PLATO: Understanding Gameplay Data Through Visualization

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Abstract
With the increasing popularity of instrumentation to automatically collect gameplay data the need for adequate analysis tools to fully capitalize on the data has arisen. This includes techniques to visually explore the usually large multivariate data sets. In this paper we describe ongoing work on our spatiotemporal visual analytics system – called PLATO – which currently focuses on providing different representations and methods in order to support analytical reasoning.

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Game Metrics, Gameplay Visualization, Visual Analytics

ACM Classification Keywords
K.8.0 [General]: Games; H.5.m [Information Interfaces and Presentation]: Miscellaneous

General Terms
Measurement; Human Factors.

Introduction
In the last couple of years game developers have started to increasingly make use of instrumentation as a supplement to qualitative user testing, such as playtesting or videotaping. However, in order to capitalize on the collected data adequate (visual) analysis techniques are

required. Several academic papers dealing with gameplay visualization have been published in the last decade, for example, [1, 3, 6, 8].

In our previous work [11] we presented a way to formally describe gameplay by decomposing it – for the purpose of analysis – into (1) states, (2) actions and (3) players. A state describes a certain configuration of the game or of an entity within the game. While interacting with the game a player will perform certain actions at specific points in time (e.g., firing a weapon or collecting an item) which will influence the current state. Mathematically, this concept can be expressed as a labeled directed multigraph for which we will use the term *playgraph*. By treating gameplay as a graph we have the benefit of a general representation which is not tied to a specific game or genre.

PLATO

You can discover more about a person in an hour of play than in a year of conversation. [*Plato*]

In the aforementioned work we also presented a first prototype of a visualization system – called PLATO (short for Playgraph Analysis Tool) – which utilizes this concept and visualizes gameplay as a node-link diagram. States are visualized as nodes with the node-size being proportional to the number of players arriving at that state and actions are depicted as directed edges. To reduce visual clutter edges between the same two nodes are merged into a single meta-edge whose thickness is proportional to the number of underlying edges. Edges and nodes are color-coded to indicate the type of the action and state respectively. Figure 1 shows a screenshot of the current prototype.

Current Work

Our current work focuses on improving the system based on informal feedback which we received on our former prototype and on including techniques to facilitate exploratory data analysis. Much of this work centers around three broad areas: (1) providing alternative visualizations and subsequently to evaluate which visualizations are preferred for which kinds of gameplay analysis tasks, (2) techniques for comparative data analysis and (3) (semi-)automated methods to find common or unusual patterns in play-behavior.

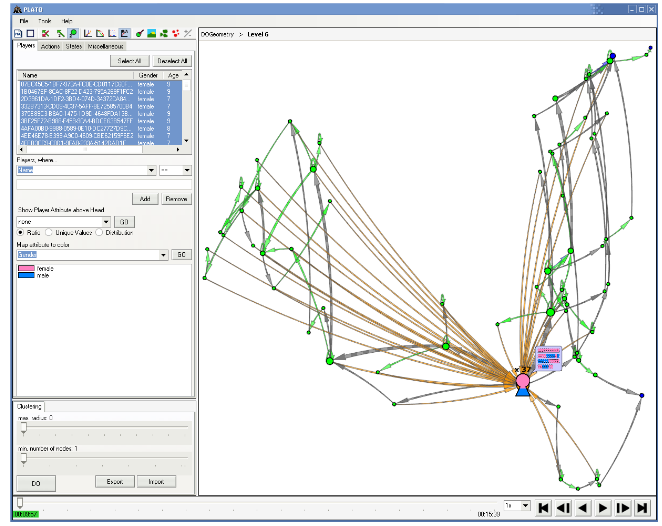

Figure 1: Interface of the current version of PLATO with visualization area (right), various functions for, e.g., searching, filtering, clustering as well as chart generation (left) and time slider for time-dependent simulation (bottom).

Representation Techniques

In our previous prototype node-link diagrams were the only way for visualizing a playgraph. However, node-link diagrams tend to suffer from visual clutter – especially for large and dense graphs – which makes them incomprehensible. We are currently exploring alternative

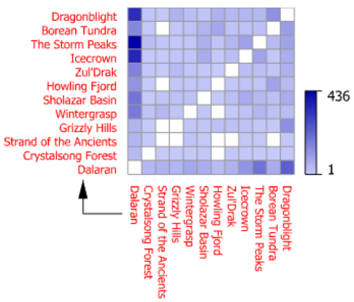

Figure 3: Adjacency matrix of the node-link diagram shown in Figure 2. The color gradient depicts the number of players traveling from one zone to another.

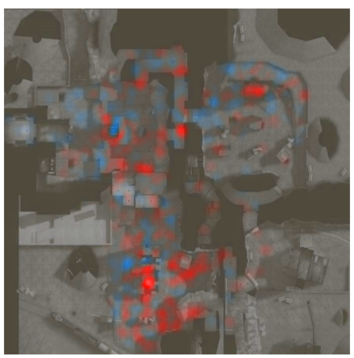

Figure 4: A heatmap of the *Team Fortress 2* map *Gravelpit* showing the relative differences of the number of deaths (aggregated over 20 rounds) in respect to team membership.

visualization techniques like, for example, matrix representations. User studies [4, 7] have shown that matrix representations outperform node-link diagrams for large and dense graphs in several tasks except path-finding.

Consider, for example, the node-link diagram in Figure 2 that shows players migration between the different zones on the *World of Warcraft* (*WoW*) continent *Northrend* on January 5th 2009 (the data for this example was taken from the *WoW* avatar history dataset [9]). Finding the most frequented edges between zones in this node-link diagram is – despite its small size – quite difficult due to the many edge crossings. The corresponding adjacency matrix in Figure 3 on the other hand is well readable and conveys these edges immediately. Moreover, if the vertices are ordered properly, matrix representations can reveal complex relationships and structures.

Comparative Data Analysis

While visualization of game metrics has received increasing attention in the last years, comparative analysis of game-related datasets is largely unexplored. However, visualizations which support the depiction of differences in the data would be helpful to compare various aspects of the same dataset (e.g., are there differences in the play-behavior in respect to age?) or even of datasets from different time periods (e.g., to assess the effect of changes developers make over time, for example, by altering the balance of units, by introducing a new weapon or by releasing a patch). In its current version, PLATO supports different methods to visualize differences, for example, difference graphs between two playgraphs and heatmaps that show the relative differences between variables.

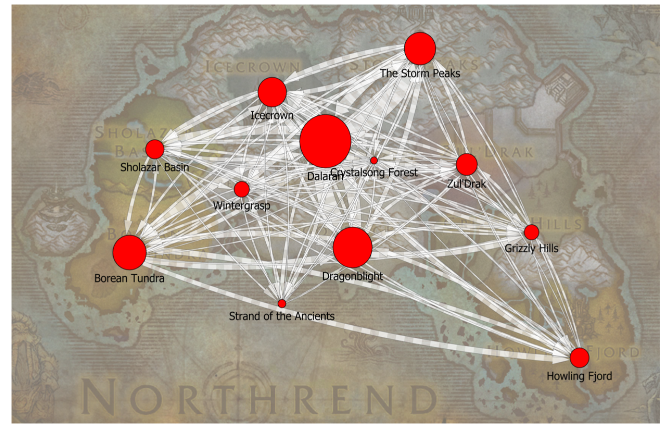

Figure 2: Node-link diagram depicting player migration between the different zones on the *WoW* continent *Northrend*. Node sizes are proportional to the number of visits to a zone.

For instance, the heatmap in Figure 4 shows the relative differences of the number of deaths in respect to team membership for a *Team Fortress 2*[2] map. In blueish areas members of the *BLU* team die more often, similarly reddish areas depict locations were players of the *RED* team get killed more frequently. In this scenario, such heatmaps can, for example, help to detect areas where one team has unfair advantages over the other.

Pattern Mining

One of the biggest potentials of game metrics is the possibility to find common patterns or anomalies in the behavior exhibited by players. However, due to the large amount of data, (semi-)automated techniques are necessary to assist in this task. For example, techniques like self-organizing maps (e.g., [2]) or classical

[2] *Team Fortress 2* is a team-based shooter where two opposing teams – called RED and BLU – are competing for certain objectives, like capturing specific control points.

multidimensional scaling (e.g., [10]) have already been applied to detect patterns of playing behavior. However, it should be explored further how techniques used in other areas dealing with large-scale data can be applied or adopted to the analysis of play-related data.

Inspiration could, for example, be drawn from frequent pattern mining (refer, e.g, to the survey of Han et al. [5] for a high-level overview) in order to reveal correlations, associations and interesting relationships among the collected data. For instance, if a certain subsequence like dying after performing a double jump is repeatedly occurring this may indicate that timing a double jump successfully is too difficult. Moreover, automatically detecting patterns which deviate from the common behavior can help to identify unintended player behavior. We are therefore currently investigating how pattern mining techniques can be integrated into our existing system.

References

[1] Andersen, E., Liu, Y.-E., Apter, E., Boucher-Genesse, F., and Popović, Z. Gameplay analysis through state projection. In *Proc. of FDG 2010*, ACM Press (2010), 1–8.

[2] Drachen, A., Canossa, A., and Yannakakis, G. N. Player modeling using self-organization in Tomb Raider: Underworld. In *Proc. of CIG 2009*, IEEE Press (2009), 1–8.

[3] Gagné, A. R., El-Nasr, M. S., and Shaw, C. D. A deeper look at the use of telemetry for analysis of player behavior in RTS games. In *Proc. of ICEC 2011*, Springer (2011), 247–257.

[4] Ghoniem, M., Fekete, J.-D., and Castagliola, P. On the readability of graphs using node-link and matrix-based representations: a controlled experiment and statistical analysis. *Information Visualization 4*, 2 (July 2005), 114–135.

[5] Han, J., Cheng, H., Xin, D., and Yan, X. Frequent pattern mining: current status and future directions. *Data Min. Knowl. Discov. 15*, 1 (Aug. 2007), 55–86.

[6] Hoobler, N., Humphreys, G., and Agrawala, M. Visualizing competitive behaviors in multi-user virtual environments. In *Proc. of VIS 2004*, IEEE Computer Society (2004), 163–170.

[7] Keller, R., Eckert, C. M., and Clarkson, P. J. Matrices or node-link diagrams: which visual representation is better for visualising connectivity models? *Information Visualization 5*, 1 (Mar. 2006), 62–76.

[8] Kim, J. H., Gunn, D. V., Schuh, E., Phillips, B., Pagulayan, R. J., and Wixon, D. Tracking real-time user experience (TRUE): A comprehensive instrumentation solution for complex systems. In *Proc. CHI 2008*, ACM Press (2008), 443–452.

[9] Lee, Y.-T., Chen, K.-T., Cheng, Y.-M., and Lei, C.-L. World of Warcraft avatar history dataset. In *Proc. of MMSys '11*, ACM Press (2011), 123–128.

[10] Thawonmas, R., Kurashige, M., Iizuka, K., and Kantardzic, M. M. Clustering of online game users based on their trails using self-organizing map. In *Proc. ICEC 2006*, LNCS, Springer (2006), 366–369.

[11] Wallner, G., and Kriglstein, S. A spatiotemporal visualization approach for the analysis of gameplay data. In *Proc. CHI 2012*, ACM Press (2012), 1115–1124.

Günter Wallner is currently senior scientist at the University of Applied Arts Vienna where he received his doctorate degree in natural sciences for his thesis about GPU radiosity in 2009. Before that he studied computer science at the Vienna University of Technology from which he received his diploma degree for his thesis on game design in 2005. He also lectured on scientific and information visualization at the University of Vienna for the last four years. His research interests include computer graphics, rendering and visualization, as well as the design, development, and evaluation of digital games. His current research focus lies on analysis and visualization of game telemetry data.

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