Modeling Emotions in Simulated Learning

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Abstract. This paper presents an overview of the COVE model, a computational model of learning that integrates models from *Cognitive* science, the *OCEAN* model of psychology, *OCC* model of emotions, *Visual-Auditory-Kinesthetic* perception and the *Environment* (social and physical expectations). The model enables software agents in an example application – simSchool - to possess some of the emotional, psychological, physical, cognitive, and social behaviors of classroom learning. These characteristics enable the representation of behaviors of students in formal learning environments and allow simulation of theories of instruction and learning that are proving useful in teacher education.

Keywords: emotion modeling, cognitive modeling, simulation, computational learning theory

1 Introduction

Typologies have arisen to describe a wide variety of classroom learners in terms of physiological and psychological factors, and how differing forms of intelligence arise in cultures and communities of practice [1, 2]. Learners have psychological, physiological and cognitive preferences and capabilities and these characteristics shape the way they learn. Integrated with these conceptions and refining them, layered approaches to cognition have been discussed by neuroscientists [3, 4], psychometricians [5-7], cognitive scientists [8] and computer scientists [9-11]. For example, Bruner [8] discussed cognitive development using a three-stratum framework of “enactive, iconic and symbolic” and Carroll’s [7] factor-analytic model defined three layers as “narrow, broad, and general.” These layered models have in common the idea that learning progresses from specifics negotiated at a “lowest level” active layer interfacing with the environment, to generalities synthesized from abstractions at higher levels.

The COVE model embodied in the simSchool application reflects this knowledge base by integrating concepts and frameworks from cognitive science, psychometrics, individual and social psychology, studies of perception, and the learning environment. The computational model enables software agents posing as students in a simulated classroom to possess dynamic descriptions of the emotional, psychological, physical, cognitive, and social aspects of learning, which undergirds the simSchool simulation of theories of instruction and learning. In the domain of classroom learning, the model simulates what it is like for each student to have a physical and emotional experience [12] as a processing backdrop for learning. The COVE framework is capable of representing a wide variety of learners, how learning can occur within an agent, how the agent can be aware of others as well as the environment of learning, and how feedback from the simulation user can shape the agent's experience.

COVE uses three layers to organize the internal variables of the learning personality and one layer to represent the external context of learning (Figure 1). The E layer is the external environment, which in a classroom includes the task set before a student by the teacher and things the teacher might say to the student, as well as what others in the class say and do in reaction to the same stimuli. The V layer is the visceral, early-stage physical and pre-emotional processing stratum. The O layer contains the emotions and other pre-conscious processing, and the C layer contains conscious processing.

Other agent models discussed below focus on virtual responses in action-oriented environments (e.g. how an agent might act on a battlefield, choose from among options, or enact a story narrative) in contrast with COVE, which focuses on a learning environment. However, most share the approach of representing emotions in an artificial intelligence agent using a computational engine to cognize the world in terms of the place, role, decisions, attitudes and goals of the agent. The simSchool application models classroom-based teaching and learning using the COVE framework and has shown promise for impact and scalability in teacher education [13].

2 C – Complex Cognitive Characteristics

The term "cognitive" is used to mean the components of intelligence in the "C" layer that are neither the purely physiological nor purely emotional-psychological components, even though we think along the lines of Carroll (1966) that all the layers are equally "cognitive" in the sense that information processing and action decisions are taking place.

There are several widely varying theories of intelligence that could be used as a foundation for computationally modeling the higher cognitive characteristics of learning. See [14] for a review of several models, which might be classified into either hierarchical factor-analytic (e.g. Spearman, Thorndike, Thurstone, Vernon, Cattell, Horn, Carroll), or structural-functional models (e.g. Guilford, Campione, Brown & Borowski, Sternberg, Gardner, Ceci, Piaget). The COVE model uses a modified psychometric approach based on the factor-analytic model proposed by Cattell-Horn-Carroll (the CHC theory of intelligence), which has been validated and is widely used to understand cognitive abilities. COVE also uses a blend of the structural-functional theories, which are needed to fully model the holistic context of the learning framework. The "C" layer of the COVE model utilizes 6 of the 16 CHC factors to model conceptual knowledge (Figure 1): general storage and retrieval (Gc, Glr, Gkn); and specific storage and retrieval abilities (Gq, Grw, Gp). The "O" layer of the COVE model utilizes five CHC factors involved in processing and reasoning (Gf, Gs, Gt, Gps, Gsm). The "V" layer of the COVE model includes the five factors related to sensory perception (Gv, Ga, Gk, Go, Gh).

For each factor, the COVE model adopts a representation as either a bipolar continuum of qualitatively different capabilities or a combination of a threshold with a qualitative continuum. For example, in mathematics, computation can be represented as a skill continuum where low positions on the scale represent basic arithmetic skills and high positions represent abstract or symbolic computations of higher orders. The number of positions on each continuum is selected to balance computational flexibility with representational accuracy (e.g. typically from five to twenty in the simSchool application). The choice of number of levels and factors increases the computational possibilities and challenges for modeling. A fully connected 16 factor cognitive model with 5 levels on each factor has 5^16 connection possibilities.

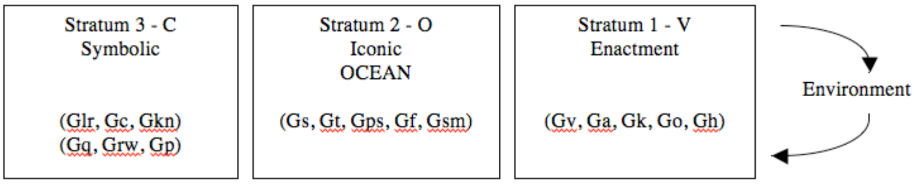

Figure 1. COVE model of cognition integrating the CHC theory of intelligence

Fortunately, evidence for simplifying the number of relationships through layering and hierarchical networks is available from intercorrelation data among the broad factors [15]. For example, for people aged 14-19 who took part in the development and standardization of the Woodcock-Johnson III, comprehensive knowledge (Gc) was .62 correlated with fluid reasoning (Gf) but only .37 with processing speed (Gs). This suggests that there may be a closer relationship between Gc and Gf. In addition, structural and functional considerations suggest a narrowing and channeling of the factors. For example, perception usually precedes cognition and the consolidation of long-term memory is facilitated by emotional arousal [16] implying that the layers handling perception (V) must link with emotional and psychological layers (O) before linking with long-term memory and crystallized knowledge (C). These kinds of considerations lead to a hierarchical and time-based model consistent with Hawkins' [17].

3 O - Emotional & Psychological Characteristics

The "O" layer is an interface between intelligence and personality in which one's psychological make-up is dominant and involved in basic central information processing mediated by emotions. Following Ortony, Clore, and Collins [18], the "O" layer assumes that emotional reactions developing during the appraisal of a situation influence performance. The COVE model is a componential theory of perception, emotion and cognition with continuous factor subcomponents, which thus treats emotions as a large number and wide range of preconscious to conscious states that result from several subprocesses; similar in spirit to Russell's continuous two-factor model [19], but with a core of 9 factors in its present state.

Individual psychology or personality theory in COVE utilizes the "Five Factor Model of Personality," "Big Five," or OCEAN model [20, 21]. OCEAN stands for Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism. Each factor has an opposite (e.g. the opposite of Extroversion is Intraversion). The OCEAN taxonomy encompasses several important psychological characteristics of learners and is represented by a continuum. The end of each continuum has maximum value in a variable or its opposite.

As an example, in simSchool, the OCEAN variables are set on a scale from –1 to 1, with 0 at the midpoint, which allows the software agent to possess emotional valences and base its behavior on a range of possibilities. SimSchool divides the scale into .1 units, giving 21 positions from –1 to 1 (e.g. –1, -.9, -.8 … .8, .9, 1). This gives the "O" layer of the agent learning model a mathematical possibility of representing 21^5 or over 4 million OCEAN emotional personality states. The SimSchool application (www.simschool.org) narrows the descriptions of these possibilities by grouping the factors into 5-position narratives, representing clusters near –1, -.5, 0, .5 and 1. This provides 5^5 or 3125 emotional personality descriptions, which provide the user with clues about the underlying 4 million actual states, in "student records" that a user can read in the role of playing the teacher of a simSchool class. The narratives are dynamically assembled from a database to create each unique personality and are presented to the user on demand as well as during the course of a simulation. This method of representing pre-conscious states that overlap with unconscious emotional states results in a higher number of "emotions" than in other models. Links between the COVE model and categorical models of emotion have not yet been developed.

Linking the OCEAN to CHC (Figure 1 and 2) has been proposed by Chamorro-Premuzic and Furnham [22] based on correlation evidence from studies of subjectively assessed intelligence (SAI). An example of SAI is a student who has often failed tests, which leads the student to an expectation to fail a future test, and thus lowered performance on the future test influenced by his or her appraisal. Citing a number of studies, Chamorro-Premuzic and Furnham propose that SAI mediates between personality, intelligence and performance, and list a number of correlations noted by researchers, including:

- Personality traits are significant predictors of academic achievement
- (Gf) and (Gc) are both positively correlated with performance
- Openness (O) is positively correlated with intelligence
- Conscientiousness (C) is a positive predictor of performance
- Extraversion (E) is positively correlated with intelligence which is assumed to be due to higher speed of response (Gs, Gt, Gps) and lower arousal (N-)
- Neuroticism (N) is a negative predictor

The COVE model links OCEAN to CHC at the "O" layer reasoning that OCEAN is more complex than receptor-based perception at layer "V", and more immediate but less complex than conceptualization and long term memory at layer "C." In addition, following Eysenck and Eysenck [23] who suggested that SAI should be considered a part of personality rather than intelligence and Chamorro-Premuzic and Furnham [22] who note the "considerable conceptual overlap between the concept of SAI and Openness" (p. 256), the COVE model layer "O" situates psychology, emotions, and reasoning fluidity (Gf) to fulfill the SAI appraisal function.

The correlation evidence and structural-functional considerations lead to a model of "O" that includes causal precedence in the incoming signals from the environment

(Figure 2). Intercorrelation of Neuroticism and Extroversion with Openness, Conscientiousness and Agreeableness is suggested based on neurophysiological evidence from animal and human studies that posits two large clusters: (1) Extraversion, Exploration, Novelty seeking, Sensation Seeking, Positive Affectivity and Impulsiveness, versus (2) Neuroticism, Anxiety, Fearfulness and Negative Affectivity [24]. The two large E & N clusters are mediated by independent neurobiological mechanisms (e.g. catecholamines, dopamine and norepinephrine for E; and the amygdala and the benzodiazepine / GABA receptor system for N). The arrows in Figure 2 all represent positive correlations.

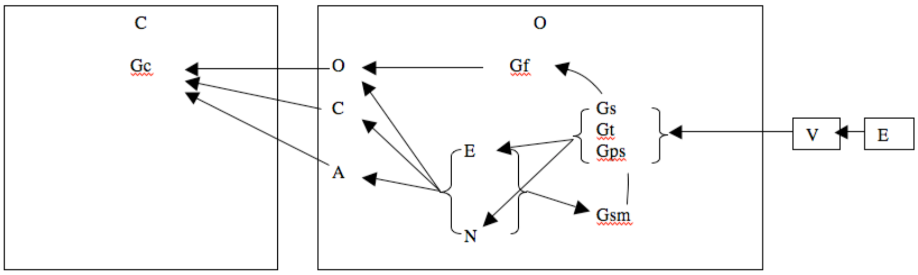

Figure 2. Linking CHC to OCEAN variables

The COVE model is an attempt to describe the contents and the mechanisms of environmental responsiveness, information processes, emotions and thought, but much work remains to be done. For example, the pathways in Figure 2 focus on the "incoming" signals leading to crystallized knowledge; however, returning pathways from pattern formation, recognition, beliefs, and decisions to intentions and action exist at every level too. The simSchool application creates a simple mapping of current state to the mechanisms that update the state over time and the externally supplied goal of responding to the environment. Appraisal of a situation is an unconscious process that in simSchool takes place in 9 dimensions (3 V-layer, 5 O-layer, 1 C-layer) and results in behaviors that become visible to the player. The simSchool model developed to date narrows the focus of appraisal to that of learning-task performance (objects in the environment), teacher conversations (agents in the environment) and the evolution of both of those influences in sequences (internal as well as external events in all layers).

The arrow in Figure 2 from the E to N subcomponent sends a reentrant signal within the O layer via short term memory (Gsm) to the (Gs, Gt, Gps) cluster dealing with processing and leading to flexibility (Gf) and Openness. This mapping allows for reinforcement learning as well as cyclic reappraisal [25]. In addition, with the addition of returning pathways that would provide internal situational content [26], the mechanism described by Lahnstein [27] can be supported, where the onset and decay of an emotive episode is shaped by dynamics of interactions with previous states. Finally, the reentrant loop also introduces time and time delay into the mapping, without which Figure 2 would be a primarily feed-forward network.

There is a need for further development of mappings to higher levels of abstraction, as plausible linkages become known consistent with the biological, cognitive science and psychometric evidence in the COVE model. Constructs from other models of emotion-based behavior could then be added presumably as aggregations to the model, such as Beliefs, Desires and Intentions (BDI) [28-30] and Disposition, Emotion, Trigger, and Tendency (DETT) [31]. Comparing these with the COVE model, the "O" layer should include links or clustered relationships to Desires and Intentions (Beliefs are perhaps a longer-term object of memory and belong in the "C" layer) and to all but the "Triggers" in the DETT model (which would perhaps come from the "V" layer) indicating that additional work is needed to integrate these higher-level constructs with the CHC-OCEAN level of abstraction at the "O" layer. The BDI, DETT, OCC and other models are discussed further below.

3 V - Physiological Characteristics

The physiological characteristics involved in learning entail both sensory (afferent) and motor (efferent) neural pathways. While learning is sometimes thought of as primarily the organization of incoming sensory signals, recent work in artificial intelligence and robotics as well as constructivist learning theories suggests that pre-motor and motor systems - the body's exploration and action in the world - plays a major role in the development of intelligence [32]. The "V" layer concentrates on the sensory components of learning. In the simSchool engine, only (Gv, Ga, Gk) are used since those are more typical in classroom learning.

In these physiological or "V" variables, unlike the bipolar "O" psychological variables, there is the possibility of a complete absence of an input pathway, such as in blindness or deafness, thus the use of a threshold level in addition to a range of ability or preference. The concept of preference is useful for connecting the model to "learning styles theory" [33, 34] and that of ability is useful for connecting to theories of intelligence. For example, if someone is not blind, then to what extent do they tend to favor or prefer to organize learning through the visual pathway?

4 E – Environmental Characteristics

The "E" layer of Environment variables in the COVE model includes learning tasks that involve the nature of knowledge (objects), interpersonal relationships and expectations states theory [35, 36] (agents) and the effects of sequences of interactions (events). In a recent review of learning theory [37], environment also includes "community," which reflects the social context of learning and the feedback role of external "assessment." In addition, some aspects of the nature of knowledge itself are external to the individual learner, namely objective reality. The COVE model is thus evolving to contextualize cognition as a social, cultural, and psychological interaction of internal and external factors, not solely as an "information processing" or "knowledge acquisition" problem of an individual.

5 The COVE Model in Practice: simSchool

In 2003 with funding from the U.S. Department of Education, simSchool was created to simulate a classroom, with the user in the role of a teacher. An agent model of learning was developed and put into practice, which has led to the COVE model. This section will provide details about the computational and representational implementation of the COVE model in simSchool's simulated students.

The details of how simSchool works - how the simulated students respond to tasks and teacher talk - have been detailed elsewhere [38-42] and is only briefly outlined here in order to focus on the COVE model in practice. In brief, simSchool uses a dynamic modeling approach in which the user is a teacher who is an independent actor that chooses tasks and talking interactions, which in turn act as attractors for the simstudents. The artificial intelligence driving each simulated student is a 9 dimensional hill-climbing algorithm; each student will attempt to reach equilibrium by attaining the goals of a given task if the task and setting do not impose too many barriers and the system is not perturbed by any other user actions. The time it takes simstudents to reach equilibrium with a task is determined by how their personality variables (V-layer physical, O-layer emotional and C-layer cognitive variables) interact with the requirements of the tasks and the teacher's talking choices.

The simSchool user faces a classroom with from 1 to 18 software agents that simulate students, each of which has a COVE model personality in an initial condition. Future plans call for additional variables, including swappable sets of variables for different simulation purposes, such as teaching a specific level of a mathematics class. Settings on the 9 dimensions determine the initial conditions of the agents at simulation start time. Two environmental conditions – classroom tasks and teacher talk - can be independently selected by the user in the E layer and operate as attractors toward which each dimension within each agent is pushed and pulled over time. Tasks operate as long-term goals, and teacher talk acts as short-term pulses of influence in the environment. The structure of the E variables is 1:1 with the 9 dimensional personality model, based on the idea that the cognitive load [43] of learning during a class is related to the emotional-cognitive requirements of a classroom task as well as the emotional-cognitive impacts of a teacher's speaking to a student before, during or after a task.

For example, the task of "working with a peer to design a hypothesis" has a 9-dimensional representation signifying the requirements needed to succeed with that task. An agent's personality current state or profile is then compared with the task's profile and is updated every 10 seconds during a simulation. Incremental changes in each variable are computed based on an underlying set of rules, which relate the agent's variables to each other as well as the target. The rules embody an overlapping set of theories related to the learning sciences that include the zone of proximal development (ZPD) [44], cognitive load theory [43], circumplex theory [45] and a theory relating circumplex theory to the OCEAN model [46]. For example, to embody the ZPD, if the task goal on a dimension is too far above the agent's current state, the update of that variable in the agent is minimized and might be zero; a goal that is closer to the agent's current state causes a larger increment in the update and thus faster learning.

As the rule set updates the simulation state and causes the agent personality to evolve, external behaviors of the agent give clues to the user. The student might sit up straight and appear to be listening, or go to sleep, or begin talking to a neighbor agent. If a student completes a task, but others are still working, that student might get restless or bored. In a large class, a student with an agreeable personality who is not making progress might not draw the attention of the user, while an extroverted student who is learning might appear to be off task bothering others. Agent behaviors include phrases spoken in cartoon bubbles, and body positions at the desks, an admittedly narrow range of options. So additional visualizations of internal states are presented that provide status information about the "speed of learning," "degree of completion of the current task," "state of efficacy concerning the task environment (power)" and "state of affiliation concerning the task environment (happiness)."

The time-course of evolution of a classroom of agents is a complex landscape of behaviors all of which are traceable to the decisions made by the user concerning which task and whether or not to talk, to whom, at what times, and whether or not to give different tasks to different students during a class period. This gives the simulation a wide range of behaviors that mimic real classrooms.

The user analytics of a session are based on the running record of decisions and the impacts those had on each agent. An inductive network representation application called Leverage runs on the database of all simSchool events, attributes and queries and sets the weights of networks that represent user experiences with the application [47]. Events are any operation of any algorithm during a simulation; attributes are metadata about those events, and queries are rule sets that describe combinations of events and attributes of interest for additional processes such as analysis, adaptive behavior of the application, and displays. One such visual representation of the simulation is a graph over time (Figure 3). The Leverage engine also currently supports 10 million users of an online massively multiplayer game called "America's Army," and is being readied for similar scalable simSchool deployment for improving the recruitment, preparation, induction, mentoring and professional learning of teachers worldwide.

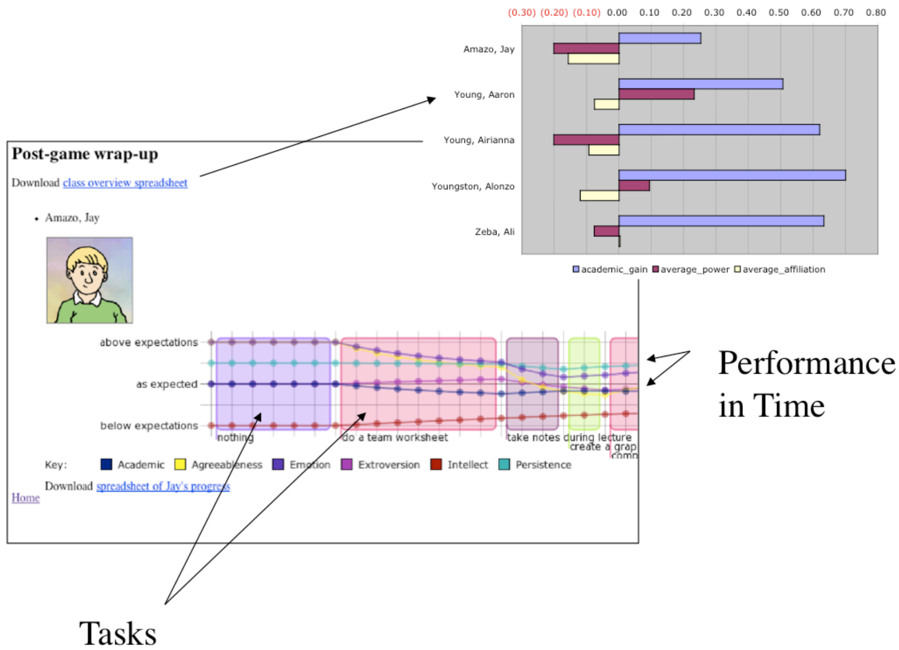

Figure 3. Time-based visualization of a simSchool session.

SimSchool has been evaluated in several ways: expert review, impacts on users, and a comparison study that validated some of the model's strengths and found some weaknesses. The comparison study was the subject of a doctoral dissertation in which five agents were created that matched the profiles of five real students, each with a specific learning disability. The study found strong validation of the shape and directionality of the model compared with real students, but also found that real students appeared to learn more than the simulated students indicators showed. It is possible this result was due to a ceiling effect of the ranges that maximize at 1. Expert reviews [40] have thus far indicated that the model effectively represents important aspects of classroom learning, and measured impacts on users has validated that time spent with the simulator results in increased teaching skills, sense of efficacy as a teacher and strengthened belief that the locus of control for learning rests in large measure with choices of the teacher [13].

6 Alternative Agent Models

The Brisbane Model

A research group in Brisbane [48, 49] uses an abridged version of the Big Five (AB5C, see [46]) and a story-boarding interface to facilitate the personality and emotion control of the body language of a dynamic story character. Game and simulation designers can devise a story context, which their engine then uses to predictably motivate personality and emotion values to drive the appropriate movements of the characters. In the Brisbane model, personality, emotion, self-motivation, social relationships, and behavioral capabilities are taken into account together. The Brisbane method of dealing with the OCEAN variables produces 32 personality combinations that provide descriptive lexicons for their computational personality model.

The research-based lexicon of personality terms used in the Brisbane model is defined by a "high and low" position on each of the OCEAN variables (10 possible positions). Then the OCEAN variables are taken in pairs, representing a major and minor loading on a personality trait. This produces 10*9 or 90 possible traits, which the Brisbane team simplifies to 32 personality combinations. For example, a software agent might be described as "conventional, traditional, prim, mundane, and law abiding" if the agent has low Openness and high Conscientiousness.

The OCC Model

The OCC model [18] presents a cognitive framework for emotional reactions, including behavior. An agent's emotional reaction is initiated with a triggering event that is appraised in conjunction with a prior emotional state as well as inputs from the rest of the environment. Three classes of emotion (being pleased or not in reaction to events, approving or not in reaction to agents, and liking or not in reaction to objects) have the simplest "eliciting conditions" and thus in a sense the most basic emotional reactions (p.33). These classes are then differentiated further to produce six groups of emotion types: Fortunes-of-Others, Prospects for Self, Well-Being, Attribution, Attraction and a compound group of both Well-Being and Attribution. Emotions are represented as a set of "substantially independent groups based on their cognitive origins" (events, agents or objects) and responses are determined by the way that an agent "construes the world or changes in it" which causes a "valenced reaction" within the six types (p. 13). Several games and simulation developers have used the OCC model as a basis for agent [50-53].

The BDI Model

The BDI model [54] uses concepts of belief, desire and intention [30] and is a mature and commonly adopted "bounded rationality" [55] architecture for intelligent agents; it is "an abstract architecture of a family of parallel and distributed systems" [28]. *Beliefs* are formed from sensor-based perceptions while *Desires* are long-term goals. Both feed into an analysis that includes procedural knowledge encoded as action step sequences (*Plans*) from which a current state of actions is drawn (*Intention*), which then changes agents' relationship to the *Environment* through *Effectors*. Environments (such as classrooms or the multitude of mental models in an individual considering alternatives) can be highly uncertain; and in uncertain circumstances, bounded rationality models are often "stiff." That is, they only know how to deal with a narrow version of reality and may fail when situations get complex or uncertain. Solutions have been proposed by extending the semantics of intentions for collective action of groups of agents and by adding more flexible algorithms.

The operational semantics of intentions can be extended to collaborative tasks involving teams of agents by using distributed nested transactions [28], giving the BDI model a robust, reliable foundation. Distributing the *Intention* across several cooperating agents increases reliability by engaging several agents in parallel fulfillment of an objective. This increases performance when uncertain events in the environment interfere with or exceed the boundaries of the *Plan*. The distributed agent solution can be compared to the "society of mind" concept of Minsky and applied to the COVE layers within a single agent. In a classroom example, there may be both individual and group applications of distributed intelligence. For example, when a learner employs multiple strategies to solve a problem, or "multi-tasks" when solving a problem, or when a collaborative learning group divides a problem into parts, may be cases where the distributed BDI model would be helpful.

Another approach to help deal with uncertainty expands the bounded rationality of the BDI system with a "graded BDI agent" (g-BDI) approach [29]. The g-BDI expands the values in the logic as well as the rules and processes of the logic to account for uncertainty in the environment as well as in its appraisal. Graded BDI is applicable to representations of collaborative action as well as in individual goal-directed behaviors and may well find its way into simulated teaching environments in the future. In the COVE model, for example, the g-BDI architecture might represent a higher level schema within the three internal layers C,O and V and be applied to the social relationships in the E layer.

The DETT Model

The Disposition, Emotion, Trigger, Tendency (DETT) model of emotion [56] for situated agents captures the essential features of both the OCC and BDI models in a computational framework for combat simulations. Having developed in a military context, the DETT model is an environmentally mediated model of emotion in a computationally tractable framework designed to support large numbers of agents. Because of the battlefield context, the DETT theorists sought to minimize "extensive symbolic reasoning" in the agents, a critical feature with important details for learning theorists, especially cognitivists and constructivists. DETT may be applicable to classroom and school settings where large-scale group interactions are the focus of the simulation, and also where a "society of mind" approach is needed in modeling individual intelligence.

The simplification of an agent's internal processing in the DETT model serves as a useful example and can be compared to the simSchool framework's simplification of emotions, psychology and cognition. The simplification of emotional reasoning in DETT comes from quantizing critical values into –1, +1 (e.g. avoid, move toward), as simSchool quantizes cognitive variables. In addition DETT introduces persistent states into the agent-environment interaction, as does simSchool. There is a 1:1 relationship between *Dispositions* and *Emotions*, in simSchool there is a 1:1 relationship between task characteristics (compare with *Desire* in the BDI model*)* and the COVE model of the learner. Dispositions remain constant during a simulation, where Emotions can vary. In simSchool, the task (object) remains invariant for as long as the teacher has it assigned and the physiological variables also remain constant during the simulation; the learner's O & C variables adapt to the changing landscape of tasks, agents and events faced as time evolves in the simulation.

Integrating Data from Sensors

Early stage research using sensor networks to collect data while users engage with digital media indicates some potential to integrate high-resolution information with computational models of emotion and other cognitive processes [57]. Multiple sensor sources, including wireless headsets, provide a variety of frame rates of data concerning EEG, facial recognition, skin conductance, and emotion sensing cluster analyses based on these sources. Most of the data from these sensors are from non-conscious processes and thus may one day be associated with underlying features of cognition, emotion and behavior during engagement with digital media. Preliminary analyses (unpublished) using data mining and inductive artificial intelligence methods show promise for computational modeling of highly specific states of cognition, emotion and behavior.

Conclusion

In summary, the COVE computational model of physical, emotional and cognitive learning utilizes the OCEAN theory of psychology, the CHC theory of intelligence and a variety of cognitive and learning theories. It arranges factors into a temporal hierarchical model, with receptors at the boundary between the agent and the environment as well as between three broad layers leading to the acquisition and long-term storage and retrieval of both general and specific knowledge. The linkages among the factors are guided by two considerations: strengths of linkages based on intercorrelation data from biological, cognitive science and psychometric measures and structural-functional precedence based on evolutionary and developmental models.

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