizations. Coaches, analysts, and the players themselves will want to see the actual video clips in order to really accept the validity of the findings.

These requirements serve as the design rationale for the choices we made in developing our interactive visual analytics application.

4 DATA EXTRACTION PIPELINE

The collection of spatio-temporal information through ball and player tracking systems, such as HawkEye [20], has become commonplace at major professional tennis tournaments. These systems are typically employed for line calls challenges and for match enhancement for fans. Although some researchers are able to get access to this data to generate insights into shot selection, for example (e.g., [34], [36], [18]), the proprietary nature of this data makes it hard to come by. Therefore, as part of our semi-automated data collection, we annotated two tennis matches (one professional match and one amateur match). In this section, we briefly describe how we collected and annotated the data and the transformations we performed (using domain expertise) to make the data suitable for further analysis and visualization. We believe the pipeline we propose can be beneficial both to researchers who already have access to this type of data as well as those who must collect it themselves.

4.1 Data Collection

We collected spatio-temporal data from two tennis matches; one from a professional match broadcast on television, the other from an amateur match using a single consumer-level camera. In both cases, we were only concerned with getting the minimum amount of data needed to reasonably represent the 2-D shots in a tennis match, including the player and ball locations, along with match context data, such as who is serving, serve side, serve number, and the match score.

Although we had to collect our data by manually annotating videos (taking about 3 hours per hour of video), we recognize the ability of state-of-the-art systems to automatically collect ball and player tracking information. To efficiently integrate score progression and other context information with ball and player locations, we developed a finite state machine, shown in Figure 2, along with keyboard and mouse accelerators, to input this data. We also generated a homography using Java libraries available from OpenCV (Open Source Computer Vision Library).

4.2 Data Transformation

The data, at its simplest level, is a series of play events, where each play event is either a bounce event or a hit event. For each event, we include the 2-D location data of the ball and the players, along with the score context information and a time stamp (taken directly from the video). We also include summary point information, including who was serving, serve side, whether the point started from a first or second serve, the number of shots in the point, and the point outcome (winner, unforced error, etc.). To make this data more usable for the visual analytics application we propose in this paper, we perform a series of transformations, including data mirroring, transforming play events into shots, spatial data discretization, and feature generation.

Data mirroring. Each player's location data is transformed as needed to keep them on one half of the court.

Transforming play events into shots. Players win points by making good shots or forcing their opponent to make bad shots. Using the raw spatial data, we convert hit-bounce event pairs (or, less frequently, hit-hit event pairs) into shots for each player. Each shot is referenced by a sequence number and a reverse sequence number (i.e., number of shots until the last shot) and indicates the hitting player, the receiving player, and whether the shot was a forehand or a backhand. This indexing scheme is useful, since the last few shots in a point are likely to be key determinants of the point outcome. Location data for the players and the ball at the start of the shot, when the ball bounces (if it is not a volley), and at the end of the shot is also included, as is an indication of the shot being a serve or a volley.

Spatial data discretization. In our present and past discussions with tennis coaches and teaching professionals, we learned they typically divide the court into three sections horizontally (left, center, and right). In terms of depth, coaches looked for shots that originated from either behind the baseline, inside the baseline, or at the net and that landed either short (within the service box area) or deep (past the service box). This results in nine left-to-right one-dimensional shot patterns and six depth-based one-dimensional shot patterns and, when combined, 54 two-dimensional shot patterns. In order to indicate which pattern each shot belongs to, the location data is adjusted to the nearest anchor point. We also maintain the original location data, allowing the user to see more accurate shot data if desired.

Feature generation. In addition to the traditional features that coaches are interested in, such as who is serving, serve side, serve number, who won the point and how they won it, we included these additional features only possible with the integration of context data with the spatio-temporal data:

- **Wide serve.** Boolean value that is true if the returner hit the service return from outside the singles sidelines (i.e., was a wide serve).
- **Serve speed.** Indicates the approximate velocity of the serve. Values are calibrated separately for each player based on knowledge of their
abilities. Valid values include slow, medium, and fast.

- **Return of serve stroke side.** Indicates if the return was a backhand or forehand.
- **Point length.** Short points are defined as 0–4 shots, medium points as 5–8 shots, and long points as 9+ shots. These ranges were validated with multiple tennis coaches and teaching pros in a prior study.
- **Point differential.** The number of points within a game separating the players. The valid range for standard games is -3 to +3 and, for tie-break games, -6 to +6. Negative values indicate player one is behind and positive values indicate player one is ahead.
- **Game differential.** The number of games within the current set separating the two players. The valid range is -5 to +5.
- **Player dominant stroke side.** Indicates if a player hit more forehand shots than backhand shots in a point. Valid values are forehand, backhand, and none. One stroke side is considered dominant only if it accounted for at least 60% of the shots.
- **Player dominant playing depth.** Indicates if a player hit more shots from behind the baseline or inside the baseline. A depth is considered dominant only if at least 60% of the shots are made from that depth. Otherwise, this feature is set to neutral.
- **Shots from outside the sidelines.** Boolean feature indicating if a player hit any of their shots from outside the singles sidelines.
- **Short shots.** Boolean feature indicating if any of a player’s shots landed within their opponent’s service box.

These features were generated through interviews with local area teaching professionals and coaches and are by no means an exhaustive list of features. Our application can be easily extended to add whatever additional features are desired, as long as those features can each be represented by a relatively small number of discrete values so they can also be used as filters. The raw spatial data, transformed and combined with match context data to generate semantically meaningful features, serves as the foundation of our visual analytics system and helps us realize the high-level design requirements enumerated in Section 3.

## 5 VISUAL ANALYTICS APPLICATION

In this section, we describe the components of our visual analytics application designed to enable tennis players and coaches to analyze tennis matches from a variety of starting points. Users can start from a high-level overview and then drill-down into specific points or they can immediately filter the data to look for specific situations, such as first serves on the deuce side by player one. They can also use interactive clustering techniques at the point level and sorting techniques at the shot level to facilitate finding and investigating shot and player movement patterns. For each component, we indicate the relevant design requirements underpinning the design choices we made and how we applied those requirements to develop a specific design rationale.

There are three main components that make up our visual analytics system, each aimed at different levels of analytical granularity. In the following, we make use of the annotated screenshot of our system depicted in Figure 1 to indicate which area we refer to. The first is the **Point Selector** (D) that allows users to view summary-level statistics about a match as a way to identify points of interest for further analysis. The second is the **Point Analyzer** (C) that presents the user with several alternative small multiples views of every point in the match, including the ability to view points sequentially in a match or to cluster similar points using user-specific features. The third component is the **Shot Analyzer** (B) that visualizes the key shots in each point, including the serve, return, and the last three shots made in a point by each player (6 shots in total). This enables tennis players and analysts to dig deeper and look for patterns of play that lead to successful or unsuccessful point outcomes for the players.

Moreover, there is a fourth component, the **Video Player**, that allows users to cue up and play points and shots of interest. Clicking on a point or shot opens a new window with a video playing the selected situation.

### 5.1 Point Selector

The **Point Selector**, depicted in Figure 1 (D), provides a faceted filtering capability that allows users to drill-down to specific sets of points based on feature attribute values. The filter selection is then propagated to the **Point Analyzer** and **Shot Analyzer** for further analysis. The driving requirements behind the design of the **Point Selector** are **R1** (Familiar overview first, details later), **R2** (Support multi-faceted, multi-level search), **R3** (Focus on point outcomes), and **R5** (Keep the human in the analysis loop).

We exemplify **R1** by listing the most familiar point features first, including who is serving, which side they are serving from (deuce or ad), and serve number (first or second). We exemplify **R3** by displaying stacked bar charts showing the number of points won by each player for each feature attribute value. These are shown as a backdrop to the feature attribute values. Everything is displayed from the perspective of player one, with blue bars indicating points won by player one and red bars indicating points won by player two.

By default, all points are displayed. The more familiar features are followed by the remaining features that may provide meaningful insights into the kinds of situations in which a player is winning or losing more points than expected. For example, features like return stroke type may reveal a specific strength or weakness of a player that otherwise goes unnoticed with traditional summary statistics.

To support **R2** (Support multi-faceted, multi-level search) and **R5** (Keep the human in the analysis loop), we immediately apply the selected filters to the **Point Analyzer** and **Shot Analyzer** components and update the stacked bar charts in this component. We provide complete flexibility to users to iteratively select additional feature attribute values to filter on. For example, a user may select just player one first serves from the deuce side, revealing an unusually large number of points won by player one when player two hits a backhand return.

When analyzing a tennis match, a coach or analyst is either looking for confirmation of what they expect about a player (e.g., they have a strong serve and will win more points on first serves), or they are looking for anomalies where the win/loss point split is skewed in one direction or the other. These anomalies can reveal unexpected strengths by a player or indicate areas for improvement. For example, a coach may notice their player losing far more points on serves from the ad side as compared to the deuce side. This can be an indication that the player needs to work on returns from the ad side. Using the faceted filtering capability, coaches or analysts can discover and isolate points of interest.

### 5.2 Point Analyzer

The **Point Analyzer**, depicted in Figure 1 (B), displays 1-D Space-Time Charts of all of the points selected by the user in the **Point Selector** using one of three layout schemes (point sequence, similarity, or point length), each providing a distinctive perspective on the point data. Each chart is a small multiple that displays 1-D line charts of player and ball locations for all shots in a point. Users can display either the left/right dimension or the depth-based dimension and can also toggle the display of the player locations and the ball location. Each chart also serves as a toggle button that includes or excludes that point from the Shot Analyzer, allowing users to focus on specific subsets of points for a more detailed analysis. In this section, we first describe the design of the space-time charts, including the rationale and how it evolved, and then describe the clustering and ordering capability that aids players and coaches in finding patterns of interest.

#### 5.2.1 1-D Space-Time Charts

The design of the 1-D space-time charts is driven primarily by requirement **R4** (Facilitate finding patterns), but is also influenced by requirement **R3** (Focus on point outcomes) and **R5** (Keep the human in the analysis loop). To understand how these requirements influence the design, we describe how the design evolved to its current form. This is shown in Figure 3.

In our design, we use the tennis court diagram as a backdrop to provide a reference point for the location data. Players are represented as colored circles (blue for player one, red for player two). The stroke
side players hit a shot from (backhand or forehand) is very important, as one side tends to be weaker or less reliable than the other. Therefore, we encode forehand shots as solid circles and backhand shots as hollow circles. Ball landing locations are also encoded using colored circles that are noticeably smaller than the player circles. These were initially encoded using yellow, maintaining the metaphor of a tennis ball. However, we soon discovered this made it difficult to distinguish which player hit which shot. We therefore encoded each ball color based on who hit the ball. Following the Gestalt law of continuity, we connected the player locations using blue lines for player one, red lines for player two, and yellow lines for the ball landing locations.

Figure 3 (A) depicts an early design, where we kept each player on their side of the court. In this design, the time dimension starts from both the left and right sides and continues towards the middle of the court. The main problem with this design is the difficulty in directly comparing player locations at the same time due to the dual time axes. It also requires more space because each player’s location remains on their half of the court.

We then plotted both players as playing from the left side of the court, as shown in 3 (B). This allows us to use a single time axis, running from left to right. This type of plot requires flipping both the x- and y-coordinates of the player on the right to put them on the left (i.e., so the player’s relative court location is maintained). The main issue with this approach is that, when players are on opposite sides of the court (i.e., diagonal from one another), they appear co-located on this chart. Similarly, when players are on the same side of the court (i.e., near the same sideline), they are plotted in different locations on this chart, which appears counter-intuitive.

For the left/right dimension, we therefore settle on the design shown in Figure 3 (C). In this design, we only horizontally flip the right-side player’s location data, so that when players are on opposite sides of the court, that is also depicted in the chart. We then add additional context information to this chart to make it more meaningful, including the match score, a serve indicator, and a point outcome indicator.

To visualize the depth-based information, it comes natural to keep players on their respective side of the tennis court and run the time axis from top to bottom, with the ball and player locations being staggered along the time axis to indicate the order of shots. The challenge is to plot the ball location in a way to effectively differentiate short shots from deep shots. In our first attempt, shown in Figure 3 (D), we apply horizontal lines connecting the hitting player to the bounce location. The main issue with this approach is that the chart is overly dominated by the yellow lines and it is difficult to see the flow. We overcome this problem in our second attempt, shown in Figure 3 (E), by connecting the ball landing locations together, thus giving a better impression of the back and forth shots. However, this design is dominated by the ball trajectories, posing a challenge to effectively interpret the situation.

We finally settle on the design shown in Figure 3 (F), where we only connect the ball landing locations on the same side of the court. Although we lose the back and forth nature of the shots, this approach takes the focus from the specific ball trajectory to the overall situation and creates a distinct depth pattern for each player, thus making these patterns easier to see (supporting requirement R4). All of the same treatments applied to the left/right chart to include context information are incorporated here.

The final design and its encoding is explained in Figure 4. The top left is the resulting graphic if we try to display all the player movements and shots on one single tennis court. In addition to the problem of occlusions, there is no easy way to follow the progression of shots and movements in the point. We therefore split out the left/right component and depth component separately and then plot each one over time. The top right image depicts the left/right movements of the players and ball on the court and the bottom left image depicts the depth movements.

Context information is also encoded on the graphics. This includes score information (both in the current game and in the overall match), and the indication of the serving player using a red or blue vertical line on the left side of the chart. A solid line indicates the point started from a first serve, while a dashed line indicates it started from a second serve. Similarly, we use a color-coded line on the right side of the chart to indicate who won the point. A solid line means they won the point due to a “winner” shot, while a dashed line means they won the point due to an error by their opponent. This exemplifies our support for requirement R3.

Most tennis players have one stroke side (backhand or forehand) that is better than the other. One typical strategy is to try make your opponent hit shots from their weaker side while you try to make shots from your stronger side. Therefore, we incorporate stroke side information into the chart. A solid red or blue circle indicates a forehand stroke, while a hollow red or blue circle indicates a backhand stroke. For the ball landing locations, we use smaller-diameter circles that share the same color as the player that hit the ball. This color coding is essential since users have the option of only plotting ball locations.

We recognize that the design choices we have made for the 1-D Space-Time Charts involve trade-offs between temporal alignment and spatial alignment, with an emphasis on maintaining temporal alignment in order to facilitate the direct, dynamic comparison of player positions (i.e., hitting diagonally across the court to one another or down-the-line). Of course, spatial fidelity is maintained in the Shot Analyzer, described in section 5.3. To help minimize clutter, the user can toggle off the player and/or ball visualization components, allowing them to
5.2.2 Point Ordering and Clustering

The Point Analyzer is designed to support three distinct analytical perspectives on the data: sequential and similarity-based. The user can switch between perspectives using a drop-down list box. The sequential perspective provides the user with a familiar overview of the entire match in the order the points were played and is in direct support of design requirement R1 (Familiar overview first, details later). Each row contains one game’s worth of data and the background color of the row corresponds to who won the game (i.e., blue for player one and red for player two, see 1 (B)). A game where one player is serving but the other player wins is known as a service break and is considered an important event in tennis. To emphasize this event, service breaks are surrounded with a dark border to make them stand out. The small multiples themselves, separated into game-rows, also visually mimic a bar chart, making it easy to distinguish long games, where players were struggling, from short games, easily won by a player.

The similarity-based perspective, driven by design requirement R4 (Facilitate finding patterns), helps users find patterns in the one-dimensional space-time charts by applying simple but effective ordering and clustering capabilities. We also support R5 (Keep the human in the analysis loop) by allowing users to specify which features to consider when calculating similarity measures. These include all of the features listed in Section 4.2.

To order the points based on user-defined similarity measures, we compute the pairwise distance between each pair of points A and B using the Gower Metric [9]. The Gower Metric can be applied to compute the similarity between two feature vectors that comprise different data types, as is the case for the tennis data. Gower’s idea to compute the similarity is to feature scale all dimension-wise similarity values and then compute the weighted average.

The Gower Metric is a straight-forward, easily understood method to compute the distance between a pair of points. Its simplicity and effectiveness make it suitable to communicate results to end users who may not have a background in statistics. CourtTime includes a panel where the user can select the features affecting ordering. For simplicity, we assume all features are weighted equally. For nominal and binary features, similarity is zero if the values are the same, and one otherwise. For discrete, numerical values, the difference is computed and normalized in the range zero to one. We then apply a dimensionality reduction technique to perform the ordering. We exclude non-linear techniques, because they create local orderings that outline similarity by means of local clusters. A meaningful ordering requires a global view on the data. The best-known linear techniques are PCA [13] and MDS [6]. Numerical attributes are a must-have for applying PCA, but MDS computes pairwise distances between data records, which are preserved in a planar layout. The merit of applying MDS to determine an ordering is that pairwise distances can be computed between any data records as long as a respective distance metric is defined. The MDS represents a perfect match to the Gower metric, which unifies several of the features available for defining similarity in points ordered close together.

This user-based ordering scheme enables users to see if there are any spatio-temporal patterns that can account for the similarity in points ordered close together.

The interplay between the Point Selector and the Point Analyzer enables users to identify subsets of points they are interested in (the what). The Point Analyzer, depicted in Figure 1 (C), helps them see the why by displaying individual shots for the points selected in the Point Analyzer. Each row displays shots from a single point. From left to right, we display the serve and the return, followed by the last three shots hit by each player. Except for the serves and returns, the shots are always aligned such that all of the shots in a single column belong to one player, making it easier to compare shots across points. In our discussions with tennis teaching pros and coaches, we verified that effective serves and returns are key elements of understanding point outcomes. Furthermore, if there are any multi-shot patterns associated with winning or losing a point, these are likely to be manifested in the last few shots of a point.

The main design requirements underpinning this component are R4 (Facilitate finding patterns) and R5 (Keep the human in the analysis loop). There are a number of novel design features that help achieve these requirements, including shot encoding, dimension selection with spatial simplification, shot sequence alignment, and ordering and clustering facilitated by user-specified shot similarity features.

5.3 Shot Analyzer

The interplay between the Point Selector and the Point Analyzer enables users to identify subsets of points they are interested in (the what). The Shoot Analyzer, depicted in Figure 1 (C), helps them see the why by displaying individual shots for the points selected in the Point Analyzer. Each row displays shots from a single point. From left to right, we display the serve and the return, followed by the last three shots hit by each player. Except for the serves and returns, the shots are always aligned such that all of the shots in a single column belong to one player, making it easier to compare shots across points. In our discussions with tennis teaching pros and coaches, we verified that effective serves and returns are key elements of understanding point outcomes. Furthermore, if there are any multi-shot patterns associated with winning or losing a point, these are likely to be manifested in the last few shots of a point.

The main design requirements underpinning this component are R4 (Facilitate finding patterns) and R5 (Keep the human in the analysis loop). There are a number of novel design features that help achieve these requirements, including shot encoding, dimension selection with spatial simplification, shot sequence alignment, and ordering and clustering facilitated by user-specified shot similarity features.

5.3.1 Shot Encoding

Points are won by either making good shots or forcing your opponent to make bad shots. To help coaches and analysts understand why one player or the other won a specific point, we encode player and ball location data along with other context information for key shots within each point (i.e., the serve, return, and last 3 shots by each player). We use the same encoding scheme we employed in the Point Analyzer. For shots other than the serve, we encode the location of the players, the ball bounce location, the shot trajectory, and whether the shot was a forehand or backhand. For the serve, we encode a first serve using a solid trajectory line and a second serve using a dashed trajectory line. For shots, we use solid circles to represent forehands and hollow circles to represent backhands.

Furthermore, our interviews with local area teaching pros and coaches shows that they typically distinguish the side-to-side aspect of the game from the depth-based components when discussing strategies. To facilitate this perspective, we provide them the option of viewing shot data from a single dimension (left/right or depth) or in both dimensions simultaneously. To emphasize visual shot patterns, we allow users to apply a spatial discretization scheme (described in Section 4.2) to the location data. For the left/right dimension, this will result in only nine possible shot trajectories. For the depth dimension, this is even simpler with only six possible shot trajectories. Once a particular pattern has been found, users can toggle back to the raw data view in order to display the actual location data, supporting R6 (Provide ready access to the raw data).

5.3.2 Shot Ordering and Clustering

To further help players and coaches find meaningful patterns in the shot data, we apply an ordering and clustering scheme similar to the Point Analyzer. The key difference lies in the features available for defining similarity and that these features are applied to individual shots. For shots other than the serve, the available features include each player’s x- and y-location, the x- and y-location of the ball, and whether a shot is a forehand or backhand. For serves, features include server x-location, receiver x- and y-location, ball x- and y-location, serve number, serve speed, and serve side (deuce or ad).

To apply the ordering scheme, the user finds a point containing one or more shots of interest and selects it as the baseline. This point is then
we present a case study where the tool is used to analyze a professional tennis match. This same match was also used to gather feedback from a high-level, amateur tennis player with whom we analyzed a recent match he played against Roger Federer and Fernando Gonzalez (won by Federer 7-6, 6-4, 6-4). The basic summary statistics from this match revealed that Federer won 56% of the overall points compared to Gonzalez’ 44%. Federer also won 80% of the points he was serving, while Gonzalez only won 60% of his service points. While this information certainly indicates Federer had a particularly good service game, it provides little in the way of actionable insights these players could use to evaluate their relative strengths or weaknesses or how these points were won or lost.

To start our analysis of this match, we first get an overall picture of how the match unfolded (supporting R1). We do this by selecting the Point Sequence ordering option and then zoom out the Point Analyzer to display the entire match. Although we cannot see details from individual games, we can see several very long games and that these happened when player two (Gonzalez) was serving. We also easily see the back-to-back service breaks in the first set and the single break of serve in each of the other two sets. One particularly long game in the third set included some of the longest points in the match and resulted in a service break for player one (Federer), as seen in Figure 7 (A).

After selecting to view the left/right dimension for the 1-D Space-Time Charts, we scan the points to see if there are any general playing tendencies for the players, such as how they construct their points or where they make most of their shots from. In doing so, we notice that both players are directing most of their shots to their opponent’s backhand side (considered the weaker side). We note a few exemplary instances of these type of weak-side cross-court battles in Figure 7 (B). Experienced tennis players also know the value of moving your opponent from side and so we also look for these patterns and find many, several of which are shown in Figure 7 (B). We switch to the depth-based analysis perspective to see how aggressively players attack short balls by coming into the net. We note that this is done far more often by player one and with great success. We show several examples of this in Figure 7 (B). This supports R2 and R4.

We dig deeper to understand how player one is able to create circumstances where he can attack short balls by coming to the net. We set the Point Selector filters to only display points won by player one by him hitting a winner (as opposed to the opponent making an unforced error). The filters demonstrate the support for R2 and R3. The last column of shots then correspond to the winning shots made by player one. We scan down this column across points and then find an example of him hitting a winning shot from near the net. We select this point as the baseline, causing it to come to the top of the list. For the winning shot, we then select player one’s y-location (depth component) and the ball’s x-location (left/right component) as the similarity measure used to cluster the points. In scanning the reordered list, we notice several instances where, two shots prior to the final winning shot, player one is attacking player two’s backhand, causing player two to hit a short ball back to him, allowing him to hit a shot that will then setup the subsequent winning shot. We bring this into more focus by selecting the forehand/backhand similarity measure on player two’s second to last shot. This is shown in Figure 7 (D).

Fig. 5. The inset shows tennis court graphics that, in the application, appear above each column in the Shot Analyzer and that allow users to select shot attributes used to sort similar points. They indicate that player two’s and the ball’s x-coordinate (left/right dimension) were selected for the last shot in the point by player two and player two’s y-coordinate (depth dimension) and player one’s and the ball’s x- and y-coordinates were selected for player one’s last shot. The last shots in the first point listed here (highlighted in blue) serve as the baseline used to find similar points. The similarity between the last two shots of all four of these points illustrates the effect. Reverse Shot Index (RSI) indicates how many more shots until the last shot by a player. so RSI 0 here indicates the last shot by each player.

Fig. 6. Color-codings for hierarchical clusters. Width of each bar corresponds to number of points in cluster.
6.2 Feedback from an Amateur Tennis Player

To see if our approach can help tennis players find actionable insights into their matches that are not normally available, we recorded a tennis match between two advanced-level amateur players, manually collected the spatial data, annotated it with context information, and then loaded it into our prototype for analysis. One of the authors has significant domain expertise and served in the analyst role by using the prototype to analyze this match and develop an initial report for the player losing the match. We met with the player and presented the results as a way to describe the application and then worked with the player to perform a player-driven ad-hoc analysis. The match we used was unusual in that the player who has won the vast majority of past match-ups with this opponent actually lost in the match we recorded, making it fruitful for the losing player to understand “what went wrong?”.

The main findings discovered through use of the application were that 1) player one won points by hitting winners, but allowed his opponent to win points by making too many unforced errors; 2) player one was not serving well, particularly on the ad court side when serving to player two’s backhand; 3) player one’s backhand returns of serve on the ad side was very vulnerable; and 4) player two was far more effective at coming to the net than player one. These findings were discovered through the combined use of the stacked bar chart point filters in the Point Selector (see Figure 1 (D)) and the 1-D Space-Time Charts displayed in the Point Analyzer (see Figure 1 (B)). Findings 3 and 4, in particular, are examples of actionable insights only possible with the integration of spatial data with context information.

During the review, the player indicated surprise at several of the findings while acknowledging that some of the findings were expected. Specifically, he knew that he had a weakness in service returns on the ad side to his backhand side and that it is a part of his game he needs to improve. He was most surprised by the opponent’s large winning percentage when the opponent came to the net, stating “I try to basically bring them [to the net] to my trap and, does that work? Is it something that is actually working or is it only 50%?”. The player said he liked the idea of being able to setup “what if” scenarios in order to see how effective a specific strategy might be. This indicates support for R5. He also liked the ability to examine short points vs. long points as they seem to have a different dynamic to them (i.e., looking for the quick finishing shot vs. patiently waiting for your opponent to make a mistake). In reviewing player two’s service games, the player wanted to see the difference between long and short points. So, we ordered the points in the Point Analyzer by point length, bringing the short points to the top in both the Point Analyzer and Shot Analyzer. Scrolling through the points, the player noticed a number of his down-the-line returns from the deuce side. Two points seemed to be identical, where he hit a down-the-line return to his opponent’s backhand and then rushed the net for a put-away. We launched the video for these two points so he could see this shot pattern in action. In summarizing his review of the application, the player mentioned the value of being able to get right to specific points in the match to see the actual video footage (supporting R6). This is consistent with finding from our previous research with coaches and teaching pros.

6.3 Feedback from Tennis Coaches

To determine if the CourtTime application indeed provided coaches and analysts with insights into tennis matches not available from summary level statistics, we sought feedback from three experts - an ex assistant women’s tennis coach from a mid-size university and two tennis teaching pros (who also coach). We used a paired analysis approach with one of the authors serving as the visual analytics expert.
(VAE) and the coach or teaching pro serving as the hands-on subject matter expert (SME). Although the VAE initially “drove” the system, the SMEs typically took over the reins once all of the components were demonstrated. After first reviewing the main components of the application and explaining the 1-D Space Time Charts, we analyzed the same professional men’s tennis match used in the case study.

6.3.1 Procedure
For each of our SMEs, our analysis followed a similar path, with the complete session taking 90-120 minutes. We started out by focusing on the Point Analyzer using the point sequence ordering, with the left-right perspective for the 1-D Space-Time Charts selected by default. This view, shown in Figure 7 (A), allowed the users to see the high-level flow of the match, particularly when the view was zoomed out, allowing nearly the entire match to be displayed on the screen. We then switched to the depth-based perspective.

After scanning through points looking for specific playing patterns or tendencies, we switched to the similarity ordering and reviewed the 19 attributes available for inclusion in the similarity scoring. A few simple attributes, like server ID and point outcome, were selected to demonstrate how the clustering works and then the SME could select their own attributes of interest.

The next step in the paired analysis process was to apply various point filters in the Point Selector (see Figure 1 (D)) and then use this in conjunction with the Shot Analyzer (see Figure 1 (C)) to look for shot patterns or tendencies in the filtered points. A point of interest, such as a point ended by player one hitting a winner from the net, was selected as a baseline and then the specific characteristics of this final shot were selected, such as player one’s depth coordinate and the left/right coordinate of the ball landing position. This sorted the remaining points by their similarity to this final shot and the SME could look for any patterns that lead to this outcome. They could then select other points as baselines and set the similarity criteria.

In the paired analysis process, we audio recorded the SMEs and the amateur tennis player and took written notes about key insights or comments made by the SMEs. We then conducted a structured interview in which each SME was asked a series of questions and given the opportunity to provide additional comments about issues they had with the system or additional features they would like to see.

6.3.2 Results
The three teaching pros/coach SMEs indicated they could learn to use the system without the aid of a visualization expert. However, the tennis player felt this system would be beyond the capabilities of the average tennis player. The biggest learning curves came from interpreting the left/right perspective of the 1-D Space-Time Charts and from the complexity inherent in the large number of analysis options.

When asked about how they have analyzed tennis matches in the past, one SME indicated he used simple charting forms that only captured basic information like if the point ended by a winner or an error, serve percentages, first serves, etc. The others relied more on ad hoc notes taken during the match or when watching a video replay. All SMEs indicated that this system gives them a far more in-depth analysis where positional information (like playing behind the baseline or inside the baseline) can be associated with point outcomes (winners and errors).

When asked about what insights they garnered from the system and how these insights would help them coach, two SMEs indicated the benefit of seeing how a player progresses throughout the match. This was clear when comparing the first set, filled with unforced errors to the second set where winners were much more prevalent. All of the teaching/coaching SMEs commented on the benefit of being able to break down individual points as a way to help their players see what they are doing right and what they are doing wrong. The tennis coach commented that her goal as a coach is to get players from A to B to C to D and that this system could help identify the weaknesses and (in future matches) verify those weaknesses have been alleviated.

We asked each of the SMEs if they would incorporate this system into their analytical processes if it was available. All agreed they would include it. One indicated it could help coaches substantiate their hunches but also show them new insights. The three SMEs that coach or train players commented how this system could provide teachable moments and how sometimes players are unaware of what they are doing until you can show them. The tennis player indicated he would only use this type of system for his more important matches.

6.3.3 Discussion
Several key findings resulted from observing the users interacting with the system and from the structured interviews. First, the point sequence view in the Point Analyzer provided a useful, high-level overview of the match and served as good starting point for the analysis. Second, users struggled with how to interpret the left/right 1-D Space-Time Charts.

In our design, we traded off spatial consistency in order to have a single time axis and for compactness. This finding suggests this trade-off may not have been justified. Third, many of the comments we received from our participants centered around the theme of being able to break down the details of a point and to provide concrete evidence to players. They indicated that their players are often unaware of how they are playing or the kinds of mistakes they are making. The ability to show them specific examples adds credence to their coaching guidance.

In addition to the findings related to existing components in the system, we also identified one additional key finding: the need to analyze multiple matches. Several of the SMEs commented that, while analyzing a single match was useful, the ability to analyze a specific player against different opponents could potentially reveal more insights about a player’s strategies, strengths, and weaknesses since players adjust their games to their opponents.

7 Conclusion
We presented CourtTime, an interactive visual analytics application that integrates spatial data with match context data to provide actionable tennis match insights not possible with summary-level data alone. We discussed challenges associated with integrating the spatial and context data and described a state-machine approach and other techniques to make this integration more efficient. We described a visual approach for the analysis of the annotated tennis data, enabling players, coaches, and analysts to infuse their domain knowledge into the pattern detection process. We also validated the utility of our approach through a case study and an expert review from three experienced tennis teaching pros and a high-level amateur player.

Although the application was tailored specifically to analyze tennis matches, there are design aspects relevant to other sports analytics applications and beyond. The 1-D Space-Time Charts could potentially be applied to any context involving 2-D movement of people or objects within a defined space over time. For example, in soccer, a 1-D Space-Time Chart charting the depth of all players and the ball over the course of a match would easily show overall field dominance, counter-attacks, and perhaps player misalignments - particularly if these charts were annotated with relevant context data. The spatial discretization approach we used to simplify higher-resolution spatial data into a relatively small set of domain-relevant spatial patterns could be applied in other domains to help in visually detecting spatial patterns.

Limitations and future work. Since we only analyzed two tennis matches (due to the difficulty of manual data collection), we must acknowledge the limited scope of our results. However, the application is designed to give coaches the ability to find actionable insights, such as “my player has trouble with wide serves on the ad side of the court”, from individual tennis matches to share with their players, much like the “Monday morning quarterback” sessions of football coaches. In the future, we plan to enhance the system to visualize data from multiple matches, allowing users to identify more pervasive trends and insights.

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