Through Space and Time: Spatio-Temporal Visualization of MOBA Matches

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Abstract. With data about in-game behavior becoming more easily accessible, data-driven tools and websites that allow players to review their performance have emerged. Among the many different visualizations used as part of these systems, spatio-temporal visualizations which do not rely on animations have received little attention. In this paper, we explore if the established space-time cube (STC) visualization is a suitable means for simultaneously conveying information about space and time to players. Towards this end, we have created a STC visualization for reviewing matches, focusing on *Heroes of the Storm* as a use case, and conducted a study among 30 Multiplayer Online Battle Arena (MOBA) players to establish how successfully various tasks can be performed and how this kind of 3D representation is received. Our results indicate that such a visualization, despite its complexity, can be usefully applied for match analysis if the design and interaction possibilities are well chosen.

Keywords: Gameplay visualization · Space-time cube · Replay analysis

1 Introduction

Understanding player behaviour in video games through data-driven methods often requires suitable visualizations to facilitate sense-making of the collected data. As such, various visual representations of behavioral in-game data have been proposed to date [53]. Initially, such gameplay visualizations were primarily targeting game developers to assist in games user research activities. However, over time efforts have also been directed towards creating visualizations for players to visually review their own gameplay and those of others to foster skill development [55]. This development has been further spurred by the increased popularity of competitive gaming and esports. This, in turn, has spawned a range of community-driven efforts directed towards visualizing in-game data and performance as evidenced by a variety of websites and tools [30] and increased academic discourse on this subject (e.g., [30,36,55]).

However, expressive gameplay visualizations are not straightforward to design as play is complex, regularly resulting in spatio-temporal datasets (e.g., movement over time) that are difficult to visualize. Consequently, visualizations of in-game data often resort to presenting a temporal (e.g., [2,43]) or spatial slice (e.g., [14,54]) of the data to reduce visual complexity which, however, can be insufficient for analyzing spatio-temporal patterns (cf. [18]). Current spatio-temporal gameplay visualizations that show both dimensions simultaneously (e.g., [1,36]; see Sect. 2) primarily rely on multiple views using different visualization types or on animations. As such they may impose additional cognitive load, e.g., for context switching and drawing comparisons between the views or frames (cf. [23,26]) or require extra time to run through the animation.

In this paper, we propose and explore the usefulness of a space-time cube (STC) representation of player movement and event data to avoid using animations to communicate temporal information. In a STC two axis form the spatial space and the third axis represents the time. Originally proposed by Hägerstrand [22] in 1970, the concept has since then been applied in a variety of domains as it enables a *clear observation of various features in time and space* [17]. In addition, various studies have confirmed analytic benefits of the STC compared to other representations (e.g., [5,35,37]). As such we consider a STC to also be an appropriate visualization of in-game data to observe spatio-temporal gameplay patterns. As use case we employ a STC to help players review the course of multiplayer online battle arena (MOBA) matches, specifically from *Heroes of the Storm* [8] (*HotS*). Towards this end, an interactive online tool that presents match data extracted from replay files has been developed.

However, while having several benefits, STCs have also shown to be potentially difficult to interpret [20] and to be affected by visual clutter [17,37]. As such the effectiveness of STCs may vary across different target groups which makes it essential to assess its value based on domain and target audience. Therefore, we evaluated our STC implementation through an online user study involving 30 MOBA players to establish a) how correctly the data in the STC can be interpreted and b) how this kind of visualization is perceived by the community. For this purpose, the study followed a predominantly task-based approach – following established practices in visualization research to ascertain its effectiveness – but also included a lightweight insight-based evaluation to probe into how the visualization promotes insights [19] as well as qualitative feedback questions.

Our results indicate that players can, by and large, successfully deduct facts from the STC and take a positive stance towards such kind of representation. Yet, visual clutter and interactions have to be carefully considered to counteract misreadings of the data. Based on our results, we discuss potential implications to help spark further research on 3D visualizations in the games analytics field.

2   Related Work

In the following we briefly review works concerned with the visualization of in-game data in general, visualizations particularly targeting players for reviewing gameplay, and previous work on spatio-temporal visualization, with particular attention towards STC visualizations.

Gameplay Visualization: Heatmaps that show the density of observations (e.g., kills) across space through color coding are one of the most frequently used visualizations in game analytics but they usually do not work well if more than one variable needs to be analyzed (cf. [34]). To address this issue other distribution maps such as hexbin maps in combination with glyphs [54] have been proposed to show multiple in-game metrics simultaneously. Like heatmaps, these are, however, two-dimensional and do not consider the temporal dimension. They also do not lend themselves well to displaying player trajectories which are often, as in our case, of key interest. Trajectories are frequently visualized using connected line segments, either within the games environment itself (e.g., [15]) or projected onto a two-dimensional map of it (e.g., [51]) but without consideration of timings. Such approaches are useful for studying overall navigation patterns or unexpected paths but they do not allow for temporal analysis. Hoobler et al. [24], for instance, therefore addressed this by encoding the passing of time in the width of the lines while Dixit and Youngblood [13] used color coding. Others have used animation to show how movement unfolds over time. For instance, *ECHO* [40] allows to playback positional information through a time slider. Goncalves et al. [21] animated player icons over a 2D map. Wallner and Kriglstein [52] took a different spatio-temporal approach, abstracting game states into nodes and showing temporal progression through animating transitions between the nodes. While animation over time seems a natural choice to convey temporal information, literature is not conclusive about its effectiveness (e.g., [23]). Tversky et al. [50], for instance, surveying literature on animation found that in many cases animation did not have benefits over static representations. In contrast, a STC allows to observe space-time paths without the need to rely on animations.

Purely temporal approaches, except basic charts, to visualize sequences of actions are less common in game analytics. Some, such as Li et al. [38], have proposed visualizations of sequences of actions without taking the timings between them into account which, however, can sometimes be of interest as well. Agarwal et al. [2] proposed a timeline-based visualization to help explore dependencies between interactions of multiple players. Interactions of a player are shown along individual rows and interactions between entities through vertical lines. *Stratmapper* [3], in contrast, juxtaposes a map visualization and a timeline showing in-game events to achieve a spatio-temporal perspective on gameplay. The timeline can be used to filter the information visible on the map. As such time and space are represented through two different visualizations which need to be related to match the spatial with the temporal information and may thus require additional cognitive demand. In contrast, a STC displays both space and

time within a single representation. Multiple views provide different perspectives on the STC, thus showing the same visualization rather than different ones.

Player-Facing Analytics: While visualizations of in-game data have historically emerged from a need to facilitate sense-making of collected player data, players too have developed an increased interest in reviewing play data to improve their gaming skills. However, as Kleinman and Seif El-Nasr [30] argue, research currently lacks an understanding of how players use their data to gain expertise. Wallner et al. [55] studied the information needs of players particularly with respect to post-play visualizations, focusing on three popular competitive genres. Among others, information about movement and positioning of units has shown to be highly relevant for players. Kleinman et al. [31] started to develop a taxonomy of user interactions with spatio-temporal gameplay visualizations using *Defense of the Ancients 2* (*DotA 2*) as a use case. Being able to study movement and positioning and consequently *form hypothesis of context and behavior that evolves over time* [31] have shown to be critical user activities. A STC visualization (see below) can facilitate these goals. As such we contribute to current research on player-centric visualizations. Previous systems in this space mostly relied on 2D map-based solutions such as *VisuaLeague* [1] which depicts player trajectories using animated maps or the system by Kuan et al. [36] which combines a global view, showing summarized troop movements, and a local view of individual unit movements using animations. In contrast, our proposed approach is 3D-based, integrating space and time without a need to resort to animations.

Spatio-temporal Visualization and Space-Time Cubes: Spatio-temporal visualization is a rich and active research field with numerous techniques having been published over the years. An extensive review goes beyond the scope of this paper but commonly used techniques in this space include animations and multiple views but also single view approaches (see also [6]). Animations may require higher cognitive load and time and complicate comparisons as discussed above. As such multiple views, each showing different aspects of the data, are frequently employed. These are then usually linked together to provide a coherent picture of the data [6], e.g., often through linking a map and a timeline view. For instance, Ferreira et al. [16] used such a combination to represent taxi trips, while Slingsby and van Loon [47] employed it for the analysis of animal movement.

In contrast, the STC attempts to convey the data within a single three-dimensional view. The STC was initially described by Hägerstrand [22] in 1970. With computer technology making 3D visualizations much easier to produce, interest in the approach has revived [18]. Consequently, the STC visualization technique has been used in many different settings. For example as a narrative tool to revisit a historical event [42], in the context of geospatial visualization [18,27,33], to visualize eye movement [39] or the movement of animals [32], in sports [45], and recently for conveying spatio-temporal patterns of *COVID-19* [44]. In addition, the STC visualization technique has also been applied in mixed [49] and virtual reality [17] settings. STCs usually use lines to display the individual trajectories but for the sake of completeness it should also be

mentioned that variants of it exists. For instance, Demšar and Virrantaus [12] used a kernel density technique to visualize the density of movement rather than the individual trajectories to address the issue of clutter. We were, however, interested in showing the details of the individual trajectories.

Various studies have compared the STC to different 2D representations. Among them, Kristensson et al. [35] have shown that a STC visualization resulted in faster response times when users had to solve complex spatio-temporal questions compared to a 2D map. Likewise, Amini et al. [5] found that the STC is beneficial in instances where users have to inspect sequences of events in order to identify complex behaviour in movement data. Kveladze et al. [37], studying a geo-visualization environment with multiple coordinated views using three different graphical representations (including a STC), observed that domain as well as non-domain experts mostly used the STC for all involved tasks. However, STCs also have drawbacks such as being prone to visual clutter [17,37], being potentially difficult to interpret [20], and having a steep learning curve [37].

Nevertheless, given the many benefits, it is surprising that the STC representation has not been studied more extensively in the context of gameplay visualization where spatio-temporal movement data is also ubiquitous. In fact, we are only aware of a single paper which utilized a STC for visualizing player behaviour, namely the work of Coultan et al. [10] who used a STC to visualize movement of players in a location-based game. However, in their paper the STC was used to facilitate their own analysis of the data. In contrast, we report on a user study assessing the effectiveness of the STC for analyzing play by players.

3   Use Case: Heroes of the Storm

Heroes of the Storm (*HotS*) [8] is a MOBA game in which two teams of five players each compete against each other. The team who first destroys the opponent's main building, the so-called 'King's Core', wins. In contrast to other MOBA's, *HotS* offers a wide range of maps which have different secondary objectives, which when achieved provide an advantage to the respective team. Each map has multiple so-called lanes, i.e. direct pathways connecting the bases of the teams and in which typically the majority of combat takes place. Controlling them gives an advantage to the team and they thus form important geographic features of the maps. In addition, defensive structures such as towers and forts are placed across the maps which attack enemies within their range. Destroying these structures can also bring additional benefits to the team. Players can choose from a variety of heroes, each one having unique abilities and talents. These heroes are divided into different categories, e.g., tank, healer, assassin.

HotS allows players to record replays of matches that contain all events and actions necessary to reconstruct a match. These replays were parsed using the *Heroes.ReplayParser* library [7] to extract information about player movement and events. In particular, we extracted the players' positions on a per-second interval. In case no position data was available for a specific time interval, the
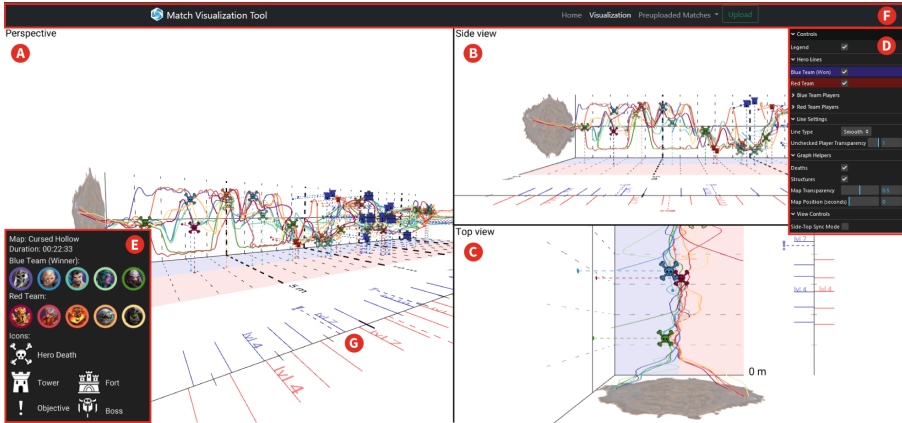
Fig. 1. Interface of the visualization, consisting of perspective, side, and top view (A-C), controls and filters (D), legend (E), menu bar (F), and auxiliary time axis (G). The legends and controls can be collapsed.

position was linearly interpolated. Apart from the positions of the players each second, we also extracted match specific data (map, game length), player deaths, team levels, map objectives, destroyed structures, and major camp captures. This data is stored in a JSON file that serves as input to the visualization.

4   Visualization Approach

The visualization was developed as a web-based application using the *Three.js* library [48]. It uses *WebGL* to enable 3D GPU-accelerated graphics and is broadly supported by web browsers. Some GUI elements were implemented using the *lil-gui* library [9]. The visualization is shown in Fig. 1. The landing page of the visualization lists the supported and tested web browsers and gives a brief introduction to the visualization approach and the navigation controls. At the top of the visualization itself, a menu (Fig. 1, F) allows to access a number of pre-uploaded matches but also to upload one own's replays that have been processed with our parser beforehand.

Space-Time Cube: The extracted data from the replay file is displayed in the form of a STC [22]. A STC is a visual representation that shows how spatial data changes over time. Two-dimensions of the cube form the geographical space and the third axis the temporal dimension. Spatio-temporal data (in our case player movement and events) can then be visualized within the coordinate system defined by the cube. Traditionally, the height of the cube represents the time axis. However, in our implementation time progresses along the depth axis as traditional time diagrams usually depict time along the x-axis, which is better resembled using this configuration.

Movements of players are visualized as lines connecting the recorded positions. The paths of the players are color coded to distinguish between the 10

players. Since *HotS* uses the colors blue and red for the two teams we used cold colors, shades of blue and green, for one team and warm colors, i.e. shades of red and yellow for the other. In this way players of different teams should be more easily distinguishable from each other.

In addition two major types of events are depicted through icons: player deaths and the destruction of structures. Player deaths are shown using color-coded skull icons (using the same colors as the paths). Likewise, the destruction of buildings (towers and forts) is indicated with icons. Since structures belong to a team, the icons are either colored in blue or red. Blue icons represent a structure destroyed by the blue team, red icons structures destroyed by the red team. As the icons are two-dimensional objects, billboarding (cf. [29]) is used to ensure that they always face the camera. To avoid icons being heavily occluded by the players' paths they are always rendered on top of them. These events are also projected onto the ground and back plane (indicated with dashed lines) to help identify patterns more easily than in 3D where the depth could be misleading. However, we refrained from projecting them onto the basemap since a) the map can be moved and b) the dashed lines would have followed the principal direction of the trajectories which would have increased clutter. Circles indicate deaths and use the same color coding as used for the players' paths. Squares denote destroyed structures colored according to the team who destroyed them.

The ground plane is further divided into two halves which are colored based on the teams to convey in which team's territory the game events have happened. The time axis (z-axis) is divided into one minute intervals represented by dashed lines. Every fifth minute is accentuated by using a thicker line and is additionally labelled. Level milestones, achieved map objectives, and major camp captures are not shown within the STC itself to reduce visual clutter. Instead these are visualized along an auxiliary time axis to the right of the STC and placed on the ground plane (Fig. 1, G). Level milestones are depicted as lines with talent-unlocking milestones (i.e. levels 4, 7, 10, 13, 16, and 20) also having a label. Map objectives are visualized as team-colored exclamation marks connected to the time axis using dashed lines. In the same manner but using different icons, major boss camps and achieved map objectives are indicated.

Three panels provide a perspective, side, and top view of the STC (see Fig. 1, A-C). The perspective can be freely rotated (left mouse button), translated (right mouse button), and zoomed in and out (mouse wheel). The top and side view can be zoomed in and out as well as translated along one axis.

Legend & Control Panel. A legend located in the bottom left corner (Fig. 1, E) contains the name of the map, the match duration, and an explanation of the icons. In addition, it shows the heroes of each team surrounded by a circle matching the color used to encode the hero in the STC. The winning team is also marked. The legend can be expanded or collapsed by the user.

The control panel (Fig. 1, D) provides means to filter the data shown in the STC and to adjust the appearance and the view navigation. In particular, the paths of the players can be toggled on or off on a per-team basis or for individual players. Lines can either be displayed using the raw coordinates extracted from
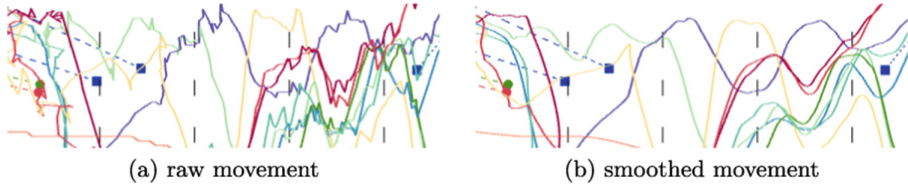
(a) raw movement   (b) smoothed movement

Fig. 2. Comparison of player trajectories using the raw position data (left) and path interpolation (right).

the replay or can be interpolated (default setting). Interpolation was added to help reduce visual noise and clutter and to abstract from fine-grained movement details as the goal of the visualization is to provide an overview of movement rather than showing its intricacies (see Fig. 2 for a comparison). In addition, the transparency of the lines of filtered players can be changed which allows to display them semi-transparently to enable comparisons. Icons representing hero deaths and destroyed structures can also be toggled on and off. The position of the map can be moved along the time axis which eases contextualization of the data at later time points within the map. Lastly, the views can be synchronized to link them. If enabled, translations performed in one view are automatically performed in the others as well. As the legend, the controls can be collapsed.

5   User Study

To evaluate the visualization, we conducted an online survey to

a) assess how correctly the visualization is interpreted by players, and
b) understand how this kind of visualization is perceived by the players.

For the former we followed a task-based methodology using tasks which inquiry about different aspects of the data. For the latter we included qualitative feedback questions as well as an open-task asking about gained insights.

Participants were sourced via *Reddit*, *Discord*, and *Facebook* communities associated with *HotS* and other MOBAs as well as through the first author's network. Participants had to have some previous experience with MOBAs, either by actively playing or passively watching matches. We recruited players of *HotS* as well as players of other MOBA games to see if the visualization is also understandable for players who prefer related games within the same genre.

5.1   Survey Design

The first part of the survey provided a short introduction to the purpose of the study and consent information. Next, the survey gathered demographic data about age and gender (female, male, non-binary, prefer not to disclose, other) and inquired into participants interest and experience with post-match game analysis as well as experience with gameplay visualizations. Both interest and

Table 1. Task types used in the evaluation.

Type	Description	Tasks
Events	Analyzing which events happened during a specified time interval	T-1, T-2, T-3, T-19
Counts	Analyzing how many events of a certain kind happened within a specified time interval	T-10, T-11, T-12, T-13
Location	Analyzing the locations at which certain events happened	T-6, T-7, T-8, T-14
Time	Identifying when specific events happened	T-18, T-21, T-22
Comparison	Comparing which team achieved more	T-9, T-15, T-16
Basic	Reading basic variables	T-5, T-17, T-20, T-23

experience were measured on a 7-point scale anchored by *1 = not at all interested/experienced* and *7 = very interested/experienced*. In addition, participants were asked about their preferred MOBA game (*League of Legends*, *DotA 2*, *HotS*, Other). This was included because we hypothesized that – despite MOBAs sharing the basic gameplay rules – players preferring other MOBAs than *HotS* might not be as knowledgeable about the used maps which might impact the ability to solve the tasks, especially when they referred to locations (e.g., lanes) on the maps. Lastly, we inquired about their experience with their preferred MOBA game, e.g., rank, average hours spent playing per week. The answer options for the latter varied based on the selected game.

Next, the participants were instructed to open the visualization, read the overview provided on the webpage, and familiarize themselves with the user interface and controls. When ready the participant had to click the 'Next' button of the survey to proceed to the main part. This part consisted of 23 tasks (see Table 2). For the tasks (T), we took into account existing task taxonomies, specifically the triad framework by Peuquet [46] which distinguishes between three components of spatio-temporal data: *what*, *where*, and *when*. Several of the tasks related directly to these individual elements as their proper identification is essential for more complex tasks. Some, such as T-6 or T-14, however also required the simultaneous consideration of two components. The triad framework also formed the foundation for the task typology of Andrienko et al. [6] which extended it in various ways, amongst others, by distinguishing between identification and comparison tasks with respect to the three components, an aspect which we also took into account in our tasks. In addition, our tasks should also relate to the different types of game-related information shown and vary in difficulty. These tasks were categorized into six task types (see Table 1).

In addition, to probe into which insights about gameplay participants can gain from the visualization, we included an open task (T-4) asking *Which are the three main insights you can get when analyzing this match with the visualization?*

The tasks were posed with respect to four predefined matches taking place on four different maps (Blackheart's Bay, Battlefield of Eternity, Towers of Doom,

and Cursed Hollow). This was done to reduce potential bias caused by using only one specific replay or map. Table 2 shows which tasks were performed on which map. T-4 was conducted on Blackheart's Bay. The upload of personal replays was turned off for the study. Once all tasks were completed, the survey asked participants to rate the usefulness of the three different views (perspective, top, side), the legend, and of the control panel on a 7-point scale anchored by *1 = not useful at all* and *7 = very useful*. Open-text questions further asked for three aspects participants liked about the visualization, three weaknesses of it, suggestions for improvements, and additional features which would be desirable. Participants could also share additional feedback. In total, the survey took about 20 to 30 min and fulfilled Masaryk University's ethical guidelines.

5.2 Participants

In total, 30 participants took part in the study. The age ranged from 18 to 40 years (M = 27, SD = 4.9). The gender ratio was skewed towards males, with 26 participants indicating to be male and 4 to be female, reflecting the overall general gender split observed in MOBA games [56]. The sample consisted of three players whose preferred MOBA game is *DotA 2*, 13 who preferred *League of Legends*, and 14 who preferred *HotS*. Participants expressed rather high interest in post-match game analysis (All: M = 5.6, SD = 1.1; *HotS*: M = 6.1, SD = 0.9; Other MOBAs: M = 5.1, SD = 1.1) while experience with post-match game analysis (All: M = 4.5, SD = 1.7; *HotS*: M = 4.4, SD = 1.7; Other MOBAs: M = 4.6, SD = 1.8) and gameplay visualization (All: M = 4.1, SD = 1.9; *HotS*: M = 3.9, SD = 2.0; Other MOBAs: M = 4.4, SD = 1.9) where both slightly above the scale's midpoint. In terms of experience with their selected MOBA game, participants indicated to spend 8.4 h on average per week (SD = 5.1) playing them. *HotS* players mainly had ranks of Gold (2), Platinum (5), and Diamond (4) and can thus be considered as highly skilled in the game. One player was at Masters rank and hence extremely skilled while the other two indicated a rank of Bronze and no rank (but having more than 12,000 games of quick match). In case of *League of Legends* ranks were a bit more distributed but the majority as well had a rank of Gold (2), Platinum (3), and Diamond (1). Three had a rank below Gold and three reported no rank. The three *DotA 2* players indicated ranks of Guardian, Crusader, and Archon, which can be considered low to middle ranks.

6 Results

Open-ended questions (e.g., insights reported during T-4, feedback questions) were analyzed individually using an inductive qualitative content analysis approach (cf. [41]). First, responses were coded by two of the authors individually to derive a set of keywords which were then grouped into categories. Participants' statements (or parts of them) were then assigned to these categories. Discrepancies in the assignment to the categories were resolved in discussion with a third

researcher and the naming of the categories was adjusted. Below we only report categories that have been mentioned by at least 10% (N=3) of the participants.

Correctness of the tasks was established as follows. Tasks with a single answer (e.g., T-6, T-10) counted as correct if exactly this answer was provided. Tasks with multiple answers (e.g., T-1, T-2) only counted as correct if all correct answers (and only these) were given. Times of events had to be reported in minutes and were counted as correct if they referred to one of the 1-minute-bounds within the event took place. For instance, if an event took place at 7:30 min, both 7 and 8 min counted as correct.

6.1   Task Correctness

To asses if there are differences in terms of the number of correctly solved tasks between *HotS* players and players of other MOBA games (*DotA 2* and *League of Legends*) in our sample, we conducted – after confirming normality of the data using Shapiro-Wilk – an independent samples t-test. No statistically significant differences were observed ($t(28) = -.378$, $p = .708$). Additionally, we conducted Fisher exact tests (due to sparse contingency tables in the majority of cases, i.e. tables with expected cell frequencies less than five) to compare the correctness of the individual tasks. For all tasks, no significant differences were found with $p > .05$. As such we will not differentiate between them in the following.

Table 2 gives an overview of how many participants correctly solved the different tasks. Across all tasks, average correctness is 74.1%. Next, we discuss the results based on the task types specified in Table 1.

With respect to analyzing EVENTS that occurred during a certain time span, the two tasks (T-2, T-3) asking about which champions died within a certain interval were more successfully solved than tasks requiring to check different types of events (T-1, T-19). As these were only counted as correct if all correct answer options were checked, we more closely inspected these. Correct answer options for T-1 where selected with 70.0% to 93.33% correctness and those for task T-19 with 76.67% to 93.33%, suggesting that participants either missed a correct answer or selected an additional false one.

COUNTS related questions showed quite some variation in correctness. T-13, asking about the number of deaths about a certain champion, was solved correctly most frequently, likely because the task only involves counting the number of death icons of a particular color. Only about two-thirds could, however, solve T-11 correctly. This is likely caused by the fact that the user has to either rotate the perspective view or additionally refer to the side and top views to check if the paths are really adjacent (Fig. 3a,b). Likewise, T-12 was only solved correctly by slightly more than half of the participants. While the asked for information can also be extracted from the projected circles in addition to the 3D view, these circles may overlap too, causing participants to miss a certain death. However, T-10 was the least correct answered one in this group. As we could see from the feedback, participants thought that respawns were less obvious than other events (see Sect. 6.3). This is likely because respawns were only indirectly depicted through lines restarting at the location of the team's base (Fig. 3c).

Table 2. Tasks and percentage of participants correctly solving them. Tasks within each task type are sorted in ascending order according to correctness. (BB = Blackheart's Bay, BE = Battlefield of Eternity, CH = Cursed Hollow, TD = Towers of Doom)

	ID	Map	Question		Correctness
Events	19	CH	Check everything that also happened in the given time frame, you entered above. (→ T-18)	▮	13.33%
	1	BB	Check all correct statements that describe what happened between 6 - 7 minutes of the match.	▬	46.67%
	3	BB	Check member(s) of the RED team that died between 6 - 7 minutes of the match.	▬	73.33%
	2	BB	Check member(s) of the BLUE team that died between 6 - 7 minutes of the match.	▬	80.00%
Counts	10	BE	How many RED team players respawned between 9 - 11 minutes?	▬	46.67%
	12	BE	At 15 minute a team fight happened. How many players were involved?	▬	56.67%
	11	BE	Analyze the gameplay between 14 - 15 minutes. How many players moved together in the biggest group?	▬	63.33%
	13	TD	How many times the player, who played CASSIA, died?	▬	83.33%
Location	8	BE	In which lane did the final push happen?	▬	73.33%
	6	BE	In which lane did the first death happen?	▬	90.00%
	7	BE	In which lane was the first structure destroyed?	▬	90.00%
	14	TD	In which lane did the last death of the player, who played CASSIA, happen?	▬	90.00%
Time	18	CH	Identify the time frame when the large number (3+) of structures was destroyed by the BLUE team.	▬	80.00%
	22	CH	Time (in minutes) when the first structure was destroyed.	▬	80.00%
	21	CH	Time (in minutes) when both teams reached level 10.	▬	96.67%
Comp.	9	BE	How many RED team members were dead when BLUE team destroyed the first structure?	▮	6.67%
	16	TD	Which team finished the game with more levels?	▬	80.00%
	15	TD	Which team managed to reach more objectives?	▬	100.00%
Basic	5	BE	Check the correct statement about the map.	▬	93.33%
	17	TD	Was the boss captured in this match?	▬	93.33%
	20	CH	Identify the game length in minutes.	▬	93.33%
	23	CH	First destroyed structure type?	▬	100.00%

(a)   (b)   (c)
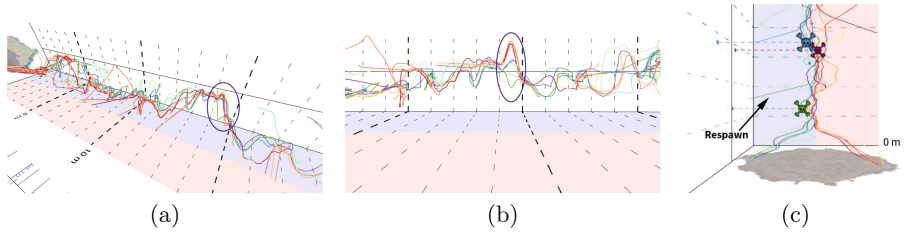
Fig. 3. Examples of visual representation issues causing difficulties with interpretation. (a & b) Estimating distances and visual depths can be difficult in a 3D perspective and thus may cause uncertainties when judging the proximity of heroes as required by T-11. (a) suggests that all except one player moved together between 14 and 15 min. Rotating the view (b) or observing other views is required to resolve this ambiguity. (c) Respawns were not explicitly marked in the visualization. Rather they had to be inferred from the paths originating at the base, potentially impacting T-9 and T-10.

Tasks requiring to infer the rough LOCATION of specific events where generally answered with very high correctness of 90%, except T-8 which has shown to be a bit more difficult. While the other tasks focused on events represented by icons, this task required to check the paths of the players and relate them to the map. Tasks dealing with when (TIME) certain events were happening were also answered with overall high correctness, independent of whether the information had be read from the STC itself or the auxiliary time axis.

However, COMPARISON tasks appear to have been considerable more difficult if they had to be solved using the STC itself (T-9) compared to when the information was depicted along the auxiliary time axis (T-15, T-16). However, it should be mentioned that T-9 was rather complex because it involved observing the death icons as well as the respawns within the proximity of the destruction event. If we neglect the respawn shortly before the event, 40% provided the correct answer. This again, indicates that respawns are not clearly visualized. In addition, participants also found the color coding of the structures unclear (see Sect. 6.3). The BASIC tasks were, as expected, solved without major issues.

6.2   Insights

In addition to the specific tasks above, we also included an open task (T-4) asking participants about the insights they can extract from the visualization. The derived categories of insights are summarized in Table 3. As we can see from the table, a bit less than half of the participants (N = 13) gained insights related to time such as when somebody died or a structure was destroyed.

The focus on time confirms the value of the STC for depicting temporal in-game data. Related to the spatio-temporal nature of the STC, participants also commented on spatial aspects (N = 7), notably on the positioning of players (e.g., closeness of players, positioning over time) and the spatial distribution of events.

Table 3. Categories of insights participants gained when asked about the main insights they could extract from the visualization (T-4, # = number of participants).

Category	#	Category	#
Tactics and strategies	▮▮▮▮▮▮▮▮▮▮▮▮▮▮▮▮ 16	Team Advantage	▮▮▮▮▮▮▮ 7
Number of deaths	▮▮▮▮▮▮▮▮▮▮▮▮▮▮ 14	Levels	▮▮▮▮▮▮ 6
Time-related information	▮▮▮▮▮▮▮▮▮▮▮▮▮ 13	Number of objectives	▮▮▮▮▮▮ 6
Positions	▮▮▮▮▮▮▮ 7	Win/Loss	▮▮▮ 3

Slightly more than half of the participants (N = 16) also reflected upon the different general tactics and strategies which might have been used by the teams. P12 was particularly detailed in this respect as the following quote illustrates:

> *Blue was more consistent about objective, but Red primarily turned in after kills. Probably blue was hanging back farming camps more aggressively, but would push in to Red's territory too far and lose their stockpiled coins to a team fight. In a more general sense, Red team didn't throw the game, but capitalized on their advantage when they had it. Blue team played consistently well, but did not have enough of an advantage late game to avoid a decisive, opportunistic blow from Red. I'd say 'the comeback is real', but while that may have been the interpretation of the players in the match, Red never slipped too far behind on XP [experience points] despite losing significantly more structures and having fewer turn ins. Essentially, Blue team's lead was an illusion. They were doing more but not pulling far enough head in the process.* [P12]

Related to this, participants discussed instances of how teams compared to each other (N = 7), particularly which team had an advantage over the other, often also related to time aspects. Apart from higher-level inferences regarding strategies, participants also commented on the visualizations ability to gain insights about particular aspects such as the number of deaths (N = 14), level gains (N = 6), number of objectives (N = 6), and who ultimately won or lost the match (N=3).

6.3   Feedback

In terms of usefulness of the different parts of the visualization, the perspective view (M = 5.31, SD = 2.00), the legend (M = 5.31, SD = 1.99), as well as the control panel (M = 6.00, SD = 1.69) were rated to be similarly useful with all scoring at the higher end of the scale. The top (M = 3.79, SD 1.72) and side view (M = 4.07, SD = 1.73) scored lower around the midpoint of the scale.

The categories developed with respect to the benefits and weaknesses of the visualization as well as regarding suggestions for improvements and additional data to include are summarized in Table 4 and will be further discussed next.

Table 4. Categories of participants' feedback regarding benefits, drawbacks, and potential improvements (# = number of participants).

Category	#
Benefits	
Filters and controls	■■■■■■■■■■ 10
Design and usability (e.g., color coding, icons, lines)	■■■■■■■■■ 9
Overall approach	■■■■■■■■ 8
Overview	■■■■■■■■ 8
Timeline	■■■■■■ 6
Navigation	■■■■ 4
Visualization of movement	■■■ 3
Weaknesses	
Color coding of players can be hard to distinguish	■■■■■■■■■■■■■ 13
Lack of interaction possibilities (e.g., filter options)	■■■■■■ 6
Visual clutter	■■■■■ 5
Respawns of the players are poorly visualized	■■■■ 4
Movement is sometimes not clear	■■■ 3
Suggestions for improvement	
Graphical representation (e.g., display of respawns, colors)	■■■■■■■■■■■■■■ 14
Interactions (e.g., more filter options, highlighting of players)	■■■■■■■■■■■■ 12
Strictly orthogonal top and side view	■■■■■ 5
Suggestions for additional data to include	
Additional statistics (e.g., gold, damage, precision, healing)	■■■■■■■■■■■■■■ 14
Information about camps	■■■■ 4
Talent choices	■■■ 3

Benefits: The filter possibilities and the control options received the most positive comments (N = 10). Related to this, four participants highlighted the intuitive navigation in the views themselves. Participants also made general comments about the design and usability of the system (N = 9), e.g., mentioning the well-chosen color coding, the descriptive icons, and the interpolation of lines.

The approach in general was also received positively, with eight participants commenting about the novelty of the visualization in this particular application domain. Three also specifically mentioned the 3D aspect. For instance, P22 who was initially not convinced commented: *While I initially thought the 3D view wasn't that interesting, I think it can bring a very interesting insight at a short glance.* Eight participants also appreciated the overview of the data (i.e. of the different aspects of a match) which comes with the STC approach. Three participants specifically lauded the visualization of movement. For example, P22 thought that it *provides a very clear view of the match, with movement of*

players across the map. It is easy to track the main events. Lastly, the temporal perspective the visualization provides was also appreciated by six participants.

Weaknesses: While some people mentioned the color coding as benefit, it was also the most mentioned drawback of the visualization (N = 13). While participants thought that the players of the red and blue team could be well-distinguished, players within a team were less differentiable due to the color hues sometimes being too similar. Three of them also found the color coding of the destroyed buildings confusing since it was not exactly clear if the color indicates the team who destroyed it or the team the building belonged to.

Participants also commented about a lack of interaction possibilities (N = 6) such as missing options to filter the data and to be able to turn off the grid. Five participants considered the visualization to be crowded which, in turn, caused the displayed information to overlap, especially in places with high activity. This sometimes made it difficult to infer information, as P3 commented: *Deaths can overlap, making it hard to be sure who exactly died.*

As reported by four participants, respawns were not well recognizable in the visualization which made it difficult to find them. As discussed previously in Sect. 6.1 this is likely due to them not being explicitly encoded (see Fig. 3c). Indeed, one participant suggested to use icons to make them more obvious.

Lastly, while three participants liked the visualization of movement, an equal number of participants found it unclear. We assume that the clutter mentioned by other participants could be a reason for this.

Suggestions for Improvements and Additional Data: Made suggestions for improving the visualization are partly in line with the identified drawbacks and include changes to the graphical representation (N=14), particularly with respect to the encoding of respawns and adjusting the colors within the teams. Likewise, participants proposed additional interactions (N=12) such as more filter options and ways to navigate the views and customize their arrangement. Lastly, participants suggested to use a strictly 2D orthographic top and side view instead of having a perspective camera viewpoint from the top and side as in our case. We conclude that this is due to the slight perspective effect which was caused by this choice and which causes small displacements of the viewed data based on the position of the camera.

When asked about additional features, participants only reflected which additional data would be useful for their analyses. Primarily, participants (N = 14) suggested to include further statistics such as about gold, damage dealt, precision in team fights, healing done, and more. Four participants suggested to add information about camps which were currently not considered at all. Lastly, talent choices were also thought worthwhile to include by three participants.

7   Discussion

While various visualization types have been employed for visually representing in-game data, a substantial number uses 2D representations. If three dimensions

have been used for depicting behavioral in-game data these are mostly concerned with visualizing trajectories in the actual 3D game environment (e.g., [11, 15, 28]). In this work, we thus adapted the established STC representation to explore its value in the context of spatio-temporal match review and if the added complexity poses difficulties for players. With respect to our two study goals we can conclude that a) facts about the data can on overall be well retrieved from the STC and b) that it was generally well received.

With respect to the correct interpretation of the data, we can summarize that across all tasks overall correctness was rather high with participants on average solving 74% of the tasks correctly (regardless of the preferred game). However, correctness also varied between the tasks from about 7% (T-9) to 100% (T-15 and T-23). This is, however, in line with findings from other studies in other domains. For instance, Filho et al. [17] reported task success rates in a similar range. Lower performance on certain tasks can usually be attributed to visual clutter (i.e. occlusions) or to a lack of depth cues which made it difficult to estimate the proximity of graphical elements (e.g., lines, icons) inside the STC. Both are well-known drawbacks of the STC representation as reported in the literature (cf. [12, 17]). For icons we attempted to address this, by projecting them onto the bottom and back plane of the STC which, however, could only solve this issue partially as occlusions may still occur. The issue with the proximity of lines could potentially be addressed by automatically detecting co-located champions and visually encoding them (e.g., through the transparency of the lines).

The 3D representation and the complexity arising through it can be a disadvantage (e.g., [5]) but this did not appear to cause issues in our study. On the contrary, participants appreciated this approach (see Table 4, Benefits), taking a positive stance towards the 3D representation. We assume that this is because players are in general familiar with navigating 3D environments and adjusting camera perspectives. Previous work such as [5, 18] has highlighted the importance of interactions to manipulate the STC. Although we supported already various ways for navigating the camera and filtering the data – and this was appreciated by the participants – they also called for further interaction possibilities such as additional filters. As such, if 3D visualizations are used for gameplay analysis an appropriate set of interactions should be provided to support data inference. Another opportunity could be to offer a set of pre-defined configurations of the display that align with commonly performed analysis tasks.

Another issue was mainly caused by a particular design choice we made: respawns were only visible through the players' paths. This made them less obvious to detect in the STC, also because the visibility depends on the perspective from which the cube is viewed. This could be resolved by, as proposed, marking those respawns explicitly with icons. Related to this, participants also made suggestions for including further game-related information. However, this will add further visual elements to the STC which, in turn, can contribute to visual clutter. An interesting observation in this regard is that albeit participants reported visual clutter as a drawback of the STC they, at the same time, requested to display further information. As such it is important to carefully

weight the importance of different gameplay aspects to be shown within the STC. Another possibility could be to show specific information only on demand, for instance, when hovering over lines and icons. In conclusion, we can say that the drawbacks mainly revolved around specific design aspects (e.g., colors, respawns) and a lack of interaction possibilities but less about the actual 3D representation.

Displaying space and time simultaneously has shown to be valuable to the players as our participants reported insights related to both spatial and temporal aspects. At this point it is, however, important to note that our evaluation was mainly task-based to assess if the data can be correctly inferred from the visualization. This is an important prerequisite to construct higher-level insights [4]. While we probed briefly into the types of insights players can derive, further studies will be necessary to evaluate the STC for higher-level analytical tasks. However, even if only touched upon this briefly, we could see that participants were reflecting about the tactics and strategies used by the different teams.

On the other hand, the STC does not seem an appropriate choice for all games. As we could see from our results, even when only showing the data of ten players visual clutter already caused difficulties when interpreting the data in case of certain tasks (e.g., group movements, overlapping of icons). Results from the field of geographic information sciences [12] also do not recommend STCs for a larger number of movers. As such we consider the STC more helpful in games with a small number of actors. A possible direction forward could also be to combine individual space-time paths with a density-based approach (e.g., [12]) to aggregate movement, for instance, to allow players compare their own with the average behaviour of others. It should also be noted that a STC is only suitable for games where movement can be reasonable described in two dimensions, as the third axis is used to represent time. As such it may have limited use for games in which 3D movement patterns are important.

Lastly, we would like to acknowledge some limitations arising from the study itself. First, our sample was composed of players who indicated to have an above-average interest in and experience with post-match game analysis. It should also be kept in mind, that our sample mostly consisted of intermediate to more highly experienced players. Previous work such as [20] has shown that STCs can potentially be difficult to interpret. Hence, it would be interesting to expand the demographics to players with less pre-knowledge and skill to investigate in more depth if novice players can interpret and benefit from the visualization in the same way. Secondly, due to the online setup we did refrain from measuring timings for the individual tasks as those may be unreliable and focused only on task correctness. Future work should thus further investigate the effectiveness of the visualization by not only considering correctness but also factors such as mental effort and time spent on the task (see [25]). Lastly, we used multiple matches to avoid potential bias caused by using only a single match. While we visually picked matches of similar complexity, some impact on the results caused by the different particularities of each match cannot be completely ruled out.

While our results showed that the tasks, with some exceptions, were well performed we need to highlight that many tasks were rather elementary and spatial

tasks were few. Nevertheless, the findings still provide a promising path forward as elementary tasks are important for higher-level inferences. Related to this, future work also needs to look into comparative evaluations to assess whether the STC is more or less helpful compared to existing gameplay visualization methods such as animated maps. This was outside the scope of this study.

8   Conclusions

Visualizations of in-game data are an increasingly important asset of data-driven tools that allow players to review their in-game performance. However, spatio-temporal visualisations that provide an integrated perspective of both space and time in a single view found little attention in games-related literature. Such visualizations are often realized in 3D, which adds additional complexity and may thus not be suitable for all user groups. In this paper, we focused on the established STC visualization to study how it is received by players and if they can observe the displayed data correctly. Our results show that such representations do have potential for this application scenario with players being able to extract data with comparatively high overall correctness and responding positively to this kind of approach. However, it also shows that interaction- and design choices need to be made with care to provide adequate means to adapt and manipulate the visualization. Given our findings, we would advocate for further research in this direction to explore the prospects of 3D visualizations for gameplay analysis.

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