MAMIPEC - Affective Modeling in Inclusive Personalized Educational Scenarios

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Abstract—**In this paper we introduce the MAMIPEC project. The aim of this project is to explore the application of affective computing to accessible and personalized learning systems. To this end, we consider a user context which includes appliances and devices to enrich user interaction. We describe the research objectives and present on-going work towards understanding the affective support needed in educational scenarios.**

Index Terms—**Affective computing, educational scenarios, emotions, personalized and inclusive learning.**

I. Introduction

ADAPTATION is a long-standing need in educational/training systems. Adaptive systems are supported by an underlying user model that gathers information about the student´s previous knowledge, preferred learning styles, interaction needs (covering those related to disabilities) or any other factors that may be useful to support a personalized and inclusive learning process. A natural and increasingly demanded extension of current approaches to adaptation is to consider more complex sources of interaction data in order to develop more complete and descriptive user models that support the provision of additional and more precise adaptation functionality. One such source of information is the user's affective state, which features a strong relationship with the cognitive process [1-4].

In this context, the MAMIPEC project (Multimodal approaches for Affective Modeling in Inclusive Personalized Educational scenarios in intelligent Contexts) focuses on integrating cognition with user's emotions, to provide adaptive learning via a comprehensive user model based on available standards and specifications.

In this paper we introduce some related work, present the MAMIPEC project and describe the work in progress since it started 10 months ago.

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II. Related Works

There is a need for a holistic approach in dealing with accessible e-learning [5] to provide a learning experience that is accessible at all levels, from content via learning paths to overall learning objectives. From the aDeNu experience in the EU4ALL project [6], this holistic approach can be provided by combining two existing perspectives: i) universal design, based on specifications and standards (such as those defined by W3C, ISO and IMS) that model, at design time, the needs and preferences of the learners in relation to the learning needs, and ii) runtime adaptation, generated by using diverse artificial intelligence techniques (data mining, machine learning, user modeling, recommender systems…). In this case, the dynamic support provided to the learner in a given context relies on the analysis of users' interactions and could benefit from the standard-based descriptions of the universal design approach.

In this context, a thriving research field named affective computing reflects a growing interest in improving all aspects of the interaction between humans and computers, and thus, including personalized and inclusive learning mediated by technology. Affective computing aspires to reduce the gap between the emotional human and the emotionally challenged computer by developing computational systems that recognize and respond to the affective states (e.g., moods and emotions) of the user [7]. The basic tenet behind most affective computing systems is that automatically recognizing and responding to a user's affective states during interactions with a computer can enhance the quality of the interaction, thereby making a computer interface more usable, enjoyable, and effective, which in learning may lead to a better personalization to the learner.

Affect detection is usually done by means of human observation or by analysis of hardware sensor data, such as facial expressions, posture analysis, pressure on the mouse, etc. [8]. Most of the technology and tools involved in the detection of affective states in the educational domain are common to other affective computing areas: hardware sensors that monitor physiological parameters, and subsequent methods and tools to adequately process and interpret the signals (pattern recognition techniques); machine learning techniques (e.g., Bayesian Networks, hidden Markov models) for predicting affect from user computer interactions (e.g., typing speed, keystroke duration or number of clicks [9]) and sensor data; and qualitative methods (i.e. interviews) or self reported information.

In affective e-learning, the student interactions with the e-learning platform have to be dynamically collected, focusing on data relevant to learning progress and on behaviors that can be seen as affect expressions (e.g., inappropriate task strategies, procedural errors, misconceptions, problem-solving behavior, questionnaire responses, time spent on hints, number of hints selected, etc.). Machine-learning techniques can be used to discover existing relations between affect (e.g., revealed in a post-survey) and observable behavior [10]. In addition to the former particularities, the emotions that are relevant in a particular educational context have to be precisely defined [2-3], according with cognitive principles. Despite the numerous studies focusing on affect detection, it still remains a complex task.

Given the lack of solid and widely-accepted theories, pedagogical interventions are normally based on heuristics defined ad-hoc. These interventions do not only depend on the current emotional status of the student but are also customized for each student and each context via a learner model [1, 11]. As well as including general heuristics, affective e-learning systems often make use of machine learning optimization algorithms to search for strategies to give affective support adapted to individual students [12].

Another related field we are exploring in our research is imaging processing. In a classical classroom based learning environment, students' gesture and facial expressions offer valuable information to the lecturer. Such visual information helps detecting relevant student feelings (e.g. boredom, confidence, interest, excitement or frustration). In a similar way, e-learning systems may use computer vision techniques to support detection of relevant events related to the user's affective state that influence the learning process. Latest developments in facial feature detection, new peripherals (e.g., Kinect) and processing software facilitate low level feature extraction at a low cost. Most emotion recognition methods use appearance-based holistic approaches [13]; or rely on geometrical facial features that represent the shape, relative position and/or deformation of representative face elements, e.g. mouth, nose, eyebrows. In many cases [14-16] these data are used to identify the activation of the facial Action Units (AU) of the Facial Action Coding System (FACS) defined in [17]. Each AU is anatomically related to the contraction of one or a set of specific facial muscles; and the FACS associates certain AU combinations with prototypic emotional facial expressions. The output is generally processed with supervised learning methods and combined with other information sources in an attempt to reliably estimate user emotions [7].

Therefore, there is a need to research how affective support can enrich the learning experience in inclusive and personalized educational scenarios through a proper modeling of the user features, course settings and device capabilities, and making use of appropriate sensors to get data from the environment. Ideally, this information could be modeled and used by the environment to allow a natural interaction with the learner by providing alternative ways of communication based on non-intrusive, gradual and intuitive methods. For this, embedded systems that are context aware, capable of knowing and anticipating the environment requirements, responding with optimal actions, and adapting the environment to the scenery can be used to feel the presence of people to achieve what is called Ambient Intelligence [18].

III. MAMIPEC PROJECT

MAMIPEC is a three-year project, involving a multi-disciplinary team that comprises researchers from different areas of expertise: i) engineers and computer scientists specialized in human computer interaction and artificial intelligence techniques, ii) psychologists with experience in psycho-educational support and emotional management, and iii) engineers with experience in image treatment and data fusion. The first two of these groups are with UNED (the Spanish National University for Distance Education) and the third is with the University of Valencia, both in Spain.

The project aims to explore the application of affective computing to develop accessible and personalized learning systems that consider a user context where appliances and devices are included to provide a richer and more sensitive user interaction. To this end, six research objectives have been defined and are currently being addressed. They are summarized in Table I.

TABLE I.
OBJECTIVES OF MAMIPEC PROJECT

Obj.	Goal
1	Study different approaches based on ambient intelligence for inclusive personalized interaction that include diverse and complex forms of interaction and assistive technologies to provide effective communication and a non intrusive, non-overwhelming, interactive, natural and co-adaptive environment where the student learns by interacting with the environment in their most adequate way.
2	Explore possible applications of affective computing in inclusive learning which includes a) the study of strategies that address the affect detection paradigm by using computer vision as the most informative interaction channel; and b) the use/design of alternative and inexpensive sensors which may provide reasonable accuracy and additional sources of observable information.
3	Design, build and provide access to standards-based models for inclusive and personalized learning that take into account affective states and the enriched environment, and contribute to standards

	the extended descriptions to deal with affective computing, multimodal user interfaces and ambient intelligence.
4	Explore machine learning algorithms and multimodal fusion approaches to feed the models that a) effectively merge the data that they hold to infer useful information that can be used in the learning process and b) are able to trigger a convenient educational action in response to this information.
5	Provide inclusive, personalized and affective dynamic support through multimodal user interfaces in terms of a) personalized services that consider the user affective state, abilities, competences and skills, and b) inclusive and personalized responses that take into account the entire multimodal educational setting.
6	Evaluate the level of learning gain improvement in different scenarios to determine the impact of integrating affective computing, context awareness and ambient intelligence techniques.

To cope with the above objectives from the technological point of view and following previous works in the EU4ALL project, we have proposed an open standard-based service oriented architecture [19]. Fig. 1 shows the main components involved (where the arrows show the data flow): i) User Model (**UM**), which manages information about the learner (e.g. learning styles, learning objectives, accessibility preferences, personality, etc.) ; ii) Device Model (**DM**) which store the capabilities of the device used to access the e-learning system; iii) Emotional Data Processor (**EDP**), which process the data gathered in the environment through the sensors; iv) Multimodal Emotional Detector (**MED**), which combines the different sources of information, including EDP, UM, DM; v) Inclusive Personalized Affective Dynamic Support Component (**IPADSC**), which includes a recommender system, and vi) Emotional Delivery Component (**EDC**), which produces the output to be delivered to the learner through the appropriate actuators.

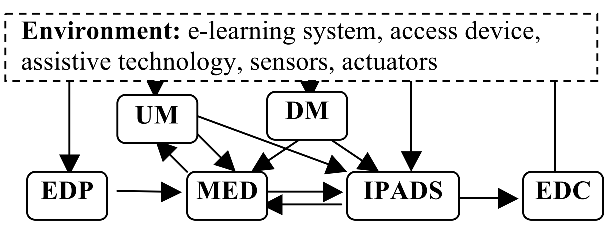

Figure 1. MAMIPEC service oriented architecture

While the learner is working on the educational scenario, the UM processes the learners interactions in the e-learning system and updates the UM accordingly. This processing can be as simple as updating the progress in the course after a questionnaire has been passed of as complex as inferring the collaboration level with machine learning techniques. The UM is also updated with user emotional information computed by the MED (which combines information obtain from the environment by the EDP, the UM and the DM). At a certain moment, the e-learning system asks the IPADSC for some inclusive personalized and affective dynamic support for a given learner in a specific educational (course situation) and environmental context (i.e. device). The IPADSC requests information to the UM, DM and MED, process it and obtains the emotional feedback to be given to the learner.

In the following section we briefly introduced the work that is being carried out to address the above objectives.

IV. On going work

In these first months of the project we have focused on understanding the affective support needed in educational scenarios as proposed in objective 2. In parallel to a review of the state of the art in affective computing for educational scenarios, we have carried out a pre-pilot experiment in July 2012 with two participants to clarify how we could induce emotions and detect them through varied sources of information. In particular, in this experiment we recorded data from different sources simultaneously, namely, eye movements with the ASL 504 eye tracker which also detects the pupil dilatation, face expressions from Kinect, using its SDK to detect position and/or deformation of representative face elements, video from a web cam, cardiovascular events such as cardiac period, and blood pressure (systolic and diastolic values) by means of the PowerLab, breath frequency with a pneumograph and mouse movements and keystrokes. To complement the data gathering through the above devices, several questionnaires were filled in by the participants, namely the Five Factor Model personality questionnaire [20] at the beginning of the course, and Self Assessment Manikin scale [21] after each exercise to measure the caused emotions with the dimensional approach. We are currently processing the data obtained, trying to both automate its processing for forthcoming sessions and its usage as input to machine learning algorithms [22], as afore mentioned in objective 4. The obtained results will be used to build the standard-based models proposed in the objective 3.

In these pre-trial sessions, participants were asked to carry out mathematical exercises with several levels of difficulty and varied time restrictions. Exercises have been designed so that they elicit different emotions. Mathematical exercises have been used because they are useful to produce emotions in the learner, as remarked by related literature [23]. In relation to this, the University of Valencia counts with previous experience in the development of a tutoring system to assist students at learning arithmetic and algebraic problem solving [24]. The availability of such a system provides a platform for testing future developments. Controlled experiments in this type of scenarios may be an accurate source of information and data collection of emotions towards learning for the evaluations proposed in objective 6.

Moreover, to address objective 5, we are currently applying the TORMES methodology. TORMES adapts the ISO standard 9241-210 to guide educators in identifying recommendation opportunities in the experimental scenario that deal with affective issues and aim to produce the personalized affective support needed [19]. Thus, an exhaustive and methodical compilation of heuristics concerning affective learning is being carried out to model, in terms of recommendations, best practices in everyday instruction support. Judging from the current literature on this topic, large parts of this knowledge have not yet been collected. In our view, the affective support can be provided in different ways: i) modifying the emotional mode of the recommendation to match the affective state of the learner, ii) providing an open learner affective model where learners can be aware of their affective state as computed by the system and iii) offering specific recommendations that support the learners in managing their emotional state (e.g. to reduce anxiety when carrying out certain exercise).

V. Conclusion

In this paper we have summarized the main objectives of the MAMIPEC project, and some of the initial works already undertaken. In particular, possible applications of affective computing in inclusive learning have been explored. To this end, we have run a pre-pilot experiment in July and will carry out a large scale two week experiment in November, where we aim to gather around 200 participants. This large-scale experiment will be carried out in different stages. Each of them will be directed to a different audience type, and therefore with different learning styles, and difficulties facing mathematics: general public, high school kids, high school and college youth. The aim is to obtain a complete database from which to infer learning emotions. This is the first step to building a user model that considers the student's emotions and getting a better personalization to the learner.

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