A Model of Artificial Emotions for Behavior-Modulation and Implicit Coordination in Multi-robot Systems

Supplementary Material

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A MULTI-ROBOT NAVIGATION: MODEL AND INTERNAL STATE

We illustrate the details of the agent's internal state and navigation behavior b_{nav} introduced in Section 3.

A.1 Definitions and notation

At time t, a (two-dimensional) robotic agent is at positioned at $\boldsymbol{p} \in \mathbb{R}^2$, with heading $\alpha(t) \in S(1)$, and moves with velocity $\boldsymbol{v}(t) \in \mathbb{R}^2$ towards a target $\boldsymbol{q} \in \mathbb{R}^2$.

The agent uses its sensors to detect the radius r_a, position, and active emotion $e_t(a)$ of all neighbor agents $a \in N(t)$, which lie inside a circular sector defined by horizon H and field of view $\text{FOV}(t) = [\alpha(t) - \psi, \alpha(t) + \psi] \in S(1)$. The ground occupancy of neighbor agent a is approximated by the agent's physical shape inflated by a social/safety margin $m_a \geq 0$.

From this information, for any direction $\beta \in \text{FOV}(t)$, the robot computes: (a) how much free space there is around it, i.e., the distance to the nearest obstacle $0 \leq D(\beta) \leq H$; (b) the maximal distance $f(\beta)$ that it could advance before eventually colliding with any visible obstacle considering the obstacles' current velocity. With $s(\beta)$, we denote the segment connecting $\boldsymbol{p}$ with the point at distance $f(\beta)$ along direction β (i.e., the point of first collision for heading β).

A.2 Navigation behavior

When there are no obstacles to avoid, the agent moves directly towards the target, with optimal speed $v_{\text{opt}} \in \mathbb{R}^+$. When instead the agent needs to avoid obstacles, it may decide to turn towards a desired angle $\alpha_{\text{des}}(t)$ and adapt its speed too, following a navigation behavior that has several [biomimetic] parameters that were modulated in Section 3 using affective states: *caution* η, *safety margins* m_a, *optimal speed* v_{opt}, and *angle of view* ψ.

First, the agent determines its desired heading $\alpha_{\text{des}}(t)$ as the direction allowing the most direct path to destination point $\boldsymbol{q}$, taking into account the presence of obstacles:

$$\alpha_{\text{des}}(t) = \operatorname{argmin}_{\beta \in \text{FOV}(t)} d\left(s\left(\beta\right), \boldsymbol{q}\right), \tag{1}$$

where d is the minimal distance between segment and point.

Then, the agent computes its desired speed $v_{\text{des}}(t)$ to allow stopping in a fixed time η within the free distance $D(\alpha_{\text{des}}) \in [0, H]$, *currently* seen in direction α_{des}:

$$v_{\text{des}}(t) = \min\left(v_{\text{opt}}, \frac{D\left(\alpha_{\text{des}}\right)}{\eta}\right). \tag{2}$$

The actual velocity vector $\boldsymbol{v}(t)$ is continuously adjusted depending on $\boldsymbol{v}_{\text{des}}(t)$:

$$\frac{d\boldsymbol{v}}{dt}(t) = \frac{\boldsymbol{v}_{\text{des}}(t) - \boldsymbol{v}(t)}{\tau}, \tag{3}$$

where the fixed parameter τ represents the *time constant* characterizing the exponential speed profile.

Once the agent arrives at the n-th target at time T_n, the agent chooses a new target $q_{n+1} \in \mathbb{R}^2$ and estimates the minimal time Δ_n to reach it:

$$\Delta_n = \frac{\| \boldsymbol{p}(T_n) - \boldsymbol{q}_{n+1} \|}{v_{\text{opt}}}.$$

A.3 Internal state

The part of the agent's internal state that is relevant to the navigation task, and maps to emotions' activation, is given by $\boldsymbol{\mu}(t) \in \mathbb{R}^5$:

(efficacy) $$\mu_{\text{eff}}(t) = \frac{\boldsymbol{v}_{\text{opt}}(t) \cdot \boldsymbol{v}(t)}{v_{\text{opt}}(t)} \tag{4}$$

(free space) $$\mu_{\text{fs}}(t) = \frac{\max_{\beta \in \text{FOV}(t)} D(\beta)}{H} \tag{5}$$

(nearby frustration) $$\mu_{\text{nf}}(t) = \frac{|\{a \in N(t) | e_t(a) = \text{frustration}\}|}{|N(t)|} \tag{6}$$

(task delay) $$\mu_{\text{td}}(t) = \frac{t - T_n - \Delta_n}{\Delta_n} \tag{7}$$

(extra rotations) $$\mu_{\text{rot}}(t) = \| \alpha(t) - \alpha_{\text{des}}(t) \| \tag{8}$$

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