The Relationship between Affective States and Dialog Patterns during Interactions with AutoTutor

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Abstract: In an attempt to discover links between learning and emotions, this study adopted an emote-aloud procedure in which participants were recorded as they verbalized their affective states while interacting with an intelligent tutoring system, AutoTutor. Various characteristics and assessments of the participants' interactions with AutoTutor were recovered by mining its log files. These interaction patterns were correlated to the affective states expressed by the participants. We identify significant correlations and speculate on their implications for the larger project of extending the AutoTutor system into a non-intrusive, affect-sensitive, intelligent tutoring system.

Introduction

While the 20th century has been ripe with learning theory, these theories have typically ignored the importance of the link between learning and a person's emotions or affective states (Meyer & Turner, 2002). However, toward the end of the twentieth century, emotions started to get more attention. Some seminal contributions to the literature in psychology include the facial action coding system developed by Ekman and Friesen (1978), theories that relate goals, cognition and emotion (Ortony, Clore, & Collins, 1988; Mandler, 1976; Stein & Levine, 1991), and more recently Russell's (2003) theory of emotion.

It is widely acknowledged that cognition, motivation, and emotions are three components of learning (Snow, Corno, & Jackson, 1996). Until recently, emotion has been viewed as source of motivational energy (Harter, 1981; Miserandino, 1996; Stipek, 1998), but has not been a direct focus as an independent factor in learning or motivation (Ford, 1992; Meyer & Turner, 2002). However, in the last decade, the link between emotions and learning has received more attention (Craig, Graesser, Sullins, & Gholson, 2004; Kort, Reilly, & Picard, 2001; Meyer & Turner, 2002; Picard, 1997). For example, Linnerenbrink and Pintrich (2002) reported that the posttest scores after physics training decrease as a function of negative affect during learning. Craig, Graesser, et al. (2004) reported that increased levels of boredom were negatively correlated with learning of computer literacy, whereas levels of confusion and the state of flow (being totally absorbed, Csikszentmihalyi, 1990) were positively correlated with learning.

The Craig, Graesser, et al. (2004) study used the AutoTutor program as its learning environment. AutoTutor is an intelligent tutoring system that uses naturalistic dialog patterns to tutor users, as will be elaborated below. One gap in the literature is the role that the dialog of the learning experience plays in the emotions experienced.

It is important to understand the mechanisms of dialog and cognition before one can dissect the links between dialog and emotions. For example, a collaborative theory of communication (Schober & Clark, 1989) stipulates that it is important to understand the participants' roles in conversation as well as the grounding criterion, i.e., a mutual belief "that the addressees have understood what the speaker meant to a criterion sufficient for current purposes" (Clark & Shaefer, 1989). This notion of a grounding criterion could also point to possible links between dialog and affective states in the learning process. While the participants are working toward a grounding criterion, the addressees are in a state of attempting to understand the content. When this fails, there is a state of cognitive disequilibrium (Graesser, Lu, Olde, Cooper-Pye, & Whitten, in press; Otero & Graesser, 2001), which produces confusion (Craig, Graesser, et al., 2004). The grounding criterion is often restored in a state of understanding, which is occasionally preceded by an abrupt transition of eureka (quick insight). However, if the addressees fail to reach a grounding criterion, then they should eventually give up and disengage, resulting in boredom. Frustration would occur when the speaker moved ahead before the addressee had reached understanding.

The current research reports the first step in a larger project to integrate affect sensing into an intelligent tutoring system, AutoTutor (D'Mello, Craig, Gholson, Franklin, Picard, & Graesser, 2005; Graesser, Chipman, Haynes, & Olney, in press; Graesser, K. Wiemer-Hastings, P. Wiemer-Hastings, Harter, Kreuz, & TRG, 1999; Graesser, Person, Harter, & TRG, 2001). The purpose of this study is twofold. First, we want to identify affective states that occur frequently during learning. The affective states of interest in this study were anger, boredom, confusion, contempt, curiosity, disgust, eureka, and frustration. Second, we want to correlate AutoTutor's overt responses to the learner's dialog contributions with affective states expressed by the participants.

AutoTutor's Mixed Initiative Dialog

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 (Graesser, Chipman, et al., in press; Graesser, et al., 1999; 2001). The design of AutoTutor was inspired by explanation-based constructivist theories of learning (Aleven & Koedinger, 2002) and by previous empirical research that has documented the collaborative constructive activities that routinely occur during human tutoring (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; Graesser & Person, 1994). 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* 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 turns between the student and tutor (just as with human tutors).

AutoTutor's knowledge about the topic he is tutoring (computer literacy in this study) is represented by a curriculum script on the material and also Latent Semantic Analysis (LSA) (Foltz, 1996; Foltz, Britt, & Perfetti, 1996; Landauer & Dumais, 1997; Landauer, Foltz, & Laham, 1998). LSA is a statistical technique that measures the conceptual similarity of any two texts that can range from 1 word to a lengthy article. LSA computes a geometric cosine (ranging from 0 to 1) that represents the conceptual similarity between the two text sources. In AutoTutor, LSA is used to assess the quality of student responses and to monitor other informative parameters, such as Topic Coverage and Student Ability Level. Student response quality is measured by comparing each response against two classes of content stored in the curriculum script: one that contains potential good answers to the topic being discussed (called *expectations*) and one that contains the anticipated bad answers (called *misconceptions*). The higher of the two geometric cosines (i.e., a measure of the conceptual match between student input and expectations versus misconceptions) is considered the best conceptual match, and therefore, determines how AutoTutor responds to the student contributions in a dialog turn. We have found our application of LSA to be quite accurate in evaluating the quality of learner responses (P. Wiemer-Hastings, K. Wiemer-Hastings, & Graesser, 1999).

A session with AutoTutor is comprised of a set of subtopics (difficult questions or problems) that cover specific areas of the main topic (hardware, Internet, and operating systems). Each subtopic is manifested by a series of turns in which AutoTutor maintains a conversation with the student in an attempt to construct an answer to the current subtopic. When an acceptable answer with the appropriate details is gleaned from the student's responses (usually after 30 – 200 turns) AutoTutor moves on to the next subtopic. At the end of each student turn, AutoTutor maintains a log file that captures the student's response, a variety of assessments of the response, and the tutor's next move. Temporal information such as the student's reaction time and response time are also maintained.

Table 1 provides an overview of the various channels of information in the student's interaction history. These are stored and extracted from AutoTutor's log files. Information channels that are not relevant to this study have been ignored. The information can be divided into five categories: session information, response information, LSA assessments, the dialog advancer, and the tutor's feedback.

Channel	Sub channel	Description
Session Information	Subtopic Number Turn Number	The current subtopic (question) in this session The number of the conversation turn within a subtopic
Response Information	Number of words Number of characters	The number of words in the student's turn The number of characters in the student's turn
Latent Semantic Analysis Assessments	Local Good Score Delta Local Good Score Global Good Score Delta Global Good Score Local Bad Score Delta Local Bad Score Global Bad Score Delta Global Bad Score	Similarity of content of student's turn to an expectation The change in the Local Good Score Similarity of the history of student turns to expectations The change in the Global Good Score Similarity of content of student's turn to a bad answer The change in the Local Bad Score Similarity of the history of student turns to bad answers The change in the Global Bad Score
Dialog Advancer	Pump Hint Prompt Assertion Summary	Minimal information provided. e.g. "What else" Provides a hint to the student to fill in proposition Prompts student to fill in a missing content word Asserts information about an expectation Provides a summary of the answer
Tutor Feedback	Positive Neutral Positive Neutral Neutral Negative Negative	Provides feedback terms such as: "good job", "correct" Provides feedback terms such as: "yeah", "hmm right" Provides feedback terms such as: "uh huh", "alright" Provides feedback terms such as: "possibly", "kind of" Provides feedback terms such as: "wrong", "no"

Table 1: Description of the Information Mined from AutoTutor's Log Files at the End of Each Student Turn.

Session Information

The session information can be interpreted as a combination of global and local temporal markers that span across the period of interaction. The *subtopic* number indicates the number of questions answered. Therefore, the subtopic provides a global measure of position within the entire session. For example, for a one hour session comprised of three subtopics, the third subtopic would indicate that the student is approximately in the 40 – 60 minute time span. The *turn* on the other hand provides a local measure of the number of student responses directed toward the current question (subtopic). Intuitively, one would expect tiredness or boredom with high subtopic numbers and probably frustration with a high turn number because the student is stuck in the current subtopic.

Response Information

Since AutoTutor relies on LSA for the majority of its assessments of the student's responses to a question, we only consider the verbosity of the response in this section. The verbosity is considered to be the number of words and characters in the student's response. The motivation behind this approach is that short responses could indicate frustration or confusion. Long responses may be indicative of a deeper grasp of concepts probably due to the experience of the student being in a state of flow (Csikszentmihalyi, 1990).

Latent Semantic Analysis (LSA) Assessments

AutoTutor relies on LSA as its primary source of student response assessments. The local assessments for a given turn measure the student's response for that turn on the basis of its similarity to good and bad answers. The Local Good Score is the highest match to the set of expectations representing good answers. The Local Bad Score is the highest match to the set of bad answers. A high Local Good Score is indicative of progress, while a high Local Bad Score can be interpreted as a student's misconception. The Delta Local Good Score and the Delta Local Bad Score measure changes in the Local Good Score and the Local Bad Score, respectively. Therefore, a large Delta Local Good Score could be caused by one of those rare *eureka* experiences.

The four Global parameters perform the same assessments as the Local parameters with the exception that the text used for the LSA match is an aggregation of all of the student's responses in a given subtopic. With this scheme, a student's past responses to a subtopic are considered in AutoTutor's assessment of his or her current response.

Dialog Advancer

At the end of each student turn, AutoTutor incorporates the various LSA assessments when choosing its next pedagogically appropriate dialog move. The dialog move chosen can be regarded as an indicator of the amount of information revealed to the student. The five dialog moves presented in Table 1 can be mapped onto a scale in the order: pump, hint, prompt, assertion, and summary. A pump conveys the minimum amount of information (on the part of AutoTutor) and a summary conveys the most amount of explicit information. Within the context of the emote-aloud study, one might expect confusion to heighten after the occurrence of hints and prompts (when the student is expected to think, often to no avail) and to diminish in the presence of assertions and summaries (when the student can simply receive information from AutoTutor rather passively). Similar predictions can be made for various other affective states.

Tutor Feedback

AutoTutor's feedback is manifested in its verbal content, intonation, and other non-verbal conversational cues. Table 1 shows examples of AutoTutor's responses, characterized by the type of feedback provided. One could predict the occurrence of particular emotions as a result of the type of feedback provided. For example, repeated negative feedback could cause frustration in a motivated student, but boredom in a student lacking motivation.

Emote-Aloud Study Methodology

Participants

The participants in this study consisted of 7 undergraduates. They were selected from the department of psychology subject pool at the University of Memphis. Two participants were discarded because they rarely expressed any emotions.

Materials

Electronic materials. Participants interacted with AutoTutor on topics in computer literacy. AutoTutor asked questions about computer hardware. The questions were deep-level (such as *why, how, what-if*) and required about a paragraph of information to answer correctly. AutoTutor holds a mixed initiative dialog to assist the students in answering each question, as discussed in the previous section.

Knowledge tests. Two 24-item multiple-choice tests on the domain of computer literacy were used to assess prior domain knowledge and learning gains. The tests were counterbalanced as pretest and posttest and have been shown to provide equivalent measures of computer literacy in prior research (Craig, Driscoll, & Gholson, 2004).

Procedure

As participants came into the lab, they were given an informed consent followed by a pretest. Then the participants interacted with AutoTutor for approximately an hour and a half, during which they engaged in an emote-aloud activity. The participants were videotaped during the interaction with AutoTutor. They were asked to make verbal reports when they experienced an affective state. Participants were given a list with eight affective states along with definitions. The list of affective states consisted of anger, boredom, confusion, contempt, curiosity, disgust, eureka, and frustration.

The affective states were functionally defined for the participants, based on a dictionary. *Anger* was defined as a strong feeling of displeasure and usually of antagonism. *Boredom* was defined as the state of being weary and restless through lack of interest. *Confusion* was defined as a failure to differentiate similar ideas or to relate ideas. *Contempt* was defined as the act of despising, with a lack of respect or reverence for something. *Curious* was defined as an active desire to learn or to know. *Disgust* was defined as marked aversion aroused by something highly distasteful. *Eureka* was defined as a feeling used to express triumph on a discovery. *Frustration* was defined as a feeling of making vain or ineffectual all efforts however vigorous; a deep chronic sense or state of insecurity and dissatisfaction arising from unresolved problems or unfulfilled needs. After the hour and a half session ended, a posttest was administered, followed by a debriefing.

Data Treatment

Data Cleaning: Due to a lack of observations, Anger (n = 17), Contempt (n=8), Curious (n=3), and Disgust (n=5) were not included in the current analysis. This data cleaning procedure resulted in reliable data only for boredom, confusion, eureka, and frustration. Additionally, due to a lack of expressed emotions, data from two participants were also discarded. Therefore, the original database of 212 emote-alouds was reduced to 168 "emote-alouds", or verbal expressions of an emotion or affective state.

Data Selection: After eliminating the participants and the emotions mentioned above, the AutoTutor log files were mined to obtain data on the various dialog channels described above. More specifically, the turn that immediately preceded the emote-aloud was selected as the representative turn for that emote-aloud. If any of the 22 dialog parameters for such a turn were missing, that turn and the associated emote-aloud were discarded from the analysis. This caused a further reduction in the database from 168 to 145 records.

Results and Discussion

Information from AutoTutor's log files for the turn immediately preceding an emote (short for one emote aloud observation) was correlated with the affective state expressed by the participant. Significant Pearson correlations were found for confusion, eureka, and frustration. No significant correlations were discovered for boredom. All correlations had df = 143 and reached a significance level of at least $p < .05$ on a two tailed test. Correlations significant at the .05 level are signified with one asterisk (*) and at the .01 level with two asterisks (**).

Correlations with Confusion

Table 2 presents significant correlations between confusion and AutoTutor's dialog channels.

AutoTutor Dialog Channel	r
Delta Global Good Score	$-.19^{*}$
Assertion	$-.22^{**}$
Hint	$.17^{*}$
Neutral Negative Feedback	$.18^{*}$
Neutral Feedback	$.20^{*}$
Positive Feedback	$-.27^{*}$

Table 2: Correlations between Confusion and Parameters of AutoTutor's Dialog Channel.

The negative correlations reported in Table 2 can be easily explained. Since a high Delta Global Good Score is an indicator of understanding, it is negatively correlated with confusion. Additionally, a student's confusion tends to dampen when presented with an assertion. During an assertion, the tutor merely states facts and minimally engages the student in thought. Finally, confusion is negatively correlated with positive feedback. This indicates that when the student is in a state of confusion, his or her answers are generally not very accurate. This relationship would be expected because during confusion, the student is in a state of cognitive disequilibrium (Craig, Driscoll, et al., 2004).

The positive correlations presented in Table 2 are not so straightforward. However, overall these findings are consistent with the grounding criterion hypothesis of emotions in dialog. Confusion is occurring during the grounding process because the student is still attempting to build understanding of the material. We see that confusion is positively correlated with the presence of a hint, neutral negative feedback, and neutral feedback. One can speculate that this is associated with confusion at two different levels. The confusion that is emoted when the participant is presented with a hint could be attributed to the higher level of thought required to answer the hint. In the hint, the learner is given a small bit of information and must follow that thread to establish the answer. If the learner does not follow the correct path then they might become confused when the path is incorrect. However, confusion accompanying neutral negative and neutral feedbacks may be explained by the learner contributing information to the dialog and expecting some directional feedback on the information, but receiving neutral feedback that does not give them any conclusive information on the content of their contribution. In some cases, the language understanding module can misclassify a correct answer as being incorrect, which triggers some sort of neutral or neutral-negative feedback. This also can lead to confusion on the part of the student.

Correlations with Eureka

Table 3 presents significant correlations between eureka and AutoTutor's dialog channels.

AutoTutor Dialog Channel	r
Subtopic Number	$.23^{**}$
Global Good Score	$.24^{**}$
Delta Global Good Score	$.20^{*}$
Local Good Score	$.26^{**}$
Delta Local Good Score	$.19^{*}$
Negative Feedback	$-.41^{*}$
Positive Feedback	$.51^{**}$

Table 3: Correlations between Eureka and Parameters of Auto Tutor's Dialog Channel.

The correlations with eureka are relatively easy to interpret. In general, more eureka occurs as the user's LSA scores for good answers increase. This would be an indication that users are learning the materials. Eureka also shows a strong relationship to both negative feedback and positive feedback, indicating that eureka can be influenced by AutoTutor's feedback. These findings lend some weight to our grounding criterion hypothesis' claim that eureka will occur during learning when the grounding criterion is established. When grounding occurs during the learning process, a level of understanding is reached between the participants in the conversation (i.e. learner and AutoTutor). It is this understanding that led our learners to emote the Eureka response. However, this response is most likely affiliated with happiness from giving a correct answer rather than a full Eureka experience. True Eureka experiences are much more rare than our data suggest (Craig et al., 2004).

Correlations with Frustration

Table 4 presents significant correlations between frustration and AutoTutor's dialog channels.

AutoTutor Dialog Channel	r
Assertion	$.17^{*}$
Negative Feedback	$.41^{**}$
Positive Feedback	$-.33^{**}$

Table 4: Correlations between Frustration and Parameters of Auto Tutor's Dialog Channel.

The correlation between assertions and frustration was small but significant. Frustration is positively correlated with negative feedback and negatively correlated with positive feedback. The lack of positive feedback and high frequency of negative feedback associated with frustration would indicate that a student was having trouble in reaching a grounding criterion with the tutor. The positive relationship between the number of assertions given and frustration would seem to correspond to this. The assertion move is used by AutoTutor to deliver information (e.g. RAM stands for random access memory.) This move should be used if the student is not able to reach a level of understanding to give this information before that point in the conversation. So AutoTutor asserts the information in an attempt to move on. According to the grounding criterion hypothesis, the high frustration level occurs because the student either could not establish the criterion with the AutoTutor program (as shown by the negative and positive feedback correlations) or the program moved on (as in the case of the assertion) before the student could establish the criterion.

Conclusions

It appears that there are significant relationships between the content of dialog and affective states experienced during learning. The current study found significant correlations between dialog and the affective states of confusion, eureka (or perhaps better viewed as delight), and frustration. These correlations were supportive of a grounding criterion hypothesis of dialog and emotions. However, more conclusive testing must be conducted to further test the validity of these links. If the grounding criterion holds, then it would give indications of how to help structure a dialog to generate the best interaction between emotions and learning.

The grounding criterion hypothesis received general support from our findings. If the observed patterns hold up to further analysis, the predictions of the grounding criterion hypothesis could be used to guide emotions during learning. For example, according to the grounding criterion hypothesis, the process of attempting to reach a grounding criterion will be affiliated with confusion. While the learners are in the state of confusion, the confusion could be prolonged by neutral feedback or remedied by hints from the system. Positive feedback is intended to acknowledge that the criterion has been reached. According to the grounding criterion hypothesis, the positive feedback should be associated with eureka, as our data demonstrates. By giving the assertion, the system is declaring the correct answer to the learner. This would be synonymous to the system asserting the critical content supporting the grounding criterion to the learner. As predicted by our hypothesis and supported by the data, this setting of a non-negotiated criterion should be associated with frustration. If a learner is in a state of confusion, then the learner can transition to other affective states based on the dialog moves chosen.

For the most part, it appears that the emotions experienced during interactions with AutoTutor are based on dialog moves moving on two dimensions. These are how direct the systems are with the user (e.g. assertions are direct whereas hints are indirect) and the type of feedback (positive feedback to negative feedback) given to the learner. The two scales seem to produce drastically different results in the emotions experienced during learning with AutoTutor. Our future research will investigate further the effects of these two scales on emotions experienced during AutoTutor interactions.

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