Exploring Problem-Solving Behavior in an Optics Game

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ABSTRACT
Understanding player behavior in complex problem solving tasks is important for both assessing learning and for the design of content. Previous research has modeled student-tutor interactions as a complex network; researchers were able to use these networks to provide visualizations and automatically generated feedback. We collected data from 195 high school students playing an optics puzzle game, Quantum Spectre, and modeled their game play as an interaction network. We found that the networks were useful for visualization of student behavior, identifying areas of student misconceptions, and locating regions of the network where students become stuck.

1. INTRODUCTION
This work presents preliminary results from our attempts to derive insight into the complex behaviors of students solving optics puzzles in an educational games using a complex network representation of student-game interactions. An *Interaction Network* is a complex network representation of all observed student-tutor interactions for a given problem in a game or tutoring system [3]. Professors using *InVis* were successful in performing a series of data searching tasks; they were also able to create hypotheses and test them by exploring the data [5]. *InVis* was also used to explore the behavior of students in a educational game for Cartesian coordinates. Exploration of the interaction networks revealed off task behavior, as well as a series of common student mistakes. The developers used the information gained from the interaction networks to change some of the user interface to reduce these undesirable behaviors [4]. Regions of the network can be discovered by applying network clustering methods, such as those used by Eagle et al. for deriving maps high-level student approaches to problems [2]. This paper reports gameplay data from 195 students in 15 classes collected as part of a national Quantum Spectre implementation study in the 2013-14 academic year.

The Education Gaming Environments (EdGE @ TERC) research group studies how games can be used to improve learning of fundamental high-school science concepts. EdGE games use popular game mechanics embedded in accurate scientific simulation so that through engaging gameplay, players are interacting with digitized versions of the laws of nature and the principles of science. We hypothesize that as players dwell in scientific phenomena, repeatedly grappling with increasingly complex instantiation of the physical laws, they build and solidify their implicit knowledge over time. Previous work for a game *Impulse* used an automated detector of strategies in the game [1]. In this study, we examine how interaction networks can be used to visually measure the implicit science learning of students playing *Quantum Spectre*, a puzzle-style game that simulates an optics bench students might encounter in a high school physics classroom.

2. QUANTUM SPECTRE
Quantum Spectre is a puzzle-style designed for play in browsers and on tablets. Each level requires the player to direct one or more laser beams to targets while (potentially) avoiding obstacles. For each level, an inventory provides the player with access to resources, such as flat and curved (concave, convex, and double-sided) mirrors, (concave and convex) lenses, beam-splitters, and more, that can be placed and oriented within the puzzle and that interact with and direct the laser beams in a scientifically accurate manner. When the appropriate color laser beam(s) have reached all the targets, a level is complete. The player earns three "stars" if the puzzle has been solved in the fewest possible moves, two "stars" for a low number of extra moves, and one "star" for any solution. Each placement or rotation of an object on the game board counts as one move. A player can go onto to the next level as soon as a puzzle is complete, regardless of the number of moves used, but the stars system provides an incentive for level replay and an understanding of the puzzle's solution. The game includes a range of scientifically accurate optical instruments and related science concepts, but for the research, three key scientific concepts were identified: The Law of Reflection; Focal Point and Focal Length of Concave Mirrors; and Slope.

3. RESULTS AND DISCUSSION
To construct an Interaction Network for a problem, we collect the set of all solution attempts for that problem. Each solution attempt is defined by a unique user identifier, as well as an ordered sequence of interactions, where an interaction is defined as {initial state, action, resulting state}, from the start of the problem until the user solves the prob-

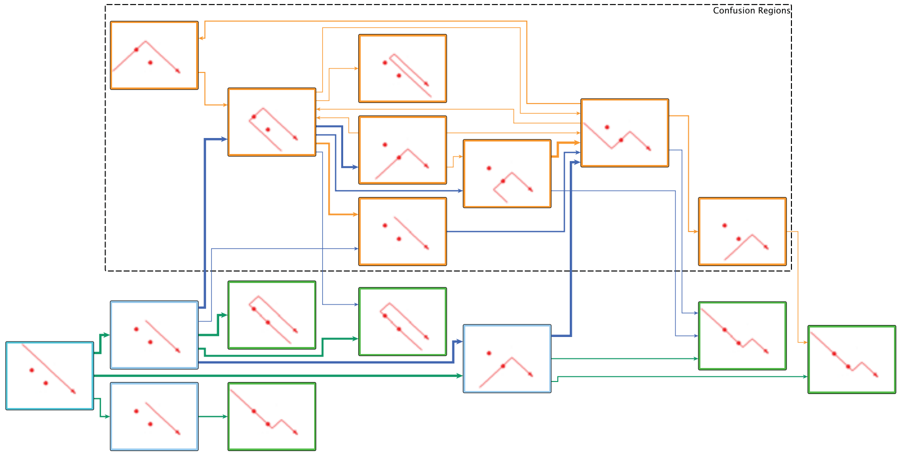

Figure 1: The approach map for problem number 18. This is a high-level view at student approaches to this puzzle. The vertices represent sub-regions of the overall interaction network. Vertices are colored according to their game "star" score, with green being the optimal score, blue the less optimal, and orange for very suboptimal states. The approach map is capturing students with poor approaches to the problem, these regions are indicated by the dotted line.

lem or exits the system. The information contained in a *state* is sufficient to precisely recreate the tutor's interface at each step. Similarly, an *action* is any user interaction which changes the state, and is defined as {action name, pre-conditions, result}. We chose to use only objects the player can interact with. We ignore the distinction between objects of the same type, so the order of placement does not matter. An example state could be {Flat_Mirror(4,1,90), Flat_Mirror(5,5,180)}: which would be a state describing two mirror objects with the first two numbers representing the X and Y coordinates and the last representing the mirrors angle.

The full graph of every state space and every action taken was large, complex, and difficult to interpret in terms of player understanding. In order to provide a high-level view that game designers and instructors could use to gauge players' mastery of game concepts, we clustered states using the Approach Map method from Eagle et al. [2]. The interaction network for problem 18, which had over 1000 unique states, is concisely represented as 17 region-level nodes as seen in figure 1.

This image is a simplified representation of the game board, with a mirror drawn in every location where a mirror was placed by an edge entering the cluster. "Active" pieces (the piece that was moved or rotated to enter the cluster was considered active for that move) were shown in blue, and inactive pieces (any pieces that remained unmoved on the board during that action) were in black. The intention was to show a milestone for each cluster: by looking at how each student who entered a cluster got into that cluster, the reader could trace a given path from cluster to cluster and get an idea of how the students on that path had progressed through the puzzle.

Using the approach map we are able to derive an overview of the student behaviors. Several of the derived regions represent poor approaches to solving the problem, this mirrors the results from Eagle et al. [2]. The region vertices are particularly useful for discovering the locations where students transfer into the confusion regions, as these highlight the places where student approaches contain misunderstandings. These results support the use of approach maps and interaction networks for use in this game environment. In future work we will look for differences in student performance on pre and posttest measures to see if there are differences in overall approach that are predicted by pretest score or can predict posttest score.

4. ACKNOWLEDGMENTS

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