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Beyond Cognition: Modeling Emotion in Cognitive Architectures

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Abstract

Recent research in psychology and neuroscience has identified both the critical role of emotion in decision-making and social interaction, and some of the mechanisms mediating the functioning of emotion. Yet the majority of cognitive architectures do not include models of emotion. In this paper I first motivate the need for including emotion in cognitive architectures, and then describe a generic methodology for modeling the effects of emotion within a symbolic cognitive architecture, as well as some of the associated representational requirements. I then present preliminary results, and conclude with an outline of key issues and future work in emotion modeling.

Introduction

When is it necessary to include emotion in cognitive architectures? The answer depends entirely on the purpose of the architecture, which also defines the constraints on the modeling effort (e.g., level of resolution, which emotions to include, which emotion effects to represent, which processes to model, etc.) (Hudlicka, 2003b). There are a number of reasons why emotion may be necessary, including: 1) research-motivated emulation of human decision-making and appraisal processes, to better understand their mechanisms; 2) enhancing agent and robot realism (e.g., for training and educational purposes, or assistive roles); 3) developing user and operator models for improved adaptive HCI. Depending on the specific purpose, an explicit model of emotion within the architecture may or may not be necessary. For example, it may be sufficient to 'fake' distinct affective states to enhance the effectiveness of tutoring systems, without including any of the underlying mechanisms that actually generate these states within the agent.

While much has been accomplished in the affective computing area since Picard coined the term in 1997, (Picard, 1997), most agent and cognitive architectures do not address the 'emotion issue'. There seems to be a degree of polarization within the field, with some researchers avidly embracing the need for emotion, at times perhaps even uncritically so, while others dismiss the need for modeling emotion. To make an informed decision regarding emotion modeling within a particular agent, a deeper understanding is necessary of: (1) the contexts that require emotion models, (2) the methods available to model emotions, and their effects, within cognitive architectures, and (3) the appropriateness of alternative modeling strategies, as a function of the specific context.

The purpose of this paper is twofold. *First,* to provide background information about recent emotion research, and its relevance to cognitive modeling. *Second,* to describe a generic methodology for modeling emotion effects within symbolic architectures, in terms of parametric manipulations of the architectural processes and structures, as well as the associated cognitive-affective architecture that implements this methodology – the MAMID architecture, and present preliminary results.

Background: Emotion Research

What are emotions?

There are many terms in the emotion research literature describing what we generally refer to emotions (Ekman and Davidson, 1994). *Affective states* generally refer to high-level stimulus evaluations yielding a positive or negative valence, and leading to correspondingly high-level behavioral directives such as approach or avoid. *Emotions* refer to transient states described by the familiar terms such as joy, fear, anger, etc. Some researchers divide these further into *basic emotions* (e.g., joy, sadness, frustration, anger, fear and anxiety), and more *cognitively-complex and self-oriented emotions* (e.g., guilt, pride, shame, jealousy). There are also *dimensional characterizations* of emotions, which identify sets of two or three dimensions defining spaces within which the individual emotions can be placed (e.g., valence and arousal, hedonic and tense arousal (Matthews & Deary, 1998)). Any and all of these may be candidates for modeling within a cognitive architecture, depending on the objective of the model.

Roles of Emotions

Three primary roles of emotion have been proposed, both interpersonal and intrapsychic: (1) *Emotions as Interpersonal Communication Mechanisms,* serving to communicate intentions and behavioral tendencies (e.g., imminent attack or withdrawal, pleasure vs. displeasure), thereby improving social behavior coordination; (2) *Emotions as Internal Goal Management Mechanisms,* required to coordinate physical and mental activities aimed at satisfying agent's multiple goals in an uncertain and unpredictable environment, and monitoring and regulation of goal-directed behavior; and (3) *Emotions as Behavior Preparation Mechanisms,* with distinct emotions linked to distinct desired behavior, improving the organism's chances for survival (Oatley & Johnson-Laird, 1987; Frijda, 1986).

Appraisal

Key components of emotional processing are the mechanisms that evaluate a current situation (internal and external), in terms of an affective label (affective state or emotion). This process is referred to as *appraisal*, (also *cognitive appraisal*), and has been studied extensively over the past 15 years (e.g., Scherer, 2003; Ellsworth & Scherer, 2003).

Earlier studies focused on descriptive characterizations of the phenomenon, a type of black-box, I/O view, attempting, for example, to identify types of elicitors required for particular emotions. More recently, attempts have been made to identify the mechanisms mediating these processes, as exemplified by the work of Smith and colleagues (Smith & Kirby, 2001), who elaborated earlier models of Lazarus into mechanistically-oriented process models, which lend themselves to computational implementations.

Appraisal processes are typically divided into two stages, an *automatic appraisal*, generating a high-level initial assessment, followed by a slower, more *deliberate appraisal*, with more idiosyncratic components and frequently including assessment of the individual's coping potential.

Emotion effects

A critical aspect of understanding and modeling emotions concerns their effects on attention, perception and cognitive processing. The specific effects on attention and cognition of a number of affective states have been studied extensively (e.g., anxiety and fear, anger and frustration, positive and negative affect, etc.). These effects include *altering the nature of attentional processing* and *working memory* (e.g., changes in capacity and bias) and helping to activate (or inhibit) particular perceptual and cognitive schemas that enhance (or inhibit) the perception and processing of specific stimuli. These include the following: *perceptual categorization biases* towards threats; *memory encoding and recall* effectiveness and biases; and a variety of additional *influences on reasoning, judgment, and decision-making* (Williams et al., 1997; Isen, 1993; LeDoux, 1989). Effects thus exist at both the low levels of processing (attention and working memory speed and capacity), and the higher levels (situation assessment, decision making, planning, learning and judgment).

Emotion mechanisms

The theories of emotion mechanisms have evolved over the past 100 years, with recent neuroscience findings stimulating much progress by providing concrete data, and demystifying earlier theories. The recent consensus regarding emotions is that they play a pervasive neuromodulatory role across the brain circuitry, replacing the earlier views of isolated 'emotion' modules (e.g., the amygdala) or emotion circuits (e.g., the limbic system) (Fellous, 2004).

Requirements for Modeling Emotion

How then do we model emotion within cognitive architectures? What specific structures and processes are necessary? What representational formalisms and inferencing strategies are most appropriate? Again, the answers depend on the ultimate purpose of the modeling effort.

In some cases, researchers explore the fundamental architectural features and configurations capable of producing emotion (e.g., Sloman, 2003), providing what we might call *deep emotion models*. In other cases, it is sufficient to reason 'about' emotion, focusing on *shallow emotion models*. In either case, a number of available symbolic (as well as non-symbolic) representational and inferencing mechanisms are appropriate. For example, in a shallow model of emotion, rules or belief nets can represent patterns such as "If user exhibits behavior xxx, then s/he is likely experiencing emotion yyy".

A middle ground approach, such as the MAMID architecture described below, assumes that certain structures and processes are necessary to adequately model both the *effects of emotions*, and some of the *core processes* involved (e.g., appraisal). Specific *representational requirements* include the explicit representation of the following: particular mental constructs (e.g., situations, expectations, goals); the self and self-relevant stimuli and states; particular attributes of these constructs (e.g., threat level, valence, desirability); and long-term and working memories. Specific *processing requirements* include explicit representation of the processes mediating the mapping of external and internal stimuli onto particular affects, via distinct stages, and the processes whereby specific affects exert particular influences on attention, perception and cognitive processing, including situation assessment, goal management, decision-making, and action selection.

Below we briefly describe one approach to modeling emotions within a symbolic cognitive architectures: the MAMID methodology and architecture.

MAMID Methodology and Architecture

The key components of the MAMID emotion modeling approach are: (1) an architecture capable of deriving an affective state via an appraisal process; and (2) a means of representing the effects of the resulting affective state on processing. The latter is implemented via a generic methodology capable of representing the effects of emotions (and other individual differences, including personality traits) within a symbolic cognitive architecture via parametric manipulations of the architecture processes and structures. We describe both components below.

MAMID Cognitive Architecture

The cognitive architecture implements a sequential see-think-do processing sequence (figure 1), consisting of the following modules: *sensory pre-processing*, translating incoming data into task-relevant cues; *attention*, filtering incoming cues and selecting a subset for processing; *situation assessment*, integrating individual cues into an overall situation assessment; *expectation generation*, projecting current situation onto possible future states; *affect appraiser,* deriving the affective state (both valence and four of the basic emotions) from a variety of external and internal elicitors, both static and dynamic; *goal selection*, selecting critical goals for achievement; and *action selection,* selecting the best actions for goal achievement.

These *modules* map the incoming stimuli (cues) onto the outgoing behavior (actions), via a series of intermediate internal representational structures (situations, expectations, and goals), collectively termed *mental constructs*. This mapping is enabled by long-term memories (LTM) associated with each module, represented in terms of belief nets or rules.

Mental constructs are characterized by their attributes (e.g., familiarity, novelty, salience, threat level, valence, etc.), which influence their processing, by determining their rank and the consequent likelihood of being processed within a given execution cycle; (e.g., cue will be attended, situation derived, goal or action selected). (Note that the availability of the mental constructs from previous frames of the execution cycle allows for dynamic feedback among constructs, and thus departs from a strictly sequential processing sequence.)

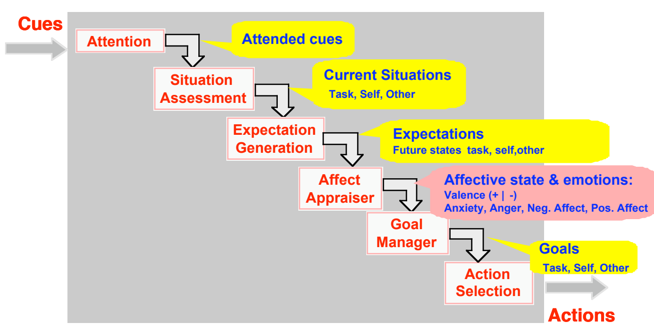

Figure 1: MAMID Cognitive Architecture: Modules & Mental Constructs

Affect Appraisal Process

The Affect Appraiser module (figure 2) incorporates elements of several recent appraisal theories: *multiple-levels* (Leventhal & Scherer, 1987; Sloman, 2003; Smith & Kirby, 2001), and *multiple stages* (Scherer, 2003), and incorporates empirical data.

The Affect Appraiser module generates both a *low-resolution assessment* of the current set of stimuli, in terms of a valence, and a *higher-resolution categorical assessment,* in terms of four of the basic emotions: anxiety/fear, anger, sadness, happiness. Its multiple stages use both *universal elicitors* (e.g., novelty, threat level, (un)pleasantness, unexpectedness), to generate a valence, using an *automatic appraisal* (roughly corresponding to the largely 'hardwired', 'primitive' appraisal components), and more *cognitively-complex and idiosyncratic elicitors* (e.g., individual history, expectation- and goal-congruence), to generate a categorical assessment using an *expanded appraisal.*

The MAMID Affect Appraisal module consists of three stages: *automatic appraisal, expanded appraisal*, and *current state modulator. Automatic appraisal* emphasizes the stimulus properties to calculate the valence state (positive or negative); specifically, unexpectedness ("is situation part of current expectations"), novelty ("is situation part of individual history"), and the situation's intrinsic threat and "pleasantness" levels. Trait effects are included via a bias factor, reflecting the agent's temperamental predisposition toward negative or positive states. For example, high extraversion and low neuroticism individuals tend to be predisposed towards positive affective states, whereas low extraversion and high neuroticism individuals tend towards negative affective states.

Expanded appraisal emphasizes the influence of the agent's internal motivational context, by taking into consideration the congruence of the current situations and expectations with the agent's goals, the general level of success in achieving the current goals (e.g., number of goals met vs. failing), and the individual idiosyncratic effects of particular elicitors (e.g., previous experiences with a specific stimulus). This latter factor captures the domain-, task-, and individual-specific emotion-eliciting stimuli, situations or expectations. These are encoded in a set of belief nets, associated with a particular emotion, for each agent type.

The belief nets vary in type and structure, reflecting the differences in individual histories (e.g., previous negative / positive experience in a particular situation), sensitivity to particular factors (e.g., considerations of own sense of competence or control in affect appraisal), and responsiveness (e.g., magnitude of particular affect generated in response to a set of situations or expectations). For example, a trait-anxious agent considers own competence and sense of control during appraisal to determine the level of anxiety, whereas a non-trait anxious individual does not consider these factors.

Trait effects are included as above, with specific trait combination biasing towards a particular emotion (e.g., high neuroticism - low extraversion predisposes towards anxiety and negative affect (Matthews & Deary, 1998)). The current valence also influences the expanded appraisal, by contributing to the intensity of the valence-congruent emotions; thus negative valence increases the intensity of anxiety, anger and negative affect, while positive valence increases the intensity of positive affect.

The expanded appraisal produces a vector of intensities for each of the four represented emotions. This representation, along with the multi-level appraisal structure, supports the representation of mixed, ambiguous, and possibly conflicting emotions, which are quite common in real life, but have not been adequately explored in models (Scherer, 2003). We are just beginning to explore the behavioral consequences of these complex representational possibilities.

Both valence and emotion intensities are calculated via linear functions of the weighted eliciting factors. The weights controlling the contributions of the individual eliciting factors can be modified interactively by the model developer. This allows model tuning to reflect emerging empirical data and alternative theories regarding the mechanisms of appraisal and state / trait effects, as well as modeling of a wide range of individual differences (e.g., differences in sensitivity to the valence produced by the automatic appraisal can be explored by modifying the weight of the valence component in the expanded appraisal functions).

The *Current State Modulator,* the final stage of the appraisal process, consists of modulating the newly-derived valence and emotion values by the valence and emotions generated in the previous execution cycle, thereby assuring smooth transitions among states. Traits exert an effect on this stage by influencing the ramp-up and decay rates of individual emotions, as well as their maximum intensities.

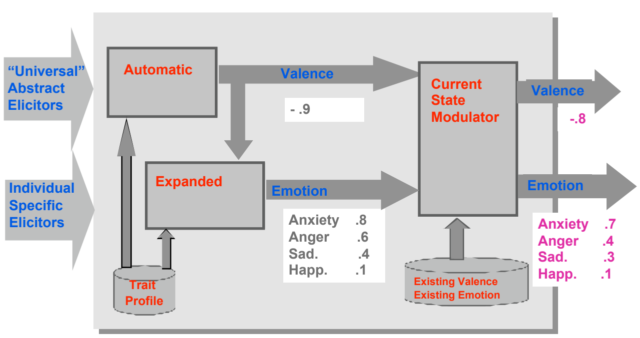

Figure 2: Affect Appraisal Model

The resulting affective states then influence processing in several ways. *First*, they are used directly in the rules selecting the agent's goals and actions. *Second*, they influence the speed and capacity of the architecture modules – a parameter-controlled effect analogous to the system-wide neuromodulatory role of emotions. *Third*, they influence mental construct ranking, thus determining whether a specific cue or situation is processed, or specific goal selected. The last two effects have been a particular focus of this effort, and aim to emulate some of the empirically-identified mechanisms of emotion effects.

Generic Modeling Methodology

We used a previously described methodology for modeling state and trait effects within a cognitive architecture (Hudlicka, 2002; 1998), which consists of mapping particular state / trait profiles onto specific architecture parameter values (figure 3). These parameters then control processing within the individual architecture modules.

Functions implementing these mappings were constructed on the basis of the available empirical data. For example, reduced attentional and working memory (WM) capacity, associated with anxiety / fear, are modeled by dynamically reducing attention and WM capacity of the architecture modules, which then reduce the number of constructs processed (fewer cues attended, situations derived, expectations generated, etc.). Attentional threat bias is modeled by higher ranking of threatening cues, thus increasing their likelihood of being attended, and by higher ranking of threatening situations and expectations, thus increasing the chances of a threatening situation / expectation being derived. Trait-linked structural differences in LTM are supported by allowing the flexible selection of alternative LTM clusters, reflecting distinct personality traits. Traits also influence the dynamic characteristics of the emotional responses (ramp up, decay, and maximum intensities).

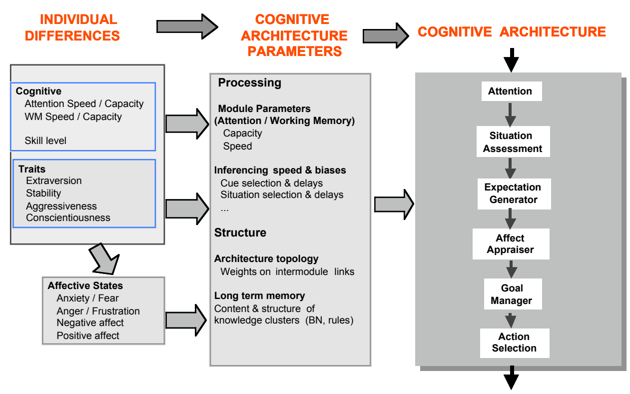

Figure 3: Parametric State / Trait Modeling Methodology

A key objective of the methodology was to provide flexibility regarding the *types of factors* selected for inclusion in a model, the *nature of their influence* on cognitive, perceptual, and decision-making processing, and the *degree of this influence*. This approach is necessitated by the fact few definitive theories exist regarding the exact mechanisms of the emotion influences, particularly with respect to the more complex, internal processes of situation assessment, expectation generation, and goal management and planning. In addition, new data regarding these effects continue to emerge and need to be rapidly accommodated.

The MAMID methodology, and the architecture and testbed that implement it, were designed with the explicit purpose of facilitating a rapid accommodation of these emerging findings. The methodology achieves this flexibility through a high-degree of parameterization of the processes and structures that comprise the distinct architecture modules, and the analyst's interactive access to these parameters and their weights. The distinct individual differences factors are mapped onto distinct configurations of the cognitive architecture parameters, which in turn produce different processing within the model, and ultimately produce different behavioral outcomes for the associated simulated agent.

There are several advantages of this methodology for modeling both emotions, and a broad range of individual differences (behavior moderators). *First,* it facilitates rapid modeling of a broad range of distinct individual profiles. *Second*, the rich architecture parameterization allows the definition of additional individual characteristics (e.g., additional traits can be introduced into the model by identifying a mapping between that trait and the corresponding set of architecture parameters). *Third*, it provides a means of integrating (possibly conflicting) effects of multiple, interacting emotions and traits, much as these influences interact in humans. *Fourth*, it is psychologically grounded, with both the emotions and their corresponding architecture parameters selected on the basis of empirical data and psychological theory. This is in contrast to some recent efforts that have adopted this approach, but use parameters such as global system noise to degrade system performance, which has no direct counterpart in specific psychological processes (e.g., Ritter et al., 2002). While such high-level manipulations may be sufficient to model the surface manifestations of some emotion effects at the shallow level, they tell us little about the mechanisms that mediate these effects.

Preliminary Results

The MAMID architecture and methodology were evaluated by modeling agent decision-making in the context of a peacekeeping scenario. Several simulated commander types (anxious, aggressive, normal) encountered a series of 'surprise' scenario situations (e.g., destroyed bridge, hostile crowd), designed to elicit different reactions as a function of their state and trait differences. The agents' affective states were dynamically generated by the Affect Appraisal module, in response to each surprise situation.

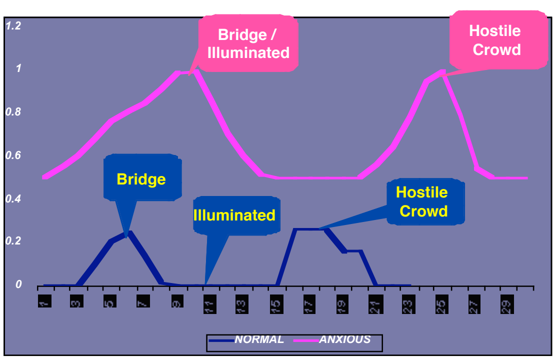

Figure 4: Anxiety Fluctuations Over Time for Normal and Anxious Commanders

The resulting emotions then influenced processing within each of the architecture modules, as outlined above (e.g., contributed to lower or higher processing capacities, threat bias, etc.). Figure 3 shows the fluctuating anxiety levels of a normal and a trait-anxious commander, during the course of the simulation scenario. The different emotions, together with the trait-related differences in both processing and memory, then resulted in differences in behavior, in response to the identical set of external circumstances produced by the scenario simulation (figure 4). Thus, for example, an anxious commander used inappropriate force against a hostile crowd, moved more slowly, and spent more time in situation assessment than his 'normal' counterpart.

Figure 5: Distinct Behavior of Different Agent Types

Related Work

A number of models addressing emotion have been developed in cognitive science and AI. These models range from individual processes to integrated architectures, and explore several of the emotion roles outlined above. The most frequently modeled process has been *cognitive appraisal.* Several alternatives have been proposed for these processes in the psychological literature (Ortony et al., 1998; Frijda, 1986; Lazarus, 1991; Smith and Kirby, 2001; Scherer, 2003). A number of these models have been implemented, both as stand-alone versions, and integrated within larger agent architectures (e.g., Scherer, 2003; Bates et al., 1992; Elliot et al., 1999; Andre et al., 2000). Other emotion model implementations include models of emotions as goal management mechanisms (Frijda and Swagerman, 1987), models of interaction of emotion and cognition (Araujo, 1993; Hudlicka, 2002), and effects of emotions on agent's belief generation (Marsella & Gratch, 2002). Examples of *integrated architectures* focusing on emotion include most notably the work of Sloman and colleagues (Sloman, 2003). There are also recent efforts to integrate emotion effects in Soar (Jones et al., 2002), and ACT-R (Ritter et al., 2002), the latter using in-part a parametric-manipulation approach analogous to MAMID.

Conclusions and Future Work

The model described above has merely begun to 'scratch the surface' of emotion modeling. Many extensions are possible, and necessary, to develop a more accurate model of the complex appraisal processes and emotion effects on decision-making. One of the most challenging issues is validation of these computational models, whereby specific empirical data are compared with model performance over time. To date, this has typically been done at the I/O level, comparing model input/output on some particular task with those of humans.

Validating deep emotion models at the process level, by matching the mechanisms involved rather than just the input/output, is particularly challenging, since the types of internal data required about the detailed structures and processes are not available.

Some of the potential future directions for this work include: additional processing levels; parallelism and interaction among processing levels; more complex elicitors; inclusion of coping potential in elicitors (Lazarus' deliberate appraisal); additional emotions (basic and complex); more complex functions calculating the architecture parameters and emotion dynamics; and explicit models of meta-cognition.

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