Students' Walk through Tutoring: Using a Random Walk Analysis to Profile Students

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ABSTRACT

The purpose of this study was to investigate students' patterns of interactions within a game-based intelligent tutoring system (ITS), and how those interactions varied as a function of individual differences. The analysis presented in this paper comprises a subset (n=40) of a larger study that included 124 high school students. Participants in the current study completed 11 sessions within iSTART-ME, a game-based ITS, that provides training in reading comprehension strategies. A random walk analysis was used to visualize students' trajectories within the system. The analyses revealed that low ability students' patterns of interactions were anchored by one feature category whereas high ability students demonstrated interactions across multiple categories. The results from the current paper indicate that random walk analysis is a promising visualization tool for learning scientists interested in capturing students' interactions within ITSs and other computer-based learning environments over time.

Keywords

Intelligent Tutoring Systems, sequential pattern analysis, random walk analysis, individual differences

1. INTRODUCTION

A growing trend in the field of educational technology has been to use aggregated or summative analysis to trace students' interactions with game-based features inside of Intelligent Tutoring Systems (ITSs) [1-5]. These analyses capture students' interactions with the system overtime and at fixed intervals [3-5]. For example, aggregated analysis on the frequency of students' utilization of game-based features across multiple training sessions found that patterns of interactions varied as a function of individual differences in performance orientation [4]. Similarly, summative methods have been used to investigate how the availability of game-based elements inside of a system impacts students' overall enjoyment [3].

Although aggregated and summative analyses shed some light on users' overall system interactions, those statistical methods cannot trace nuances in students' paths in adaptive learning environments. The current study utilizes sequential pattern analysis to reveal distinct differences in students' propensity to interact with various game-based features.

Sequential pattern analysis places an emphasis on fine-grained detail. Therefore, this means of analysis may give researchers a deeper understanding of students' interactions in a system by examining nuances in patterns overtime. Random walk analysis is just one of many available sequential pattern analysis tools (e.g., Euclidean distance and dynamic time warping). A random walk analysis is a mathematical tool that generates a spatial representation of a path [6]. This technique has been used in a variety of domains such as economics [7], ecology [6], psychology [8] and medicine [9-10]. For instance, this method has been used in the study of genetics and aptly renamed DNA walks [9-10]. DNA walks provide researchers with a simple visualization of genome codes and patterns [10]. Overall, random walk analysis has been a useful technique for visualizing the nuances of fine grain patterns in categorical data over time.

The current study employs a random walk analysis in the visualization of students' interactions with the game-based ITS, iSTART-ME. We are particularly interested in examining how students' patterns of interactions with game-based features vary as a function of individual differences across numerous sessions. Investigating these patterns as they unfold over time is expected to provide researchers with a deeper understanding of variations in students' tendency to use game-based features.

1.2 iSTART-ME

The Interactive Strategy Training for Active Reading and Thinking – Motivationally Enhanced (iSTART-ME) is a game-based ITS developed on top of an existing system, iSTART [11]. iSTART was developed to provide instruction and practice in comprehension strategies and improve student comprehension of difficult science texts.

iSTART-ME training includes three initial phases where reading comprehension strategies are *introduced*, *demonstrated*, and *practiced* (phases are discussed in more detail in [1]). A fourth phase includes *extended practice*, where students apply the strategies across numerous texts and multiple sessions. iSTART-ME situates this extended practice within a game-based selection menu (see Figure 1), which includes: generative practice games, personalizable features, achievement screens, and identification mini-games. *Generative practice games* are designed so that students must generate text and practice applying the reading comprehension strategies. *Identification mini-games* provide examples and require students to identify the specific strategy being used. *Personalizable features* are incentives designed to afford students a higher locus of control and investment with the environment. *Achievement screens* allow students to track their progress and performance across the iSTART-ME system. All four features are available during interactions with iSTART-ME, and students are free to choose among the options at any time.

Figure 1. Screenshot of iSTART-ME Interface

2. METHODS

2.1 Participants

Participants in the current work (n=40) were a subset of 124 high school students who participated in a study at a large university campus in the Mid-Southern United States [12]. The current analyses focus only on those students who were randomly assigned to interact with the game-based iSTART-ME system (other students in the original study were assigned to an ITS or a no-tutoring control). The students included here consisted of 20 males and 20 females, with an average age of 16 years.

2.2 Procedure

Students in this study completed an 11-session experiment that consisted of a pretest, 8 training sessions within iSTART-ME, a posttest, and a delayed retention test. During session 1, participants completed a pretest to assess their attitudes, motivation, prior self-explanation (SE) quality, vocabulary knowledge, and prior reading ability. SE quality was measured at pretest using the iSTART algorithm, which ranges from 0 (poor) to 3 (good) [13]. This score provides a rough indicator for the amount of cognitive processing involved, and represents the quality of a student's self-explanation [14]. Prior reading ability was assessed using the Gates MacGinitie Reading Test [15]. Students interacted with the iSTART-ME system during sessions 2 through 9. During session 10, students completed a posttest, which included measures similar to the pretest. Finally, five days after the posttest, students returned to complete a retention test, consisting of similar self-explanation and comprehension measures.

2.3 Analysis

The current study employs a random walk algorithm to visualize student interaction patterns across time (sessions 2 through 9). Game-based features were grouped into four distinct categories and each was assigned to a vector on an X, Y scatter plot. Although the current study used only four dimensions, the number of dimensions that can be included when using random walk analyses is relatively unlimited. The walk proceeds by placing an imaginary particle at the origin (0, 0) and, each time a participant interacts with a specific feature, the particle moves in the direction of the vector assignment (see Table 1 for directional assignment).

Table 1. Directional Assignment per Interaction

System Interaction	Directional assignment
Generative Practice Games	-1 on X-axis (move left)
Identification Mini-Games	+1 on Y-axis (move up)
Personalizable Features	+1 on X-Axis (move right)
Achievement Screens	-1 on Y-axis (move down)

Figure 2 is an example of what a walk may look like for a student with four interactions corresponding to the following sequence: 1) generative practice game (move left), 2) identification mini-game (move up), 3) personalizable feature (move right), and 4) a second identification mini-game (move up). These simple rules are used for every interaction a student makes and give us their "walk" through the system.

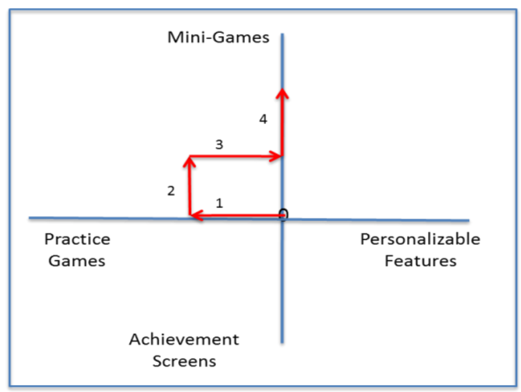

Figure 2. Example of Directional Rules for Walk Sequence

3. RESULTS

The current study examined students' patterns of interactions with game-based features and how they may vary as a function of individual differences. Students' data logs from their eight sessions in iSTART-ME were used to categorize every interaction into one of the four possible game-based feature types: generative practice games, personalizable features, achievement screens, and identification mini-games. The random walk algorithm was then used to construct a unique pattern for each participant (see Figure 3 for one student's complete "walk" pattern).

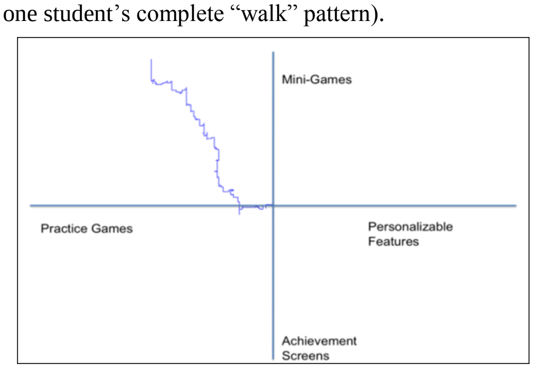

Figure 3. Individual Walk for a Student in the iSTART-ME Study

A slope was calculated as a coarse measure of each student's unique walk pattern. This slope provides a measure of each student's interaction trajectory across the time spent within the game-based portion of iSTART-ME. Slope calculations obscure a portion of the variability in walk patterns. On the one hand, some information is lost in that analysis. On the other hand, this metric provides valuable insight into students' interaction trajectories over time. Utilizing these slopes, we examined the relation between slope magnitude and individual differences in prior reading ability, prior SE quality, and prior vocabulary knowledge (see Table 2). A correlation analysis revealed that the magnitude of walk slopes was negatively related to prior reading ability and prior SE quality. This analysis also indicated a marginally significant relation between slopes and pretest vocabulary knowledge. Students with higher reading and SE quality pretest scores demonstrated a more vertical trajectory in their patterns of interactions. That is, higher ability students were more likely to interact with both generative practice games and identification mini-games and were less likely to hover around the generative practice game function.

Table 2. Correlations between Slope of Students' Walks and Individual Difference Variables

Individual Difference Variables	***Slope (r)***
Prior Reading Ability	-.593**
Prior SE Quality	-.496**
Vocabulary Knowledge	-.297*(M)*
p<.05*; p<.01**; *M*= Marginally Significant, p<.10	

A median split on pretest reading comprehension scores was used to classify students as either high or low ability. A one-way ANOVA examining trajectory differences between high and low reading ability students indicated that high reading ability students had significantly steeper slopes (M = -1.76, SD = 0.96) compared to low reading ability students (M = -0.58, SD = 0.56, $F(1,38)$ = 23.58, p < 0.001[1]. The effect size for this relation (η^2 = 0.38) suggests a moderate to high practical significance [16]. Figure 4 provides a visualization of those differences. In summary, the results indicate that low reading ability students are more likely to use the generative practice game features and are less prone to interact with the other game features.

A similar ANOVA examined differences in walk slopes for students with high and low pretest SE quality scores[1] These results reveal that students with higher quality self-explanations at pretest had significantly steeper slopes (M = -1.62, SD = 1.00) compared to those with low SE quality (M = -0.62, SD = 0.60, $F(1,38)$ = 14.99, p < 0.001). The effect size for this relationship (η^2 = 0.68) suggests a high practical significance [16]. These results indicate that students who generated low quality self-explanations prior to training tend to hover consistently around a specific feature (generative practice games) whereas, high SE quality students seem to interact at a more balanced rate between generative practice games and identification mini-games. Figure 5 provides a visualization of these differences.

[1] Multivariate regression analyses confirmed results of the median-split analyses.

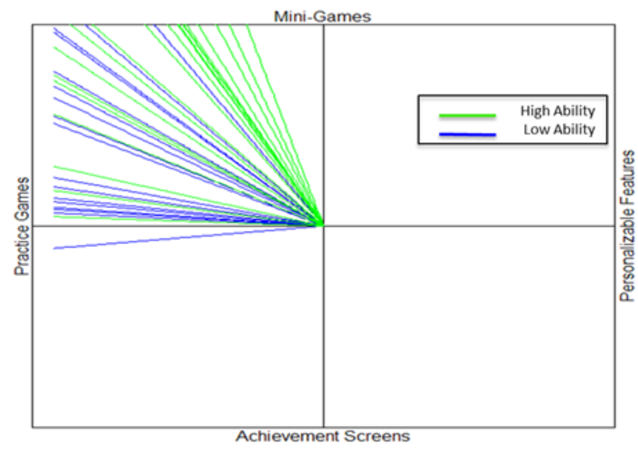

Figure 4. Visualization of Slope Trajectories for High and Low Reading Ability Students

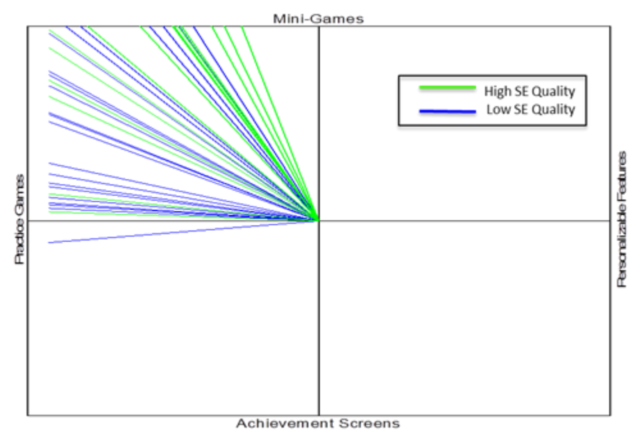

Figure 5. Visualization of Slope Trajectories for Students with High and Low Prior Self-Explanation Quality Scores

4. DISCUSSION

The current study used a random walk analysis to view sequences of patterns in students' interactions within the game-based ITS, iSTART-ME. We suggest that sequential pattern analysis may benefit learning scientists by providing a new method for tracking and viewing students' interactions with game-based features across time. Using the slopes of each student's unique walk we found that there was a relation between a students' trajectory through the system and their prior reading comprehension ability and prior self-explanation (SE) quality scores. Investigating this relation further, we found that students with higher reading ability and higher SE quality scores showed significantly different trajectories compared to low reading ability and those students with lower quality self-explanations. Low ability students tended to interact more with generative practice games, whereas high ability students interacted in a more balanced way with both generative practice games and identification mini-games.

The implications of the current study are promising for researchers in two ways. First we have shown that random walk analysis can be used to view fine-grained patterns of interactions within an ITS. Researchers can use this analysis technique to track students' interactions within a system across time. Although this method is well known and used in many diverse fields [6-9], this is the first time, to our knowledge, that random walk has been used to investigate users' trajectories inside of an adaptive learning environment. Secondly, we have shown that individual differences can be distinguished by using slopes derived from each student's walk. These slopes show us the trajectory of students' interactions and what features are anchoring them. This may be useful for real time analysis of system usage. For instance, if students' patterns of interactions are too stagnant, the system may need to prompt them to interact with a different feature. Random walk analyses may also improve the adaptability of adaptive environments by allowing researchers to monitor and track users' behaviors inside the system.

The current analysis opens the door for a wide range of time series analysis techniques, a full description of which is beyond the scope of this paper. For example, we are currently exploring the benefit that long-range correlations and probability analysis may offer to the study of students' interaction patterns. Future work will also focus on the order in which students interact with features and how much time students spend on each feature. Examining time and order will give us a better understanding of students' patterns of interactions and how these patterns may evolve across time.

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6. REFERENCES

[1] Jackson, G. T., Boonthum, C., and McNamara, D. S. 2009. iSTART-ME: Situating extended learning within a game-based environment. In *Proceedings of the Workshop on Intelligent Educational Games at the 14th Annual Conference on Artificial Intelligence in Education*, (Brighton, UK, July 06 -10, 2009). AIED, IOS Press, 59-68.

[2] Malone, T., and Lepper, M. 1987. Making learning fun: a taxonomy of intrinsic motivations for learning. In *Aptitude, learning, and instruction*, R. Snow and M. Fair, Eds. Vol. 3. Cognitive and affective process analyses. Erlbaum, Hillsdale, NJ, 223-253.

[3] Rai, D., and Beck, J. 2012. Math learning environment with game-like elements: An experimental framework. *International Journal of Game Based Learning*, 2, (2012), 90- 110.

[4] Snow, E. L., Jackson, G. T., Varner, L. K., and McNamara, D. S. In Press. The impact of performance orientation on students' interactions and achievements in an ITS. *In Proceedings of the 26th Florida Artificial Intelligence Research Society Conference* (St. Petersburg, FL, May 21 – May 25, 2013). FLAIRS-26. AAAI Press.

[5] Rowe, J., McQuiggan, S., Robison, J., and Lester, J. 2009. Off-task behavior in narrative-centered learning environments. *In Proceedings of the Workshop on Intelligent Educational Games at the 14th Annual Conference on Artificial Intelligence in Education*, (Brighton, UK, July 06 - 10, 2009). AIED, IOS Press, 99-106.

[6] Benhamou, S., and Bovet, P. 1989. How animals use their environment: a new look at kinesis. *Animal Behavior*, 38, (1989) 375-383.

[7] Nelson, C. R., and Plosser, C. R. 1982. Trends and random walks in macroeconmic time series: some evidence and implications. *Journal of Monetary Economics*, 10, (1982) 139-162.

[8] Collins, J. J., and De Luca, C. J. 1994. Random walking during quiet standing. *Physical Review Letters*, 73, (1994) 764-767.

[9] Arneodo, M., Arvidson, A., Badełek, B., Ballintijn, M., Baum, G., Beaufays, J., and Prytz, K. 1995. Measurement of the proton and the deuteron structure functions, *Physics Letters B*, 364, (1995) 107-115.

[10] Lobry, J. R. 1996. Asymmetric substitution patterns in the two DNA strands of bacteria. *Molecular Biological Evolution*, 13, (1996) 660–665.

[11] McNamara, D. S., O'Reilly, T., Rowe, M., Boonthum, C., and Levinstein, I. B. 2007. iSTART: A web-based tutor that teaches self-explanation and metacognitive reading strategies. In *Reading comprehension strategies: Theories, interventions, and technologies*, D. S. McNamara, Ed. Erlbaum. Mahwah, NJ, 397-420.

[12] Jackson, G. T., and McNamara, D. S. In Press. Motivation and performance in a game- based intelligent tutoring system. *Journal of Educational Psychology*. (in press).

[13] McNamara, D.S., Boonthum, C., Levinstein, I.B., and Millis, K. 2007. Evaluating self-explanations in iSTART: Comparing word-based and LSA algorithms. In *Handbook of Latent Semantic Analysis*, T. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch, Eds. Erlbaum. Mahwah, NJ, 227-241.

[14] Jackson, G.T., Guess, R.H., and McNamara, D.S. 2009. Assessing cognitively complex strategy use in an untrained domain. In *Proceedings of the 31st Annual Meeting of the Cognitive Science Society* (Amsterdam, The Netherlands, July 29 – August 01, 2009). Cognitive Science Society, Austin, TX, 2164-2169.

[15] MacGinitie, W., and MacGinitie, R. 1989.*Gates MacGinitie reading tests*. Riverside. Chicago, IL.

[16] Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum. Hillsdale, NJ.