Artificial Emotions as Dynamic Modulators of Individual and Group Behavior in Multi-robot System

Robotics Track

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ABSTRACT

We propose a model for adaptation and implicit coordination in multi-robot systems based on the definition of artificial emotions, which play two main roles: modulators of individual robot behavior, and means of communication among different robots for system-level social coordination. We model emotions as *compressed* representations of a robot's internal state that are subject to a dynamics influenced by internal and external conditions; they can be efficiently exposed to nearby robots, allowing to achieve local, group-level behavior adaptation and modulation, with minimal computational and bandwidth requirements.

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1 INTRODUCTION

In animals, emotions play a dual role: they act as internal modulators of behavior and as mediators of social interaction. The former role is exemplified by an animal's increased responsiveness to external stimuli when experiencing fear. The latter role is made possible by the fact that the animal *exposes* its emotional state (e.g., by changing body posture), thus implementing a simple yet immediate form of communication, resulting in a social modulation effect.

We present a general, high-level robot control architecture with similar mechanisms, encompassing *artificial emotion generation and dynamics*, *behavior modulation*, and *emotion-based information sharing*. Artificial emotions are used to represent a robot's internal state in a compressed yet informative form. The emotional state modulates the robot's behavior and, at the same time, can be effectively exposed to other members of the system with very low bandwidth requirements, resulting in system-level behavior modulation and coordination in a *multi-robot system*.

Previous works on affective computing [18] have developed computational emotion models [9, 16], often with explicit biological inspiration [13, 20, 22]. Different roles of emotions for multi-agent and multi-robot [6, 19] systems have been investigated in detail, namely: behavior modulation [4, 11, 12]; emotion-based information sharing [1, 5, 23]; compressed state representation [10].

Up to our knowledge, our work is the first which encompasses these three roles in a *unified, coherent, high-level architecture.* We exploit the general notion of artificial emotions to obtain, at the same time, *adaptive behaviors for the single robots* and the *emergence of coordinated behaviors at the system-level.*

In fact, we aim to improve the performance of multi-robot systems through intrinsic adaptivity and emerging coordination, for which emotional modeling is a good candidate, as shown by several related works [2, 3, 14, 17, 21]. We present the high-level robot control architecture in Section 2 as our main contribution. We use a *multi-robot navigation scenario* as a *reference example.*

2 ARTIFICIAL EMOTIONS MODEL

We illustrate in Figure 1 the basic components of the model — emotions as compressed internal state; emotions as behavior modulators; and emotion-based information sharing for system-level coordination — from the point of view of a robotic agent, part of a team of cooperative agents, that, at time t, is engaged in task T and has a set of abilities A, a personality P, and an energy level $L(t)$.

2.1 Compressed Internal State

At a time t, a robot acquires sensing information $\boldsymbol{x}(t) \in \mathbb{R}^M$ to update its *internal state* $\boldsymbol{\mu}(t) \in \mathbb{R}^N$, i.e., a description of the current situation that is useful to solve the task. For instance, for a navigation task, this might include velocity, presence of obstacles, activity of nearby robots, as well as higher-level notions, such as how predictable the motion of a neighbor is.

We model the internal state as a collection of N *micro-states* that influence K *affective macro-states* $\boldsymbol{\varepsilon}(t) \in [0,1]^K$ through a time-independent surjective function $\nu : \mathbb{R}^N \twoheadrightarrow [0,1]^K$, a concept loosely borrowed from statistical mechanics. Affective macro-states should be part of a universally shared vocabulary (e.g., every human as an idea of what *fear* is and how it affects behaviors); should be relevant to the task and the characteristics of the robot, i.e., they should map to available behavior modulations; and should be a compressed representation of internal states, $K \ll N$. In this context, we define *emotions* as labels of affective macro-states. Namely, the k-th affective macro-state ε_k is interpreted as the activation of the k-th emotion $e_k \in E$. For example, *Confusion* emotion is associated to an affective macro-state aggregating a collection of micro-states that describe "how well a sensor is working", "how often robot's goal is changing", and "how predictable a neighbor is".

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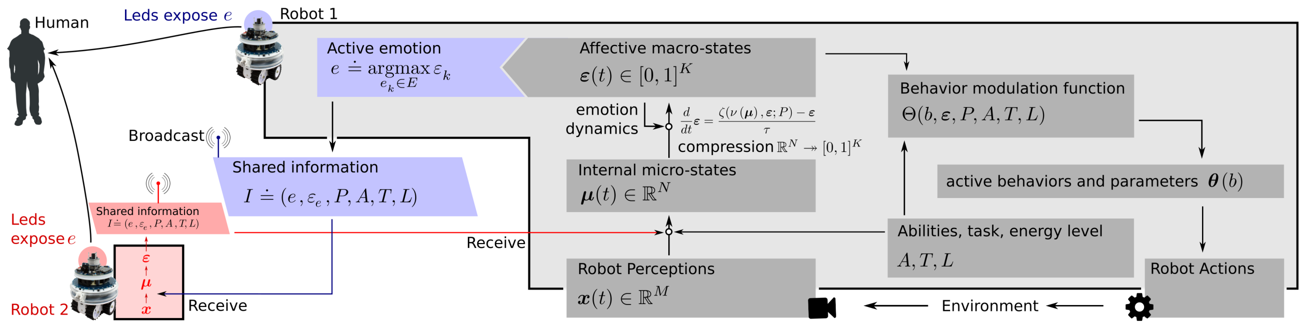

Figure 1: Information flow in the proposed modular architecture based on affective states: exploded view for Robot 1 and summarized view for (neighbor) Robot 2. The central part illustrates the emotion dynamics of Robot 1, where affective macro-states ε are also influenced by the emotional state of neighbor robots (red box). The current active emotion e (blue box) of each robot can be exposed through a very low-bandwidth link (like an RGB LED) and shared with humans.

Active Emotion. At any time, all emotions contribute to modulate the robot's behavior; nonetheless the predominant macro-state has a particular importance and defines the robot's *active emotion* $e(t) \doteq \operatorname{argmax}_{e_k \in E} \varepsilon_k(t)$. More precisely, to make the overall response robust and avoid oscillations, the selection uses a hysteresis: the robot keeps the currently-active emotion until the activation decreases enough or another emotion's activation rises enough.

Dynamics. In humans, emotions are temporally modulated [15]; here we assume that artificial emotion activations follow a *stimulus-response* dynamic $\frac{d}{dt}\boldsymbol{\varepsilon}(\boldsymbol{t}) = \frac{\zeta(\nu(\boldsymbol{\mu}(\boldsymbol{t})), \boldsymbol{\varepsilon}(\boldsymbol{t}); P) - \boldsymbol{\varepsilon}(\boldsymbol{t})}{\tau}$ (where τ is the emotion life-time once the stimulus is removed), coupled with an internal dynamic ζ that stimulates the activation of an emotion from (other) emotions and from the compressed internal state, depending on the personality. For example, a robot that is experiencing confusion and has a personality linked to impulsive, quick-tempered emotion dynamics, may quickly become frustrated (which in turn may trigger a behavior that deals with the cause of confusion).

2.2 Behavior Modulation

We assume that a robot is provided with a set B of *predefined behaviors*. At time t, each behavior $b \in B$ can be activated and tuned by adjusting R_b parameters $\boldsymbol{\theta}(b;t) \in [0,1]^{R_b}$. A robot uses the compressed information about its internal state as well as information about its task, abilities, energy level and personality, to select the active behaviors and their parameters through a behavior modulation function $\boldsymbol{\theta}(b;t) = \Theta(b, \boldsymbol{\varepsilon}(t), P, A, T, L(t))$. For example, when the robot increases its *Confusion-level*, there could by behavior modulations such as: decrease moving speed to avoid collisions; activate an help-seeking behavior to lower the reliance on its sensors; increase the number of raw data samples that are filtered to update $\boldsymbol{\mu}$.

2.3 Emotion sharing for coordination

The active emotion is the information that describes the robot's state best and should be shared with neighbors to favor *emerging coordination* in multi-robot systems with minimal communication overhead; the robot should complement it with data that increases its predictability. Therefore, the robot publishes, as another instance of generic emotional behavior modulation, the message $I(t) \doteq (e(t), \varepsilon_e(t), P, A, T, L(t))$. Neighboring agents that receive such message, add its content to their own internal state; this, in turn, closes the loop by modifying the recipient's affective macro-states, active emotion, and communication content and yields an automatically-regulated shared *social emotional state* that, if correctly designed, increases the performance of the system as a whole.

Table 1: Emotional dynamic and modulation in multi-robot navigation.

Emotion	Stimulus	Behavior modulation
Neutral	no other active emotion	default behavior and parameters
Fear	lack of free space and many frustrated neighbors	$\uparrow$ cautiousness and $\downarrow$ speed
Frustration	slow progress to target	escape crowds
Urgency	close to deadline	$\downarrow$ cautiousness ($\uparrow$ neighbors' cautiousness)
Confusion	many changes of direction	$\downarrow$ speed ($\uparrow$ neighbors' cautiousness and willingness to help)

2.4 Multi-robot navigation

Table 1 summarizes the example of the proposed framework in the context of multi-robot navigation that we have been following. Few, legible, bio-inspired rules (emotionally) modulate the navigation behavior [8] and define the emotional dynamics. For example, we impose that fearful agents should be more careful and slow down. Although the task by itself has no emotional content, introducing emotions {*Neutral*, *Fear*, *Frustration*, *Urgency*, *Confusion*} has been shown [7] to have a positive impact on performance by preventing deadlocks, favoring robots with time-critical tasks, and assisting robots with sensing issues.

3 CONCLUSIONS

We presented a control architecture for robotic agents that is inspired by the dual nature of animal emotions, which act both as an internal behavior modulator, and as an implicit communication mechanism that allows for emerging coordination. This approach simplifies the system design, which decomposes into two modular, bio-inspired, interpretable and potentially reusable mappings: compression of internal state and emotional behavior modulation.

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