A Flexible Scheme to Model the Cognitive Influence on Emotions in Autonomous Agents

Article *in* International Journal of Cognitive Informatics and Natural Intelligence · October 2018

DOI: 10.4018/IJCINI.2018100105

2 authors:

Sergio Castellanos
Instituto Tecnológico de Sonora

Luis-Felipe Rodríguez
Instituto Tecnológico de Sonora

A Flexible Scheme to Model the Cognitive Influence on Emotions in Autonomous Agents

Sergio Castellanos, and Luis-Felipe Rodríguez
Sonora Institute of Research, Mexico

ABSTRACT

Autonomous Agents (AAs) are designed to embody the natural intelligence by incorporating cognitive mechanisms that are applied to evaluate stimuli from an emotional perspective. Computational Models of Emotions (CMEs) implement mechanisms of human information processing in order to provide AAs for a capability to assign emotional values to perceived stimuli and implement emotion-driven behaviors. However, a major challenge in the design of CMEs is how cognitive information is projected from the architecture of AAs. This paper presents a cognitive model for CMEs based on appraisal theory aimed at modeling AAs' interactions between cognitive and affective processes. The proposed scheme explains the influence of AA's cognition on emotions by fuzzy membership functions associated to appraisal dimensions. The computational simulation is designed in the context of an Integrative Framework to facilitate the development of CMEs, which are capable of interacting with cognitive components of AAs. We present a case study and experiment that demonstrate the functionality of the proposed models.

Keywords: Cognitive Model of the Brain, Emotion Process, Software Agent, Fuzzy Logic.

INTRODUCTION

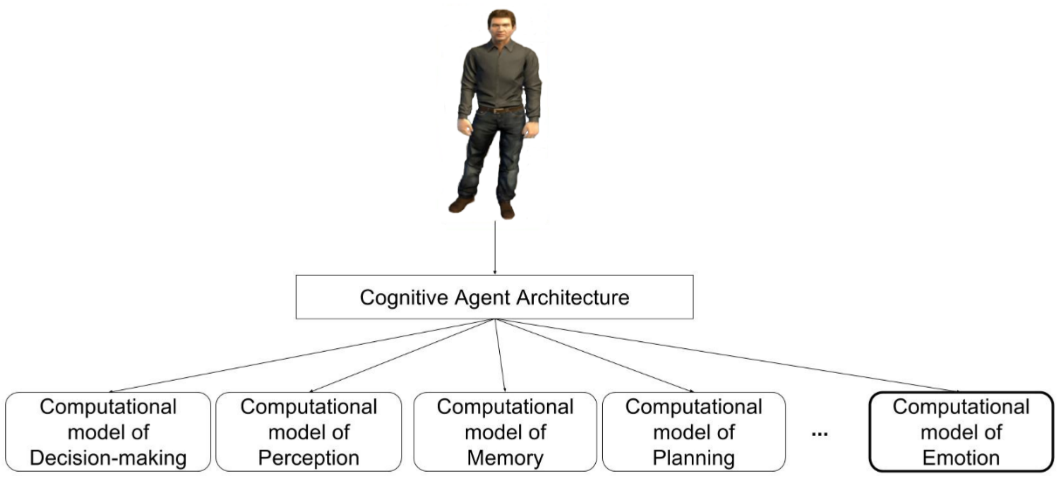
Autonomous Agents (AAs) are software and robot entities that act on behalf of users or other programs with certain degree of independence and autonomy. In doing so, AAs make use of knowledge about the environment and representations of desires and goals (Franklin & Graesser, 1997; Wang, 2010; Wang, Zatarain, & Valipour, 2017). This type of intelligent system has been crucial for the advance of fields such as software engineering (SE), human-computer interaction (HCI), and artificial intelligence (AI). In these fields, AAs have been designed to carry out tasks that require the imitation of human cognitive functions, including decision making, planning, and reasoning (Ligeza, 1995; Maes, 1995; Sun, 2009). Giving AAs such cognitive functions allow them to carry out more complex tasks by minimizing human intervention. That is why research in these fields (e.g., AI, HCI, and SE) focuses on improving problem solving, reasoning, and communication skills of AAs. Particularly, the research community in the AI field has devoted efforts to create human-like systems for communication and reasoning as well as to reproduce in computer environments the associated brain processes (Ligeza, 1995). In the HCI field some interfaces and mechanisms that improve the interaction of these systems with other agents (computational or human agents) have also been developed (Martínez-Miranda & Aldea, 2005; Perlovsky & Kuvich, 2013).

Evidence shows that emotions influence cognitive functions (Ayesh, Arevalillo-Herráez, & Ferri, 2016; Hurtubise, 1995; Phelps, 2006). The emotional significance of perceived stimuli influences the normal operation of brain processes such as attention, perception, and decision making. According to fields such as psychology and neuroscience, emotions result from the interaction of several cognitive and affective processes, including memory, perception, motivations, and attention (Frijda, 2005; Goldie, 2002; LeDoux, 2000; Smith & Lane, 2016). Emotions are psychophysiological reactions that represent ways of adapting to perceived stimuli from an important object, person, place, event, or memory. Psychologically, emotions alter attention, trigger certain behaviors, and activate relevant associative networks in memory (Wang, 2012). According to Breazeal (1998) and Wang (2010), emotions are necessary to establish long-term memories. In addition, emotions play a key role in learning, from simple reinforcement learning to complex and conscious planning.

A key objective of artificial intelligence is the development of software systems capable of doing complex tasks that produce intelligent responses (Perlovsky & Kuvich, 2013), systems that act and reason like humans. In this context, the literature reports an increasing interest in the development of AAs with abilities to evaluate and respond to emotional stimuli (Cañamero, 1997; Dias, Mascarenhas, & Paiva, 2014; Gebhard, 2005; Rodriguez, Ramos, & Wang, 2011; Wang et al., 2012; Wang, Wang, Patel, & Patel, 2006). Recent works have proposed the incorporation of affective processing in AAs by designing Computational Models of emotions (CMEs), which are software systems designed to synthesize the mechanisms of the human emotion process (Rodríguez, Ramos, & Ramos, 2014; Rodríguez & Ramos, 2015). These CMEs are designed to be included in cognitive agent architectures to provide AAs with mechanisms for the processing of affective information, generation of synthetic emotions, and generation of emotional behaviors. Ortony, Clore, & Collins (1990) propose that CMEs provide AAs with the capacity for affective processing; they synthesize operations and architectures of some components that represent aspects of the human emotional process. In general, CMEs include mechanisms for the evaluation of stimuli, generation of emotions, and generation of emotional responses, providing this type of intelligent systems with the ability to recognize emotions of humans and other virtual agents. For example, Alma is a CME designed to provide virtual humans with emotions, mood and personality, facilitating the generation of emotions by evaluating the stimuli coming from agents' verbal and non-verbal expressions such as wording, length of phrases, and facial expressions (Gebhard, 2005; Gebhard, Kipp, Klesen, & Rist, 2003).

Despite of the importance of the relationship between cognitive and affective processes in humans, such interaction is not usually considered in the design of cognitive agent architectures (Rodríguez, Gutierrez-Garcia, & Ramos, 2016) (Figure 1 shows an example of the types of components included in a representative cognitive agent architecture). Moreover, although the literature reports a variety of CMEs, most of them do not take into account the influence on the emotion evaluation process of human key aspects such as personality, culture, past experiences, social context, and physical context, among others, which are processes that may be implemented in cognitive agent architectures and which influence human emotions (Gebhard, 2005; Martínez-Miranda & Aldea, 2005; Wang, 2007; Wang et al., 2006). In this context, although findings in psychology and neuroscience indicate that (1) the evaluation of emotional stimuli is influenced by the results of various cognitive functions and that (2) elicited emotions modulate cognitive processes (e.g., attention, perception, and decision-making), there are several challenges to be addressed in the modeling of this extensive interaction between mechanisms associated with cognitive and emotional functions in cognitive agent architectures (Wang, 2007, 2011).

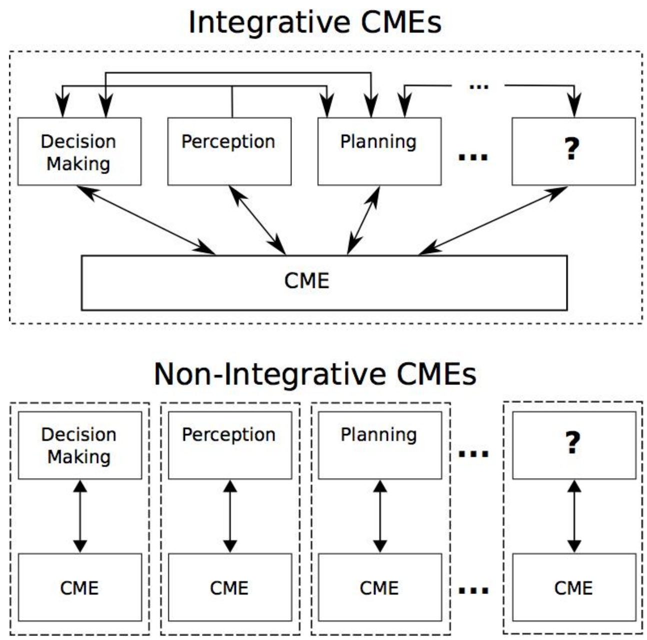
Figure 1. Representative cognitive agent architecture.



The following are some of such challenges and issues involved in the modeling of the interaction between cognition and emotion in cognitive agent architectures (Castellanos, Rodríguez, Castro, & Gutierrez-Garcia, 2018; Rodriguez et al., 2011; Wang, 2007; Wang et al., 2006):

- A cognitive agent architecture may include a variable number of cognitive components. As we discuss above, there are many cognitive processes involved in the emotional process which makes it complex to implement them all. The domain in which the agent operates determines which components to implement.
- Each cognitive component in a cognitive agent architecture projects very particular information using different data structure and formatting. Each cognitive component is complex by itself and its mechanisms are not standardized. In many cases they are not even implemented, and each researcher proposes solutions from very specific perspectives and for specific objectives. This leads to different models that make it difficult their integration, due to, for example, these would hardly share the same format.
- The information provided by cognitive components changes frequently depending on the type of cognitive function these components implement. For example, the physical context changes very frequently but information regarding the agent’s culture and personality changes very slowly.
- The emotion component must weight differently the influence of each cognitive process on the emotion process. It refers to the fact that the same cognitive information does not produce the same influence. Mainly because if a same stimulus is perceived more than once, the agent learns how to deal with it and is already prepared. It is possible that the result is very similar, but the emotion intensity should vary.

Figure 2. Integrative and non-integrative frameworks of CMEs.



In addition, Ojha & Williams (2017) state that CMEs have the following limitations regarding their underlying design in cognitive agent architectures:

- Low replicability. The design and implementation of the underlying components of CMEs are explained only at high-level description.
- Domain dependency. The model design of CMEs is only applicable in one or very few predefined scenarios or domains. Also, CMEs model emotions according to specific implementation needs. Depending on the problem, the emotional evaluation process is designed by selecting one or two aspects of the complex human cognitive-affective interrelationship (Ortony, 2003; Paiva, Parada, & Picard, 2007).
- Poor scalability and integration. It is hard to add new components to CMEs because their design is domain-specific.

In this paper, we present a computational scheme designed to model the influence of cognitive information on the emotional evaluation process of CMEs in autonomous agents. The level of influence on such evaluation process depends on the cognitive information projected from components of cognitive agent architecture. The evaluation process in a CME is responsible of assessing from an emotional perspective the stimuli perceived by an agent. The evaluation process is a crucial phase of the operating cycle of CMEs since the consistency of the results of other phases (e.g., emotion and behavior generation) depend on the consistency of such emotional assessment. In turn, the consistency of the evaluation process in a CME depends on the cognitive information taken into account. In particular, the computational scheme is designed in the context of the Integrative Framework proposed by Rodríguez et al. (2016), which is a framework designed to facilitate, through input and output interfaces, the development of CMEs capable of interacting with cognitive components implemented in a given cognitive agent architecture and which are involved in the emotion process (e.g., personality, culture, perception, motivations, and attention). Importantly, the proposed computational scheme is designed to promote the modeling of the interaction between cognitive and affective processes in autonomous agents as occurs in the human brain.

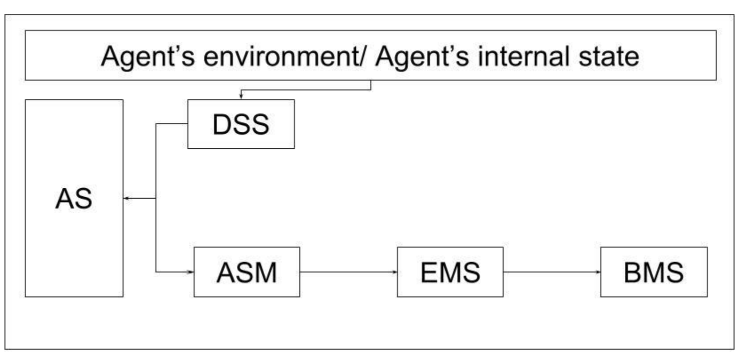
RELATED WORK

The literature reports a variety of CMEs designed to be included in cognitive agent architectures. These computational models consider a variety of cognitive information in their emotion evaluation phase. In this section, we analyze influential CMEs and some frameworks (integrative and non-integrative frameworks, see Figure 2) in order to understand the role of cognitive information in their evaluation process and how researches incorporate them into CMEs (Castellanos et al., 2018; Wang, 2007; Wang et al., 2006). There are several efforts that attempt to provide AAs with emotional components; we review some of the strategies used in different CMEs. We provide a detailed description of the role of some key human elements such as motivations, internal drives, personality, and learning in some CMEs and analyze their influence in AAs.

In non-integrative CMEs, their underlying architecture represents a closed system that does not allow including new components (at least not in a simple way). Non-integrative models are developed for a specific purpose and context. This type of model includes one or two emotional aspects in their evaluation process, which in many cases is sufficient to obtain a functional system (see Figure 2). For example, Armony (2010) presents EMA, a computational model of emotions designed to integrate the emotional component in a cognitive-emotional agent architecture. EMA is based on the psychological theory of appraisal, which consists in establishing emotional processing as a series of relationships between individuals and their environment. Another example is Flame (El-Nasr, Yen, & Ioerger, 2000), which is a computational model that uses fuzzy logic to link emotional states to certain events, in this way considers factors such as past experiences and memory to influence decision making.

There are more recent designs of CMEs dealing with the problem of complexity in emotional appraisal from another perspective, not as part of a CME intended for a specific application, but as a more complete and varying representation of the process. These proposals focus on modeling the complexity of emotional assessment through scalability-oriented mechanisms and are considered as integrative models (see Figure 2). An example of this type of integrative model is FeelMe (Broekens & Degroot, 2004), which is a framework designed to address the problem of scalability in computational models of emotions for agent architectures. It is implemented in a modular and extensible way so that it becomes feasible to include new characteristics to the emotional model to make it more complete. FeelMe is based on the psychological theory of appraisal, which characterizes emotion as the result of a process of evaluation of events that occurs differently in each individual, usually taking into account aspects such as their goals, beliefs, and past experiences.

Figure 3. Framework FeelMe (Broekens & Degroot, 2004).

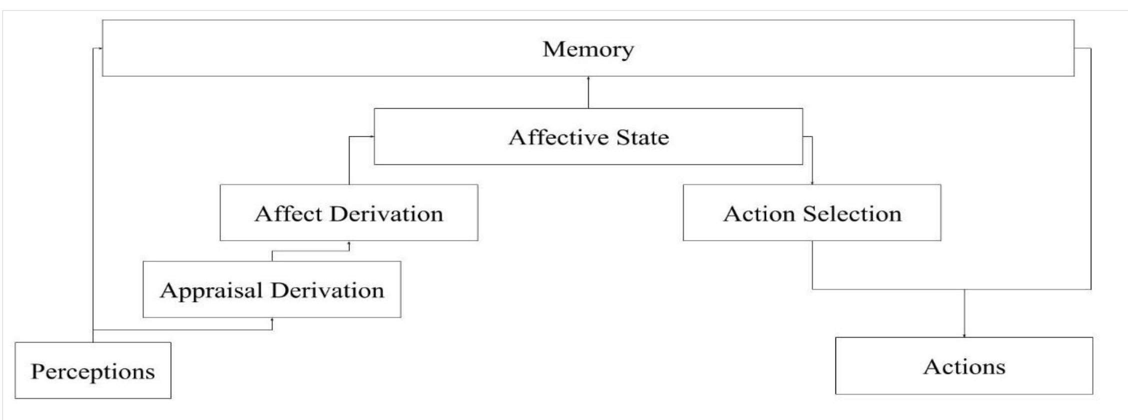


FeelMe is proposed with a modular scheme, in which the emotional process is separated into five steps (see Figure 3):

1. Decision Support System (DSS). It converts the environment information into viable objects to be evaluated.
2. Assessment System (AS). It evaluates the objects generated in step 1 continuously and interprets them in terms of dimensions (variables) of evaluation, whose number and type are configurable. It generates continuously a vector of size n, where n is the number of dimensions (variables) with the values resulting from the evaluation process.
3. Assessment Signal Modulator (ASM). It adjusts the results (vectors) obtained in the previous step, amplifying them, reducing them or correlating them.
4. Emotion Maintenance System (EMS). It integrates the results to form a vector of values of integrated dimensions, which conforms in the emotional state of the agent.
5. Behavior Modification System (BMS). It selects, controls, and expresses the emotional behavior of the agent based on its emotional state.

Modular FATIMA (FearNot Affective Mind Architecture) (Dias et al., 2014) is an architecture for autonomous agents that implements personality and emotions to generate an influence on the agent's behavior. This architecture proposes a modular scheme to provide the scalability feature. Figure 4 shows the operation of FATIMA. First, FATIMA perceives information from the environment with which the internal state is updated (memory of the agent) and begins the process of evaluation, which is divided into 2 phases. The result of this latter process is stored in the affective state and is used to influence the action to be performed, which generates an agent response to the change in the environment. The evaluation process is divided into two parts, appraisal derivation and affection derivation according to the structural theories of appraisal (Reisenzein, 2001).

Figure 4. Fatima Architecture (Dias et al., 2014).



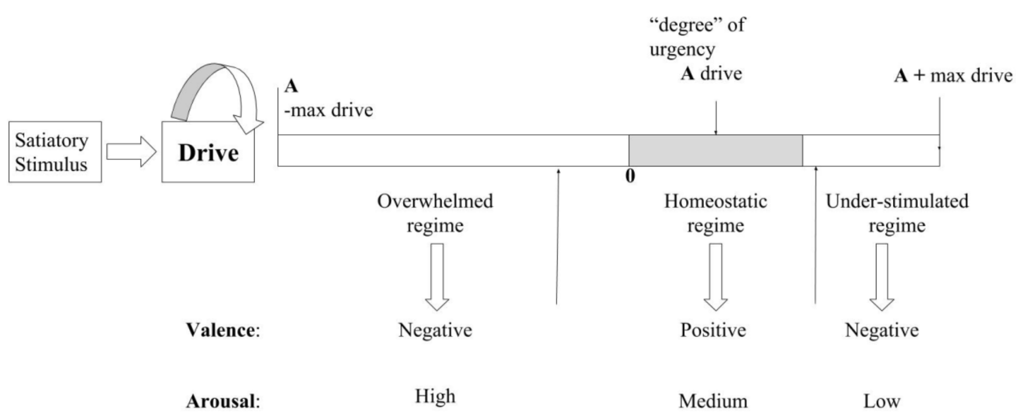
In Table 1 we present a summary of the role of cognitive functions in the emotion process of some CMEs reported in the literature (Armony, 2010; Breazeal, 2003; El-Nasr et al., 2000; Hudlicka, 2005; Gebhard, 2005; Velásquez, 1996; Becker-Asano & Wachsmuth, 2009). In the rest of the section we provide a detailed description of the role of Motivations and Internal Drives in Kismet (Breazeal, 2003), Learning (El-Nasr et al., 2000), and the role of personality in Mamid (Hudlicka, 2005), which are CMEs that have proven useful in several application domains.

Table 1. Cognitive processes involved in the emotion process in some CMEs.

Model	*Cognitive Processes*
EMA	Provides support for cognitive, perceptual, and motor operators. However, the model does not implement such processes directly (Armony, 2010).
Kismet	Perception and attention processes, learning mechanisms, behavior and expressive systems, and motor functions (Cynthia Breazeal, 2003).
Flame	Decision-making process, memory and experiential systems, and learning and adaptability processes (El-Nasr et al., 2000).
Mamid	Perceptual and attentional processes, memory systems, expectation and goal managers, and decision-making processes (Hudlicka, 2005).
Alma	Dialog generation processes, decision-making and motivation functions, and behavior and expression generation systems (Gebhard, 2005).
Cathexis	Perceptual processes, memory systems, behavior systems, and motor processes (Velásquez, 1996).
WASABI	Perception and reasoning processes, memory systems, and processes for the generation of expressions and voluntary and non-voluntary behaviors (Becker-Asano & Wachsmuth, 2009).

Motivations and Internal Drives. Motivations refer to an internal phenomenon that results from the interpretation of the agent's internal and external condition (Breazeal, 2003; Rodriguez et al., 2011; Wang, Patel, & Patel, 2013; Wang et al., 2006). Motivations regulate the agent's behavior in order to attain a certain state of affairs. Particular instances of motivations are drives, a factor that is often considered as participating in the processing of emotions in CMEs. In Kismet, a social robot designed to learn from humans by interacting with them, a motivational system is designed to carry out the processing of drives and their influence on emotions. The drives implemented in Kismet are social drive, stimulation drive, and fatigue drive. They represent the robot's basic needs and always have an intensity level associated. The levels of intensity tend to increase in the absence of stimuli and decrease when appropriate stimuli are being perceived. Furthermore, there is a bounded range called the "homeostatic regime," which establishes a desirable status for each drive as shown in Figure 5.

Figure 5. The model of internal drives in Kismet (Breazeal, 2003).



When the intensity of a particular drive is out of this range, the drive is into one of the following two states: under-stimulated (increased intensity) or overwhelmed (decreased intensity). In Kismet, drives influence the dynamics of emotions by contributing to their level of valence and arousal. As shown in Figure 5, when the intensity of a drive is within the overwhelmed regime, the valence of emotions becomes negative and their arousal high; when the drive is within the homeostatic regime, the valence is positive and arousal medium; and when the drive is within the under-stimulated regime, the valence is negative and the arousal low (Breazeal, 2003). In this manner, the intensity of emotions in Kismet depends on the status of its drives.

Personality. This term is seen in the domain of CMEs as the set of individual traits in which people differ from each other (Averill, 1997; Hampson, 2006). These traits are considered consistent patterns of behavior that provide support to individual differences. In MAMID (Hudlicka, 2005), a model that includes a methodology for modeling the effects of individual differences in cognitive affective architectures, personality traits influence the agent's cognition and behavior. The personality traits modeled are extraversion, introversion, aggressiveness, and conscientiousness. These traits are combined to form personality profiles which are characterized in terms of parameters that control the processing (e.g., speed), structure (e.g., long term memories), and content (e.g., beliefs) of architectural components. In particular, in the affect appraiser module, responsible for deriving the agent's affective state, personality contributes to the elicitation of emotions. For example, high neuroticism and low extroversion makes the agent susceptible to negative valence emotions as well as negative and anxiety affect.

Learning. FLAME (Fuzzy Logic Adaptive Model of Emotions) is a CME that focuses on memory systems and learning processes to improve the dynamics of emotions (El-Nasr et al., 2000). This model implements decision-making process, memory systems based on experience, and processes of learning and adaptation to elicit a coherent emotion and different states for each agent; these experiences contribute a degree of individuality to the agent, which helps to elicit different emotions for a same stimulus according to the bias that was experienced from the past events.

As seen in Table 1 and the analysis of models presented in this Section, cognitive information plays a key role in the emotion evaluation process. In particular, cognitive functions are highly involved in the process of evaluating stimuli from an emotional perspective in CMEs. Nevertheless, the complexity of such evaluation process has led to the design of CMEs whose architecture takes into account very specific types of cognitive information projected from components of cognitive agent architecture. For example, Kismet (Breazeal, 2003) considers only Motivations and Internal Drives whereas Mamid (Hudlicka, 2005) considers the influence of personality on the evaluation process. In this sense, most CMEs are not designed to take into account other type of cognitive information that may be available in a given cognitive agent architecture. This type of computational model is usually developed to work on very specific applications. In contrast, the complexity of the emotion process in humans involves an extensive interaction between cognitive and emotional components (Castellanos et al., 2018; Rodriguez et al., 2011; Wang et al., 2006). The consistency of the emotional evaluation process in CMEs depends on projections from several cognitive processes. Therefore, CMEs should be designed considering that the more cognitive information considered in the emotion process, the more consistency and accuracy in the agent's affective states and emotional behaviors.

INTEGRATIVE FRAMEWORK

The Integrative Framework (InFra) proposed by Rodríguez (2016) follows the idea that instead of developing a CME that tries to unify cognitive and affective information in order to generate consistent emotional signals that allow AAs to implement believable behaviors, we can approach this problem by creating a framework that enables the development of CMEs whose architectures provide a convenient environment for the unification of cognitive and affective information. A basic assumption in the design of such InFra is that CMEs should comprise in their design only those mechanisms related to affective processing, leaving aside other mechanisms associated with cognitive processes and psychological constructs such as perception, action selection, motor action, culture, and personality. The design of the InFra considers that these latter processes are fundamental elements of cognitive agent architectures and that therefore these should be implemented there (see Figure 1 for an example of representative cognitive agent architecture and its components). Nevertheless, this assumption does not mean that the internal processing and appropriate behaviors of CMEs are independent of those cognitive processes and psychological constructs. Instead, what the InFra suggests is that the design of a CME should be focused on two major aspects: 1) the modeling of mechanisms underlying affective processes such as emotions and mood states, and 2) the incorporation of input and output interfaces that facilitate the exchange of data between affective processes implemented in CMEs and cognitive processes implemented in agent architectures (see Figure 6 and Table 2).

Figure 6. Design of the integrative framework. It shows the relationships of a CME (part 'B') with cognitive agent architectures (part 'A' and part 'C'). Note that numbers on the arrows are only for explanation purposes within the text; these do not explain the temporal relationships between the model's data flows.

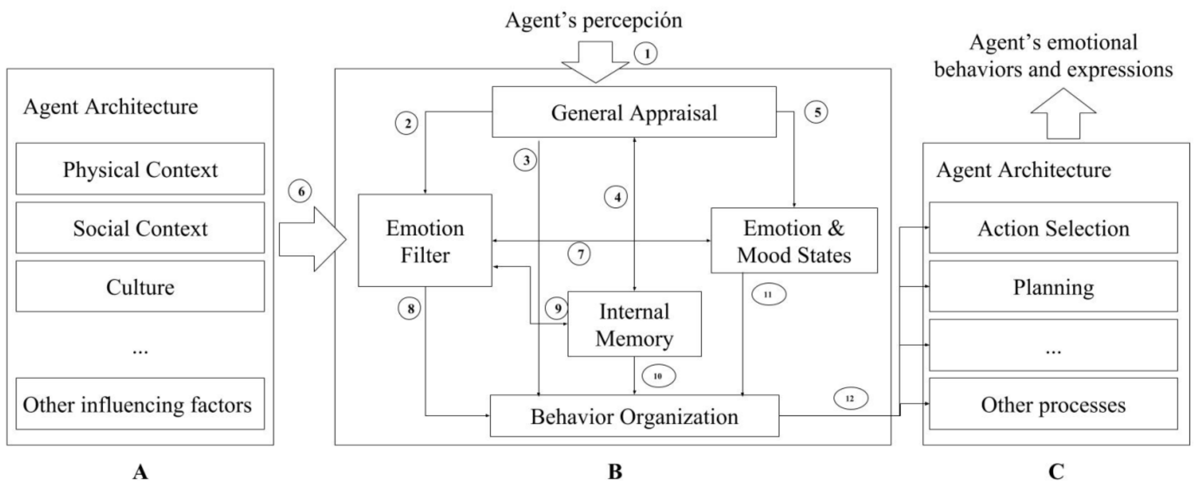


Table 2. Components of the InFra.

Component	*Abbr.*	*Description*
General Appraisal	GA	Determines the emotional value of the stimuli perceived by the agent.
Emotional Filter	EF	Amplifies, attenuates, or maintains the emotional significance of the stimuli perceived by the agent.
Behavior Organization	BO	Decides the type of emotional behavior that the agent should implement in order to deal with the emotional stimuli presented.
Emotion & Mood States	EMS	Maintains the agent's current emotional and mood states.
Internal Memory	IM	Provides knowledge to most components in the model and is highly involved in associative learning.

Based on this assumption for the InFra's design (mentioned above), there are two key characteristics that were considered:

1) The framework should enable CMEs to take as input all information available from agent architectures in order to accurately evaluate the emotional stimuli perceived by an agent and to generate more consistent emotional states and emotional behaviors.
2) The framework should enable CMEs to deliver appropriate emotional signals to those components in a cognitive agent architecture that are involved in the control of the agent's behaviors and expressions in order to exert an emotional bias.

In this context, among the requirements underlying the InFra's design, there are three related to this assumption, which recognize the need for more integrative designs in CMEs that facilitate the interactions between cognitive and emotional processes in cognitive agent architectures:

1) *Adaptable input interface*: the model should incorporate an input interface to handle all data that a cognitive agent architecture can communicate to contribute to the proper functioning of the CME.
2) *Reasoning with variable information*: the system should be able to reason about available information to generate coherent emotional signals. This information is received from the CME and components of cognitive agent architecture.
3) *Compatible output signals*: the model should be able to deliver appropriate emotional signals to all components of cognitive agent architecture that are involved in the control of the agent's emotional behavior.

In this paper, the proposed computational scheme is designed to address the first and second requirement: *Adaptable input interface* and *Reasoning with variable information*. In the InFra, these requirements involve the components of the called indirect route (see Figure 6 and Table 3). This indirect route starts in the General Appraisal (GA) module, goes through the Emotion Filter (EF) module, and ends in the Behavior Organization (BO) module.

Table 3. Interactions among the InFra's components (numbers in the first column correspond to the numbers in Figure 6).

	Description
1	Stimuli perceived by the agent.
2	Emotional significances of perceived stimuli.
3	Information about stimuli identified as highly emotional.
4	Information about the stimuli received and evaluated by the GA is sent to the IM component. Information about the emotional significance of incoming stimuli is sent from the IM to the GA component.
5	Initial emotional values determined for perceived stimuli.
6	Data projected by components of the agent's architecture.
7	Updated emotional significances of perceived stimuli are sent from the EF to the EMS component. In the opposite direction, the EMS sends to the EF information about the current agent's emotional and mood states.
8	Updated emotional significances of perceived stimuli.
9	Updated emotional significances of perceived stimuli are sent from the EF to the IM component. Information about the emotional significance of incoming stimuli is sent from the IM to the EF component.
10	Behavior tendencies associated with the stimuli perceived.
11	Current agent's emotional and mood states.
12	Emotional signals are sent from the BO component to various components in the agent's cognitive architecture.

In general, the indirect route in the InFra comprises processes that allow a CME to assign accurate emotional values (according to the agent's current internal and external condition) to the stimuli perceived by the agent and enables the agent to appropriately deal with social and emotional situations (see Table 3). In particular, there are two assessment phases in this route, one taking place in the GA and the other in the EF component. The main purpose of the evaluations performed by the GA is to determine the inherent emotional significance of incoming stimuli. The EF component carries out a second assessment of perceived stimuli. The main purpose of this evaluation is to re-appraise the initial emotional significance assigned by the GA. This evaluation process takes into account more information than that stored in the

IM component (which provides the emotional significance of stimuli previously perceived and acquired by experience). Particularly, the operating cycle implemented by the EF is influenced by cognitive signals received from components in the agent architecture that are mainly involved in determining the agent's internal condition and interpreting its external environment (these signals are supposed to be crucial for the processing of emotional stimuli in humans). For instance, these components may handle information underlying the processing of the following cognitive functions and psychological constructs:

- The agent's culture,
- The agent's motivations,
- The agent's personality,
- The agent's social norms,
- The agent's beliefs,
- The agent's goals and desires,
- The agent's physiological signals,
- The agent's expectations,
- The agent's past experiences,
- The agent's physical context,
- The agent's social context, and
- The agent's current situation.

As mentioned above, the presented computational scheme is focused on addressing the first and second requirement of the InFra (*Adaptable input interface* and *Reasoning with variable information*), leaving aside any other process involved in the operating cycle and architecture of the InFra. In particular, the computational scheme is designed to provide mechanisms for the cognitive modulation of appraisal variables used in the emotion evaluation process of autonomous agents.

SCHEME FOR MODULATING APPRAISAL VARIABLES

As shown above, most CMEs have been designed to address a particular problem or application, reducing the complexity of modeling the human emotion process to an implementation of specific mechanisms according to specific design goals. A novel approach promotes the development of CMEs whose architecture integrates cognitive information in the emotion evaluation process. This involves designing scalable CMEs capable of considering information projected from cognitive components of agent architectures even when a CME was not initially designed to consider a particular type of cognitive information. In this section, we present a computational scheme designed to provide mechanisms for the cognitive modulation of appraisal variables used in the emotion evaluation process of autonomous agents.

As mentioned above, the proposed computational scheme addresses some of the design requirements of the integrative framework proposed by Rodríguez (2016). In the InFra the evaluation of emotional stimuli takes place in the EF component (see Figure 6). This process of evaluating stimuli from an emotional perspective is based on the Appraisal Theory, a psychological theory that explains the elicitation of emotions based on the relationship between individuals and their environment as shown in (Ortony et al., 1990; Roseman, Spindel, & Jose, 1990). This evaluation of the individual-environment relationship is carried out using a series of appraisal dimensions such as pleasantness; goal conduciveness, suddenness, and controllability (see Figure 7).

In this context, in the proposed model, emotions are characterized in terms of a set of values corresponding to appraisal dimensions. Moreover, cognitive components of agent architectures are assumed to send information that should be considered when evaluating such appraisal dimensions. In this sense, it is necessary to define a scheme to determine the level of influence of cognitive information on each appraisal dimension, as shown in Figure 8. A computational schema for modeling the influence of cognition on appraisal dimensions, which characterize emotions, involves two main challenges:

1) Given that cognitive components in agent architectures vary in terms of their relevance to the emotion evaluation process, it is necessary to define the particular influence that a cognitive

function exerts on each appraisal dimension implemented to carry out the evaluation of emotional stimuli, and

2) The mapping of the information projected from cognitive components should be translated into dimensional values that characterize an emotional state and which are integrated into the evaluation process.

Figure 7. Evaluation of emotional stimuli in the Appraisal Theory.

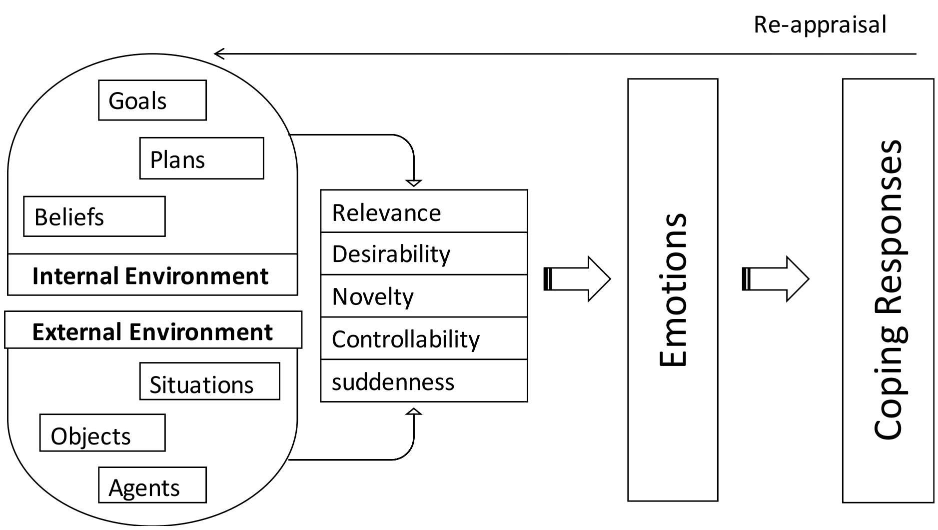
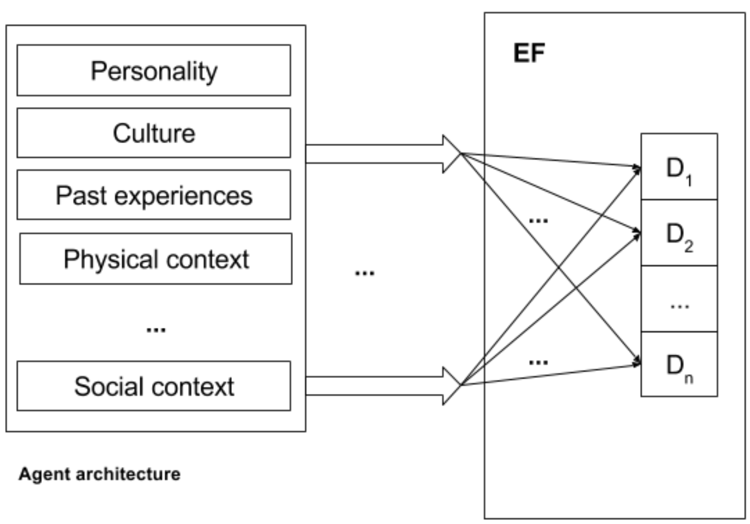


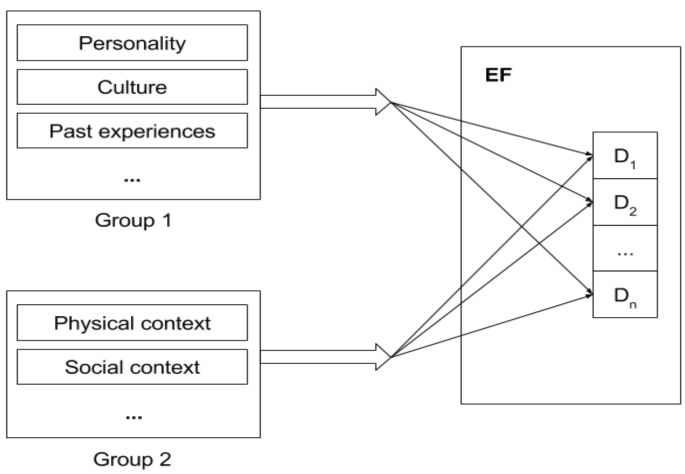
Figure 8. Influence of cognitive components of agent architectures on appraisal dimensions.



The proposed schema assumes that the GA module in the InFra assigns an initial value to each appraisal dimension according to the stimuli perceived by the agent. The modulation of these values is then determined according to what theories and models explain about the influence of cognition on the emotion process in humans. Although these theories and models are still scarce and limited, this information helps to define tendencies on the relationship between cognitive functions and appraisal dimensions. For example, Han & Northoff (2008) present a study that concludes that individuals' culture (characterized as collectivist and individualist) influence the situation assessment. The study indicates that in collectivist individuals occurs a more intense assessment of negative situations (based on the goals and objectives of the individual) but a more tenuous assessment of positive situations. Considering this type of evidence from human studies, in the proposed schema logical relationships are defined to model the influence of cognitive information and psychological constructs (e.g., personality and culture) on appraisal dimensions. Moreover, the scheme takes advantage of similarities among some aspects of cognitive components to classify cognitive information and thus manages specific types of influence on appraisal dimensions.

An aspect of interest for the modeling of the influence of cognition on the evaluation process in CMEs has to do with the temporality of cognitive components. For example, components such as those modeling personalities barely change over time. In contrast, components in charge of assessing the agent's social context change very frequently. In this case, both components influence the emotional evaluation of situations perceived by the agent and particularly both components may influence the evaluation of appraisal dimensions such as suddenness. This type of similarity suggests a grouping of cognitive components included in cognitive agent architectures. In the proposed computational scheme cognitive components are divided into two groups according to their temporality (see Figure 9): components that change slowly over time (e.g., personality and culture) and components that change very frequently (e.g., the agent's physical and social context). In this manner, regardless of the number and type of cognitive components in agent architectures, they are included in one of these two classes according to their characteristics. In turn, each group will exert a consolidated cognitive influence.

Figure 9. Grouping of components.

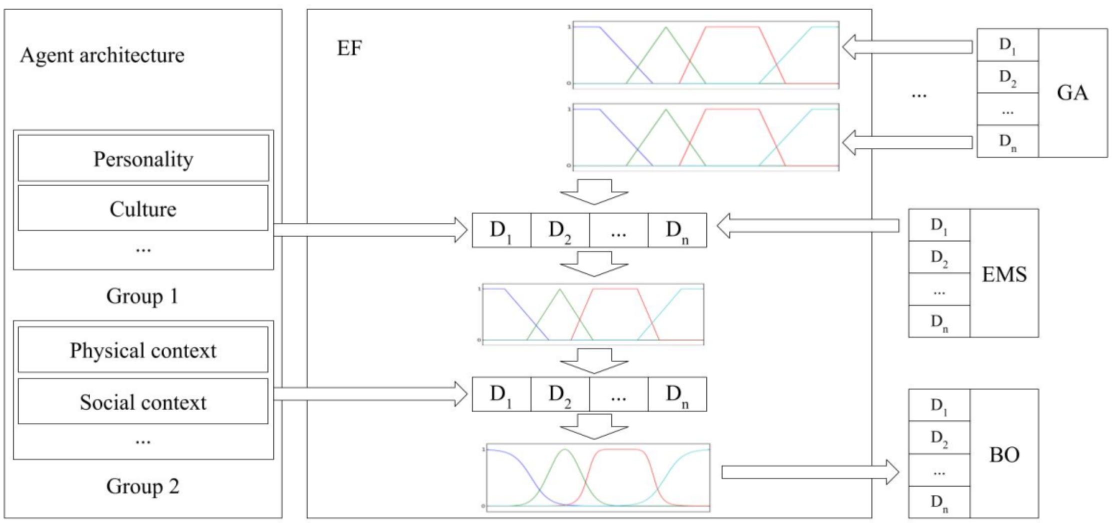


The model associates a fuzzy membership function to each appraisal dimension so that the values generated by the GA component of the InFra are analyzed in terms of such membership functions. In this way, the influence of cognitive components (grouped in the two mentioned categories) is represented by the alteration of the limits of membership functions. Figure 10 shows this computational scheme for the cognitive modulation of appraisal dimensions. The modulation in the evaluation process occurs as follows:

1) The General Appraisal (GA) component calculates an initial value to each appraisal dimension based on the event perceived by the agent and the internal mechanisms of the InFra.
2) These initial values are then fuzzified using the membership functions defined for each appraisal dimension. Initially, the limits of these membership functions are predefined.

3) Each component in the agent architecture that conform the first group of cognitive information (i.e., components that change slowly) is analyzed in terms of the structure and the format of the information it sends. For example, the component of personality will send a type of personality such as neuroticism or extraversion. Information provided by all components of the group are consolidated and sent to the modulation component (i.e., the EF component in the InFra).
4) The modulation component modifies the limits of the membership functions for each appraisal dimension according to the received information. Afterwards, this component analyzes the initial values assigned by the GA to each appraisal dimension considering the adjusted membership functions.
5) The third and fourth steps are repeated in order to consider the influence of cognitive information of the second group (i.e., components that change very frequently).
6) Finally, the modified values of each appraisal dimension are sent as the output to other components in the CME.

Figure 10. Model of appraisal dimensions modulation.



The following pseudocode illustrates the modulation in the evaluation process carried out by the scheme (see Figure 10):

```
Start
   General Appraisal Component
       Novelty(event)
       Pleasure(event)
       Goal_Orientation(event)
       ...
       Nth-appraisal_variable(event)

   Emotional Filter
       modulation_Group1(Novelty)
       modulation_Group1(Pleasure)
       modulation_Group1(Goal_Orientation)
       ...
       modulation_Group1(Nth-appraisal_variable)

       modulation_Group2(Novelty)
       modulation_Group2(Pleasure)
```

```
        modulation_Group2(Goal_Orientation)
        ...
        modulation_Group2(Nth-appraisal_variable)

        ...

        modulation_GroupNth(Nth-appraisal_variable)

        calculateEmotion(Novelty, Pleasure, Goal_Orientation, ...
        Nth-appraisal_variable)
End
```

As mentioned above, the cognitive modulation on appraisal dimensions is reduced to the influence of two types of cognitive components (organized in two groups). However, there are still two key challenges: 1) the integration of individual outputs of cognitive components so that these are represented by a consolidated value that influences appraisal dimensions, and 2) the structure and format of the output information of each cognitive component. The first challenge may be addressed by performing the summation of the outputs of each cognitive component multiplied by an adjustment factor. Regarding the second challenge, although each cognitive component may represent the information in different ways, we consider that cognitive components deliver a limited number of outputs.

A CASE STUDY TO ILLUSTRATE THE SCHEME

In order to illustrate the functioning of the schema proposed to modulate appraisal variables, let's suppose the following situation: it is the day of a very important job interview and the agent finds itself driving when suddenly a tire bursts, immediately there is an emotional reaction to that event, surely the agent would feel angry, frustrated, desperate; the agent could even take it with calm, it depends on the agent's personality, state of mind, past experiences among other aspects.

How does the proposed scheme evaluate this situation? The scheme is implemented within the modules of the InFra, which receives an event and runs two evaluation circuits: direct route for handling fast reactions and an indirect route for handling more cognitive biased responses. As mentioned above, we focus on the indirect circuit as in this route takes place the cognitive evaluation, which involves all cognitive modules of this framework.

In the InFra, first the stimulus is received by the general evaluation component (GA). In our case study the event is *get a flat tire*. This component implements a series of dimensions that allow us to evaluate the stimuli and assign them an emotional meaning; these can be any type of variable. We use the following appraisal variables: Desirability, Expectation, Novelty, Pleasure, Goal Orientation, and Coping Potential. The event *get a flat tire* is evaluated first according to the desirability, that is, the degree to which we want an event to occur. Obviously, the agent does not want anything to stop from getting to the job interview so the event would be evaluated as undesirable.

We then evaluate whether we expected or contemplated that this event (*get a flat tire*) occurred. Some people try to think about everything that could go wrong and prepare for it and if something happens does not take them by surprise. In other cases, it may be because of the characteristics of the environment we see that something will happen. For example, if we go down a poor road we can expect with a certain probability that we strike a tire of our car. Let us think that, in our case study, it never crossed the agent's mind that a tadpole would strike it, being "unexpected" the value for the *Expectative appraisal dimension*.

Then we evaluate the *novelty dimension* of the event that just happened, i.e. if the agent had already experienced the same event or one very similar. The memory of the agent is consulted in this dimension. Suppose that the agent had already experienced this event in the past, the intensity of anger or frustration would be higher than if it were the first time it happened. Memory has the memories and the number of times an event occurs to us so it is easier to access past emotions and use them to amplify or minimize emotions to current events. So, suppose that the event had already happened before and the agent was late and lost that job, the *novelty dimension* would have the value "not novel".

Once we evaluate the *novelty dimension*, we calculate the pleasure that causes the agent the occurrence of the event. Pleasure is a positive feedback mechanism that motivates the system to recreate situations that were pleasant and evade those that caused pain. When presenting the same situation, we know the possible result, not getting employment. Thus, the value for this dimension when the event *get a flat tire* happens again when we go to another interview is "unpleasant".

We then assess how much it affects the objectives, *goal conduciveness dimension*, of the agent. The agent has a series of goals that it is always looking to fulfill. The initial goal was to arrive at the interview as a possibly sub-goal of the goal “obtain work”, so the event *get a flat tire* directly obstructs one or more objectives of the agent giving it a value of *goal conduciveness* is "negative".

Finally, we evaluate the potential of facing the event that occurs to us, i.e. if we can somehow face a negative event and minimize its impact or solve the problem. Returning to the event *get a flat tire* the agent asks itself what to do or whether it has to ask for a taxi or if it needs to change the tire or If it has time to do that and to arrive at time to the interview. Imagine that the agent does not have the tool to change the tire or has no money to ask for a taxi, the *potential dimension* to face this event and get to the interview is null.

From the values obtained by the appraisal variables and the use of a series of fuzzy rules we relate the event to an emotion. We use Plutchik's theory, Plutchik (2001) proposes a circle of emotions to generate rules for emotion generation (see Table 4).

Table 4. Extract of rules to generate emotions.

Emotion	**Rules**
Sadness	**IF** Desirability (E) **IS** highly undesirable **AND** Expectation (E) **IS** expected **AND** Novelty (E) **IS** low_novelty **AND** Pleasure (E) **IS** not_pleasant **AND** Goal-conduciveness (E) **IS** negative **AND** Coping potential (E) **IS** approachable **THEN** Emotion (E) **IS** Anger
Anger	**IF** Desirability (E) **IS** undesirable **AND** Expectation (E) **IS** unexpected **AND** Novelty (E) **IS** not_novelty **AND** Pleasure (E) **IS** not_pleasant **AND** Goal-conduciveness (E) **IS** negative **AND** Coping potential (E) **IS** null. **THEN** Emotion (E) **IS** Anger

Having the following results in appraisal dimensions: Desirability is *undesirable*, Expectation is *unexpected*, Novelty is *not_novelty*, Pleasure is *not_pleasant*, Goal-conduciveness is *negative*, and Coping potential is *null*. Deriving in “Anger” as the emotion resulting from the first step of evaluation. All this happens, as we mentioned above, in the GA (general appraisal) component of the Infra.

Each of the appraisal variables has different levels of intensity whose initial value is predefined, for example the variable novelty can take values of "Low novel", "Medium novel" or "High novel" which is associated with the following three membership functions:

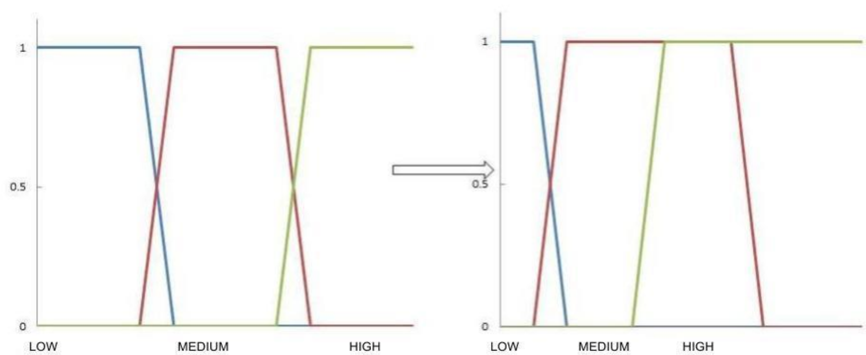
$$\mu LOW = \{1, \quad si\ \ x \leq 0\ \frac{0.4 - x}{0.4 - 0.3}, \quad si\ 0.3 < y \leq 0.4\ 0, \quad si\ x > 0.4$$

$$\mu MEDIUM = \{0, \quad si\ \ y \leq 0.3\ \frac{y - 0.3}{0.4 - 0.3}, \quad si\ 0.3 < y \leq 0.4\ 1,$$
$$si\ 0.4 < y \leq 0.7\ \frac{1 - y}{1 - 0.7}, \quad si\ 0.7 < y \leq 0.1\ 0, \quad si\ y > 1$$

$$\mu HIGH = \{0, \quad si\ \ z \leq 0.6\ \frac{z - 0.6}{0.1}, \quad si\ 0.6 < z \leq 0.7\ 1, \quad si\ z > 0.7$$

These functions are initially predefined and are then adjusted according to the cognitive modulation exerted by the two groups of cognitive components. Let's assume that the literature reports that the personality and other factors such as the physical context influence the emotion evaluation. For example, considering the calculation of the *novelty dimension* and that in the past the agent already experienced the event *get a flat tire on Sunday* (not exactly the same situation as to *getting a flat tire on the way to an important interview*). The resulting emotion is different for the same stimulus since its physical context and the agent's personality is different. In this case, such influence is represented by the modification of the membership function limits associated to each appraisal dimension (including the *novelty dimension*). For example, a neurotic or euphoric personality increases the probability for the agent to perceive and assess an event as novel. In this context, the limits of the membership function LOW would be reduced, the limits of the membership function HIGH will be increased, and possibly, the limits of the membership function MEDIUM will increase in one side (see Figure 11). As mentioned above, this second evaluation takes place in the emotional filter (EF) component of InFra.

Figure 11. A possible effect of the agent's personality on the membership functions associated to the novelty dimension.



CONCLUSION

In this paper, we presented a scheme to model the cognitive bias on appraisal dimensions involved in the emotion evaluation process of autonomous agents. The level of modulation depends on the cognitive information projected from cognitive components of agent architectures. The proposed scheme is designed as part of an integrative framework which was developed to address a key challenge of designing integrative CMEs. We presented a case study to demonstrate the functionality of the mechanisms presented to model the influence of cognition on the appraisal dimensions involved in the evaluation of emotional stimuli perceived by an agent. This work presents a model that allows researchers to consider different appraisal theories by defining new influencing rules based on information reported in the literature about cognitive functions and their influence on the emotion process. In this sense, the current proposal promotes the design of CMEs whose underlying architecture includes mechanisms that consider that cognitive information available in cognitive architectures and are useful to achieve very consistent emotional states and emotional behaviors in autonomous agents.

REFERENCES

Armony, J. (2010). Computational models of emotion. In *Proceedings 2005 IEEE International Joint Conference on Neural Networks, 2005.* (Vol. 3, pp. 1598–1602). IEEE. https://doi.org/10.1109/IJCNN.2005.1556117

Averill, J. R. (1997). The Emotions. In *Handbook of Personality Psychology* (pp. 513–541). Elsevier. https://doi.org/10.1016/B978-012134645-4/50022-6

Ayesh, A., Arevalillo-Herráez, M., & Ferri, F. J. (2016). Towards Psychologically based Personalised Modelling of Emotions Using Associative Classifiers. *International Journal of Cognitive Informatics and Natural Intelligence*, *10*(2), 52–64. https://doi.org/10.4018/IJCINI.2016040103

Becker-Asano, C., & Wachsmuth, I. (2009). Affective computing with primary and secondary emotions in a virtual human. *Autonomous Agents and Multi-Agent Systems*, *20*(1), 32–49. https://doi.org/10.1007/s10458-009-9094-9

Breazeal, C. (1998). Regulating human-robot interaction using “emotions”, “drives” and facial expressions. *Proceedings of the 2nd International Conference on Autonomous Agents*, 14–21. https://doi.org/10.1.1.56.6651

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International Journal of Human Computer Studies*, *59*(1–2), 119–155. https://doi.org/10.1016/S1071-5819(03)00018-1

Broekens, J., & Degroot, D. (2004). Emotional Agents need Formal Models of Emotion. In *Proc. of the 16th Belgian-Dutch Conference on Artificial Intelligence* (pp. 195–202).

Cañamero, D. (1997). Modeling motivations and emotions as a basis for intelligent behavior. In *Proceedings of the first international conference on Autonomous agents* (pp. 148–155). https://doi.org/10.1145/267658.267688

Castellanos, S., Rodríguez, L.-F., Castro, L. A., & Gutierrez-Garcia, J. O. (2018). A computational model of emotion assessment influenced by cognition in autonomous agents. *Biologically Inspired Cognitive Architectures*, *25*, 26–36. https://doi.org/10.1016/j.bica.2018.07.007

Ortony, A., Clore, G. L., & Collins, A. (1989). The Cognitive Structure of Emotions. *Cambridge University Press*

Dias, J., Mascarenhas, S., & Paiva, A. (2014). FAtiMA Modular: Towards an Agent Architecture with a Generic Appraisal Framework. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 8750, pp. 44–56). https://doi.org/10.1007/978-3-319-12973-0_3

El-Nasr, M. S., Yen, J., & Ioerger, T. R. (2000). FLAME—Fuzzy Logic Adaptive Model of Emotions. *Autonomous Agents and Multi-Agent Systems*, *3*(3), 219–257. https://doi.org/10.1023/A:1010030809960

Franklin, S., & Graesser, A. (1997). Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents. *Intelligent Agents III Agent Theories, Architectures, and Languages*, 21–35. https://doi.org/10.1007/BFb0013570

Frijda, N. (2005). Emotion experience. *Cognition & Emotion*, *19*(4), 473–497. https://doi.org/10.1080/02699930441000346
Gebhard, P. (2005). ALMA. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems - AAMAS '05* (p. 29). New York, New York, USA: ACM Press. https://doi.org/10.1145/1082473.1082478
Gebhard, P., Kipp, M., Klesen, M., & Rist, T. (2003). Adding the Emotional Dimension to Scripting Character Dialogues. In *International Workshop on Intelligent Virtual Agents* (pp. 48–56). Springer, Berlin Heidelberg. https://doi.org/https://doi.org/10.1007/978-3-540-39396-2_9
Goldie, P. (2002). *The emotions: A philosophical exploration. The Emotions*. Oxford University Press. https://doi.org/10.1093/0199253048.001.0001
Hampson, S. (2006). *Creative Management and Development Creative management and development*. *Psychologist* (Vol. 12). 1 Oliver's Yard, 55 City Road, London EC1Y 1SP United Kingdom: SAGE Publications Ltd. https://doi.org/10.4135/9781446213704
Han, S., & Northoff, G. (2008). Culture-sensitive neural substrates of human cognition: A transcultural neuroimaging approach. *Nature Reviews Neuroscience*, *9*(8), 646–654. https://doi.org/10.1038/nrn2456
Hudlicka, E. (2005). Modeling Interaction Between Metacognition and Emotion in a Cognitive Architecture. In *AAAI Spring Symposium: Metacognition in Computation* (pp. 55–61).
Hurtubise, R. (1995). Damasio, Antonio R., Descartes' Error: Emotion, Reason, and the Human Brain. *Relations Industrielles*, *50*(2), 463. https://doi.org/10.7202/051028ar
LeDoux, J. E. (2000). Emotion Circuits in the Brain. *Annual Review of Neuroscience*, *23*(1), 155–184. https://doi.org/10.1146/annurev.neuro.23.1.155
Ligeza, A. (1995). Artificial Intelligence: A Modern Approach. *Neurocomputing*, *9*(2), 215–218. https://doi.org/10.1016/0925-2312(95)90020-9
Maes, P. (1995). Artificial life meets entertainment: lifelike autonomous agents. *Communications of the ACM*, *38*(11), 108–114. https://doi.org/10.1145/219717.219808
Martínez-Miranda, J., & Aldea, A. (2005). Emotions in human and artificial intelligence. *Computers in Human Behavior*, *21*(2), 323–341. https://doi.org/10.1016/j.chb.2004.02.010
Ojha, S., & Williams, M.-A. (2017). Emotional Appraisal : A Computational Perspective Emotional Appraisal : A Computational Perspective. In *Fifth Annual Conference on Advances in Cognitive Systems* (pp. 1–15).
Ortony, A. (2003). On Making Believable Emotional Agents Believable. In *Emotions in humans and artifacts* (pp. 189–212).
Paiva, A., Parada, R., & Picard, R. (Eds.). (2007). Affective Computing and Intelligent Interaction: Second International Conference, ACII, Lisbon, Portugal, September 12-14, 2007, Proceedings (Vol.4738). Springer
Perlovsky, L. ., & Kuvich, G. . (2013). Machine learning and cognitive algorithms for engineering applications. *International Journal of Cognitive Informatics and Natural Intelligence*, *7*(4), 64–82. https://doi.org/10.4018/ijcini.2013100104
Phelps, E. A. (2006). Emotion and Cognition: Insights from Studies of the Human Amygdala. *Annual Review of Psychology*, *57*(1), 27–53. https://doi.org/10.1146/annurev.psych.56.091103.070234
Plutchik, R. (2001). The Nature of Emotions. *American Scientist*, *89*(4), 344. https://doi.org/10.1511/2001.4.344
Reisenzein, R. (2001). Appraisal processes conceptualized from a schema-theoretic perspective:

Contributions to a process analysis of emotions. In *Appraisal processes in emotion: Theory, methods, research* (pp. 187–201).
Rodríguez, L.-F., Gutierrez-Garcia, J. O., & Ramos, F. (2016). Modeling the interaction of emotion and cognition in Autonomous Agents. *Biologically Inspired Cognitive Architectures*, *17*, 57–70. https://doi.org/10.1016/j.bica.2016.07.008
Rodríguez, L.-F., & Ramos, F. (2015). Computational models of emotions for autonomous agents: major challenges. *Artificial Intelligence Review*, *43*(3), 437–465. https://doi.org/10.1007/s10462-012-9380-9
Rodríguez, L.-F., & Ramos, F. (2014). Development of Computational Models of Emotions for Autonomous Agents: A Review. *Cognitive Computation*, *6*(3), 351–375. https://doi.org/10.1007/s12559-013-9244-x
Rodriguez, L.-F., Ramos, F., & Wang, Y. (2011). Cognitive computational models of emotions. In *IEEE 10th International Conference on Cognitive Informatics and Cognitive Computing (ICCI-CC'11)* (pp. 75–84). IEEE. https://doi.org/10.1109/COGINF.2011.6016124
Roseman, I. J., Spindel, M. S., & Jose, P. E. (1990). Appraisals of emotion-eliciting events: Testing a theory of discrete emotions. *Journal of Personality and Social Psychology*, *59*(5), 899–915. https://doi.org/10.1037/0022-3514.59.5.899
Smith, R., & Lane, R. D. (2016). Unconscious emotion: A cognitive neuroscientific perspective. *Neuroscience & Biobehavioral Reviews*, *69*, 216–238. https://doi.org/10.1016/j.neubiorev.2016.08.013
Sun, R. (2009). Cognitive Architectures and Multi-agent Social Simulation. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 4078 LNAI, pp. 7–21). https://doi.org/10.1007/978-3-642-03339-1_2
Velásquez, J. D. (1996). *Cathexis : A Computational Model for the Generation of Emotions and their Influence in the Behavior of Autonomous Agents*. Retrieved from http://hdl.handle.net/1721.1/10651
Wang, Y. (2007). The Theoretical Framework of Cognitive Informatics. *International Journal of Cognitive Informatics and Natural Intelligence*, *1*(1), 1–27. https://doi.org/10.4018/jcini.2007010101
Wang, Y. (2010). Cognitive Robots. *IEEE Robotics & Automation Magazine*, *17*(4), 54–62. https://doi.org/10.1109/MRA.2010.938842
Wang, Y. (2011). Towards the Synergy of Cognitive Informatics, Neural Informatics, Brain Informatics, and Cognitive Computing. *International Journal of Cognitive Informatics and Natural Intelligence*, *5*(1), 75–93. https://doi.org/10.4018/jcini.2011010105
Wang, Y. (2012). On Abstract Intelligence and Brain Informatics. *International Journal of Cognitive Informatics and Natural Intelligence*, *6*(4), 54–80. https://doi.org/10.4018/jcini.2012100103
Wang, Y., Anderson, J. A., Baciu, G., Budin, G., Hsu, D. F., Ishizuka, M., Kisner, W., Mizoguchi, F., Nishida, T., Sugara, K., …, Zhang, D. (2012). Perspectives on eBrain and Cognitive Computing. *International Journal of Cognitive Informatics and Natural Intelligence*, *6*(4), 1–21. https://doi.org/10.4018/jcini.2012100101
Wang, Y., Patel, S., & Patel, D. (2013). The Cognitive Process and Formal Models of Human Attentions. *International Journal of Software Science and Computational Intelligence*, *5*(1), 32–50. https://doi.org/10.4018/ijssci.2013010103
Wang, Y., Zatarain, O. A., & Valipour, M. (2017). Building cognitive knowledge bases sharable

by humans and cognitive robots. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 3189–3194). IEEE. https://doi.org/10.1109/SMC.2017.8123119

Yingxu Wang, Ying Wang, Patel, S., & Patel, D. (2006). A layered reference model of the brain (LRMB). *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, *36*(2), 124–133. https://doi.org/10.1109/TSMCC.2006.871126