Understanding Student Attention to Adaptive Hints with Eye-Tracking

Mary Muir[1], Alireza Davoodi[1], Cristina Conati[1],

[1] Department of Computer Science, University of British Columbia,
{marymuir, davoodi, conati}@cs.ubc.ca

Abstract. Prime Climb is an educational game that provides individualized support for learning number factorization skills. This support is delivered by a pedagogical agent in the form of hints based on a model of student learning. Previous studies with Prime Climb indicated that students may not always be paying attentions to the hints, even when they are justified. In this paper we discuss preliminary work on using eye tracking data on user attention patterns to better understand if and how students process the agent's personalized hints, with the long term goal of making hint delivery more effective.

Keywords: Adaptive help, educational games, pedagogical agents, eye-tracking

1 Introduction

Educational games (edu-games) are one of the most promising media for the development of innovative computer-based pedagogy, however, while there is ample evidence that edu-games are highly engaging, there is less direct support for evidentiary claims about what is learned through play [e.g. 1, 2]. We believe that edu-games effectiveness can be improved by making them more adaptive to the specific needs of individual students, and we are doing so by devising intelligent pedagogical agents that can provide individualized support to student learning during game playing [3]. Providing this support is challenging because it requires a trade-off between fostering learning and maintaining engagement. Our long-term goal is to enable our agents to achieve this trade-off by relying on models of both student learning and affect [3]. In this paper, we focus on an issue that has been raised in the context of various user-adaptive learning environments: are interactive, personalized didactic hints effective? Do students pay attention to them [e.g. 11]? We investigate this issue in relation to the user-adaptive hints provided by the pedagogical agent in Prime Climb, an edu-game for number factorization. The current agent's version provides hints based on a model of student learning [3]. A previous study showed that the adaptive version of Prime Climb did not perform better than a version with random hints, and provided initial indications that one reason for this outcome is student limited attention to the agent's adaptive hints. In that study, attention was estimated from how long students had the hints open on the screen. In this paper, we start looking at a more accurate measure of attention, based on eye-tracking data. We present preliminary results from the analysis of one student's interaction with Prime Climb, as a proof of concept for this methodology.

User-adaptive educational games are receiving increasing attention [e.g. 4, 5] although most of the existing work has not been formally evaluated in terms of how adaptive game components contribute to learning. There has also been increasing interest in using eye-tracking to gain insights on the cognitive and perceptual processes underlying a user's performance with an interactive system [6, 11]. In this paper, we contribute to this line of research by using gaze information to understand if/how users attend to a system's adaptive interventions. Adaptive incremental hints are commonly used in personalized learning environments, but their effectiveness is in question because there are students who ignore them, or use them to extract quick solutions from the system [8, 11]. Researchers have proposed predictive models of hint processing based on reaction-time (lapsed time between the hint being displayed and the next observable student action) [8, 9]. Despite encouraging results, these models cannot capture the details of the student's cognitive reactions to a hint because these are unobservable when using only reaction time. We investigate how to uncover these details by relying on attention patterns captured via eye-tracking. In the rest of the paper, we first describe the Prime Climb edu-game and its personalized agent. We then provide an example of attention analysis and the insights that it can provide.

2 The Prime Climb Game

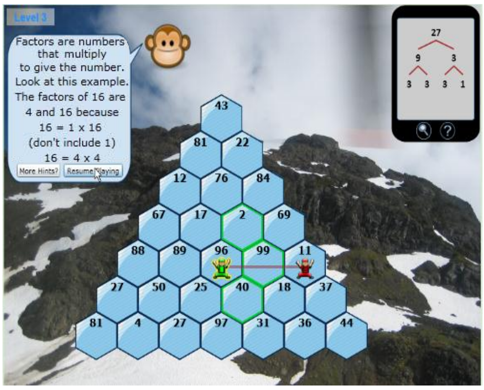

Figure 1: The Prime Climb interface.

In Prime Climb, students in 6th and 7th grade practice number factorization by pairing up to climb a series of mountains. Each mountain is divided into numbered sectors (see Figure 1), and players must move to numbers that do not share common factors with their partner's number, otherwise they fall. To help students, Prime Climb includes the Magnifying Glass, a tool that allows players to view the factorization for any number on a mountain in the device at the top-right corner of the interface (see Figure 1). Each student also has a pedagogical agent (Figure 1) that provides individualized support, both on demand and unsolicited, when the student does not seem to be learning from the game. To provide appropriate interventions, the agent must understand when incorrect moves are due to a lack of factorization knowledge vs. distraction errors, and when good moves reflect knowledge vs. lucky guesses. Thus, Prime Climb includes a probabilistic student model that assesses the student's factorization skills for each number involved in game playing, based on the student's game actions [3]. The agent gives hints at incremental levels of detail, if the student model predicts that the student doesn't know how to factorize one of the numbers involved in the current move (regardless of move correctness). The agent starts by reminding the student to evaluate her move in term of number factorization, then it generates a *tool* hint that encourages the student to use the magnifying glass to see relevant factorizations. If the student needs further help, the agent gives *definition* hints designed to re-teach what is a factor via explanations and generic examples. There are two different factorization definitions ("Factors are numbers that divide evenly into the number", "Factors are numbers that multiply to give the number"). The agent alternates which definition to give first, and gives the second the next time it needs to provide a hint. The generic examples that accompany the definitions change for every hint. Finally, the agent provides a *bottom-out* hint giving the factorization of the two numbers involved in the current move. Students can choose to progress through the various levels by asking. Otherwise, the agent goes through the progression as the student model calls for a new hint. A hint is displayed until the student selects to resume playing or to access the next hint level, if available.

3 Sample gaze analysis

Previous studies with Prime Climb suggested that students may often ignore agent's hints, even when these hints are well justified (i.e. based on a reliable student model's assessment) [3]. Those results were based on hint *display time* (duration of time a hint stays open on the screen) as a rough indication of attention. However, display time can be unreliable because students may not attend a displayed hint, or be fast readers and thus processing a hint even when display time seems short. For a more precise analysis, we are using a Tobii T120 eye-tracker to capture students' attention patterns. At the time of writing we have reliable data for only one subject, which we present as an example of the type of analysis that eye-tracking can support.

Table 1: Summary of statistics on fixation time and display time for each hint type

	Tool hint	Definition Hint	Bottom-Out Hint
Number of hints	16	34	15
Fixation Time Mean (st dev)	1.22 (0.99)	2.14 (2.31)	1.53 (1.1)

The agent's adaptive hints can be divided into two categories: *short hints*, which are on average 8 words long and include tool or *bottom-out* hints; *long hints*, which are on average 25 words long and include all *definition* hints. The amount of time it would take an average-speed reader to read the text would be 2.3 seconds and 7.3 seconds for the *short* and *long* hint respectively. Table 1 shows mean and standard deviation of total fixation time (i.e. total time a student's gaze rested on a displayed hint) for each hint type. These numbers show that, although this particular student spent more time looking at the longer hints (*definition* hints), the increase is not proportional to the increased hint length, and in fact there is no statistically significant difference between the reading time for these three hint types (as tested via ANOVA). Furthermore, fixation time is much shorter than the time an average-reader would need to read the hints. The high standard deviation on all three measures indicates a trend of selective attention. Figure 2 visualizes this trend by showing total fixation time on each individual hint, for each hint category. The x-axes show hint number in each category.

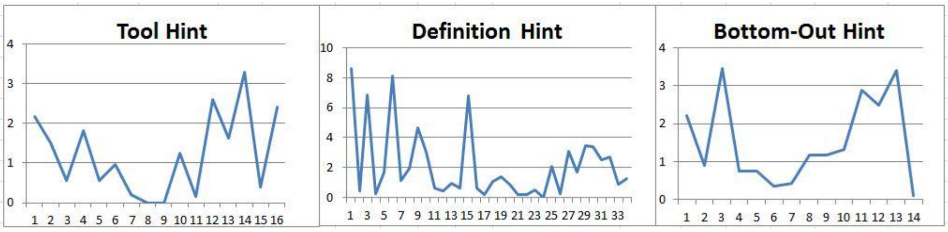

Figure 2: Total fixation time for each displayed hint

It is interesting to see that, for about the first half of the displayed *definition* hints, there is a pattern of attention being high for one hint, and low for the *definition* hint given as the next step in the hinting cycle. This pattern suggests that this student tends to ignore the second *definition* hint, possibly because two subsequent *definition* hints are perceived as redundant. Student attention then decreases substantially for all of the second half of *definition* hints provided. In contrast, attention to *tool* and *bottom-out* hints reaches its low in the middle of the interaction, but picks up again towards the end. A possible explanation for these trends is that *definition* hints become less useful overtime, as mountains get more difficult (i.e. include larger numbers), because the student is already familiar with the factorization definitions and the generic examples in the hint don't help directly with the current moves. However, apparently the student still needs help dealing with the higher numbers, so she does read *short* hints when they appear and specifically attends to *bottom-out* hints because they provide the information needed to understand the outcome of the current move. We need of course to collect more data before drawing any firm conclusion. These trends, however, are consistent with previous indications that attention to some the Prime Climb hints can be scarce and start providing specific information on why and how the current hinting strategy needs to be revised to make it more effective. Further insights can be derived from a more detailed analysis of the attention patterns associated with specific hints, e.g. attention shifts between a hint and relevant places of the mountain (or lack thereof). Following the approaches proposed in [4] and [10], we plan to apply data mining techniques to discover patterns associated with learning/reasoning vs. confusion or distraction. In the long term, we want to use this information to add to the Prime Climb user model a classifier that can recognize these patterns in real time, and use the information to generate adaptive interventions geared at focusing student attention when needed.

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