Cognitive Architecture for Affective eLearning

H. Ekanayake[1], D.D. Karunarathna[2] and K.P. Hewagamage[3]
University of Colombo School of Computing
35, Reid Avenue, Colombo 7, Sri Lanka.
{[1]hbe, [2]ddk, [3]kph}@ucsc.cmb.ac.lk

Abstract

Learning is a psychological experience one receives to make behavioral modifications to improve his/her capabilities while gaining knowledge or skills. Even though the traditional learning is a teacher-centered pedagogical instruction, the modern learning framework is centered under a student-centered LMS and thus it is weak in cognitive, emotional, behavioral and social measures. Meanwhile, more research work has been conducted to improve the pedagogical factors under themes of adaptive and personalized eLearning. However, none of these solutions are capable of responding to a learner's psychological reactions while delivering an adaptive content. This paper proposes an architecture to fulfill this need by integrating the techniques and knowledge from cognitive science disciplines to the modern eLearning framework.

Keywords: eLearning, Cognitive Science, Cognitive Modeling, Affective Computing, Emotion, Behaviorism, Pedagogy, Psychology, Biofeedback Sensing, Semantic, Ontology, Automata Modeling

1. Introduction and Motivation

The early instruction was teacher-centered, where a human teacher is responsible for presenting whatever facts, ideas or techniques to students who benefit from the learning. In this practice, depending on the teacher's abilities, he/she is able to dynamically organize the presentation adaptively for the capabilities of the students by monitoring the dynamic behavioral responses of students. Therefore, this conventional teacher-centered instruction is considered as pedagogy, where it is enriched with cognitive, emotional, behavioral and social factors [23].

In contrast, modern instruction is fully student-centered and computer-based, where student has the freedom to receive pre-organized instruction from a computer system depending on his/her requirements, and it is now referred to as eLearning. Even though this method demands many advantages, especially commercial values, like many students can be served at the same time, it is lacked of pedagogical measures. Thus the research community is now working on this issue to improve the pedagogical measures under adaptive and personalized eLearning [4]. However, still these solutions are based on learner's learning preferences or motor actions (mouse clicks, key presses).

Human level learning was under the consideration of research community since early ages. This trend has changed as the introduction of primitive computers in 1950s, where researchers were more motivated towards replicating human learning under the discipline of Machine Learning (Artificial Intelligence), while other issues surrounding the human learning, such as, the biological functioning of human brain, linguistics processing and how cultural settings effects thinking, were become subjects or remained under Psychology, Linguistics, Neuroscience, Anthropology and Philosophy.

However, soon it was realized that machine learning alone cannot be used to understand human level learning or intelligence [19, 20]. In the meantime, a major development has reported in neuroscience due to founding of more advanced brain scanning technologies in early 1990s, such as MRI, PET and fMRI [1]. As a result researchers were able to study and understand the human level functioning and learning in more detail and as a result, the distinct disciplines were reorganized under the common theme of cognitive science in mid 1990s to model aspects of human cognition with the aid of computer science (cognitive modeling) [3, 16].

In the same time, a sub-area of cognitive science born to study how emotions influence human cognition in computing platforms, which is referred to as Affective Computing [2]. Collectively these emerging areas gained the potential to study the pedagogical process of human instruction in computing platforms, which leads to our proposed cognitive architecture for affective eLearning.

2. Background and Proposed Approach

2.1. Modeling Human Cognition

The cognitive modeling is the process of simulating human problem solving and mental task processes in a computerized model. Soar [8] and ACT-R [3] are two cognitive systems that models human cognition.

The generally agreed cognitive architecture consists of 3 layers, namely, sensory layer, perceptual layer and the cognitive layer, where sensory processing is described as the resulting neural excitation when visual, auditory and haptic sensory systems constantly stimulated by a stream of events from the environment. The transformation of continuous sensory stream into discrete percepts of visual, auditory and haptics is called perception. The cognition refers to the process involved in knowing, understanding, remembering, judging and thinking [14]. In addition, memory organization is discussed under sensory (action) memory, short-term memory and long-term memory [24].

The higher layers of the cognitive systems assumes that the information available as percepts as we discussed in the previous paragraph. These percepts of information then processed by the cognition and construct a conceptual network of knowledge, which is referred to as a semantic knowledge organization (ontology). Therefore, this resulting semantic network pretends one’s view of some aspect about the world. However, a semantic gap exists when there is lack of transformation methodologies for conversion of low-level sensations into percepts and subsequently into concepts [14] which leads to incomplete or misleading representations. Therefore, a cognitive system should try to minimize this semantic gap in order to properly model the worldly aspects.

2.2. Study of Emotions and Biofeedback Sensing

Cognitive science has initially ignored the study of emotion. However, soon it has been realized that the emotions are an inherent part of even rational decision making. As a result, now the study of emotions is an integral component of the cognitive science framework [1, 6, 12].

Most cognitive scientists are agreed upon two categories of emotions, one concerning judgments about a person’s general state or personality, and the other one as bodily reactions, such as, anger, fear or happiness, caused when people are failed to accomplish goals [1]. When modeling cognitive behaviorism, Chittaro and Serra [9] propose a method based on personality and probabilistic automata. In this method, the personality is described using a Five-Factor Model (FFM), where personality traits are summarized in five continuous dimensions (openness, conscientiousness, extraversion, agreeableness, and neuroticism), whose values range from 0 to 100. In contrast, Bécheiraz and Thalmann [22] use emotions as in the form of bodily reactions, deployed by the autonomous nervous system [5], and perceptual states of humans to determine a possible behavior.

A school of new techniques has been emerged to measure the biological feedback caused by emotions, such as, Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), Respiration and Electromyogram (EMG) [11]. Moreover researchers have been able to determine the emotional state of a human based on psychological signals sensed by these biofeedback sensors [7].

Meanwhile, another camp of researchers is studying the emotional quality of multimedia information [10]. Thus, an expected emotional response of a multimedia data stream could be calculated.

Collectively these techniques and technologies provide a way to recognize the dynamic psychological reaction of a learner caused by an emotional eLearning presentation.

2.3. Cognitive Affective eLearning Architecture

As we have discussed, affective computing is the computing that relates to, arises from, or deliberately influences emotions [2]. In affective eLearning, the learner is presented a real-time adaptive eLearning content while monitoring the dynamic psychological behavior of the learner to the learning content sensed by biofeedback sensors attached to the learner. The learning content is further determined by the learner's personality and the mood. Therefore, the overall system represents a virtual human teacher who is acting on a pedagogical teaching campaign. The proposed cognitive architecture for affective eLearning is denoted in figure 1.

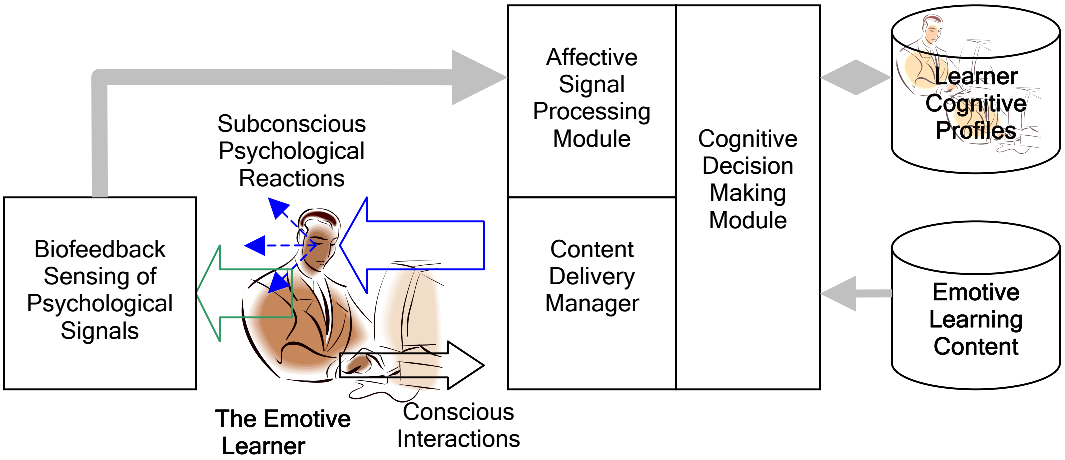

Figure 1: The High-level Diagram of Cognitive Architecture for Affective eLearning

The operation of the system starts by identifying the current learner who has signed-up for the lesson. The system then loads the cognitive profile of that learner to determine the personality, emotional profile and behavioral patterns of the learner. After, the system processes the initial psychological signals sensed by the biofeedback sensors attached to the learner to determine the initial mood of the learner. Finally, the cognitive decision making module initiates the eLearning presentation while dynamically adjusting the content according to the expected emotional response, mood, personality and dynamic psychological feedback of the learner. In addition, the learner is permitted limited conscious interactions with the system in a form of key presses or mouse movements to adjust the content for the learner's needs. Meanwhile, the cognitive decision making module updates the measurements of cognitive profile of the learner.

The learning content is organized under a semantic multimedia object model. An example for such multimedia organization is Macromedia Flash DOM [18] and SCORM [17]. However, our proposed semantic multimedia object model is charged with expected emotional cues. In addition, the cognitive decision making module adjust the delivering presentation based on a semantic schema [13]. So that it can expand, shrink or determine an alternative path for the presentation.

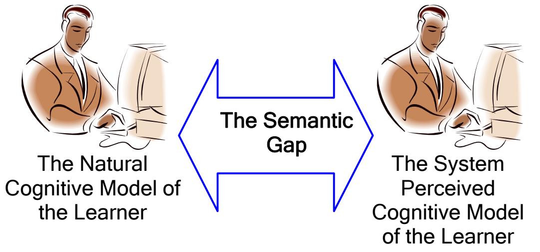

Figure 2: The Semantic Gap Generated as a Lack of Transformation Methodologies

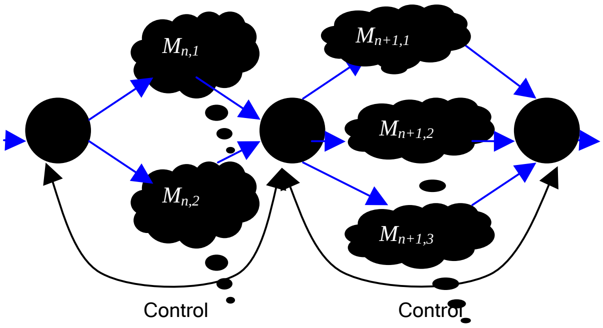

Figure 3: A Hybrid Automata Model for Behavioral Modeling (Cognitive Automata)

When updating the learner's cognitive profile, the system should spell the learner's psychological responses accurately, otherwise a semantic gap generates at higher layers (see figure 2). This gap depends on the accuracy of sensing equipments, processing of affective signal and emotional schemas. Therefore, the system needs to be tuned perfectly before it is used in real eLearning environments.

The cognitive decision making module consist of activating behaviors influenced by emotions, personality, mood and learning patterns of the learner. Cognitive scientists use different approaches to model behaviorism. In ACT-R, the behaviorism may be described as the activation of production rules and attentional responses to its buffers. In contrast, scientists who are active with cognitive agents (robots) are flavored to model behaviorism using finite-state machines (FSMs). Bécheiraz and Thalmann [22] proposes a method to compose possible behaviors using FSMs, whose selection is determined by perceptual and emotional state of an agent. The Chittaro and Serra [9] use personality and probabilistic automata to model behaviorism.

In contrast, we are proposing a hybrid-solution using the concept of FSM, probabilistic automata [21], ACT-R activation and timed-automata [25] to model behaviorism with self-adaptive capabilities. The complete description of this model is beyond the scope of this paper. Figure 3 depicts a possible instance of a behavioral network.

The proposed automata model is expandable along the clouds and also scalable as introduction of more decisional paths to the model. The circles represent major decisional points, where external stimuli are considered and actions are executed. The possible transitions are decided by the previous state, knowledge availability, emotional appraisal and personality.

3. Results of Preliminary Investigations

The learner is attached biofeedback sensors to constantly monitor the learner's bodily reactions (biofeedback) to external stimuli. The figure 4 depicts a simple LEGO Mindstorms-based GSR meter [15], which is used to measure the skin resistance changed as a result of sweat gland activity controlled by the sympathetic autonomous nervous system [5]. Figure 5 depicts a GSR waveform generated as a result of a subject is observing a simple presentation consist of emotional images (a sunset, a map of a city, a girl is crying, a robot …).

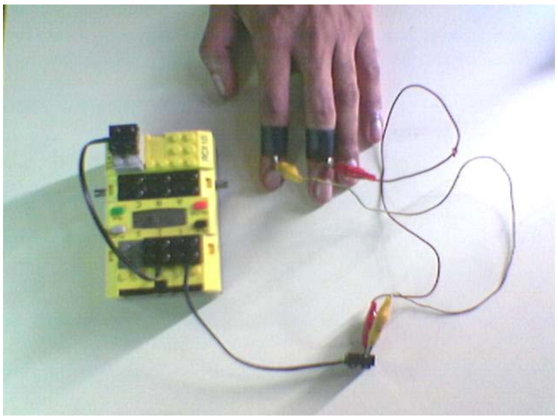

Figure 4: A simple LEGO Mindstorms-based GSR meter

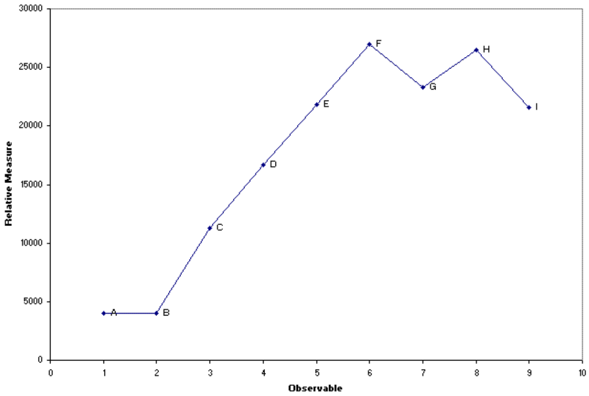

Figure 5: The GSR Waveform as a Result of the Subject is Observing a Presentation

These psychological signals are then fed to the affective signal processing module, which is responsible for recognizing the emotional state of the learner. The methodologies and algorithms used in this process is beyond the scope of this paper (refer [7]). The output of this module is the current emotional appraisal of the learner and it is name and attributes (threshold and intensity) pairs of emotions.

E.g.

Emotion Name: anger
Emotion Intensity: 0.6
Effective Threshold: 0.2

Emotion Name: distress
Emotion Intensity: 0.7
Effective Threshold: 0.1

The personality appraisal is based on the five factor model (FFM) giving a value between 0 and 100 for each factor, openness (open-minded close-minded), conscientiousness, extraversion (extravert introvert), agreeableness, and neuroticism.

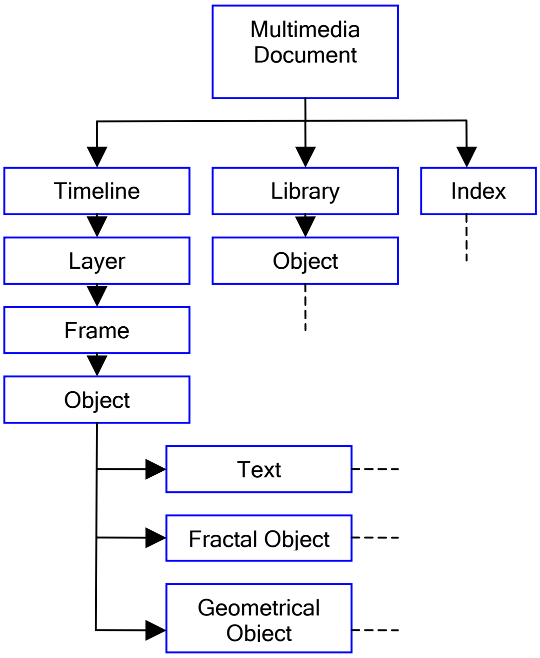

Figure 6: A Semantic Organization of Multimedia Information

An event driven multimedia document object model (MMDOM) data structure is used to organize the learning content (figure 6). This is a hierarchical structure where learning objects are organized respect to time and their semantic nature. In addition, this organization also contains the expected emotional appraisals for scenes.

4. Discussion and Conclusions

This paper has examined the current eLearning architecture to enrich it with more pedagogical measures. In this effort, we have discussed the current technological landscape with respect to modeling human cognition, the critical role of emotions and processing of psychological signals.

When implementing the system, the authors assume that the psychological experiments which leaded to positive hypothetical conclusions are stable enough despite the context. This may be evidence when emotional appraisal of a learner has to be extracted from psychological signals in the form of biological feedbacks [7]. According to our reference researches, the accuracy reported is not less than 75% for most instances; however it varies with the type of emotion which is under consideration. In addition, the categories of sensors we expect to use are relatively cheap compared to using brain waves or other advanced biological feedback sensing techniques.

In this research we assumed that the cognitive decisions are only dependent on knowledge factors, emotional appraisal, mood and personality of the learner. And the decisions are non-deterministic (probabilistic and timed). Even though the complete architecture is not discussed here, someone can argue that decisions are also dependant on some other factors, such as, experience, context. However, the idea was to develop a minimal architecture that considers at least emotional feedbacks when deciding possible behaviors, in addition to knowledge.

Considering the above feasibilities with respect to technologies and architectures, we can expect that the system will soon get realized and deployed. So that we can increase the attraction for eLearning and more knowledge can be delivered to our succeeding generations effectively.

5. Future Work

This study is only a preliminary attempt of a more advanced solution. More work has to be done in order to perfect the architecture and functionality of the system. We have considered only a subset of available psychological feedback signals for constructing a relationship with learning and behaviorism. However literature suggests that many other alternatives are available. Therefore this work can be extended by finding most appropriate feedback sensing methodologies and their relationships to learning.

As we have discussed in the previous section, one can think of more factors for effective cognitive decision making. Here we have used dynamic automata modeling for deciding decisions; however it may be inefficient under the non-deterministic manner. So one can think for improving the model or propose a more efficient solution for the problem.

In addition, the outcome of this solution can be extended for more application domains. One important domain is enabling learning environments for disablers. Other domains are cognitive robotics, virtual reality and autonomous systems.

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