G-Player: Exploratory Visual Analytics for Accessible Knowledge Discovery

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ABSTRACT

Understanding player behavior and making sense of gameplay actions is a non-trivial and time-consuming process that requires both thorough domain knowledge of game design, and advanced technical skills in database query languages and statistical packages. Researchers, technology partners and content creators are developing tools to aid in the process of knowledge discovery to gain insights and understanding player behavior. This is important for game production, as it is crucial for formative evaluation of game designs, but is also important for research applications to understand human behavior. In this paper we present G-Player, a tool that aims at democratizing advanced intelligence and knowledge discovery from players' behavior. G-Player leverages spatial visualizations, such as heat maps and event/movement plotting, to answer complex queries on spatio-temporal data. It allows quick turn-around time between data analysis, hypothesis forming and verification on multimodal datasets, and lets users gain levels of insight beyond simple descriptive statistics. As a first step, we evaluated our tool for production, through domain experts, who were asked to compare it to their current tools. Through this comparison, we enumerate advantages and disadvantages of G-Player's design as a tool to expand our understanding of player behaviors through space and time analysis.

Keywords

Visual analytics, Data visualization, Multimodal data analysis, Heat maps, Boolean operators, Spatial and temporal representation

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INTRODUCTION

Gathering players' behavioral data through game telemetry is now a widely accepted and used practice in the arsenal of techniques available to Game User Researchers (Seif El-Nasr et al. 2013). Understanding player behavior and making sense of the actions performed in a game is a time-consuming process, most often left to experts in data science or analytics. Even though the field of visualization has produced much research that can allow non-experts to view data and make sense of patterns emerging from such large data, the current techniques are limited. Games and simulations are complex and dynamic systems with many variables that affect and are affected by users' behaviors. Much of the visualization research is focused on how to visualize different data types, such as action sequences (Nguyen et al. 2015; Andersen et al. 2010), movement (Andrienko and Andrienko 2013), spatial-temporal data (Chittaro et al. 2006; Ferreira et al. 2013). Other visualization research investigated interactive techniques to allow users to explore data, such as (Roberts 2007), but these techniques are still limited given the complexity of game play data. Andrienko et al. (2013) identified several limitations that they cited as the reason why interactive techniques have not been utilized in commercial environments: a) amount and complexity of data, b) dimensionality of data, and c) dynamic nature of data. To avoid (a) and the subsequent overplotting, often data is aggregated. This, however, is a problem if stakeholders intend to account for individual behaviors. In dealing with (b) several views are needed, each unpacking a different set of features, but such solutions are not scalable with high dimensions. For (c), the authors are unable to mention a system that can cope with dynamic data in a satisfactory manner, where dynamic is defined as data streamed and evolving through time. While visualization research has not yet offered a satisfactory solution, there is a need for a tool that addresses this high dimensional, dynamic and complex data in a manner that allows designers (non-data analysts), researchers, learning scientists, psychologists or any other stakeholder interested in understanding human behaviors within game environments, to explore and make sense of such data.

To address these challenges (size and complexity, high dimensionality and dynamic data), we developed G-Player: a spatio-temporal interactive visualization that utilizes multimodal dynamic heat maps to visualize and analyze the occurrence and cooccurrence of events. Aggregated data, such as heat maps, are normally impaired by intrinsic limitations; for example, one cannot properly account for sequences of events or the temporal dimension of events; at the same time heat maps provide extremely contextual information rooted in a given game space and an instant overview of the distribution and frequency of a certain event. With G-Player we want to push this strength to a new level by allowing stakeholders to select any game event, generate topical heat maps that account for the temporal dimension and perform elaborate operations across heat maps. The system is designed to allow the selection of a subset of game events, define a certain area of the map and/or a certain time distance between events and finally combine the selected events through the Boolean operators. The operators allow to join, intersect and subtract across different heat maps representing separate events. Selecting the desired features, being able to set spatial and temporal thresholds and the possibility to intersect, add or subtract features is a viable strategy to overcome the intrinsic limitations of heat maps. This novel interactive visualization system allows users to filter, augment, overlay and interact with spatio-temporal data to make sense of players' behaviors. G-Player advances the state of the art by: accurately and flexibly visualizing users' behaviors in a spatio-temporal virtual environment; presenting an interactive representation that accounts for the dynamic nature of the environment and the agents acting in it, and allowing researchers to use visual operators to query the data and understand user behaviors, which empowers potential stakeholders who may not have advanced statistical knowledge.

In this paper, we first provide an overview of previous work; we then introduce the dataset we utilized as a case study. We follow with a description of the features of G-Player. We then present the evaluation method, and the feedback collected from domain experts to validate the efficacy of G-player.

BACKGROUND AND RELATED WORK

In order to gain insights on player behaviors or strategies formed in games, researchers often adopt either or both of the two main approaches: invite participants to a lab study (Laurel 2003; Bernhaupt et al. 2008; Isbister and Schaffer 2008), or remotely track gameplay logs while participants interact with the game in their naturalistic setting (Seif El-Nasr et al. 2013). Lab studies imply the use of one of the many game user research methods or other methods of inquiry, such as think-aloud, in-lab play-testing, physiological sensor recordings, observation methods, or retrospective interviews (Laurel 2003; Bernhaupt et al. 2008; Isbister and Schaffer 2008). All of these techniques require direct interaction with participants. For example, besides requiring users to be in the lab. physiological assessments need them hooked up to sensors, while play-testing is conducted with researchers observing or play sessions being recorded. Such techniques may not scale well since they require the subjects to be physically present during the study. While video recording could be done remotely, researchers adopting this practice face the issue of not being able to fully control the users' play environment, which makes data collected unreliable. An alternative and complementary option is the use of game telemetry (Seif El-Nasr et al. 2013) and game analytics – a set of techniques designed for collecting and analyzing play traces remotely, i.e. records of players' in-game actions and states when they engage with the game. Thanks to game analytics methods, the process of collecting player behavior data is automated and easily scalable (Seif El-Nasr et al. 2013). Quantitative techniques leveraging machine learning and data mining can then be used to process the data. Since such analyses are textual or numerical in nature, there has been an









emerging trend of adopting visualization tools to present the analysis results in an easily interpretable form. There are four main types of visualization techniques to represent visually spatiotemporal data (Figure 1): simple bar charts (Medler et al. 2011; Scarlatos and Scarlatos 2010; Milam and Seif El-Nasr 2010; Mirza-Babaei et al. 2012; Kim et al. 2008), node-link graphs (Nguyen et al. 2015; Thawonmas and Iizuka 2008; Wallner and Kriglstein 2012; Liu et al. 2011), heat maps (Drachen and Canossa 2009a; Ashton and Verbrugge 2011; Drachen and Canossa 2009b), movement visualizations (Hoobler et al. 2004; Miller and Crowcroft 2009; Coulton et al. 2008; Moura et al. 2011), and systems that use a hybrid of these (Wallner and Kriglstein 2012; Moura et al. 2011). Simple bar charts present users with visualizations of aggregated statistics on the whole set or some user-defined subsets of players (Medler et al. 2011; Kim et al. 2008), or behavior patterns of specific players in some temporal order (Scarlatos and Scarlatos 2010; Milam and Seif El-Nasr 2010; Mirza-Babaei et al. 2012). Popular aggregated statistics include kill/death ratios, experience points gained, daily numbers of play rounds, etc. (Medler et al. 2011). For instance, Figure 1a shows the bar graph of the number of players charted against session length in a puzzle game; most players only play at most 10 levels within one session. Behavior patterns, on the other hand, are projections of player in-game behaviors onto some high-level semantic space, e.g., movement actions mapped as path target pattern, or item pickup as a collection pattern (Milam and Seif El-Nasr 2010). By encoding different patterns with different colors and placing them at different heights, a player's behavior trace can be visualized as shown in Figure 1b.

Node-link visualizations (Nguyen et al. 2015; Thawonmas and Iizuka 2008; Wallner and Kriglstein 2012; Liu et al. 2011) take a more abstracted approach in visualizing data. Unlike heatmaps, whereby data is associated with spatial locations, node-link visualization requires game states and transitions to be defined from the data (Figure 1e). Usually, a game state represents a snapshot of all in-game aspects influencing the decision made by the player, and transitions denote such decisions (Nguyen et al. 2015). As such, this type of visualization can handle non-spatial data such as dialog choices, or tech-tree decisions, or data from puzzle games. Heat maps (Drachen and Canossa 2009a; Ashton and Verbrugge 2011; Drachen and Canossa 2009b) and movement visualizations (Hoobler et al. 2004; Miller and Crowcroft 2009; Coulton et al. 2008; Moura et al. 2011; Gagné et al. 2011) are techniques used to analyze spatial behaviors. They tie data points to their respective geographical locations on the game map and display pertinent information using visual cues such as color clouds, color-coded icons, or simple bar charts. Given a data set of location-tagged events (such as physical positions, or death events), heat maps employ a color gradient to show the occurrence frequency the events on the map, with "hotter" color indicating high frequency and "cooler" color low frequency; no color means zero occurrence. For example, Figure 1c shows a heat map of player death events in a role playing game (RPG), with magenta areas being deadliest regions, and gradually fading shades of blue being less and less deadly regions. Figure 1d, on the other hand, depicts the movement visualization of a player, with circles representing location snapshots and temporally color-coded (yellow earlier, red later). Heat maps excel in showing population behaviors, but make individual play trace comparison an involved process. At the same time it is impossible to evaluate behaviors unfolding over time. Movement visualizations, on the other hand, focus on showing individual traces, leaving questions on aggregated behaviors open to users.

To solve this issue, Pathways and Dada were developed. Pathways (Gagné et al. 2011) is a movement visualization system, with movement displayed as line and death events as color pixels. Using playback function and coordinated views, the system allows comparison of play data of different player cohorts (such as winners versus losers) at the moment-to-moment level. Player trajectories are visualized in transparent colors, so that color saturation can indicate popularity of cohort movements, a technique often seen in heatmap-based visualizations. Moura et al. (Moura et al. 2011) proposed a visualization system that combines movement visualization, node-link, and charts, to facilitate comparison of telemetry data. The system combines clustering techniques to show different groups of users to make navigation of user behavior easier and comparable. However, both these systems have not been tested beyond thousands of play-throughs with Pathways and tens of participants with Dada. Also, both systems do not offer ways of doing Boolean operations on behaviors to make sense and abstract behaviors to understand meaningful patterns in the action space.

In sum, existing approaches are limited because of the three challenges listed earlier and either because of poor scalability or because they focus either on individual traces or excessive overall aggregation without offering ways to abstraction. The tool we envisioned is able to connect directly to a large database, define features, pull data directly into the interactive visualization, filter it using time and space in combination with any defined feature, and perform complex operations utilizing Boolean operators. The visual analytic techniques and system we are proposing are based on objective data, scalable, and provide multiple perspectives for examining play data. The tool presented leverages techniques to present charts for displaying behavior patterns, heat maps and movement visualizations. G-Player allows users to examine the collective behavior of all player population via overlaid heat maps of different location-relevant events (e.g. death, item pick-up, etc.). As mentioned earlier, both technology providers and content creators are working hard to push the boundaries for visual analytic tools, this article compares Gplayer with DNA, a tool developed at Ubisoft to service their development teams, and with the Heatmap plugin, developed by the analytics team at Unity Technologies and made available to all developers using Unity 4.6 and higher.

A RICH MULTIMODAL DATASET: VPAL CASE STUDY

The dataset used for this case study comes from the VPAL (Virtual Personality Assessment Lab) game – a virtual environment designed to study the correlation between in-game behaviors and personality. We chose this dataset because it is exemplar insofar as it embodies all the characteristics of a dataset that can challenge interactive visualization systems: it contains a large amount of high dimensional dynamic data (hundreds of thousands of data points for each user). The game was created as a mod based on the title *Fallout: New Vegas* (Obsidian Entertainment 2010). The game has been instrumented so that each play session records all actions performed in the game as comma-separated values (CSV), including location information, object interaction, dialog choices, and NPC interaction (talking, fighting, killing, etc.). A sample segment of play data goes as follows.

```
Position_Outside,212,658.1,-2027.22,9239.34,1579.85, 30.26,-0.00,126.76
Attacked,212,1248.90,Mr. Walker,Friendly NPC
NPC Spider attacked first,212,1109.60
InteractionNPC,Outside,212,Johnson,658.3,-2027.220, 9239.342,1579.849
Dialogue,212,676.50,8,Johnson,I always have a minute to talk.
Quest,212,519.88, AAAMrWDia, Started
```

The first value indicates the datum type that is reported, which can be location, interaction, attack, dialog choice, quest, movement modifier, being attacked, being killed. For example, "Position Outside" indicates the datum is a location record in a region

called Outside, "Quest" is a label used to indicate progress towards a formal game goal, , "InteractionNPC" the event that player starts engaging in an interaction with an NPC, "Dialogue" a dialogue choice record. The rest of the values are, respectively:

- PlayerID, e.g. 212
- Time stamp in seconds (note how it increases in regular intervals of 0.2 seconds)
- Datum-type specific
- For location: two 3D vectors for location coordinates and facing direction for the virtual camera.
- For dialog: time stamp, NPC name, and dialog response text.
- For quests: time stamp, name of quest, step towards quest completion
- For Interaction: object or NPC that player interacted with
- For player attacking: NPC that player attacked, whether friendly or hostile, whether related to quest completion or not
- For player being attacked: NPC that attacked player, whether related to quest completion or not.
- For movement modifiers: sneaking, jumping and running

The game has been designed and instrumented in order to conduct an exploratory data analysis. This dataset allows testing our system according to the three parameters that show the limitations of other current systems: amount and complexity of data, multidimensionality of data and dynamic nature of data. Based on these requirements we developed research questions to help design G-Player:

- 1. Map accessibility: During the game, where do players spend the most time at? Which areas of the level are underutilized? This question addresses the problems raised by amount of data, since this dataset contains position sampled five times every second from dozens of players, the risk of overplotting is very real.
- 2. Locations of event occurrence: Where do players spend the most time interacting with game objects? Where do players often perform special events such as accessing the inventory or reloading a weapon? This question addresses the problems raised by high dimensionality of data since we have 15 total features both with time and location stamps.
- 3. Combined event question: Where do players interact with NPCs while at the same time sneaking within a span of 5 seconds? This questions addresses the problems raised by the dynamic nature of the dataset, since being able to answer it requires that the system can account for the evolution of any feature in time.

These questions have been used as sorts of requirements when designing the features for G-Player. They will also be used when asking the experts to evaluate and compare G-Player with the tools that they developed in their professional capacity.

G-PLAYER: SYSTEM DESCRIPTION

In order to visualize behavioral spatial data, we designed G-Player, a visualization system that makes use of feature-based heat maps, spatial and temporal constraints, Boolean operators, path visualizations, overlays of icons, and a playback feature to visually



Figure 2: G-Player, (a) the main interface with a center display, left and right menus, and (b) center display with showing death events as overlaid icons on a position heat map to indicate death locations; the colored circles represent players.

convey information on how players perform in a game level. In addition, the tool can show movement animations as game replays from 2D top-down view, constructed using game play data on the backdrop of heat maps and overlays (Figure 2). The main interface consists of three regions as shown in Figure 2a. The center region displays visualization results as heatmaps or overlaid icons on the map. The menu on the right allows selection of events to be displayed in the center map and to perform Boolean operations, while the menu on the left allows selection of cohorts of players. Playback is controlled through central menu. For visualization of events, users can choose to display them as either icon overlays or as an occurrence frequency heat-map that encodes regions with denser event occurrence as hotter (redder).

The timeline control with a play button underneath the map can be used for replaying the full match (beside the map). Figure 2 shows the tool in action displaying data from the case study VPAL, a mod for *Fallout: New Vegas*, but the system is designed to support data input as diverse as CSV, Mongo DB or MySQL. The dataset is parsed and labels are requested for each type of event. Using heat maps as the main device to visualize query results, in G-Player we incorporate two new features to enhance the query capability of the system, i.e. space-time modifiers and Boolean-compound heat maps, accounting for a higher demand of more interactive controls and complex queries. The first feature allows users to impose a specific spatial and temporal constraint on heat map queries, effectively limiting the amount of data to retrieve from the database to a small set, thus improving the responsiveness of the system. The second feature leverages Boolean algebra to obtain visual results of complex queries, by allowing users to describe these queries as Boolean combinations of events. The final result is a single compound heat map that possesses similar expressive power as the set of multiple heat maps resulted from manually querying all individual events, while much less cognitively overloading.

Space-time Constraint Modifiers

The timeline already present in the interface is re-used to let users indicate a temporal period of interest by placing two markers specifying the starting and ending time points (Figure 4a). Time constraints can also be set while performing Boolean operations across heat maps. In addition, users can also draw a region of interest on the game map while in



(a) Selecting time period of interest



- (b) Basement location heat map minute 1-10
- (c) Basement location heat map minute 20-30

Figure 4: Selection of spatial-temporal regions; (a) represents a mid-game time period of about 10 minutes, and (b-c) the basement room in the game map Introhouse in (b) minutes 1-10, (c) minutes 20-30.

query mode. Figure 4b and 4c depict the heat maps of player locations in the basement room as indicated by the rectangular bounding box, respectively in (4b) the first 10 minutes and (4c) the middle 10 minutes of game play. By constraining the heat map's time period, researchers can detect temporally influenced behaviors of players that would otherwise be clumped together in an ordinary heat map. For instance, looking at the data from the VPAL map the basement section of the 'Introhouse' shown in Figure 4b shows that players who enter the basement room in the first 10 minutes (i.e. group 1) have very different movement patterns than those of who enter the room mid-game (group 2). Group 1 spends a significant amount of time at the top left corner of the 2D room map, while group 2 seems to only care about the bottom left corner, or retreat from the room quickly (the hot area in the middle of the room). As it turns out, at the top left corner, there are some shelves full of items to be looted (e.g. health packs, valuable gems), while at the bottom left corner there is a rat to be killed in order to complete a side quest. The quest is presented to players soon after they start the game, so Group 1 consists of players who enter the room for the first time with some knowledge on the quest. As such, the heat map as shown in Figure 4b demonstrates that a large number of these players proceeded to attack the rat, and/or spent a significant amount of time examining the shelves (whether they loot the items is not shown here). In contrast, Group 2 players either go to the rat's position or retreat from the room. Upon examining the raw game logs, it is clear that those who loiter around the rat have already killed it in their first visit and came back to get a bonus item, while those who retreated entered the room late in the game, oblivious of the rat's existence, and decided to leave when seeing it. The above example demonstrates how spatial and temporal constraints can reveal behavior patterns that cannot be discovered with ordinary heat maps that disregard temporal information.

Boolean Combination of Heat Maps

Heat maps are traditionally associated with single event or action types, such as locations, kills, looting, or deaths. As a result, spatial queries that require information beyond just



(b) item interaction

Figure 5: The heat maps of compound event "pickpocket" (numbers and letters highlighted in yellow indicate notable heat regions), defined as the intersection of (a) "sneaking movement" and (b) "item interaction" events.

one type of events require users to manually stitch together heat maps of related events and action types to get the answers. To provide a simple yet powerful method to address this need, in G-Player we allow users to retrieve heat maps of compound events defined using Boolean operators.

This operation can be used on heat maps of both single players and player groups. Note that users can further constrain the output to specific spatio-temporal regions of interest, using the operations described in the previous section. To illustrate how the feature can be used, take for example the following question: "In the map Introhouse, where are the regions that players exhibit pick-pocketing behavior?" This behavior is not logged in the raw data but can be exhibited when a player manages to retrieve an item from the NPC's possession without being noticed by the NPC. It is possible to describe the action "pickpocket" in terms of a co-occurrence of two other events that are logged, namely "sneaking" and "item interaction". Sneaking is achieved by walking while pressing the 'Shift' key, while item interaction happens when the player press the key "E" near an ingame item. Note that when an NPC nearby notices the player's presence while he/she is trying to interact with an item, the "E" key will start a dialog with the NPC instead of resulting in the item interaction. While there could be other ways to define pickpocketing, we adopt the notion of "pick-pocketing" as the event in which players are interacting with items while sneaking around NPCs. Figure 5c illustrates the visualized result of *intersecting* the 'sneaking' event heat map and 'item interaction' heat map, retrieved from data of a single player. As shown in the sneaking heat map (Figure 5a), there are three locations that the player sneaks: at the top left corner (1), lower left corner (2), and lower right corner (3). Meanwhile, Figure 5b shows several locations (highlighted in yellow from a to f) where the player interacts with and/or picks up items, scattered in rooms around the house. When intersecting the two heat maps, the resulting heat map (Figure 5c) shows clearly that pickpocketing happens in regions (1a) and (3f), but not anywhere else in the map. This information would have not been contained from any heat maps created from existing events. Note that while it might be possible to anticipate all such compound behavior a priori in the design process and define dedicated event types to record them, there is always the possibility that game user researcher, designers or any other stakeholders can be interested in new types of event combinations that were not foreseen. Allowing Boolean combinations of queried events increases the flexibility and robustness of G-Player, permitting stakeholders more complex queries with immediate feedback. Besides, refraining from recording redundant data such as compound events, keeps the game logger's activity to the minimal. This generally improves the game's responsiveness performance, specifically avoiding hogging the computer processor, which can negatively impact the frame rate, as well as keeping the size of game log data sent to data servers small.

EVALUATION STUDY

We follow the guidelines and categorizations suggested by Lam et al. (Lam et al. 2012) to evaluate G-Player. Since our tool is at a prototype stage, our goals are limited to evaluating usefulness of features, performance of the tool and experience. As such, a limited usability test was devised in which domain experts are invited to one-on-one trial sessions.

Expert evaluations have been successfully used before and have been shown to be more informative than evaluations, specifically for formative evaluation. In fact, in a previously published survey (Vredenburg et al. 2002), expert review was found to be in the top 3 most important user-centered design methods influencing product development. In our study, Ubisoft was chosen because of its investment to advancing Game User Research and their innovations in the development and use of tools, methods and practices throughout their product development lifecycle. Unity was chosen because of their commitment to democratizing game development tools and the fact that they recently release an advanced heatmap tool at Unite 2015. All the experts have explicitly agreed to be named as it was the only way for us to argue for their level of expertise.

Due to geographical constraints, all our sessions were conducted on online video conference platforms such as Google Hangout and Skype. The sessions were also recorded for posterior transcription, with appropriate approvals from participants. In the usability test, both quantitative performance as well as qualitative comments and critiques are recorded.

Study Protocol

For each participant, the following protocol was conducted, comprising of four steps:

(1) *Demonstration*: Different components and features of the system are briefed, including interaction options, visual cues and representations,

(2) *Exploration*: Participant is given 10-15 minutes to freely explore the tool, while the interviewer stands by to answer questions that arise in the exploration,

(3) *Task Execution*: Participant is given three tasks corresponding to the three challenges described above. The tasks are:

• Identify areas of the game where players spend most their time. Which areas of the level are underutilized? (Size and complexity challenge)

- Identify areas where players spend most of the time interacting with game objects, areas where players are engaged in combat, areas where players access the inventory and areas where players reload a weapon? (high dimensionality challenge)
- Investigate if players interact with NPCs while at the same time sneaking, within a span of 5 seconds; define the areas of the game where players receive damage while reloading a weapon; identify areas where players are engaged in combat but do not receive damage within a radius of 10 meters (dynamic data challenge)

(4) *Post-study Interview*: We asked participants for their opinions on G-Player, direct comparison of features with their own tools, as well as suggestions and recommendation. The tasks assigned are derived from the questions utilized to define the requirements for the design of G-Player, as described above. These tasks mirror the typical questions faced by researchers when looking for behavior trends and understanding individual behaviors.

One issue with this approach is bias. The Hawthorne effect posits that subjects tend to perform better when under observation and the task-selection bias (Lewis 2001) is a very practical instantiation of that effect: subjects believe that just because they have been selected to perform a task they'll be able to do so successfully. Another form of the Hawthorne effect is the social-desirability bias (Tourangeau 1999): subjects will assume that there are norms defining desirable attitudes and behaviors, and that they are concerned enough about these norms to distort their answers to avoid presenting themselves in an unfavorable light. Fortunately all the participants in our evaluation had recently developed tools that are very similar to G-Player, creating a self-defensive bias, the subjects are in fact recruited because they are domain experts. The fact that we directly ask the experts to compare their solution to G-Player compensates for the two biases, they are in fact opposite: the desire to please the interviewers is compensated by allegiance to a tool developed in house and that the experts are already familiar with.

UBISOFT DNA: SYSTEM DESCRIPTION

Ubisoft is the 3rd independent publisher in the world, with 30 studios, 9000 team members, and around 500 million games sold worldwide. The company has Game User Research staff of 13. Ubisoft has evolved cutting edge Games User Research practices,



Figure 6: Ubisoft's DNA. (a) shows the three sections, (b, c) show different heat map displays.

including biometrics, eye-tracking, lab observation, analytics and telemetry. DNA (Jonathan Dankoff 2014) is Ubisoft's internal tool used by designers, producers, managers and researchers to quickly gather an overview of a level's flow and narrow down possible solution for emerging issues. The tool has been used by at least 20 unique users a week since 2012. DNA, seen in Figure 6, is structured in 3 sections: the left column allows progressive filtering of users according to parameters, such as missions completed, health, or player identity. The central view allows a tridimensional representation of the level and plotting layers of dots or traces to create topical heatmaps or movement visualizations. The third section defines which event should be plotted as a layer and how it should be represented.

UNITY HEATMAPS: SYSTEM DESCRIPTION

Unity Technologies is the developer behind Unity 3D, one of the most popular licensed game engines. Unity supports 21 platforms, with 4.5 million registered developers and 1 million monthly active users. 47% of all mobile game developers use Unity. In 2014 Unity acquired the analytics company Playnomics and absorbed it as Unity Analytics, one of their tasks was to bring the intelligence from telemetry and analytics to their developer community in an easy and accessible manner, reflecting the philosophy of the company: "democratize game development'. At Unite 2015 in Boston, Unity Analytics released the first version of their Heatmap Tool, a plugin developed natively for the Unity engine that shows game developers where players are spending their time in a game or where other events happen in the level (Figure 7). The tool is seamlessly integrated in the editor, representing events in the same environment used by designers to edit the game, allowing for seamless flow when analyzing player behavior and tweaking the design to solve issues. The tool allows for fetching raw custom events as logged by their analytics plugin, aggregating events and visualizing animated density maps. Users can control playback through advanced time parameters and define the length of the period that should be replayed.



Figure 7: Unity Analytics Heatmap tool.

RESULTS

Following the evaluation procedure described above, we were able to gain access to Sebastien Hinse, project lead for the telemetry and analytics group, and Daniel Natapov, user research manager at Ubisoft. Sebastien led the development of DNA, and thus, is perfectly qualified to evaluate G-Player. Daniel, as user research manager, is the ideal stakeholder to represent the needs of designers who use their tool daily to iterate over design solutions. Both Sebastian and Daniel followed the procedure and performed the task successfully. In addition to Ubisoft experts, we were also able to interview Marc Tanenbaum, Senior Software Engineer at Unity Analytics. He was in charge of gathering feedbacks and desired features from the Unity community of developers and developed the architecture for the Unity heatmap plugin. The feedback is summarized in Table 1.

	G-Player	DNA	Heatmap	Dada	Pathways
Features for handling data size and complexity					
Supports multiple games and maps simultaneously	•	•	0		
Filter users by features	•	•		•	0
Quick dataset parsing	•				
Massive, tested scalability		•		0	0
Features for handling high-dimensional data					
Selection of multimodal events	•	•	0	•	
Creation of different layers of heat maps	•	•			
Boolean operations on events	•				
Easy to use progressive filtering, cohort definition and drilldowns	0	•		•	
Three dimensional representation of game space		•	•		
Features for handling dynamic spatiotemporal data					
Data playback	0		•		•
Boolean intersection based on spatial and/or temporal bracketing	•				
Joint spatial and temporal constraints	•			•	0
Usability and interface					
Intuitive map controls and navigation	•	•	•	•	•
Flexible and easy to upload maps and edit data	•	•			
Enhanced general usability (tooltips, labeled icons)		•	0	•	
Seamless integration with the editor environment			•		

Table 1. The feedback from experts has been categorized along the three challenges defined initially: data size and complexity, dimensionality and dynamic, and an additional category based on feedback related to user interface and usability. The symbols \bullet , \circ indicate fully supported and partially supported feature, and a blank is unsupported.

Table 1 shows the features supported by each tool examined. In each of the first three categories G-Player has equal if not higher amounts of features than any other tool presented. Only in the category usability are other tools outperforming G-Player. Both Sebastian and David agreed that in the next iteration of DNA they intend to include a playback feature, a time and space constraint feature and Boolean operations to combine different layers of heat maps. They concluded saying: "We both found the tool extremely interesting and useful. I think your tool is really impressive, and offers some really great functionality. For companies (even large studios) that don't currently have such a tool, this will be a life saver." Marc praised the ability to filter players according to game

events and behaviors, the ability to display all game events and create/display easily and concurrently several heat maps based on any feature, and finally the ability to leverage Boolean operators to combine heat maps. He also mentioned how he would consider including these features in the next iteration of Unity's heat map plugin.

CONCLUSION

In this paper, we presented G-Player a visualization tool designed for exploratory analysis of multimodal data utilizing as a case study data from a role-playing game. G-Player uses heat maps as the main device to visualize answers for queries on spatial data portion (such as locations, interactions with items and NPCs, etc.). Equipped with visualization querying techniques such as spatial-temporal constraint modifiers and Boolean operators on events this visualization tool allows quick and easy comparison of individuals and between individuals and player groups. Using the VPAL game, a mod based on Fallout: New Vegas, for illustrative examples, we demonstrated how this tool leads to improved understanding of player behavior data. Corroborated with the opinion of experts whom developed similar tools, we were able to verify that all the three challenges identified initially (size, multidimensionality and dynamics) were overcome. Moreover, validated by the opinion of domain experts, we propose that the use of G-Player, with minimal modifications, may be beneficial to game user researchers and designers analysing player data in those games. In the future, we will continue examining the applicability of G-Player to other popular game genres such as multiplayer online battle arena (MOBA) games, in which G-Player is suitable for analyzing teams and individuals' in-game behavior. Both sets of respondents recruited as experts, provided feedback that went beyond the expectations. We set out to evaluate whether the features developed for G-Player could be seen as useful by domain experts belonging both to a technology provider (Unity) and a content creator (Ubisoft). Not only did we receive positive feedback on the features, but both groups also mentioned the very concrete outcome that such features could be included in the next iteration of the tools developed by Unity and Ubisoft.

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