Sensor Based Adaptive Learning - Lessons Learned

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Abstract: Recent advances in sensor technology allow for investigating emotional and cognitive states of learners. However, making use of sensor data is a complex endeavor, even more so when considering physiological data to support learning. In the BMBF-funded project *Learning Analytics for sensor-based adaptive learning (LISA)*, we developed a comprehensive solution for adaptive learning using sensor data for acquiring skin conductance, heart rate, as well as environmental factors (e.g. CO_2). In particular, we developed, (i) a sensor wristband acquiring physiological and environmental data, (ii) a tablet application (SmartMonitor) for monitoring and visualizing sensor data, (iii) a learning analytics backend, which processes and stores sensor data obtained from SmartMonitor, and (iv) learning applications utilizing these features. In an ongoing study, we applied our solution to a serious game to adaptively control its difficulty. Post-hoc interviews indicated that learners became aware of the adaptation and rated the adaptive version better and more exciting. Although potentials of utilizing physiological data for learning analytics are very promising, more interdisciplinary research is necessary to exploit these for real-world educational settings.

Keywords: sensor based learning, learning analytics, adaptive learning system

1 Introduction

The current wave of digitization has enormous potential to impact education and training. Consider, for instance, the situation of teachers. The nature of teaching, especially in schools and universities, has not changed significantly for more than 200 years. However, the prevalent type of direct instruction rarely allows individual learning states to be addressed. Digital learning environments can help collecting data at the individual learner level and providing (semi-)automated feedback on indicators for cognitive and emotional states such as mood or concentration [Sb15]. This may help to identify students' individual needs, but it also may allow for giving targeted feedback. Learning analytics – utilizing data from digital learning environments appropriately to understand and support learning processes – becomes particularly challenging when going beyond conventional user interaction data by considering data provided from physiological sensors such as heart rate, skin conductance response, and others. Sensor data are particularly interesting as they allow for deeper insights into individual cognitive and emotional states crucial for

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doi:10.18420/delfi2019_355

learning. Consequently, increasing research interest has been devoted to the role of learning analytics considering physiological data [Sb15]. In the BMBF-funded project *Learning Analytics for sensor-based adaptive learning (LISA)*[6], we pursued sensor based adaptive learning in an interdisciplinary approach. When starting to think about sensor-based support for individual learning in LISA, some questions arose: Which sensors should be used for a successful learning solution? However, which of them are suitable to support self-regulated learning [YFP17]? And which sensors are easily available and suited for non-intrusive and non-distracting learning support? Moreover, even when the most appropriate (physiological) sensors were chosen, further questions arise with respect to how to process the acquired data by means of sensor based learning analytics. Can cognitive and emotional states of learners be measured and predicted reliably? How can a sensor based system become a learning companion? Which user centric design should be used? Is such a system capable of giving empathetic feedback and/or recommendations? In the following sections, we will refer to some of these questions in the context of our research project.

2 From Sensor Data to Learning Indicators

Among different sensor data, measures derived from electrodermal activity (EDA), electrocardiogram (ECG) or photoplethysmogram (PPG) were often found to be sensitive to emotional states [Kre10]. Furthermore, combinations of measures derived from EDA and ECG were used to describe different dimensions of emotions [Gr15], [MO13]. To derive learning indicators from these sensor data, practical approaches such as machine learning were previously used to classify emotions, and it was shown that aggregated sensor data could reflect emotions reliably [PVH01].

Requirements for the selection of a LISA sensor device were, amongst others: 1) utilization of sensors indicative of emotional and cognitive states, 2) easy application in real learning situations, 3) data privacy. From these requirements, EDA and PPG sensors were chosen, as well as sensors for skin temperature, total volatile organic compounds (TVOC) and CO_2. Using the developed LISA sensor device, we successfully evaluated emotion detection using different methods (e.g. qualitative, quantitative, machine learning and fuzzy logic approaches, see [Yu17, Yu19]). Additionally, we are on the way to also be able to indicate cognitive states of learners, in addition to their emotional states.

3 Bringing all parts together

A LISA learning application consists of 4 components: 1) sensor wristband, which records EDA, PPG, temperature, TVOC, CO_2 data, 2) tablet application (SmartMonitor), which processes sensor data and acts as a learning companion, visualizing sensor data and

[6] Förderkennzeichen 16SV7534K, see http://tel.f4.htw-berlin.de/lisa

providing awareness/feedback to the learner, 3) LISA learning analytics backend, which receives sensor data from SmartMonitor, stores learner data and provides learning analytics services to 4) learning applications (see Fig. 1).

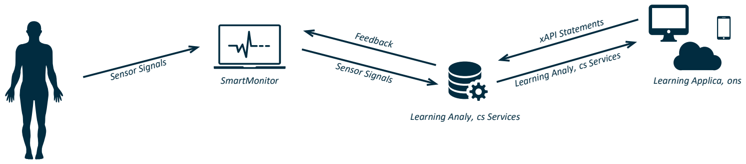

Fig. 1: Illustration of sensor-based learning as a distributed application

To provide multimodal learning analytics services, the LISA data model can hold learner activities and streams of raw sensor data, but also aggregated sensor data like heart rate (variability) or timestamps when e.g. heart rate exceeds critical values. Multimodal learning analytics services range from predicting emotional and cognitive states to detecting learning situations. In addition to providing a complete learning analytics solution to learners, data privacy and ethical issues were investigated to ensure learner's ownership and agency over their data. In LISA, sensor data can only be used under the strict permission of the learner. For this purpose, a model of trust has been developed in LISA which controls the usage of data by user preferences. To achieve this goal, a learning application provides a token which a learner can use to establish a learning session, connecting the personal SmartMonitor device to the respective learning application. Thus, sensor data can be mapped to learner IDs without the need to store any information about a learner in SmartMonitor or LISA backend

4 Sensor-based Learning Applications

4.1 LISA Learning Companion

A first adaptive learning solution developed under the LISA project is a learning companion which promotes self-regulated learning. The learning companion is a human-like interactive peer which utilizes sensor data to provide learners with a positive learning experience along with self-regulated learning support [YFP17]. The learning companion gains information about learners' mental states by using physiological and environmental data. Based on analyses of these sensor data, both alerts (e.g., exceeding a critical threshold in air quality) and interpreted recommendations (e.g., volitional control strategies) were designed. In LISA, we considered human computer interaction design and technical feasibility along with pedagogical concepts (Fig. 2). The LISA learning companion enriches learners' learning experience by providing an opportunity to set and also track their learning goals (an active learning goal can be seen on the left side of Fig. 2). While learning, learners can also attain volitional control strategies like self-efficacy enhancement or stress reducing actions [MG99]. To make interaction with the learning companion more enjoyable, learning related humors and motivational quotes have been chosen from online resources. The first field test with a group of students who used the learning companion provided promising feedback. In particular, the learning companion was considered *sweet* and *cool* and reported to keep learners from distraction. The results also showed that it engaged learners to reflect on their learning and allowed them to apply the current reflected experience to plan their next learning more effectively.

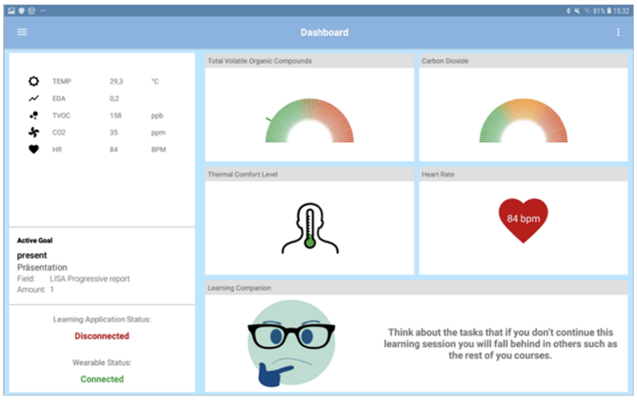

Fig. 2: Screenshot of LISA Learning Companion

4.2 An Adaptive Learning Game

In the project, we developed an adaptive version of *Emergency*, a serious game by Promotion Software[7], as one potential application scenario for sensor based learning. In this game players coordinate firefighters and rescue services in different scenarios such as train and car crashes to save and patch up wounded characters and prevent houses and vehicles from burning down. The difficulty of the game is related to the number of tasks that need to be addressed simultaneously, which creates stressful situations. For instance, with increasing difficulty, more wounded characters had to be cared for concurrently, or the risk of fire was higher. Hence, adaptation of the level of difficulty within the game seems desirable for keeping learners in the "sweet spot" of the Yerkes–Dodson Law [YD08] postulating an inverted U-shaped pattern for the interrelation between performance and arousal: individuals' maximum performance should be achieved on a medium level of arousal whereas performance should decrease when the arousal becomes too low or too high.

For adapting the game's difficulty level, we used the LISA SmartMonitor with a particular focus on heart rate data due to its close link to stress and arousal [Je11]. Moreover, previous pilot studies indicated that heart rate is linked to the difficulty levels of the game. Therefore, we developed a mechanism adapting the difficulty based on the player's

[7] https://promotion-software.de/

individual heart rate. During an initial heart rate perception phase, we measured the resting pulse of a player to automatically implement a baseline and threshold values (i.e., 5 beats above or below resting pulse) for triggering adaptations in the game. For instance, given a baseline of 75 beats per minute (BPM), the game became easier when heart rate exceeded 80 BPM, whereas it became more difficult when BPM fell below 70 BPM. To support overstrained players, helicopters appeared and automatically patched up patients so that the player no longer had to care for them. In contrast, when arousal was low, bystanders appeared at accident sites and got hurt, which increases the number of patients to be cared for by the player.

In an ongoing piloting study, we examine the feasibility of adapting the game's difficulty based on changes in players' heart rate. So far, 12 participants (M_{age}=28.83 years; SD=5.25 years) not aware of the experimental manipulation played both an adaptive and a non-adaptive version. Initial results of interviews after the playing sessions focusing on user experience revealed that participants became aware that the game became easier/more difficult in the adaptive version. Interestingly, participants also rated the adaptive version to be better (58%), more exciting (75%), but also more demanding (83%), indicating feasibility of the current implementation of an adaptation based on physiological data.

5 Lessons Learned and Future Considerations

Our endeavor to consider sensor data in a context of learning started ambitiously, and we included psychological, technical and real-life learning considerations into our research. Using sensor data for learning support requires decisions on a lot of questions, e.g. statistical significance vs. ecological validity, data ownership vs. learners' agency, human computer interaction design vs. pedagogical support. From our research we learned that quick and easy results are often neither realistic nor meaningful. In particular, the process of considering sensor data for learning analytics is by no means straightforward. It entails complex analysis and modification of signals to provide information about behavior and/or states of a user. Using user interaction data for learning analytics is also complex and becomes even more challenging when physiological data are used in learning scenarios to detect emotional, motivational, and cognitive states. The reason is that physiological data provide indicators for such mental states which cannot be measured directly. For instance, changes in heart rate as observed in players of the *Emergency* game may indicate emotional arousal but may also be an indicator for cognitive effort as well as motoric activity, or in the worst case just noise from the sensor. Nevertheless, the potential for user centered adaptation of learning environments is immense, and collaborative interdisciplinary research involving various stakeholders (e.g. universities, research institutes, industry partners) – as pursued in LISA – will allow mastering such complex research and applying real-life questions successfully.

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