Chapter 17
Managing Learner's Affective States in Intelligent Tutoring Systems

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Abstract. Recent works in Computer Science, Neurosciences, Education, and Psychology have shown that emotions play an important role in learning. Learner's cognitive ability depends on his emotions. We will point out the role of emotions in learning, distinguishing the different types and models of emotions which have been considered until now. We will address an important issue concerning the different means to detect emotions and introduce recent approaches to measure brain activity using Electroencephalograms (EEG). Knowing the influence of emotional events on learning it becomes important to induce specific emotions so that the learner can be in a more adequate state for better learning or memorization. To this end, we will introduce the main components of an emotionally intelligent tutoring system able to recognize, interpret and influence learner's emotions. We will talk about specific virtual agents that can influence learner's emotions to motivate and encourage him and involve a more cooperative work, particularly in narrative learning environments. Pushing further this paradigm, we will present the advantages and perspectives of subliminal learning which intervenes without conscious perception. Finally, we conclude with new directions to emotional learning.

17.1 Emotions and Learning

Learning involves mainly two processes: reasoning and memorizing. Reasoning is developed during cognitive tasks in which a learner tries to solve a problem using deductions or inductions. If a new knowledge (fact, rule) is obtained then the knowledge will be memorized in long term memory. Memorizing is also triggered when a learner tries to remember a previously acquired element using several means such as similarity, imagery, case-based analysis, etc. The two processes work alternatively and can be considered as a "Cartesian" approach of brain functions. Recent researches in neurosciences, education, and psychology have shown that emotions play an important role in learning. People often separate emotions and reason, believing that emotions are an obstacle in rational decision making or

R. Nkambou et al. (Eds.): Advances in Intelligent Tutoring Systems, SCI 308, pp. 339–358.
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reasoning but recent work have shown that in every case the cognitive process of an individual is strongly dependent on his emotions which can drastically influence performance (Damasio 1994; Spering et al. 2005). Numerous students submitted to an examination have been faced to stress and anxiety and by consequence to the "memory blank", a situation in which they are unable to neither retrieve any information nor make any deductions. Generally, negative emotions reduce or block thought processes, slow down the decisions and memory capacity (Idzihowski and Baddeley 1987). Positive emotions provide better conditions for problem solving and improve innovation. Students expressing anxiety or showing hyperactivity will not store knowledge efficiently (Isen 2000; Pekrun 2008). The learning process involves in particular three cognitive processes, namely attention, memorization, and reasoning, with respect to each of which the learner's cognitive ability depends on his emotions.

Attention means focusing. Learning can take place only if the student listens. A necessary condition for successful learning is hence to gain the *attention* of the student (Gagné 1985) depending on the learner's emotions, this first step can be more or less difficult. In fact, strong emotions, particularly if they are negative, disturb any kind of attention and concentration and prevent the learner from focusing on a subject. Moreover, negative emotions lead to difficulties in switching the attention to a new focus (Compton 2000).

Memory is one of the most important concepts in learning. Knowledge memorization represents a principal objective of instruction and is necessary for the major complex cognitive tasks of learning process (Bloom 1994). Memorizing is a process which involves the storage of information as well as the retrieval of knowledge and the following properties (Bower 1992):

- The effectiveness of the memorization process is narrowly linked to someone's emotions: Whereas positive emotions enhance the memory performance in general, unrelated and negative emotions disturb in particular the retrieval process.
- On the other hand, emotions which are related to the content to be memorized help in storing it.
- The retrieval process is improved when the emotional state is closest to the one at the time the desired information to retrieve was memorized.

Reasoning is the subsequent task attached to memory in which the learner is supposed to reason with the acquired knowledge. The process of reasoning enables a learner to perform more complex cognitive tasks – such as comprehension, classification, application of knowledge, analysis, and problem solving – which represent the ultimate goal of the learning process (Bloom 1994):

- Positive emotions improve any kind of reasoning since relations can be made more easily between objects or ideas (Isen 2000). In general, such emotions lead to a more creative, flexible, and divergent thinking process, whereas negative emotions cause a more linear, convergent, and sequential thinking (a step by step process) (Lisetti and Schiano 2000).
- Positive emotions promote efficiency and thoroughness in decision making and problem solving (Isen 2000).

Emotions can be used in the learning content to increase learner's attention and improve his memory capacity. In the following section we examine what types of different emotions can be considered.

17.2 The Different Types of Emotions

In the literature, there is sometimes confusion between the terms emotions, feelings, and affects. Although there is no common agreement on the definitions, it is important to make a distinction (Shouse 2005).

A *feeling* is an internal perception of a situation (or sensation) which is compared with previous experiences. Feelings (and ability to feel) differ from an individual to another as the volume and variety of previous sensations is different. They need an evaluation of a given situation.

An *emotion* is the consequence and display of a feeling. Emotions are comprised in a set of emotional states which can trigger different reactions (heart rate, transpiration, skin conductivity, muscle tension, blood pressure). It is a visible or measurable consequence of a feeling. Emotion is an immediate reaction to a feeling.

An *affect* is a stimulation state, or instinct able to change or provoke affective situations or experiences; affects are unconscious, without individual control. Successive affects will create different feelings according to the time. It is a physiological property of the body to generate intensities of affective situations. An individual can affect or be affected.

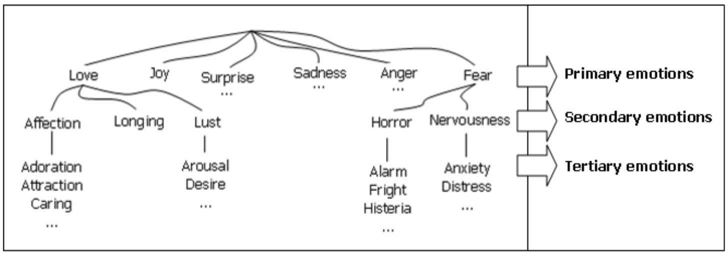


Fig. 17.1 Tree like taxonomy of Philipp Shaver

Thus affects will create feelings, which will be displayed as emotions. For instance, as babies have no previous history of feelings their emotions will be direct expression of the affective stimulations (Shouse 2005). Different models of emotions have been determined and hence different ways to represent them. Commonly, researchers have defined several types of emotions, called basic emotions. The first computational model of emotions was established by Ortony, Clore and Collins (Ortony et al. 1988), known since that time as the OCC model. This model specifies 22 types of emotions: fortunes of others (happy-for, resentment, gloating, pity), well-being (joy, distress), Prospect-Based (satisfaction, fear-confirmed, relief, disappointment), Attribution (pride, shame, admiration, reproach), Attraction (love, hate), Well-Being/Attribution compounds (gratification, remorse, gratitude, anger). This model might be too complex for the development of emotional characters, so Philipp Shaver in (Parrott 2001) asked college students to rate 213 emotional terms on how much emotion they conveyed. This study conducted to the definition of 5 or 6 clusters of basic emotions: *love, joy, surprise, sadness, anger, fear* and each emotion leading to secondary and tertiary emotions.

With the objectives to proceed to a facial recognition of emotions, Ekman (Ekman et al. 2002) distinguished then six different basics emotions: *sadness*, *happiness*, *disgust*, *fear*, *surprise*, and *anger*. The faces help to moderate and choreograph conversations, and conveyed information. Even if all emotions are not perceived easily and clearly on a human face, we believe that each emotion has a specific facial expression with flagrant or subtle modifications. An example: sad, mournful expressions: use eyebrow depression, eye narrowing, nasal muscle elevation, lip compression, and mouth lowering (turned down at edges).

As emotions can have an impact on the voice, Juslin and Sherer (Juslin and Scherer 2005) has shown how different emotions can change the tone, articulation and intensity of the voice. Elliot (Elliot 1992) built a computing system combining facial expression and voice tones, based on 13 couples of opposed emotions. This system produced emotions which were better recognized by users than emotions expressed by humans.

Table 17.1 Elliot's set of emotions

Joy	Distress
Satisfaction	Disappointment
Liking	Disliking
Happy-for	Resentment
Relief	Fear-confirmed
Gratitude	Anger

Sorry-for	Gloating
Pride	Shame
Gratification	Remorse
Hope	Fear
Admiration	Reproach
Love	Hate
Jealousy	non-Jealousy

However, we must be conscious that on some learner faces, we may not see facial expressions, because of impassive faces or cultural barriers and this represents a limitation of this method. Ochs (Ochs and Frasson 2004) built a system called Case Based Emotioning System (CBE), enabling any user to indicate on a scale how he would feel in a given hypothetic situation. After a period of data acquisition the Case Base Reasoning System was able to make rather accurate predictions using an Emotional Case library.

More recently, researchers considered not only the simplified set of basic emotions (anger, disgust, fear, happiness, sadness and surprise) but also learning-centered affective states such as : anxious, confusion, boredom, contempt, curiosity, eureka, frustration (D'Mello et al. 2009). Transition states from one emotional state to another as well as duration of emotional state are still to be clarified as they depend on individual characteristics.

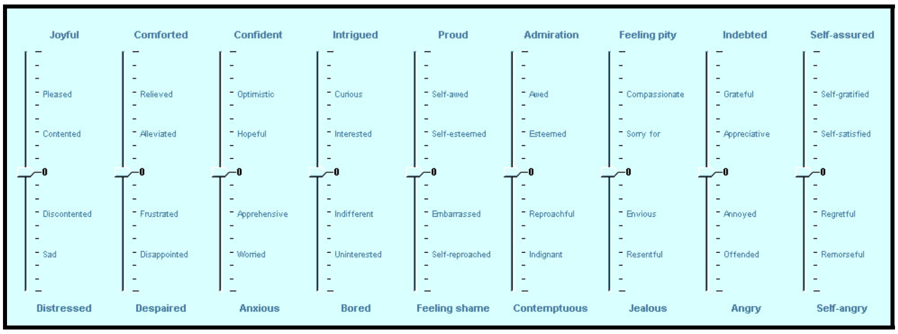


Fig. 17.2 Och and Frasson's Case Based Emotioning system

17.3 Detecting Emotions

Various sensors can be used to detect emotions during a learning session. The following table from (Arroyo et al. 2009) gives an idea of some of them. Sensors are associated with specialized software able determine an emotion or a set of emotions. Several sensors may give a more precise conclusion as to the predicted emotion.

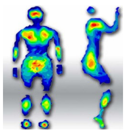
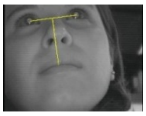
Other physiological sensors have a direct correlation with emotions (Chalfoun and Frasson 2009; Lang 1995). For instance, the following sensors can measure emotion according to two dimensions: *valence* (positive or negative emotion), and *arousal* (intensity of emotion). The GSR sensor (Galvanic Skin Response) allows recording skin conductivity measuring the rate of skin transpiration. RSP sensor (respiration) allows recording variations of respiration. GSR and RESP are positively correlated with arousal. BVP sensor (Blood Volume Pressure) allows recording blood flow variations from which we can extract heart rate (HR). TEMP sensors allow recording temperature variations. BHV, HR, and TEMP are positively correlated with valence.

All these means are in fact indirect consequences of emotional stimuli. Their intensity varies with individuals and can just give an indication on the type of triggered emotion.

Brain interface

In the human brain, each individual neuron communicates with the other by sending tiny electrochemical signals. When millions of neurons are activated, each contributing its small electrical current generating a signal that is strong enough to be detected by an electroencephalogram (EEG) (Cantor 1999; Heraz and Frasson 2009). These devices can be used to detect and measure emotions. Fig. 17.4 represents a learner wearing a pendant EEG able to transmit brainwave activity wireless. The EEG cables are connected to the ears and sensors on the brain.

Table 17.2 Emotional sensors

Sensor	Name	Descriptions
	Postures analysis seat	Detects if the learner is moving back or front to the screen.
	Conductance Bracelet	Measures skin conductivity which in turn has been known to correlate with arousal.
	Facial Expression Sensor	Predicts states such as acknowledgment, interest, reflexion, incertitude.
	Pressure Mouse	Measures learner global pressure using mouse manipulation.
	Blood pressure measurement system	Measures blood pressure distribution on the back and under the learner.
	Eye detection	Detects coordinates of eyes and mouth in order to predict facial expression

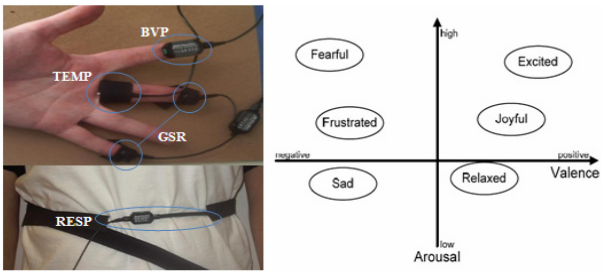


Fig. 17.3 Physiological devices for emotion detection

Commonly, brainwaves are categorized into 4 different frequency bands, or types, known as delta, theta, alpha, beta and gamma waves. Each of these wave types often correlates with different mental states. Fig. 17.5 lists the different frequency bands and their associated mental states, even if we have to note that there

Fig. 17.4 A learner wearing Pendant EEG

Table 17.3 Brainwaves Categories

Bandwith name	Frequency range	Mental states (General characteristics)
Delta (δ)	1-4 Hz	Sleep, repair, complex problem solving
Theta (θ)	4-8 Hz	Creativity, insight, deep states
Alpha (α)	8-12 Hz	Alertness and peacefulness, readiness, meditation
Beta (β)	13-21 Hz	Thinking, focusing, sustained attention
SMR	12-15 Hz	Mental alertness, physical relaxation
High beta	20-32 Hz	Intensity, hyperalertness, anxiety
Gamma(Y)	38-42 Hz	Cognitive processing, learning

is presently no consensus over the use of a fixed threshold to split the frequencies into bands.

Delta frequency band is associated with deep sleep. Theta is dominant during dream sleep, meditation, and creative inspiration. Alpha brainwave is associated with tranquility and relaxation. By closing one's eyes can generate increased alpha brainwaves. Beta frequency band is associated with an alert state of mind and concentration (Demos 2005). Response preparation and inhibition is one of the roles of the cortical sensorimotor beta rhythm (Zhang et al. 2008).

In the present case of pendant EEG, the electrical signal recorded by the EEG is sampled, digitized and filtered to divide it into 4 different frequency bands: Beta, Alpha, Theta and Delta (Fig. 17.5).

Our previous work (Heraz and Frasson 2007; Heraz et al. 2008) indicated that an EEG is a good source of information to detect emotion. Results show that the student’s affect (Anger, Boredom, Confusion, Contempt, Curious, Disgust, Eureka, and Frustration) can be accurately detected (82%) from brainwaves By looking on the signal produced at a given time we can guess deduce in which mental state is the learner, how long this state can exist and what event can change it. The

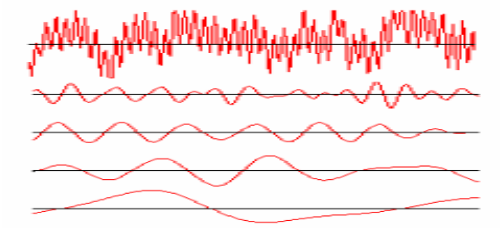


Fig. 17.5 A raw EEG sample and its filtered component frequencies. Respectively (from the top): Recorded EEG signal, Beta, Alpha, Theta and Delta brainwaves

difficulty of this approach is however to remove any noise effect in the outputs and to interpret their variations. The signals are by nature complex, and so, difficult to interpret from an emotional perspective. Measuring the intensity of emotions represents another challenge but this research track is promising and upcoming works should allow discovering new perspectives. By combining all sensors we should understand better not only the types of emotions but also the transitions between emotional states.

17.4 Inducing Emotions

As we mentioned earlier, some emotional states can strengthen knowledge acquisition while other affective situations will slow down or even block cognitive abilities. However, few works in computer science attempted to induce emotions and verify their impact on learning and cognitive capabilities. For instance, at MIT Media Lab, (Picard et al. 2001) used pictures to induce a set of emotions which include happiness, sadness, anger, fear, disgust, surprise, neutrality, platonic love and romantic love. Moreover at affective Social Computing Laboratory, Nasoz et al. (Nasoz et al. 2003) used results of Gross and Levenson (Gross and Levenson 1995) to induce sadness, anger, surprise, fear, frustration, and amusement.

Researchers in psychology have developed a variety of experimental techniques for inducing emotional states aiming to find a relationship between emotions and thought tasks; one of them is the Velten procedure which consists of randomly assigning participants to read a graded set of self-referential statements for example, "I am physically feeling very good today". A variety of other techniques exists including guided imagery (Ahsen 1989) which consists of asking participants to *imagine* themselves in a series of described situations, for example: "You are sitting in a restaurant with a friend and the conversation becomes hilariously funny and you can't stop from laughing". Some other existing techniques are based upon exposing participants to films, music or odors. Gross and Levenson found that 16 video clips could induce really one of the following emotions (amusement, anger, contentment, disgust, fear, neutrality, sadness, and surprise) from a set of the 78 films shown to 494 subjects (Gross and Levenson 1995).

In addition, active listening, empathy, sympathy and venting may be strategies aimed at reducing negative effect (Klein et al. 1999). For instance, by playing a computer game, user indicated on a scale the level of frustration that he experienced with the system. Then, a support agent can offer an affective feedback by sending the user some text that mirrored the level of frustration that the user reported. It has been shown that, with this method, some of the user's negative feelings are reduced and the tendency of people to interact with computers is boosted.

Moreover, other researchers have developed systems that are able to control and influence the learner's emotions using empathy. For instance, the "affective companion" adapts to the learner's emotions, by adjusting the difficulty of an exercise (Isen 2000); the "affective tutor", on the other hand, is itself affectively adaptive to user's emotions (Estrada et al. 1994). McQuiggan developed and tested the advantage of affect-based empathetic responses on hints and suggestions (McQuiggan and Lester 2006).

Similarly, Partala focused on human-computer interaction, studying especially the effects of affective interventions using synthetic speech with emotional content (Partala and Surakka 2004). The interventions were given when subjects' problem solving had been interrupted by mouse delays. Compared to no intervention condition, the results showed that the use of positive worded affective intervention has improved the smiling activity. At the same time frowning activity was clearly decreased during affective intervention.

Other researchers have developed hybrid techniques which combine two or more procedures; Mayer et al. used the guided imagery procedure with music procedure to induce four types of emotions, joy, anger, fear, sadness (Mayer et al. 1995). They used guided imagery to occupy the foreground attention and music to emphasize the background. According to Prendinger, human-computer interaction would become more productive by offering help and assistance to confused users (Prendinger and Ishizuka 2005). The authors studied the effect of *empathic* embodied feedback on deliberately frustrated users. These interfaces include guided imagery vignettes, music and images in the context of a job interview simulation and preparation.

In (Chaffar and Frasson 2006), a specific module (ESTEL) was developed to induce an optimal emotional state, which represents a positive state of mind that maximizes learner's performance. Using a Personality Identifier which determines

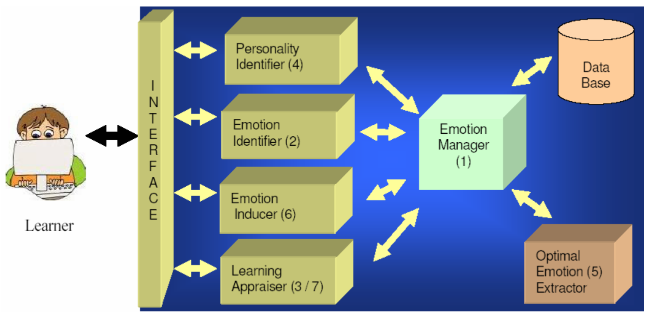


Fig. 17.6 ESTEL's Induction System

his personality (for instance extraversion), the Optimal Emotion Extractor retrieves joy as the optimal emotional state for this personality. The Emotion Inducer will elicit joy in this learner by using a hybrid technique which consists of displaying different interfaces.

The Emotion Inducer is inspired by the study of Mayer et al. (Mayer et al. 1995) that has been done to induce four specific emotions (joy, anger, fear, and sadness). After inducing emotion, the Emotion Manager module will restart the Learning Appraiser module for evaluating learning efficiency.

This architecture shows that managing emotional conditions requires a complete cycle including: identification of emotional state of the learner, identification of adequate emotional state to improve the performances, induction of new emotion, and verification of learning improvement. These modules are also components of emotional Intelligent Tutoring Systems (ITS).

17.5 Emotionally Intelligent Tutoring Systems

Emotional intelligence is the ability to recognize, interpret, and influence someone's emotions (Goleman 2010). When the effect of feeling on thinking is known, this can be used in order to improve someone's cognitive abilities (Salovey et al. 2000). It is hence natural to include emotional intelligence into the learning process. A human tutor is in fact an emotional practitioner in the sense that he can influence learner's emotions with the objective of improving his learning efficiency (Hargreaves 2002). Since interaction with a computer triggers similar responses as if it was with another person a new generation of ITS should be able to influence learner's emotions in a same way as a human tutor.

Motivated by this principle we have introduced the concept of an Emotionally Intelligent Tutoring System (EITS) in (Ochs and Frasson 2004). An EITS is an ITS which includes functional capabilities able to (1) know learner's emotions and, (2) induce emotions to the learner in order to improve his performance. More precisely, an EITS needs to achieve the following conditions:

1. know the current emotional state of the learner,
2. determine the impact of an action on learner' emotional state,
3. identify the most advantageous emotional state of a learner to enhance his performance.

We have developed and tested the two first conditions. The first condition was achieved using nine emotional scales allowing the user to indicate his current emotional state. In order to realize the second condition we used methods derived from Case Based Reasoning (CBR) to create a Case Based Emotioning system (CBE) able to predict the emotional effect of specific actions on the emotional state of a learner. To model the impact of these actions on learner's emotion we have used a directed graph, where the vertices are emotional states and the connecting edges the possible actions which can occur in a learning session (for instance criticism, encouragement, congratulation …). This representation allows the CBE system to assess the emotional state resulting from an action on an initial emotional state. Including this CBE into an ITS allows to generate in a user a specific emotional state.

Knowing which emotion to generate we need however to determine which one will be able to improve learner performance (condition 3 mentioned above). We focus on this point by analyzing the different effects of emotions on learner performance and particularly the emotional conditions for reaching the best performance.

For instance, a computer that flatters a user will generate positive emotions in him. A learner will, hence, experience a variety of emotions upon interacting with an ITS in the same way as in the context of traditional learning, and similarly to the human teacher, a virtual tutor can be viewed as an emotional practitioner able to influence the learner's emotions. Moreover, these emotions will strongly influence his cognitive abilities (Isen 2000). Given these two facts, ITS should, therefore, be able to manage these emotions in a way beneficial for the learning process, e.g., to generate specific emotions in the learner.

By consequence of the above discussion it appears advantageous to include specific capabilities of emotional intelligence into ITS: Learning involves a variety of cognitive processes, and someone's performance therein highly depends on his emotions. An ITS able to manage learner's emotions contains additional human capabilities and is potentially more efficient.

17.6 Affect in Virtual Environments

The intertwined relationship between affect and intelligent tutoring system took a step further in the virtual world. This section will examine the three most active areas of research in emotions and virtual environments: Embodied agents, narrative learning environments or NLE and quite recently a new subliminal teaching technique that has provides promising results regarding performance and students affect.

17.6.1 Embodied Agents

An embodied agent can be defined as a digital, visual representation of an interface, often taking a human form (Cassell 2002). Virtual agents expressing affect started to appear in an ITS as early as 1997 with COSMO (Lester et al. 1997). This pedagogical agent expressed joy and even jubilation when learners achieved successfully a task. Since then, communication through embodied agents within virtual environments in the ITS community has only grown in popularity and complexity. Affective issues such as empathy, self-efficacy and motivation have been implemented in various forms in a very broad range of different virtual environments (four such environments are shown in Fig. 17.7). Because of their strong life-like presence, animated pedagogical agents can capture students' imaginations and play a critical motivational role in keeping them deeply engaged in a learning environment's activities (Lester et al. 1997). Indeed, one of the main goals of an

ITS is to be able to recognize and address the emotional state of the learner and react accordingly through the presence of the pedagogical agent.

The affective tutor is one such system where frustration is detected real-time with a multi-modal approach combining Gaussian affective process classification and Bayesian inference (Kapoor 2007). The Wyang Outpost is another ITS intended for middle school and high school level mathematics learning. We can see Jake and Jane, two virtual agents drawn in flash, mirror emotions to emulate empathy and thus help keep high school children more engaged in the lesson (Arroyo et al. 2004).

Affective tutor Wyang Outpost AutoTutor MOCAS

Fig. 17.7 Four virtual I.T.S. systems employing various forms of embodied agents

AutoTutor is another ITS employing a pedagogical agent that helps students learn by employing a constructivism approach when analyzing their responses using natural language processing. The animated agent uses synthesized speech, gestures and facial expressions to encourage learners to articulate lengthy answers that exhibit deep reasoning, rather than to recite small bits of shallow knowledge (D'Mello et al. 2005). Finally, MOCAS (Motivational and Culturally Aware System) employs the self-determination theory to produce pedagogical agents whose behaviors are closely aligned to learner’s motivational and cultural needs (Blanchard and Frasson 2004). MOCAS’s autonomy-supportive design and the rule-based methodology adapt its teaching given the cultural backgrounds of its learners. All four presented systems in Fig. 17.7 employ physiological sensors to record affective data in order to express synthetic human emotions through various multimodal channels (i.e. voice, text, gesture). As previously mentioned in this chapter, physiological signals are generally correlated with emotions by associating specific signals, such as skin conductance and heart rate, to valance and/or arousal (Lang 1995). For further reading on the impact of emotional agents on learner’s interactions, we highly recommend the recent excellent review from Beale and Creed (Beale and Creed 2009).

17.6.2 Narrative Learning Environments

Narrative has been an important form to transmit knowledge across generations, and is innate to the human nature. Narrative is also a valuable vehicle to structure knowledge and to help us in the process of meaning making. Cognitive psychologists have recognized narrative as relevant to the way we store and make sense of episodic experience, often described as the phenomenon of narrative construction of reality. Due to the explorative and complex nature of narrative, an intelligent learning environment (ILE) based on a narrative approach can promote several kinds of activities for learners:

- co-construction: participate in the construction of a narrative;
- exploration: engage in active exploration of the learning tasks, following a narrative approach and trying to understand and reason about an environment and its elements;
- reflection: engage in consequent analysis of what happened within the learning session.

By applying a narrative approach in the development of ILEs, it is possible to attain an application that may help learners by illustrating phenomena and procedures, and by motivating them to stay engaged and immersed in learning tasks. Additionally narrative learning environments can facilitate activities associated with learning such as role-playing and exploration, reflection, and the sharing of ideas. Fig. 17.8 presents four NLE's that utilize different pedagogical strategies and affect in the context of narration.

Crystal Island FearNot! EMMA Prime Climb

Fig. 17.8 Four different NLE's each utilizing a different pedagogical approach

Crystal Island is one such narrative-centered learning system used for the teaching of microbiology and genetics (McQuiggan and Lester 2007). The animated agents in Crystal Island are built on empathy (they can express emotions as shown in Fig. 17.8) in order to promote intrinsic motivation in high school students. Overcoming a challenging task provides a student with a personal sense of achievement and a test of her abilities. Indeed, excessively low-challenge periods may cause the student to feel bored, but high-challenge periods may bring about frustration and feelings of hopelessness. FearNot! is a completely different and very interesting interactive NLE developed for education against bullying behavior in schools (Aylett et al. 2005). The autonomous agents in FearNot! implements emotional expressiveness and personality, two important characteristics of synthetic characters, to attain a desirable level of empathy and believability in order to help deal with virtual bullies. The third illustrated NLE, called EMMA, makes a contribution to the issue of what types of automation should be included in interactive narrative environments, and as part of that the issue, of what types of affect should be detected and how. The generation of emotional believable animations based on the detected affective states contributes to the ease and innovative user interface in edrama, which leads to high-level user engagement and enjoyment (Zhang et al. 2007). Prime Climb is another very interesting NLE where Merlin, the virtual tutor, interacts with learners by recognizing multiple user emotions during the interaction with an educational computer game (Conati and Maclaren 2009). The model is based on a probabilistic framework that deals with the high level of uncertainty involved in recognizing a variety of user emotions by combining in a Dynamic Bayesian Network information on both the causes and effects of emotional reactions. The tutor intervenes intelligently by processing information through the complex model in order to help 6th and 7th grade students practice number factorization.

The NLE make extensive use of animated agents to interact with the user. While this is common practice, it is important to not neglect the degree of behavioral realism of these agents for it can have different effects depending on the users. For a complete review on the subject please see (Campbell et al. 2009; Groom et al. 2009).

17.6.3 Subliminal Learning

In recent years, researchers in human-computer interfaces (HCI) as well as in various fields such as Intelligent Tutoring Systems (ITS) have taken advantage of adaptive and customizable HCI to record and analyze emotions (Villon and Lisetti 2006). This is not surprising since emotions, especially motivation and engagement, are widely related in various cognitive tasks as described earlier in this chapter. Learning in virtual worlds has taken a very important part in the HCI community for recent evidence has shown the relevance of using such virtual ITS for affective feedback and adaptation (Blanchard et al. 2007; McQuiggan and Lester 2006). Nevertheless, cognitive learning theories base mostly their intervention on attention to the specified task at hand. Complex information is broken down into pieces to gradually enable the learner to concentrate on one small part of the puzzle at a time. However, a large body of work in neuroscience and other fields lead us to believe that learning simple to complex information can be done without perception or complete awareness to the task at hand (DeVaul et al. 2003; Dijksterhuis and Nordgren 2006; Nunez and Vincente 2004; Watanabe et al. 2001). In fact, the existence of perceptual learning without perception has been neurologically proven and accepted (Del Cul et al. 2007). Furthermore, recent work has put forth the performance increase in performance when using a subliminally teaching Intelligent Tutoring System (Chalfoun and Frasson 2008). Yet, subliminal learning systems are still widely absent in the HCI community. The work by Chalfoun and Frasson focuses on subliminal stimuli in a 3D virtual system to enhance learning (Chalfoun and Frasson 2008).

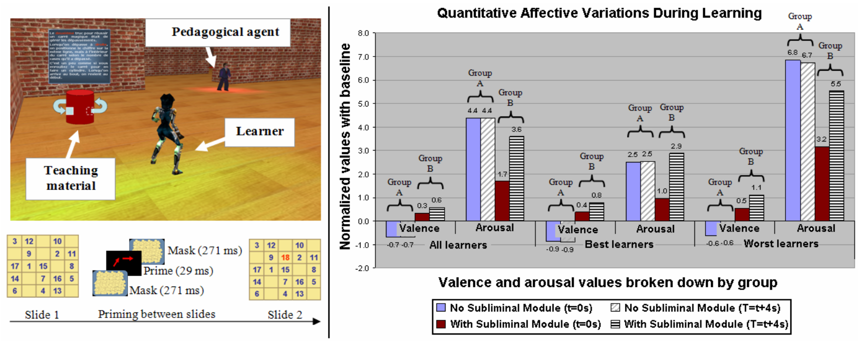


Fig. 17.9 Subliminal module implemented in the immersive version of MOCAS and results

Before going further however, we need to clearly establish the terminology that will be used. Indeed, the simple mention of the word subliminal can lead to discord and confusion. We establish a stimulus as being subliminal when it is sent too fast for a user to consciously report its existence. Conscious perception is well established in neuroscience and its properties are well known. One of those properties is the existence of a visual threshold for conscious access called VT. It is precisely this VT that we establish as being the "line" between conscious and unconscious perception. The technique used to send a given stimuli *below* the VT of awareness is called subliminal projection, as opposed to a paraliminal projection where flashed stimuli is consciously perceived for it is presented at speeds *above* the VT (Del Cul et al. 2007).

The current experiment presented in Fig. 17.9 uses precise and timed subliminal projections in a 3D intelligent tutoring system while monitoring the physiological reactions of the learner. Those visual recording are crucial to remove noise and identify events of special interest. Moreover, we constructed the subliminal cues in a way which would accelerate the learning process by triggering and enhancing an already possessed knowledge without the user's awareness. This step is important for it enables the learner to feel responsible for his own success and hopefully help him stay motivated. The histogram on the right hand side of the figure presents a detailed and precise look at the optimal affective conditions that set the best learners apart. These signal values are normalized by mean-shifting, that is subtracting each signal's value from the signal's baseline mean then dividing the result by the signal's standard deviation. This widely accepted technique enables us to compare learners' results for it solves the problem of extra-individual physiological differences. The figure shows the average affective values for a period of 4 second following every subliminal stimulus. The full brown bars represent the average value of the signal for all subliminal stimuli at the precise moment the stimulus was projected (t=0s, s is for seconds). The horizontal dashed bars represent the same averaged value except that it is computed for the 4 seconds following that projected stimulus (T=t + 4s). Since one was not primed with subliminal stimuli, we placed markers for each learner at the precise moment where subliminal cues would have been projected if these learners would have been taking the course with the subliminal module.

The results shown in Fig. 17.9 are not only statistically significant ($p<0.001$, $\alpha=0.05$) but very important for they enable us to distinguish between the best and worst learners in terms of valence and arousal but also in terms of how much variation is considered optimal for success. In this case, having an average positive valence variation increase of about 0.8 and arousal increase between 2.5 and 2.9 is what our system should be looking for. In fact, we can clearly see at the far right part of the figure that the worst learners, those who made the most mistakes, were the ones who had a negative valence variation. Checking the results with Lang's two dimensional space (Lang 1995) informs us that a negative valence could lead to a negative emotional state and thus not optimal for learning. Since subliminal projections increase valence variations, our system could then detect this negative emotional state and start projecting more stimuli until an optimal state is reached. We demonstrated in (Chalfoun and Frasson 2008) that the subliminal module helped reduce dramatically the number of mistakes made. Fig. 17.9 might have helped explain why in terms of valence and arousal.

17.7 Future Directions

The affective issues addressed here have focused on the important contribution of emotions on the cognitive processes involved in learning such as attention, memorization and reasoning. Indeed, a great body of work has addressed the various approaches to detect and induce emotions with sensors and smart interfaces respectively within an EITS. The same could be said with emotions in virtual environments. Narrative learning environments, simulators and affective agents have shown the importance of empathy and role-playing in keeping learners engaged and motivated throughout the learning session.

It is the authors' belief that resolving future affective issues within an EITS resides within a multidisciplinary approach to affect. Indeed, the potential integration of EEG into the ITS community can greatly enhance mental state detection and adaptation. Indeed, recent work in the ITS field combined neuroscience, psychology and pedagogy by demonstrating that using neurological properties of unconscious cognition can have a positive impact on learner's intuition as well as his self-esteem in problem solving tasks (Chalfoun and Frasson 2010; Jraidi and Frasson 2010). Finally, Chaouachi and al. have shown that learner's affective states can have a direct impact on his engagement level measured by a well established EEG-mental engagement index developed at NASA (Chaouachi et al. 2010).

When looking at research on Artificial Intelligence how can we try to reproduce human behavior if we ignore emotions which in fact sustain knowledge acquisition? The same remark applies to other disciplines as emotions play an important role in their domain. Artificial Intelligence, Education, Neuroscience, Psychology, Medicine are just some of them. Being at the crossroads of these exchanges constitutes a highly exciting experience.

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