Autonomous Cognitive Robots Need Emotional Modulations: Introducing the eMODUL Model

Marwen Belkaid, Nicolas Cuperlier, and Philippe Gaussier

***Abstract*—Emotion is an integral part of cognition. There is significant evidence of mutual, bi-directional influence between cognitive and emotional processes. Also, more and more research works propose an integrative view of emotion and cognition. In this paper, we review a large literature on emotion–cognition interactions in psychology, neuroscience, and computational modeling. Then, we introduce eMODUL, which consolidates this literature into a conceptual model. In particular, this model stresses the importance of emotional modulations and the roles they play with respect to the system autonomy depending on the targeted computational/cognitive processes (e.g., allocation of resources, organization of behavior). To illustrate these aspects and support our theoretical model, we review two robotic experiments where eMODUL is instantiated. The results demonstrate the interest of our approach for the development of interaction/communication and autonomy/adaptation capabilities in cognitive robots. In terms of natural cognition understanding they give additional insights into the emergence of emotion, the construction of multilevel appraisal, and the link between emotion and cognition in task-related emotions.**

***Index Terms*—Emotional modulations, emotion–cognition interactions, metacontrol, robot emotions.**

I. Introduction

THE FIELD of autonomous cognitive robotics has two complementary goals: 1) to create artificial systems that exhibit cognitive capabilities and interact efficiently with their environments and 2) to deepen our knowledge of biological cognition through a process of understanding by design. Typically, cognitive (natural or artificial) systems carry out tasks related to perception, attention, learning, decision-making, and so on. In general, the autonomy of such systems depends on their capacity to evolve and adapt in dynamic environments without human intervention. To do so, they have to filter their inputs, allocate their computational resources, organize their behavior, adapt to novel situations, learn/develop new competences, etc.

Manuscript received May 31, 2017; revised November 2, 2017; accepted December 27, 2017. Date of publication April 3, 2018; date of current version December 14, 2018. This work was supported in part by ANR DIRAC under Grant ANR-13-ASTR-0018, and in part by Equipex Robotex. This paper was recommended by Associate Editor A. Hussain. *(Corresponding author: Marwen Belkaid.)*

M. Belkaid was with the ETIS Laboratory, UMR 8051, Université Paris Seine, ENSEA, CNRS, Université de Cergy-Pontoise, F-95000 Cergy-Pontoise, France. He is now with CNRS UMR 7222, Institut des Systèmes Intelligents et de Robotique, Sorbonne Université, UPMC Univ Paris 06, F-75005 Paris, France (e-mail: marwen.belkaid@ensea.fr).

N. Cuperlier and P. Gaussier are with the ETIS Laboratory, UMR 8051, ENSEA, CNRS, Université Paris Seine, Université de Cergy-Pontoise, Cergy-Pontoise, France.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSMC.2018.2792542

In this paper, we would like to present our view on how artificial emotion can help roboticists respond to these challenging issues. Indeed, the importance of emotion in cognition is more and more acknowledged by researchers in a variety of disciplines. Despite the absence of a consensual definition of what (natural) emotion is, there is quite an agreement across scientific communities that it involves partially dedicated neural circuits, response systems, and feeling state/process that allow for assessing events, focusing attention, enhancing communication, and motivating cognition and action [1].

In our view, emotion is an integral part of cognition; cognition in a broad sense, i.e., all mental activities that are necessary to perceive the world, control the behavior and attain goals. But, in order to stress the contribution of emotion, the term cognition in the rest of this paper will be used to refer to nonemotional processes like perception, attention, memory, and so on.

Converging analyses of existing findings suggest that emotion and cognition are not easily separable. In fact, they appear to continuously influence each other. Processes like perception, attention, memory and reasoning, which are associated to cognition, influence emotional experiences through appraisal and affect elicitation. In return, they are also modulated by emotional signals. There is indeed a large body of evidence in the literature that emotion has an influence en perception, attention, memory, and decision. The model of emotion–cognition interaction we propose in this paper focuses on these emotional modulations in particular.

Biologically, emotion–cognition interactions seem to be represented by the bi-directional influence between neural activities and neurochemical modulations. Computationally, dynamical systems theory appears to provide a good framework to study such a coupling. On a higher level of abstraction, we propose a conceptual model that represents interactions between processes—similarly to a workflow diagram for example. It illustrates how the system continuously: i) appraises events from the body and the world with a particular interest in emotionally relevant stimuli and ii) processes emotionally modulated signals and reintegrates them in the information processing flow for the purpose of higher order processing and appraisal.

Emotions are generally studied from two perspectives: a) their role in communication and social interactions and b) their role in behavior control, adaptation, and autonomy. For a roboticist, such a functional view of emotions makes them interesting to model in artificial systems. In fact, these external and internal roles of emotion are two sides of the same coin. As long as there is an embodied physical and social interaction with the environment, internal regulatory processes of emotions are expressed in the agent behavior. This improves communication and in return benefits to the adaptation capacity through social interactions.

In light of the aforementioned first goal of autonomous cognitive robotics, artificial emotions offer an elegant approach for the purpose of: 1.a) enhancing robot–robot and human–robot interactions and 1.b) increasing robot autonomy and adaptation capabilities. In this paper, we will summarize two experiments of which the results highlight the interest of our model in these two contexts [2]–[4]. As for the second goal we enumerated, it is important that 2) robotic experiments be informative about natural cognition. In our case, we will discuss the model and the experimental results with regards to the emergence of emotion, the construction of multilevel appraisal, and the link between emotion and cognition in task-related emotions.

II. Cognitive Influence on Emotion

Appraisal theories of emotion provide a very interesting framework for studying the set of cognitive processes involved in the activation of emotions [5]–[7]. These models suggest that organisms constantly explore their environment and react to relevant stimuli. Thus, the aim is to describe the computational processing of information that leads from an external event to a change in the behavior. Appraisal theories postulate that different emotions result from different patterns of evaluation (processing).

In this tradition, some theories conceptualize emotion as an information-processing system just like any cognitive mechanism [6]. However, they are particularly subjects to general criticisms of appraisal/cognitive views of emotion [8]: e.g., relying on symbolic representations and high-level information processing or not accounting for the rapid onset of some emotional reactions.

Scherer's CPM model attempts to address these criticisms with a multilevel approach to appraisal [7]. In this model, the appraisal module responsible for the evaluation of objects and events is organized as a rapid succession of stimuli-processing stages called stimulus evaluation checks). Four major appraisal objectives are listed: 1) relevance; 2) implication; 3) coping potential; and 4) normative significance. For instance, to evaluate relevance, there is a check for novelty, for intrinsic pleasantness, and for the importance with respect to goals and needs. Moreover, according to Scherer, all the criteria can be processed in parallel at three hierarchically organized levels. First, the sensorimotor level, in which the checking mechanisms are mostly genetically determined and based on pattern matching. Second, the schematic level, in which the processing is automatic and unconscious based on social learning and repeated experiences. Third, the conceptual level, involving propositional knowledge and requiring consciousness.

Appraisal checks require cognitive processes related to attention, memory, motivation, reasoning, and self [7]. This is in line with several findings showing the influence of cognition on the evaluation of the affective value of different stimuli or the initiation/alteration of emotional responses [9], [10]. For instance, Rolls *et al.* [10] reported various fMRI studies showing that language-level description of taste, olfactory, and tactile properties (e.g., rich, delicious, moisturizing) modulated the participants subjective rating of the stimuli pleasantness. Additionally, another experiment demonstrates that the processing of affectively and socially salient signals is modulated by voluntary attention [11]. The experiment used a dichotic-listening paradigm; meaning that angry and neutral prosody were presented simultaneously to both ears while participants were asked to perform a gender decision task on voices heard in one ear, while they had to ignore voices presented on the other side. The results show that the amygdala (AM) responded to anger stimuli independently of attention and that the orbitofrontal cortex (OFC) showed greater activation to the same emotional stimuli when presented on the to-be-attended side compared to the to-be-ignored side. These two brain areas are generally associated with "low-level" and "high-level" emotional evaluation of stimuli and states respectively [12], [13]. On the other hand, voluntary cognitive regulation/modulation of emotion is thought to involve the prefrontal cortex (PFC) and the anterior cingulate cortex (ACC), two regions that are generally associated with cognitive control and working memory [9], [10]—i.e., the ability to maintain information in mind.

III. Emotional Influence on Cognition

A. Perception

The effect of emotion on perception can be observed from the modulation of visual processing. For example, emotional stimuli induce an increase in the activation of the visual cortex [14] after affective conditioning. Also, [15] showed that emotionally arousing stimuli (fearful faces) lowered the contrast threshold in comparison with neutral stimuli. In other words, participants were more sensitive to visual contrast when they had previously seen emotional faces than when they had seen neutral faces.

More evidence can be found in studies investigating the perception of space and distance from objects and individuals. For example, positively valenced objects tend to be perceived as closer and more reachable than negative ones [16], [17]. Also, Coello *et al.* [18] showed that a knife seems farther when oriented toward us, i.e., when potentially dangerous. This proves that an on-line evaluation of the harmful consequences of physical interactions alter the perception of peripersonal space, but not the semantic knowledge about the object. Moreover, a positive affective state, induced by pleasant music, for instance, reduces the area needed to feel comfortable in over-crowded spaces [19]. Conversely, personal space expands when placed in threatening contexts [20]. The perception of our peripersonal space in social interactions indeed seems to depend on a emotional evaluation of external stimuli. For example, AM lesions appear to impair the estimation of interpersonal space [21].

B. Attention

Emotions also influence attentional processes. For instance, fear-related stimuli (snakes and spiders) are detected faster than nonthreatening ones [22].

Another example can be found in emotional stroop tasks used by psychologists [23]–[25]. Typically, two stimuli are presented simultaneously. The task or action to perform is related to the nonemotional stimulus (i.e., press a button corresponding to the color in which a word is written). A delay is noted when the second, co-occurring stimulus (the meaning of the word in the previous example) carries an emotional valence. This phenomenon is called the emotional stroop effect. But since these tasks capture an attentional bias toward emotionally significant stimuli, the term "emotional intrusion" was claimed to better describe this phenomena [24].

Yet another evidence comes from the attentional blink effect. It consists in the impairment of the detection of a target stimulus (T2) when presented rapidly after a first target stimulus (T1). Anderson [26] suggested that the effect depends on the arousal but not the valence of the emotional stimuli. The attentional blink has also been shown to be modulated by the emotional significance of both T1 and T2 [27]. That is to say, the emotional relevance of T1 increases the effect while that T2 reduces it.

C. Memory

Studies on working memory provide additional support for the influence of emotion on cognition. For example, it was found that the valence of the face stimuli that participants were asked to memorize modulated the activity of the dorsolateral PFC [28]; which is thought to be a critical area for working memory. Besides, Gray *et al.* [29], [30] investigated the effect of emotion induction on the ability to memorize word and face stimuli in 3-back tasks. Interestingly, the results showed that emotional states consistently exerted opposite effects on working memory for verbal versus nonverbal information. More precisely, the performance on the face task was enhanced by a unpleasant state and impaired by a pleasant one, and inversely in the word task. They also showed that the dlPFC neural activity was greater in the word-unpleasant and face-pleasant conditions, intermediate in the neutral conditions, and lower in the word-pleasant and face-unpleasant conditions. Additionally, low- and high-intensity stimulation of the AM, respectively, impair and enhance memory [31]. Furthermore, McGaugh [32] provided a review of findings indicating that emotion also consolidates long-term memory.

IV. Integrative Views of the Emotion–Cognition Interplay

In the examples presented above, either cognitive processing (appraisal) is at the root of emotional elicitation and continuous updating or noncognitive, emotional processing influences cognition. These views are not in contradiction. As a matter of fact, several research works attempt to provide an integrated view of the relation between emotion and cognition. For example, it was proposed that cognitive control can be understood as an emotional process [33]. The authors note that cognitive errors are associated with physiological changes such as increased skin conductance, cardiac activity, and pupil dilation, which are also considered as emotional primitives. In addition, they point out that negative affect increases the saliency of goal conflicts and motivates goal-directed behavior in order to minimize the conflict. We do not necessarily agree that cognitive control must be considered as an emotional process. However, this view gives an interesting perspective on the close relation between emotion and cognition, especially in task-related emotions like those we address in this paper.

Pessoa [34], [35] also made a case against the segregation between emotion and cognition. He highlights the interactive and integrative potential that exists in brain structures like AM and PFC. He also argues that complex behaviors have their basis in dynamic coalitions of networks of brain areas involved in both emotion and cognition. Instead of a one-to-one mapping between areas and functions, he stresses that brain areas have many-to-many links with different types of neural computations generating behavior. The behavior space is described using affective and cognitive axes. Thus, any behavior is by definition both cognitive and affective. Importantly, the axes are not orthogonal, such that any change in one of the behavior dimension affects the other. Additionally, specific brain areas belong to several intersecting networks. Therefore, neural computations have to be seen as implemented by the interaction of multiple areas.

As an example of overlapping networks, there is a large literature acknowledging the existence of multiple cortico-basal circuits implementing both motor and nonmotor functions [36]–[38]. The nonmotor circuits include emotional/limbic and cognitive/associative loops. The former represent interactions with OFC and ACC while the latter concern interactions with the dlPFC. This functional description in the shape of loops encompasses neuronal connections (information transmission) and neurochemical projections (modulation).

There exists indeed a variety of neuromodulation systems in the brain that rely on chemical messengers like dopamine, serotonin, acetylcholine, norepinephrine, and oxytocin. They are implicated in emotion-related mechanisms such as metabolic regulation, bodily responses, pleasure and pain sensations, motivation, and motor activation [39], [40]. Fellous argues that emotions should be understood as dynamical patterns of neuromodulation rather than patterns of neural activity [39]. In fact, two notions are encompassed in this view. First, that emotion and cognition are integrated and implemented by the same structures: the former corresponds to the state of neuromodulation while the latter corresponds to the state of neural computation. This approach radically puts the chemical signaling system at the center of the question of emotion–cognition interaction. The neuromodulatory state is biased by the various levels of computation. In return, the neural activity (cognition, information processing) depends on the aforementioned neuromodulatory states.

The second fundamental notion encompassed in Fellous's view is that of dynamical states. Emotions such as fear and anger, that are usually identified as basic emotions, here correspond to attractors that are temporally and/or spatially stable. This idea is also developed by Lewis [41]. Indeed, in order to account for the bidirectional relation between cognition (appraisal) and emotion, he proposes to study them through the lens of dynamical systems theory. He builds on a set of principles from this theory to describe internal states as attractors and transitions. In this view, emotional episodes, triggered by perceptual events, physiological events or memories, emerge from appraisal–emotion interactions. The meaningfulness of changes in the world or the body is evaluated in areas like AM and OFC that initiate new neurochemical patterns. This can be characterized as a phase transition that disrupts the orderliness of the existing state. This results in a self-amplification phase then a self-stabilization phase: positive feedback recruits more neural components to an emerging state and negative feedback couples them in a stabilizing regime.

In line with these models, Hasson *et al.* [42] proposed to represent an embodied system as two coupled abstract controllers, respectively, dedicated to interactions with the physical and social environments. The purpose is not to claim that interactions with the physical and social environments must be handled by separate modules or structures, but rather to put together the processes that are related to the same type of interaction in one abstract entity in order to insist on the interplay between them. Thereby, emotions result from the dynamics of: 1) internal interactions between those two kinds of processes (physical and social) and 2) external interactions with the environment. This view illustrates our approach to emotion modeling: emotions are grounded in the whole architecture through the integration with other perceptual, attentional, decisional, and regulatory processes, which can be handled by the two coupled controllers.

V. Model of Emotional Cognitive Systems

eMODUL is a conceptual model of the emotion–cognition interaction. Similarly to a workflow diagram, the model illustrates interactions between processes rather than structures. First, this allows to easily map the model to descriptions that are also generally process-oriented. Second, it provides a generic view of the concept regardless of any implementation or application. Its purpose is to capture, at an abstract, high level of description, the way emotion-related signals are extracted from and influence the information processing flow in a sensorimotor system. The next two sections will briefly describe concrete implementations in two different experiments using artificial neural networks.

In order to introduce the model, let us first illustrate a nonemotional sensorimotor architecture in this kind of representation. As shown in Fig. 1 (white boxes only), an embodied system interacts with the environment by receiving sensory inputs and performing actions that influence the forthcoming sensations. The information processing flow involves *parallel computational processes* such as reflexes (prewired, evolution-based), memory (temporal integration), conditioning, and categorization (higher level representations). Representations obtained from the cognitive processing can be reintegrated as

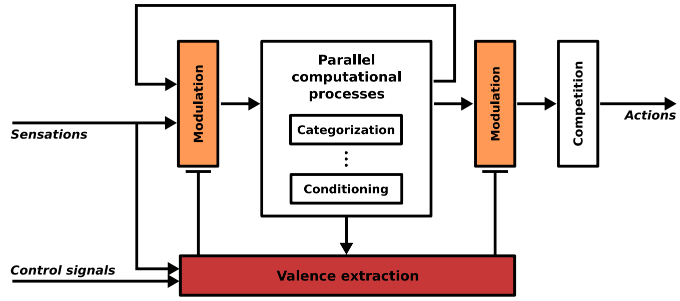

Fig. 1. eMODUL, a conceptual model of the emotion–cognition interaction in a autonomous cognitive system. Colored boxes show the introduction of emotional processes in a nonemotional sensorimotor architecture (white boxes only). The system, situated in its physical and social environment, constantly appraises events from the body and the world with a particular interest in emotionally relevant stimuli that affect other processes. It continuously processes emotionally modulated signals and reintegrates them in the information processing flow for the purpose of higher order processing. *Parallel computational processes* include memory, conditioning, categorizations, and so on. *Valence extraction* consists in the evaluation (appraisal) of the emotional values of more or less complex representations.

input to the information processing flow. For instance, local views from the visual input categorized as landmarks can be reintegrated to encode objects and places. This may also require the integration of additional input—e.g., merging the what and where information. Additionally, among the parallel computational processes are those that allow for shifting to the action space. Thereby, the information processing uses the sensory input (in different levels of representations) to trigger behaviors in the sensorimotor pathway: e.g., raw stimulus-driven startle reflex, landmark–direction navigation strategy or object–action association generating arm movements. The actions that are actually performed by the system result from the *competition* between those sub-behaviors computed in parallel. The competition can be strict or soft, allowing the cooperation between sub-behaviors.

In line with the literature reviewed above, implementing emotional competence in such an architecture requires (partially) dedicated networks that assess events with regard to survival and well-being. That is to say, capturing physiological and sensory inputs which carry an emotional valence. This is illustrated in Fig. 1 by the *Valence extraction* block. Like in Scherer's model [7], the term *valence*—in a broad sense—refers to pleasantness, novelty, goal conduciveness, etc., Such type of processing can be nonlearned, evolutionarily acquired in order to regulate bodily functions and handle stimuli with intrinsic affective properties (e.g., auditory or visual stimuli [22]). But the emotional value can also be acquired through pavlovian (stimulus–stimulus) or instrumental (stimulus–reward) learning. The result of this emotional evaluation (appraisal) is the *modulation* of the computational processes that govern the system behavior. More concretely, since we use artificial neural networks, emotional modulation consists in increasing or decreasing the synaptic efficacy of targeted populations of neurons involved in these processes. This models the neuromodulatory function of the chemical brain system mentioned earlier.

In eMODUL, emotion influences sensing-related and action-related processes in the information processing flow. Thereby,

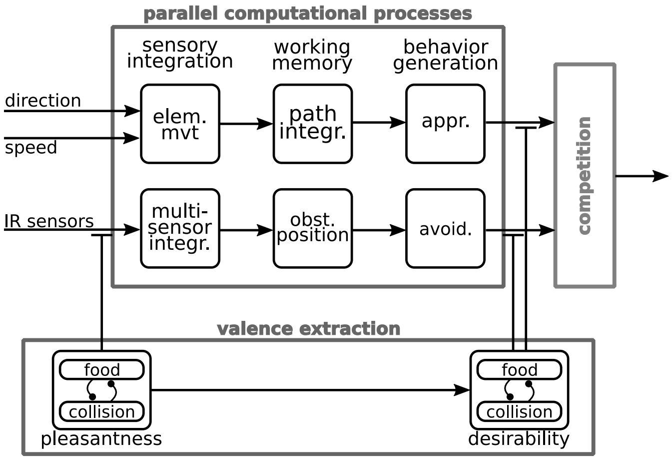

Fig. 2. Schematic view of the architecture implementing eMODUL in Experiment 1. See text for description.

the system sensations and actions are no longer neutral and objective, but rather emotionally colored. For example, when occurring on the sensation space, emotional modulation affects perception and memory. When occurring on the action space, it can modulate action selection and motor expression. In terms of the system autonomy, these two types of modulations, respectively, have an impact on the allocation of cognitive/computational resources and the organization of behavior appropriately with regards to the system survival, well-being, and task/goal demands.

VI. Emotional Modulation of Peripersonal Space

A. Method

The representation of emotionally modulated perception of the near-space can be used to control robots approach and avoidance behaviors [2], [3]. Here, we present an experiment that illustrates this idea in the context of a survival problem. The robot has two drives: 1) feeding and 2) protecting its own physical integrity. Of particular interest in terms of action selection will be the situations where approach and avoidance are in contradiction.

Each run involves two identical robots and one resource. We define a cycle as an interval in which a robot, initially satiated, consumes the energy obtained from the previous ingestion and returns to the resource in order to feed once again. Each of these cycles is considered as an independent sample of the multirobot competition for the resource. Once its feeding drive satisfied, the robot gets away from the resource. It randomly navigates in the environment updating its path integration field [43] to be able to return to the resource when needed.

In this experiment, the eMODUL model is instantiated as illustrated in Fig. 2. Sensory inputs consist in proximity signals (IR sensors) and proprioception (direction and speed). Control signals are given by collision (pain) and resource ingestion (pleasure). The computational processes involved are: sensory integration (multisensor proximity detection, elementary movement calculation merging direction and speed) and working memory (obstacles positions, path integration summing elementary movements). The competition between approach and avoidance, based on the output of these processes (goal direction versus obstacle), determines the robot action. Last, to allow emotional modulation, valence extraction is determined by the pleasantness of collisions and food ingestions and drive-related desirability. Also, we use a simple lateral inhibition between the appetitive and the aversive pathways to model dynamic interactions between neuromodulatory systems. As suggested in eMODUL, emotional modulation occurs on the sensory level (e.g., accentuating obstacle proximity when in a negative state due to previous collision [19]) and the action level (e.g., increasing/decreasing speed according to the current drive state and desirability of stimuli [16], [18]). Due to space limitation, we cannot provide here all the equations and parameters used in the neural architecture. We invite the readers to refer to our previous papers [2], [3] for more implementation details.

In the experiment, we compared this *model* architecture to a *sham* version. Robots from this group either have no modulation of approach/avoidance at all, or the modulation is based on raw pleasure/pain and drive signals with no lateral inhibition between the appetitive and aversive pathways. In the evaluation of our results, we were interested in the robots ability to survive (i.e., to feed when needed) but also in the way they handled the competition for the resource (i.e., how they alternated their accesses to it).

B. Experimental Setup

In this experiment, we used the *Promethe* neural network simulator [44]. In Promethe, each operation of the information processing flow can be computed as soon as the information from previous modules is updated. Independent modules are executed in parallel (i.e., in separate threads). Moreover, the experiment was performed on Webots simulator developed by Cyberbotics providing realistic physics. The simulated robotic platform used IR sensors for proximity detection and a color sensor for the resource detection. Simulated odometry was used for path integration (see Fig. 3).

C. Results

A Mann–Whitney (M–W) test shows no difference between the two groups in terms of food depletion ($U = 277.00, p = 0.95$; Mean ranks: 25.81 for *model*, 26.09 for *sham*). In other words, with the used parameter values (e.g., determining the robots velocity or the time to consume the ingested resource during a cycle) the emotional modulation had no effect on the robots capacity to survive.

In contrast, there is an impact on the way robots interacted and alternated their access to the resources when both were hungry. First, there is a strong tendency in term of interruptions within a feeding cycle ($U = 201.00, p = 0.05$; Mean ranks: 30.94 for *model*, 23.74 for *sham*). That is to say, using the *model*, robot tended to be interrupted more often while they were feeding. Additionally, a main effect of emotional modulation on the number of interferences is observed ($U = 187.00, p = 0.01$; Mean ranks: 31.78 for *model*, 23.36 for *sham*). Here, an interference corresponds to a concurrent

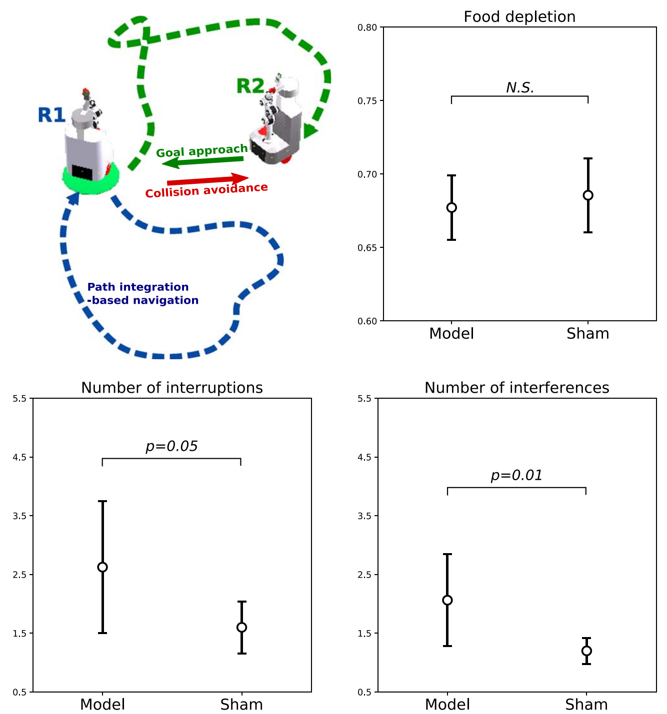

Fig. 3. Experiment 1. Top-Left: Illustration of two robots competing for a resource. Top-Right: Food depletion measured as the lowest level of the physiological variable. Bottom-Left: Number of interruption endured by robots while they are feeding. Bottom-Right: Number of interference, i.e., concurrent/simultaneous accesses to the resource. The overlaps between the confidence intervals are in line with differences shown by the M–W tests between the 2 groups (p values reported on the figures).

access to the resource during the ingestion of the resources; either leading to an interruption or to simultaneous feeding.

The statistical results are in line with the effect magnitude measured by the confidence intervals shown in Fig. 3. In particular, the small overlap in the interruptions and interferences intervals confirms the difference between the *model* group and the *sham* group. These differences capture the fact that the emotional modulation make the robots more determined to access the resource and feed; as opposed to simply wait until the other robot frees the access.

It is worth noting that we could tune the parameters so that food consumption is faster. In such a case, we would expect an effect of emotional modulation in terms of food depletion. Indeed, intermediate accesses to the resources (i.e., accesses that do not lead to full satiation) should then make a bigger difference with regards to the survival of individuals between the two groups.

VII. Emotional Modulation of Visual Attention

A. Method

In this second experiment, we consider a visual search task, which is a common experimental paradigm in psychology. This type of perceptual task involves attentional mechanisms that allow the subject to scan the visual environment in order to find a target object among distractors. Here, we consider three objects—two targets and a distractor—of which the visual

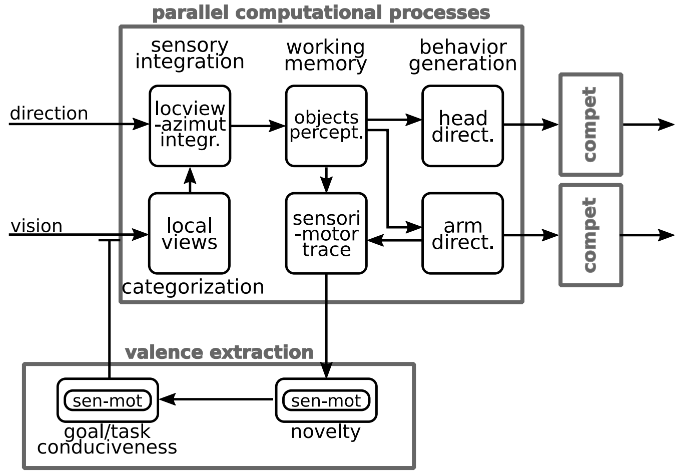

Fig. 4. Schematic view of the architecture implementing eMODUL in Experiment 2. See text for description.

saliency is as follows: Target1 < Distractor < Target2. The goal is to search for and recognize as many target objects as available in the visual scene and perform the corresponding learned actions to confirm the recognition.

The protocol includes two phases. First, during task learning, the three objects are presented one by one in front of the robot. The latter learns a set of local views of the objects for the purpose of visual recognition. It also associates an action with each of the target objects: Target1 → push right, Target2 → push left. Second, the experiment consists of a set of trials in which the objects are presented pairwise; interchangeably on the left or right position. The robot performs one of the learned actions to show the experimenter that one of the target objects was recognized. A 30 s timeout per trial is imposed, which defines an acceptable upper bound in case of deadlock given the dynamics of the system.

In this experiment, the eMODUL model is instantiated as illustrated in Fig. 4. Sensory inputs consist in vision (color images) and proprioception (head direction). The computational processes involved are: extraction and categorization of local views, sensory integration (localview—Azimuth), working memory (local views positions) and visuomotor learning (not shown in figure). The robot performs two types of actions: 1) turning toward most salient objects in the scene and 2) moving the arm if a target is recognized. Last, emotional modulation relies on novelty detection [7], [45] with respect to a memory trace of "normal" sensorimotor experience [46]. The ability to predict sensory inputs based on past experiences (absence of novelty) is used for self-assessment [47], [48], i.e., assessing the compatibility between skills and task demands. In other words, the systems appraises its sensorimotor behavior in terms of goal conduciveness [7], or how much the current behavior allows for performing the task. Incompatibility between skills and task demands can either result in frustration or boredom [49] if learned behavior does not allow to perform the task or if there is no new challenge after a task is performed, respectively. Either way, this information is used to modulate attention by inhibiting the extraction of local views in the area on which attention is currently focused;

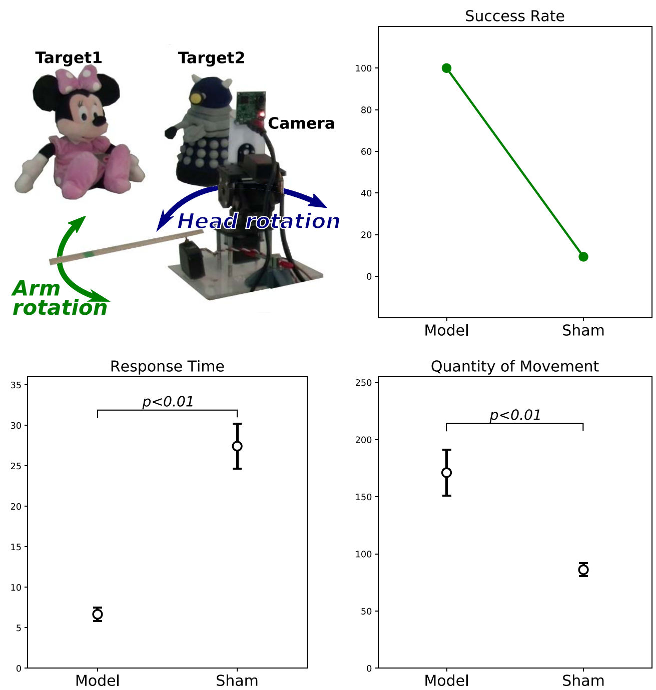

Fig. 5. Experiment 2. Top-Left: Illustration of the visual search task in a configuration where the robot has to find two target objects. Top-Right: Success rates as the percentage of trial in which Target1, the least salient object in the search task, is found. Bottom-Left: Response time for Target1. Bottom-Right: Quantity of movement measured as the total head rotations. The important gaps between the confidence intervals of the two groups in both measures are consistent with the significant effects revealed by the M–W tests (p values reported on the figures).

which results in visual exploration. We refer to this top-down modulation operated by an emotional second-order controller "emotional metacontrol." Due to space limitation, we cannot provide here all the equations and parameters used in the neural architecture. We invite the readers to refer to our previous paper [4] for more implementation details.

In this experiment, the above-mentioned *model* was compared to a *sham* feed-forward architecture, where no emotional metacontrol modulates attention. In the evaluation of our results, we were interested in both the capacity to recognize nonsalient targets and to explore the visual scene.

B. Experimental Setup

Here, we also used the *Promethe* neural network simulator. This experiment was performed on a robotic platform comprising a pan-camera and a 1-degree of freedom (DoF) arm (see Fig. 5).

C. Results

In the visual search task, the subjects performance is evaluated in terms of the ability to recognize target objects. Of particular interest in this experiment is the recognition of Target1, the least salient object, when presented along with Target2 or Distractor. In this case, the *model* group obtains 100% of success while the *sham* groups success rate is only about 10%. The response time (RT) provides an additional measure of the system success: given the 30 s timeout, RT = 30 represents a failure. An M–W test shows a significant difference between the *model* and *sham* groups ($U = 91.00$, $p < 0.01$; Mean ranks: 19.34 for *model*, 37.31 for *sham*). Thus, the emotional modulation makes a difference in terms of performance since Target1 is hardly recognized without the top-down attentional bias.

Additionally, an M–W reveals a significant effect of the emotional modulation on the quantity of head movement, that is, the total head rotations within a trial ($U = 50.00$, $p < 0.01$; Mean ranks: 71.46 for *model*, 25.54 for *sham*). This illustrates the robot tendency to switch attention and explore the visual scene thanks to the emotional metacontrol.

These statistical results are confirmed by the confidence intervals observed for both the reaction time and the quantity of movement. As shown in Fig. 5, the important gaps between the *model* group and the *sham* group are consistent with the significant effects revealed by the M–W tests. All in all, these results demonstrate that the emotional modulation of attention in visual search task increases the robot performance and fosters the exploratory behavior to avoid deadlocks.

VIII. General Discussion

A. Cognitive Systems Autonomy

The first goal of autonomous cognitive robotics is to (1) create artificial systems that exhibit cognitive capabilities and interact efficiently with their environments. In this paper, we proposed to tackle this objective by integrating emotion in these systems architectures. Indeed, the literature suggests that designing artificial emotion would benefit autonomous robots in two ways: 1.a) enhancing robot–robot and human–robot interactions and 1.b) increasing robot autonomy and adaptation capabilities [50], [51]. Hence, we presented two experiments that address these two—so-called external and internal—aspects, respectively. In Experiment 1, we showed how emotion had an impact on the way two robots interact in a survival task. In Experiment 2, we showed how emotion allowed self-regulation in a visual search task.

The robotic architectures used in these two experiments instantiate the eMODUL model presented in this paper. This conceptual model aims to stress the importance of emotion–cognition interaction in autonomous systems. In particular, a key notion in eMODUL is emotional modulation, which we argue occurs at the sensation and at the action levels of the sensorimotor information processing flow. We believe these two types of modulations are necessary to address the challenges faced by autonomous systems because they play distinct roles, respectively, in the allocation of the systems limited computational resources and the organization of its behavior. The experiments we presented provide an illustration of these two aspects. In Experiment 2, the emotional modulation of attention allows nonsalient objects to be noticed by the system. In Experiment 1, the emotional modulation of action selection generated an "aggressive," "determined" behavior as opposed to a "fearful," "patient" behavior.

It is quite commonly admitted that emotion influence decisions and actions. But, the natural bias in favor of emotionally relevant information cannot only intervene at the level of action selection and decision-making. From the functional perspective, it is essential that it occur at earlier stages. Indeed, objects and events compete for limited processing capacity—memory and computation—and brain resources must be recruited appropriately. Therefore, emotion filter information with respect to survival and well-being and modulate a variety of brain activities accordingly. We believe this is a key feature for autonomous cognitive systems. In the experiments we presented, we modeled some aspects of the emotional influence on perception and attention—which had an indirect influence on (short-term) working memory. But, there is still a lot to investigate in that matter. For instance, a more precise modeling of the visual cortex would open the way for numerous experiments linked to emotion influence on low-level perception [15], [22].

Emotion is also essential for autonomous cognitive robots as a *metacontroller*; that is to say, a second-order controller for the purpose of behavior regulation. For instance, a well-known problem faced by nondeliberative behavior-based robotics is the local minima problem: due to the use of local information, reactive architectures can get stuck in deadlocks. Emotion-based metacontrol provides an elegant and efficient solution in such situations. Based on a generic model of sensorimotor novelty detection, we proposed that self-assessment serve as an input to a feedback loop for the purpose of self-regulation. Typically, self-assessment can elicit frustration or boredom in deadlock situations. In Experiment 2, we showed how emotional metacontrol can be an efficient solution for the recognition of nonsalient objects in a visual search task. In previous works, the emotional metacontrol was used to modulate action selection in a navigation task [48], which demonstrates the genericness of our approach.

Although the role of emotion in learning was not addressed here, it is very relevant to this paper and to the question of cognitive systems autonomy. For example, novelty detection is known to trigger the learning of new categories and/or associations [45]. Oudeyer *et al.* [52] worked in developmental robotics also highlights the importance of novelty in self-improvement. Thanks to the artificial curiosity mechanism, the robot seeks situations in which learning progress is maximal and engages in increasingly challenging activities. Similarly, in this paper, the robot avoids situations of frustration or boredom that denote an incompatibility between its skills and the task demands. But, it could also use these signals to capture situations in which learning is required. Additionally, triggering an exploratory behavior should allow the discovery of new sensorimotor patterns. For example, behaviors involving the combination of the basic actions associated with two known objects when found together. Moreover, self-assessment-based emotional mechanisms should facilitate "selective" learning and avoid overfitting in a variety of sensorimotor tasks. Further work is necessary to assess the potential contribution of our model in a developmental learning framework.

B. Bio-Inspired Artificial Emotions

The study of the neurobiology of emotion demonstrates that there is no specialized brain area implementing an emotional system. Rather, emotions involve decentralized processes that operate on different behavioral levels [34], [35], [53]. Several brain regions participate, with different functions supported on different levels. Emotional experiences imply complex interactions between these regions. Therefore, it is difficult to even decompose the brain in specialized structures responsible for specific functions. Yet, some regions seem to be more involved in the appraisal processes that trigger emotion. Among these are the AM, the OFC and the ACC, which allow more or less complex emotional evaluations, from pure stimuli-based level, to contextualized appraisal, to conscious experiences. On the other hand the execution of emotional responses is at least partially orchestrated by areas like the hypothalamus, the brainstem, and the nucleus accumbens through their connections with neuromodulatory systems. The eMODUL model conceptually captures these aspects by representing the valence extraction and the modulation of sensorimotor information processing. Additionally, the two experiments we presented provide more concrete implementations of artificial emotion on different levels, based on different types of information and in different application contexts.

In Experiment 1, we attempted to model low level emotional reactions elicited by extrinsic factors, e.g., objects, resources, others agents. From a constructionist perspective, pleasure and pain are at the basis of emotional phenomena [53], [54]. Another key component is motivation [7], [53]—in a broad sense, including drives. This paper did not aim to provide a detailed model of the complex brain machinery involved in these mechanisms. However, basic motivated behavior in biological organisms can be represented in terms of approach and avoidance. Therefore, we were interested in functionally mimicking simple interactions between appetitive and aversive signals to construct dynamic, meaningful emotional states.

Experiment 2 involved a close emotion–cognition interaction for the elicitation of higher level emotional reactions: frustration and boredom. Importantly, this paper did not aim to give a definition of these two affects; nor to exhaustively enumerate their triggering factors, functions or associated responses. In contrast, we were interested in the undesirable states characterizing an incompatibility between skills and task demands [49]. As opposed to the first experiment, this kind of appraisal depends on intrinsic information: these states of skills–task incompatibility emerge from a process of self-assessment analyzing the dynamics of novelty, which we model as prediction errors anchored in the robot sensorimotor experience.

Through these works, we want to advocate the idea that to be meaningful in artificial systems, emotions have to be integrated in the whole architecture through bidirectional influences with sensory, attentional, decisional, and regulatory processes. Otherwise, they are merely scripted responses to external stimuli that the designer labels as emotional. Taken together, our results provide evidence of how this approach to emotion modeling could foster efficient physical and social interactions with the environment.

C. Emotion and Cognition Understanding

In addition to designing human- and animal-like cognitive capabilities, the field of autonomous cognitive robotics also aims to provide artificial systems as models and tools for a better understanding of natural emotion and cognition. Despite their complementarity, these goals are not easy to conciliate. As a matter of fact, a significant number of the artificial emotion systems are intended to facilitate interactions with humans. Generally, this kind of approach translates into top-down implementations of existing models with no interest in providing more insights to biological emotions. The main objective lies in the application. In contrast, our approach rather favors bottom-up simulations of elementary properties related to emotion (e.g., neuromodulatory functions, motivated behaviors, regulatory feedback loops) for the sake of more informative computational modeling.

In this regard, this paper provides evidence that emotions emerge from a coupling between internal dynamics and the dynamics of physical and social interactions with the environment. In that matter, we also highlighted the importance of both sensorimotor and neurochemical signals. Additionally, we showed that emotional modulations played different roles depending on the targeted processes (e.g., sensory space versus action space).

Furthermore, concrete implementations such as those we presented here provide a complementary perspective to theoretical research. For example, in Scherer's model, the appraisal of novelty occurs at the sensorimotor (novel sensory input), the schematic (adequacy with learned preferences), and the conceptual level (ability to predict the input). However, little is said about the processes leading from one level to another. This paper gives an idea about how a novelty detection mechanism that is rooted in the sensorimotor experience of an embodied and situated agent can lead to higher level appraisal like the (self-)assessment of the skills–task compatibility. It can also help bridge related theories in the literature. Indeed, in the flow theory, the incompatibility between skills and challenges is characterized by frustration and boredom [49]. When people are too competent for a task, they get bored. But when the task is too difficult, people get anxious and frustrated. Thus, the optimal experience, conceptualized as the flow channel, lies in the balance between these two attractor states [49]. Here, we show how the appraisal of such situations in terms of goal/task conduciveness allows the system to activate regulatory feedback loops that change its behavior consequently.

Last, this paper addressed the bi-directional influence between emotion and cognition. These effects are historically studied and theorized separately, taking a particular perspective either departing from cognitive or emotional processes. But more and more researchers advocate an integrated view of this relation. A variety of terms exist in the literature: interplay, interaction, coupling, and integration. These terms reflect subtle nuances with regards to the kind and strength of the linkage. However, this points out the need for a clearer definition of what belongs to the cognition domain and what belongs to the emotion domain. For example, if most (if not all) of the computational processes are modulated by emotion, is it possible to talk about "pure" cognition and neglect emotion? In our opinion, the answer should be no, both for natural and artificial autonomous systems.

Acknowledgment

The authors would like to thank the anonymous reviewers for their constructive comments which helped improve the quality of this paper.

References

[1] C. E. Izard, "The many meanings/aspects of emotion: Definitions, functions, activation, and regulation," *Emotion Rev.*, vol. 2, no. 4, pp. 363–370, 2010.

[2] M. Belkaid, N. Cuperlier, and P. Gaussier, "Emotional modulation of peripersonal space as a way to represent reachable and comfort areas," in *Proc. IEEE Int. Conf. Intell. Robots Syst.*, Hamburg, Germany, 2015, pp. 353–359.

[3] M. Belkaid, N. Cuperlier, and P. Gaussier, "Emotional modulation of peripersonal space impacts the way robots interact," in *Proc. Eur. Conf. Artif. Life*, 2015, pp. 431–437.

[4] M. Belkaid, N. Cuperlier, and P. Gaussier, "Emotional metacontrol of attention: Top-down modulation of sensorimotor processes in a robotic visual search task," *PLoS ONE*, vol. 12, no. 9, pp. 1–21, 2017.

[5] M. B. Arnold, *Emotion and Personality: Neurological and Physiological Aspects*, vol. 2. New York, NY, USA: Columbia Univ. Press, 1960.

[6] A. Ortony, G. L. Clore, and A. Collins, *The Cognitive Structure of Emotions*. Cambridge, U.K.: Cambridge Univ. Press, 1988.

[7] K. R. Scherer, "Appraisal considered as a process of multilevel sequential checking," in *Appraisal Processes in Emotion: Theory, Methods, Research*, vol. 92. Oxford, U.K.: Oxford Univ. Press, 2001, p. 120.

[8] G. Coppin and D. Sander, "Contemporary theories and concepts in the psychology of emotions," in *Emotion-Oriented Systems*, C. Pelachaud, Ed. Hoboken, NJ, USA: Wiley, 2012, pp. 1–31.

[9] K. N. Ochsner and J. J. Gross, "The cognitive control of emotion," *Trends Cogn. Sci.*, vol. 9, no. 5, pp. 242–249, 2005.

[10] E. T. Rolls, "A biased activation theory of the cognitive and attentional modulation of emotion," *Front. Human Neurosci.*, vol. 7, p. 74, Mar. 2013.

[11] D. Sander *et al.*, "Emotion and attention interactions in social cognition: Brain regions involved in processing anger prosody," *Neuroimage*, vol. 28, no. 4, pp. 848–858, 2005.

[12] J. E. LeDoux, *The Emotional Brain: The Mysterious Underpinnings of Emotional Life*. New York, NY, USA: Simon Schuster, 1996.

[13] E. T. Rolls, "The functions of the orbitofrontal cortex," *Brain Cogn.*, vol. 55, no. 1, pp. 11–29, 2004.

[14] S. Padmala and L. Pessoa, "Affective learning enhances visual detection and responses in primary visual cortex," *J. Neurosci.*, vol. 28, no. 24, pp. 6202–6210, 2008.

[15] E. A. Phelps, S. Ling, and M. Carrasco, "Emotion facilitates perception and potentiates the perceptual benefits of attention," *Psychol. Sci.*, vol. 17, no. 4, pp. 292–299, 2006.

[16] B. Valdés-Conroy, F. J. Román, J. A. Hinojosa, and S. P. Shorkey, "So far so good: Emotion in the peripersonal/extrapersonal space," *PLoS ONE*, vol. 7, no. 11, 2012, Art. no. e49162.

[17] E. Balcetis and D. Dunning, "Wishful seeing: More desired objects are seen as closer," *Psychol. Sci.*, vol 21, no. 1, pp. 147–152, 2009.

[18] Y. Coello, J. Bourgeois, and T. Iachini, "Embodied perception of reachable space: How do we manage threatening objects?" *Cogn. Process.*, vol. 13, no. 1, pp. 131–135, 2012.

[19] A. Tajadura-Jiménez, G. Pantelidou, P. Rebacz, D. Västfjäll, and M. Tsakiris, "I-space: The effects of emotional valence and source of music on interpersonal distance," *PLoS ONE*, vol. 6, no. 10, 2011, Art. no. e26083.

[20] M. A. Dosey and M. Meisels, "Personal space and self-protection," *J. Personality Soc. Psychol.*, vol. 11, no. 2, pp. 93–97, 1969.

[21] D. P. Kennedy, J. Gläscher, J. M. Tyszka, and R. Adolphs, "Personal space regulation by the human amygdala," *Nat. Neurosci.*, vol. 12, no. 10, pp. 1226–1227, 2009.

[22] A. Öhman, A. Flykt, and F. Esteves, "Emotion drives attention: Detecting the snake in the grass," *J. Exp. Psychol. Gen.*, vol. 130, no. 3, pp. 466–478, 2001.

[23] J. M. G. Williams, A. Mathews, and C. MacLeod, "The emotional Stroop task and psychopathology," *Psychol. Bull.*, vol. 120, no. 1, pp. 3–24, 1996.

[24] F. P. McKenna and D. Sharma, "Reversing the emotional Stroop effect reveals that it is not what it seems: The role of fast and slow components," *J. Exp. Psychol. Learn. Memory Cogn.*, vol. 30, no. 2, pp. 382–392, 2004.

[25] C. Frings, J. Englert, D. Wentura, and C. Bermeitinger, "Decomposing the emotional Stroop effect," *Quart. J. Exp. Psychol.*, vol. 63, no. 1, pp. 42–49, 2010.
[26] A. K. Anderson, "Affective influences on the attentional dynamics supporting awareness," *J. Exp. Psychol. Gen.*, vol. 134, no. 2, pp. 258–281, 2005.
[27] L. Schwabe *et al.*, "Emotional modulation of the attentional blink: The neural structures involved in capturing and holding attention," *Neuropsychologia*, vol. 49, no. 3, pp. 416–425, 2011.
[28] W. M. Perlstein, T. Elbert, and V. A. Stenger, "Dissociation in human prefrontal cortex of affective influences on working memory-related activity," *Proc. Nat. Acad. Sci. USA*, vol. 99, no. 3, pp. 1736–1741, 2002.
[29] J. R. Gray, "Emotional modulation of cognitive control: Approach-withdrawal states double-dissociate spatial from verbal two-back task performance," *J. Exp. Psychol. Gen.*, vol. 130, no. 3, pp. 436–452, 2001.
[30] J. R. Gray, T. S. Braver, and M. E. Raichle, "Integration of emotion and cognition in the lateral prefrontal cortex," *Proc. Nat. Acad. Sci. USA*, vol. 99, no. 6, pp. 4115–4120, 2002.
[31] P. E. Gold, L. Hankins, R. M. Edwards, J. Chester, and J. L. McGaugh, "Memory interference and facilitation with posttrial amygdala stimulation: Effect on memory varies with footshock level," *Brain Res.*, vol. 86, no. 3, pp. 509–513, 1975.
[32] J. L. McGaugh, "Consolidating memories," *Annu. Rev. Psychol.*, vol. 66, pp. 1–24, Jan. 2015.
[33] M. Inzlicht, B. D. Bartholow, and J. B. Hirsh, "Emotional foundations of cognitive control," *Trends Cogn. Sci.*, vol. 19, no. 3, pp. 126–132, 2015.
[34] L. Pessoa, "On the relationship between emotion and cognition," *Nat. Rev. Neurosci.*, vol. 9, no. 2, pp. 148–158, 2008.
[35] L. Pessoa, "Emergent processes in cognitive-emotional interactions," *Dialogues Clinical Neurosci.*, vol. 12, no. 4, pp. 433–448, 2010.
[36] G. E. Alexander, M. R. DeLong, and P. L. Strick, "Parallel organization of functionally segregated circuits linking basal ganglia and cortex," *Annu. Rev. Neurosci.*, vol. 9, no. 1, pp. 357–381, 1986.
[37] F. A. Middleton and S. P. L, "A revised neuroanatomy of frontal-subcortical circuits," in *Frontal-Subcortical Circuits in Psychiatric and Neurological Disorders*, D. G. Lichter and J. L. Cummings, Eds. New York, NY, USA: Guilford Press, 2001, p. 44.
[38] M. Jahanshahi, I. Obeso, J. C. Rothwell, and J. A. Obeso, "A fronto-striato-subthalamic-pallidal network for goal-directed and habitual inhibition," *Nat. Rev. Neurosci.*, vol. 16, no. 12, pp. 719–732, 2015.
[39] J.-M. Fellous, "From human emotions to robot emotions," in *Architectures for Modeling Emotion: Cross-Disciplinary Foundations, American Association for Artificial Intelligence*. Menlo Park, CA, USA: AAAI Press, 2004, pp. 39–46.
[40] A. E. Kelley, "Neurochemical networks encoding emotion and motivation," in *Who Needs Emotions? The Brain Meets the Robot*, M. A. Arbib and J.-M. Fellous, Eds. Oxford, U.K.: Oxford Univ. Press, 2005, pp. 31–77.
[41] M. D. Lewis, "Bridging emotion theory and neurobiology through dynamic systems modeling," *Behav. Brain Sci.*, vol. 28, no. 2, pp. 169–194, 2005.
[42] C. Hasson, P. Gaussier, and S. Boucenna, "Emotions as a dynamical system: The interplay between the meta-control and communication function of emotions," *Paladyn J. Behav. Robot.*, vol. 2, no. 3, pp. 111–125, 2011.
[43] P. Gaussier *et al.*, "A model of grid cells involving extra hippocampal path integration, and the hippocampal loop," *J. Integrative Neurosci.*, vol. 6, no. 3, pp. 447–476, 2007.
[44] M. Lagarde, P. Andry, and P. Gaussier, "Distributed real time neural networks in interactive complex systems," in *Proc. CSTST*, 2008, pp. 95–100.
[45] D. Grandjean and C. Peters, "Novelty processing and emotion: Conceptual developments, empirical findings and virtual environments," in *Emotion-Oriented Systems*. Heidelberg, Germany: Springer, 2011, pp. 441–458.
[46] P. Gaussier, K. Prepin, and J. Nadel, "Toward a cognitive system algebra: Application to facial expression learning and imitation," in *Embodied Artificial Intelligence*. Heidelberg, Germany: Springer, 2004, pp. 243–258.
[47] J. Schmidhuber, "Curious model-building control systems," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, Singapore, 1991, pp. 1458–1463.
[48] A. Jauffret, M. Belkaid, N. Cuperlier, P. Gaussier, and P. Tarroux, "Frustration as a way toward autonomy and self-improvement in robotic navigation," in *Proc. IEEE 3rd Joint Int. Conf. Develop. Learn. Epigenetic Robot.*, Osaka, Japan, 2013, pp. 1–7.
[49] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience*. New York, NY, USA: Harper Perennial, 1991.
[50] M. A. Arbib and J.-M. Fellous, "Emotions: From brain to robot," *Trends Cogn. Sci.*, vol. 8, no. 12, pp. 554–561, 2004.
[51] L. Cañamero and P. Gaussier, "Emotion understanding: Robots as tools and models," in *Emotional Development*, J. Nadel and D. Muir, Eds. Oxford, U.K.: Oxford Univ. Press, 2005.
[52] P.-Y. Oudeyer, F. Kaplan, and V. V. Hafner, "Intrinsic motivation systems for autonomous mental development," *IEEE Trans. Evol. Comput.*, vol. 11, no. 2, pp. 265–286, Apr. 2007.
[53] A. R. Damasio, *Looking for Spinoza: Joy, Sorrow, and the Feeling Brain*. Orlando, FL, USA: Harcourt, 2003.
[54] J. A. Russell and L. F. Barrett, "Core affect, prototypical emotional episodes, and other things called emotion: Dissecting the elephant," *J. Personality Soc. Psychol.*, vol. 76, no. 5, pp. 805–819, 1999.

Marwen Belkaid was born in Hammamet, Tunisia, in 1988. He received the degree in computer science engineering from the National School of Engineers of Tunis, Tunis, Tunisia, in 2012, the M.Sc. degree in intelligent systems from the University of Cergy-Pontoise, Cergy-Pontoise, France, and ENSEA, Cergy, France, in 2013, and the Ph.D. degree in robotics and cognitive science from the ETIS Laboratory, University of Cergy-Pontoise in 2016.

He is currently a Research Fellow with the ISIR Laboratory, University of Pierre and Marie Curie, Paris, France. His current research interests include neurorobotics and computational models of biological cognition and emotion.

Dr. Belkaid is a member of the International Society for Research on Emotion.

Nicolas Cuperlier was born in Reims, France, in 1979. He received the BTEC Higher National Diploma degree in physics and chemistry and the M.S. degree in electrical engineering and industrial computing from the University Institute of Technology of Reims, Reims, France, in 2000 and 2002, respectively, and the M.Sc. degree in image and signal processing and the Ph.D. degree in computer science from the University of Cergy-Pontoise, Cergy-Pontoise, France, in 2003 and 2006, respectively.

He was Post-Doctoral Fellow with the LIMSI Laboratory (CNRS Laboratory), Orsay, France. In 2007, he joined the Department of Computer Science, University of Cergy-Pontoise, as an Assistant Lecturer, where he became an Assistant Professor in 2008, and an Associate Professor in 2009 with the ETIS Laboratory (Neurocybernetic Team). His current research interests include autonomous robotics, neurorobotics, developmental robotics, robot navigation, embodiement, sensorimotor learning, self-assessment, and the interplay between emotion and cognition.

Philippe Gaussier received the Ph.D. degree in computer science from the University of Paris XI, Orsay, France, researching on the modelization and simulation of a visual system inspired by mammals vision.

From 1992 to 1994, he conduced research in neural network applications and in control of autonomous mobile robots at the Swiss Federal Institute of Technology, Zürich, Switzerland. From 1994 to 1998, he was an Assistant Professor with the ENSEA, Cergy, France. He is currently a Professor with the Cergy-Pontoise University, Cergy-Pontoise, France, where he leads the Neurocybernetic Team, ETIS Laboratory. His current research interests include the modelization of the hippocampus and its relations with prefrontal cortex, the basal ganglia and other cortical structures like parietal, temporal areas, the modelization of the cognitive mechanisms involved in visual perception, motivated navigation, action selection and on the study of the dynamical interactions between individuals, and an empirical formalism to analyze and compare different cognitive architectures.