BUILDING AN AFFECTIVE COMPONENT TO ENHANCE AN INTELLIGENT TUTORING SYSTEM FOR SHIPHANDLING

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Abstract

Cognitive and learning theories that support Aptitude Treatment Interaction (ATI), Locus of Control, and self-efficacy suggest that a student's individual motivation, abilities, and self-efficacy are significant design considerations of instructional strategy. Specifically, the learning process would be optimized by dynamically evaluating the student's individual learning state during the training session, then adjusting the instructional intervention to increase the student's confidence and decrease anxiety. A model for dynamically tailoring instructional intervention in real-time based upon his/her individual learning characteristics and affective responses is proposed. This model describes the use of an affective component for such factors as anxiety, to be monitored and adjusted throughout the training session. The affective component interfaces with the instructor model to optimize the student-instructor interaction process (i.e. frequency of feedback, directive/reflective feedback, tone of voice). Data collection and evaluation is planned for the Conning Officer Virtual Environment (COVE), a prototypical shiphandling VE training simulator located at the Naval Air Warfare Center Training Systems Division. COVE's Intelligent Tutoring System (ITS) would benefit from the capability to provide real-time, tailored instructional intervention to the student for a variety of shiphandling tasks, students ranging from initial training for novice Ensigns to skill refreshment and mission rehearsal for expert shiphandlers, such as Commanding Officers (COs), Department Head Officers, and Division Officers. In addition, the model will be tested for the interaction of the CO with the junior officer for possible use as an affect feedback generator to the CO.

Biographical Sketches

Elizabeth Sheldon is pursuing a Ph.D. in Interactive Training Simulation at the University of Central Florida on a fellowship sponsored by the Office of Naval Research. Her research interests include human behavioral modeling and training design. Ms. Sheldon was a recipient of the 1999 I/ITSEC scholarship.

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Bill Walker graduated from Auburn University with Bachelor of Science Degree in Electrical Engineering. Currently, co-Principal Investigator on the Conning Officer Virtual Environment (COVE) project.

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INTRODUCTION

There is strong evidence that tailoring instructional feedback to individual differences will enhance training. Not only do individual differences constructs include cognitive factors, but also personality and affect. The Navy appears very interested in modeling such differences and tailoring instruction through the use of computer training systems that reduce the number of active instructional personnel required during a training session. The Virtual Environment Technology Testbed and Computer Generated Forces projects at the Naval Air Warfare Center Training Systems Division have joined forces to conduct preliminary research necessary for the development of an automated instructional system that can dynamically tailor instruction based upon the student s reaction to the system. Specifically, this research is intended to enhance the intelligent tutoring system (ITS) of the Conning Officer Virtual Environment (COVE), which is a prototypical, virtual reality ITS for training shiphandling skills to naval officers. This paper discusses the plans for developing an affective component, which will be interfaced with the COVE ITS, to detect changes in the student s reaction (i.e. behavior, affect, motivation, performance) during the training session and modify instructional feedback in real-time.

The objective of the COVE project is to demonstrate the capability of advanced technologies to provide a continuum of training (i.e. novice through expert) for shiphandling (i.e. underway replenishment, harbor transit, man-overboard, etc.) and reduce instructor intensiveness. Additionally, COVE demonstrates the capabilities virtual reality technology can offer to enhance shiphandling training, by providing a naturalistic training environment that reduces the costs and risks of training in the operational setting. Furthermore, the COVE project aims to provide evidence that advanced technologies can be employed to provide automated training capabilities on deployment (i.e. pierside, aboard ship) and in the training schools. COVE runs on a dual-processor PC and provides a 3-D ocean environment (Figure 1), developed with *PowerScene* (Cambridge Associates), which is viewed on a CRT monitor. The student position in the simulated environment is located on the bridgewing of a DDG-51, and the student surveys the environment by using a mouse to look around . The student controls the ship by issuing verbal commands for course and speed changes, which are recognized by BBN s *HARK* speech recognition system. BBN s *OMAR* human performance modeling tool provides the framework for the ITS. The ITS injects real-time instructional feedback based upon the student s performance. This paper discusses a project that is focused on enhancing the COVE ITS by providing real-time feedback based on the student s reactions (i.e. affect, motivation, behavior), during the training session, in addition to performance.

Preliminary data collected on COVE at the Surface Warfare Officer School (SWOS) used 18 subjects and found improved performance using the tutor over not using the tutor. Subjects were naval officers who had not yet gone to sea to command a ship, but who had classroom instruction. Both performance and satisfaction were increased with the ITS.

BACKGROUND

Individual Differences in Learning

Research on individual differences in student ability and rate of learning (Cronbach, L.J.,

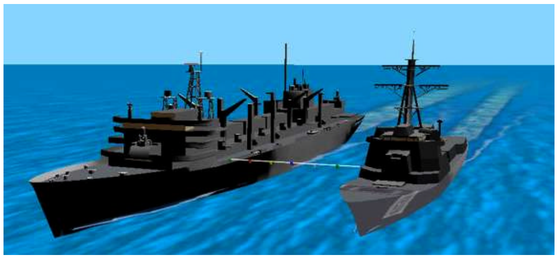

Figure 1. The COVE Environment.

1949; Ackerman, 1974; Gagne, 1989; Kyollen & Shute, 1989; Snow, 1989; Ackerman et. al, 1995; Emerson et. al, 1999) spans several decades. For instance, Cronbach s (1944) Aptitude-Treatment Interaction theory, which considers the relationship between specific instructional strategies and an individual s information processing abilities and personality traits, has served as the basis for much research in the area of individual learning differences (i.e. Ackerman, 1999; McCombs & McDaniels, 1983; Snow, 1989). Additionally, it has been suggested that personality traits have been associated with cognitive information processing abilities and that these abilities may provide a profile of an individual s strengths and weaknesses, with respect to learning new tasks (Ackerman, 1999). This research has provided supporting evidence that individual differences in cognitive and noncognitive (i.e. motor skills, self-regulation of motivation or stress, etc.) traits and abilities impact a student s ability to learn.

Self-efficacy (Bandura, 1997), which is an individual s belief in his ability to successfully complete a task, and its constructs (motivation, level of autonomy; personality traits, prior experience), have been acknowledged to affect learning and performance. External factors influence an individual s self-efficacy, and changes in self-efficacy affect an individual s motivation and behavior. For instance, teacher immediacy behaviors, which are communicative actions of the instructor aimed to decrease the psychological and physical distance between instructor and student (i.e. humor and self-disclosure), have been associated with increased student motivation (Christensen & Menzel, 1998; Noels, Clements, & Pelletier, 1999). An individual s perception of his ability to influence, or control, the outcome of events is another factor that affects student motivation and persistence in a learning environment (Noels, Clement, & Pelletier, 1999; Schunk, 1989). Bandura (1997) has also proposed that an individual s belief that his actions can influence the outcome of events is increased when the individual possesses self-regulatory skills, which enable him to filter non-productive external information and maintain task focus. Additionally, it is suggested that factors of student motivation and self-regulatory skills are predictive of the amount of knowledge acquired during the learning process (Ackerman, Kanfer, & Goff, 1995; Kanfer & Heggestad, 1999; McCombs & Whisler; 1989). Furthermore, there are noticeable individual differences in levels and strengths of self-efficacy, which vary depending upon the specific task that is being learned or performed. Therefore, it has been recommended that providing instruction tailored to the student s unique skills and abilities for the specific domain in context (McCombs and McDaniels, 1981; Snow, 1989; Hattie et. al, 1996; Alliger et. al., 1997) enhances the learning process. Since the vision of the COVE ITS is to provide automated instruction to a diverse population (novice through expert), the ITS will need to employ various instructional strategies, which differ not only in the level of complexity, but also in the manner in which the instructional intervention is provided. For instance, a novice student will require explanations of how his actions relate to concepts of hydrodynamic effects and relative motion, whereas an experienced conning officer will already have a mental model of the ship s responses and will benefit from less instructional intervention.

Emotions and Learning

It is not surprising that there also is evidence that emotional states affect the learning process (i.e. Balch, Myers, & Papotto; Forgas & Boser, 1987; Isen, et. al, 1978; Laird et. al, 1982; Lewis & Williams, 1989), as one of the learning variables previously discussed was the ability to effectively cope with emotional feelings and reactions (i.e. self-regulatory ability). For example, Bandura (1997) describes emotional self-regulation as an individual s ability to manage emotional situations through thought, action, and affect (emotion) regulation. Thought regulation refers to the individual s attentional bias, which influences the manner in which events are perceived, and the ability to control perturbing trains of thought that disrupt task relevant thought processes. Action regulation refers to an individual s behavior to change the environment, such that it has a positive influence on his emotional state. Furthermore, affect regulation is an individual s ability to lessen aversive emotional states, such as anxiety. Additionally Kanfer and Heggestad (1999, p. 297) suggest, learners with good emotion-control skills can maintain motivation and resist being side-tracked by self-blame or anticipation of negative consequences for performance failures while in the midst of task practice or training . Emotional responses can be the result of the student s self-efficacy, motivation, perceived autonomy, and current performance, which are internal processes. Finally, external factors, such as the instructor s communicative style, can affect the student s emotional state (Christensen & Menzel, 1998; Noels, Clements, & Pelletier, 1999). For instance, there is evidence that suggests instructors who are perceived as controlling contribute to student anxiety (Noels, Clements, & Pelletier, 1999).

In addition to emotional self-regulatory skills, personality factors (traits, characteristics) contribute to an individual s emotional response, and influence the learning process (Matthews, 1999; Rusting, 1999; Rusting & Larsen, 1998). For example, emotional responses may be attributed to mood management strategies specific to the individual s personality trait (Rusting & Larsen, 1998). It is also suggested that personality traits predispose an individual to perceive a situation in a specific manner. For example, there is evidence that extraverts exhibit reduced stress vulnerability and optimistic coping strategies (Matthews, 1999). Additionally, Spielberger (1966, p. 12) describes trait anxiety as individual differences in the extent to which different people are characterized by anxiety states and by prominent defenses against such states .

Student-Instructor Interaction

Communication between the student and instructor is influenced by the individual characteristics (i.e. personality traits, motivation, perceived autonomy, emotional state, skills and abilities) of both the student and the instructor. Bandura (1997) maintains that the student-instructor interaction influences students appraisal of their own capabilities. For example, crediting performance to ability provides a greater sense of student efficacy than crediting performance to effort. If credit for performance was first given to ability, the student often perceives that he is reaching the limits of his capabilities when the credit for performance is later given to effort. Additionally, Bandura recommends that providing instructional feedback on quality of the student s performance, rather than just amount of work the student has completed, increases student self-efficacy. Snow (1989, p. 44) suggests that the learning process can be viewed as the continuous reciprocal interaction between situation and person , in which the person factors are the student s perceptions and intentions, and the situation factors are the task domain and instructor feedback. McCombs and Whisler (1989) propose that instructors can positively affect student motivation by demonstrating interest towards the student, engaging the student in learning activities, providing positive feedback regarding the student s accomplishments, and encouraging the student to take pride in his accomplishments.

Implications to ITS Design

These are important issues to consider in the design of automated training simulations as student access to human instructors continues to decline. Human instructors are capable of determining whether or not a student is experiencing difficulty or boredom by observing the student s nonverbal communication (i.e. eye contact, sighs, facial expressions, posture, behavior, etc.) and verbal interactions with the student. It is important that an ITS have a similar capacity to dynamically evaluate student responses and use this information to modify the content or presentation of the instructional materials to optimize the student s use of the ITS. There have been many attempts to provide students with individualized learning environments, especially in the area of computerized and simulated training. For example, the Air Force Advanced Instructional System (AIS), a 1980 s computerized, text-based instructional system, was designed to provide instructional treatment to match student characteristics, task demands, situational factors, and alternative module design characteristics (McCombs & McDaniel, 1981, p. 16). The AIS tailored the presentation of instructional materials (i.e. visual presentations, organizational aids, explanatory feedback) based upon the individual student s cognitive abilities, level of trait anxiety, and level of trait curiosity. Results obtained from comparisons of students taught with either the modified instruction or generic (traditional) instruction indicated that the students who learned with the modified instruction performed better on learning assessments (McCombs & McDaniel, 1983; McCombs & McDaniel, 1981). However, McCombs and McDaniel (1983) suggested that the benefits of tailored instruction could be greatly extended through continued research and development. For instance, dynamic evaluation of the student characteristics to support real-time modification of the instructional presentation would provide flexibility and variation in instructional strategy as opposed to static, predetermined instructional interventions.

More recently, synthetic agents, often referred to as pedagogical agents, have been used to role-play the instructor in automated instructional applications. Johnson (1999) suggests that pedagogical agents can make a contribution to computer based learning because they provide a believable, lifelike representation to the student and can stimulate interest in learning. Rickel and Johnson (1999) suggest that in order for a pedagogical agent to effectively provide instruction, it must be able to convey and elicit emotion, and adapt instruction in real-time.

Rickel and Johnson (1999) have developed Steve (Soar Training Expert for Virtual Environments), which is a 3-D pedagogical agent for a VR ship maintenance training application, and Adele, which is a 2-D pedagogical agent used in a desktop family medicine instructional system. During a training session, Steve monitors the student s attention via a head-tracking system and interacts with the student in response to his actions (Johnson, 1999). Although Steve is able to react to the student s behavior in real-time, it does not always provide the correct response. The capability to obtain further information regarding the student s state (i.e. facial expression, vocal expression, gestures) and to make an appropriate response would greatly extend the Steve application. Adele is a 2-D agent, with scripted behavior, that provides hints or concrete answers based upon the student s progress. Additionally, Adele provides emotive gestures such as a frown when the student errs or showing a smile of satisfaction if the student answers correctly (Johnson, 1999). Again, although Adele can make appropriate responses based upon situational factors, it does not dynamically interact with the student or account for the student s emotional state. For instance, if Adele frowned at a student who did not understand the topic of instruction and was becoming stressed, the student s level of stress would most likely increase. However, if Adele, could respond to the student s stress level (i.e. smile of encouragement, offer assistance) the student would receive necessary guidance, and, most likely, the student s stress level would decrease. Other examples of pedagogical agents include three, 3-D agents developed at North Carolina State University for use in a desktop setting, which are Herman the Bug, Cosmo, and WhizLow (Rickel & Johnson, 1999). Emotional interaction between agent and student is currently implemented as the agent s response to a situation or event, rather than the student s emotional state. Rickel and Johnson (1999) report that the instructional applications with pedagogical agents demonstrate significant improvements in learning. Furthermore, they suggest that research into emotional modeling of the student is needed for the realization of truly interactive learning environments.

Emotional Modeling

Although notions on affect have been widely recorded in the psychology literature, as cited above, implementation in an automated training system has had to wait for technology to advance. A recent advance in technology is the concept of affective computing, which refers to computer systems that detect and respond to the emotional state of the user (Picard, 1997). Picard s affective computing research (1997) is based on the assumption that emotions can be identified through two constructs, as a discrete set of emotional types (Eckman, 1993; Eckman, 1992) or continuous dimensions of emotional state, such as arousal and valence, initially proposed by Schlosberg (1954; cited in Picard, 1997). Picard (1997) suggests that different applications may be better suited to one or the other emotional constructs, with applications requiring personal feedback utilizing the discrete construct and group-oriented applications adopting the continuous emotional construct.

Picard (1997) suggests that there are three levels of emotional processing: low-level (physiological), mid-level (behavioral), and high-level (cognitive). Low-level affective computing systems infer the user s emotional state from the user s physiological signals and external events. The physiological signals typically used (Picard, 1997) are electromyogram (muscle contraction), blood volume pressure (blood flow), and galvanic skin response (skin conductance). More recently, Vyzas and Picard (1999) have demonstrated the use of respiration and heart beat signals. Picard (1997) suggests that affective signals have the following properties: response decay, repeated strikes, temperament and personality influences, non-linearity, time-invariance, activation, saturation, cognitive and physical feedback, and background mood. Furthermore, she proposes that affective signals, external events and physical signals, can be modeled by categorizing inputs as positive or negative and filtering the sum of the positive and negative inputs with a sigmoid function.

Examples of affective computing applications are computers that respond to user frustration (Klein, Youngme, & Picard, 1999), computerized measurement of driver stress (Healey, Seger, & Picard, 1999), and wearable computers (Picard, 1997), which communicate the user s emotional state to the computer. Furthermore, Picard and Cosier (1997) have suggested that affective computing technology could enhance the learning environments of computerized training applications. If an ITS had the capability to detect the student s emotional state, the ITS could respond (i.e. provide instructional feedback) in a manner that would ameliorate a negative emotional state or sustain a positive emotional state. In the case of the COVE ITS, if the shiphandling student becomes frustrated with the task, the tutor could provide encouragement and attempt a different approach of instructing the student (i.e. use of metaphor to explain the ship dynamics, instructing the student where to look, etc.).

Thus, the traditional arguments against the use of affect in automated training systems may now be overcome with this advanced technique. The next step is to overcome the perception that affect is too subjective for use in an objective training system.

METHOD

Affective Component

A model (Figure 2) was constructed to illustrate how the learning variables supported by the previously discussed individual differences research can be integrated to enhance the COVE

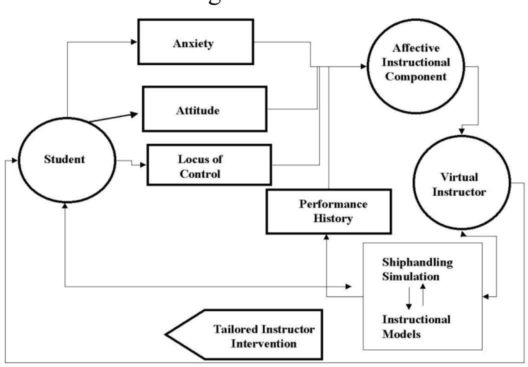

Figure 2. Model of Student Learning Variables.

ITS. The model shows that the affective component dynamically receives input of the student s current state of anxiety (affect), attitude (motivation), and locus of control (perceived level of autonomy). This information is sent to the affective component, which uses this data to develop a model of the student s affective (emotional) state. Then, the affective component provides the ITS with directions for using a specific type of instructional intervention (directive, reflective, social), which is optimized for the student s affective state. The ITS uses this input to generate the instructional feedback that would be presented to the student.

COVE data collection, using self-answer survey on user acceptance, revealed a stated degree of frustration with the technique employed in providing feedback to the student. Thus, there appears to be empirical evidence for the efficacy of evaluating affective components of automated training using the COVE system.

Instructional Intervention

The purpose of integrating the affective component with an ITS is to tailor instructional feedback, based upon the affective state of the student. Therefore, one of the first steps in this process is to determine what type of feedback will be provided to the student and how this feedback will be modified. The COVE ITS employs a combination of visual (i.e. highlighting visual cues, plotting an ideal track) and verbal (i.e. directive or suggestive) feedback. The literature on individual differences in learning clearly supports the idea that individuals have preferences for various types of feedback. For instance, some students may prefer verbal explanation, while others prefer to observe an expert performing a task. Additionally, there may be differences in student preferences for the level of intervention (frequency of feedback) and type (explanation, direct answer, suggestions). VE applications, such as COVE, support interaction for several modalities (visual, aural, haptic, proprioceptive), and the use of these various forms of interactions can be enhanced with appropriate matching of interaction type with the student s traits and abilities. For the purposes of this study, verbal feedback is the only type of instructional intervention that will be manipulated, in an effort to ensure the study has sufficient controls. However, the authors feel that exploration of multiple modalities should be the focus of future investigations.

Affective Measurement

The integration of the affective component with the ITS also involves the identification of the student s affective responses. There has been extensive research regarding the development of techniques (physiological measurement, behavioral observation, vocal and facial expression recognition) that can be used to identify emotional expressions.

There has been much investigation into the identification of measures of physiological expressions of emotion. These measures include skin conductance (i.e. galvanic skin response), electromyogram (EMG), and electroencephalogram (EEG). Skin conductance is a measure of electrodermal activity (EDA), which is the electrical activity of the skin (Fowles, 1986, p.52). Additionally, skin resistance responses (SSRRs) have been reported to detect the emotional arousal to a stimulus (Cacioppo & Petty, 1986). EMG is a measurement of muscular tension, which is obtained by placing electrodes on the shoulders, or jaw, and recording the electrical activity (Picard, 1997). Cacioppo and Petty (1986) suggested that EMG is associated with effort put forth on the task (Cacioppo & Petty, 1986), and Picard (1997) has reported results indicating that EMG is reflective of anger. EMG measurements have also been used to evaluate facial expressions in response to happy and sad stimuli (Scherer, 1993). Another physiological measurement that has been used to identify emotional responses is the EEG, which is a measure of brain activity. For example, unresolved stress creates central nervous system (CNS) activity patterns of stress response (Levine, 1986), which can be measured via EEG. Additionally, Scherer (1993) suggests that measurement of event-related, or evoked response potentials (ERPs), which can be obtained with the EEG, may enable examination of the synchronization of emotional processes. Other physiological measures of emotional response include heart rate (HR) and respiration (Cacioppo & Petty, 1986). Psychophysiological measurement typically involves the use of more than one physiological signal. Cacioppo and Petty (1986) suggest that the use of a combination of psycophysiological measures, such as SC and facial EMG, will provide more conclusive results than using either measure alone. There appears to be controversy regarding the acceptance of these various measures. The use of physiological measurements necessitates preliminary testing in order to ensure that the measures are reliable and valid. However, once a particular measure has been validated, a possible implementation would be to evaluate an individual s affective response to a given situation.

Observable behaviors (i.e. pupillary response, startle eyeblink, facial expression, vocal expression, etc.) have also been used to identify emotional expression. Pupillary responses have been used to evaluate attitude responses, such as using pupil dilation as an indicator of negative and positive reactions. There has been some reported unease with this measure that the dilation could be attributed to other factors, such as wave-length (Cacioppo & Petty, 1986). The startle eyeblink reflex is a behavioral measurement that compares the length of the blink reflex for an acoustic stimulus that is presented alone or precipitated by prepulse acoustic signals. Researchers (Vanman, Dawson, & Brennan, 1998) suggest that the eyeblink reflex is affected by emotional response. Scherer (1986) has obtained evidence that facial and vocal expressions are indicative of the emotional cognitive appraisal process. Additionally, Eckman (1993) also reports evidence that facial expression recognition is a valid and reliable means for measuring emotional responses. Finally, self-report of emotional state has often been used in conjunction with a behavioral or physiological measurement. However, self-report of emotional state is often inaccurate (Cacioppo & Petty, 1986; Schwartz, 1986). For instance, an officer in the Navy is not likely to report that he is anxious or nervous during a training session because he may feel that there would be negative consequences if he expressed those types of feelings.

It is obvious that some of the above measures may not be appropriate, depending upon the target application. For instance, Picard (1997) has developed an emotional sensing system, which utilizes SC, EMG, respiration, and blood pressure volume (a measure of HR) to detect response patterns for basic emotions, such as anger and happiness. Additionally, she has used a combination of self-report and physiological measurements for identifying emotional responses. Although these measures have worked well in a laboratory environment, physiological measurement may not be feasible in a training environment, especially if the training system is to be used in an operational setting, due to the inconvenience electrodes and additional wires may create. Additionally, in order to determine emotional changes during the training sessions, the student s emotional state must be measured in real-time. Self-report may result in an interruption in task performance and may be perceived as an annoyance by the student. Again, self-report is not considered a valid and reliable measure (Cacioppo

& Petty, 1986; Schwartz, 1986). Considering the COVE ITS, an intuitive measure of affective state is vocal expression recognition because the student interacts with the system via speech commands. Although the computations involved in the analysis of vocal expression variables are complex (i.e. analysis of frequency, pitch, amplitude, etc.), it is feasible that the evaluation of significant changes of vocal expression variables (i.e. change in affective state) is possible in real-time (Dellaert, Polzin, & Waibel, 1996; Scherer, Johnstone, & Banziger, 1998). Facial expression recognition technology is not, as yet, as advanced as vocal expression recognition, however, the outlook for real-time facial expression recognition in the near future is positive (Cohn & Katz, 1998). This technique could also be easily utilized with the COVE ITS, through the simple addition of a camera that could be attached to the computer monitor that is viewed by the student.

The techniques under consideration for the measurement of the student s affective state in this study are physiological measurement (HP, EDA, blood pressure) and the rate at which the student requests help from the ITS. As the technology for physiological measurement devices is mature as compared to vocal or facial expression recognition technology, the physiological measures are being considered as a means to validate the vocal and facial expression measures. Additionally, one of the goals of the first study is to develop objective measures of the student s affective reactions to instructional intervention, with the expectation that the measures will be indicative of a positive, negative, or neutral reaction to the instructional intervention.

In order to differentiate between positive and negative affective responses, instruction will be modified according to the student s personality type, specifically extrovert or introvert, via paper-based testing. It has been proposed that extroverts and introverts prefer specific environmental and social characteristics. For instance, extroverts prefer dynamic, variable environments with a high rate of social interaction, whereas introverts prefer low-information flow environments and reflective problem solving (Matthews, 1999). Therefore, the appropriate instructional feedback for the extrovert personality type will occur frequently and vary (directive, social, guided), and the appropriate feedback for introverts will be less frequent and reflective. Additionally, as the purpose of the measurements is the identification of a change in the student s affective state, the measurements described above will be analyzed for variance in response, rather than closeness to a predetermined value.

Thus, it appears that we can overcome two traditional arguments against use of affective components in training systems. Also, we have tested COVE and found evidence for frustration in certain people during certain feedback sessions. It therefore appears that 1) we have identified techniques for computer recognition of affect, from the discussion of affective computing, above, and 2) we have also found objective measures of affect, from the subsequent discussion, above. These findings appear to warrant a more comprehensive treatment of affect and its modeling.

COVE ITS Integration

Figure 3 depicts the data collection procedure for the objective measures of student affective responses in COVE. The following describes a more comprehensive treatment of affect in automated training systems, in order to validate our preliminary findings. Paper-based testing (i.e. NEO PPI, Myers-Brigg) will be used to classify the participants as extroverts or introverts. Additionally, a baseline will be obtained for each of the objective measurements (i.e. physiological &

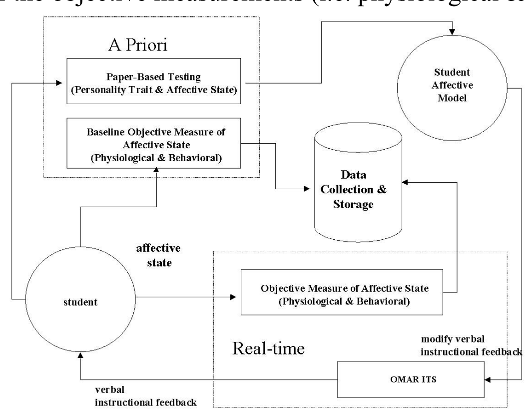

Figure 3. COVE ITS and Affective Component.

behavioral). The baseline measures of the student s affective state will be sent to the affective component to construct a model of the student s emotional state. The personality measures will be used to preset the ITS to provide responses optimized for either an extrovert or introvert. There will also be a condition in which the participant is given feedback that is opposite of their personality trait in order to obtain measurement of negative affective response (assuming that the matched type-intervention group exhibit greater positive affective responses). The physiological and behavioral measurements discussed in the prior section will be recorded and analyzed as a regression equation. The results of this study will provide a regression model, which can be used to identify the student s affective response.

CONCLUSION

This paper presented a method for developing objective measures, which can be obtained in real-time, to identify student reactions to instructional intervention during a training session with the COVE ITS. The measures will reflect significant changes in the student s physiological and behavioral processes, and can be used by COVE to determine the appropriate instructional feedback to provide to the student. Although the instructional feedback used in this study will be modified according to the results of a paper-based personality test, the goal is to use the resulting objective measures in lieu of paper-based tests. Therefore, COVE instruction can be tailored based upon the student s responses during an individual training session, rather than being fixed

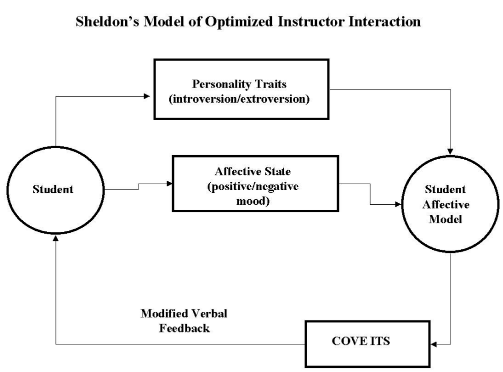

Figure 4. Real-time Measurement of Student Affective Response.

according to the student s traits. Figure 4 is a depiction of the process of evaluating the student s reactions and modifying instructional feedback in real-time with the COVE ITS, based upon the student s affective responses.

The applications of this methodology extend beyond the COVE demonstration. With the use of virtual environment technology, the affective component could be used to tailor instructional feedback for various modalities, such as visual presentations, aural cues, or haptic demonstrations. Furthermore, the affective component could be integrated with a behavior model for a 3-D animated agent to improve the believability of the agent. Finally, this technology can be extended beyond an ITS, to dynamically modify most computer interfaces to optimize an individual s interaction with synthetic workspaces (i.e. databases, web-searching, word processing, etc.).

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