AttentiveLearner: Adaptive Mobile MOOC Learning via Implicit Cognitive States Inference

Xiang Xiao, Phuong Pham, Jingtao Wang
Computer Science and LRDC, University of Pittsburgh, PA, USA
{xiangxiao, phuongpham, jingtaow}@cs.pitt.edu

ABSTRACT

This demo presents AttentiveLearner, a mobile learning system optimized for consuming lecture videos in Massive Open Online Courses (MOOCs) and flipped classrooms. AttentiveLearner uses on-lens finger gestures for video control and captures learners' physiological states through implicit heart rate tracking on unmodified mobile phones. Through three user studies to date, we found AttentiveLearner easy to learn, and intuitive to use. The heart beat waveforms captured by AttentiveLearner can be used to infer learners' cognitive states and attention. AttentiveLearner may serve as a promising supplemental feedback channel orthogonal to today's learning analytics technologies.

Categories and Subject Descriptors
H5.2 [**Information interfaces and presentation**]: User Interfaces – *Graphical user interfaces, theory and methods.*

General Terms
Design; Experimentation; Human Factors.

Keywords

Mobile Interfaces; Affective Computing; Massive Open Online Courses; MOOC; Heart Rate; Intelligent Tutoring Systems; Physiological Signals.

1. INTRODUCTION
Massive Open Online Courses (MOOCs) are growing rapidly in recent years and provide great opportunities to low-cost knowledge dissemination on a large scale. Despite the great potential, MOOCs today also face major challenges such as low completion rates, more frequent distractions, separation of learning and assessment activities, and the lack of direct, immediate feedback from students to instructors. Different from traditional classrooms, MOOC instructors can no longer rely on facial expressions or in-class behaviors to infer student engagement. Although feedback forms and learner activity logs (e.g. log-in frequency, click-through rates, and video drop-out rates) can be used to predict the quality of learning, such measurements are usually coarse-grained, highly delayed, and indirect measurements of the actual cognitive process in learning.

To explore the possibility of collecting and using fine-grained, real-time feedback from students' actual cognitive states in MOOC learning, we demonstrate AttentiveLearner, a mobile learning system that captures students' physiological signals through implicit heart rate tracking on unmodified mobile phones. AttentiveLearner uses on-lens finger gestures for tangible video control and implicitly monitors learners' heart rates based on the fingertip transparency changes captured by the back camera. We demonstrate the feasibility of inferring learners' cognitive states (e.g., mind wandering events and perceived interest/confusion levels regarding the learning materials) by analyzing the collected heart rate signals. With the low cost inference of learners' cognitive states during MOOC sessions, AttentiveLearner has the potential to enable adaptive tutoring on today's mobile phones (e.g., "mind wandering" alert, personalized learning materials). AttentiveLearner can also benefit instructors by providing fine-grained, aggregated feedback of learners' physiological, and cognitive states synchronized with the learning materials.

ICMI '15, November 09-13, 2015, Seattle, WA, USA
ACM 978-1-4503-3912-4/15/11.
http://dx.doi.org/10.1145/2818346.2823297

2. METHOD
AttentiveLearner allows learners to consume MOOC videos on mobile phones during fragmented time. There are three major components in AttentiveLearner: a tangible video control channel, an implicit heart rate sensing module, and the cognitive state inference algorithms.

2.1 Tangible Video Control
With AttentiveLearner, a learner plays a tutorial video by covering and holding the back camera lens with her fingertip, uncovering the lens to pause the video (**Figure 1**). The lens-covering gesture is detected via a linear classifier on the global mean and standard deviation of all pixels in an incoming image frame [5]. Offline benchmarking on 483 test images achieved an accuracy of 99.59% when detecting lens-covering gestures [5].

Figure 1. The back camera as both a video play control channel and an implicit heart rate sensing channel in learning

In an 18-participant study on the usability of the tangible video control channel [5], we found this channel was responsive (mean response time = 625.9ms) and easy to use (average = 4.11 on a five-point Likert scale). We also found participants preferred each video clip to be less than eight minutes in length [5] when using AttentiveLearner.

2.2 Implicit Heart Rate Sensing

AttentiveLearner captures learners' heart rate implicitly during learning via commodity camera based photoplethysmography (PPG). AttentiveLearner uses the PPG waveform extraction algorithm in LivePulse [2] for heart rate measurement. In addition to learners' beat-to-beat instant heart rate, AttentiveLearner also extracts both temporal and frequency domain features from the raw PPG waveforms captured.

2.3 Cognitive States Inference

We also conducted two additional experiments [4][5] to explore the feasibility of using raw PPG waveforms captured by AttentiveLearner to infer learners' attention [4] and cognitive states [5].

In a 24-participant study, Pham and Wang [4] found it was possible to detect learners' mind wandering (MW) events via AttentiveLearner. Both lecture content features and PPG waveform features were extracted from sliding windows (window size = 30s with 5s step) before each prediction moment (**Figure 2a**). We extracted 7 dimension lecture content features including lecture style, duration of current page etc. PPG waveform features include 12 heart rate and heart rate variability (HRV) features, e.g. mean of RR intervals and low frequency of RR intervals (0.04 – 0.15 Hz). The ground truths were obtained by randomly triggering audio beeps (auditory probes) to acquire learners' attention status (MW or not) during each video watching session. The best model (KNN) achieved Kappa=0.22, accuracy=71.2% on MW prediction.

More recently, in an 18-participant study, Xiao and Wang [5] demonstrated the feasibility of predicting learners' interest and confusion levels in MOOC learning via content-agnostic features. 14 time-domain HRV features from PPG signal, including 7 global features (extracted globally from the entire section) and 7 local features (extracted by averaging the same features of multiple local windows within the section), were extracted from the raw PPG waveforms of each topic session (**Figure 2b**). The ground truth labels were obtained via self-reports collected immediately after each learning topic. The best prediction performances were Kappa=0.29, accuracy=73.58% for boredom detection and Kappa=0.27, accuracy=77.69% for confusion detection respectively, using RBF-kernel support vector machines. Furthermore, AttentiveLearner can achieve significantly higher accuracies by predicting *extreme personal learning events* and *aggregated learning events*.

These results were user-independent, achieved on today's mobile phones without hardware modifications. The performances on cognitive states inference were also comparable with state-of-the-art systems using dedicated sensors, such as Blanchard et al. [1] (learner dependent model, kappa=0.22 for MW detection) or Hussain et al. [3] (learner dependent model, kappa=0.31 for arousal classification). In the demo session, we will provide a live demonstration of AttentiveLearner on tangible video control, implicit PPG waveform extraction, and cognitive states prediction.

3. USAGE SCENARIOS

AttentiveLearner improves mobile MOOC learning by enabling attentive and bi-directional learning on unmodified mobile phones. It is worth noting that the lens covering gesture-based control and implicit heart rate measurement can be embedded in different mobile applications and learners can comfortably watch a normal length MOOC video lecture (less than 8 minutes) [5].

From the learners' perspective, AttentiveLearner can enable adaptive and personalized learning by recommending appropriate review materials and exercises based on the learners' attention and interest levels during corresponding learning topics.

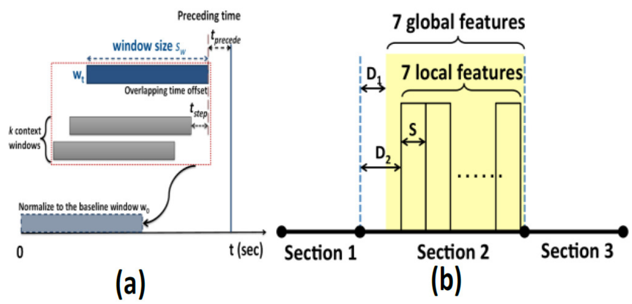

Figure 2. (a) Features from sliding windows before a prediction; (b) features from the entire session and its sliding windows

From the instructors' perspective, AttentiveLearner can provide fine-grained, aggregated visualizations of learners' cognitive states and attention levels synchronized with the lecture contents. Such visualizations can facilitate instructors to identify and reflect upon topics requiring further improvements in the current curriculum. Instructors may also use AttentiveLearner to take "virtual attendance" in flipped classrooms, where around 50% of the students do not watch the required video materials before each lecture according to a recent survey.

4. CONCLUSION

We presented AttentiveLearner, a mobile learning system to monitor learners' cognitive states during mobile MOOC learning via implicit heart rate tracking. The on-lens gesture interface in AttentiveLearner enables both tangible video control and implicit heart rate tracking on today's unmodified smart phones. We hope AttentiveLearner can facilitate and promote the use of physiological signals in large scale learning analytics in MOOCs and flipped classrooms. Additional introductions and demos of AttentiveLearner are available at http://www.attentivelearner.com.

This research is in part supported by an RDF from the Learning Research and Development Center at the University of Pittsburgh.

5. REFERENCES

[1] Blanchard, N., Bixler, R., Joyce, T., D'Mello, S. Automated physiological-based detection of mind wandering during learning. In *Proc. ITS 2014*.

[2] Han, T., Xiao, X., Shi, L., Canny, J., and Wang, J. Balancing accuracy and fun: designing camera based mobile games for implicit heart rate monitoring. In *Proc. CHI 2015*.

[3] Hussain, M. S., AlZoubi, O., Calvo, R. A., and D'Mello, S. K. Affect detection from multichannel physiology during learning sessions with AutoTutor. In Proc. *AIED 2011*.

[4] Pham, P., and Wang, J. AttentiveLearner: improving mobile MOOC learning via implicit heart rate tracking. In *Proc. AIED 2015*, pp367-376.

[5] Xiao, X., and Wang, J. Towards Attentive, Bi-directional MOOC Learning on Mobile Phones. In *Proc. ICMI 2015*.