M2LADS: System for generating MultiModal Learning Analytics Dashboards

Anonymous

Anonymous

Abstract. In this article we present a Web-based System called M2LADS, which supports integration and visualisation of Multimodal Data monitored in Learning Sessions in a MOOC in the form of Web-based Dashboards. This Multimodal Data contains Biometric and Behavioral signals (edBB platform) like electroencephalogram data (5 channels, attention, meditation, etc.), heart rate, visual attention, videos in visible and NIR spectrum, etc.; student data (LOGGE tool), and student performance (MOOC tracking logs). All this information provides a deep knowledge about the Learning Session that can be used to improve Learning Analytics Models.

Keywords: Biometrics and Behavior \cdot e-Learning \cdot Multimodal Learning Analytics \cdot MOOC \cdot Web-based Technology

1 Introduction

Massive Open Online Courses (MOOCs) are a valid source of educational content and can sometimes be endorsed and recognised by official institutions [12]. But, how are these MOOC learners behaving? How do they interact with the courses? How's their learning context? Are they concentrated when learning?

The research area that could help us to answer these questions is Multimodal Learning Analytics (MMLA), which is a subfield of Learning Analytics [11, 13, 14] that deals with collected and integrated data from different sources, allowing a panoramic understanding of the learning processes and the different dimensions related to learning [8].

The approach proposed in this article supports the proper integration and visualisation of Multimodal Data monitored in MOOC Learning Sessions in the form of Web-based Dashboards. Thanks to these Dashboards a proper analysis could be done to understand better when MOOC learners are concentrated, what course contents capture their attention, etc. Furthermore, this work have based on many LA tools [1, 3, 2] to address related challenges.

The structure of this article is as follows: in the next section, we present a detailed description of the proposed system: M2LADS; in section 3, we present the current use of the system in a case study with learners of a MOOC at edX^1 . Finally, the article ends with conclusions and future works.

¹ https://www.edx.org/

2 The approach: M2LADS

We propose a Web-based System called M2LADS (an acronym for System for generating Multimodal Learning Analytics Dashboards). This system supports the generation of Web-based Learner Dashboards. Each Learner Dashboard visualises all the Multimodal Data monitored in a Learning Session (LS) in a MOOC. We have developed the system for any edX MOOCs; however, we have tested it on a specific course (see Section 3 for more details).

The system is composed of three modules following a Model-View-Controller (MVC) approach. For simplicity, the Multimodal Data recorded in the LS and processed by the system is referred to in this approach as Activity Data (AD). Details of these Multimodal Data are found in Section 2.1.

The Modules of M2LADS System are:

- Activity Data Processing Module (Controller): see Section 2.2.
- Activity Data Store Module (Model): see Section 2.3.
- Activity Data Visualisation Module (View): see Section 2.4.

2.1 MultiModal Data Description

edBB Data The EdBB platform was used when monitoring learners during the execution of learning activities in e-learning contexts [7,9]. This platform was designed as a multimodal acquisition framework to monitor learners in remote education, capturing biometric and behavioral information. It is formed by a group of software that allows to communicate and use in a synchronized way, different sensors. It also adapts the acquisition setup to the monitoring circumstances, from using advanced sensors (smartwatch, eye tracker, etc.), to basic ones (webcam, context data, etc.), or both. Our work uses the following acquisition setup and the following sources of information/sensors (see Fig. 1):

- Video: Video data from 3 different positions: Overhead, front and side cameras, using 2 simple webcams and 1 Intel RealSense that includes 1 RGB and 2 NIR cameras; that also calculates the depth images using the NIR cameras. Lastly, the screen monitoring video is also captured.
- Electroencephalogram (EEG) data: Using a NeuroSky EEG band that obtains 5 signals: δ (< 4Hz), θ (4-8 Hz), α (8-13 Hz), β (13-30 Hz), and γ (> 30 Hz) and through the pre-processing of these EEG channels, attention, meditation, and the moment in which the blinks occur, are also obtained [4–6].
- Heart rate: To capture this in real time we use a Huawei Watch 2 pulsometer feature [10].
- Visual attention: A Tobii Pro Fusion was used and it contains two eye tracking cameras that estimate the following data: Gaze origin and point, pupil diameter, data quality, etc.; allowing us to obtain visual attention.

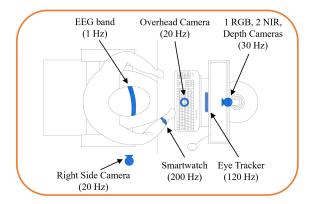


Fig. 1. The acquisition setup shows how it's been setup for student's monitoring in remote education, using the edBB platform [9]. For each sensor, the Sampling Rate used is shown.

MOOC Data While a learner is learning in a MOOC on edX, log data is generated. This log data contains detailed information about where the learner is navigating, which videos he/she visits, which assignents he/she does, etc.

All this information is correctly contextualized with the learner's data, the time stamp of each action. The log data of a LS is a json file.

Additional Data Despite the large amount of information provided by edX log data, a complementary log recording tool called LOGGE has been developed in the context of this approach.

The objective of this tool is to store additional information related to the monitored learner (sex, hand used with the mouse, heart problems, marks, etc.) and enrich the edX log traces. This information is stored as a csv file.

2.2 Activity Data Processing Module

This module allows extracting, cleaning, selecting and preprocessing the Multimodal data recorder during the LS in the MOOC in order to extract the AD of the Learner. This module is composed of the three following services.

Multimodal Data Preprocessing Service It is designed to firstly extract and clean the data of the learner's interactions in the MOOC, preprocess and organize this information in the MOOC Learner Matrix with the start and end time of each activity performed by the learner. Second, it preprocesses the biological and behavioural signals provided by biometric devices to appropriately organise this information in the Bio Learner Matrix. Finally, generate another Extra Learner Matrix with the information extracted from the additional data.

4 F. Author et al.

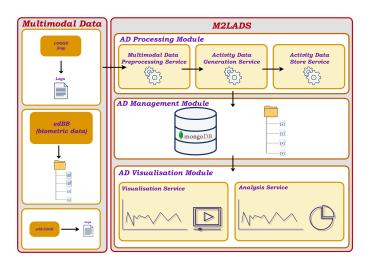


Fig. 2. M2LADS Architecture/Modules

Activity Data Generation Service With all the previous learner data organized in 3 matrixes, this service crosses the data from these matrixes and generates the final Learner Matrix (LM), where we have each biometrical data classified into a learner activity.

Activity Data Store Service This service stores the LM as data collections in a MongoDB Database and all the recorded videos during the LS are organised as audiovisual files in a set of directories.

2.3 Activity Data Management Module

This module provides the connectivity with the MongoDB and the directories with the audiovisual files.

2.4 Activity Data Visualisation Module

In this module the system creates a visualisation per learner, i.e. a Dashboard, that reflects learner activity data during the LS. With this aim, it generates and organises visual components (graphs) with the use of the framework Dash², which is based on Flask and React.js.

Visualisation Service As we can see in Fig. 3 (a), this service composes the Dashboard with: i) several graphs that show the learner attention, meditation, heart rate and neural waves along the time of the LS, ii) several videos such as: the screen captured during the LS, the different webcams, etc. All these elements in the Dashboard are synchronized.

² https://plotly.com/dash/

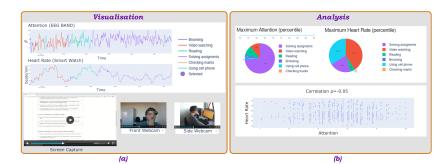


Fig. 3. Screenshot of some visualization by M2LADS

Analysis Service As we can see in Fig. 3 (b), this service adds to the Dashboard some graphs that show an analysis of the previous data and correlations.

3 Case Study

The approach presented was tested in the MOOC: "Introduction to Web Application Development" (WebApp for short), which is available at edX MOOC platform and it is offered by one University at Madrid (Spain). The contents of this course are structured in five units. This course learners can learn to develop any Web Application (Web App) based on HTML, CSS, Python, JSON, JavaScript and Ajax. Each unit is composed of several subunits. In each course subunit, there are multimedia resources (videos, html pages, pdf files, etc.), discussion forums and course evaluation activities in form of graded assignments.

We are currently conducting a research study to measure the effect of cellphones on attention levels during Learning Sessions on WebApp MOOC learners and we have decided to monitor 120 volunteers, that have been required to assist to our MMLA laboratory, where they will interact with the same contents in a course subunit in 30-minute LS and, M2LADS will be generating a webbased dashboard per user. Each monitoring session implies an aprox of 25 GB of information obtained from different chanels: biometric, behaviour, metadata, etc.

4 Conclusion and Future Work

In this article we present a Web-based System called M2LADS (an acronym for System for generating Multimodal Learning Analytics Dashboards). This system supports the integration and visualisation of Multimodal Data monitored in MOOC Learning Sessions in the form of Web-based Dashboards. These Multimodal Data are provided by the monitorisations supported by edBB platform and the data from LOGGE tool and an edX MOOC. 6 F. Author et al.

Therefore, we can conclude that, we have at our institution a MMLA Laboratory ready with the integration of M2LADS, LOGGE tool and edBB platform for new monitorings in order to exploit its utility in the e-learning context.

References

- Cobos, R., Gil, S., Lareo, A., Vargas, F.: Open-DLAs: An Open Dashboard for Learning Analytics. In: Proc. 3rd ACM Conference on Learning at Scale. pp. 265– 268 (2016)
- Cobos, R., Ruiz-Garcia, J.C.: Improving Learner Engagement in MOOCs using a Learning Intervention System: A Research Study in Engineering Education. Computer Applications in Engineering Education 29(4), 733–749 (2021)
- 3. Cobos, R., Soberón, J.: A Proposal for Monitoring the Intervention Strategy on the Learning of MOOC Learners. In: Proc. CEUR Workshop. p. 61–72 (2020)
- Daza, R., DeAlcala, D., Morales, A., Tolosana, R., Cobos, R., Fierrez, J.: ALEBk: Feasibility Study of Attention Level Estimation Via Blink Detection Applied to elearning. In: Proc. AAAI Workshop on Artificial Intelligence for Education (2022)
- Daza, R., Gomez, L.F., Morales, A., Fierrez, J., Tolosana, R., Cobos, R., Ortega-Garcia, J.: MATT: Multimodal Attention Level Estimation for e-learning Platforms. In: Proc. AAAI Workshop on Artificial Intelligence for Education (2023)
- Daza, R., Morales, A., Fierrez, J., Tolosana, R.: mEBAL: A Multimodal Database for Eye Blink Detection and Attention Level Estimation. In: Proc. Intl. Conf. on Multimodal Interaction. pp. 32–36 (2020)
- Daza, R., Morales, A., Tolosana, R., Gomez, L.F., Fierrez, J., Ortega-Garcia, J.: edBB-Demo: Biometrics and Behavior Analysis for Online Educational Platforms. In: Proc. AAAI Conference on Artificial Intelligence (Demonstration) (2023)
- Giannakos, M., Spikol, D., Di Mitri, D., Sharma, K., Ochoa, X., Hammad, R. (eds.): The Multimodal Learning Analytics Handbook. Springer Nature (2022)
- Hernandez-Ortega, J., Daza, R., Morales, A., Fierrez, J., Ortega-Garcia, J.: edBB: Biometrics and Behavior for Assessing Remote Education. In: Proc. AAAI Workshop on Artificial Intelligence for Education (2020)
- Hernandez-Ortega, J., Daza, R., Morales, A., Fierrez, J., Tolosana, R.: Heart Rate Estimation from Face Videos for Student Assessment: Experiments on edBB. In: Proc. Annual Computers, Software, and Applications Conference. pp. 172–177 (2020)
- 11. Lang, C., Siemens, G., Wise, A., Gasevic, D. (eds.): Handbook of Learning Analytics. SOLAR, Society for Learning Analytics and Research New York (2017)
- Ma, L., Lee, C.S.: Investigating The Adoption of MOOC s: A Technology–User– Environment Perspective. Journal of Computer Assisted Learning 35(1), 89–98 (2019)
- 13. Martínez Monés, A., Dimitriadis Damoulis, I., Acquila Natale, E., Álvarez, A., Caeiro Rodríguez, M., Cobos Pérez, R., Conde González, M.Á., García Peñalvo, F.J., Hernández Leo, D., Menchaca Sierra, I., et al.: Achievements and Challenges in Learning Analytics in Spain: The View of SNOLA. RIED. Revista Iberoamericana de Educación a Distancia 23(2), 187 (2020)
- Romero, C., Ventura, S.: Educational Data Mining and Learning Analytics: An Updated Survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery (2020)