Integrating Affect Sensors in an Intelligent Tutoring System

Sidney K. D'Mello[1], Scotty D. Craig[1], Barry Gholson[1], Stan Franklin[1], Rosalind Picard[2], and Arthur C. Graesser[1]

[1]The Institute for Intelligent Systems
FedEx Institute of Technology
The University of Memphis
Memphis, TN 38152, USA
{sdmello|scraig|jbgholsn|franklin|a-graesser}@memphis.edu
Phone: +1 901 678 2364
Fax: +1 901 678 1336

[2]M.I.T. Media Laboratory
Wiesner Building, E15
20 Ames Street
Cambridge, MA 02139, USA
picard@media.mit.edu
Phone: +1 617 253 5960
Fax: +1 617 258 6264

ABSTRACT

This project augments an existing intelligent tutoring system (AutoTutor) that helps learners construct explanations by interacting with them in natural language and helping them use simulation environments. The research aims to develop an agile learning environment that is sensitive to a learner's affective state, presuming that this will promote learning. We integrate state-of-the-art, non-intrusive, affect-sensing technology with AutoTutor in an endeavor to classify emotions on the bases of facial expressions, gross body movements, and conversational cues. This paper sketches our broad theoretical approach, our methods for data collection and evaluation, and our emotion classification techniques.

Keywords

Affective states, emotions, learning, intelligent tutoring systems, AutoTutor

INTRODUCTION

The scientific study of emotions was largely ignored until the late 20th century. However, the utility of the systematic study of emotions has become more apparent in several disciplines [9, 27, 30, 33]. The affective computing group at the University of Memphis was founded with the goal of integrating a theory of emotion with a theory of learning.

Our research project has four main objectives. The first is to identify the emotions that are exhibited during learning. The identification process involved investigating current theories of emotion, research on learning, and our own empirical research. Our second objective is to find methods to reliably identify these emotions during learning by developing an *Emotion Classifier*. We are currently exploring non-intrusive ways of identifying emotions as learners interact with the AutoTutor program. Some of the technologies we are exploring include a video camera that can identify facial features, a posture detector that monitors the learner's position, and features of the dialog exhibited while learners are interacting with AutoTutor. The third objective is to program AutoTutor to automatically recognize and respond appropriately to emotions exhibited by learners, and to assess any learning gains. Finally, we will test and augment theories that systematically integrate learning and emotion into educational practice.

AutoTutor

The Tutoring Research Group (TRG) at the University of Memphis developed AutoTutor, a fully automated computer tutor that simulates human tutors and holds conversations with students in natural language [14, 15, 16]. The design of AutoTutor was inspired by explanation-based constructivist theories of learning [2], and by previous empirical research that has documented the collaborative constructive activities that routinely occur during human tutoring [4, 13]. AutoTutor helps students learn by presenting challenging problems (or questions) from a curriculum script and engaging in a mixed-initiative dialog while the learner constructs an answer. AutoTutor provides *feedback* to the student on what the student types in (positive, neutral, negative feedback), *pumps* the student for more information ("What else?"), *prompts* the student to fill in missing words, gives *hints*, fills in missing information with *assertions*, identifies and corrects *misconceptions* and erroneous ideas, *answers* the student's questions, and *summarizes* topics. A full answer to a question is eventually constructed during this dialog, which normally takes between 30 and 200 student and tutor turns.

AutoTutor has been tested in several experiments on approximately 1000 students in computer literacy and physics courses. Significant learning gains were obtained in all of these experiments (an average sigma of .8), particularly at the level of deep explanations as opposed to shallow facts and ideas [16]. AutoTutor has also been evaluated on the conversational smoothness and the pedagogical quality of its dialog moves in the turn-by-turn tutorial dialog [31]. We performed a *bystander Turing test* on the naturalness of AutoTutor's dialog moves. Bystanders were unable to discriminate dialog moves of AutoTutor and dialog moves of a real human tutor.

The computational architecture of AutoTutor has been discussed extensively in previous publications [14, 15, 16]. AutoTutor operates as a distributed client-server application implementing a transient asynchronous mode of communication. The client and the server are written in the C# language within the Microsoft .NET framework.

EMOTIONS DURING LEARNING

Whereas psychological research on emotions is quite extensive, the scientific literature on the relation between emotions and complex learning is considerably more sparse and scattered [27, 37]. In the popular science literature, Goleman's [11] book *Emotional Intelligence* raises the question of how emotions impact learning, and vice versa. Is it possible to induce a state of cognitive and emotional arousal in a manner that makes instruction an interesting and engaging experience for the student? How does the learner manage frustration when learning is difficult? Goleman [11] claims, although with precious little data at hand, that expert teachers are very adept at recognizing and addressing the emotional states of students and, based upon impressions, taking some action that positively impacts learning. But what these expert teachers see, and how they decide on a course of action is an open question.

There is ample empirical evidence in the psychological literature that emotions are systematically affected by the knowledge and goals of the learner, as well as vice versa [26, 27]. As individuals interact in the social and physical world, they attempt to assimilate new information to existing knowledge schemas. When new or discrepant information is detected, a mismatch between input and knowledge occurs. Attention shifts to discrepant information, the autonomic nervous systems increases in arousal, and the new information may modify the individual's goals and knowledge. The learner experiences a variety of possible emotions, depending on the context, the amount of change, and whether important goals are blocked. In the case of extreme novelty, the event evokes surprise or curiosity. When the novelty blocks important goals, there may be anger, frustration, sadness, or fear. When the novelty triggers the achievement of a goal, the emotion is positive, such as satisfaction, happiness, joy, or even one of those rare *Eureka* experiences.

Some of the current research on links between emotions (or affective states) and learning has come from user modeling. The goal is to identify the users' emotions as they interact with computer systems, such as tutoring systems [10] or educational games [5]. However, many of these types of systems only assess intensity, or valence [3], or a single affective state [20]. For example, Guhe et al [17] have recently created a system in which a user is monitored in an attempt to detect confusion during interaction with an intelligent tutoring system. The limitation with this approach is that one affective state is not sufficient to encompass the whole gamut of learning [5]. Another recent study [6], presented evidence, for example, that confusion and flow were positively correlated with learning gains, while boredom is negatively correlated. Another problem with the single state detection approach is that a person's reaction to the presented material can change rapidly, depending on goals, preferences, expectations, and knowledge state [5].

THEORETICAL BACKGROUND

As stated earlier, most learning theories have mostly ignored the importance of the link between a person's emotions, or affective states, and learning [28]. However, the claim has been made that cognition, motivation, and emotion are the three components of learning [36]. Emotion has traditionally been viewed as a source of motivational energy [38], but is often not regarded as an independent factor in learning or motivation [28]. In the last two decades, the link between emotions and learning has received a little more attention [6, 23, 28, 33]. Three models that explore the links between emotions and learning are discussed below.

The Stein and Levine Model

Stein and Levine [37] have identified a link between a person's goals and emotions. Their model adopts a goal-directed, problem-solving approach. As with other theories of emotion that incorporate a hedonic principle, people prefer to be in some states (happiness), and prefer to avoid others (sadness). Their model assumes that people attempt to assimilate new content into existing *schemas*, which are packages of world knowledge, such as stereotypes, scripts, frames, and other categories of generic knowledge. Stein and Levine also assume that emotional experience is almost always associated with attending to and making sense out of incoming information. When the incoming information is novel, it causes a mismatch with existing schemas and results in arousal of the autonomic nervous system (ANS). When ANS arousal occurs in conjunction with a cognitive appraisal of the situation, an emotional reaction occurs. This theoretical model therefore predicts that learning almost always occurs during an emotional episode [37].

The Kort, Reily, and Picard Model

Kort, Reily, and Picard [23] have recently proposed a four-quadrant model that explicitly links learning and affective states. The learning process is broken up 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 "un-learning" at the bottom where misconceptions are hopefully identified and removed from schemas. The affect axis ranges from positive affect on the right to negative affect on the left. According to this model, learners can move around the circle in many different patterns depending on their starting point. For example, learners might move around the circle from a state of ease, to encountering misconceptions, to discarding misconceptions, to new understanding, and then back into a state of ease. However, the amount of time spent in each quadrant and the path that is followed can vary depending on various factors. The process of cycling through these emotions during learning is currently being investigated in the present project.

The Cognitive Disequilibrium Model

One class of cognitive models postulates an important role for *cognitive disequilibrium* in comprehension and learning processes [12, 32]. Deep comprehension occurs when learners confront contradictions, anomalous events, obstacles to goals, salient contrasts, perturbations, surprises, equivalent alternatives, and other stimuli or experiences that fail to match expectations [21, 26, 27, 35]. Cognitive disequilibrium has a high likelihood of activating conscious, effortful, cognitive deliberation, questions, and inquiry that aims to restore cognitive equilibrium. The affective states of confusion, and perhaps frustration, are likely to occur during cognitive disequilibrium [23]. Recent empirical research has indeed pointed to confusion as an important affective state for scientific study [6, 34]. Confusion indicates an uncertainty about what to do next or how to act [22, 34]. Thus, confusion often accompanies cognitive disequilibrium. Similarly, states of perturbation and hesitation often indicate the need for clarification or more information [34].

EMPIRICAL DATA COLLECTION

We are currently conducting three studies that directly connect with the first three objectives of this project. The first study gathers data that would extrapolate the links between emotions and learning. The second study involves the collection of sensory data to serve as training and validation data towards the development of the *Emotion Classifier*. Finally, the third study will evaluate the performance of the emotionally sensitive AutoTutor in an attempt to gauge any learning gains. The first study is complete, the second is in progress, and the third is planned for the near future.

The Emote-aloud study

The purpose of this study was to discover links between learning and emotions when participants interacted with AutoTutor. The participants went through a training session on topics in computer literacy where AutoTutor asked deep level questions about computer hardware. All interaction with AutoTutor was video recorded. During the tutoring phase, the participants were asked to perform an emote-aloud procedure in which they stated aloud their affective states. The participants were provided with a list of affective states that included functional definitions. The list consisted of anger, boredom, confusion, contempt, curiosity, disgust, eureka, and frustration.

Each participant's video was divided into 10-second clips that ended in an emote-aloud utterance. Since the expression of emotions tends to be very fast and only lasts for about three seconds [9], two raters independently scored the three seconds before the utterance was made using the Facial Action Coding System [8]. The two raters demonstrated a high reliability with an overall Kappa score of .80. Preliminary results on this study are presented below.

The Gold Standard Study

The training and testing of an emotion classifier requires a gold standard for comparison. Establishing an appropriate gold standard in such a fuzzy domain is quite challenging. Therefore, we propose three gold standards: the participants, novice judges, and trained judges. The experimental procedure of this study consists of four steps, whereas the experimental system is equipped with appropriate sensors to monitor facial features, posture patterns, and the student-tutor conversation. In step 1, a sample of college students (N = 30) complete a session with AutoTutor that lasts approximately 32 minutes. Information on the participant's facial features, body posture, and conversation history is recorded during the interaction. In step 2, the student participant views a videotape of the aforementioned recordings and is stopped at 96 points during the interaction, each point separated by a 20 second margin. At such points, the student completes a survey on their emotional state at that time from a pre-selected list of emotions that were functionally defined. The list consists of boredom, confusion, delight, surprise, flow, frustration, and neutral. A week later, they begin step 3 and serve as novice judges. Specifically, they apply the same procedure, at the same 96 points, but on one other student's interactions with AutoTutor. In step 4, expert judges (N=2) apply the same procedure to each of the student interactions. The net result is that there will be emotion ratings for 96 points in each of the 30 tutorial interactions, or 2880 events in total. These 2880 events will be described or rated by the participants, by novice judges, and by expert judges. The set of these judgments will create a composite measure and will serve as the gold standard for comparisons to the metrics and categories produced by the affect sensors.

Evaluating the Affect Sensitive AutoTutor

In order to test whether an affect-sensitive cognitive tutor is effective, we will compare different versions of AutoTutor: some that are sensitive to learner emotions and others that are not. The original AutoTutor has a conventional set of fuzzy production rules that are sensitive to cognitive states of the learner, but not to the emotional states of the learner. Our improved AutoTutor would be sensitive to these affective states. The obvious prediction is that learning gains and the learner's impressions should be superior for the affect-sensitive AutoTutor.

This experiment will have 3 phases, with approximately 20 college students randomly assigned to each of the 2 or more conditions. Phase 1 is pre-testing, where there is a test on knowledge about the subject matter. This subject matter would be computer literacy. Phase 2 is learning, where the student interacts with AutoTutor for 30 to 60 minutes. Phase 3 is the post-test, where they receive another version of the subject matter test, followed by a rating scale of their impressions of the learning experience, and finally a questionnaire about student characteristics (grade, age, gender, courses completed, etc.). The pretest and posttest versions will be counterbalanced, so half the learners are assigned version A at pretest and half version B. If there are learning gains, this should be manifested in a significant difference between the posttest and pretest scores. The magnitude of these differences should be higher for a version of AutoTutor that is sensitive to student emotions.

SENSORY CHANNELS

Our approach to affective state classification relies on an exclusive use of non-intrusive sensing devices. These include an IBM Blue Eyes camera to detect facial expressions, a Body Pressure Measurement System (BPMS) for posture information, and AutoTutor's log files for conversational cues.

Facial Expressions

Recognition of facial expressions is a multi stage process. First, the system locates and tracks the pupils of the eye. We have achieved real-time, highly accurate tracking (less than one pixel RMS error per control point), with no calibration required. Second, the system fits templates to the upper facial features (eyes and brows), where we also achieved real-time fitting performance. Third, the system labels facial action units. We achieved an initial performance of 68% on six upper facial action units; it should be noted that a person has to score 75% to qualify as a human expert. This facial recognition system provides us with a 12-dimensional vector corresponding to action units around the eyes.

Posture Patterns

We use the Body Pressure Measurement System (BPMS) developed by Tekscan to monitor student's patterns while they interact with AutoTutor. The BPMS gauges the distribution of pressure on surfaces such as seats, etc. We use two sensor pads to ascertain student's posture patterns as they interact with the tutor. The sensing area consists of 16,128 individual sensing elements measuring pressure in mmHg. The first pad is placed on the seat. The second sensor pad is placed on the back support of the chair. We hope that the combination of pressures reported by the back and seat pads may help indicate the type of emotional experience.

The output from the sensor pads will be analyzed by dividing the sensing region into quadrants (or 9 areas) and assessing the net force in each quadrant. This is preferred over a fined grained analyzes of each individual sensing point, as the former may be more indicative of gross body movement, and more computationally efficient.

In a related effort, Mota and Picard [29] have developed a system to automatically detect a learner's interest level using body posture patterns. They employed a neural network for real time classification of nine static postures (leaning back, sitting upright, etc) with an overall accuracy of 87.6% when validated on new subjects. Their system also recognized interest (high interest, low interest, and taking a break) by analyzing posture sequences with an overall accuracy of 82.3% on known subjects, and 76.5% on new subjects.

Conversational Cues

AutoTutor's log files provide a wealth of information regarding the interactive session with the student. At each student turn AutoTutor writes its assessment of the student's response along with some internal information to stable storage (disk). Assessment of the student's responses includes information such as: the correctness of an answer, the verbosity of the student, reaction and response times, the length of an answer, and a host of other parameters about the conceptual quality of the student's turns. It also classifies the student's response into five broad dialog categories: meta-communicative, metacognitive, shallow comprehension, assertions reflecting deep comprehension, and other contributions, by the Speech Act Classification System. After assessing a student's response, AutoTutor provides short feedback on the contribution (positive, negative, neutral), and makes a substantive dialog move (hint, prompt, assertion, etc) that advances the conversation. The sequence of these dialog events by the tutor and student are mined to induce learner emotions.

EMOTION CLASSFICATION

A major computational effort will be aimed at the pursuit of new methods of assessing and classifying affective emotional states. We will develop an *Emotion Classifier* that takes due consideration of cognitive and discourse metrics or categories that accumulate during the tutorial dialog. As with most classifiers, there is a set of input features {F} and a set of categories $\{C_1, C_2, \ldots C_n,\}$. The hope is that the particular category C_i, can be predicted by some mechanism that is sensitive to the input features g({F}). The input features will be obtained from the three primary sensory channels described above. The classifier that is developed will be a combination of *standard* and *biologically motivated* classifiers.

Two different approaches to classification will be applied towards the development of the *Emotion Classifier*. The first would integrate the data from all three sensory channels into a high dimensional vector before attempting classification. The second would be to individually classify each sensory channel, and then integrate the classifications of each channel into a *super classifier,* in order to output a single emotion. Each approach is associated with a set of pros and cons and reliably determining which method is superior is an empirical matter.

Since the output of the three sensory channels is inherently different in nature, it is highly unlikely that a single classifier would be able to provide an optimal classification. Therefore, all classification tasks would be replicated on a series of classifiers ranging from more traditional methods (Standard Classifiers) to more sophisticated biologically motivated, neural network based classification systems.

Standard Classifiers

Classifiers presented in this category include a list of tried and tested mechanisms, each with a set of limitations. They can be divided into broad categories such as *Decision Tree Induction, Bayesian Classification, Neural Network approaches, Fuzzy Classifiers, Genetic Algorithm Based Classifiers,* etc [18]. Each category itself consists of several classification algorithms. We intend to make use of at least three such classification algorithms from different categories in order to obtain a reliable emotion classifier. Moreover, the researchers at MIT will be investigating alternative classifiers and comparing them to these classifiers.

Biologically Motivated Classifiers

Fine grained analyses of the dynamic behaviors of neural populations having been gaining popularity towards the study of higher level brain processes [24]. The K-set hierarchy is a biologically inspired model of neural population dynamics developed by Freeman and associates. They have designed and parameterized a model that replicates experimentally recorded data of the dynamic behavior in the olfactory system [24]. The network has been tested by simulating temporal and spatial properties of neural populations. The KIII network operates as a classifier by creating low dimensional local basins of attraction, each basin associated with one class, forming a global attractor landscape. These low dimensional local basins constitute dynamic memories and can be used to solve difficult classification problems, particularly in situations where the data set is not linearly separable. The network can thereby serve as an interface between noisy environmental data and standard classifiers [24]. Additionally, the KIII network learns based on *hebbian reinforcement, habituation,* and *normalization*.

The KIII network has been experimentally validated as a highly capable pattern classifier. Examples demonstrating its classification accuracy on both synthetic and real data have been presented in [24, 25]. It has been successful in detecting faults in small machine parts, as well as in classifying spatiotemporal EEG patterns from rabbits that have been trained to discern between different visual stimuli [25].

Our exclusive use of non-intrusive sensors for emotion detection have the side effect of producing noisy data with extremely subtle variations over categories. Additionally, enforcing strict inter-rater reliability requirements between our four raters in the gold standard study would probably lead to a considerable loss of data. Therefore, our ideal data set of 2880 emotion labels will more likely be reduced to a smaller size. The KIII network's superior performance as a pattern classifier in noisy environments, coupled with its ability to learn from relatively few training samples [24, 25] motivate its use as our primary emotion classifier. We anticipate that the performance of the KIII model will be equal to or better than the standard classification algorithms.

The KA model developed by Harter & Kozma [19] is an engineering simplification of the original K-set hierarchy. It is a deterministic discrete time model. Its discrete nature is achieved by replacing the differential equations in the K model by difference equations [19]. A major advantage of the KA-model over the original K-set model is that it runs about three times faster. This motivates the use of the discrete KA model over the continuous K model for real time emotion classification.

PRELIMINARY RESULTS

The action units obtained from the Emote-aloud study described above were analyzed by association rule mining techniques [1]. After a strict data cleaning process, the only emotions considered were Frustration, Confusion, and Boredom. Action units 1 (outer brow raise) , 2 (inner brow raise), and 14 (dimpler) were primarily associated with frustration, and a strong association was found for a link between action units 1 and 2 influencing each other. This indicates that the presence of action unit 1 influences the presence of action unit 2 and vice versa. Confusion displayed associations with action units 4 (brow lowerer), 7 (lid tightener), and 12 (lip corner puller). It also showed a unique association rule of action unit 7 influencing 4, but not vice versa. Boredom showed an association with 43 (eye closure). While boredom did not display any association rules between action units, it did show several weaker trends between eye blinks and various mouth movements such as mouth opening and closing and jaw drop (perhaps a yawn). However, more research would be required to investigate the reliability of these associations (see [7] for details).

CONCLUSIONS

We have sketched out a set of ideas that guide our approach towards the development of an affect sensitive intelligent tutoring system. With the first study complete, and the second in progress, a majority of the future efforts will be directed towards extensive data mining procedures. Initial cluster analyses on posture patterns have been promising.

The broader impacts of our research activities are to advance education, intelligent learning environments, and human-computer interfaces. What the constructivist movement in cognitive science has too often overlooked is how the process of constructing meaning is optimally coordinated with learner emotions. We hope to fill this gap.

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REFERENCES

1. Agarwal, R., Imielinski, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *Proceedings of the ACM-SIGMOID International Conference Management of Data* (pp. 207-216). Washington, DC: AMC.
2. Aleven V. & Koedinger, K. R. (2002). An effective metacognitive strategy: Learning by doing and explaining with a computer-based Cognitive Tutor. *Cognitive Science, 26*, 147-179.
3. Ball, G., & Breeze, J. (2000). Emotion and personality in a conversational agent. In J. Cassel, J. Sullivan, S. Prevost, & E. Churchill (Eds.), *Embodied Conversational Agents* (pp. 189-219). Boston: The MIT Press.
4. Chi, M. T. H., Siler, S., Jeong, H., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science, 25*, 471-533.
5. Conati C. (2002). Probabilistic assessment of user's emotions in educational games. *Journal of Applied Artificial Intelligence, 16*, 555-575.
6. Craig, S. D., Graesser, A. C., Sullins, J. & Gholson, B. (2004). Affect and learning: An exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media, 29*, 241-250.
7. Craig, S. D., D'Mello, S. K., Gholson, B., Witherspoon, A., Sullins, J., & Graesser A.C. (2004). Emotions during learning: The first steps toward an affect sensitive intelligent tutoring system.In J. Nall, & R. Robson (Eds.). *Proceedings of E-learn 2004: World conference on E-learning in corporate, Government, Healthcare, & Higher Education* (pp.284-288). Norfolk, VA: Association for the Advancement of Computing in Education.
8. Ekman, P, & Friesen, W. V. (1978). *The facial action coding system: A technique for the measurement of facial movement.* Palo Alto: Consulting Psychologists Press.
9. Ekman, P. (1992). Are there basic emotions? *Psychological Review, 99*, 550-553.
10. Fan, C., Sarrafzadeh, A., Overmyer, S., Hosseini, H. G., Biglari-Abhari, M., & Bigdeli, A. (2003). A fuzzy approach to facial expression analysis in intelligent tutoring systems. In A. Méndez-Vilas and J.A.M. González (Eds.) *Advances in Technology-based Education: Towards a Knowledge-based Society Vol 3* (pp. 1933-1937). Badajoz, Spain: Junta De Extremadura.
11. Goleman, D., (1995). *Emotional Intelligence*. New York: Bantam Books.
12. Graesser, A. C. & Olde, B. (2003). How does one know whether a person understands a device? The quality of the questions the person asks when the device breaks down. *Journal of Educational Psychology, 95*, 524–536.
13. Graesser, A. C., & Person, N. K. (1994). Question asking during tutoring. *American Educational Research Journal, 31*, 104-137.
14. Graesser, A. C., Wiemer-Hastings, K., Wiemer-Hastings, P., Kreuz, R., & TRG (1999). AutoTutor: A simulation of a human tutor. *Journal of Cognitive Systems Research, 1*, 35-51.
15. Graesser, A. C., VanLehn, K., Rose, C., Jordan, P., & Harter, D. (2001). Intelligent tutoring systems with conversational dialogue. *AI Magazine, 22*, 39-51.
16. Graesser, A. C., Lu, S., Jackson, G. T., Mitchell, H., Ventura, M., Olney, A., & Louwerse, M. M. (2004). AutoTutor: A tutor with dialogue in natural language. *Behavioral Research Methods, Instruments, and Computers, 36*, 180-193.
17. Guhe, M., Gray, W. D., Schoelles, M. J., & Ji, Q. (2004, July). *Towards an affective cognitive architecture.* Paper presented at the 26th Annual Conference of the Cognitive Science Society, Chicago, IL.
18. Han J., & Kamber. M (2000). *Data Mining: Concepts and Techniques*. San Francisco, CA.: Morgan Kaufmann.

19. Harter, D. (May, 2004). Towards a model of basic intentional systems: Nonlinear dynamics for perception, memory and action in autonomous adaptive agents. *Ph.D. University of Memphis*, UMI Comprehensive Dissertation Indexing (CDI) and Publishing.

20. Hudlicka, E., & McNeese, D. (2002). Assessment of user affective and belief states for interface adaptation: Application to an Air Force pilot task. *User Modeling and User-Adapted Interaction, 12*, 1-47.

21. Jonassen D., Peck, K. & Wilson B. (1999). *Learning with technology: A constructivist perspective*. Upper Saddle River, NJ: Prentice Hall.

22. Keltner, D. & Shiota, M. N. (2003). New displays and new emotions: a commentary on Rozin and Cohen (2003), *Emotion, 3*, 86–91.

23. Kort, B., Reilly, R., & Picard, R. (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy—building a learning companion. In T. Okamoto, R. Hartley, Kinshuk, & J. P. Klus (Eds.), *Proceedings IEEE International Conference on Advanced Learning Technology: Issues, Achievements and Challenges* (pp.43-48). Madison, Wisconsin: IEEE Computer Society.

24. Kozma, R., Freeman, W.J. (2001). Chaotic resonance - Methods and applications for robust classification of noisy and variable patterns. *International Journal of Bifurcation & Chaos, 11*, 1607-1629.

25. Kozma, R., Freeman, W.J. (2002) Classification of EEG Patterns Using Nonlinear Neurodynamics and Chaos. *Neurocomputing, 44-46,* 1107-1112.

26. Mandler, G. (1976). *Mind and emotion*. New York: Wiley.

27. Mandler, G. (1999). Emotion. In B. M. Bly & D. E. Rumelhart (Eds.), *Cognitive science. Handbook of perception and cognition 2nd ed*. (pp. 367-384). San Diego, CA: Academic Press.

28. Meyer, D. K., & Turner, J. C. (2002). Discovering emotion in classroom motivation research. *Educational Psychologist, 37*, 107-114.

29. Mota, S. & Picard, R. W. (2003). "Automated Posture Analysis for Detecting Learner's Interest Level." *Workshop on Computer Vision and Pattern Recognition for Human-Computer Interaction, CVPR HCI*, June, 2003.

30. Panksepp, J. (1998). *Affective neuroscience: The foundations of human and animal emotion*. New York: Oxford University Press.

31. Person, N. K., Graesser, A. C., & the Tutoring Research Group (2002). Human or computer?: AutoTutor in a bystander Turing test. In S. A. Cerri, G. Gouarderes, & F. Paraguacu (Eds.), *Intelligent Tutoring Systems 2002* (pp. 821-830). Berlin, Germany: Springer.

32. Piaget, J. (1952). *The origins of intelligence*. New York: International University Press.

33. Picard, R. W. (1997). *Affective computing*. Cambridge, Mass: MIT Press.

34. Rozin, P. & Cohen, A. B. (2003). Confusion infusions, suggestives, correctives, and other medicines. *Emotion*, *3*, 92–96.

35. Schank, R. C. (1986). *Explanation patterns: understanding mechanically and creatively*. Hillsdale, NJ: Erlbaum.

36. Snow, R., Corno, L., & Jackson, D. (1996). Individual differences in affective and cognitive functions. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 243-310). New York: Macmillan.

37. Stein, N. L., & Levine, L. J. (1991). Making sense out of emotion. In W. Kessen, A. Ortony, & F, Kraik (Eds.), *Memories, thoughts, and emotions: Essays in honor of George Mandler* (pp. 295-322). Hillsdale, NJ: Erlbaum.

38. Stipek, D. (1998). *Motivation to Learn: From Theory to Practice, 3rd edition*. Boston: Allyn and Bacon.