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A Computational Agent Model for Hebbian Learning of Social Interaction

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Abstract. In social interaction between two persons usually a person displays understanding of the other person. This may involve both nonverbal and verbal elements, such as bodily expressing a similar emotion and verbally expressing beliefs about the other person. Such social interaction relates to an underlying neural mechanism based on a mirror neuron system, as known within Social Neuroscience. This mechanism may show different variations over time. This paper addresses this adaptation over time. It presents a computational model capable of learning social responses, based on insights from Social Neuroscience. The presented model may provide a basis for virtual agents in the context of simulation-based training of psychotherapists, gaming, or virtual stories.

Keywords: Hebbian learning, ASD, computational model, social interaction.

1 Introduction

Showing mutual empathic understanding is often considered a form of glue between persons within a social context. Recent developments within Social Neuroscience have revealed that a mechanism based on *mirror neurons* plays an important role in generating and displaying such understanding, both in nonverbal form (e.g., smiling in response to an observed smile) and in verbal form (e.g., attributing an emotion to the other person); cf. [11, 19]. Such empathic responses vary much over persons. For example, when for a person these responses are low or nonexistent, often the person is considered as 'having some autistic traits'. Within one person such differences in responding may occur as well over time, in the sense of learning or unlearning to respond. This is the focus of this paper.

It is often claimed that the mirroring mechanism is not (fully) present at birth, but has to be shaped by experiences during lifetime; for example, [3, 11, 14]. For persons (in particular children) with low or no social responses, it is worth while to offer them training sessions in imitation so that the mirror neuron system and the displayed social responses may improve. This indeed turns out to work, at least for the short term, as has been reported in, for example [7, 13]. Thus evidence is obtained that the mirror neuron system has a certain extent of plasticity due to some learning mechanism. In [14] it is argued that Hebbian learning (cf. [8, 10]) is a good candidate for such a learning mechanism.

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In this paper a Hebbian learning mechanism is adopted to obtain an adaptive agent model showing plasticity of the agent's mirror neuron system. The model realises learning (and unlearning) of social behaviour (in particular, empathic social responses), depending on a combination of innate personal characteristics and the person's experiences over time obtained in social context. A person's experiences during lifetime may concern self-generated experiences (the person's responses to other persons encountered) or other-generated experiences (other persons' responses to the person). By varying the combination of innate characteristics and the social context offering experiences, different patterns of learning and unlearning of socially responding to other persons are displayed.

In Section 2 the adaptive agent model for Hebbian learning of social behaviour is presented. In Section 3 some simulation results are discussed, for different characteristics and social contexts. In Section 4 a mathematical analysis of the learning behaviour is made. Section 5 concludes the paper.

2 The Adaptive Agent Model Based on Hebbian Learning

The basic (non-adaptive) agent model (adopted from [20]) makes use of a number of internal states for the agent self, as indicated by the nodes in Fig. 1. A first group of states consists of the sensory representations of relevant external aspects: a sensory representation of a body state (labeled by) b, of a stimulus s, and of another agent B, denoted by sr_b, sr_s, sr_B, respectively. Related sensor states are ss_b, ss_s, ss_B, which in turn depend on external world states ws_b, ws_s, ws_B. Moreover, pb_b and $pc_{B,b}$ denote preparation states for bodily expression of b and communication of b to agent B. Following [5], the preparation for bodily expression b is considered to occur as an *emotional response* on a sensed stimulus s. Feeling this emotion is based on the sensory representation sr_b of b. These b's will be used as labels for specific emotions. Communication of b to B means communication that the agent *self* believes that B feels b; for example: 'You feel b', where b is replaced by a word commonly used for the type of emotion labeled in the model by b.

The states indicated by $ps_{c,s,b}$ are considered *control* or *super mirror* states (cf. [11], pp. 200-203, [12], [16]) for context c, stimulus s and body state b; they provide control for the agent's execution of (prepared) actions, such as expressing body states or communications, or regulation of the gaze. Here the context c can be an agent B, which can be another agent (self-other distinction), or the agent *self*, or c can be *sens* which denotes enhanced sensory processing sensitivity: a trait which occurs in part of the population, and may affect social behaviour (e.g., [1, 4]). One reason why some children do not obtain a sufficient amount of experiences to shape their mirror neuron system, is that they tend not to look at other persons due to enhanced sensory processing sensitivity for face expressions, in particular in the region of the eyes; e.g., [4, 15]. When observing the face or eyes of another person generates arousal which is experienced as too strong, as a form of emotion regulation the person's own gaze often is taken away from the face or eyes observed; cf. [9]. Such an avoiding behavioural pattern based on emotion regulation may stand in the way of the development of the mirror neuron system. In summary, three types of super mirroring states may (nonexclusively) occur to exert control as follows:

- if a super mirror state for agent B occurs (*self-other distinction*), a prepared communication will be performed and directed to B
- if it occurs for *self*, the agent will *execute* the related prepared actions
- if it occurs for *sens*, the agent will regulate some aspects of functioning to *compensate for enhanced sensitivity*: to suppress preparation and expression of related bodily responses, and to adapt the gaze to avoid the stimulus s.

Expressing body state b is indicated by effector state eb_b, communication of b to B by $ec_{b,B}$, and regulated gaze to avoid stimulus s by eg_s. These effector states result in a modified body state indicated by ws_b and an adapted gaze avoiding s indicated by wg_s.

In case the stimulus s is another agent B's body expression for b (denoted by $s_{b,B}$, for example, a smiling face), then *mirroring* of this body state means that the agent prepares for the same body expression b; e.g., [11, 16, 19]. If this prepared body state is actually expressed, so that agent B can notice it, then this contributes an *empathic nonverbal response*, whereas communication of b to B is considered an *empathic verbal response*. The bodily expression of an observed feeling b together with a communication of b to B occurring at the same time is considered a *full empathic response* of *self* to B. These two elements for empathic response are in line with the criteria for empathy explicated in [6], p. 435 (assuming true, faithful bodily and verbal expression): (1) presence of an affective state in a person, (2) isomorphism of the person's own and the other person's affective state, (3) elicitation of the person's affective state upon observation or imagination of the other person's affective state, (4) knowledge of the person that the other person's affective state is the source of the person's own affective state.

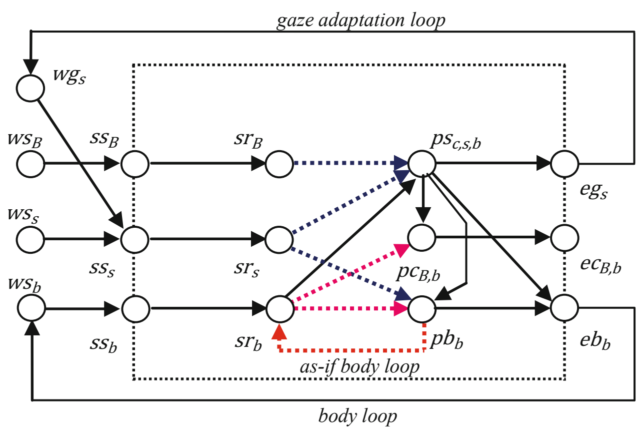

Fig. 1. Overview of the adaptive agent model

The arrows connecting the nodes in Fig. 1 indicate the dynamical relationships between the states. Most of these connections have been given strength *1*, but six of them (indicated by dotted arrows) have a dynamical strength, adapted over time according to Hebbian learning. Note that the graph of the model shown in Fig. 1 shows three loops: the body loop to adapt the body, the as-if body loop to adapt the internal body representation and integrate felt emotions in preparations for responses, and the gaze adaptation loop. The effect of these loops is that for any new external situation encountered, a (numerical) approximation process takes place until the internal states reach an equilibrium (assuming that the external situation does not change too fast). However, as will be seen in Section 3, it is also possible that a (static) external situation leads to periodic oscillations (limit cycle behaviour).

The connection strengths are indicated by ω_{ij} with the node labels i and j (the names of the nodes as indicated in Fig. 1) as subscripts. A distinction is made between expression states and the actual states for body and gaze. The first type of states are the agent's effector states (e.g., the muscle states), whereas the body and gaze states result from these. The sensory representation of a body state b is not only affected by a corresponding sensor state (via the body loop), but also by the preparation for this body state (via the as-if body loop). Preparation for a verbal empathic communication depends on feeling a similar emotion, and adequate self-other distinction.

Super mirroring for an agent A (*self* or B) generates a state indicating on which agent (*self-other distinction*) the focus is, and whether or not to act. Super mirroring for *enhanced sensory processing sensitivity*, generates a state indicating in how far the stimulus induces a sensory body representation level experienced as inadequately high**.** To cover regulation to compensate for enhanced sensory processing sensitivity (e.g., [1]), the super mirroring state for this is the basis for three possible regulations: of the prepared and expressed body state, and of the gaze.

A first way in which regulation takes place, is by a suppressing effect on preparation of the body state (note that the connection strength $\omega_{ps_{sens,s,b}pb_b}$ from node $ps_{sens,s,b}$ to node pb_b is taken negative). Such an effect can achieve, for example, that even when the agent feels the same as the other agent, an expressionless face is prepared. In this way a mechanism for *response-focused regulation* (suppression of the agent's own response) to compensate for an undesired level of emotion is modelled; cf. [9]. Expressing a prepared body state depends on a super mirroring state for self and a super mirroring state for enhanced sensitivity with a suppressing effect (note that $\omega_{ps_{sens,s,b}eb_b}$ is taken negative). This is a second way in which a mechanism for response-focused regulation is modelled to compensate for an undesired level of arousal. A third type of regulation to compensate for enhanced sensory processing sensitivity, a form of *antecedent-focused regulation* (*attentional deployment*) as described in [9], is modelled by directing the own gaze away from the stimulus. Note that node eg_s for avoiding gaze for stimulus s has activation level 1 for total avoidance of the stimulus s, and 0 for no avoidance (it indicates the extent of avoidance of s). To generate a sensor state for stimulus s, the gaze avoidance state for s is taken into account: it has a suppressing effect on sensing s (note that $\omega_{wg_sss_s}$ is taken negative).

The model has been specified in dynamical system format (e.g., [18]) as follows. Here for a node label k, by $a_k(t)$ the activation level (between 0 and 1) of the node labeled by k at time t is denoted, by $input(k)$ the set of node labels is denoted that provides input (i.e., have an incoming arrow to node k in Fig. 1), and $th(W)$ is a threshold function.

$$\frac{d\,a_k(t)}{dt} = \gamma\,[\,th(\Sigma_{j \in input(k)}\,\omega_{jk}\,a_j(t)) - a_k(t)\,] \tag{1}$$

The parameter γ is an update speed factor, which might differ per connection, but has been given a uniform value 0.8 in Section 3. The following logistic threshold function $th(W)$ with $\sigma > 0$ a steepness and $\tau \geq 0$ a threshold value has been used in the simulations (except for the sensor states):

$$th(W) = \left(\frac{1}{1+e^{-\sigma(W-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right) / \left(1 - \frac{1}{1+e^{\sigma\tau}}\right) \quad \text{or} \quad th(W) = \frac{1}{1+e^{-\sigma(W-\tau)}} \tag{2}$$

The former threshold function can be approximated by the simpler latter expression for higher values of $\sigma\tau$ (e.g., σ higher than $20/\tau$). For the sensor states for b and B the identity function has been used for $th(W)$, and for the sensor state of s the update equation has been taken more specifically to incorporate the effect of gaze on the sensor state (note that the connection strength $\omega_{wg_S ss_S}$ from the world gaze state to the sensor state is taken negative):

$$\frac{d\, a_{ss_S}(t)}{dt} = \gamma[\omega_{ws_S ss_S}\, a_{ws_S}(t)(1 + \omega_{wg_S ss_S}\, a_{wg_S}(t)) - a_{ss_S}(t)] \tag{3}$$

Hebbian Learning

The model as described above was adopted from [20]; as such it has no adaptive mechanisms built in. However, as put forward, for example, in [3, 11, 14] learning plays an important role in shaping the mirror neuron system. From a Hebbian perspective [10], strengthening of a connection over time may take place when both nodes are often active simultaneously ('neurons that fire together wire together'). The principle goes back to Hebb [10], but has recently gained enhanced interest by more extensive empirical support (e.g., [2]), and more advanced mathematical formulations (e.g., [8]). In the adaptive agent model the connections that play a role in the mirror neuron system (i.e., the dotted arrows in Fig. 1) are adapted based on a Hebbian learning mechanism. More specifically, such a connection strength ω is adapted using the following *Hebbian learning rule*, taking into account a maximal connection strength 1, a *learning rate* η, and an *extinction rate* ζ (usually small):

$$\frac{d\omega_{ij}(t)}{dt} = \gamma[\eta\, a_i(t)a_j(t)(1 - \omega_{ij}(t)) - \zeta\omega_{ij}(t)] = \gamma[\eta\, a_i(t)a_j(t) - (\eta\, a_i(t)a_j(t) + \zeta)\, \omega_{ij}(t)] \tag{4}$$

A similar Hebbian learning rule can be found in [8], p. 406. By the factor $1 - \omega_{ij}(t)$ the learning rule keeps the level of $\omega_{ij}(t)$ bounded by 1 (which could be replaced by any other positive number); Hebbian learning without such a bound usually provides instability. When the extinction rate is relatively low, the upward changes during learning are proportional to both $a_1(t)$ and $a_2(t)$ and maximal learning takes place when both are 1. Whenever one of them is 0 (or close to 0) extinction takes over, and ω slowly decreases (unlearning). This learning principle has been applied (simultaneously) to all six connections indicated by dotted arrows in Fig. 1. In principle, the adaptation speed factor γ, the learning rate η and extinction rate ζ, could be taken differently for the different dynamical relationships. In the example simulations discussed in Section 3 uniform values have been used: $\gamma = 0.8$, $\eta = 0.2$ and $\zeta = 0.004$.

3 Example Simulations of Learning Processes

A number of simulation experiments have been conducted for different types of scenarios, using numerical software. For the examples discussed here the values for the threshold and steepness parameters are as shown in Table 1. Note that first the value *3* for sensitivity super mirroring threshold was chosen so high that no enhanced sensitivity occurs. The speed factor γ was set to *0.8*, the learning rate η = *0.2* and extinction rate ζ = *0.004*. The step size Δt was set to *1*. All nonadapted connection strengths have been given value *1*, except those for suppressing connections

$$\omega_{ps_{sens,s,b}pb_b},\ \omega_{ps_{sens,s,b}eb_b} \text{ and } \omega_{wg_s ss_s}$$

which have been given the value *-1*. The scenario was chosen in such a way that after every 100 time units another agent is encountered for a time duration of 25 units with a body expression that serves as stimulus. Initial values for activation levels of the internal states were taken *0*. A first pattern, displayed in Fig. 2, is that in normal circumstances, assuming initial strengths of the learned connections of *0.3*, the model is indeed able to learn the empathic responses as expected. Here (and also in Fig. 3) time is on the horizontal axis and activation levels at the vertical axis.

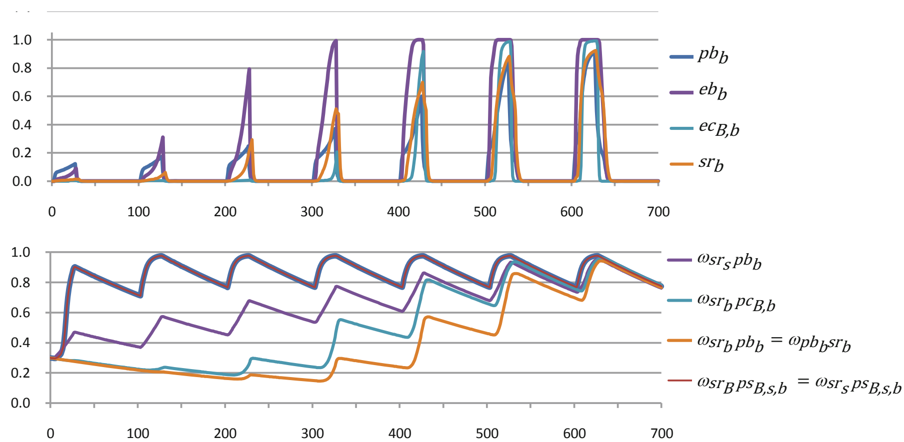

Fig. 2. Example scenario of the Hebbian learning process

The upper graph shows levels for body representation, body preparation, expressed body states and communication. The lower graph shows the learning patterns for the connections (the dotted arrows in Fig. 1). Note that the two connections

$\omega_{sr_b pb_b}$ (for emotion integration) and $\omega_{pb_b sr_b}$ (as-if body loop)

have the same values, as they connect the same nodes sr_b and pb_b, and have been given the same initial values. Moreover, also the connections

$\omega_{sr_B ps_{B,s,b}}$ and $\omega_{sr_s ps_{B,s,b}}$

have the same values, as in the considered scenario the input nodes for sr_B and sr_s have been given the same values, and also the initial values for the connections. This can easily be varied. In Fig. 2 it is shown that when regular social encounters take place, the connections involved in responding empathically are strengthened to values that approximate *1*. Notice that due to the relatively low initial values of the connections chosen, for some of them first extinction dominates, but later on this downward trend is changing into an upward trend. Accordingly the empathic responses become much stronger, which is in line with the literature; e.g., [7], [13].

Table 1. Settings for threshold and steepness parameters

		τ	σ
representing body state	sr_b	*1*	*3*
super mirroring B	$ps_{B,s,b}$	*0.7*	*30*
super mirroring sensitivity	$ps_{sens,s,b}$	*3*	*30*
mirroring/preparing body state	pb_b	*1*	*3*
preparing communication	$pc_{b,B}$	*0.8*	*3*
expressing body state	eb_b	*1.2*	*30*
expressing communication	$ec_{b,B}$	*0.8*	*30*
expressing gaze avoidance state	eg_s	*0.6*	*30*

How long the learned patterns will last will depend on the social context. When after learning the agent is isolated from any social contact, the learned social behaviours may vanish due to extinction. However, if a certain extent of social contact is offered from time to time, the learned behaviour is maintained well. This illustrates the importance of the social context. When zero or very low initial levels for the connections are given, this natural learning process does not work. However, as other simulations show, in such a case (simulated) imitation training sessions (starting with the therapist imitating the person) still have a positive effect, which is also lasting when an appropriate social context is available. This is confirmed by reports that imitation training sessions are successful; e.g., [7], [13].

In addition to variations in social environment, circumstances may differ in other respects as well. From many persons with some form of autistic spectrum disorder it is known that they show enhanced sensory processing sensitivity; e.g., [1], [4]; this was also incorporated in the model. Due to this, their regulation mechanisms to avoid a too high level of arousal may interfere with the social behaviour and the learning processes. Indeed, in simulation scenarios for this case it is shown that the adaptive agent model shows an unlearning process: connection levels become lower instead of higher. This pattern is shown in Fig. 3. Here the same settings are used as in Table 1, except the sensitivity super mirroring threshold which was taken *1* in this case, and the initial values for the connection weights, which were taken *0.7*. It is shown that the connections

$\omega_{sr_s pb_b}$ (for mirroring) and $\omega_{sr_b pb_b}$ and $\omega_{pb_b sr_b}$ (for emotion integration)

are decreasing, so that the responses become lower over time.

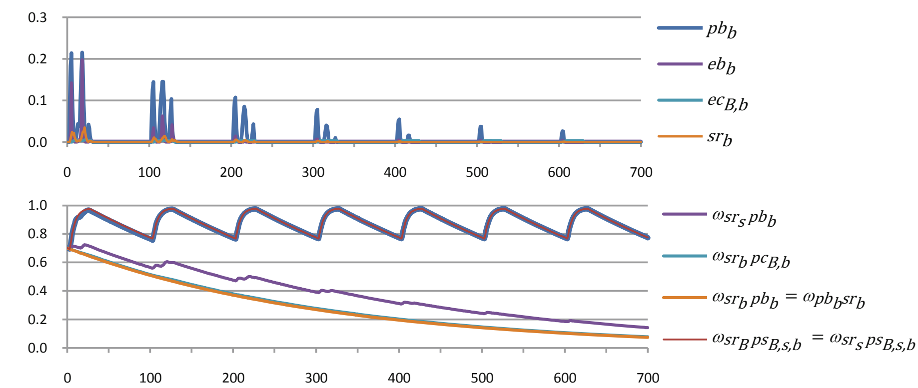

Fig. 3. Learning under enhanced sensory processing sensitivity

This is due to the downregulation which, for example, leads to a gaze that after a short time is taken away from the stimulus, and returns after the arousal has decreased, after which the same pattern is repeated; this is shown in the upper graph (the two or three peaks per encounter). Note that the values related to super mirroring of and communication to another agent stay high: the downregulation as modelled does not have a direct effect on these processes. When downregulation is also applied to communication, also these connections will extinguish. When for such a case imitation training sessions are offered in a simulation, still the connection levels may be strengthened. However, these effects may not last in the natural context: as soon as these sessions finish, the natural processes may start to undo the learned effects. To maintain the learned effects for this case such training sessions may have to be repeated regularly.

4 Formal Analysis

The behaviour of the agent's adaptation process can also be investigated by formal analysis, based on the specification for the connection strength $\omega = \omega_{ij}$ from node i to node j.

$$\frac{d\omega(t)}{dt} + \gamma\,(\eta a_i(t) a_j(t) + \zeta)\,\omega(t) = \gamma\eta a_i(t) a_j(t) \tag{5}$$

This is a first-order linear differential equation with time-dependent coefficients: a_i and a_j are functions of t which are considered unknown external input in the equation for ω. An analysis can be made for when equilibria occur:

$$\frac{d\omega(t)}{dt} = 0 \;\Leftrightarrow\; (\eta a_i a_j + \zeta)\,\omega = \eta a_i a_j \;\Leftrightarrow\; \omega = \frac{\eta a_i a_j}{\eta a_i a_j + \zeta} \tag{6}$$

One case here is that $\omega = 0$ and one of a_i and a_j is 0. When a_i and a_j are nonzero, (6) can be rewritten as (since $a_i a_j \leq 1$):

$$\omega = 1/(1 + \zeta/\eta a_i a_j) \leq 1/(1 + \zeta/\eta) \tag{7}$$

This shows that when no extinction takes place ($\zeta = 0$), an equilibrium for ω of 1 is possible, but if extinction is nonzero, only an equilibrium < 1 is possible. For example, when $\eta = 0.2$ and $\zeta = 0.004$ as in Section 3, then an equilibrium value will be ≤ 0.98, as also shown in the example simulations.

Further analysis can be made by obtaining an explicit analytic solution of the differential equation in terms of the functions a_i and a_j. This can be done as follows. Take

$$W(t) = \int_{t_0}^{t} a_i(u)a_j(u)\,du \tag{8}$$

the accumulation of $a_i(t)a_j(t)$ over time from t_0 to t; then

$$\frac{dW(t)}{dt} = a_i(t)a_j(t) \tag{9}$$

Given this, the differential equation (5) for ω can be solved by using an integrating factor as follows:

$$\frac{d e^{\gamma(\eta W(t)+\zeta(t-t_0))}\omega(t)}{dt} = \gamma\eta a_i(t)a_j(t)\ e^{\gamma(\eta W(t)+\zeta(t-t_0))} \tag{10}$$

from which it can be obtained:

$$\omega(t) = \omega(t_0)\, e^{-\gamma(\eta W(t)+\zeta(t-t_0))} + \gamma\eta \int_{t_0}^{t} a_i(u)a_j(u)\ e^{-\gamma(\eta(W(t)-W(u))+\zeta(t-u))}du \tag{11}$$

For the special case of constant $a_ia_j = c$, from (11) explicit expressions can be obtained, using $W(t) = c(t\text{-}t_0)$ and $W(t)\text{-}W(u) = c(t\text{-}u)$:

$$\begin{aligned}\int_{t_0}^{t} a_i(u)a_j(u)\ e^{-\gamma(\eta(W(t)-W(u))+\zeta(t-u))}du &= \int_{t_0}^{t} c\,e^{-\gamma(\eta c+\zeta)(t-u))}du \\ &= \frac{1}{\gamma(\eta c+\zeta))}\left[1 - e^{-\gamma(\eta c+\zeta)(t-t_0))}\right]\end{aligned} \tag{12}$$

Although in a simulation usually a_ia_j will not be constant, these expressions are still useful in a comparative manner. When $a_ia_j \geq c$ on some time interval, then by monotonicity the above expressions (11) for ω with $a_ia_j = c$ provide a lower bound for ω. From these expressions it can be found that

$$\eta c/(\eta c+\zeta) - \omega(t) = [\eta c/(\eta c+\zeta) - \omega(0)]\ e^{-\gamma(\eta c+\zeta)\mathbf{t}} \tag{13}$$

which shows the convergence rate to an equilibrium for constant $a_ia_j = c$, provides an upper bound for the deviation from the equilibrium. This has half-value time

$$\ln(2)/\gamma(\eta c+\zeta) = 0.7/\gamma(\eta c+\zeta) \tag{14}$$

When $a_ia_j \geq c$ on some time interval, then by the monotonicity mentioned earlier, the upward trend will be at least as fast as described by this expression. For example, for the settings in Section 3 with $c = 0.2$ this provides half-value time 20. This bound indeed is shown in simulations (e.g., in Figs 2 and 3) in time periods with $a_i a_j$ around or above 0.2.

For scenarios in which encounters with other agents alternate with periods when nobody is there, as in Figs 2 and 3, a fluctuating learning curve is displayed. A question is how the balance between the different types of episodes should be in order to keep the learned effects at a certain level. Given the indications (14) above a rough estimation can be made of how long a time duration td_1 of increase should last to compensate a time duration td_2 of decrease:

$$e^{-\gamma(\eta c+\zeta)td_1} = e^{-\gamma\zeta td_2} \qquad\qquad td_2/td_1 = (\eta c+\zeta)/\zeta = 1+\eta c/\zeta \tag{15}$$

For example, when $\eta = 0.2$ and $\zeta = 0.004$, as in Section 3, for $c = 0.2$ this provides: $td_2/\,td_1 = 11$. This means that for this case under normal circumstances around 9% of the time an encounter with another agent should take place leading to $a_i a_j \geq 0.2$ to maintain the empathic responses. This indeed corresponds to what was found by simulation experiments varying the intensity of encounters.

5 Discussion

To function well in social interaction it is needed that a person displays a form of empathic understanding, both by nonverbal and verbal expression. Within Social Neuroscience it has been found how such empathic social responses relate to an underlying neural mechanism based on a mirror neuron system. It is often suggested that innate factors may play a role, but also that a mirror neuron system can only function after a learning process has taken place (e.g., [3], [11], [14]): the strength of a mirror neuron system may change over time within one person. In this paper an adaptive agent model was presented addressing this aspect of adaptation over time, based on knowledge from Social Neuroscience.

The notion of empathic understanding taken as a point of departure is in line with what is formulated in [6]. The learning mechanism used is based on Hebbian learning, as also suggested by [14]. It is shown how under normal conditions by learning the empathic responses become better over time, provided that a certain amount of social encounters occur. The model also shows how imitation training (e.g., [7], [13]) can strengthen the empathic responses. Moreover, it shows that when enhanced sensory processing sensitivity [1] occurs (e.g., as an innate factor), the natural learning process is obstructed by avoidance behaviour to downregulate the dysproportional arousal [9].

In [17] a computational model for a mirror neuron system for grasp actions is presented; learning is also incorporated, but in a biologically implausible manner, as also remarked in [14]. In contrast, the presented model is based on a biologically plausible Hebbian learning model, as also suggested by [14]. The presented agent model provides a basis for the implementation of virtual agents, for example, for simulation-based training of psychotherapists, or of human-like virtual characters.

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