Laila Shoukry, Stefan Göbel, Ralf Steinmetz: **Towards Mobile Multimodal Learning Analytics** . In: Learning Analytics for and in Serious Games - Workshop, EC-TEL 2014, p. 16, September 2014.

Towards Mobile Multimodal Learning Analytics

Laila Shoukry, Stefan Göbel, Ralf Steinmetz
Multimedia Communication Lab - KOM
TU Darmstadt; Germany
{laila.shoukry; stefan goebel; ralf.steinmetz}@ kom.tudarmstadt.de

EXTENDED ABSTRACT

Smartphones nowadays are equipped with an increasing number of sensors which can offer rich information for analytics unobtrusively and their connectivity enabling natural data collection. As a naturalistic assessment of learning experiences should no longer ignore new interaction paradigms and data sources, we argue that a multimodal approach combining different logging information and sensor readings and adapted to mobile learning contexts is required. This can enable deeper insight into interactions in novel learning settings involving smartphones as pure logging of traditional interaction patterns is becoming insufficient. We call this next-generation Learning Analytics (LA) [1] Mobile Multimodal Learning Analytics. Our purpose is to investigate how different smartphone sensors can be used for collecting information which can be useful for LA and what challenges are associated with this approach. Different studies showed the use of smartphones for eye tracking, facial feature extraction, voice analysis and other techniques useful in recognizing cognition states which are considered valuable for LA. Migrating LA, from traditional settings, where they have proven successful [7, 10, 4], to mobile environments to make assessments in natural, non-stationary settings requires considering many new factors influencing the learning process like dynamic context, device capabilities and social interactions [11]. However, not only are capabilities of mobile devices on the rise, but there are also other opportunities offered by smartphones which can be exploited to cope with or even eliminate these challenges. Another considerable challenge associated with gathering data about smartphone users is getting ethical clearance as collecting and disseminating sensor data raises serious privacy and security issues [8]. The front-facing cameras of smartphones can be used for a variety of techniques to measure cognition which can also be used in LA, like eye tracking and facial feature extraction, despite their generally lower resolution in comparison to the back-facing cameras [5]. All mobile phones have built-in microphones which can be used for voice analysis. Studies have shown modest accuracy at measuring emotion and high accuracy at estimating stress [3, 6]. Instead of mouse and keyboard, users of smartphones and tablets predominantly use touch interactions with touch strength and movement additionally introducing new sources of sensory data. In addition, affect can also be measured on smartphones using phone interactions and app usage [9]. As affect detection in an intelligent tutoring environment has already been proven to improve learning effectiveness [2], we argue that collecting multimodal data from smartphones offers unprecedented opportunities for the design of adaptive learning games and applications on mobile devices.

REFERENCES

[1] R. S. J. D. Baker and K. Yacef. The State of Educational Data Mining in 2009 : A Review and Future Visions. 1(1):3-16, 2009.

[2] I. Arroyo, D. G. Cooper, W. Burleson, B. P. Woolf, K. Muldner, and R. Christopherson. Emotion sensors go to school. In AIED, volume 200, pages 17-24, 2009.

[3] K.-h. Chang, D. Fisher, J. Canny, and B. Hartmann. How's my mood and stress?: an efficient speech analysis library for unobtrusive monitoring on mobile phones. In Proceedings of the 6th International Conference on Body Area Networks, pages 71-77. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2011.

[4] U. J. E. H. Beth Dietz. Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective. Journal of Interactive Online Learning, 2013.

[5] C. S. Ikehara, J. He, and M. E. Crosby. Issues in implementing augmented cognition and gamification on a mobile platform. In Foundations of Augmented Cognition, pages 685{694. Springer, 2013.

[6] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury. Stresssense: Detecting stress in unconstrained acoustic environments using smartphones. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, pages 351-360. ACM, 2012.

[7] L. P. Macfadyen and S. Dawson. Mining LMS data to develop an early warning system for educators: A proof of concept. Computers & Education, 54(2):588-599, 2010.

[8] D. McMillan, A. Morrison, and M. Chalmers. Categorised ethical guidelines for large scale mobile hci. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '13, pages 1853-1862, New York, NY, USA, 2013. ACM.

[9] R. Rana, J. Reilly, R. Jurdak, W. Hu, X. Li, and J. Soar. Affect sensing on smartphone-possibilities of understanding cognitive decline in aging population. arXiv preprint arXiv:1407.5910, 2014.

[10] A. Skinner, C. Russo, L. Baraniecki, and M. Maloof. Ubiquitous augmented cognition. In D. Schmorrow and C. Fidopiastis, editors, Foundations of Augmented Cognition. Advancing Human Performance and Decision-Making through Adaptive Systems, volume 8534 of Lecture Notes in Computer Science, pages 67-77. Springer International Publishing, 2014.

[11] J. Traxler. Defining, discussing and evaluating mobile learning: The moving finger writes and having writ...The International Review of Research in Open and Distance Learning, 8(2), 2007.