Modeling Culturally and Emotionally Affected Behavior

Vadim Bulitko
Dept. of Computing Science
University of Alberta
Edmonton, AB, T6G 2E8, CANADA
bulitko@ualberta.ca

Steven Solomon and **Jonathan Gratch**
USC Institute for Creative Technologies
13274 Fiji Way
Marina del Rey, CA, 90292, USA
{solomon,gratch}@ict.usc.edu

Michael van Lent
Soar Technology, Inc.
3600 Green Court, Suite 600
Ann Arbor, MI, 48105, USA
vanlent@soartech.com

Abstract

Culture and emotions have a profound impact on human behavior. Consequently, high-fidelity simulated interactive environments (e.g., trainers and computer games) that involve virtual humans must model socio-cultural and emotional effects on agent behavior. In this paper we discuss two recently fielded systems that do so independently: Culturally Affected Behavior (CAB) and EMotion and Adaptation (EMA). We then propose a simple language that combines the two systems in a natural way thereby enabling simultaneous simulation of culturally and emotionally affected behavior. The proposed language is based on matrix algebra and can be easily implemented on single- or multi-core hardware with an off-the-shelf matrix package (e.g., MATLAB or a C++ library). We then show how to extend the combined culture and emotion model with an explicit representation of religion and personality profiles.

1 Introduction

There are several compelling reasons to study emotionally and culturally affected behavior. First, emotions and culture have a profound effect on most human behavior and, therefore, they should be modeled in any high-fidelity virtual human simulation. Second, emotions may play a fundamental role in human reasoning and cognition and, therefore, they should be given a serious consideration by scientists in Artificial Intelligence (AI). We are interested in both the former (i.e., the application-driven aspect) and the latter (i.e., the strong AI aspect). We will now review approaches to modeling culture and emotion effects.

Culturally Affected Behavior. Recent years have seen much interest in teaching cultural awareness, which demands flexible representations of culture. The Culturally Affected Behavior (CAB) model (Solomon *et al.* 2008) is a human behavior model in which socio-cultural knowledge is explicitly and modularly represented. CAB provides a language for ethnographers to encode cultural norms and values, and biases and stereotypes. CAB's theoretical underpinnings lie with the schema theory of D'Andrade (1992) that postulates that culture is represented by a collection of cognitive schemas – a codified version of some abstract behavior or concept. Shared conceptual meanings are accounted for by a system of constitutive rules that is known, shared and adhered to by members of a culture (D'Andrade 1984). CAB also uses the theory of mind (Nichols & Stich 2003) to model AI agent's beliefs about the human participant. CAB's socio-cultural model is representationally similar to domain models of the Virtual Human architecture (Traum *et al.* 2003) but focuses specifically on actions and states pertaining to socio-cultural satisfaction and comfort.

Figure 1: CAB in action: Iraqi Sunni and German police captains.

The current CAB prototype complements domain models for an AI-controlled police captain agent with two sample culture models (Iraqi Sunni and German, Figure 1), integrated with the graphics, animation, and voice capabilities of a simulation training environment. The human participant meets with either the Iraqi police captain (Farid) or the German police captain (Fritz). The police captain starts out executing the default task "perform normal police duties plan". The participant's goal is to persuade the police captain to provide police cooperation in solving a problem with a local market. This is done by taking actions with domain and socio-cultural effects and building up the police captain's level of socio-cultural satisfaction. Eventually the utility of the police captain's task "help participant fix market problem" can be made to exceed the utility of the default task and, as a result, the police captain agrees to cooperate.

Emotionally Affected Behavior. The last decade has seen an explosion of interest within AI in the topic of emotion. An understanding of human emotion can benefit a variety of "human centric" application that must accurately recognize and respond to human beliefs, motives and intentions. For example, some tutoring applications already incorporate emotion into user models (Conati & MacLaren 2004) and simulation techniques increasingly strive

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to model emotional-evoking situations such as how crowds react in disasters (Silverman *et al.* 2002) or how military units respond to the stress of battle (Gratch & Marsella 2003). Further, some have argued that emotional influences, seemingly irrational on the surface, have important social and cognitive functions lacking from the individualistic and disembodied view of cognition typical in AI. Thus, understanding these cognitive functions may lead to more effective AI systems (Simon 1967).

There are several theoretical perspectives on emotion. We argue that *appraisal theory* (Scherer, Schorr, & Johnstone 2001) is a fruitful theory of emotion for those interested in the design of AI systems as it emphasizes the connection between emotion and cognition. Emotion is argued to arise from patterns of individual judgment concerning the *person-environment relationship* (i.e., the perceived relationship between events and an individuals beliefs, desires and intentions). These judgments, formalized as *appraisal variables*, characterize aspects of the personal significance of events (e.g., was this event expected in terms of my prior beliefs? is this event congruent with my goals; do I have the power to alter the consequences of this event?). Patterns of appraisal elicit emotional behavior (e.g., undesirable and uncontrollable events lead to sadness) and trigger stereotypical cognitive responses formalized as qualitatively distinct *coping strategies* (e.g., planning, procrastination or resignation).

EMA is a computational model of the cognitive antecedents and consequences of emotion as posited by appraisal theory (Gratch & Marsella 2001; Marsella & Gratch 2003). In translating a psychological theory into a computational system, EMA draws extensively on common AI methods of reasoning and representation. To this end, EMA represents the relationship between events and an agent's internal beliefs, desires and intentions by building on AI planning to represent the relationship between events and their consequences. Appraisal variables are re-cast in terms of decision-theoretic inference over this representation (e.g., an event is desirable if it improves an agent's expected utility).

EMA has been fielded in several applications (Swartout *et al.* 2001; Traum *et al.* 2005) and validated against human performance data (Gratch & Marsella 2004). For example, Figure 2 illustrates the SASO negotiation training system (Traum *et al.* 2003). This prototype system allows a human trainee to engage in a natural language conversation with an AI agent. EMA informs the agent's decision-making and nonverbal behavior to create a more realistic and engaging dialogue.

Culturally *and* Emotionally Affected Behavior. While CAB and EMA systems were successful in modeling culturally and emotionally affected behavior respectively, they left several venues for future research. First, a high-fidelity virtual human simulation should be able to model *both* culture and emotions at the same time. This is not possible to do by simply running CAB and EMA in the same simulation since at any given time a virtual human's action preferred by CAB may contradict an action preferred by EMA. Second, both implementations have domain parameters (e.g., virtual human's sensitivity to perceived modesty) embedded in Jess format (CAB) or SOAR (EMA). Such design makes it more difficult to analyze the system, port it to a new platform and machine-learn the parameters.

Figure 2: EMA in action: interacting with a virtual human.

This paper addresses both issues by re-formulating core parts of CAB and EMA rigorously in matrix representation, with the following five benefits. First, the matrix representation enables a natural combination of the two systems. The joint system can simultaneously model culturally and emotionally affected behavior and henceforth is called CEMA (Culture-Emotion MAtrix). Second, it can be implemented and run on single- or multi-core hardware by using a matrix package (e.g., MATLAB or a C++ library). Third, the matrix representation can be easily extended to support explicit religion and personality profiles, thereby increasing authoring convenience and simulation fidelity. Fourth, it achieves a clean platform-independent separation between emotion and culture data and the underlying representation language (e.g., if-then rules). Fifth, the matrix representation uses simple inference rules and is well poised for machine learning of culture and emotion parameters.

The rest of the paper is organized as follows. A matrix re-write of CAB is found in Section 2. We then show how to add religion and personality profiles in Section 2.3. A matrix re-write of EMA follows in Section 3. We then show how to model cultural and emotional effects simultaneously in Section 4. Directions for future work follow in Section 5 with conclusions in Section 6.

2 CAB: Culturally Affected Behavior

There are two agents involved in a CAB scenario: a human participant and an AI agent (virtual human). The AI agent is selecting among several courses of action (or plans, as defined formally below). For instance, Figure 3 shows an AI agent (on the far right) deciding between Plan A and Plan B. Agent's decision is affected by his level of socio-cultural satisfaction which is derived from evaluating agent's "culture network" (box on the left). Thus, the task of the human participant is to make the agent select a specific plan by taking actions and affecting agent's beliefs. The game proceeds in discrete time steps with a single action taken per step. The domain plan with the highest utility is the one that the agent will take (Figure 4, line 7). Note that we use toy-scale examples throughout the paper. Actual plans in CAB and EMA are much larger and more complex.

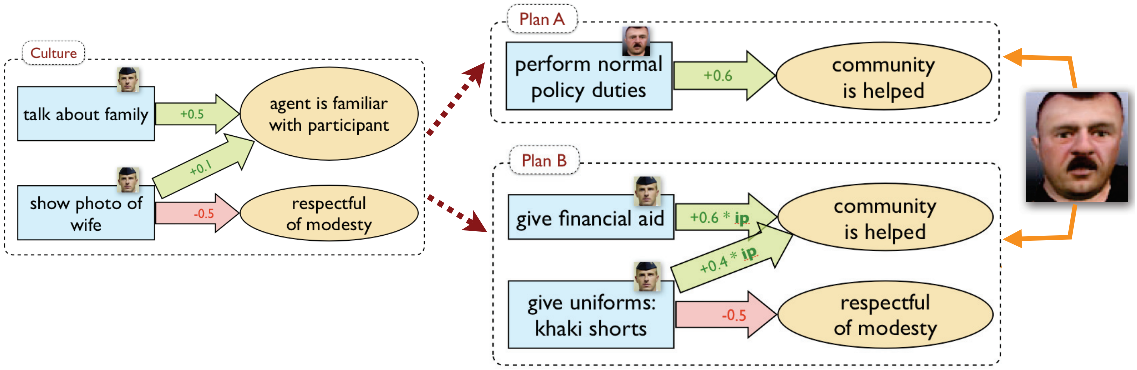

Figure 3: An overview of CAB.

CAB

load culture and domain data
do forever
  input participant's actions $\mathbf{C}^H$
  for each plan P **do**
    $U(P) \leftarrow$ **ComputePlanUtility(** $\mathbf{A}|_P$ **,** $\mathbf{S}_0|_P$ **,** $\mathbf{U}|_P$ **,** $\mathbf{C}^H$ **)**
  end for each
  announce that the agent prefers plan $\arg\max U(P)$
end do

Figure 4: The main loop of CAB.

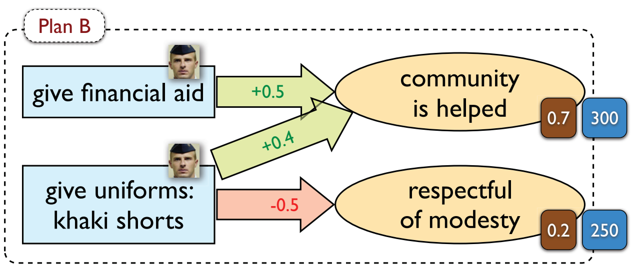

Figure 5: An example of a domain plan.

2.1 CAB Matrix Representation

The principal part of CAB can be formulated as follows.

Definition 1 *Domain plan / course of action / task network* is a directed weighted acyclic graph with two types of vertices: actions and states.

Definition 2 An *action* vertex represents an action that either the human participant or the AI agent can take.

Definition 3 A *state* vertex represents an attribute of the problem-solving state that has some *intrinsic utility / concern value* to the agent. Each state also has a *degree of belief / probability* associated with it.

Definition 4 Graph edges are weighted with *action effects*. Each edge leads from an action vertex to a state vertex. Each effect is a real number in $[0, 1]$ that affects agent's degree of belief of the state vertex at the end of the edge.

Example: the graph in Figure 5 represents a domain plan ("Plan B") and has four vertices and three edges. There are two domain actions that a human participant can take: "give financial aid" and "give uniforms: khaki shorts", shown as rectangles. There are two states: "community is helped" and "respectful of modesty", shown as ovals. Agent's degrees of belief in these states are 0.7 and 0.2 respectively; agent's intrinsic utilities of those states are 300 and 250. First action ("give financial aid") adds 0.5 to the degree of belief in state "community is helped", as shown by an arrow. The second action has two effects: 0.4 and -0.5. The negative effect reflects the fact that a representative of Iraqi culture may view shorts as immodest.

Definition 5 Action effects can be viewed as a matrix $\mathbf{A} = [a_{ij}]$ where $a_{ij} \in \mathbb{R}$ is the effect the action j has on state i (i.e., the weight of the edge between action vertex j and state vertex i).[1] Degrees of belief for all states form a column vector $\mathbf{S} = [s_i]$, $s_i \in [0, 1]$. Initial degrees of belief are $\mathbf{S}_0 = [s_i]$. Intrinsic utilities of all states form a row-vector $\mathbf{U} = [u_i]$, $u_i \in \mathbb{R}$.

Definition 6 Some domain actions of the human participant have *future* effects. Thus, their out-edges have action effects scaled by *intention probability*. In the matrix language, all action effects are multiplied by an intention probability matrix $\mathbf{I} = [\alpha_{ij}]$ where $\alpha_{ij} \in [0, 1]$ are the scaling coefficients (line 6 in Figure 7).

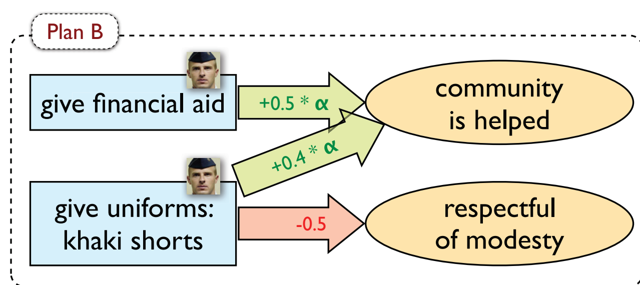

Figure 6: An example of a domain plan with intentional probabilities denoted by α.

Example: in Figure 6, the action "give financial aid" is a promise made by the human participant. Thus, its action effect (0.5) will be scaled by the intention probability $\alpha \in [0, 1]$ representing AI agent's belief as to whether the human will follow through on his/her promise. On the other hand,

[1] Henceforth we use bold variables for matrices and plain variables for scalars.

the -0.5 effect of action "give uniforms: khaki shorts" on the state "respectful of modesty" is immediate (i.e., $\alpha = 1$).

Definition 7 *Human participant's choices* are represented as a column vector $\mathbf{C}^H = \left[c_i^H\right]$, where $c_i^H \in \{0, 1\}$. For each i, $c_i^H = 1$ iff the human participant chose to perform action i.

Definition 8 *Agent's choices* $\mathbf{C}^A = \left[c_i^A\right], c_i^A \in [0, 1]$ are computed using the following procedure. Each action i of the agent is assumed to occur with the probability $c_i^A = \prod_{j \in P_i} s_j$ where P_i is a set of states that are preconditions to action i. When $P_i = \emptyset$, $c_i^A = 1$.

2.2 CAB Matrix Inference

Each domain plan utility is computed as shown in Figure 7. Once utility of each domain is computed, the AI agent selects the plan with the highest utility.

ComputePlanUtility$(\mathbf{A}, \mathbf{S_0}, \mathbf{U}, \mathbf{C}^H)$

1 $t \leftarrow -1$
2 **do**
3 $\quad t \leftarrow t + 1$
4 $\quad$ compute intention probability $\mathbf{I}$ as described in Section 2.2
5 $\quad$ compute agent's action choice $\mathbf{C}^A$ as per Definition 8
6 $\quad$ update degrees of belief:
$$\mathbf{S}_{t+1} \leftarrow F\left(\mathbf{S}_t + \mathbf{A} \cdot \left(\mathbf{I} \cdot \mathbf{C}^H + \mathbf{C}^A\right)\right)$$
7 **while** $\mathbf{S}_{t+1} \neq \mathbf{S}_t$
8 **return** $\mathbf{U} \cdot \mathbf{S}_{t+1}$

Figure 7: Plan utility computation in CAB.

In line 6, function F is a clipping function used to keep degrees of beliefs between 0 and 1; it returns 1 if its argument is above 1 and 0 if its argument is below 0. When applied to a matrix it applies itself to each of the matrix elements individually.

The intention probability matrix $\mathbf{I}$ is computed as follows. First, the utility of a *socio-cultural network* is computed. A socio-cultural network is representationally identical to a domain plan introduced in Section 2.1 but models solely socio-cultural aspects of the relationship between the human participant and the AI agent. An example is found in Figure 8. The algorithm presented in Figure 7 is run on it with line 4 set to $\mathbf{I} = [1]$ (i.e., no action effect scaling is used in computing utility of a socio-cultural network because all socio-cultural action effects are immediate).

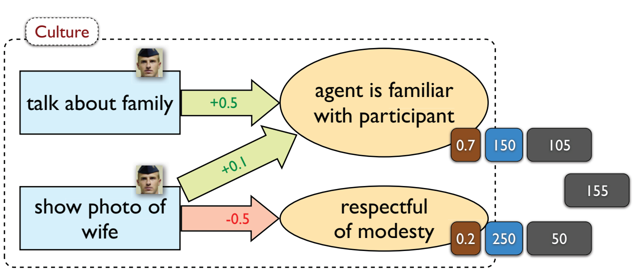

Figure 8: An example of a socio-cultural network. Its utility is computed as 155.

Second, the derived utility of the socio-cultural network is normalized with respect to the possible range of its value. The resulting number (in $[0, 1]$) is called *socio-cultural satisfaction* of the agent. Third, a non-linear mapping function applied to the satisfaction level to compute intention probability α (a scalar). The rationale is that the more socio-culturally satisfied the agent is the more faith it will have in the participant's following up on his/her promises. Finally, matrix $\mathbf{I}$ is formed with all entries corresponding to immediate action effects set to 1 and all other entries to α.

2.3 Adding Religion and Personality

The matrix approach to CAB not only separates data from the programming language cleanly but also allows us to extend the cultural model with religion and personality in a straightforward way. Consider, for instance, CAB model of Farid, an Iraqi Sunni police captain. The model consists of action effects $\mathbf{A}$, intrinsic utilities of states $\mathbf{U}$ and initial degrees of belief $\mathbf{S}_0$. These three matrices *combine* effects of Iraqi Sunni culture, Islam religion and Farid's personality (an introvert). What if we would like to change's Farid's personality to an extrovert while retaining the culture and religion? In CAB, the way to do so would be to re-write Farid's entire socio-cultural model (i.e., $\mathbf{A}$, $\mathbf{U}$ and $\mathbf{S}_0$).

A more modular way would be to decompose Farid's model into a culture component, a religion component and a personality component. With the new matrix representation, the decomposition can be done as a matrix sum:

$$\begin{aligned}
\mathbf{A} &\leftarrow \mathbf{A}^{\text{Iraqi Sunni}} + \mathbf{A}^{\text{Islam}} + \mathbf{A}^{\text{Farid}} \\
\mathbf{U} &\leftarrow \mathbf{U}^{\text{Iraqi Sunni}} + \mathbf{U}^{\text{Islam}} + \mathbf{U}^{\text{Farid}} \\
\mathbf{S}_0 &\leftarrow F\left(\mathbf{S}_0^{\text{Iraqi Sunni}} + \mathbf{S}_0^{\text{Islam}} + \mathbf{S}_0^{\text{Farid}}\right).
\end{aligned}$$

Furthermore, Farid's degree of being religious can be implemented with a scaling coefficient β:

$$\begin{aligned}
\mathbf{A} &\leftarrow \mathbf{A}^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{A}^{\text{Islam}} + \mathbf{A}^{\text{Farid}} \\
\mathbf{U} &\leftarrow \mathbf{U}^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{U}^{\text{Islam}} + \mathbf{U}^{\text{Farid}} \\
\mathbf{S}_0 &\leftarrow F\left(\mathbf{S}_0^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{S}_0^{\text{Islam}} + \mathbf{S}_0^{\text{Farid}}\right)
\end{aligned}$$

Thus, with the modular representation, changing Farid's personality is a matter of using a different personality matrix and can be done independently of other components (i.e., religion and culture). Furthermore, instead of coding a personality matrix from scratch, the designers can quickly build it as a linear combination of personality archetypes (e.g., introvert, extrovert):

$$\begin{aligned}
\mathbf{A} &\leftarrow \mathbf{A}^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{A}^{\text{Islam}} + \gamma \cdot \mathbf{A}^{\text{introvert}} + \delta \cdot \mathbf{A}^{\text{extrovert}} \\
\mathbf{U} &\leftarrow \mathbf{U}^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{U}^{\text{Islam}} + \gamma \cdot \mathbf{U}^{\text{introvert}} + \delta \cdot \mathbf{U}^{\text{extrovert}} \\
\mathbf{S}_0 &\leftarrow F\left(\mathbf{S}_0^{\text{Iraqi Sunni}} + \beta \cdot \mathbf{S}_0^{\text{Islam}} + \gamma \cdot \mathbf{S}_0^{\text{introvert}} + \delta \cdot \mathbf{S}_0^{\text{extrovert}}\right).
\end{aligned}$$

3 EMA: EMotion and Adaptation

With EMA, a virtual human also decides among several domain plans. The simulation set-up is similar to CAB insomuch as a human participant takes actions within a dialogue with an AI-controlled agent (the virtual human). Participant's actions have domain and emotion effects on the agent which prefers a domain plan with the highest utility. Thus, participant's task is to generate a sequence actions that, through their domain and emotion effects, will persuade the agent to prefer a specific plan. EMA's main simulation loop is similar to the one for CAB, shown in Figure 4. There are two primary differences between CAB and EMA. First, CAB uses the utility calculation procedure in Figure 7. EMA computes appraisals, then emotion elicitors and then combines the emotions together as described in Section 3.1. Second, CAB uses a single scalar – socio-cultural satisfaction – to derive intention probability. EMA computes intention probability from three scalars: *solidarity, credibility, and familiarity*. These numbers come from SASO's natural language processing module (Traum *et al.* 2003) and not from evaluating a separate task network.

3.1 EMA Matrix Representation and Inference

EMA provides an integrated model of appraisal and coping to inform individual action selection and expressive behavior. In this section we present a matrix re-write of the core factors that underlie EMA'a appraisal mechanism. Matrix support for the role of coping strategies in informing action selection is a topic of future work.

Domain plans are represented in a way similar to CAB's (Section 2.1). The inference mechanism, however, is different from CAB and is shown in Figure 9. Namely, the lines 1 through 7 are identical to CAB's with the exception of computing intention probability in line 4. However, instead of computing utility as a dot-product in CAB (i.e., "**return** $\mathbf{U} \cdot \mathbf{S}_{t+1}$"), lines 8 through 12 are used. Lines 8 through 11 go through n emotion types. For each type $e = 1, \ldots, n$, a column vector $\mathbf{E}_e$ is computed. Each component of the vector is 1 if the corresponding state is appraised to elicit an emotion of type e and 0 otherwise. Four basic emotion types are defined in Table 1, other emotion types can be modeled as well. In line 10, emotion intensities are computed for all states as the absolute value of the element-wise product ($\odot$) of $\mathbf{U}$ and $\mathbf{S}_{t+1}$. Since we are only concerned with states whose appraisals elicit an emotion of type e, we set emotion intensities to 0 for all other states. This is done with an element-wise product of $\mathbf{E}_e$ and $|\mathbf{U} \odot \mathbf{S}_{t+1}|$. The result is a vector of emotion intensities $\mathbf{\Upsilon}_e$. In line 12, we sum up emotion intensities for all n emotion types over all states and compute a column vector:

$$\begin{bmatrix} \sum \mathbf{\Upsilon}_1 \\ \sum \mathbf{\Upsilon}_2 \\ \vdots \\ \sum \mathbf{\Upsilon}_n \end{bmatrix}.$$

By taking a dot-product with emotion weights $\mathbf{W}$ (Table 1), we compute a scalar emotion utility of a domain plan.

With just the four emotion types defined in Table 1, it is straightforward to prove that for any domain plan, the utility values computed by CAB (Figure 7) and by EMA (Figure 9) will necessarily be the same. However, EMA's way of computing the utility results in several by-products such as the vector of $\sum \mathbf{\Upsilon}_e$. These can be used in various ways (e.g., to change character animation, tone of voice, or the natural language responses).

Table 1: Basic emotion types.

Emotion e	**For state** i, $\mathbf{E}_e(i)$ **is set to** 1 **iff:**	$\mathbf{W}(e)$
Hope	$\mathbf{S}_{t+1}(i) < 1$ & $\mathbf{U}(i) > 0$	$+1$
Joy	$\mathbf{S}_{t+1}(i) = 1$ & $\mathbf{U}(i) > 0$	$+1$
Fear	$\mathbf{S}_{t+1}(i) < 1$ & $\mathbf{U}(i) < 0$	-1
Distress	$\mathbf{S}_{t+1}(i) = 1$ & $\mathbf{U}(i) < 0$	-1

ComputePlanUtility$(\mathbf{A}, \mathbf{S_0}, \mathbf{U}, \mathbf{W}, \mathbf{C}^H)$

1 $t \leftarrow -1$
2 **do**
3 $\quad t \leftarrow t+1$
4 $\quad$ compute intention probability $\mathbf{I}$
5 $\quad$ compute agent's action choice $\mathbf{C}^A$ as per Definition 8
6 $\quad$ update degrees of belief:
$$\mathbf{S}_{t+1} \leftarrow F\left(\mathbf{S}_t + \mathbf{A} \cdot \left(\mathbf{I} \cdot \mathbf{C}^H + \mathbf{C}^A\right)\right)$$
7 **while** $\mathbf{S}_{t+1} \neq \mathbf{S}_t$
8 **for each** emotion type $e = 1, \ldots, n$ **do**
9 $\quad$ compute emotion instances $\mathbf{E}_e$
10 $\quad$ compute emotion intensities $\mathbf{\Upsilon}_e \leftarrow \mathbf{E}_e \odot |\mathbf{U} \odot \mathbf{S}_{t+1}|$
11 **end for each**
12 **return** $\mathbf{W} \cdot \begin{bmatrix} \sum \mathbf{\Upsilon}_1 \\ \sum \mathbf{\Upsilon}_2 \\ \vdots \\ \sum \mathbf{\Upsilon}_n \end{bmatrix}$

Figure 9: Plan utility computation in EMA.

4 Combining CAB and EMA

The matrix re-write of CAB and EMA allows us to combine the two systems in a straightforward way. Namely, CAB's evaluation of a socio-cultural network is used to compute the intention probability $\mathbf{I}$; EMA's way of computing emotion utilities is used to evaluate each domain plan (taking $\mathbf{I}$ into account) and choose the best one. Algorithmically, we use the code in Figure 9 but replace line 4 with the socio-cultural satisfaction computation (i.e., line 4 in Figure 7).

We implemented the joint system in a compact way in MATLAB. To illustrate, Figure 10 shows the actual MATLAB code for computing the emotion of hope. Notice that the code does not contain any domain-specific parameters (e.g., the emotional weight of hope). All such data are simply loaded as matrices from disk. This allows the user to easily swap in another culture or another emotional model (i.e., different emotion weights). Furthermore, most operations (e.g., any of the four lines in the figure) are automatically parallelized by MATLAB (or any other high-performance matrix library) and scale up well with additional CPU cores. On the contrary, the original implementations used if-then rules (either in Jess/SOAR) which are much less trivial to run in parallel. Computational efficiency can become a key in a large-scale simulation of many emotionally and culturally affected agents.

5 Future Work

The combination of CAB and EMA opens exciting avenues for future research including the following three.

Emotions from Socio-Cultural States. The combination of CAB and EMA in Section 4 computes emotions and emo-

ComputeHope

```
hopeMask = (degrees < 1.0) .* (utilities > 0);
intensity = abs(degrees .* utilities);
hopeInstances = hopeMask .* intensity;
hope = sum(hopeInstances);
```

Figure 10: Actual MATLAB code for computing hope.

tion utility only from the domain states. For instance, if the agent appraised an intrinsically undesirable state as a possibility then the elicited emotion is that of fear. A natural extension would be to compute emotions from socio-cultural states as well. For instance, an agent can be fearful of being perceived as unobservant of Islam. Note that the emotion weights for domain-state-elicited emotions can differ from those for socio-cultural-state-elicited emotions. For instance, fear of death may be stronger than fear of being perceived as a gambler.

Machine Learning. Numerous parameters are hard-coded into EMA and CAB. They were produced and tuned by hand in a time-consuming process. It would be beneficial to have an automated and validated way of generating such parameters in order to (i) reduce system production cost and (ii) increase simulation fidelity. Future research will investigate the extent to which machine learning methods can be used to derive the parameters from historic data consisting of events recorded from real-life culturally and emotionally affected negotiations. Then parameters can be fit to minimize discrepancies between agent's actions and historic data. Second, given an expert willing to label each action taken by a CEMA agent as realistic or unrealistic, positive and negative rewards can be easily defined. Then Reinforcement Learning may be used to learn the parameters.

Learning Heuristic Search is an effective mechanism for controlling adaptive and autonomous agents in an *a priori* unknown environment. Such agents start with an initial (inaccurate) heuristic and, through experience, refine it to reflect to the environment. Most experiments in search have been conducted in gridworld pathfinding and combinatorial puzzles (Bulitko & Lee 2006). Future work will investigate the extent to which learning real-time heuristic search is applicable to the space of agent's culturally and emotionally affected states.

6 Conclusions

We argued that a high-fidelity virtual human simulation must simultaneously model emotionally and culturally affected behavior. We reviewed two existing systems: CAB and EMA which are capable of modeling culture and emotion effects independently. The main contribution of our work is a formal re-write of core parts of both systems in a language of matrix algebra. The new system (Culture-Emotion MAtrix or CEMA) naturally unifies CAB and EMA and is capable of simulating culture and emotion effects on agent's behavior simultaneously. CEMA affords a clean separation of culture and emotion data from the underlying programming language and can be implemented easily with any matrix package. The matrix language also makes it straightforward to add personality and religion layers to the simulation and is a natural representation for machine learning methods.

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