

SpAtiAL: A Sensor based Framework to Support Affective Learning

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Abstract— The objective of this paper is to present SpAtiAL, a new framework to design and develop an intelligent and personalized affective educational environment that will be able to support learners in multiple education settings. The sensors-based environment will support adaptively a) learners based on their enriched affective models and b) teachers in order to orchestrate the learning procedures more efficiently. In SpAtiAL we propose a set of Electromyogram (EMG) based features such as muscles total pressure, flexors pressure, tensors pressure, and gesture stiffness, for the purpose of identifying differences in students' affective state. In identifying these EMG-based features we have developed a tool for visualizing in real-time the signals generated from a Myo sensor along with the muscle activation level in 3D space.

Keywords-component; affective learning; sensors; Myo;

I. OUR APPROACH

This work is motivated by the need that students have to be supported based on their affective state and emotional status. Until now, the available learning platforms support students only based on their cognitive characteristic about a specific domain knowledge. Especially in distance learning scenarios the support is even rarer because it is difficult for the learning systems to develop automatically concrete models for the students. Furthermore, the teachers are not able to provide or adjust the level of support to the students because they are not able to have the whole picture of students' status (not only cognitive). Our work will go a step beyond by integrating students' emotional status in their models.

We propose that the students' models can be enriched with their affective state characteristics. Apart from cognitive, social and meta-cognitive characteristics, these models contain also students' affective states. Students' affective state is monitored and updated through educational activities from various and multiple sources such as motion analysis. These models are the base to have adaptive and personalised support to the students. The main goal of SpAtiAL (Sensor bAsed Affective Learning) is to support students based on emotional problems and issues that until now were not identified or even worst ignored. SpAtiAL will lead to more effective learning procedure and to more holistically supported students.

Emotions are intertwined with most human cognitive functions e.g. learning. It has been reported that emotions can be described along two dimensions that affect cognitive performance, valence (positive-negative) and activation (activating-deactivating). In the domain of Affective Computing, multiple studies have focused on emotion

recognition and explored the use of various sensing technologies. In the domain of education, emotions exert a critical influence on the learning mechanism. One of the key issues is the ability to recognize and intelligently understand the learners' emotions and respond to them in order to enhance learning motivation and effectiveness. Moreover, the latest scientific findings indicate that emotion plays an essential role in decision-making perception and in the relevant learning domains. A slightly different emotion does not just make a learner to feel a little better but also induces a different kind of thinking, characterized by a tendency toward greater creativity and flexibility in problem solving, as well as more efficiency and thoroughness in decision making. Thus, the main and open questions we are interested in are: how various learning tools or intelligent learning environments, can objectively sense the engagement level of a learner through a learning activity? In what ways can affective computing tools support learners in multiple educational settings?

Thus, the primary objective of our framework is to design and develop a sensor-based personalized affective educational platform that will be able to support learners in multiple education settings. The sensors-based environment will adaptively support a) learners based on their enriched affective models and b) teachers in order to orchestrate and support the learning procedures more efficiently. The sensors and the relevant interfaces are able to support learners in face-to-face, distance and blended learning conditions both in formal, informal and even game-based learning scenarios. In SpAtiAL we propose a set of Electromyogram (EMG) based features such as muscles total pressure, flexors pressure, tensors pressure, and gesture stiffness, for the purpose of identifying differences in performing the same gesture during lab courses. In identifying these EMG-based features we have developed a tool for visualizing in real-time the signals generated from a Myo sensor along with the muscle activation level in 3D space.

In order to accomplish our objectives, we plan to use a) advanced sensing devices and smart learning environments to recognize and understand learners' affective state, b) enriched student models based, among others, on learning analytics and learners' affective state c) adaptive and personalized mechanisms to support both learners' cognitive, social and meta-cognitive characteristics and teachers in orchestrating lectures more efficiently, d) learning strategies and methods that will support formal and informal educational practices.

II. METHODOLOGY

Three major theoretical approaches to the representation of emotions currently co-exist in the literature [1]. The first and most frequently used model describes emotions as discrete categories that have specific motivational and regulatory functions and that can be set apart based on stable expressive signs, physiological indices, or causal motives [2]. The second approach sees emotions as states that can be represented on a common multidimensional space. The original models included three dimensions: pleasure, arousal, and dominance (or power). More recent versions propose a bi-dimensional space organized along the axes of valence and arousal and suggest that the subjective feeling of an emotion is the result of an interaction between core affect (i.e. the position in the valence per arousal space) and a cognitive component such as interpretation or attribution [3]. The third approach – appraisal models – combine elements of dimensional models – emotions as emergent results of underlying dimensions – with elements of discrete theories – emotions have different subjective qualities – and add a definition of the cognitive mechanisms at the basis of the emotion [1]. None of these approaches, is immediately applicable to the domain of adaptive learning and most attempts to use them to inform a computer –supported learning environment were inconclusive [4].

Our approach proposes a model of affective responses in learners would benefit by the combination of elements of the three approaches and include situational information specific to the learning experience. Indeed, the emotions that are most commonly experienced in learning (i.e., engagement, boredom, confusion, curiosity, happiness, and frustration, according to a recent review, [4]) share cognitive appraisals, motivational effects, and expressive behaviors to the extent that situational and contextual information is decisive.

Our model of affective reaction will be based on a reversed engineering approach to traditional computational model of emotions. In our multi-layered model the information coming directly from the user through appropriate sensors (i.g., Myo) is used to generate a first model of users’ affective state in terms of the likelihood of a pre-defined set of appraisals. Contextual information will then be used as a second layer of information to modulate the set likelihood of these appraisals. Finally, the third layer will output the likelihood for certain target emotion. The data for the development of the affective inference model will be based on available empirical studies, theoretical reasoning, and a series of new experimental studies that will be run during the course of the current framework.

Human affective information should be multimodal, as the human sensory system is. Thus, integration of different emotion modalities is an essential part of a multimodal system that may resulted in a large increase (more than 10%) in the quality in comparison with the unimodal systems [5]. In addition, sensors fusion helps to determine and understand the contribution of each of the sensors to the modelling of affect under different scenarios. Approaches for combining multimodalities include probabilistic models [6], probabilistic graphical models, such as Hidden Markov

Models, Bayesian networks and Dynamic Bayesian networks [7] and classifiers based techniques [5].

Our framework will focus on the combinations of the following sensing approaches, namely, textual and body. The combination of those four seems to be unique, specifically, for the setting of learning where the user is actively involved and initiates threads (e.g., discussion in blogs, Q&A, etc). Thus, we will consider both synchronous and asynchronous settings. The synchronous integration will be considered for the cases in which we have different sensor modalities happening at the same time (i.e., student watching a video, while her moves are monitored for emotions). Whereas, the asynchronous integration will consider, again, different sensor modalities, that were collected during different times, but related to the same “task/topic”. For both setting, we will augment the emotion information with contextual information.

The methodology for developing classifiers for emotions fusion follows the following steps: 1) Classifiers: development of machine learning algorithms using a variety of features in order to identify emotions in the train data. 2) Quality evaluation: Using the test dataset in order to evaluate the quality of the emotion identification.

Finally, student modeling will be approached via the perception of a functional system, where the identification of its components would unlock the internal and external causalities, giving access for adjustments and regulations. The learner’s emotional state will be interweaved with the structural elements of his/her learning functioning (both internal and external) when placed within an educational setting. Innovative and technological achievements in the accurate acquisition of the learner’s affective state will allow for the redesign of the ICT-based educational settings, taking into account a bilateral approach of the learner’s system that involves both cognitive and emotional processes, as reflected in the Valence/Arousal Space (VAS). This perspective clearly targets the complex coordination of cognitive processes and affective states that is evoked during learning, from a systemic modelling approach, in line with [4] point that ‘learning is indeed an emotionally charged experience’ (p. 153).

III. THE MYO SENSOR

In SpAtiAL we propose a set of Electromyogram (EMG) based features such as muscles total pressure, flexors pressure, tensors pressure, and gesture stiffness, for the purpose of identifying differences in performing the same gesture during a lab monitored course. In identifying these EMG-based features we have developed a tool for visualizing in real-time the signals generated from a Myo sensor along with the muscle activation level in 3D space.

Today, the hardware for gesture recognition is based on infrared (IR) sensors, Electromyograms (EMGs), and Inertial Motion Sensors (IMS) or combinations of them. Some IR sensors are based on projecting an infrared pattern in the room and capturing the pattern with an IR camera. A common pattern is a grid of dots. If the dots captured on a surface are dense, the surface is near the camera, and vice versa. Such devices are LEAP motion sensor [7] and MS

Kinect (Version 1) [8]. The methods based on EMGs classify movement according to the electricity on the surface of the skin, which reflects the activity of the muscles. Myo sensor is such a device [9]. Methods based on IMS(es) are exploiting several wear- able sensors worn by the user in several places in his body. The device we have employed is Myo that com- bines EMG and IMS sensors in the forearm, and there- fore, it can be used non-intrusively for pottery sessions.

Most of the bibliography in EMG gesture recognition techniques involves a sensor made by a certain lab that it is not available for the community and therefore experiments can not be reproduced accurately. Myo sensor is a relatively new device as it was released to the public at 2013 and offers a benchmark device at low cost (\$200). It is a wireless device connected to desktops or mobiles offering a good user experience. Myo is ideal for art performances such as pottery, since the other options of IR and IMS based sensors can not be used due to physical limitations. In this work, we focus on gesture recognition at the level of fingers from EMG(s). In particular, we wish to extract information about the finger-gestures, which is a particularly valuable piece of information for the learner in order to improve his performance in pottery arts. In the literature, the gesture recognition methods that rely on EMG typically refer to hand-gestures. Although we do not treat the same task, we have reviewed some of these methods so as to highlight the most interesting components.

Preliminary experimental results (based on lab course with pottery constructions namely bowl, cylindrical vase, and spherical vase) [10] verify the validity of the proposed methodology in identifying differences across the pottery gestures that may look identical, constituting a powerful framework for capturing and communicating the intangible aspects of a pottery performance that makes it unique.

IV. FUTURE WORK

SpAtiAL will try to use the power of our Myo based solution towards the affective state recognition. Moreover, it will produce innovative new scenarios through and for the use in research of affective state detection. Exploring affect in learning, scenarios will be developed across 3 axes. On the purely Affective axis, the detection of the learner’s state will be utilized both as a context and as content in the learning process. “Affectively neutral” scenarios will allow exploring content retention in multiple affective states (affective state as learning context) while “affectively charged” scenarios will allow the exploration of mood and emotion in stress or otherwise emotionally sensitive fields such as medicine (affective state as content). On the Learning Paradigms axis, content will be utilized so as to be repurposed, amongst others, between Normal instruction based learning, problem/scenario based learning, scaffolding and flipped learning approaches. The aim will be to utilize this content in order to create distance and blended learning scenarios that will explore affective impact in the aforementioned various educational approaches. Finally on the Gamification axis, traditional, game informed and game based scenarios will be developed in order to explore, once again both contextually

and content-wise the interplay between affective states and content’s gamification.

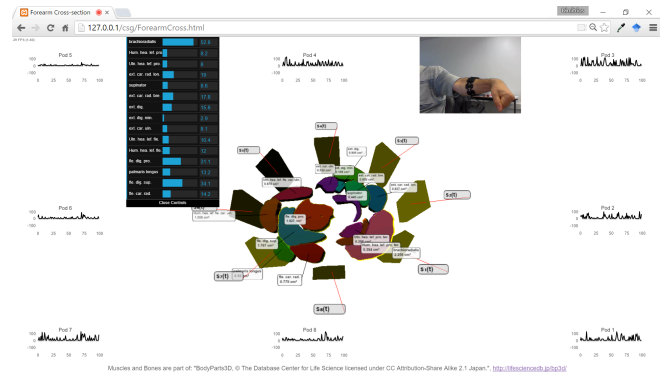


Fig.1 Live view of Myo signals and muscle electrical activity in the cross-section model of the muscles.

REFERENCES

- [1] K. R. Scherer, “The dynamic architecture of emotion: Evidence for the component process model,” *Cogn. Emot.*, vol. 23, no. 7, pp. 1307–1351, Nov. 2009.
- [2] P. Ekman, “An argument for basic emotions,” *Cogn. Emot.*, vol. 6, no. 3, pp. 169–200, May 1992.
- [3] J. A. Russell, “Core affect and the psychological construction of emotion,” *Psychol. Rev.*, vol. 110, no. 1, pp. 145–72, Jan. 2003.
- [4] S. D’Mello, S. D’Mello, and A. Graesser, “Dynamics of Affective States during Complex Learning,” *Learn. Instr.*, vol. 22, no. 2, pp. 145–157, 2012.
- [5] G. Castellano, L. Kessous, and G. Caridakis, “Emotion Recognition through Multiple Modalities: Face, Body Gesture, Speech,” in *Affect and Emotion in Human-Computer Interaction*, Berlin, Heidelberg: Springer Heidelberg, 2008, pp. 92–103.
- [6] A. Kapoor, R. W. Picard, and Y. Ivanov, “Probabilistic combination of multiple modalities to detect interest,” in *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004.*, 2004, p. 969–972 Vol.3.
- [7] A. P. Engelbrecht, L. Fletcher, and I. Cloete, “Variance analysis of sensitivity information for pruning multilayer feedforward neural networks,” in *IJCNN’99. International Joint Conference on Neural Networks. Proceedings (Cat. No.99CH36339)*, vol. 3, pp. 1829–1833.
- [8] “Leap Motion | Mac & PC Motion Controller for Games, Design, Virtual Reality & More.” [Online]. Available: <https://www.leapmotion.com/>. [Accessed: 03-Feb-2017].
- [9] “Myo Gesture Control Armband | Wearable Technology by Thalmic Labs.” [Online]. Available: <https://www.myo.com/>. [Accessed: 03-Feb-2017].
- [10] D. Ververidis, S. Karavarsamis, S. Nikolopoulos, and I. Kompatsiaris, “Pottery gestures style comparison by exploiting Myo sensor and forearm anatomy,” in *Proceedings of - MOCO ’16*, 2016, pp. 1–8.