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TOWARD COMPUTER-AIDED AFFECTIVE LEARNING SYSTEMS: A LITERATURE REVIEW

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ABSTRACT

The aim of this survey is to provide an overview of the various components of "computer aided affective learning systems." The research is classified into 3 main scientific areas that are integral parts of the development of these kinds of systems. The three main scientific areas are: I) emotions and their connection to learning; ii) affect recognition; and iii) emotional instruction and design. Affective learning instructional technology is a new, multi-disciplinary research area, which has been developed during the last decade. This article depicts the development of the core relevant areas and describes the concerns.

INTRODUCTION

Accurately identifying a learner's cognitive-emotional state is a critical mentoring skill. Although computers perform as well as or better than people in selected domains, they have not yet risen to human levels of mentoring. It is widely acknowledged by researchers that the computer community in general used to dismiss the role of affect (Picard & Klein, 2002). This tendency has been dramatically reversed due to the work of neuroscientists (Damasio, 1994, 2003), and other humanistic psychologists and educators (Best, 2003; Leal, 2002). Recent affective neuroscience and psychology have reported that human affect plays a significant and useful role in human learning and decision

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making, as it influences cognitive processes (Bechara et al., 1997; Goleman, 1995). However, the extension of cognitive theory to explain and exploit the role of affect in learning is in its infancy (Picard, Papert, Bender, Blumberg, Breazeal, Cavallo, et al., 2004).

Hence, researchers of Artificial Intelligence (A.I.) have considered the emotions in intelligent systems modeling, developing thus a new field of research in A.I.: "Affective Computing." According to Picard (1997), Affective Computing is: "computing that relates to, arises from or deliberately influences emotions." Moreover, techniques of affective computing have also been studied in order to model the emotions of the student in educational (computational) systems. Few attempts have been made to study emotions in Intelligent Tutoring Systems (ITS), though it is an area gaining increasing attention (Conati, 2002; del Soldato, & du Boulay, 1995; Lester, Voerman, Towns, & Callaway, 1999).

A step toward this direction is to provide computer-aided learning systems with an automatic affect recognizer, in order to collect data which identify a user's emotional state. With this information, the computer could respond appropriately to the user's affective state rather than simply respond to user commands (Lisetti & Schiano, 2000; Picard, 1997). An appropriate computer response to a student's affective state also requires evolving and integrating new pedagogical models into computerized learning environments, which assess whether or not learning is proceeding at a healthy rate and intervene appropriately (Kort, Reilly, & Picard, 2001a, 2001b). The risk of inappropriate interactions takes several forms. For example, if an agent is overly excited about a learner's success, the learner may feel awkward, which may lessen his motivation for continued interactions with the agent and on the task (Burleson & Picard, 2004).

In this sense, two issues arise: one is to research new educational pedagogy, and the other is a matter of building computerized mechanisms that will accurately, immediately, and continually recognize a learner's emotional state and activate an appropriate response based on the integrated pedagogical models.

Nevertheless, all the present instructional design approaches do not answer the question extensively as to how any instructional technology should be designed in order to educate children with computers in an emotionally sound way (Astleitner, 2000a, 2000b). Instructional technology should take into account issues of aesthetics and interface design, since learning through computers can be tactile, visual, audible, interactive, and sensually pleasing (Cooper, 2006).

This article is organized as follows. In the next section we describe emotion in relation to learning. A computer-aided affective learning system aims at enhancing learning through the activation of an emotional state which is beneficial to learning. Hence, the development of such systems is essentially based on knowledge about how emotions are related to learning. In the subsequent section, we refer to issues concerning affect recognition and we describe in brief the current stance in core affect recognition methods. A computer-aided affective learning system has to include methods of affect recognition. Misleading affect recognition could result in inadequate emotional feedback, ruining learning. In the last section we report on issues of emotional instruction and design. Emotional feedback should be implemented through suitable emotional strategies integrated into computer-aided learning systems whose effectiveness could increase if issues of aesthetics and interface design were taken into account.

EMOTIONS AND LEARNING

Definition and Basic Concepts of Emotion

Based on an analysis of about 100 definitions concerning emotions by Kleinginna and Kleinginna (1981), emotion

> is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can: (a) give rise to affective experiences such as feelings of arousal, pleasure/displeasure; (b) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes; (c) activate widespread physiological adjustments to the arousing conditions; and (d) lead to behavior that is often, but not always, expressive, goal directed, and adaptive."

Previous theories about emotion have suggested that there are between two and twenty basic or prototype emotions (Leidelmeijer, 1991; Plutchik, 1980). The four most common emotions appearing on the numerous theorists' lists are fear, anger, sadness, and joy. Despite the disagreement about the fundamental emotions, important theorists distinguished among eight basic families of emotions—fear, anger, sorrow, joy, disgust, acceptance, anticipation and surprise—and supported that all emotions belong to one of these families (Goleman, 1995; Plutchik, 1980).

Emotions' Impact on Learning

Several theoretical models of learning assumed that learning occurs in the presence of affective states (Craig, Graesser, Sullins, & Gholson, 2004). Henceforth, it is recognized that positive and negative emotional states trigger different types of mental states and this can have an important influence on the learning process (Table 1).

The research community is increasingly acknowledging an intense need for a comprehensive theory of learning that effectively integrates cognitive and affective factors (Picard et al., 2004).

Emotions can disorder thinking and learning. Research has shown that happiness has a positive effect on learning, memory, and social behavior (Isen, 2003). Conversely, negative emotional states, such as anger and sadness, have been shown to have a negative impact on learning and motivation (Goleman, 1995).

Table 1. Positive and Negative Emotional States Fire Different Types of Mental State and This Can Have an Important Influence on the Educational Process

	Impact on learning			
	Positive		Negative	
Emotions	Focuses mind	Broadens thoughts	Blocks thinking and memory	Mind easily distracted
Positive emotions				
Acceptance		x		x
Joy		x		x
Satisfaction		x		x
Negative emotions				
Anxiety	x		x	
Anger	x		x	
Fear	x		x	
Sadness	x		x	

Positive emotions such as joy, acceptance, trust, and satisfaction can enhance learning. On the contrary, prolonged emotional distress can cripple the ability to learn. It is well known that learning or remembering something in a state of anxiety, anger, or depression can be difficult for any individual (Goleman, 1995).

Some children and adults have difficulty managing negative emotions. Anger is a core emotion related to externalizing negative behaviors; frustration often leads to anger. Frustration occurs when desires, efforts, and plans are inhibited. Faced with frustration, despair, worry, sadness, or shame, individuals lose access to their own memory, reasoning, and the capacity to make connections (Goleman, 1995).

However, negative affect initially focuses the mind, leading to better concentration (Schwarz and Bless, 1991). In situations of an urgent threat this is favorable, for it concentrates processing power upon the danger. When creative problem solving is necessary this is unfavorable, for it leads to narrow tunnel vision (Norman, 2002). Positive affect widens the thought processes, making it easier to be distracted. When the problem involves focusing, positive affect may interfere with the subject's concentration, whereas when the problem is treated through creative thinking then the results are optimal. Similarly, the proper amount of anxiety or fear can help individuals to focus, for the reason that anxiety focuses the mind, reducing distractions. It is when the negative affect is too strong that learning tasks are inhibited (Bower, 1992).

Theoretical Models for the Role of Emotions in Learning

Stein and Levine (1991) assumed that emotional experience is related to the receiving and comprehension of inflowing information. If the inflowing information has not been met before, it appears to have low relevance with existing "schemas'' (Armbruster, 1986) and thus it provokes a particular stimulation of the central nervous system (CNS). This stimulation combined with a cognitive appraisal of "what is going on" forms an emotional reaction. Hence, Stein and Levine's theoretical model for the role of emotions in learning indicates that learning almost always occurs with the presence of an emotional sequence. This is in line with other cognitive and affective theories which state that profound knowledge appears when students face oppositions to their goals, irregular events, surprises, and experience situations that do not correspond to their expectations (Maturana & Varela, 1992). Cognitive imbalance is very likely to mobilize conscience, so that cognitive balance is restored. Emotional states such as confusion and disappointment are likely to appear during cognitive imbalance (Kort, Reilly, & Piccard, 2001a, 2001b). Recent empirical research has shown that confusion is an important emotional factor for scientific inquiry (Rozin & Cohen, 2003b).

There is a range of emotional states that arise in the course of learning. Some, like curiosity and attraction, are evidently favorable to the process. Others, like confusion and puzzlement, may be at first constructive, as long as they do not persist for too long. The Kort-Reilly-Picard dynamic model of emotions for SMET (Science, Math, Engineering, Technology) considers learning as an emotional process with four main repeated stages. According to this model, during learning the student repeatedly passes from curiosity to disappointment, frustration, and acceptance (Kort et al., 2001a). The learning process is separated by two axes, vertical and horizontal, labeled learning and affect, respectively. The learning axis ranges from "constructive learning" at the top, where new information is being integrated into schemas, and "no learning" at the bottom, where misconceptions are identified and isolated from schemas. The affect axis ranges from positive affect on the right to negative affect on the left.

However, none of the existing frameworks employ emotions frequently seen in the SMET learning experience (Kort et al., 2001a), some of which are stated in Figure 1. Whether all of these are important, and whether the axes shown in Figure 1 are appropriate, requires further evaluation before a fundamental set of emotions for learning can be established. Such a set may be culturally altered and will likely be different with developmental age as well.

Knowledge with regards to how emotions influence learning is a fundamental part of computer-aided affective learning systems. Nevertheless, this knowledge would have no use in emotional instructional technology, if these systems were not able to recognize a student's emotional state. With regard to this, the following

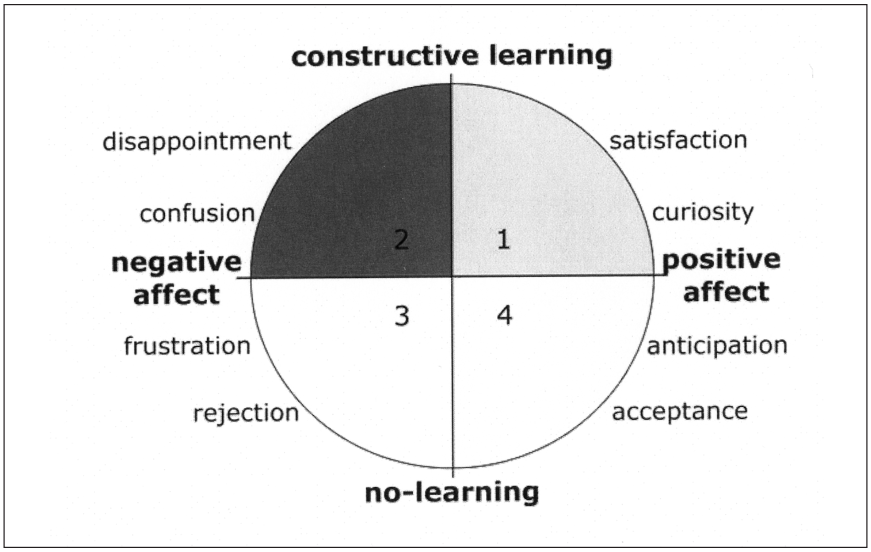

Figure 1. The Kort-Reilly-Picard dynamic model of emotions in learning.

section will aim to briefly describe the considerations that evolve regarding affect recognition and the current stance in core affect recognition methods.

AFFECT RECOGNITION

Introduction

Humans recognize emotional states in other people by a number of visible and audible cues. Facial expression is a valuable means in the communication of emotion. Moreover, there is evidence of the existence of a number of universally recognized facial expressions for emotion such as happiness, surprise, fear, sadness, anger, and disgust (Ekman, 1982). In addition, the body (gesture and posture) and tone of voice are the other core channels for the communication of emotion (Argyle, 1988). There are also a number of psycho-physiological correlates of emotion, such as pulse or respiration rate, most of which cannot easily be detected by human observers, but which could be made accessible to computers given appropriate sensing equipment. From all of these channels, researchers of Artificial Intelligence in education are attempting to infer the student's affective state.

Preferably, evidence from many modes of interaction should be combined by a computer system so that it can generate as valid estimations as possible about users' emotions. This view has been supported by several researchers in the field of human computer interaction (Oviatt, 2003; Pantic & Rothkrantz, 2003). Nevertheless, multimodal recognition of human affective states is a particularly demanding problem and is largely unexplored. Notably, the work of Picard et al. (2001) achieved 81% classification accuracy of eight emotional states of an individual over many days of data, based on four physiological signals. Pantic and Rothkrantz (2003) provided a survey of other audio-video combination efforts and a synopsis of issues in building a multimodal affect recognition system.

There have been very few approaches regarding affect recognition for learning. One which stands out is Conati's (2002) work on probabilistic assessment of affect in educational games. In addition, Mota and Picard (2003) describe a system that uses dynamic posture information to classify altered levels of interest in learning environments.

The next sections describe in brief the current stance in several core methods of affect recognition.

Emotional Recognition Frameworks using Personal Preference Information

Emotional Recognition Frameworks using Personal Preference Information are based on the assumption that people do not necessarily recognize emotions just by signals seen or heard; they also use a high level of knowledge and reason, to be able to process the goals, situations, and preferences of the user. A person's emotions could be predictable if their goals and perception of relevant events were known (Ortony, Clore, & Collins, 1988). Implemented in a computational model this can be achieved by using agents, artificial intelligence techniques, reasoning on goals, situations, and preferences (Conati, 2002). For example, if the system can reason about the reactions of a user from the input that the system receives (assumption made derived from the time of day, speed of reading, provided personal information, etc.), appropriate content could be displayed in a way adapted for the emotion or the mood of the user.

Moreover, Ortony et al. (1988) developed a computational emotion model, which is often referred to as the OCC cognitive theory of emotions and has established itself as the standard model for emotion synthesis. According to the OCC model, joy and distress emotions arise when a person focuses on the desirability of an event in relation to his goals. The OCC model defines joy as a person pleased with a desirable event, and distress as a person displeased with an undesirable event. Lately, some studies have been conducted (Conati & Zhou, 2002; Katsionis & Virvou, 2005) which used it to model user emotional states. The OCC theory specifies the way emotions causally occur from the interaction of one's goals and preferences with known states of the world. The OCC theory assumes that there is just one activated goal during the cognitive appraisal process and, therefore, the resulting emotional reaction is always deterministic.

Nevertheless, a person can have multiple goals or even conflicting goals (Zhou & Conati, 2003), which indicates that the OCC model needs enhancements.

Another "personal preference information approach" to infer a user's emotions is the BDI model (Bratman, 1990) which is based on Belief, Desire, and Intention mental states. According to this model, the agent obtains information about the user's emotions by examining his actions from his observable behavior, which includes the success or failure in the implementation of an exercise, as well as asking for or denying the tutor's help. Jaques and Viccari (2004) used the BDI approach for an affective pedagogical agent that infers a student's emotions, models these emotions and decides on a suitable affective tactic based on these emotions. This particular agent deduces the student's emotions through its appraisal of the information that it has collected about the student. In order to achieve this task, it requires knowing the student's goals and the events that are actually taking place while the student is interacting with the system.

Emotional Recognition from Facial Expressions

Knowing how facial expressions relate to the underlying emotional experiences is an important factor in using facial expression measurements as an input signal in affective computing. Therefore, the assessment of emotional experiences from objectively measured facial expressions becomes an important research topic. In the field of facial expression recognition, several efforts have been made in trying to recognize expressions of discrete emotions, especially the ones suggested by Ekman (1992). Although there is evidence for universal facial expressions of certain emotions (Ekman, 1994), it is important to realize that there are also differences in the facial behavior of different people. With regard to this issue, Ekman (1985) supported that the most accurate interpretation of facial expression benefits from the knowledge of what is normative for each individual. Hence, the findings that there are considerable differences in facial behavior between individuals recommend that the best results in emotion estimation could be obtained using a person adaptive system. This system would form an individual model of facial behavior for each individual user (Partala, Surakka, & Vanhala, 2006).

An important issue is that many of the existing facial recognition systems rely on analyzing single facial images instead of tracking the changes in facial expressions continuously (Partala et al., 2006). It would be more meaningful if the computerized learning environments could analyze the student's facial expressions continuously to be able to react to changes in the student's emotional state at the right time. Relative to this, Essa and Pentland (1997) made the point that the lack of temporal information is a significant limitation in many facial expression recognition systems.

Consequently, methods for analyzing facial expressions in human-computer interaction, especially those concerning computer-aided learning systems, should incorporate a real-time analysis. This can be achieved either by using advanced video-based techniques (Essa & Pentland,1997) or by measuring the electrical activity of muscles with EMG (facial electromyography; Partala & Surakka, 2004).

However, at present, different machine vision techniques using video cameras are the predominant methods in measuring facial expression (Cohen, Sebe, Chen, Garg, & Huang, 2003; Oliver, Pentland, & Berard, 2000; Smith, Bartlett, & Movellan, 2001). A notable application is the FaceReader, lately developed by Vicar Vision and Noldus Information Technology bv. The FaceReader recognizes facial expressions by distinguishing six basic emotions (happy, angry, sad, surprised, scared, disgusted, and neutral) with an accuracy of 89% (Den Uyl & van Kuilenburg, 2005). The system is based on Ekman and Friesen's theory of the Facial Action Coding System (FACS) that states that basic emotions correspond with facial models (Ekman & Friesen, 1977).

Emotional Recognition using Physiological Data

The measurement of physiological quantities, such as temperature or blood pressure, is important not only for the study of physiological processes and the clinical diagnostics of various diseases, but also for the estimation of the affective state. William James (1884) was the first who proposed that patterns of physiological response could be used to recognize emotion. Psychologists have been using physiological measures as identifiers of human emotions such as anger, grief, and sadness (Ekman et al., 1983). Usually, changes in affective state are associated with physiological responses such as changes in heart rate, respiration, temperature, and perspiration (Frijda, 1986).

The use of engineering techniques and computers in physiological instrumentation and data analysis is a new, challenging research practice, especially when referring to affect recognition. For instance, researchers at the MIT Media lab have been using sensors which detect galvanic skin response (GSR), blood volume pulse, respiration rate, and electromyographic activity of muscles (Picard, 1998). The emotion mouse, an example of recent advances in affective computing, measures the user's skin temperature, galvanic skin response (GSR) and heart rate, and uses this data to categorize the user's emotional state (Ark, Dryer, & Lu, 1999). It has also been suggested that facial electromyography (EMG) could be potentially useful input signals in HCI (Partala & Surakka, 2003, 2004). Therefore, there is a need for adequate measures to associate physiological measurements with definite emotional states in order to assign them to conditions meaningful to a computer (Bamidis, Papadelis, Kourtidou-Papadeli, & Vivas, 2004). Since the physiological state is so closely associated with the affective state, an accurate model of a physiological response could enable computer interactive environments to effectively determine a user's affective state in order to guide appropriate customized interactions (McQuiggan, Lee, & Lester, 2006). Nevertheless, subjective and physiological measures do not always agree, which indicates that physiological data may detect responses that users are either unconscious of or cannot recall at post-session subjective assessment (Wilson & Sasse, 2004). However, the sensors might often fail and result in missing or unfavorable data, a common problem in many multimodal scenarios, resulting in a considerable reduction in the performance of the pattern recognition system (Kapoor & Picard, 2005).

Emotional Speech Recognition

The modulation of voice intonation is one (of the) main channel(s) of human emotional expression (Banse & Sherer, 1996). Certain emotional states, such as anger, fear, or joy, may produce physiologic reactions (Picard, 1997), such as an increase of cardiac vibrations and more rapid breathing. These in turn have quite mechanical and thus predictable effects on speech, particularly on pitch (fundamental frequency F0), timing and voice quality (Oudeyer, 2003). Some researchers have investigated the existence of reliable acoustic correlates of emotion in the acoustic characteristics of the signal (Banse & Sherer, 1996; Burkhardt & Sendlmeier, 2000). Their results agree on the speech correlates that are derived from physiological constraints and correspond with broad classes of basic emotions, but disagree and are unclear concerning the differences between the acoustic correlates of fear and surprise or boredom and sadness. This is perhaps explained by the fact that fear produces similar physiologic reactions to surprise, and boredom produces similar physiologic reactions to sadness, and consequently very similar physiological correlates result in very similar acoustic correlates (Oudeyer, 2003). This also provides an explanation for the results of Tickle's (2000) experiments, demonstrating that the best emotional speech recognition score for humans was only 60%. Additionally, Tickle's experiments indicated that there is only little difference between the performance in detecting the emotions conveyed by someone speaking the same language or another language. This could be attributed to the fact that physiological effects of emotional states are rather universal, meaning that there are common tendencies in the acoustical correlates of basic emotions across different cultures (Oudeyer, 2003).

Research dealing with speech modality, both for emotional automated production and recognition by technology, has only been active for a few years (Bosh, 2000) and has gained much attention (Cowie, 2003; Dellaert, Polzin, & Waibel, 1996; Lee & Narayanan, 2005). However, it is uncertain whether research results would effectively generalize to naturally produced, rather than an "acted" emotional expression. The task of machine recognition of basic emotions in non-formal everyday speech is extremely challenging and will greatly contribute toward the evolution of computerized learning systems.

Emotional Recognition with the Use of Questionnaire

Many researchers have used static methods such as questionnaires, dialogue boxes, etc., in order to infer a user's emotions. These methods are easy to administer but have been criticized for being static and thus not able to recognize changes in affective states. Oatley (2004) recognized that self-reporting of emotions simplifies the recognition problem. Dieterich et al. (1993) stated that this approach transfers one of the hardest problems in adaptive affective interfaces from the computer to the user. Another advantage of the questionnaire is that it provides feedback from the user's point of view and not an outsider's (Zaman & Shrimpton-Smith, 2006). Questionnaires can be used to infer users' emotions, either standalone or assisting another affect recognition method.

On the other hand, the way questions are framed and demonstrated (Lindgaard & Triggs, 1990), the order in which questions are asked, and the terminology employed in questions are all known to affect the subject's responses (Anderson, 1982; Lindgaard, 1995). Similarly, there is evidence that judgments on rating scales are non-linear, and that subjects hesitate to use the extreme ends of a rating scale (Slovic & Lichtenstein, 1971). Hence, when using verbal scales, one should make sure that the terminology employed and the context in which it is to be presented, really reflect the subjective significance of the subject population (Lindgaard, 2004).

The student's recognized emotional state should be properly managed from the computer aided affective learning system, based on pedagogical models which integrate our knowledge about emotions and learning. The system would assess whether the learning process is developing at a healthy rate. If there is a positive development, the system should help the learner maintain this emotional state. If not, the system should induce the learner to an emotional state beneficial to learning. The "peak of spear" of computer-aided affective learning systems are emotional instruction strategies, through which emotional feedback is implemented. Aesthetics and interface design of such systems also play a crucial role in the culturing of emotional states favorable to learning. Hence, in the next and last section, issues of emotional instruction and design are referred to, completing the report on the new field of computer-aided affective learning systems.

EMOTIONAL INSTRUCTION SYSTEMS— DESIGN AND AESTHETICS

Introduction

Actual computerized learning environments, whether web-based or not, usually include a combination of carefully structured hypertext, animations, and test-based feedback (Economides, 2005a; Triantafillou, Georgiadou, & Economides, 2007) in a well organized and sound environment. In addition, current research aims to provide these systems with the ability to recognize a learner's emotional state and activate an appropriately tailored response based on integrated pedagogical models. Providing individualized feedback according to students' cognitive and affective states, has been neglected until recently where its value has now become more apparent (Economides, 2005b; Mavrikis, Maciocia, & Lee, 2003). However, too much feedback may also prove detrimental if it results in information overload, unnecessary interruptions or an irrational amount of pressure (Alder, 2007).

Agents able to process or simulate emotional behavior (emotional agents) are an integral part of computer-aided affective learning systems. Therefore, in the following sections we outline emotional agents' architecture, as well as issues of aesthetics and interface design that play a vital role in the effectiveness of these kinds of systems. Finally, we refer to emotional instructional strategies, which are the "peak of spear" of an affective learning system.

Designing Emotional Agents

The main unificating subject in A.I. is the idea of intelligent agent. A.I. is considered as a study of artificial agents who engage perceptions from the environment and realize energies. In that sense, an agent is each entity (artificial or human) that acts in an environment. In the information technology, an agent of software is an abstraction, a reasonable model that describes the software that acts for a user or for another program concerning a service. During the last decade there has been a serious effort in order to create artificial agents with dialogic behaviors that are based on social rules and lead to the achievement of communication objectives. In these characters the significance of emotion and personality is inherent (Cassell, Sullivan, Prevost, & Churchill, 2000).

Emotional agent systems consist of four components: a method for interpreting stimuli (input) whether internal or external; a computational model of emotions that regulates how emotions are generated and managed; a mode to direct agent behavior and actions informed by emotional state; and a process for displaying emotional state to the world (output; Camurri & Coglio, 1998).

A useful process to model agent communication and behavior is the BDI (Belief, Desire, and Intention) approach. It describes an agent as an intentional system functioning through properly determined mental states. Bratman's (1990) BDI model is based on belief, desire, and intention mental states. Beliefs correspond to information about the present state of the environment that is updated after each sensing action, and are thus considered the informative factor of the system state. Desires are the motivational status of the system; they carry information about the priorities associated with the goals to be achieved. Accordingly, the agent activates a set of desires that can be fulfilled under particular circumstances. Therefore, intention represents the currently chosen course of action that has been selected to be executed according to the schedule, under the condition that it can be accomplished according to the agent's beliefs.

Recently, Emotional-BDI (EBDI) architecture was introduced (Pereira, Oliveira, & Moreira, 2006; Pereira, Oliveira, Moreira, & Sarmento, 2005, 2006) based on the previous work of Oliveira and Sarmento (2003) on emotional agent architecture. Emotional-BDI agents are concerned with computational agents whose behavior is guided by interactions between beliefs, desires, and intentions influenced by the role of emotions in reasoning and decision-making. According to Jiang et al. (2007), in order for EBDI architecture to include emotions in agents, three issues need to be addressed:

1. how to evaluate or present emotions;
2. how emotions influence the decision-making procedure; and
3. how to keep informed the status of emotions.

They stated that the details of the solutions depend on specific applications. Thus, EBDI architecture combines these three concerns into a BDI architecture based on a human's practical reasoning process, while leaving the details available to designers. At the moment, there are various agents' methodologies and frameworks based on the BDI model (Damjanovic et al., 2005).

Another valuable method to generate emotions for embodied characters is the OCC model (Ortony et al., 1988). The OCC model is most likely the most broadly implemented of the emotion models (Bartneck, 2002) and it categorizes 22 diverse emotion types based on the positive or negative reactions to events, actions, and objects. However, the OCC model indicates what emotions occur when events, actions, or objects in the environment are evoked, but not what actions an agent is expected to take as a result (Silverman, Johns, O'Brien, Weaver, & Connwell, 2002). Bartneck (2002) proposed a framework to provide the OCC model with further features in order to serve more efficiently the needs of emotion modeling in embodied characters. These features include a history function, a personality designer and the interaction of the emotional states. The history function helps to calculate the probability, realization, and effort of events. The personality designer enables the designer of the character to methodically vary the parameters of the character, such as its values and attitudes. The interaction function combines the emotional values of events, actions, and objects with the character's emotional state in progress. The emotion model must be capable of evaluating all situations that the character might come across (history function) and must also supply a structure for variables which have an impact on the intensity of the emotion (personality designer). Such an emotion model enables the character to display the right emotion with the right intensity at the right time (interaction function).

A very fundamental and effective method commonly used by humans to express their affection is empathy. Carl Rogers (1959) defines empathy as the ability to perceive another person's inner psychological frame of report with precision, but without ever losing consciousness of the fact that it is a hypothetical situation. Therefore, empathy is to feel, for example, someone else's pain or pleasure and to perceive the ground of these feelings as perceived by the other person, without setting aside self-awareness. There is research evidence indicating that humans orient toward computers in a way similar to the social behavior exhibited between human-human interactions (Nass & Moon, 2000; Reeves & Nass, 1996). Furthermore, a number of authors argued that the presence of empathic emotion in a computer agent has significant positive effects on a user's impression of that agent and as a result will advance human-computer interaction (Brave, Nass, & Hutchinson, 2005; Dehn & Van Mulder, 2000; Economides & Moridis, 2008).

Klein et al. (2002), developed and tested an interfering module planned to reduce user frustration, deliberately caused by a computer application to serve the needs of the task at hand. A group of people were asked to play a computer game and at some point indicate on a scale how much frustration they were experiencing. Then these people were given feedback from what the authors call a support agent. A text-based interaction, based on a dialogue strategy considered to be successful at lowering negative emotion in human–human interactions, was employed via a computer agent. This agent merely presented to the user various texts that mirrored the level of frustration that the user complained about. The authors found that when the support agent was functioning, users showed a considerably increased attentiveness to dedicate time to interact with the system. This may indicate that the acknowledgment and understanding of the user's level of frustration is essential to user engagement.

Designing the Interface

Griffiths and Hunt (1995) showed that the machine's impression, typified by characteristics such as music, lights, colors, and noise, was perceived as one of the machine's most stimulating qualities for a significant number of the adolescents questioned. Of the 269 computer players (12-16 years of age) who gave reasons for playing their favorite game, 16% stated the game was fun, 14% that it had good graphics, 10% that it was exciting, and 4.5% that it had good sound effects. Unfortunately, many virtual learning environments or web-based learning portals continue to be predominantly text-based (Cooper, 2006).

Moreover, Lester et al. (1997) mentioned that users respond in a different way to interfaces which include an interface character than to those without an interface character. This could provide support for the realism hypothesis, according to which designed realism of an interface character increases the user's participation with that interface character.

Relative to realism, one can distinguish between form realism and behavioral realism. Form realism defines the external appearance of an interface character, for example, whether it will resemble a human or look more like an animal. Form realism can be essential in terms of social identity and therefore with the engagement of the character (Van Vugt, Konijn, Hoorn, Keur, & Eliens, 2007). Behavioral realism of interface characters deals with the character's behavioral patterns, such as facial expressions, body and head movements, gestures etc. (Cassell, Pelachaud, Badler, Steedman, Achorn, Becket, et al., 1994).

Recent research results (Van Vugt, 2007; Van Vugt, Hoorn, Konijn, & de Bie Dimitriadou, 2006) state that apparent aesthetics was the most significant variable that had an impact on the user's engagement with the interface character. The more beautiful users found the character in regard to its exterior appearance, the more engaged they were.

Hone's (2005) experiments confirmed the frustration reducing effect of the Klein et al. (2002) text-based affective agent. They also provided evidence that an embodied affective agent exhibiting the same approach could lessen user frustration more effectively than the text-only version and that a female embodied agent may be more effective than a male agent character. In the case of embodied agents (text vs. embodied agent and male vs. female agent gender), the outputs displayed were the same as the text-based agent, but rather than appearing in a text-box, they appeared to come from an on-screen character by means of a speech bubble. The female character proved more effective than the male character since the female gender is generally more associated with qualities such as empathy. Interestingly, gender stereotypes coming from the real world can apply to human–computer interaction (Reeves & Nass, 1996; Lee, Nass, & Brave, 2000).

Another important factor which should be taken into consideration when designing computer aided affective learning systems is the use of language. Light (2004) has demonstrated that language can be manipulated within a system to have a major impact on the user's perceptions. For instance, according to Light, the use of the word "submit" on the button which participants use to register for a site does not have to be seen as a direct synonym for "send." This is important for the dynamics of the relationship between the producer and the user.

Designing Emotional Instructional Strategies

One can distinguish between domain dependent and domain independent instructional strategies. Domain dependent strategies assist students by providing appropriate suggestions and strategies in order to ameliorate the worried student's emotional state. This is done by softening the demanding environmental factors, for instance, by seeking information about a suitable action. Domain independent or emotion-focused strategies are applied to help students handle their emotions. Domain independent strategies utilize coping statements, such as "this task is achievable" or "this problem from another point of view seems to be more manageable," and relaxation methods, such as muscle and head exercises (Gross, 1999; Lazarus, 1991; Yusoff & du Boulay, 2005).

A framework for designing emotional instructional strategies is the FEASP-approach (Astleitner, 2000a, 2000b). FEASP signifies the five most important dimensions of instructional related emotions: Fear, Envy, Anger, Sympathy, and Pleasure. The FEASP-approach refers to 20 instructional strategies aiming to decrease negative feelings (fear, envy, and anger) and to increase positive feelings (sympathy and pleasure) during instruction. The FEASP-approach has not only been developed for traditional instruction, but also for designing modern instructional technology. The FEASP-approach has been significantly recognized in international research, both on traditional and computer-based instruction (Chapnick & Meloy, 2005; Ferdig & Mishra, 2004; Glaser-Zikuda et al., 2005; Niegemann, Heasel, Hochscheid-Mavel, Aslanski, Deiman, & Kreuzberger, 2004; Pekrun, 2005).

For evaluating the weight and the effects of the FEASP-approach, an instrument based on a questionnaire was developed and validated within an Austrian sample of high school teachers and university students (Astleitner, 2001). A relevant study (Sztejnberg, Hurek, & Astleitner, 2006) attempted to re-validate the findings of the Austrian sample within a sample of Polish secondary education teachers and students. The re-validation results were comparable to those found within the Austrian sample, indicating that teachers and students are convinced that emotions are in most cases essential during instruction. Regarding the relevance of the FEASP-emotions, both studies argued that fear, anger, and pleasure were important in view of teachers and students, whereas envy and sympathy were considered less important.

Emotional instructional strategies can be implemented by using beneficially positive emotions, while preventing, controlling, and managing negative emotions. Moreover, the emotional feedback (Economides, 2006) can also be implemented using negative emotions in order to increase the student's devotion and engagement. These "strategies" can be applied using humor and jokes, amusing games, expressions of sympathy, reward, pleasant surprises, encouragement, acceptance, praises but also through criticism and punishment (Economides, 2005b). Emotional instructional strategies can be applied in several domains of emotional learning and can generate further research.

CONCLUSIONS

Current research indicates that emotions are essentially involved in the course of each learning or training activity. The scientific community henceforth recognizes the need for more extensive research with regard to how emotions are related to the process of learning. We suppose that such research, if advanced further, could specialize itself also per cognitive object. For example, the model of Kort-Reilly-Picard suggests an emotional process that refers to SMET (Science, Math, Engineering, and Technology). In a similar way, a number of different emotional models could be developed for the teaching of Literature, for the teaching of the English Language and so on. Toward this direction, it is fundamental to acquire deeper knowledge about the involvement of emotions in learning which would lead to the formulation of a new educational pedagogy.

Although the presence of technology is very obvious in computerized learning environments, it does not, however, take into consideration the affective reactions experienced while using such learning environments. These observations have led Artificial Intelligence in Education during the last decade to integrate emotional factors to computerized learning systems. An essential condition for the suitable management of emotions by a computerized affective learning system is the valid and convenient diagnosis of these emotions. A school teacher would most likely be able to recognize the emotions of his students easily. To the extent at which we want to manufacture a computer-aided affective learning system, the field of affect recognition is fundamental. Improving the accuracy of recognizing people's emotions would greatly improve the effectiveness of the computer-aided affective learning systems. Currently, the core affect recognition methods are using personal preference information, facial expressions, physiological data, speech recognition, and questionnaire (either standalone or assisting another affect recognition method). Preferably, evidence from many modes of interaction should be combined by a computer system so that it can generate as valid hypotheses as possible about users' emotions.

With regard to learning, there have been very few approaches for the purpose of affect recognition. The adoption of affect recognition methods using personal preference information and questionnaires would probably be more preferable for certain affective learning systems (e.g., web-based for distance learning). These methods do not require special equipment, such as video cameras, microphones, sensors, etc., rendering the affective learning system more user-friendly.

While experienced teachers can modify their teaching style according to the stimuli that they receive from their students, computerized learning systems in general are not capable of receiving and providing feedback, and as a result become inadequate for learning. These are the voids which the computer-aided affective learning systems aim to fill. The heart of such a system is substantially an emotional agent, that is to say, an agent that is capable of managing emotional situations.

Based on the given research, we can say that an "emotional-learning agent" is supposed to:

1. recognize the running emotional condition of the student;
2. recognize when to intervene in order to influence the student's emotional state, based on a new educational pedagogy integrating emotional models in learning; and
3. produce the most optimal emotional state for learning.

There is evidence that the presence of empathic emotion in an embodied computer agent has significant positive effects on a user's impression of that agent and as a result will advance human-computer interaction. In addition, there is evidence that an embodied computer agent, exhibiting the same empathic approach, can reduce user frustration more effectively than a text-only version. Moreover, a female character may be more effective than a male character because female gender is more commonly associated with qualities such as empathy.

Another characteristic which may be essential to the effectiveness of an affective learning system is the apparent aesthetics of an interface character. The more beautiful users think a character is, the more engaged they will be with that character. Language can also be manipulated within a system to have a major impact on a user's perception.

A framework, significantly reckoned in international research, for designing emotional instruction strategies is the FEASP-approach. The FEASP-approach refers to 20 instructional strategies aiming to decrease negative feelings (fear, envy, and anger) and to increase positive feelings (sympathy and pleasure) during instruction.

Further research related to the above mentioned theories and methods, although they belong to different fields of research, will contribute to the evolution of the new field of computer-aided affective learning systems. The knowledge and the technologies from these different fields will need to be adapted individually as well as collectively, so as to serve the development and successful operation of these systems.

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