MODELING THE INTERACTION OF EMOTION AND COGNITION

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ABSTRACT
Research on the interaction between emotion and cognition has become particularly active along the last years, so that lots of computational models of emotion have been developed. However, to the date, none of them address fully the integration of emotion generation and its effects in the context of cognitive processes. This work tries to unify several models of computational emotions for embodied agents with the work done in cognitive architectures, based on psychological theories and applications.

Keywords: *Emotions, Cognition, Embodiment, Computational Models.*

1. INTRODUCTION

Emotions are evasive concepts. Usually tied to common sense or folk psychology there are strong disagreements both concerning their nature and the functions they serve. No surprise. Emotions share almost all problems that mental concepts present concerning scientific explanation and prediction, and some additional ones. To begin with, there is a mismatch between what folk psychology assumes about emotions and the results of scientific research in Psychology. People use to believe that emotions can be perceived with a high grade of accuracy. We feel anger, sadness or fear in ourselves by introspection, and in other people, by perceiving gestures, facial expression, and so forth. However, current scientific research is far from establishing a clear set of necessary and sufficient conditions for affirming when a given emotion is present or not (Barrett, L. F. 2006). In this sense, the very idea that emotions constitute a natural kind has been put in question (Griffiths, P. 1997; Barrett, L.F. 2006a). It is unclear what Barrett means with this claim. At first glance, it seems that to deny that something is a natural kind excludes it from the possibility of scientific research, but she explicitly affirms that emotions admit scientific treatment. As it seems, she tries to deny that emotions are concrete entities accessible for scientific treatment. No surprise again. The usual criteria for the existence of natural kinds were proposed for substance terms such as *water*, *gold* or *tiger* (Kripke, 1972; Putnam, 1975). Nonetheless, some accounts as the ones of Evolutionay Psychology (Cosmides, L., & Tooby, J. 2000), that propose different cognitive modules producing distinct kinds of emotions, or the idea that there are specific causal mechanisms in our neural circuitry detectable by available techniques as magnetic resonance or positron emission tomography (PET) are akin to the consideration of emotions as substance natural kinds.

The problem, in our view, is that the term "emotion", as it is currently used, responds to a wide variety of ontological status: sometimes this term refers to physiological processes, or even to perceptions of physiological processes, or to neuro-psychological states, to adaptive dispositions, to evaluative judgments, to computational states, or even to social facts or dynamical processes. All this ontological variety does not always corresponds to different conceptions about emotions, but also to the crude fact that the term covers a great variety of things. This fact could explain, for instance, the current criticisms to appraisal theories. These theories, as it does folk psychology, assume that each emotion of a particular type is evoked by the agent's interpretation of a given stimulus. Then it normally follows a response in correspondence (Frijda, 1988). However, empirical evidence seems to suggest so far that the lack of coherence in the responses to each category of emotion is the rule rather than the exception (Barrett, 2006a; Ellsworth & Scherer, 2003).

We guess that the deep reason that explains that scientists have failed to observe stable response patters following each emotion type is not, as Barrett suggests, that emotions are not natural kinds, but that emotions share the general problems of mental concepts, as has been said at the beginning of this paper. As any mental concept, emotions can be representational, that is to say, they can have formal objects or content, although sometimes they posses also non conceptual content, as it happens with perceptions. As in the case of some prototypical mental concepts, like propositional attitudes, emotions have both descriptive and normative dimensions. Each time we attribute propositional attitudes to a person, for instance, beliefs and desires, we try to describe and explain her behavior, but at the same time, these attributions demand normative assessment: beliefs and desires can be correct and incorrect, rational and irrational, and we cannot do without assuming some amount of rationality in our behavior explanations. Furthermore, the range of possible behavioral responses for each attitude attribution is almost unlimited. Just the same occurs with emotions. They call for rational assessment in several senses: they may or may not be appropriate for the situation that triggers them; they seem to have an indispensable role in solving rationality puzzles in real life (Damasio, A. 1994), but at the same time, they can undermine rational thought and behavior.

None of the above difficulties should prevent us from trying cognitive computational models of behavior, even embodied computational systems. We share D. Dennetts' (1994) claim that unless "you saddle yourself with all the problems of making a concrete agent take care of itself in the real world, you will tend to overlook, underestimate, or misconstrue the deepest problems of design". As conceptual ground, we assume J. Prinz's account of emotions, the embodied appraisal theory (J. Prinz, 2004). This theory claims, in line with the seminal proposals of W. James, that emotions are feelings of changes in the body. We do not enter in the discussion about whether judgments are constitutive of emotions. Prinz thinks that they are not. In any event, this theory admits as uncontroversial that judgments can elicit emotions, and that emotion, in turn, determines changes in attention, memory and behavioral dispositions.

This way, objections in the sense that emotions are not natural kinds, can be overcome. It is hard to believe that emotions are not realized in neural bases. It may be that some emotions are not located in specific brain areas, but they can be widespread along large neural circuits that are not the same each time a given emotion is instantiated. This holds also for P. Griffiths' point to the extent that while some emotions have bodily basis, others can involve central cognitive states. Even if we accept a modular account of the mind, as J. Fodor's one, that excludes central processes from scientific research (J. Fodor, 2000), given that in the account assumed, emotions are feelings of changes in the body that are normally, but not necessarily, related with judgments, the objection does not affect this view.

We also assume the thesis of the extended mind. Cognition does not take place only "in the head", operating exclusively on internal mental models of the world. Our perception of the world, our thoughts, and our social interactions depend crucially on our bodies and our embodied interaction with the physical and social environment. This is the main idea of situated cognition (see for example, A. Clark, 1997 and Kisley et al., 2011).

Within the framework of the extended mind and situated cognition, a main hypothesis is that emotional mechanisms play a critical role in structuring the high-level processes of cognitive systems. Some models of these mechanisms can be usefully integrated in artificial cognitive architectures. This constitutes a significant step in order to build models of cognitive systems able of reasoning and behaving, externally and internally, in accordance with emotional requirements.

According to somatic theories of emotion, self-regulation emerges from multiple levels of homeostatic bodily self. For instance, Damasio (1994) maintains that nature has built the rationality apparatus not on the top of the system of biological regulation. The goal therefore is to model the interaction of mechanisms at different levels in a neurocomputational cognitive-affective architecture.

In this work, we will discuss some psychological approaches on the interaction between cognition and emotion, examining how they could be integrated within a mental architecture for embodied agents, based on the insights obtained from rich computational and robotic models.

2. PSYCHOLOGICAL MODELS

Psychological models try to explain how changes in speech, facial expression, posture and physiological processes provide nuclear keys to a person's beliefs, desires, intentions and actions. This kind of influence has had a broad impact in several areas as, for instance, the role of emotion in human decision making (Loewenstein & Lerner, 2003), the human-computer interaction, where responding to student's emotions improves tutoring (Graesser et al., 2008), and the role on non-conscious judgments (Barrett, Osher & Gross, 2007), among others. These findings have grown our interest about the ways in which cognition is influenced by the socio-emotional context.

Emotions are synchronized with several mental and somatic components like cognitive processes (appraisal), physiological processes (somatic processes) and actions (facial expressions). Furthermore, some accounts emphasize the crucial role of awareness. However, emotion is generally considered as short-term and unstable, in contrast with longer term moods like personality. At least in come cases, emotions are considered as intentional because they make reference to a specific event, situation or target[1].

[1] This is a controversial issue. Some emotions require clearly intentional objects, for instance, fear. Other emotions, i.e. regret, cannot be described without reference to a propositional object. However, it isn't clear that sadness has any object at all. A taxonomy of emotions concerning whether or not they have directness, or are about some target or propositional object is needed. These problems emphasize as well the complex relations between moods and emotions.

The integration of emotion and cognition in cognitive architectures for embodied agents should be considered as a necessary task. At first glance, we have are two options: one possibility is that the envisaged architecture could have different modules for deliberative reasoning and emotions; another possibility, by adopting a more integrated approach, the system could derive and manage emotions within the same deliberative module. In the second case, the interplay of cognitive and emotional processes can proceed in two directions. Firstly, from cognition to emotion, for domain-specific, as appraisal mechanisms, where the situation circumstances of the organism is the cause of eliciting or differentiating emotional responses. By contrast, in the case of domain-independent appraisal, the belief-desire-intention system can be exploited to derive emotional impulses during the decision process (Gratch & Marsella, 2005). Secondly, we have to see how emotions can influence cognition as self-beliefs or as modulators of the decision process. This influence of the emotions on the deliberative module has had many difficulties to be computationally modeled for embodied agents.

One cognitive theory has been considered as the standard model for emotion synthesis (Ortony, Clore & Collins, 1988). This OCC model was designed as a computational model of emotions. It assumes that 22 discrete emotion categories can be derived as valence reactions to situational contexts, based on deliberative reasoning. It is conceptually close to the methodologies applied in symbolic AI, and it has been frequently applied to integrate emotions into agent architectures. However, this model has been strongly criticized, among other things, because it does not take into account the mutual interaction of emotion categories, and for not keeping track of their development in time. In order to solve these limitations, it might be appropriate to assume that the agent evolves richer emotional experience by means of machine learning techniques.

Recently, Bechara et al. (2000) put forward an idea of emotions as being evoked at deliberation time from the decision process. They state that somatic markers occur as values assessing the emotional quality of outcomes of possible actions; these markers constrain the decision-making space, making it more manageable for logic-based and cost-benefit analysis.

2.1. From cognition to emotion

The main differences between theories rely on the issues about which components are intrinsic to an emotion (cognition, somatic processes, and behavioral tendencies), the interaction between these components and representational distinctions. Therefore, depending on the emotion's function, the architecture of the cognitive system can affect the survival in an adaptive world. Two main approaches have been proposed.

On the one hand, discrete emotion theorists hold that emotions are a set of discrete sensory-motor programs (Ekman, 1992; LeDoux, 1996; Öhman & Wiens, 2004). These programs consist of a coherent brain circuit that links eliciting cognitions and somatic responses into a single neural system.

Appraisal theories focused on the cognitive antecedents of emotional experience assume a main theoretical perspective. The sensory or cognitive events are evaluated in function of their impact on the emotions of the agent. Although it is not a deliberative process, appraisal is informed by cognitive processes involved in understanding and interacting with the environment (such as planning, explanation, perception, memory, linguistic processes). According to these theories, the impact of inputs on organism's beliefs or desires is characterized in a set of discrete judgments (appraisal variables). These variables serve as an intermediate description of the agent-environment relationship; that is, different responses are organized around how a situation is appraised.

Within the domain-specific emotion simulation, the agent is involved in cognitive appraising incoming events and then sends appropriate impulses to the emotion system. Researchers use task–oriented algorithms to implement appraisal routines specifically designed for the current task of the agent.

Concerning domain-independent emotion simulation, few approaches bring about emotional appraisal to a conceptually higher level. Here the architecture must have a more general interplay of cognition and emotion. It is more complicated to model the mechanisms that cause an agent to feel emotions depending of his reasoning processes, independently of a particular scene. To get it, Gratch and Marsella (2004) argue that it is necessary an explicit representation of intermediate knowledge states for agent's inferences and appraisal.

On the other hand, dimensional theories (Russell, 2003) consider emotions as cognitive labels to be applied retrospectively to sensed physiological activation. In contrast to discrete motor programs, emotions are characterized as broad bipolar dimensions like valence and arousal.

Here emotion can be characterized as a continuous progression in a dimensional space of connotative meaning. Several researchers (for instance, Mehrabian, 1995) have provided statistical evidence for this assumption. Using principle component analysis it has been found that three dimensions are sufficient to represent the connotative meaning of emotional categories. These dimensions are normally labeled as Pleasure/Valence (P), representing the overall valence information, Arousal (A), representing the degree of activeness of an emotion, and Dominance/Power (D), representing the experienced control over the emotion or the situational context that it originates from PAD-space. For emotion recognition, this space is often reduced to the first two dimensions (Lang,

1995). The restriction to two dimensions is due to the fact that Dominance cannot be derived from sensor (physiological) data, as it depends on an actor's subjective feeling of control over a situation.
On the contrary, embodied agents are embedded in a situational context, enabling them to derive this sense of control analytically. For instance, the emotion system of the robot Kismet (Breazeal, 2002) is based on a very similar three dimensional space.

2.2. From emotion to cognition

Emotions have a strong influence on our behavior. Emotional influences are manifested across a variety of levels and modalities for a challenging general architecture. For example, there are physical features, such as facial expressions, body language, and some acoustic features of speech. Furthermore, there are impacts on cognitive processes that include coping behaviors such as wishful thinking or resignation.
Being things so, the task is to examine the ways in which an emotional state can influence the cognitive mechanisms. If we have an explicit reasoning infrastructure, plan-based approaches are good candidates to address how emotions influence decision-making. Emotional states can act as a search control or focused inference in relation to specific goals or actions.
Oatley & Johnson-Laird (1987) affirm that emotions work as a specific system of internal communication in order to coordinate multiple plans under the constraint of time. For instance, emotions can change the relative priorities of goals in a parallel system of planning, in order to indicate the evolving success of plans and the overall performance of the agent.
Some attempts try to account for the factors that give rise to emotions, examining as well the impact that emotions have on cognitive and behavioral responses, especially coping responses. For instance, the model EMA (Gratch & Marsella, 2005) has been implemented for an application where people can interact with the virtual humans through natural language in high-stress social settings.
Coping determines in a great extent the agent's response to the appraised significance of events (as we have seen above). The agent is motivated to respond to some events in different way depending on this evaluation. Frequently, theories characterize these coping responses into problem-focused coping strategies (that attempt to change the environment) and emotion focused coping (that involves inner-directed strategies for dealing with emotions). The goal of these strategies is a change in the agent's interpretation of his relationship with the environment, which can lead to new re-appraisals.
The problem, in this concern, is to capture this dynamics over time within a computational model. Coping is usually treated as a control mechanism that identifies a particular intense response to overturn (e.g., in case of negative emotions) or support (e.g., in case of positive emotions) and directs control signals to other reasoning modules to influence their processing (i.e., planning, beliefs, etc.). Coping tries to maintain or not those features that produced the appraisals of the agent (e.g., by suggesting to abandon a goal).
Coping strategies work in the opposite direction of appraisal, identifying the precursors of emotion in the causal interpretation that should be maintained or altered (for instance, intentional states such as beliefs, desires, and so forth). Strategies include some operations such as action (select one for execution), planning (form an intention to perform some act), positive reinterpretation (of an act with a negative outcome), mental disengagement (lower utility of desired state), etc..., in such a way that these strategies provide input to the cognitive processes that actually execute these directives.
Emotions can be considered as cognitive states that involve beliefs, or well as modulators. In the first case, the simplest model incorporates emotions as variables in the deliberative processes. These beliefs influence agent's goals and plan selection process in a symbolic level. Such behavior strategies were defined beforehand and considered as reactive plans in front of certain agent's emotion category.
If emotions are considered as modulators, they work by adjusting the functioning of cognitive processes such as planning and decision making. For instance, negative emotional state influence problem-solving strategies towards local, bottom-up processing, whereas positive emotional state points to global, top-down approach (positive interactions between goals and plans). In the negative case, the agent can only focus on his most important goal and leave off the plan or immediate goal. In the positive case, the agent can broaden problem-solving attempts to achieve multiple goals simultaneously; the agent can retry and achieve other sub goals.
Some simulation-based models, on the contrary, are inspired by models other that appraisal theory, and rarely concentrate on low-level cognitive functions. For instance, Armony et al. (1997) present a model of the fear circuit. Other robotic researchers have been influenced by ethology-inspired drive models to help inform robotic control systems (Arkin, 2005). Furthermore, some researchers have explored non-appraisal models of the influence of emotion on higher-level cognition, generally by extending classical decision models. For example, the Decision Field Theory proposed by Busemeyer (2002) tries to integrate a notion of drives into classical decision theory in order to explain the influence of emotions on decision making.

As we will see below, these psychological models support several computational systems. These systems go beyond a focus on the elicitation of emotion (appraisal) seen in the earlier approaches and adopt a more comprehensive treatment of cognitive antecedents and consequences of emotion. For instance, communicative approaches consider emotion as a dynamic and adjustment to the social and physical environment (Boehner et al., 2007).

3. COMPUTATIONAL MODELS

In order to characterize a computational model of emotion, it is necessary to take into account different interdisciplinary uses to which computational models can be destined, such as improving human-computer interaction or enhancing general models of intelligence.

Some integrated computational models have tried to incorporate a variety of cognitive functions (e.g., Anderson, 1993). More recent cognitive systems in AI focus on the role of emotion in order to address control choices by driving cognitive resources on problems of adaptive significance for the agent (Blanchard & Cañamero, 2006). For example, human computer interaction attempts to recognize user's emotion including physiological indicators and facial and vocal expressions. In a similar way we find the use of emotion or emotional displays in avatars that interact with the user, for instance, to increase student motivation in a tutoring system.

In this sense, computational models take different frameworks in research and applications. On the one hand, psychological models emphasize the fidelity with respect to human emotion processes. On the other hand, AI models evaluate how the modeling of emotion influences the reasoning processes or improves the fitness between the agent and its environment. That is to say, the model improves and makes more effective the human-computer interaction.

Several models have been proposed and developed. However, fundamental differences arise from their underlying emotional constructs. For instance, as we will see below, some discussions on whether emotion precedes or not cognition disappears if one adopts a dynamic system perspective. Here, we will examine the three main approaches.

3.1. Discrete approach

This approach emphasizes appraisal theories of emotion (e.g., Ellsworth & Scherer, 2003). According to these theories emotions are connected to the ways in which organisms sense events, relate them to internal needs, characterize appropriate responses and recruit cognitive, physical and social resources to act in adaptive ways.

Some models focus on appraisal as the core process to be modeled. In this sense, emotion is not completely elaborated. Mechanisms for deriving appraisal variables, via if-then rules, model specific emotion label. Emphasizing on a cognitive model of the situation, many models assume that (i) specific appraisal patterns are needed for emotion arising; and (ii) cognitive responses are determined by these appraisals.

This perspective is mainly centered on the cognitive structure of emotions and not on the overall emotion process. As we will see below, the resulting computational models reflect this limitation (see Gratch, Marsella & Petta, 2009). Embodied emotion is considered as a dynamic and situated process, adjusting to the changing demands of the environment, instead of making an appraisal of cognitive representations (Niedenthal, 2007).

In this concern, we can distinguish between a specific emotion instance and a more general affective state. For example, Marsella & Gratch (2009) proposed EMA in order to generate specific predictions about how human subjects will afford with emotional situations. An agent that tries to operate in real time, multi-agent environments, would need these appraisal processes. Such as for human computer interaction, these techniques create an interactive agent that deals with emotion.

These authors illustrate how emotions are a function of dynamics in the world and cognitive processes. They emphasize a clear distinction between the construction of an internal representation of the situation (which may be slow and sequential) and appraisal (rapid and parallel), and they argue that a sequence to appraisal is not necessary. It emerges from the agent's task demands, the underlying dynamics of the environment and the sequential nature of some cognitive processes.

3.2. Dimensional approach

Dimensional theories argue that emotions are not discrete entities. Rather, they are distributed in a continuous dimensional space (Barrett, 2006). These theories conceptualize emotion as a cognitive label attributed to a perceived body state, mood or core affect (Russel, 2003). An agent is considered in an affective state at a given moment, and the space of possible states, in turn, within broad and continuous dimensions.

Although there is a relationship between both approaches, appraisal dimension is a relational construct that characterizes the relationship between some specific event, or object, and the agent's emotion. Furthermore, several appraisal variables can be active at the same time. On the contrary, the dimension of affect is a non-relational construct, indicating only the overall state of the agent.

These dimensional theories focus on the structural and temporal dynamics of core affect and often do not deal with affect's antecedent in detail. It is conceived as a non-intentional state, the affect is not about something. Here, despite of symbolic intentional judgments, many sub-symbolic factors could contribute to a change in main affect.
Dimensional models are generally used for animated agent behavior generation. They translate emotion into a small number of dimensions that are continuously mapping features of behavior such as the spatial extent of a gesture. Similarly, these representational models can recognize human emotional behavior and are better at discriminating user affective states than the approach that only relies on discrete labels (Barrett, 2006).
Dimensional research has to take seriously into account this question: how to develop models where emotion interacts with cognitive processing? Communicative theories of emotion, where emotion processes function as a communicative system, have tried to answer this question. They have a mechanism for informing other agent of one's mental state (so, facilitating social coordination) and also a mechanism for demanding changes in the behavior of other agents (as in threat displays; Parkinson, 2009).

3.3. Communicative approaches

These theories account for the social-communicative function of displays and argue for the dissociation between internal emotional processes and emotion displays that need not be selected on the basis of an internal emotional state. Their models often embrace this dissociation and dispense with the need for an internal emotional model, centering the attention on the mechanisms that can decide when an emotional display would affect the behavior of an agent.
One example is the work of Pitterman et al. (2010) where speech-based emotion recognition and adaptive human-computer modeling are combined. With the robust recognition of emotions from speech signals as their goal, the authors analyze the effectiveness of using a plain emotion recognizer, a speech-emotion recognizer that combines speech and emotion recognition, and multiple speech-emotion recognizers simultaneously. The semi-stochastic dialogue model employed relates user emotion management to the corresponding dialogue interaction history and allows the device for adapting itself to the context, including altering the stylistic realization of its speech.
Similarly, Bicho, Louro & Erlhagen (2010) have tried to validate a Dynamic Field model of joint action that implements neuro-cognitive mechanisms supporting human joint action. It has explained the existence of persistent inner states that lead to the emergence of high-level cognitive function. That is, cognitive processes unfold continuously in time under the influence of multiple sources of information.
Their robotics experiments show: (i) principles of DFT scale to high-level cognition in complex tasks (e.g., decision making in a social context, goal inference, error detection, anticipation, and so forth.); (ii) embodied view of "motor cognition" strongly contrasts with traditional AI approaches, e.g., Joint Intention Theory (Cohen & Levesque, 1990). In this framework, taking the right actions is the result of efficient cognition: (i) action understanding and goal inference; (ii) anticipation of the user's needs (for fluency of team performance and acceptance); (iii) action monitoring, error detection and repair.
It does not look like a classical AI architecture (see Oudeyer, 2003). It is a complex, fully integrated dynamical system, with no encapsulated modules or subsystems and an embodied view: high level cognitive functions like goal inference are based on sensorimotor representations. Furthermore, learning can be integrated in the DF framework.
So, for a 'natural' dialogue we need to integrate cognition and emotion within an embodied agent. A first approximation in this sense makes reference to human-computer interaction, where we need to include in the design of inputs and outputs, several issues such as adaptability, consistency and error modification.

4. MULTIMODAL SYSTEMS

Some fusion techniques are required in order to integrate inputs from different modalities. In this concern, several fusion approaches have been developed. In order to support more wide ranging functional multimodal systems, general processing architectures have been developed. They try to joint together a variety of multimodal patterns and their processing.
A typical feature of multimodal data processing is that multisensory data are processed separately and only combined at the end (Jaimes & Sebe, 2007). But, as has been said previously, several inputs cannot be considered in an independent way and must be combined according to a context dependent model and processed in a joint feature space of sensors, cognition and emotion.
This integration has been performed a several levels. On the one hand, some fusion techniques have been applied at the feature level. For instance, in audio-visual integration, one simply can concatenate the audio and visual feature vectors to obtain a combined vector. To reduce the length of this audio-visual vector, dimensionality reduction techniques are applied. The recognition module (e.g., hidden Markov model) can be trained to classify this mixed vector.

There have been proposed some intermediate fusion techniques. Early fusion fails to model the fluctuations in the relative reliability and the asynchrony problems, for example, between the audio and video streams. Often we have to deal with imperfect data in the inputs. This has been achieved by considering the time-instance vs. time-scale dimension of human non-verbal communicative signals (Pantic & Rothkrantz, 2003). Here, we need some kind of probabilistic inference to manage previously observed data with the current inputs. Several probabilistic graphical models have been proposed, such as hierarchical hidden Marcov models (e.g., for facial expression recognition; Cohen et al. 2003) and dynamic Bayesian networks (e.g., for recognizing user intent and event detection in video; Garg, Pavlovic & Rehg, 2003).

Finally, it is possible to integrate the body of different information at a higher semantic level. We have to fuse common meaning representations derived from different input modalities (sensorial, cognitive and emotional) into an interpretation framework (e.g., audio-visual speech recognition; Potamianos, et al., 2004).

The latter aspect is a crucial issue in order to integrate sensors, cognition and emotion within an agent. Despite important advances, further work is required to investigate this general problem. We could employ individual recognizers that can be trained by using particular data, but they have to interact with a number of input modes or increasing representations. This research area has to address the fusion of heterogeneous input features and combine them in different kind of contexts.

5. DISCUSSION

As experimental data show, activating accessible constructs or attitudes through a set of stimuli can facilitate the cognitive processing of other stimuli under certain circumstances, and can interfere with given other circumstances. Some results support and converge on those centered on the constructs of current concern and emotional arousal.

Researchers have built several computational models of cognition and emotion, based on psychological theories. A typical implementation of emotion generation is bound to a single theory, which usually conflicts with competing theories on the issue about which factors generate emotion and how. Computational models of emotional effects tend to focus on a single effect of emotion on cognition or behavior. This perspective has led to incomplete, competing models which do not take account of the problem of a complete integration of emotion and cognition.

Given our purpose of modeling emotion generation, we have centered our analysis on appraisal theories, which are the prevailing basis for that type of computational model. Appraisal theories generally argue that agents are continuously evaluating their environment, and that evaluations result in emotions such as fear or anger. Each theory differs in its appraisal variables and the way in which appraisals are generated (simultaneously vs. specific order).

Since all cognitive processes work with the associative network, and emotional information is embedded within all the nodes, any process can use emotion data to model emotional effect. EmoCog (Lin et al., 2011) is designed to be flexible, in such a way that further dimensions can be incorporated both into the associative network and mechanisms (arousal and valence). It tries to integrate emotions within a cognitive architecture with an associative network memory, cognitive attention and appraisal following cognition. The associative network enables concepts to influence each other emotionally, and also holds emotional information for cognitive processes and emotion generation. The cognitive attention subcomponent allows for controlled elaboration and emotional rise and decay. The last subcomponent is devoted to account for the issue of how appraisal and association management follow cognition in the associative network, and how cognition influences emotional generation.

Several global principles can be drawn from the possibilities offered by this kind of models. Three of these are arguably the most important. Firstly, attention, as a control system to filter lower-level brain activity in order to allow few input representations to enter the higher level of thought and manipulation of neural activities (e.g., filters controlled by activity in parietal and pre-frontal cortices). This way, higher level processes such as thinking and reasoning work on a smaller number of input representations. Secondly, emotion, in terms of value maps learnt in orbito-frontal cortex (also coded in associated amygdala sites) in order to bias what is to be processed and to guide choice of task goals (by their associated predicted rewards), constraining the inference chain. These value maps, joined with body activations and automatic brain-stem responses, are used to give emotional value to decisions for action. Thirdly, long-term memory created on-line, in order to allow for incremental wisdom about the environment for use as a guide for further interactions.

Other global principles could be added to these three possibilities, such as the use of hierarchical processing (as can be noted in vision, in order to create flexible visual codes for complex objects which can be used at a variety of scales). Another possibility involves the use of synchronization of neurons over long distances, such as 40 Hz frequency, in order to solve the binding problem of combining the different codes for objects (as happens in multi-modal hierarchical coding schemes). A further principle is that of recurrent loops of neural activity, to allow for the creation of short-term (or working memory) sites for the temporary holding of such activity for spreading around to other similar sites, in order to acting as report centers in the brain. Finally, there are the principles of integration and segregation of the neural systems of the brain that play a core role in brain processing efficiency.

Although there are several psychological theories of emotion (see Rolls, 2005), it is generally azssumed that emotions serve the purpose of increasing our ability to interact with our environment in a successful way. We have discussed that emotions can thus be used to increase collective behavior in a dynamic model, as it happens in the communicative approaches. We have analyzed also the use of computational emotions toward increasing collaboration and collective behavior for both avatar and agent.

There exists an extensive experimental evidence on grounded language comprehension, such as action related speech activates, mirror system or action Sentence Compatibility Effect (Glenbach & Kaschak, 2002), where verbal description of spatially directional actions facilitates movements in the same direction. For instance, "Give me the wheel" activates the motor representation of a pointing/request gesture; whereas "I give you the wheel" activates the "reach-grasp-hold out" sequence.

In this sense, we have shown that Dynamic Field Theory offers a powerful theoretical language to endow autonomous robots with high-level cognitive capacities. DF-architecture for joint action represents a complex dynamical system of coupled neural populations, each with a specific functionality. Embodied and dynamic view on cognition strongly contrasts with more traditional AI approaches (see e.g. Bringsjord & Clark, 2012). It will be interesting in the future to develop a system in which each agent could evolve his communication strategies to evaluate how the agent's dynamics and collective behavior are both affected by this additional dynamic.

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REFERENCES

Anderson, JR (1993). *Rules of the mind*. Hillsdale NJ: LEA.

Arkin RC (2005). Moving up the food chain: Motivation and emotion in behavior-based robots. In J Fellows & M Arbib (eds.) *Who needs emotions: The brain meets the robot*. New York: oxford University Press.

Armony JL, Servan-Schreiber D, Cohen JD & LeDoux JE (1997). Computational modeling of emotion: Explorations through the anatomy and physiology of fear conditioning. *Trends in Cognitive Science 1*, 28-34.

Barrett, L. F. (2006) "Solving the emotion paradox: Categorization and the experience of emotion", *Personality and Social Psychology Review* 10, nº 1: 20 – 46.

Barrett, L. F. (2006a) "Are Emotions Natural Kinds?" *Perspectives in Psychological Science* **1:** 28-58.

Barsalou LW, Simmons WK, Barbey AK & Wilson C (2003). Grounding conceptual knowledge in modality-specific systems. Trends Cog. Sci. 7, 84-91.

Becker-Asano C & Wachsmuth I (2008). Affect simulation with primary and secondary emotions. *8th International Conference on Intelligent Virtual Agents*. Tokio: Springer.

Bicho E, Louro L & Erlhagen W (2010). Integrating verbal and nonverbal communication in a dynamic neural field architecture for human-robot interaction. *Frontiers in Neurorobotics* 4, article 5.

Blanchard A & Cañamero L (2006). Developing affect-modulated behaviors: stability, exploration, exploitation or imitation? *6th International Workshop on Epigenetic Robotics*. Paris.

Boehner K, DePaula R, Dourish P & Sengers P (2007). How emotion is made and measured. *Int.J. Human-Computer Studies 65*, 275-291.

Breazeal CL (2002). *Designing sociable robots*. Cambridge: MIT Press.

Bringsjord, S & Clark, M (2012). Red-pill robots only, please. *IEEE Transactions of Affective Computing 3*(4), 394-397.

Busemeyer JR, Townsend JT & Stout JC (2002). Motivational underpinnings of utility in decision making: Decision field theory analysis of deprivation and satiation. In S Moore (ed.), *Emotional cognition*. Amsterdam: John Benjamins.

Clark A.(1997) *Being There: Putting Brain, Body and World Together Again*, Cambridge: MIT Press, Bradford Books.

Cosmides, L., & Tooby, J. (2000) "Evolutionary psychology and the emotions", in M. Lewis & J.M. Haviland-Jones (Eds.), Handbook of emotions (2nd ed., pp. 91–115). New York: Guilford.

Damasio, A. (1994) *Descartes' Error: Emotion, Reason, and the Human Brain*, New York: G.P. Putnam's Sons.

Dennett, D. (1994) "The practical requirements for making a conscious robot", in *Philosophical Transactions of the Royal Society,* A349: 133-146.

Ekman P (1992). An argument for basic emotions. *Cognition and Emotion 6*, 169-200.

Ellsworth, P.C., & Scherer, K.R. (2003). "Appraisal processes in emotion", in R.J. Davidson, K.R. Scherer, & H.H. Goldsmith (Eds.), *Handbook of affective sciences* (pp. 572–595). New York: Oxford University Press.

Fodor, J. (2000) *The Mind Doesn't Work That Way. The Scope and Limits of Computational Psychology*, Cambridge, Mass: MIT Press.

Frijda, N.H. (1988). "The laws of emotion" *American Psychologist*, **43**, 349–358.

Garg A, Pavlovic V & Rehg, J (2003). Boosted learning in dynamic Bayesian networks for multimodal speaker detection. *Proceedings of the IEEE 91*(9) 1355-1369.

Glenbach AM & Kaschak MP (2002). Grounding language in action. *Psychon. Bull. Rev. 9*, 558-565.

Graesser AC, D´Mello SK, Craig SD, Witherspoon A, SullinsJ, et al. (2008). The relationship between affect states and dialogue patterns during interactions with AutoTutor. *Journal of Interactive Learning Research 19*, 293-312.

Gratch J & Marsella S (2004). A domain-independent framework for modeling emotion. *Journal of Cognitive Science 5*, 269-306.

Gratch J & Marsella S (2005). Evaluating a computational model of emotion. *Autonomous agents and multi-agent systems 11*, 23-43.

Gratch J, Marsella S & Petta P (2009). Modeling the cognitive antecedents and consequences of emotion. *Journal of Cognitive Systems Research 10*(1), 1-5

Griffiths, Paul, (1997) *What Emotions Really Are: The Problem of Psychological Categories*, Chicago: University of Chicago Press

Jaimes A & Sebe N (2007). Multimodal human-computer interaction: A survey. *Computer Vision and Image Understanding 108*, 116-134.

Kripke, S. (1972). *Naming and necessity*. Cambridge, MA: Harvard University Press.

Lang PJ (1995). The emotion probe: Studies of motivation and attention. *American Psychologist 50*(5), 372-385.

LeDoux J (1996). *The emotional brain: The mysterious underpinnings of emotional life*. New York: Simon & Schuster.

Lin J, Spraragen M, Blythe J & Zyda M (2011). EmoCog: Computing integration of emotion and cognitive architecture. *Association for the Advancement of Artificial Intelligence* [www.aaai.org].

Loewenstein G & Lerner JS (2003). The role of affect in decision making.IN R Davidson, H Goldsmith & K Scherer (eds.), *Handbook of affective science*, pp. 619-642. Oxford: Oxford University Press.

Mehrabian A (1995). Framework for a comprehensive description and measurement of emotional states. *Genetic, Social and General Psychology Monographs 121*, 339-361.

Niedenthal PM (2007). Embodying emotion. *Science 316*, 1002-1005.

Oatley K & Johnson-Laird PN (1987). Toward a cognitive theory of emotions. *Cognition and Emotion 1*, 29-50.

Öhman A & Wiens S (2004). The concept of an evolved fear module and cognitive theories of anxiety. In A manstead, N Frijda & AH Fischer (eds.), *Feelings and emotions*, pp. 58-80. Cambridge: Cambridge University Press.

Ortony A, Clore GL & Collins A (1988). *The cognitive structure of emotions*. Cambridge: Cambridge University Press.

Oudeyer, PY (2003). The production and recognition of emotions in speech: features and algorithms. *International Journal of Human Computer Studies 59*(1-2), 157-183.

Pantic M & Rothkrantz LM (2003). Toward and affect sensitive multimodal human-computer interaction. *Proceedings of the IEEE 91* (9), 1370-1390.

Potamianos G, Neti C, Luettin J & Matthews I (2004). Audio-visual automatic speech recognition: an overview. In E Vatikiotis-Bateson and P Perrier (eds), *Issues in visual and audiovisual speech processing*. MIT Press.

Prinz, J. (2004) *Gut reactions*: *a Perceptual Theory of Emotion*, Oxford: Oxford University Press

Putnam, H. (1975). "The Meaning of 'Meaning'", in *Mind, language, and reality*. New York: Cambridge University Press.

Rolls E (2005). *What are emotions, why do we have emotions, and what is their computational basis in the brain*. Oxford University press.

Russell JA (2003). Core affect and the psychological construction of emotion. *Psychological Review 110*, 145-172.