The Use of Multidimensional Biopsychological Markers to Detect Learning in Educational Gaming Environments

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ABSTRACT

This project explores how multidimensional bio-psychological measures are used to understand the cognitive aspects of student learning in STEM (Science, Technology, Engineering and Math) focused educational games. Furthermore, we seek to articulate a method for how learning events can be automatically analyzed using these tools. Given the complexity and difficulty of finding externalized markers of learning as it happens, it is evident that more robust measures could benefit this process. The work reported here, with funding from National Science Foundation grant (NSF DRL-1417456), aims to incorporate more diverse measures of behavior and physiology in order to create a more complete assessment of learning and cognition in a game based environment. Tools used in this project include eye tracking systems, heart rate sensors, as well as tools for detecting electrodermal activity (EDA), temperature and movement data. Findings indicated both the utility of more varied measures as well as the need for more precise tools for synchronization of diverse data streams.

Author Keywords
Eye-tracking; Educational Games; Game Based Learning; STEM Education; Electrodermal Activity.

ACM Classification Keywords
H.1.2 [User/Machine Systems Subjects]: Human information processing.

INTRODUCTION

Measurement of learning in game based environments has typically proven to be a complex process [1]. While explicit measures of knowledge are useful, assessments of content knowledge in this manner only give one dimension of understanding and the underlying cognitive processes. With this is in mind, this paper is part of a larger project focused on addressing 2 questions related to this complex problem: How can contextualized learning or knowledge be assessed in game based environments, and how can this information be validated by multidimensional measures of physiological information?

If one approaches these problems with data rich subject information that includes physiological measures related to cognition, then one could potentially create a more complete assessment of knowledge in game based environments. Some researchers have approached this problem space by assessing not only explicit knowledge of content, as in psychometric testing, but also by exploring physiological responses to educational material and ways that these measures may map to cognitive states [2, 3]. One of the most straightforward ways of doing this may be through the use of eye tracking technology.

EYE MOVEMENTS AND COGNITION

Eye movements have long been used to study visual information processing [4]. Advances in eye tracking technology and a mature understanding of key characteristics of eye movements has allowed for the detailed analysis of complex visual information processing tasks including reading, visual search, and scene perception [5]. Attention, and in particular visual attention, has been the cognitive construct most closely linked to eye movements, however eye movement data has been used to measure and model other cognitive constructs as well.

While the mechanisms for attention control and eye movement control are distinct, they share a lot of neural anatomy and often co-occur [6]. Visual quality and color perception are strongest at the center of a fixation and drop off rapidly at the periphery of the visual field. Eye movements closely follow shifts in attention for both voluntary and involuntary eye movements [7]. Exceptions to this coupling do exist on occasion, but primarily in highly automatized tasks with items that are closely packed (e.g. simple words skipped during reading). Even when this coupling is disrupted, as is the case occasionally in reading, close examination of the eye movement record has allowed for the development of robust models of attention and eye movement control [8], and for modelling the use of distinct cognitive strategies in solving mental processing tasks [9].

Access to short-term memory cannot be directly measured using eye tracking technology, however extensive research has established the persistence of visual information in short-term memory following fixations. Studies have shown, that information about objects that have been attended to is retained in short-term memory and that the length of a fixation correlates with the likelihood that a change in an object can subsequently be detected [10, 11]. Therefore, we can use fixation durations to estimate the likelihood that information at a fixated location has made it into short-term memory. Eye tracking technology does not give us a way of directly measuring the formation of long-term memories; however, it does allow us to collect implicit measures that allow us to infer when long-term memories have formed and when knowledge has been gained. For example, we typically read familiar words far more quickly than unfamiliar words even when controlling for the length of the word [12], and novice drivers exhibit starkly different scanning patterns than expert drivers [13].

While eye tracking data has the potential to reveal much about the underlying cognitive processes of learning, high temporal accuracy is of utmost importance for understanding many components. Much of the aforementioned work is predicated on the ability to distinguish between millisecond level differences in fixation durations as a result of the characteristics of distinct visual stimuli. Achieving a very high degree of temporal accuracy and synchronization is critical for this and poses a far greater challenge synchronization needs that are merely on the 1 or even .1 of a second scale. What follows is a description of the challenges we faced in addressing this problem along with an approach we were able to adopt to minimize the lag inherent in synchronizing eye tracking and other physiological measures with game data.

Use of educational games for students with disabilities

The sample we intend to use in the project associated with this study is unique in that students with diagnosed learning disabilities will be included along with students who are more typically developing, in order to ensure that overall estimates and findings are robust to differences in learning approach. Using eye tracking as a means of interacting with games and for game input has been demonstrated to be effective for people both with and without disabilities [14]. Furthermore, interventions for students with autism have been explored using eye tracking systems that attempt to mitigate some of their difficulties [15]. One aspect of this research is to gain greater insight into the nature of cognition in not only typically developing populations but also those with diagnosed learning disabilities and autism.

Multiple physiological measures and cognition

Using diverse tools to understand physiological aspects of attention, stress, arousal or relaxation has been historically approached in a number of ways. There is some precedent for the use of this kind of information while observing heart rate as a proxy for cognitive load while subjects perform math related tasks [16]. However there is a lack of this type of research in educational contexts.

INSTRUMENTS AND SOFTWARE

Eye tracking equipment

The eye tracking tool use in this study is the EyeLink 1000 (SR research). The system was used in the desktop configuration and was sampling at 500 Hz. Furthermore, data was captured and processed using Screen Recorder and Data Viewer respectively (SR Research).

Physiological monitoring equipment

To monitor a variety of physiological responses this study we used the E4 wristband (Empatica). This system monitors a subject's heart rate, electrodermal activity, movement data and body temperature. This data is streamed via Bluetooth to an iPad and then uploaded to Empatica Connect cloud-based storage system.

The educational game: Impulse

To explore the underlying cognitive processes related to physics understanding, this study will use a game called Impulse. This study builds on past research related to game based educational research using impulse [17]. Methodological approaches for coding and analysis established by prior research will be continued in future analyses.

Figure 1. Screenshot of Impulse

Impulse is an attempt by designers to immerse a player in what is known to physicists as an *n-body simulator*. One assumption is that user's interactions with the particles, and their reactions to the force imparted by the impulse, will build implicit knowledge of forces and motions. This game challenges players use an "impulse" (a click or touch on the screen) to move their ball to a goal without crashing into any other (ambient) objects on the screen (Figure 1). All the objects have mass and obey Newton's laws of motion. As the progresses through the game, more ambient objects are introduced, with including objects with that have more or less mass.

The first 30 levels of the game introduce players to 4 objects of different mass, providing 5 levels of experience with each of the 4 balls; across these 5 levels, the number of particles in the game space increases from 1 to eventually 10. Players encounter objects with different masses simultaneously. As players reach higher levels (more objects and a greater variety of masses), they need to understand and anticipate physics behavior to predict the motion of all objects in the system. Most importantly, this anticipatory behavior will likely map to specific eye motions and physiological responses.

PROCESS

Automated processing of game stream data

In prior attempts to capture and automatically assess the range of strategies players develop during gameplay, members of our project team identified and coded 6 strategic moves (Table 1). Three of these strategic moves are theorized to constitute evidence of implicit understandings of Newton's First Law: each particle will keep moving on its path without an impulse or force from another particle. The remaining three strategic moves reflect an understanding of the game mechanic, but are not considered strong evidence of implicit understanding of Newton's First Law.

Using video observations of gameplay, prior work by members of our team developed a set of automated detectors of player's strategic moves consistent with an implicit understanding of these concepts [17]. These detectors were cross-validated and had inter-rater reliability Cohen's Kappas between 0.51 and 0.86 and A' between 0.78 and 0.97 [18]. Path models were built to estimate the mediating role of each strategic move between prior achievement and post assessment scores using SmartPLS [19]. These revealed a significant mediating role for the use of the Float, Stop/Slow Down, and, unexpectedly, the Buffer strategies (Rowe, Baker & Asbell-Clarke, 2015). Our goal with incorporating eye movement data and other biopsychological measures is to improve our ability to model and understand the cognitive events underlying our identified strategies, and to identify general measures of attention to the game and game objects that can be generalized to other online learning contexts.

Strategic Move	Coding Definition
*Float	The player particle was not acted upon for more than 1 second
Toward goal	The learner intended to move the player particle toward the goal
*Stop/slow down	The learner intended to stop or slow the motion of the player particle
*Player path clear	The learner intended to move non-player particles to keep the path of the player particle clear
Goal clear	The learner intended to move non-player particles to keep the goal clear
Buffer	The learner intended to create a buffer between the player and other particles to avoid collision

Table 1. Strategic moves and coding definitions

*Evidence of implicit understanding of Newton's First Law

Syncing of data streams

Previous attempts to incorporate these types of measures have been frustrated by problems associated with syncing of dissimilar data streams. For example, differences in eye tracking events, fixations (looking at a point) and saccades (the movement between two points), across typical experimental conditions are often on the order of 20-30 milliseconds. Because of the time/latency sensitivity of eye tracking data, it is of central importance to this study that latency be as low as possible.

In order to understand event level data, this system must not only be able to acquire data at the millisecond level, but it must also reliably sync all data streams with the same degree of accuracy. This issue is complicated by data streams that may not have timestamps that do not have an absolute starting time point (e.g. POSIX time) or data streams that have sampling frequencies that are not scaled relative to each other.

A major challenge in our attempt to use the data from the eye tracker log and the game logs to make inferences about implicit learning was that there was no simple way to synchronize the signal from the two data streams at the millisecond level. The lag between when events occurred in the game and were reported to our data logger was variable due to the many underlying processes involved. While lags of a few milliseconds are not noticeable for most purposes, they are critical for our ability to compare changes in cognitive processing across conditions. Likewise, no common clock existed to allow us to sync the occurrence of eye events and game events at a millisecond level. The eye tracker uses an internal clock to produce a very high accuracy temporal signal and we are able to sync this signal with when game events were logged by our data logger but not with when the events actually occurred. To address this challenge we looked for a common signal that could exist in both streams and would allow us to both align the two streams and to estimate the lag affecting each game event. Mouse click events served this purpose for us.

The eye tracker is able to log mouse events with a high degree of accuracy in the eye tracker log, likewise, the game data logger tracks mouse click events and logs them in game logs albeit with a lag (significant at the millisecond level) that is inherent in most computer game implementations. Our first goal was to reduce the lag to the greatest extent possible. All unnecessary applications were terminated and the game was placed at highest priority for processing and memory resources. Any networking activities not essential to the game or eye tracking system were terminated.

These changes reduced the average lag from one on the order of 300 ms to one on the order of 30ms. However, there was still a wide range of latency affecting individual events and this range peaked at over 100 ms at times. Alignment therefore involved offsetting the start time of the game data log stream to reduce the absolute difference between the mouse events logged by the eye tracker and the mouse event logged by the game. This gave us a fairly good estimate of where game events would occur but we needed to find some way of reducing the effects of variable lag on each event given that some of these lags were on the order of 100 ms. To do so we used neighboring mouse events to estimate lags on individual game events.

		Mouse click event present in next 250 ms	
		No	Yes
Mouse click event present in prior 250 ms	No	Use average lag for all mouse click events	Use lag of closest following mouse click event
	Yes	Use lag of closest preceding mouse click event	Use average closest preceding and following mouse click event lags

Table 2. Matrix for using mouse event lags to estimate game event lags.

The following assumptions guided our efforts to estimate the lag affecting game events. Mouse events that did not occur close to game events were unlikely to accurately reflect the lag affecting game events therefore we set a 250 ms limit as the maximum temporal distance we would allow for estimating lag affecting a game event. Our second assumption was that the mouse click events closest to the game event were most likely to be predictive of the lag affecting individual game events. With that in mind, the lag affecting each game event was estimated using the matrix described in Table 2.

FUTURE DIRECTIONS

As this research progresses, we plan to incorporate additional streams of data to improve our ability to understand and model the cognitive events underlying learning. In addition, we will be using the streams synchronized using the approach described in this paper to analyze the implicit learning of students with and with disabilities as they play impulse. Finally, we plan to develop web-based instruments to collect more coarse measures of attention using native webcams. We hope that this work will allow us to better understanding the implicit learning process across a neuro-diverse spectrum of learners and inform an adaptive version of Impulse that is able to meet the needs of a wide range of learners.

CONCLUSION

Use of this system to integrate a variety of streams of data has proven to be an effective means of observing interactions within this educational game. As new tools for assessing psychophysiological data becomes more accessible and affordable, new multidimensional methods for assessment of cognition and learning in educational environments will likely become more commonplace.

The approach described in this paper has allowed us to significantly reduce the discrepancy we experienced between the logging of game events, eye movement measures, and physiological measures. While the accuracy of our measures are still not synchronized at the millisecond level, they are small enough to allow us to start to explore changes in our measures across different game states. Further improvements in tools and technologies aimed at supporting our ability to measure and synchronized game events with cognitive states at the millisecond level are needed to help us better understand the cognitive underpinnings of learning.

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