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On the Interplay of Interpersonal Synchrony, Short-Term Affiliation and Long-Term Bonding: A Second-Order Multi-Adaptive Neural Agent Model

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Abstract. When people interact, their behaviour tends to become synchronized, a mutual coordination process that fosters short-term adaptations, like increased affiliation, and long-term adaptations, like increased bonding. This paper addresses for the first time how such short-term and long-term adaptivity induced by synchronization can be modeled computationally by a second-order multi-adaptive neural agent model. It addresses movement, affect and verbal modalities and both intrapersonal synchrony and interpersonal synchrony. The behaviour of the introduced neural agent model was evaluated in a simulation paradigm with different stimuli and communication enabling conditions. The outcomes illustrate how synchrony leads to stronger short-term affiliation which in turn leads to more synchrony and stronger long-term bonding, and conversely.

1. Introduction

Whenever people interact, their behaviour tends to become mutually coordinated in time, or synchronized. Interpersonal synchrony has been found to enhance relationship functioning, for example, by inducing greater levels of closeness, concentration, coordination, cooperation, affiliation, alliance, connection, or bonding; e.g., (Accetto, Treur, Villa, 2018; Hove and Risen, 2009; Koole and Tschacher, 2016; Ramseyer and Tschacher, 2011; Tarr, Launay, Dunbar, 2016; Wiltermuth and Heath, 2009). Notably, the benefits of interpersonal synchrony include patterns of mutual adaptation both in the short term and in the long term. For instance, in the context of psychotherapy, a patient and therapist who synchronize their movements (Ramseyer and Tschacher, 2011) may experience a stronger sense of sharing the present moment during a therapeutic session (Tschacher, Ramseyer, Koole, 2018). Over multiple sessions, this increased social presence may strengthen the therapeutic bond, which allows the patient

and therapist to work together more effectively (Koole and Tschacher, 2016). This paper addresses how such different forms of short-term and long-term behavioural adaptivity induced by synchronization can be modeled computationally by a human-like adaptive neural agent model.

The present model of a neural agent is based on a number of mechanisms in the literatures on cognitive, behavioural, and affective neuroscience. A neural basis for short-term behavioural adaptivity can be found in the recent work on the (nonsynaptic, intrinsic) adaptive excitability of (neural) states; e.g., (Chandra and Barkai, 2016; Debanne, Inglebert, Russier, 2019; Williams, O’Leary, Marder, 2013; Zhang et al, 2021). By contrast, a neural basis for long-term adaptivity can be found in the classic notion of synaptic plasticity; e.g., (Hebb, 1949; Shatz, 1992). Together, these two fundamentally different forms of adaptation yield a model of a multi-adaptive neural agent. The two forms of adaptation may also interact with each other, a possibility that we address more fully later on in the present paper.

The amount of adaptation that an agent requires may vary from situation to situation. The capacity to adjust plasticity to the demands of the situation relates to metaplasticity (e.g. Abraham and Bear, 1996; Robinson, Harper, McAlpine, 2016). The present model of a neural agent models metaplasticity as a second-order form of plasticity. The resulting model yields a second-order multi-adaptive neural agent, which is human-like in the sense that it incorporates an interplay of three major mechanisms for adaptivity that according to the neuroscientific literature characterize human agents.

The present model of a neural agent further includes intrapersonal synchrony and interpersonal synchrony and their links to short-term and long-term behavioural adaptivity. To model the pathway from synchrony patterns to this behavioural adaptivity, we included both built-in intrapersonal synchrony and interpersonal synchrony detectors. Here, intrapersonal synchrony means that within an agent actions for the different modalities occur in a coordinated manner. Interpersonal synchrony means that for each modality the actions of the two agents occur in a coordinated manner. The addressed modalities are movement, affect and verbal modalities. We included these three modalities because they have each been shown to be influential in interpersonal behavior (Koole & Tschacher, 2012).

We evaluated the neural agent model in a series of simulation experiments for two agents with a setup in which a number of stochastic circumstances were covered in different (time) episodes. The simulations included not only episodes with a stochastic common stimulus for the two agents, but also episodes with different stochastic stimuli for the agents. Moreover, to analyze the role of communication, stochastic circumstances were also included for episodes when communication was enabled by the environment and episodes when communication was not enabled.

2. Main Assumptions and Background Knowledge

In this section, we present the main assumptions behind the introduced adaptive neural agent model and relate them to the relevant neuroscience literatures. This grounding in neuroscience is based on pathways for a circular interplay of synchrony with both nonsynaptic plasticity (Debanne, Inglebert, Russier, 2019) and synaptic plasticity

(Hebb, 1949), thereby covering both short-term time scales and long-term time scales and their interaction. More specifically, the following underlying assumptions are made for the pathways involved.

Interpersonal synchrony leads to adaptation of joint behaviour

Interpersonal synchrony is often followed by a behavioural change or adaptation of mutual behaviour; e.g., (Accetto, Treur, Villa, 2018; Fairhurst, Janata, Keller, 2013; Hove and Risen, 2009; Kirschner and Tomasello, 2010; Koole and Tschacher, 2016; Koole et al, 2020; Palumbo et al, 2017; Prince and Brown, 2022; Tarr, Launay, Dunbar, 2016; Valdesolo, Ouyang, DeSteno, 2010; Valdesolo and DeSteno, 2011; Wiltermuth and Heath, 2009). This adaptive shift in mutual behavioral coordination has been observed, for instance, in psychotherapy sessions. Research has shown that therapists were rated more favorably and as more empathic when, beforehand, they were instructed to make their movements more synchronized with the client (Trout and Rosenfeld, 1980; Maurer and Tindall, 1983; Sharpley et al., 2001). Similarly, Ramseyer and Tschacher (2011) found that initial movement synchrony between client and therapist was predictive of the client's experience of the quality of the alliance at the end of each session. Also Koole and Tschacher (2016) reviewed converging evidence that that movement synchrony has a positive effect on the working alliance between patient and therapist. More generally, synchrony in face-to-face interactions has been found to promote interpersonal affiliation (Feldman, 2007; Wiltermuth and Heath, 2009).

Behavioural adaptation after interpersonal synchrony occurs both in the form of short-term adaptation and long-term adaptation

Much research on interpersonal synchrony has focused on short-term adaptive changes in interpersonal coordination (Accetto, Treur, Villa, 2018; Hove and Risen, 2009; Tarr, Launay, Dunbar, 2016; Tichelaar and Treur, 2018; Wiltermuth and Heath, 2009). However, several lines of research have observed effects of interpersonal synchrony on long-term adaptation as well. First, developmental research has observed that movement synchrony between infant and caregivers predict social interaction patterns of the child several years later (Feldman, 2007). Second, research on close relationships suggests that early patterns of interpersonal synchrony predict subsequent indicators of relationship functioning. For instance, one study found that spouses' patterns of cortisol variation converged over a period of years, indicating longterm shifts in interpersonal coordination (Laws et al., 2015). Third and last, research on psychotherapy processes has found that markers of interpersonal synchrony in early sessions can predict the development of the therapeutic relationship (e.g., Ramseyer and Tschacher, 2011) and therapeutic outcomes (see Koole et al., 2020). Long-term adaptation processes remain less well-studied than short-term adaptation processes. Nevertheless, the convergence of evidence is sufficient to conclude that interpersonal synchrony is likely to promote both short-term and long-term adaptation in interpersonal relationships.

The behavioural adaptation relies on different neural mechanisms: synaptic plasticity of connections and nonsynaptic plasticity of intrinsic excitability

In the neuroscientific literature, a distinction is made between synaptic and nonsynaptic (intrinsic) adaptation. The classical notion of synaptic plasticity has been used to

explain long-term behavioural adaptation; e.g., (Hebb, 1949; Shatz, 1992). This addresses how the strength of a connection between different states is adapted over time due to simultaneous activation of the connected states. By contrast, the nonsynaptic adaptation of intrinsic excitability of (neural) states has been addressed in more detail more recently; e.g., (Chandra and Barkai, 2016; Debanne, Inglebert, Russier, 2019; Zhang et al, 2021). The latter form of adaptation has been related, for example, to homeostatic regulation (Williams, O’Leary, Marder, 2013) and also to how deviant dopamine levels during sleep make that dreams can use more associations due to easier excitable neurons; e.g., (Boot et al, 2017). Moreover, both (synaptic and nonsynaptic) forms of adaptation can easily work together; e.g., (Lisman, Cooper, Sehgal, Silva, 2018). In the neural agent model these two adaptation mechanisms and their interaction have been used to model behavioural adaptivity: the former for long-term adaptation and the latter for short-term adaptation. Here an interplay of two types of adaptivity occurs. Synchrony does not only lead to short-term adaptation, but short-term adaptation itself also intensifies interaction which can lead to more synchrony which in turn can strengthen the long-term adaptation. Besides, also long-term adaptivity strengthens interaction which leads to more synchrony and consequently stronger short-term adaptivity. In this way, via multiple circular pathways a dynamic interplay occurs between synchrony, short-term adaptivity and long-term adaptivity.

Plasticity is not a constant feature, it often is highly context-dependent according to what is called metaplasticity; e.g., (Abraham and Bear, 1996; Robinson, Harper, McAlpine, 2016). For example, ‘Adaptation accelerates with increasing stimulus exposure’ (Robinson et al, 2016). To enable such context-sensitive control of plasticity, second-order adaptation (i.e., adaptation of the adaptation) has been included in the neural agent model, which makes the model more realistic.

The pathways from synchrony to behavioural adaptation involve synchrony detection states

If synchrony occurs for a person and due to this the person adapts the interaction behaviour, this suggests that persons possess a facility to notice or experience synchrony patterns for the different modalities. Indeed, the assumption is made that persons do in some way (perhaps unconsciously) detect synchrony and from there may trigger behavioural adaptation for their interaction behaviour. In the pathway from synchrony patterns to changed interaction behaviour patterns, such synchrony detection states can be considered as specific mediating mental states. In (Treur, 2007a, 2007b) such a state p in general is called a mediating state for the effect of a past pattern a on a future pattern b entailed by pattern a ; similarly, in (Tse, 2013) such a (brain) state is referred to as describing ‘informational criteria’ for future activation; see also (Treur, 2021). In line with previous research described in (Hendrikse et al, 2022c), it is assumed that not only the detected interpersonal synchrony but also the detected intrapersonal synchrony relating to a conscious emotion has a causal effect on the behavioural adaptivity.

3. Self-Modeling Network Modeling

The presented neural agent model is based on network-oriented modeling. Following (Treur, 2020a, 2020b), a temporal-causal network model is characterized by (here X and Y denote nodes of the network, also called states):

- *Connectivity characteristics*
Connections from a state X to a state Y and their weights $\omega_{X,Y}$
- *Aggregation characteristics*
For any state Y , some combination function $c_Y(\cdot)$ defines the aggregation that is applied to the impacts $\omega_{X,Y}X(t)$ on Y from its incoming connections from states X
- *Timing characteristics*
Each state Y has a speed factor η_Y defining how fast it changes for given causal impact

The following difference (or related differential) equations that are used for simulation purposes and also for analysis of temporal-causal networks, incorporate these network characteristics $\omega_{X,Y}$, $c_Y(\cdot)$ and η_Y in a standard numerical format:

$$Y(t + \Delta t) = Y(t) + \eta_Y [c_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)] \Delta t \quad (1)$$

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. Note that (1) has a format similar to that of recurrent neural networks. Within the software environment described in (Treur, 2020a, Ch. 9), a large number of currently around 60 useful basic combination functions are included in a combination function library. The above concepts enable to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. The examples of combination functions that are applied in the model introduced here can be found in Table 1.

Table 1 The combination functions used in the introduced network model

	Notation	Formula	Parameters	Used for
Advanced logistic sum	alogistic $_{\sigma,\tau}(V_1, \dots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\dots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}} \right] (1+e^{-\sigma\tau})$	Steepness σ Excitability threshold τ	X_4 - X_5 , X_{10} - X_{16} , X_{24} - X_{26} , X_{31} - X_{38} , X_{45} - X_{47} , X_{54} - X_{59} , X_{63} - X_{71} , X_{75} - X_{93}
Complemental difference	compdiff (V_1, V_2)	$0 \text{ if } V_1 = V_2 = 0$ $1 - \frac{ V_1 - V_2 }{\max(V_1, V_2)} \text{ else}$	-	X_{18} - X_{23} , X_{39} - X_{44} (synchrony detectors)
Random Stepmod	randstepmod $_{\rho,\delta}(V)$	$0 \text{ if } 0 \leq \text{time } t \bmod \rho \leq \delta$ $aV + (1-a)\text{rand}(1,1) \text{ else}$	Repetition ρ Step time δ	X_3 (common stimulus) X_{60} - X_{62} , X_{72} - X_{74} (communication enablers)
Random Stepmodopp	randstepmodopp $_{\rho,\delta}(V)$	$0 \text{ if } \delta \leq \text{time } t \bmod \rho \leq \rho$ $aV + (1-a)\text{rand}(1,1) \text{ else}$	Repetition ρ Step time δ	X_1 - X_2 (individual stimuli)
Euclidean	eucl $_{n,\lambda}(V_1, \dots, V_k)$	$\sqrt{\frac{V_1^n + \dots + V_k^n}{\lambda}}$	Order n Scaling factor λ	X_6 - X_9 , X_{27} - X_{30} (sensing) X_{48} - X_{53} (communication)

Here, for the third and fourth function, $\text{rand}(1, 1)$ draws a random number from $[0, 1]$ in a uniform manner and a is a persistence factor (with value 0.5 used in the simulations).

Realistic network models are usually adaptive: often not only their states but also some of their network characteristics change over time. By using a *self-modeling network* (also called a *reified* network), a similar network-oriented conceptualization can also be applied to adaptive networks to obtain a declarative description using mathematically defined functions and relations for them as well; see (Treuer, 2020a; Treuer, 2020b). This works through the addition of new states to the network (called *self-model states*) which represent (adaptive) network characteristics. In the graphical 3D-format as shown in Sect. 4, such additional states are depicted at a next level (called *self-model level* or *reification level*), where the original network is at the *base level*.

As an example, the weight $\omega_{X,Y}$ of a connection from state X to state Y can be represented (at a next self-model level) by a self-model state named $\mathbf{W}_{X,Y}$. Similarly, all other network characteristics from $\omega_{X,Y}$, $c_Y(\cdot)$ and η_Y can be made adaptive by including self-model states for them. For example, an adaptive excitability threshold τ_Y (for a logistic combination function) for state Y can be represented by a self-model state named \mathbf{T}_Y and an adaptive speed factor η_Y can be represented by a self-model state named \mathbf{H}_Y .

As the outcome of such a process of network reification is also a temporal-causal network model itself, as has been shown in (Treuer, 2020a, Ch 10), this self-modeling network construction can easily be applied iteratively to obtain multiple orders of self-models at multiple (first-order, second-order, ...) self-model levels. For example, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the speed factor $\eta_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$ which in turn represents the adaptation of connection weight $\omega_{X,Y}$. Similarly, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{T}_Y}$ representing the speed factor $\eta_{\mathbf{T}_Y}$ for the dynamics of first-order self-model state \mathbf{T}_Y which in turn represents the adaptation of excitability threshold τ_Y for Y .

In the current paper, this multi-level self-modeling network perspective will be applied to obtain a second-order adaptive network architecture addressing controlled adaptation induced by detected synchrony. In this self-modeling network architecture, the first-order self-model models the adaptation of the base level network, and the second-order self-model level the control over this. As an example, the control level can be used to make the adaptation speed context-sensitive as addressed by metaplasticity literature such as (Abraham and Bear, 1996; Robinson et al, 2016). For instance, the metaplasticity principle ‘Adaptation accelerates with increasing stimulus exposure’ formulated by (Robinson et al, 2016) can easily be modeled by using second-order self-model states; this actually has been done for the introduced model, as will be discussed in Sect. 4.

4. The Adaptive Neural Agent Model

In this section, our adaptive neural agent model is explained in some detail. The controlled adaptive agent design uses a self-modeling network architecture of three

levels as discussed in Sect. 3: a base level, a first-order self-model level, and a second-order self-model level. Here the (middle) first-order self-model level models how connections of the base level are adapted over time, and the (upper) second-order self-model level models the control over the adaptation.

4.1 Base level

Fig. 1 shows a graphic overview of the base level of the agent model (agents are indicated by the big boxes) and the available Appendix provides explanations for all of its states (see Linked Data at <https://www.researchgate.net/publication/359635368>). For each agent, a number of interaction states were modeled: states involved in sensing (indicated by sense) are on the left-hand side of each box, and states involved in execution or expression of actions (move, exp_affect, talk) on the right-hand side. In between these interaction states, within a box are the agent's internal mental states; outside the boxes are the world states. Note that we assume that each agent also senses its own actions, modeled by the arrows from right to left outside the box.

For each agent, we modeled a number of internal mental states such as sensory representation states (rep) and preparation states (prep) for each of the three modalities: movement m , expression of affect b , and verbal action v . Furthermore, each agent has a conscious emotion state for affective response b (cons_emotion). Each of the mentioned states is depicted in Fig. 1 by a light pink circle shape. For each modality, its representation state has an outgoing (response) connection to the corresponding preparation state and it has an incoming (prediction) connection back from the preparation state to model internal mental simulation (Damasio, 1999; Hesslow, 2002).

Last but not least, there are the six synchrony detector states (depicted in Fig. 2 by the darker pink diamond shapes) which are introduced here. As in (Hendrikse et al, 2022c) we cover three *intrapersonal synchrony detection states* for the three pairs of the three modalities:

- movement - emotion ($m-b$)
- movement - verbal action ($m-v$)
- emotion - verbal action ($b-v$)

These intrapersonal synchrony detection states have incoming connections from the two execution states for the modalities they address. The conscious emotion state is triggered by incoming connections from the preparation state for affective response b together with the three intrapersonal synchrony detection states, following (Grandjean, Sander, Scherer, 2008). In addition, the conscious emotion state has an incoming connection from the verbal action execution state (for noticing the emotion in the verbal utterance) and an outgoing connection to the preparation of the verbal action (for emotion integration in the verbal action preparation).

There are three *interpersonal synchrony detection states* for the three modalities m , b , and v . Each of them has two incoming connections: from the sensing state (representing the action of the other person) and the execution state (representing the own action) of the modality addressed.

For a number of states and connections, their excitability and connection weights are adaptive depending on detected synchrony: detected synchrony leads to becoming more sensitive to sensing a person and expressing to that person (short-term effect) and

to connecting stronger to the person (long-term effect). Here, two different time scales for the adaptations are considered:

- on the short term enhancing the excitability of such internal states, so that they become more responsive or sensitive (a form of instantaneous homeostatic regulation)
- on the long term making the weights of such connections stronger so that propagation between states is strengthened (a form of a more enduring bonding)

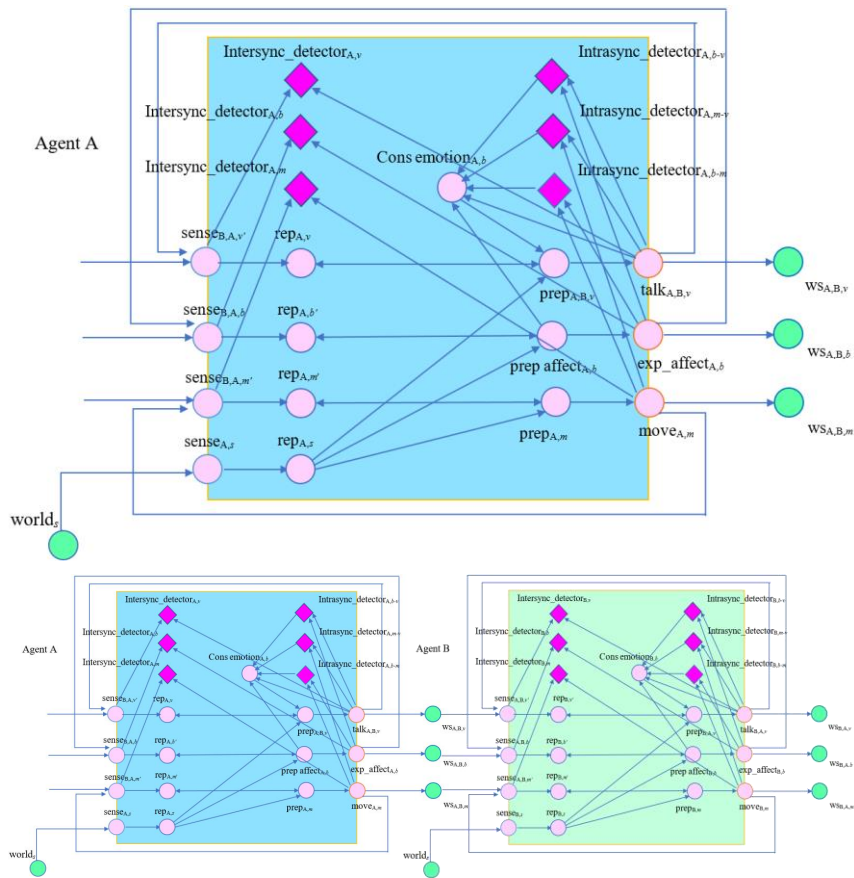


Fig. 1 Base level of (1) the introduced adaptive agent model (upper picture) with three modalities and (in dark pink) six synchrony detection states for intrapersonal and interpersonal synchrony and (2) how the agents interact (lower picture) according to the three modalities

This applies to two types of states and four types of connections in particular, all playing an important role in the interaction behaviour of the two agents:

- **Short-term adaptive excitability for internal states**
 - the representation states for each of the three modalities
 - the execution states for each of the three modalities
- **Long-term adaptive internal and external connections**
 - the (representing) connections from sensing to representation states for each of the three modalities

- the (executing) connections from preparation to execution states for each of the three modalities
- the (observing) connections from world states to sensing states
- the (effectuating) connections from execution states to world states

Thus, more synchrony detected will lead to enhanced excitability for these types of states (short-term adaptation) and for these connections to become stronger (long-term adaptation); each type of all these adaptations contributes in its own way (and time scale) to the interaction behaviour of the persons. In the short term, more sensitive states for representations will lead to gaining better images of the modalities of the other person; this will make the sensed signals better available and accessible for the brain. More sensitive states for execution will lead to better expressed own modalities, so that the other person can sense them better.

Over time and repeated interactions, a stronger (external) observing connection will lead to sensing the other person better (e.g., turning sensors in the right direction and bending or getting closer to the other), and a stronger representing connection again (but now in a more endurable manner) will make the sensed signals better available and accessible for the brain. Conversely, a stronger executing connection will also contribute (in an endurable manner) to stronger expression and acting toward the other and a stronger effectuating connection to better availability (for the other) of the action effects in the world (e.g., more visible, better hearable by directing and positioning in the right direction and bending or getting closer to the other). In Sect. 4.2, we discuss in more detail how we modeled these forms of adaptivity and their control using the principle of self-modeling of the network model.

Finally, at the base level some world states are modeled for stimuli s that are sensed by the agents. In the simulations, they have stochastic activation levels. In some episodes one common stimulus is observed by both agents (for example when they physically meet and therefore are in the same environment), but in other episodes the agents receive different stimuli. Furthermore, also the world situation's suitability for enabling communication between the two agents is modeled by similar stochastic fluctuations. Moreover, two context states are included to model the conditions to maintain excitability thresholds well.

4.2 Modeling adaptation and its control

We modeled adaptation and its control needed in the neural agent model using a 'self-modeling network'; see Sect. 3 or (Treur, 2020a, 2020b). Following what has been described in Sect. 4.1, for a number of states Y adaptive excitability has been modeled via the excitability threshold τ_Y of the logistic function used for these states (see Table 1). Moreover, the strengthening of connections from X to Y has been modeled via adaptive connection weights $\omega_{X,Y}$. Following Sect. 3, these adaptations have been modeled in particular through self-modeling for these τ_Y and $\omega_{X,Y}$ by adding the following first- and second-order self-model states:

- first-order self-model **T**-states \mathbf{T}_Y for short-term adaptation of the adaptive base excitability thresholds τ_Y for the internal representation states and execution states Y for the three considered modalities (movement, affective response and verbal action)
- first-order self-model **W**-states $\mathbf{W}_{X,Y}$ for adaptation of the adaptive base connection weights $\omega_{X,Y}$ for both internal and external connections for the three considered

modalities; internal connections from sense states to representation states and from preparation states to execution states, and external connections from execution states to world states and from world states to sense states

- second-order self-model \mathbf{H}_T -states for control of the adaptation of the adaptive excitability thresholds τ_Y for the internal representation states and execution states Y
- second-order self-model \mathbf{H}_w -states for control of the adaptation of the adaptive base connection weights $\omega_{X,Y}$.

Fig. 2 shows the overall design of the network model; here, the first-order self-model states are in the middle (blue) plane and the second-order self-model states in the upper (purple) plane. The first-order states include \mathbf{T} -states representing the excitability thresholds of representation and execution states and \mathbf{W} -states representing the weights of the different types of adaptive connections addressed. By changing the activation values of these \mathbf{T} -states and \mathbf{W} -states, the corresponding excitability thresholds and connection weights change accordingly. This change occurs due to the influences from the detected synchronies, modeled by the upward (blue) arrows in Fig. 3 from the synchrony detection states in the base plane to the \mathbf{T} -states and \mathbf{W} -states in the middle plane.

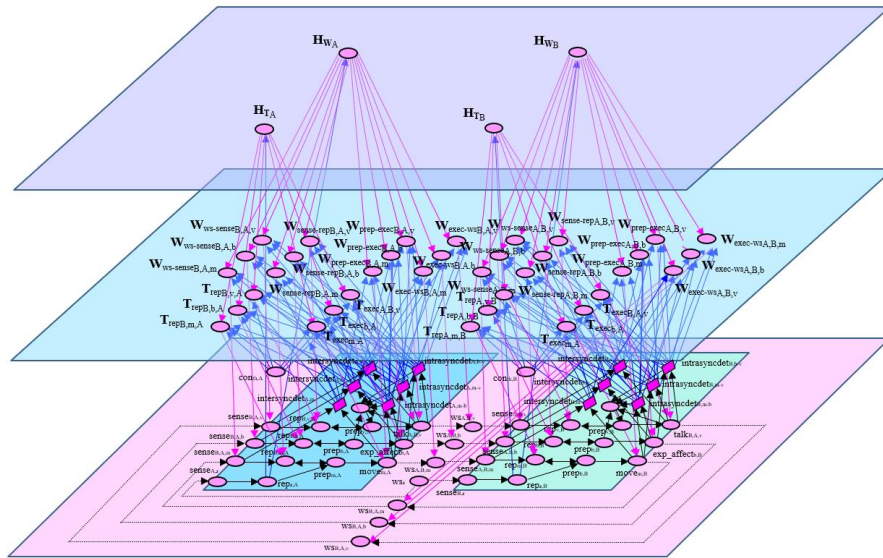


Fig. 2 Overview of the overall second-order adaptive network model

There are four second-order self-model states to control the adaptation: two second-order self-model states \mathbf{H}_{T_A} and \mathbf{H}_{T_B} for excitability adaptation control, one for each agent, and two second-order self-model states \mathbf{H}_{w_A} and \mathbf{H}_{w_B} for connection weight adaptation control, also one for each agent. These represent the adaptation speed (learning rate) for the adaptive excitability and connections for the concerning agent. They model the second-order adaptation (or metaplasticity) principle ‘Adaptation accelerates with stimulus exposure’ (Robinson et al, 2016). To this end they have

incoming connections (blue upward arrows from base plane to upper plane) from the stimulus representation states at the base level.

5 Simulation Results

5.1 Design of the simulation experiments

In this section, we evaluate our neural agent model in an experimental simulation paradigm. Our paradigm was set up in such a way that we could evaluate the behaviour of our two agents during four different types of consecutive episodes (see Table 2 and Fig. 3) which are explained below. Each of these types of episodes lasted for 30 time units, so that a cycle of four episodes equaled 120 time units. Our total simulation run had a duration of 840 time units and the step size (Δt) was 0.5, resulting in 1680 computational steps in total for each simulation run. This means that each cycle of four episodes was repeated 7 times in each simulation. As it concerns a partly stochastic simulation, we ran 20 repetitions of each simulation with the same episodic paradigm and parameter settings, to get a sense of the robustness of the neural agent model’s behaviour. It turned out that general patterns were approximately similar across all independent simulations. Therefore, we selected one simulation to discuss in the upcoming subsections.

Regarding the four different types of episodes in this simulation, they manipulate both whether or not the two agents received the same or a different stochastic stimulus and whether or not they were able to communicate (with some stochastic variations in enabling conditions, due to environmental changes and noise) with each other (Table 2). The specific episodes for the considered example simulation are shown in Fig. 3. The world states $w_{s,A}$ and $w_{s,B}$ indicate the different stimuli for agent A and B from the world (activated from time 0 to 60 and then repeated every 120 time units; see the dark solid and dashed blue lines for A, resp. B). Similarly, world state w_s indicates the common stimulus (activated from time 60 to 120 and then repeated every 120 time units; see the purple line). These three states have values stochastically fluctuating approximately between 0.7 and 0.9. Furthermore, the self-model states $\mathbf{W}_{\text{exec-}w_{s,A,B}}$ (from A to B) and the states $\mathbf{W}_{\text{exec-}w_{s,B,A}}$ (from B to A) indicate the communication enabling conditions in the environment. They are activated from time 30 to time 60 thereby fluctuating stochastically roughly between 0.45 and 0.65 and then repeated every 60 time units. All these stochastic activation patterns indeed follow Table 2.

Table 2 Simulation paradigm of each run with the neural agent model

Four different types of episodes: timing and conditions				
type	stimulus	communication enabled	duration	time intervals
Episode 1	Different	No	30	0-30 + repetition after each 120
Episode 2	Different	Yes	30	30-60 + repetition after each 120
Episode 3	Common	No	30	60-90 + repetition after each 120
Episode 4	Common	Yes	30	90-120+ repetition after each 120

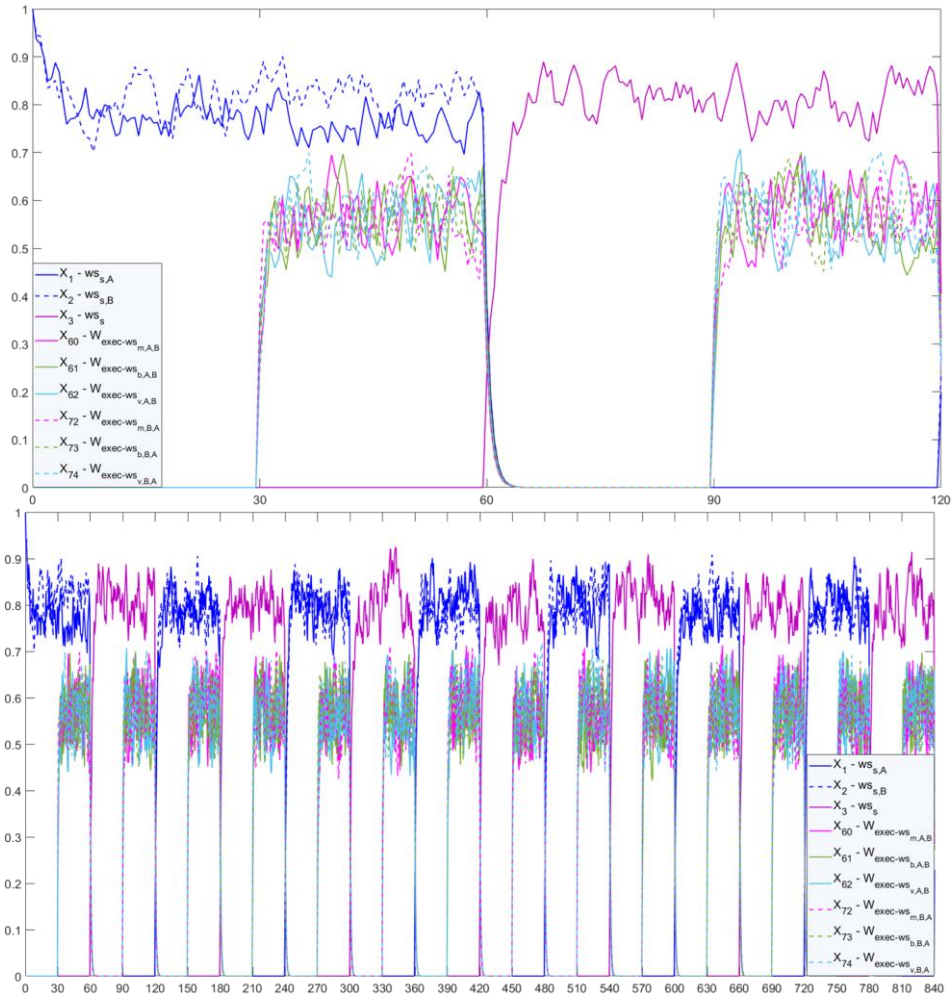


Fig. 3 The stimuli and interaction enabling states in the neural agent model from 0 to 120 time units (upper graph) and from 0 to 840 time units (lower graph).

5.2 Behaviour of the base states of the neural agent model

For the base states, in the first phase for time 0 to 10 the representations (states $rep_{s,A}$ and $rep_{s,B}$) for the stimulus are activated (the curves fluctuating around 0.8) and preparations (states $prep_{x,A}$) for actions are triggered (curves going to 1); see the upper graph in Fig. 4. This leads, together with the intrapersonal synchrony detection activation (see Fig. 5 and 6), to the conscious emotion around time 10 (red curve going to 1), but this still is only internal processing as no executions of actions take place yet. The action executions (states $move_{m,A}$, $exp_affect_{b,A}$, and $talk_{A,B,v}$) for both agents start to come up after time 10 (e.g., the purple line); this also depends on the short-

term adaptations that will be discussed in Sect. 5.4. The curves immediately under these executions concern the sensing of the other agent's actions (the $sense_{A,x,B}$ and $sense_{B,x,A}$ states); in some periods they are slightly fluctuating due to environmental noise on the communication channels. The actual communication level (the $ws_{x,A,B}$ and $ws_{x,B,A}$ states) is seen below it from 30 to 60 and from 90 to 120. For the longer term, the lower graph in Fig. 4 shows that each interval with enabling conditions for communication leads to higher activations of the action executions (the purple line) until values around 0.8 are reached. This is due to a long-term behavioural adaptation that is discussed in Sect. 5.5. Accordingly, the sensing states become higher as well over this longer term, but not as high as the action executions, due to a communication bias incorporated in the model. This overall pattern shows that the enabling conditions for communication have a stronger adaptive effect on the actions than having a common stimulus.

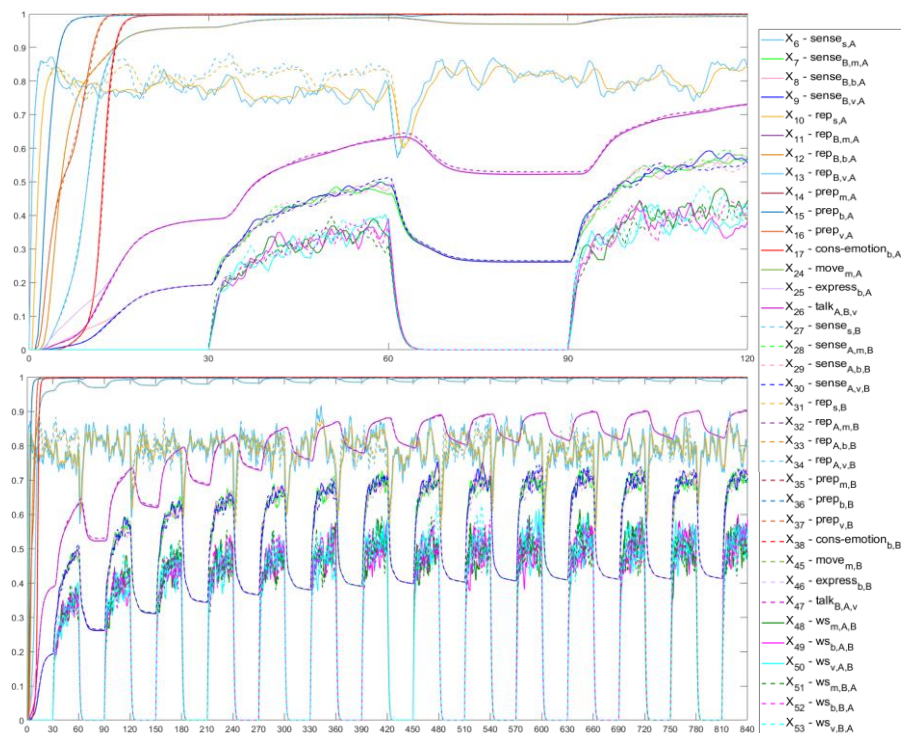


Fig. 4 The base states in the neural agent model from 0 to 120 time units (upper graph) and from 0 to 840 time units (lower graph).

5.3 Behaviour of the intrapersonal synchrony and interpersonal synchrony detector states

The curves that the graphs in Fig. 5 and Fig. 6 have in common depict the detected intrapersonal synchrony and interpersonal synchrony. Here:

- the detected intrapersonal synchrony detection is represented by the states $\text{intrasyncdet}_{A,x-y}$ and $\text{intrasyncdet}_{B,x-y}$ shown as the light green and light blue curves going to 1 from time 0 to 15
- the interpersonal synchrony detection is represented by the states $\text{intersyncdet}_{A,B,x}$ and $\text{intersyncdet}_{B,A,x}$ shown as the red and blue curves going to 0.4 from time 0 to 30 and further to 0.8 from time 30 to 60

Here it can be observed that the detection of intrapersonal synchrony takes place already in the first episode from time 0 to 30, meaning no common stimulus or communication is required. In contrast, the detection of interpersonal synchrony strongly depends on the interaction between the two agents. Note also that the former type of detected synchrony reaches a perfect level of 1, due to the coherent internal makeup of the agents, while the latter type does not get higher than around 0.8. At first sight this may look strange, given that the actual executions of actions of both agents are practically the same, as discussed above (see Sect. 5.2 and Fig. 5). However, this is due to the communication bias that was also noted above in Sect. 5.2. This demonstrates the capability of the model that it is able to distinguish a subjective personally detected interpersonal synchrony from an objective form of interpersonal synchrony detection as might be assigned by an external observer but not by the agent itself.

5.4 The interplay between synchrony and short-term adaptation

In Fig. 5 the synchrony detection states are shown together with the states involved in the short-term adaptation: the first-order self-model \mathbf{T} -states that represent the adaptive excitability thresholds for representation and execution states and the second-order self-model \mathbf{H}_T -states that represent the \mathbf{T} -states' speed factors (adaptive learning rates). Except the synchrony detection states already discussed in Sect. 5.3, the graphs show two light green curves fluctuating around 0.6 for the \mathbf{H}_T -states and a blue curve going down to below 0.3 for the \mathbf{T} -states.

According to the metaplasticity principle 'Adaptation accelerates with increasing stimulus exposure' (Robinson et al., 2016), the \mathbf{H}_T -states indeed fluctuate with the stimuli. Also in accordance with this, when one stimulus period is in transition to another stimulus period, it can be seen that there is a short dip in the values of the \mathbf{H}_T -states, as stimuli start from 0, so there is a very short period of a lower level, as can also be seen in Fig. 3. Moreover, it is clear that the \mathbf{T} -states (e.g., the blue curve) show an opposite pattern compared to the pattern of the interpersonal synchrony detection states. In particular, in the episodes from 30 to 60 and from 90 to 120 (and so on), where the detected interpersonal synchrony is the highest, the \mathbf{T} -states for the excitability thresholds are the lowest. This is a short-term adaptation that makes that these agent states related to the communication with the other agent have a higher excitability due to the detected interpersonal synchrony, which will have an intensifying effect on their communication. Not coincidentally, the mentioned periods are also the periods with good enabling conditions for communication (see also Sect. 5.2). It can also be noted that this tendency is a short-term effect and is reversible: the \mathbf{T} -states get higher again when the detected interpersonal synchrony gets lower.

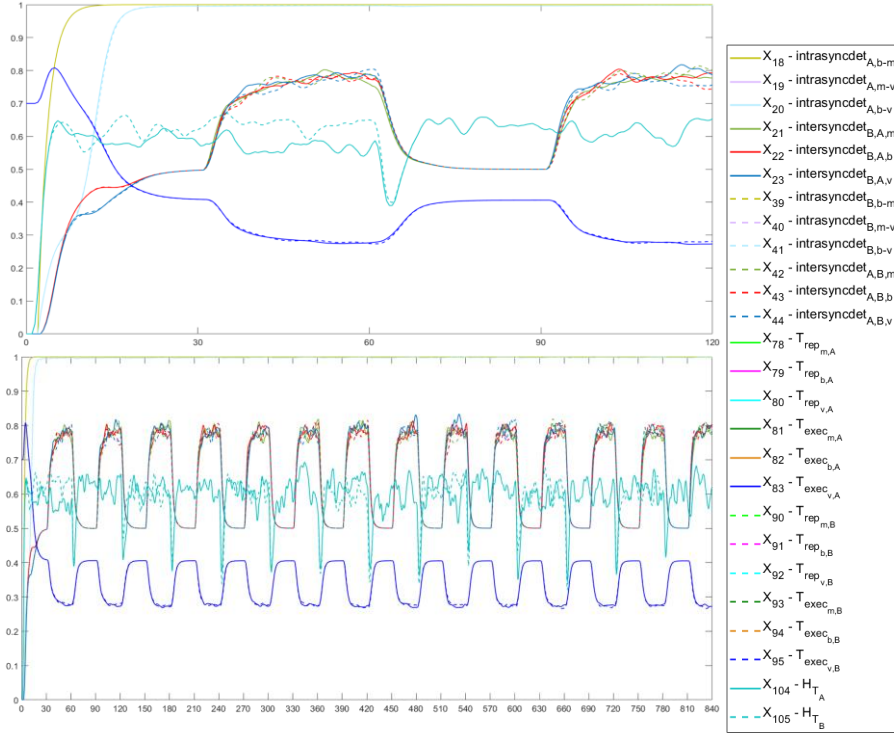


Fig. 5 The detected intrapersonal synchrony, interpersonal synchrony and short-term adaptation **T**-states in the neural agent model from 0 to 120 time units (upper graph) and from 0 to 840 time units (lower graph).

5.5 The interplay between synchrony and long-term adaptation

In Fig. 6 the synchrony detection states are shown together with the states involved in the long-term adaptation: the first-order self-model **W**-states that represent the adaptive weights for the connections to the representation and execution states and the second-order self-model **Hw**-states that represent the **W**-states' speed factors (adaptive learning rates). Here, except the synchrony detection states already discussed in Sect. 5.3, the graphs show the **W**-states (e.g., a blue curve) slowly and gradually going up to above 0.5 at time 120 and further up to about 0.8 at time 840.

Moreover, at a very low level, the curves for the **Hw**-states can be seen. They also fluctuate according to the metaplasticity principle 'Adaptation accelerates with increasing stimulus exposure' (Robinson et al., 2016), but at a very low level around 0.005 (see the lower graph in Fig. 6). Again, following the same principle, when one stimulus period is in transition to another stimulus period, it can be seen that there is a short dip in the values of the **Hw**-states. This happens because stimuli start from 0, so there is a very short period of a lower level (see Fig. 3).

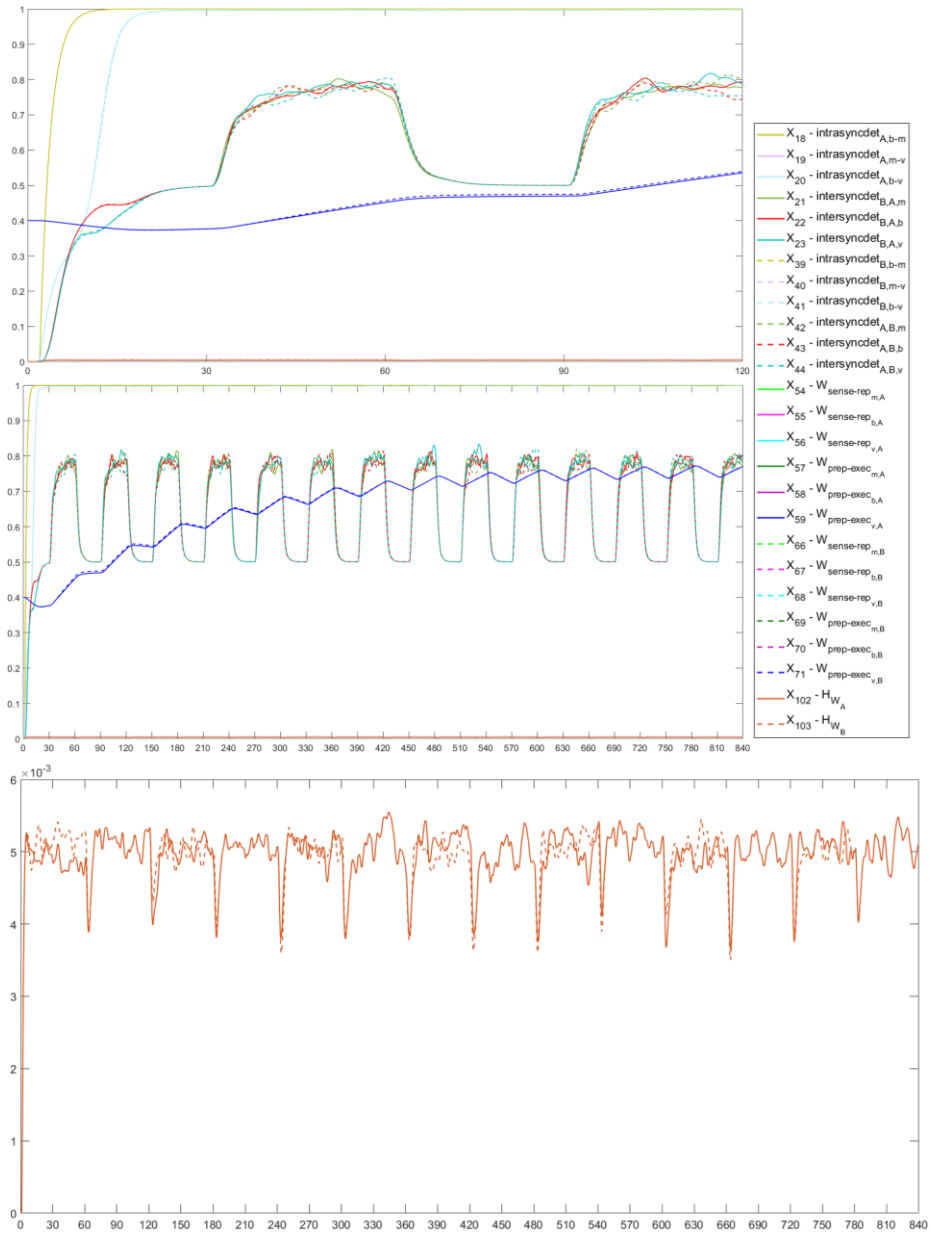


Fig. 6 The detected intrapersonal synchrony, interpersonal synchrony and long-term adaptation **W**-states and **Hw**-states in the neural agent model from 0 to 120 time units (upper graph) and from 0 to 840 time units (middle graph). The lower graph depicts the **Hw**-states with a different vertical scale (times 10^{-3}).

The pattern of the **W**-states indeed shows a long-term adaptation effect. It highlights that they get a repeated boost in the time intervals 30-60, 90-120, and so on, and show a form of persistency. These boosts occur specifically in these intervals for a reason. These intervals are when there are communication enabling conditions and as discussed in Sect. 5.4 that induces synchrony and the short-term adaptation via the **T**-states, which in turn add to synchrony. Therefore these two effects are at the basis of these boosts for the long-term adaptation. In this way there is a form of interaction between short-term and long-term adaptation.

6 Discussion

In this paper, a neural agent model was introduced for the way intrapersonal and interpersonal synchrony induce behavioural adaptivity between the synchronized persons; e.g., (Accetto et al., 2018; Hove and Risen, 2009; Kirschner and Tomasello, 2010; Koole and Tschacher, 2016; Palumbo et al, 2017; Prince and Brown, 2022; Tarr et al, 2016; Valdesolo et al, 2010; Wiltermuth and Heath, 2009). The model is multi-adaptive in that the behavioral adaptivity covers both short-term and long-term adaptations, reflecting short-term affiliation and long-term bonding. The former type of adaptation was modeled using (nonsynaptic) adaptive excitability (Chandra and Barkai, 2016; Debanne et al, 2019; Williams et al, 2013; Zhang et al, 2021), whereas for the latter type a more classical synaptic type of adaptation (Hebb, 1949; Shatz, 1992) was used. Following the aforementioned literature on synchrony, both types of adaptivity were modeled as driven by the (internally detected) intrapersonal synchrony and interpersonal synchrony for the agent. By also including metaplasticity (Abraham and Bear, 1996) in the model to control the adaptations in a context-sensitive manner, the agent model became second-order adaptive.

We already engaged in computational modeling of synchrony between agents in earlier work such as (Hendrikse et al, 2022a; Hendrikse et al, 2022b). However, in the models described there, no (subjective) internal detection of synchrony takes place. Moreover, in (Hendrikse et al., 2022b) no adaptivity was covered, whereas in (Hendrikse et al., 2022a) another type of adaptivity was incorporated, namely of internal connections from representation states to preparation states. As far as we know, (Hendrikse et al, 2022c) describes the only other computational agent model where subjective synchrony detection is addressed. However, by that model no long-term behavioural adaptivity is covered and also no adaptive intrinsic excitability is addressed, whereas both are included in the current model.

Earlier work addressing behavioural adaptation due to coordinated actions can be found in (Accetto, Treur, Villa, 2018; Tichelaar and Treur, 2018). In these cases, a dynamic form of the ‘bonding based on homophily’ principle (McPherson, Smith-Lovin, Cook, 2001) was used to model the effect of coordination of emotions and actions on behavioural adaptivity but no (subjective) detection of synchrony was used.

Thus a flexible human-like second-order multi-adaptive neural agent model was obtained for the way in which detected synchrony leads to different types of behavioural adaptivity concerning the short-term affiliation and long-term bonding between the two agents. For further work, many more simulation experiments can be designed and conducted, for example to explore the question which types of short-term

synchrony are most likely to become translated into long-term benefits for a relationship, or to explore in more detail the roles of intrapersonal synchrony and interpersonal synchrony.

Considered from a wider scientific perspective, the model can provide a basis to develop adaptive virtual agents that are able to concentrate on each other by short-term behavioural adaptivity and bond with each other by long-term behavioural adaptivity in a human-like manner.

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