A SYMBOLIC-CONNECTIONIST FRAMEWORK FOR REPRESENTING EMOTIONS IN COMPUTER GENERATED FORCES

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ABSTRACT

In concert with the I/ITSEC '01 theme, "Warfighting Readiness Through Innovative Training Technology", this paper explores an innovative approach to enhancing the realism and hence the efficacy of training – developing the capacity for synthetic forces to act and respond emotionally. Emotions, along with moods and dispositions, have been shown to be important determiners of behaviors. They influence how situations are interpreted, how attention is focused, which actions are considered, and how these actions are executed. For example, individuals who are afraid will more readily interpret a situation as dangerous, have their focus of attention narrowed down to the source of their fear, and be biased toward actions that can reduce their level of fear. Similarly, individuals who are angry will more readily interpret others as being hostile, have their focus of attention narrowed down to the source of their anger, and be biased toward aggressive and/or retaliatory actions. Understanding and modeling variations in emotions will be crucial for producing realistic human-like behavior in synthetic forces. The Army has recognized this potential and is now emphasizing the need for such human behavioral characteristics as being vitally important to training. This paper discusses fundamental principles of emotions research and then applies these principles to the development of a computational, emotional framework for synthetic forces.

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INTRODUCTION

CGF/SAF/IFOR Background

Currently, distributed battlefield simulations use computerized behavioral models of combatants to serve as opponents and friendly forces. These computer-controlled combatants are known as Computer Generated Forces (CGFs) and usually generate multiple battlefield entities (e.g., tanks, aircraft or infantry) using computer algorithms rather than a human crew to control the actions of those entities. For CGFs to be effective, the controlling software ought to be flexible enough to react to what is happening in the simulated battle and robust enough to produce intelligent and realistic actions. The behavior of the CGF may be generated by a human operator assisted by software, in which case the class of CGF is referred to as a semi-automated force (SAF), or it may be generated completely by software, in which case we use the terms autonomous force (AF) or intelligent force (IFOR). At a minimum, the behavior generated by CGFs should be feasible and doctrinally correct. For example, CGF behaviors should be able to emulate the use of formations in orders, identify and occupy a variety of tactical positions (e.g., fighting positions, hull down positions, turret down positions, etc.), and plan reasonable routes.

Historically, SAF behaviors have most often been implemented in procedural languages (e.g., Ada or C) and organized around state transition constructs such as finite state machines (FSMs) or Petri Nets (Cisneros et al., 1996; Gugel & Pratt, 2001; Henninger et al., 2000; Smith and Petty, 1992). For example, a SAF behavior such as “Occupy a Battle Position” might be constructed around states such as: “Start FSM”, “Travel”, “Calculate Position”, “Move Into Position”, and “End FSM”. Any one of these states, in turn, could be (1) an embedded FSM, (2) a simple function call representing some low-level primitive action, or (3) any combination of the two. This type of organization provides a useful means for structuring and communicating the intricacies of the behavior.

An alternative to SAFs, IFOR models are based on a general architecture for human cognition, Soar. The Soar[1] software architecture has been under continuous development for over 18 years as a model of natural intelligence (Rosenbloom, et al, 1993; Newell, 1990). It combines the abilities to react immediately to situations, use knowledge in deliberative decision making, step back from the immediate situation to perform various forms of problem solving and planning, and learn from experience. As an indicator of the maturity and utility of Soar-based IFOR entities, the system has been used successfully as the production model in a number of large-scale military exercises (Hill et al., 1997; Jones et al., 1999; Nielsen et al., 2000).

Emotions in CGFs, SAFs, and IFORs

A recent panel report sponsored by the National Research Council has called for the use of personality factors, behavior moderators and emotions to develop more realistic CGFs (Pew and Mavor, 1998). These recommendations have spawned a number of studies incorporating fatigue representations (French, 2001; Jones et al., 1997), defeat mechanisms (Heeringa & Cohen, 2000), personality paradigms (Hudlicka & Billingsley, 1999; McKenzie et al., 2001), and emotion models (Fransechini et al., 2001; Gratch & Marsella, 2001; Hudlicka & Billingsley, 1999) in prominent CGF systems. While we currently know of no studies that have investigated whether military training is improved by the use of CGFs with these capabilities, Army instructional courseware designers have recognized the significance of emotions in learning and training (Abell, 2000).

[1] The Soar architecture is in the public domain, with source code available at: http://ai.eecs.umich.edu/soar/

EMOTIONS LITERATURE

History

The study of emotion has had a fickle history in psychology, which appears to be correlated to prominent psychological theories of the day (Schultz, 1981). Over the last two decades, rapid growth in our understanding of brain function and in how it relates to behavior has renewed interest in emotion as a research area. Also, exciting progress in experimental neurobiology paralleled by explosive development of connectionist models has contributed to the resurgence of emotions research. The term "connectionist", coined by psychologists, is used to convey the fact that many psychological constructs are better explained in terms of distributed, parallel networks of adaptive units as opposed to terms of serial symbolic processing units. Practically speaking, a connectionist system can be thought of as the application of neural networks to high-level cognition (Barnden, 1995). A variety of neural network studies have already begun to address a wide range of issues (e.g., motivation, emotion, and goal direction) in cognition and behavior (see Levine, 1992). Interestingly, many of the concepts of connectionist psychology are strongly related to work in behaviorism, where the former provides a stronger "internal structure" using simple units with explicit learning rules rather than simple stimulus-response probabilities.

Because the field of emotion is a complex, immature discipline, it constantly changes as new knowledge is acquired. There is currently no universally accepted, comprehensive theory of emotions. Instead, there exist a host of "mini-theories" that emphasize cognitive, motivational, physiological, and behavioral dimensions of emotion. Thus, formal attempts to define emotion have been like the proverbial blind men who were asked to place their hands on an elephant and articulate what "an elephant looks like" – i.e., the description is specific to the individual's experience. For example, cognitive theorists tend to focus on thoughts and evaluations when defining emotions, physiologists tend to focus on physiological reactions, behaviorists on emotional behavior, and so on. For instance, one camp of researchers will treat the term emotion as it applies to a particular set of feelings (Schwarz and Clore, 1983). That is, a person feels anger if someone is offensive to him, pleasure if he receives a gift, or fear if a fierce animal is about to attack him. On the other hand, Behaviorists consider this to be an unscientific language and instead view an emotion as a response (Lindsay and Norman, 1977). "Response" in this case can either be interpreted as an overt behavior (cognitive response), or an internal process (physiological response) that occurs as a result of a particular stimulus.

Other researchers view emotions in terms of motivation (Ferguson, 1982). That is, emotions correspond to strong motives, and an organism will proceed to eliminate the motive. In the psychological literature this is called "drive reduction." For example, researchers have shown that rats learn new responses in order to remove themselves from an environment in which they had been shocked. The anxiety that motivated them to learn the avoidance-response can be considered as both an emotion and a motive. In this view, emotions can activate and direct behavior in the same way biological or psychological motives can, they can simply accompany motivated behavior, or they can simply be considered a goal.

Common Emotional Constructs

While individual camps exist, there is now a growing list of researchers (Lazarus, 1984; Ortony, 1988; Levine and Leven, 1992) which generally support the notion that emotional states can be manipulated by a combination of *different* factors. At a minimum, these factors seem to include cognitive processes (expectations) and physiological states (usually interpreted as arousal). Other factors have included: environmental influences and behavioral expressions. These notions have lead some psychologists, such as Lazarus (1984), to argue that emotion is multifaceted, and that all facets must be present in order to label something as an emotional state.

A second concept that is common to many emotion theories is the existence of a central evaluative mechanism that determines whether a given situation is potentially harmful or beneficial to the individual. For example, LeDoux and Fellous (1995) have discovered neural circuitry that processes stimuli according to whether they threaten or enhance the survival of the organism or its species. Also, a related discovery of an emotional memory system that works in concert with this circuitry has further added to the recent thrust of emotion research. Emotional memory has been associated with the amygdala and appears to add an "emotional flavor" to a declarative memory, which is thought to primarily originate in the hippocampus. This theory, exercised at its most primitive level, suggests that emotions are strong, "hard-wired" responses to stimuli that have a positive or negative survival value. The accompanying work on emotional memory suggests that these responses are mostly learned through classical conditioning (LeDoux, 1992) and performed as unconscious processes (Damasio, 1995).

EMOTIONAL IFOR FRAMEWORK

Clearly, the models of emotions proposed in the psychological community are not only complex, but still in their formative stages. This gives rise to a system that is difficult to express in computational terms. After all, the integration of an emotion model in a computer agent ultimately requires the expression of that model in a formal and executable language, and making the translation from an imprecise model to a formal language is an onerous task. However, there are some consistencies among the theories, and it is our strategy to use these generally accepted common themes to the extent possible. In those cases where no one theme prevails, we adopt a more functional, physiologically based approach as it tends to be more readily expressed in computational terms.

Our model adopts the position that emotions are correlated to survival value. The model extends Kaplan et al.'s (1991) work by building on the premise that primitive emotional responses enhance survival and that more complex emotions (e.g., those based on cognition) should then serve the same purpose. In this instance, a primitive emotional response such as "fearing a bear" is treated the same way as a cognitive emotional response such as "fearing a gun". In both cases fear is an appropriate response, useful for avoiding potentially dangerous situations.

Our model of emotion and its interactions with cognition is based on a symbolic-connectionist hybrid architecture. A number of researchers have investigated and advocate the use of this type of architecture for a variety of cognitive modeling tasks (Frasconi et al., 1995; Shavlik et al., 1991; Sun & Alexander, 1997; Tan, 1997). In our system, cognition is represented within Soar, a symbolic cognitive architecture, and emotional intensity is represented within a connectionist model (Chown, 1993). In using this approach, our work explicitly distinguishes the subconscious processes (in a connectionist implementation) and the decision making that is subject to emotional influences (in a symbolic cognitive architecture). It is the combination of these two systems that we refer to as our "emotions model" or "emotions architecture".

Once an emotions model has been established, we need some organizing framework within which to exercise it. After all, different people have different reactions to the same situations. Thus, emotions and emotional responses are unique to individuals and most meaningfully expressed in terms of individual differences. Such differences can be thought of as an "emotional style" or temperament. Adopting such a framework allows us to distinguish between the characteristic way a person experiences emotions (emotional style) and the way those emotions are realized (emotional content). In this framework, for example, referring to someone as frightened or angry would involve referring to the content of a person's emotional experience. On the other hand, referring to someone as hot headed or stoic would involve referring to the style with which a person may be inclined to experience emotions.

The following two sections on Cognition and Emotional Intensity review the two major components of the emotions model, the symbolic component and the connectionist component, respectively. The third section, Temperament, reviews personality-related literature and presents a preliminary temperament framework within which the emotion model will be exercised and evaluated.

Cognition – Symbolic Model

As illustrated in Figure 1, both the Decision Making and the Emotional Appraisal component of the emotions model occur within Soar, the cognitive model. Specifically, these two components reside in long-term memory where they are represented in the form of productions. Although decision making is not a new component to Soar-based IFORs, modeling the influence of emotions on decision making is new. Thus, in the following two sub-sections, we explain both how the Emotional Appraisal system works as well as how the Decision Making process is influenced by the resulting emotions.

Emotional Appraisal. Following Gratch (1999, 2000a,b), appraisal in our system is based around goals. The most straightforward types of appraisal require monitoring whether goals have been achieved, have become likely or unlikely to be

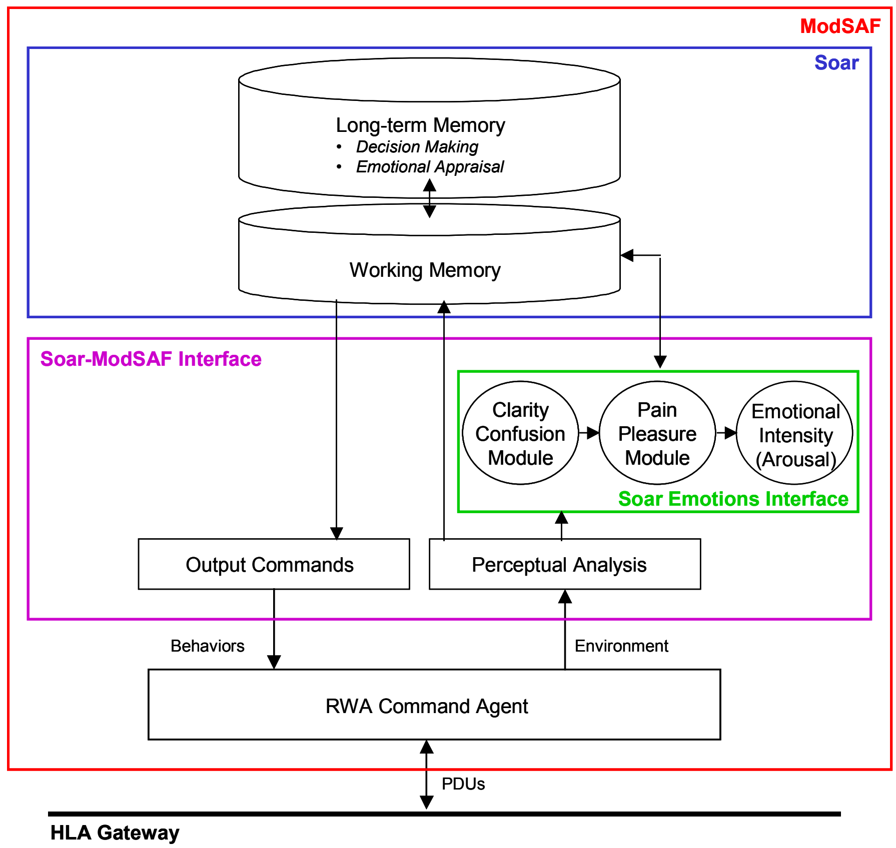

Figure 1. Block Diagram of CGF Emotion Framework

achieved, or have been deemed unachievable. The determination of the status of these goals comes from the cognitive system's assessment of situational awareness information, which is, in turn, provided by the Perceptual Analysis module in the Soar-ModSAF Interface, together with long-term situation-interpretation knowledge. Each of these types of appraisals results in signals to the "pleasure/pain" and "clarity/confusion" centers of the Emotions Interface. Again, since this form of appraisal is centered around the goals in the agent's current plan, only certain types of situational information are relevant for particular types of goals. The system will only be "concerned" about whether it is clear or confused about inputs when those inputs are germane to the current set of goals. For example, to satisfy the goal of destroying an enemy tank, the agent must be able to detect the location of that tank. If the agent could not detect the location, it would experience an increase in confusion. On the other hand, if the agent's planner had not established the goal of destroying a particular tank, then lacking contact with that tank is of no concern to the planning system[2].

Decision Making. The primary input from the emotions interface into the planning agent is a signal representing a level of arousal. One of the primary effects of a high level of arousal is to narrow the focus of attention. In the planning agent, we represent a narrowed focus of attention by restricting the knowledge that will be brought to bear on the plan monitoring, execution, and re-planning processes. One aspect of the narrowing of focus is that, when highly aroused, an agent will neglect to apply knowledge that is not well rehearsed. This will cause the agent to migrate its behavior toward its "core personality" or expertise during episodes of heightened arousal. For example, if an agent has a strong tendency toward risky behavior incorporated into its knowledge

[2] Since the goal to attack doesn't exist, the agent would not experience an increase in confusion as a result of being unable to locate the enemy tank's position. Lack of contact with enemy tank may, however, affect confusion as it relates toward other types of goals (e.g., avoiding enemy contact).

base, but it has been briefed with a low-risk mission, an increase in arousal will cause the agent to ignore the low-arousal knowledge (from the mission briefing) and revert to well-rehearsed, ingrained high-risk behavior. We accomplish this in the emotional planner by tagging agent rules with arousal thresholds. Only those rules with a threshold exceeding the current level of arousal are allowed to fire. The side effect of this approach is to allow much more thoughtful and deliberative reasoning under conditions of low arousal.

Other input from the emotions system includes current levels of pleasure and pain. These inputs may influence the preferences and evaluations that the agent uses when comparing alternative courses of action during re-planning or alternative interpretations during situation assessment. The combination of processing arousal, pleasure, and pain will likely lead to non-linear interactions between the narrowed focus of attention (reducing the knowledge brought to bear on reasoning) and the alteration of preferences (changing the selection of proposed courses of action). One of the benefits of this approach is that it is not necessary to posit specific mechanisms for differing emotions, as has been done in several other synthetic emotional systems (Gadanho & Hallam, 1998; Velasquez, 1997, 1998).

While other researchers opt to specifically assign symbolic labels (Gratch, 1999; Ortony, Clore, and Collins, 1988), our emotion model does not make such high-level explicit assignments (e.g., fear, anger, happiness, sadness, etc). However, emotional states in this model could be viewed as arising from a combination of pleasure/pain, arousal, attention and temporal components. A simple example of how two of the factors, arousal and affect (pleasure/pain) might interact can be seen in Figure 2. In this figure, “fear” is associated with high levels of arousal stemming from the anticipation of pain. Because our system ultimately has four dimensions, many combinations for different emotional labels exist. For example, if the arousal trigger is a past event instead of an anticipated event, the emotional interpretation of “fear” might change to “remorse” (if the attentional dimension is directed at something other than the source of the pain) or “anger” (if the attentional dimension is directed at the source of the pain).

Emotional Intensity – Connectionist Model

Once the appraisal system has derived values for the clarity/confusion input and the pleasure/pain input, the connectionist model uses this information to derive a change in the agent’s level of arousal. The connectionist model, illustrated in Figure 1 as residing in the Emotions Interface, consists of several components:

1) An arousal level system
2) A pleasure/pain system
3) A clarity/confusion mechanism

Whereas pleasure/pain and confusion/clarity all work to detect events of importance to an agent, the arousal system functions to determine the intensity of the response to these events. The following three sub-sections review the arousal mechanism, pleasure/pain module, and clarity/confusion module, respectively.

Arousal. Increased arousal has a number of well-studied effects on cognitive factors such as memory and attention (D’Ydewalle, et al., 1985; Hebb, 1972; Milner, 1991). An extremely high level of arousal, however, can impair performance in situations that are more complex tasks (e.g., requiring discrimination among multiple cues). Expressed graphically in Figure 3, the relationship between level of arousal and performance is an inverted U-shape. This rise in the graph represents an improvement in performance as alertness, interest, and positive emotion are increased. After performance reaches the optimum level, however, there is an increase in anxiety and emotional disturbances as arousal level becomes greater, and a subsequent decline in performance. Theoretically, there is an optimal level of arousal in terms of internal and external stimuli. Conditions that depart too severely from

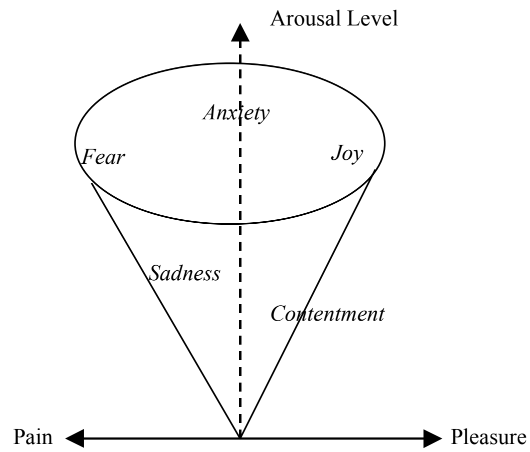

Figure 2. Example of Interaction Between Arousal Level and Pain/Pleasure Continuum

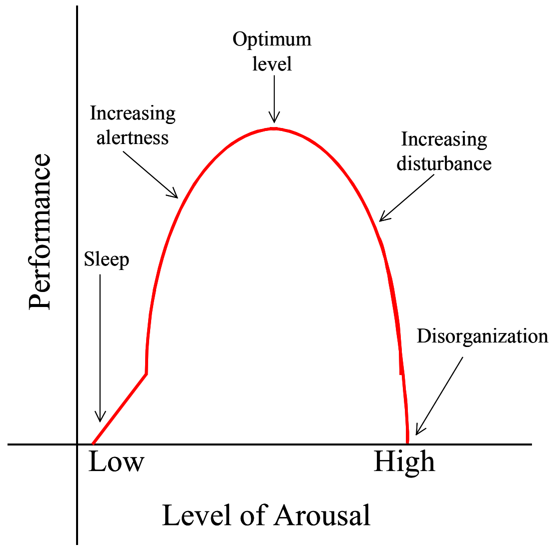

Figure 3. Generalized Effects of Arousal on Performance

this optimal state in either direction incite the organism to act to restore the equilibrium.

To model increases in arousal, we use a model like that offered in Kaplan et al (1991):

$$A(t+1) = A(t) + \Delta A \qquad (1)$$

where

$$\Delta A = S_{(A)}(t+1)\{P_{(+)}(t+1) - P_{(-)}(t+1)\}$$
$$A = \text{arousal level}$$
$$S_{(A)} = \text{sensitivity to arousal variable}$$
$$P_{(+)} = \text{positive factors}$$
$$P_{(-)} = \text{negative factors}$$

and to represent the subsequent recovery of arousal to its equilibrium, we use

$$A_d(t+1) = (1 - A(t)) + \alpha_r \qquad (2)$$

where

$$A_d = \text{arousal decay}$$
$$\alpha_r = \text{arousal recovery rate}$$

In this case, positive factors would include stimulation of factors such as: pleasure and pain, affectively coded cognition (e.g. anticipation of pleasure or pain), and stimuli that carry inherently arousing or calming properties. Because of the domain, the focus of our efforts will be on the second factor, affectively coded cognition such as the anticipation of pleasure or pain. In a combat domain, for example, this deals with threat assessment, anticipation of victory, etc. Sometimes this could occur through direct perception (e.g., "a missile is coming at me"), other times it would be more of a cognitive assessment (e.g., "the enemy is about to retake an important hill").

The sensitivity to arousal variable in equation (1) is calculated according to equation (3):

$$S_{(A)}(t+1) = S_{(A)}(t) + A(t)^2 \cdot \lambda_{(A)} \qquad (3)$$

where

$$\lambda_{(A)} = \text{susceptibility to arousal constant}$$

In this equation, the Arousal term is squared to more highly differentiate high levels of arousal from lower levels of arousal and then it is multiplied by the susceptibility to arousal constant. It is this parameter that distinguishes an individual's general sensitivity to become aroused. For example, as reviewed in the future section on Temperament, personality literature has long theorized that the critical factor that distinguishes introverts and extroverts is the relative susceptibility to becoming aroused (D'Ydewalle, et al., 1985; Eysenck & Eysenck, 1985). Thus, we can distinguish between these temperaments by adjusting λ_A, the susceptibility to arousal constant.

Affect (Pleasure/Pain). The pleasure/pain continuum system is designed to interpret the level to which a stimulus represents a threat or enhancement to the survival of the species. In other words, stimuli that impede one's chances of survival would be tagged as painful and stimuli that would help one survive or reproduce would be tagged as pleasurable. As shown in the coupling of equations (1) and (4), instances of pain and pleasure combine to stimulate arousal.

$$P_{(+)}(t+1) = \lambda_{(+)} \sum \rho_{(+),i}(t+1) w_i \qquad (4)$$
$$P_{(-)}(t+1) = \lambda_{(-)} \sum \rho_{(-),i}(t+1) w_i$$

where

$$\rho_{(+)} = \text{pleasure inputs}$$
$$\rho_{(-)} = \text{pain inputs}$$
$$\lambda_{(+)} = \text{susceptibility to pleasure constant}$$
$$\lambda_{(-)} = \text{susceptibility to pain constant}$$
$$w = \text{weight for pleasure/pain input}$$

Perception (Clarity/Confusion). The clarity and confusion constructs represent the cognitive dimension of pleasure/pain. Accordingly, the pleasure/pain inputs in equation (4) can be interpreted as either physical or cognitive. Kaplan (1991) considers cognitive pleasure and cognitive pain as important correlates of pleasure and pain in forms of higher intelligence, because they facilitate the survival of the individual and the species. For example, because humans are not particularly fast, fierce, or camouflaged, we rely on our ability to organize, store, and use information to enhance our survival. As a result, confusion is a potentially dangerous attribute and clarity is a desirable attribute, since an organism that is confused is less likely to respond in accord with its best interests. In this sense, clarity and confusion incorporate the influence of information quality and perceptual accuracy on the level of arousal. That is, the confusion/clarity mechanism becomes a measure that evaluates the relationship between the world and the person's knowledge of the world.

Temperament

Using the framework presented in the previous section, we will consider the effects of individual differences in temperament by changing the constant parameters in the emotional intensity subsystem. So, just as we can adjust λ_A, the susceptibility to arousal constant, to distinguish between introverts and extraverts, we can adjust other parameters in our emotions model to distinguish between other temperament classes. This approach allows us to model an individual's emotional style such that it can lead to distinct decision making profiles in a variety of emotionally charged scenarios.

A wealth of literature exists on personality typing in humanistic psychology (Keirsey & Bates, 1984; Myers & McCaulley, 1985) to scientific psychology (Eysenck, 1991; Digman, 1989). Humanistic approaches tend to be based on the work of Carl Jung, while Experimental approaches tend to rely on data analysis techniques using factor analyses. Interestingly, some work has been done to correlate the two approaches (McCrae & Costa, 1989; Saggino & Klein, 1996).

One of the primary factor models used in the personality-related research is the three factor PEN model (Eysenck, 1981). This model maintains that three super traits (i.e., psychoticism, extraversion, neuroticism) are sufficient to describe the organization of personality. Another prominent personality model, the "“Big Five Theory" or “Five Factor Model” (Costa and McCrae, 1995; Digman, 1990) also contains the factors of extraversion and neuroticism (alternatively known as surgency and emotional stability), but these five factor models claim that an additional two higher-order terms are required to adequately represent personality. As indicated in Table 1, many of these factors are presumed to represent the same dimension, but are assigned different names by different researchers.

	Eysenck (PEN)	Costa & McCrae (Big 5)	Digman (FFM)
1	Extraversion	Extraversion	Extraversion
2	Psychoticism	Agreeableness	Friendly Compliance
3		Conscientiousness	Will to Achieve
4	Neuroticism	Neuroticism	Emotional Stability
5	Intellect*	Openness	Intellect

* not included in Eysenck's domain of “temperament” traits

Table 1. Comparison of 3-Factor and 5-Factor Models

Despite the lack of agreement on the number of basic traits, some overlap does occur (Eysenck, 1991). Two dimensions common in most factor-analytic studies of personality are Extraversion (vs. Introversion) and Stability (vs. Instability). The extraversion dimension refers to the degree to which one's basic orientation is turned inward towards the self or outward toward the external world. It is essentially the same distinction made by Jung, although Jung used the terms to refer to a personality type rather than positions along a scale. Stability-instability is a dimension of emotionality, with calm, well-adjusted, reliable individuals at the stable end and moody, anxious, temperamental, and unreliable individuals at the other.

The relationships of some these personality dimensions and emotions have been analyzed thoroughly (Costa & McCrae, 1980; Meyer & Shack, 1989; Rusting & Larsen, 1996; Williams, 1989). The results of these studies show that extraversion is linked mainly with average levels of positive affect, and neuroticism and psychoticism are linked with average levels of negative affect. For example, when subjects were exposed to positive, negative or neutral guided imagery scenarios, it was found that extraversion correlated with positive mood following the positive imagery task, but not with negative mood following the negative imagery task. Neuroticism, on the other hand, correlated with negative mood following the negative imagery task, but not with positive mood following the positive imagery task. These relationships have been replicated repeatedly using various measurement scales, time scales, and report types. This suggests that extraversion represents an increased susceptibility to positive affect, and that neuroticism predisposes greater susceptibility to negative affect. Thus, by adjusting the parameters $\lambda_{(+)}$ and $\lambda_{(-)}$, we are able to distinguish between an individual's predisposition toward pleasure and pain, respectively.

The review of literature on how temperament influences emotional experiences is ongoing, but findings such as these provide some confidence that we can develop a coherent mapping between temperament and emotion that is rooted in empirical research results.

RELATED RESEARCH

As indicated in the introduction to this paper, other researchers in the military simulation and training community are investigating approaches to incorporate emotions in CGF systems. As the framework for our system has now been defined, this section attempts to distinguish it from the models developed by other researchers in this community.

Our work most closely resembles the work of Gratch and Marsella (2001). In large part, this is due to the fact that both systems make use of the Soar architecture for decision making. Thus, similar constructs for relating an agent's emotions to the agent's decisions are required. However, differences in the systems do exist. For example, the model of emotional intensity presented in this paper is influenced by more factors. Also, this model can be influenced by individual differences in temperament.

Hudlicka and Billingsley (1999) also make the connection between emotional content and leadership style by representing the effects of temperament in their framework. However, emphasis appears to be placed on the influence of emotions on decision making, with little focus placed on the complexity or variability of the emotional intensity model.

Alternatively, Fransechini et al (2001) place a much greater emphasis on deriving emotional intensity through a highly biologically based, neurophysiological approach. The model is based on two dimensions including arousal and distress, but its precise form is not discernible from current publications.

Given the immaturity of the research in this area, we are not able to conclusively state that one approach is better than another, only that differences exist. Moreover, as indicated in the Introduction, we know of no research that studies whether emotional CGFs will even improve training. But, we expect that the models developed from this generation of research will be useful in assessing whether military training is indeed improved through the integration of emotional models into synthetic forces. Also, given that military communities consistently demand greater realism from their simulations, this research will be useful in providing the groundwork for meeting this demand and improving future models of cognitive-emotive behaviors.

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