A Human-Like Agent Model for Attribution of Actions Using Ownership States and Inverse Mirroring

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Abstract. This paper presents a neurologically inspired human-like agent model addressing attribution of actions to agents. It is not only capable of attribution of own actions to itself, but also of showing situations where self-generated actions are attributed to other agents, as, for example, for patients suffering from schizophrenia. The mechanisms underlying the model involve prior and retrospective ownership states, and inverse mirroring to generate a mental image of the agent to which an action is attributed. The model is adaptive in that the inverse mirroring can develop based on Hebbian learning. The model provides a basis for applications to human-like virtual agents in the context of for example, training of therapists or agent-based generation of virtual stories.

Keywords: action attribution, cognitive agent model, ownership states, inverse mirroring, schizophrenia

1 Introduction

To design human-like agent models, the fast growing amount of neurological literature is a useful source of information. For example, in this way virtual agents can be designed with high extent of biological plausibility, which may not only show idealised behaviour but also realistic shortcomings characteristic for humans. This paper contributes a human-like agent model for attribution of actions to agents. In the first place the modelled agent is able to attribute own actions to itself and other agents' actions to them. However, it is also possible for the agent model to display false attribution of own actions to other agents or other agents' actions to itself, as sometimes occurs in human agents, for example, in those who have symptoms of Schizophrenia. Due to such variation possibilities, the model covers large parts of the variety in types of behaviour as occurring naturally in the overall human population.

In the neurological literature used as inspiration for the agent model, two aspects are put forward as playing an important role in attribution of actions: (1) prediction of action effects, and (2) mirroring of actions of other agents. Concerning (1) it has been found that action effect prediction capabilities relate to proper attribution of own actions to oneself (e.g., [21], [24], [7], [9], [10], [18]). Concerning (2), note that not attributing a self-generated action to oneself is not the same as attributing such an action to another agent. Actions may simply be not attributed to any agent (e.g., the wind may have caused it). To attribute an action to another agent, a mental image of somebody else performing the action has to be generated. When it concerns an action of another agent who is observed, such a mental image is formed based on the incoming sensory information. However, when an own action is attributed to another agent who does not perform this action or is even not present, forming this mental image requires a shift from a representation of an action from a first-person to a representation from a third-person perspective (mental rotation; e.g., [17]). This is the inverse operation of what happens in mirroring where a shift is made from a representation from a third-person to a representation from a first-person perspective; cf. [14], [15], [17], [20]. Persons suffering from Schizophrenia, for example, not only fail to attribute self-generated actions to themselves, but they also attribute them to other agents (which can be real or imaginary); e.g., [6, 8, 9, 10, 21, 24].

The human-like agent model presented in this paper is based on the perspective put forward in the literature discussed above in relation to both (1) and (2). For (1) elements of the agent model for ownership introduced in [22] were adopted. Here a distinction is made between prior ownership states, among others based on prediction of effects of a prepared action, and retrospective ownership states, for which in addition the monitored execution of the action and the sensed actual effects play an important role. Prior ownership states play an important role in controlling the actual execution of actions, whereas retrospective ownership states are important for acknowledging authorship of an action in a social context. For (2) elements from the agent model for inverse mirroring introduced in [23] were adopted, and integrated in the agent model obtained from [22]. The resulting integrated agent model is able to display action attribution as in normally functioning humans, and false attribution as in deviant functioning of, for example, persons suffering from Schizophrenia.

In this paper, in Section 2 the agent model is introduced. Section 3 presents some simulation results. Finally, Section 4 is a discussion.

2 The Cognitive Agent Model for Attribution of Actions

In this section the design of the cognitive agent model is presented. First some background knowledge is discussed, next the example scenario used is described, the modelling format used is introduced, and finally the agent model is addressed in detail.

Background knowledge Concerning attribution of own actions to oneself, it has been found that poor predictive capabilities relate to false attributions of actions (e.g., [21], [24]). It turns out that co-occurrence of predicted effects and sensed actual effects after execution of an action is an important condition for proper self-attribution of a self-generated action (e.g., [7], [9], [10], [18]). Here within the process the predicted effect leads to suppression of the sensed actual effect (e.g., [3], [8]). The predicted effect and the sensed actual effect are not simply compared (as claimed in earlier literature such as [9], [10]), but are added to each other in an integration process (e.g., [18], [21], [24]). In the cognitive agent model described below, these principles have been incorporated by adopting the relevant elements from [22].

In other work, such as [8] it is debated whether this is a complete explanation: empirical results are reported that indicate that differences in these respects between patients with schizophrenia and a control group are limited. Therefore, in [16] it is argued that another important role is played by what is called 'the sense of agency', and which relates to a generated mental image of the agent to whom the action is attributed.

One of the recent neurological findings relating to agency concerns the *mirroring function* of certain neurons; e.g., [5], [14], [15], [20]. Mirror neurons are active not only when a person prepares for a specific action or body change, but also when the person observes somebody else intending or performing this action or body change. When states of other persons are mirrored by some of the person's own states that at the same time are connected via neural circuits to states that are crucial for the person's own feelings and actions (shared circuits), then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other's actions and feelings; e.g., [14]. Mirroring involves a change of perspective from another agent (third person) to oneself (first person). This requires a nontrivial *mental rotation* transformation of the representations involved (cf. [17]): sensory representations of observed actions of other agents are mapped onto representational structures for self-generated actions. Attribution of a self-generated action to another agent uses a reverse process. It requires a change of a first-person perspective from preparation for a self-generated action to a third-person perspective: a reverse mental rotation transformation of the available representations. This is *inverse mirroring*, as introduced in [23]: the representational structures for self-generated actions are mapped onto sensory representations of observed actions of other agents, thus forming a mental image of somebody else performing the action.

A further question is how such a reverse mental rotation mapping can develop. This is modelled assuming a *Hebbian learning* principle: connected neurons that are frequently activated simultaneously strengthen their connecting synapse. The principle goes back to Hebb [12], but has gained enhanced interest by more extensive empirical support (e.g., [2]), and more advanced mathematical formulations (e.g., [11]). In the cognitive agent model described below this principle has been adopted to realise an inverse mirroring connection from preparation of an action to sensory representation of a similar observed action.

Example Scenario The designed agent model will be illustrated for the following scenario. Any sensed stimulus s leads to a sensory representation SR(s) of this stimulus, which in turn triggers the preparation state PA(a) of an action a as a response of the agent; see the causal chain from SR(s) to PA(a) in Fig. 1. The stimulus s can be any stimulus s1 from the world, but also a stimulus s2 which is the observation that another agent performs action a. In the former case, the arrow from SR(s1) to PA(a) models a reactive response of the agent triggered by stimulus s1. In the latter case the sensory representation SR(s2) indicates the mental image of another person performing the action a, and the arrow from SR(s2) to PA(a) models the agent's mirroring capability for action a; e.g., [14], [15], [20]. When this latter chain of events happens (i.e., whenever mirroring takes place), for the model introduced here it is assumed that by Hebbian learning this will strengthen the reverse connection from preparation PA(a) to sensory representation SR(s2) (mental image of the observed action), thus developing inverse mirroring capabilities (the dotted arrow). When such a learning process has achieved substantial connection strength, the agent's response on stimulus s1 may have changed. When s1 is sensed (in the absence of s2), not only will the agent trigger preparation (and execution) of action a as before, but in addition it will generate a mental image of another agent performing action a (the sensory representation SR(s2)), thus creating a third person perspective on the action.

In the model s denotes a stimulus, c a context, a an action, and b a world state affected by the action. Examples of contexts are another agent B, or the agent self. The effect state b is considered to be positive for the agent (e.g., in accordance with a goal).

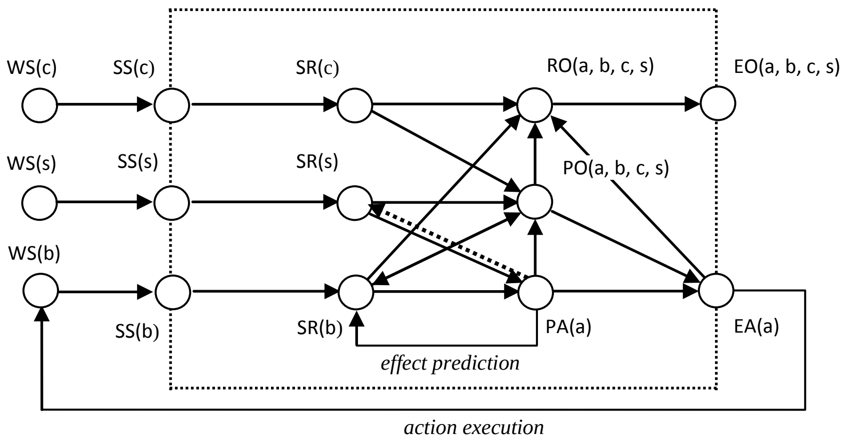

Fig. 1. Overview of the cognitive agent model

The state properties used in the model are summarised in Table 1. The cognitive agent model distinguishes prior and retrospective ownership states for actions, indicated by PO(a, b, c, s) and RO(a, b, c, s), respectively (see Fig. 1). These states are taken specific for a given action a, effect b, context c, and stimulus s (triggering preparation of a). When the context c is self, an ownership state for c indicates self-ownership attribution, whereas for context c another agent B, it indicates ownership attributed to B. Note that the stimulus s triggering preparation of action a can be of any type; for social scenarios, it can be taken as a body state (e.g., face expression) of the other agent B. An action effect state b can be any state of the world (possibly including body states).

The prior ownership state PO(a, b, c, s) is affected by the preparation state PA(a) for the action a, the sensory representation SR(b) of the (predicted) effect b, the sensory representation SR(s) of the stimulus s, and the sensory representation SR(c) of the context c; see the four arrows to PO(a, b, c, s) in Figure 1. Similarly, the retrospective ownership state RO(a, b, c, s) is affected by the sensory representation SR(c) of the context c, the sensory representation SR(b) of the effect b of the action, the prior ownership state PO(a, b, c, s), and the execution EA(a) of the action a; see the arrows to RO(a, b, c, s) in Figure 1.

Action prediction is modelled by the connection from the action preparation PA(a) to the sensory representation SR(b) of the effect b. Suppression of the sensory representation of the effect is modelled by the (inhibiting) connection from the prior ownership state PO(a, b, c, s) to sensory representation SR(b). The control exerted by the prior ownership state (similar to a super miror neuron function; e.g., [13], [15]) is modelled by the connection from PO(a, b, c, s) to EA(a). Finally, acknowledging of ownership is modelled by the connection from the retrospective ownership state RO(a, b, c, s) to the communication effector state EO(a, b, c, s).

Table 1. State properties used

notation	description
WS(W)	world state W (W is a context c, stimulus s, or effect b)
SS(W)	sensor state for W
SR(W)	sensory representation of W
PA(a)	preparation for action a
EA(a)	execution of action a
PO(a, b, c, s)	prior ownership state for action a with b, c, and s
RO(a, b, c, s)	retrospective ownership state for a with b, c, and s
EO(a, b, c, s)	communication of ownership of a with b, c, and s
cs(ω)	strength of connection ω (from preparation of a to sensory representation of s2)

Connections between state properties (the arrows in Fig. 1) have weights ω_k, as indicated in Table 2. In this table the column LP refers to the (temporally) Local Properties LP1 to LP10 presented below. A connection weight ω_k has a value between *-1* and *1* and may depend on the specific context c, stimulus s, action a and/or effect state b involved. By varying these connection strengths, different possibilities for the repertoire offered by the model can be realised. Note that usually connection weights are assumed non-negative, except for the inhibiting connections, such as ω_{2o} which models suppression of the sensory representation of effect b (so that you cannot tickle yourself; cf. [3]).

Table 2. Overview of the connections and their weights

from states	to state	weights	process	LP
SS(W)	SR(W)	ω_1	representing world state W: stimulus s1 or context c	LP1
SS(s2), PS(b)	SR(s2)	ω_1, ω	representing observed action / inverse mirroring	LP2
PA(a), PO(a, b, self, s), SS(b)	SR(b)	ω_2, ω_{20}, ω_3	representing effect state e	LP3
SR(s), SR(b)	PA(a)	ω_4, ω_5	action preparation/mirroring	LP3
SR(c), SR(s), SR(b), PA(a)	PO(a, b, c, s)	ω_6, ω_7, ω_8, ω_9	prior ownership	LP4
PO(a, b, self, s), PA(a)	EA(a)	ω_{10}, ω_{11}	action execution	LP5
EA(a)	WS(b)	ω_{12}	action effect	LP6
WS(W)	SS(W)	ω_{13}	sensing world state	LP7
SR(c), SR(b), PO(a, b, c, s), EA(a)	RO(a, b, c, s)	ω_{14}, ω_{15}, ω_{16}, ω_{17}	retrospective ownership	LP8
RO(a, b, c, s)	EO(a, b, c, s)	ω_{18}	expressed ownership	LP9
SR(s2), PA(a)	cs(ω)	η, ζ	learning inverse mirroring	LP10

Below, the dynamics following the connections between the states in Fig. 1 are described in more detail. This is done for each state by a dynamic property specifying how the activation value for this state is updated based on the activation values of the states connected to it (the incoming arrows in Fig. 1).

The cognitive agent model has been computationally formalised in this way using the hybrid modeling language LEADSTO; cf. [4]. Within LEADSTO a dynamic property or temporal causal relation a $\twoheadrightarrow$ b denotes that when a state property a (or conjunction thereof) occurs, then after a certain time delay, state property b will occur. Below, this delay will be taken as a uniform time step Δt. Each time first a semiformal description is given, and next a formal specification in the hybrid LEADSTO format. Parameter γ is an update speed factor, indicating the speed by which an activation level is updated upon received input from other states.

During processing, each state property has a strength represented by a real number between *0* and *1*; variables *V* (possibly with subscripts) run over these values. In dynamic property specifications, this is added as a last argument to the state property expressions (an alternative notation activation(p, V) with p a state property has not been used for the sake of notational simplicity).

Below, *f* is a function for which different choices can be made, for example, the identity function *f(W) = W* or a combination function based on a continuous logistic threshold function of the form

$$th(\sigma,\ \tau,\ X) = \left(\frac{1}{1+e^{-\sigma(X-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right)(1+\ e^{-\sigma\tau})$$

with σ a steepness and τ a threshold value. Note that for higher values of $\sigma\tau$ (e.g., σ higher than $20/\tau$) this threshold function can be approximated by the simpler expression:

$$th(\sigma,\ \tau,\ X) = \frac{1}{1+e^{-\sigma(X-\tau)}}$$

In the example simulations, for the states that are affected by only one state (i.e., in LP1, LP7, LP8, LP10), *f* is taken the identity function *f(W) = W*, and for the other states *f* is a combination function based on the logistic threshold function: $f(X_1, X_2) = th(\sigma, \tau, X_1+X_2)$, and similarly for more arguments. In this choice common practice is followed, but other types of combination functions might be used as well.

The first properties LP1 describes how sensory representations are generated for context c and stimulus s1 (together indicated by variable W), and for stimulus s2, which is the action a performed by another agent.

LP1 Sensory representation for world state W: stimulus s_1 or context c
If the sensor state for W has level V_1
and the sensory representation of W has level V_2
then after duration Δt the sensory representation of W will have
level $V_2 + \gamma\,[\,f(\omega_1 V_1) - V_2\,]\ \Delta t$.
SS(W, V_1) & SR(W, V_2) $\twoheadrightarrow$ SR(W, $V_2 + \gamma$ [f($\omega_1 V_1$) – V_2] Δt

LP2 Sensory representation for stimulus s_2 indicating another agent's action a
If the sensor state for s_2 has level V_1
and preparation of a has level V_2
and the sensory representation of s_2 has level V_3
then after duration Δt the sensory representation of s_2 will have
level $V_3 + \gamma (f(\omega_1 V_1,\ \omega V_2) - V_3)\ \Delta t$.
SS(s2,V_1) & PA(a,V_2) & SR(s2, V_3) $\twoheadrightarrow$ SR(s2, $V_3 + \gamma$ (f($\omega_1 V_1$, ωV_2) - V_3) Δt)

The sensory representation of an effect state b as described by property LP2 is not only affected by a corresponding sensor state for b (which in turn is affected by the world state), as in LP1, but also by two action-related states:

- via the predictive loop by a preparation state, to predict the effect b of a prepared action a
- by an inhibiting connection from the prior self-ownership state, to suppress the sensory representation of the effect b of the action a, once it is initiated (e.g., [3], [8])

This is expressed in dynamic property LP3. Note that for this suppressing effect the connection weight ω_{2o} from prior ownership state for action a to sensory representation for effect b is taken negative, for example $\omega_{2o} = -1$.

LP3 Sensory representation for an effect state
If the preparation state for action a has level V_1
and the prior self-ownership of action a for b, self, and s has level V_2
and the sensor state for state b has level V_3
and the sensory representation of state b has level V_4
then after duration Δt the sensory representation of state b will have
level $V_4 + \gamma\,[\, f(\omega_2 V_1,\ \omega_{2o} V_2,\ \omega_3 V_3) - V_4\,]\,\Delta t$.

$PA(a, V_1)\ \&\ PO(a, b, self, s, V_2)\ \&\ SS(b, V_3)\ \&\ SR(b, V_4)$
$\twoheadrightarrow\ SR(b, V_4 + \gamma\,[\,f(\omega_2 V_1, \omega_{2o} V_2, \omega_3 V_3) - V_4\,]\,\Delta t)$

Preparation for action a is affected by a sensory representation of stimulus s (triggering the action), and also strengthened by predicted effect b of the action:

LP4 Preparing and mirroring for an action
If sensory representation of s has level V_1
and sensory representation of b has level V_2
and the preparation for action a has level V_3
then after duration Δt the preparation state for action a will have
level $V_3 + \gamma\,[\, f(\omega_4 V_1,\ \omega_5 V_2) - V_3\,]\,\Delta t$.

$SR(s,V_1)\ \&\ SR(b,V_2)\ \&\ PA(a, V_3)$
$\twoheadrightarrow\ PA(a, V_3 + \gamma\,[\,f(\omega_4 V_1, \omega_5 V_2) - V_3\,]\,\Delta t)$

Prior ownership of an action a is generated by LP5.

LP5 Generating a prior ownership state
If the sensory representation of context c has level V_1
and the sensory representation of s has level V_2
and sensory representation of b has level V_3
and the preparation for action a has level V_4
and prior ownership of a for b, c, and s has level V_5
then after duration Δt prior ownership of a for c, s, and b will have
level $V_5 + \gamma\,[\, f(\omega_6 V_1,\ \omega_7 V_2,\ \omega_8 V_3,\ \omega_9 V_4) - V_5\,]\,\Delta t$.

$SR(c,V_1)\ \&\ SR(s,V_2)\ \&\ SR(b,V_2)\ \&\ PA(a, V_4)\ \&\ PO(a, b, c, s, V_5)$
$\twoheadrightarrow\ PO(a, b, c, s, V_3 + \gamma\,[\,f(\omega_6 V_1, \omega_7 V_2, \omega_8 V_3, \omega_9 V_4) - V_3\,]\ \Delta t)$

In case the context c is self, the prior ownership state strengthens the initiative to perform a as a self-generated action: executing a prepared action depends on whether a prior self-ownership state (for the agent self) is available for this action. This models control over the actual execution of the action (go/no-go decision) and can, for example, be used to veto the action in a late stage of preparation. This is modelled by LP6.

LP6 Action execution
If prior ownership of a for b, self, and s has level V_1
and preparation for action a has level V_2
and the action execution state for a has level V_3
then after duration Δt the action execution state for a will have
level $V_3 + \gamma\,[\, f(\omega_{10} V_1,\ \omega_{11} V_2) - V_3\,]\,\Delta t$.

$PO(a, b, self, s, V_1)\ \&\ PA(a, V_2)\ \&\ EA(a, V_3)$
$\twoheadrightarrow\ EA(a, V_3 + \gamma\,[\,f(\omega_{10} V_1, \omega_{11} V_2) - V_3\,]\ \Delta t)$

Property LP7 describes in a straightforward manner how execution of action a affects the world state b.

LP7 From action execution to effect state
If the execution state for action a has level V_1,
and world state b has level V_2
then after Δt world state b will have
level $V_2 + \gamma\,[\, f(\omega_{12} V_1) - V_2\,]\,\Delta t$.

$EA(a, V_1)\ \&\ WS(b, V_2) \twoheadrightarrow WS(b, V_2 + \gamma\,[\,f(\omega_{12} V_1) - V_2\,]\,\Delta t)$

The following property models how sensor states are updated. It applies to stimulus s1, s2 effect b, and context c (indicated by variable W).

LP8 Generating a sensor state for a world state
If world state W has level V_1
and the sensor state for W has level V_2
then after Δt the sensor state for W will have level $V_2 + \gamma [f(\omega_{13}V_1) - V_2] \Delta t$.
$WS(W, V_1) \;\&\; SS(W, V_2) \twoheadrightarrow SS(W, V_2 + \gamma [f(\omega_{13}V_1) - V_2] \Delta t)$

A retrospective ownership state takes into account the prior ownership, the execution of the action, the context, and the sensory representation of the action's effect:

LP9 Generating a retrospective ownership state
If the sensory representation of context c has level V_1,
and the sensory representation of effect state b has level V_2
and prior ownership of a for b, c, and s has level V_3
and the execution state for action a has level V_4
and retrospective ownership of a for b, c, and s has level V_5
then after Δt retrospective ownership of a for b, c, and s will have level $V_5 + \gamma [f(\omega_{14}V_1, \omega_{15}V_2, \omega_{16}V_3, \omega_{17}V_4) - V_5] \Delta t$.
$SR(c,V_1) \;\&\; SR(b,V_2) \;\&\; PO(a, b, c, s, V_3) \;\&\; EA(a, V_4) \;\&\; RO(a, b, c, s, V_5)$
$\twoheadrightarrow RO(a, b, c, s, V_5 + \gamma [f(\omega_{14}V_1, \omega_{15}V_2, \omega_{16}V_3, \omega_{17}V_4) - V_5] \Delta t))$

Note that LP9 applies to context c that can be self as context, but also another agent B. For another agent as context the connection strength ω_{17} in LP9 is assumed *0* or negative; in the simulated scenarios discussed in Section 3 it was taken $\omega_{17} = -1$. The communication to attribute authorship (to any context c) depends on the retrospective ownership state as specified in LP10.

LP10 Communication of ownership awareness
If retrospective ownership of a for b, c, and s has level V_1,
and communication of a for b, c, and s has level V_2
then after duration Δt communication of a for b, c, and s will have level $V_2 + \gamma [f(\omega_{18}V_1) - V_2] \Delta t$.
$RO(a, b, c, s, V_1) \;\&\; EO(a, b, c, s, V_2)$
$\twoheadrightarrow EO(a, b, c, s, V_2 + \gamma [f(\omega_{18}V_1) - V_2] \Delta t)$

Finally, it is shown in LP11 how the Hebbian learning process of the connection from preparation state for b to sensory representation s2 of an observed action was modelled. This takes place using the following *Hebbian learning rule*, with maximal connection strength *1*, a *learning rate* η, and *extinction rate* ζ (usually taken small):

$$\Delta\omega = \gamma [\eta V_1 V_2 (1 - \omega) - \zeta\omega] \Delta t$$

Here V_1 and V_2 are (time-dependent) activation levels of the connected nodes, and γ is an adaptation speed factor. In differential equation format it can be written as

$$\frac{d\omega}{dt} = \gamma [\eta V_1 V_2 (1 - \omega) - \zeta\omega] = \gamma [\eta V_1 V_2 - (\eta V_1 V_2 + \zeta) \omega]$$

A similar Hebbian learning rule can be found in [11], p. 406. By the factor $(1 - \omega)$ the learning rule keeps the level of ω bounded by *1*. When the extinction rate is relatively low, the upward changes during learning are proportional to both V_1 and V_2 and maximal learning takes place when both are *1*. Whenever one of them is close to *0*, extinction takes over, and ω slowly decreases. This is specified as follows:

LP11 Learning for inverse mirroring
If the sensory representation of stimulus s2 has level V_1,
and the preparation for a has level V_2,
and the connection weight from preparation for a to sensory representation of s2 has level W,
then after duration Δt the connection weight from preparation for b to sensory representation of s2 will have level $W + \gamma [\eta V_1 V_2 (1 - W) - \zeta W] \Delta t$.
$SR(s2, V_1) \;\&\; PA(a, V_2) \;\&\; cs(\omega, W) \twoheadrightarrow cs(\omega, W + \gamma [\eta V_1 V_2 (1 - W) - \zeta W] \Delta t)$

3 Simulation Results

This section presents some simulation results for the model described in Section 2. A number of simulations have been performed with the focus of simulating *normal functioning* and *deviant functioning* of the model. Moreover its effect with the case of an agent having a *poor action prediction capability* and *satisfactory prediction capability* is modeled and results are presented here (see also [22]), relating to *deviant functioning* and *normal functioning*, respectively. For the simulation results shown in Figures 2 and further, time is on the horizontal axis and the activation level of the state properties on the vertical axis. The initialized connection strengths between different states for *normal functioning* are shown in Table 3 below.

Table 3. Overview of the connections and their weights

Connection	ω_1	ω_2	ω_{2o}	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9
Self	1	0.8	-0.6	0.5	0.8	0.8	1	1	1	1
Other	1	-	-	-	-	-	1	1	1	1
	ω_{10}	ω_{11}	ω_{12}	ω_{13}	ω_{14}	ω_{15}	ω_{16}	ω_{17}	ω_{18}	ω_{19}
Self	1	1	1	1	1	1	1	1	1	1
Other	-	-	-	1	-	-	-	-0.4	-	-

These values are kept fixed throughout the simulation, except the connection strength ω which is initialized with *0* and is adapted over time by the Hebbian learning rule given in LP10 in Section 2. Other parameters are set as $\Delta t = 0.1$, learning rate $\eta = 0.3$, extinction rate $\zeta = 0.05$, speed factor $\lambda = 0.001$. A relatively slow value *0.3* for the update speed parameter γ was applied for external processes (action execution, effect generation and effect sensing) modelled by LP6, LP7, and LP8, and a fast value *0.6* for γ for the internal processes modelled by the other LP's. Threshold and steepness values for different states are given in Table 4.

Table 4. Overview Steepness and Threshold values

State	SR(b)	PA(a)	PO (other)	PO (self)	RO (other)	RO (self)	EA(a)	EO (other)	EO (self)
Steepness (σ)	4	4	8	8	20	20	20	40	40
Threshold (τ)	0.1	0.8	4	3	0.87	3.6	1.5	0.6	0.8

For the initial duration of 50 time units the stimulus s2 for the observed action occurs three times for 250 time units alternatively, i.e., for the first 50 time units thw world state for s2 has value *1* and for the next 250 time units value *0*, and so on (see Fig. 3) to generate the similar scenario as described for inverse mirroring case in Section 3. During these 900 time units the world state for context self was kept *0* (see Fig. 4). This represents the situation in which a person observes somebody else performing some action (or bodily change) and the mirroring function of the preparation state makes the person prepare for this action for him or herself.

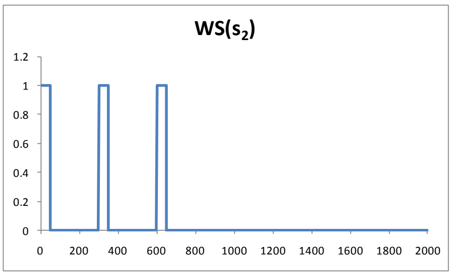

Fig. 3. World State for observed action

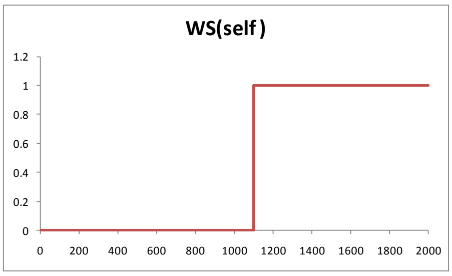

Fig. 4. World State for self

The fluctuation in the activation level of the sensor state repeats the same pattern between *0.1* to *0.9* as it only depends (via LP8) upon the world state for observed action, which also is repetitive. Due to space limitation those graphs are not included here but Fig. 5 shows how the sensory representation for the observed action reacts to the situation described above. For this particular case , as the stimulus for observed action remain present for a very short time i.e 50 time points, after attaining higher activation level, SR(s2) start declining immediately and as WS(self) is *0* during this time hence SR(self) remains *0*.

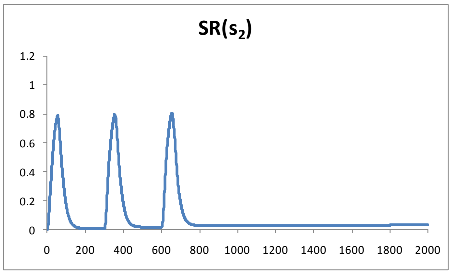

Fig. 5. Sensory Representation for (observed action)

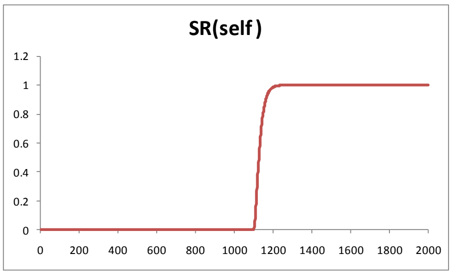

Fig. 6. Sensory Representation for (self)

Consequently prior other-ownership i.e PO(a, b, other, s) did not attain reasonably higher activation level whereas retrospective other-ownership i.e RO(a, b, other, s) keep on fluctuating similar to SRS(other). Moreover prior self-ownership i.e PO(a, b, self, s) and retrospective self-ownership i.e RO(a, b, self, s) remain almost *0* during this time. (see Fig. 7 and Fig. 8)

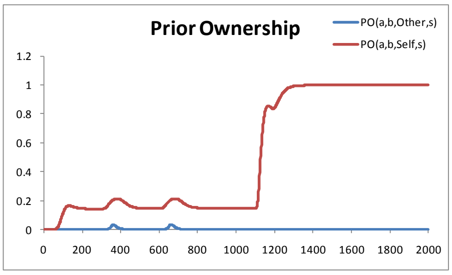

Fig. 7. Prior Ownership

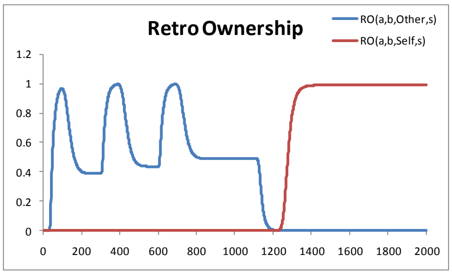

Fig. 8. Retrospective Ownership

Fig. 9 and Fig. 10 show the behavior of preparation state for action a and the representation of the action effect b, respectively.

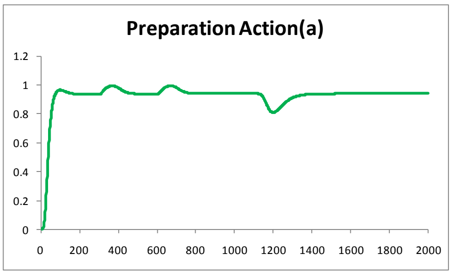

Fig. 9. Preparation Action for a

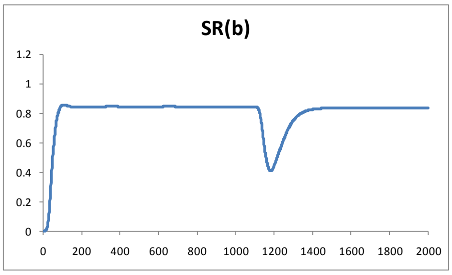

Fig. 10. Sensory representation of b

Due to quite low activation of both *self* and *other* prior-ownership (Fig. 7), one does not observe any action execution for a during this time as shown in Fig. 11.

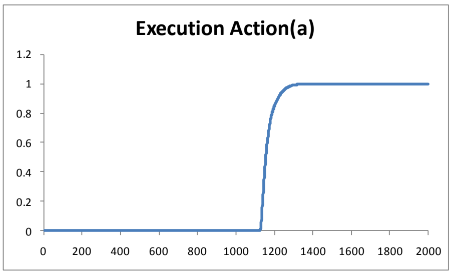

Fig. 11. Action execution for a

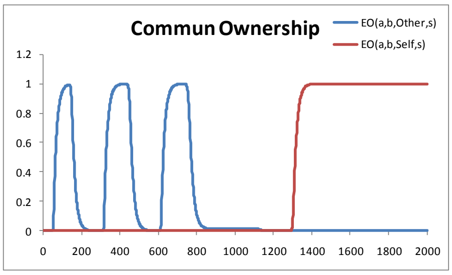

Fig. 12. Communication of ownership

As communication of ownership state is directly related to the retrospective ownership, it shows similar fluctuating activation level as of RO(a, b, c, s) (see Fig. 12). Furthermore the inverse link from preparation state for action a to the sensory representation for the observed action i.e. SR(s2) is not strengthened during this phase which reflects the *normal functioning* of the agent (see Fig.13). Thus in the absence of WS(other), SR(other) also remain zero (see Fig. 13)

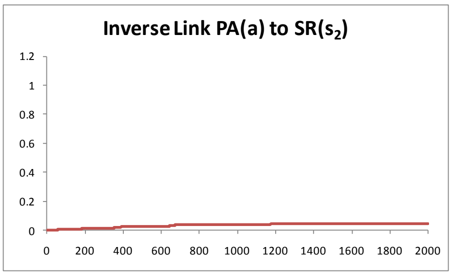

Fig. 13. Normal Functioning

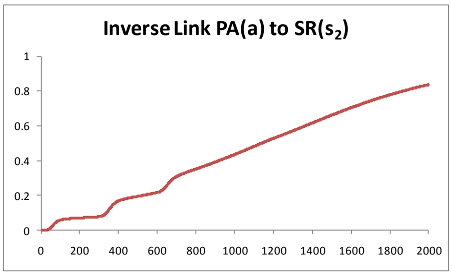

Fig. 14. Deviant Functioning

After that, for 200 time units both the world states stimulus for *self* and *other* are kept *0* from time point 900 to 1100, so that the effect of any stimulus on different states is neutralized as shown in Fig. 3 and Fig. 4. Then after 200 time points the world state for *self* WS(self) is set to 1 while keeping WS(other) at *0*. As from now on WS(self) remains *1*, high activation levels for sensory representation for *self*, prior self-ownership and retrospective self-ownership occur. This in turns produces high activation levels of action execution for a, i.e., EA(a) shown in Fig. 11. Similar behavior can be observed for communication of ownership represented in Fig. 12.

Now to simulate the deviant behavior, again all parameters were initialized with the same values as used to simulate normal behavior shown in Table 3 and Table 4 earlier except the extinction and learning rate: $\eta = 2$, $\zeta = 0.01$ respectively. In contrast to the previous results, by using these parameter settings the inverse link from preparation state for action a to sensory representation of observed action is learnt substantially during first 900 time units as shown in Fig. 14. Due to this higher connection strength of the inverse link, SR(s2) also gains a higher activation level, even in the absence of WS(s2) from 900 onwards (see Fig. 15). Fig. 16 shows the activation level of SR(self).

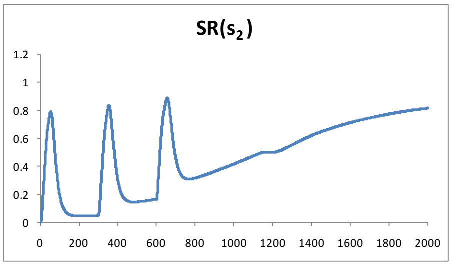

Fig. 15. Sensory Representation for Observed Action

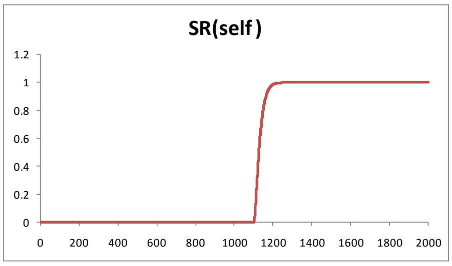

Fig. 16. Sensory Representation for Self

Thus, it results in increasing the value of the retrospective other-ownership, i.e. RO(a, b, other, s) and communication of other-ownership i.e. EO(a, b, other, s) to *0.69* and *0.95* respectively (see Fig. 17 and Fig. 18). Hence an agent develops a mental image of somebody else performing action a and the same is communicated based on the high activation level of the retrospective ownership state.

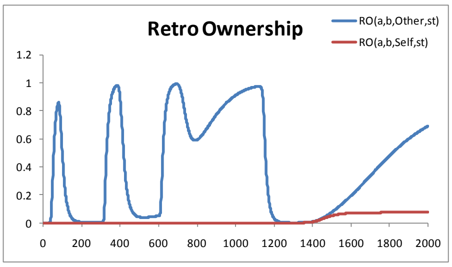

Fig. 17. Retrospective Ownership

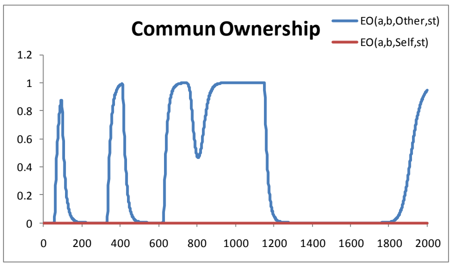

Fig. 18. Communication of Ownership

4 Discussion

The human-like agent model presented in this paper incorporates two mechanisms that play an important role in attributing actions to agents. In the first place it exploits prior and retrospective ownership states for an action based on principles from recent neurological theories; this was adopted from [22]. A prior ownership state is affected by prediction of the effects of a prepared action, and exerts control by strengthening or suppressing actual execution of the action. A retrospective ownership state depends on whether the sensed consequences co-occur with the predicted consequences. In the second place, the agent model incorporates an adaptive inverse mirroring mechanism (adopted from [23]) to generate mental images of an agent to whom an action is attributed. It is shown how poor action effect prediction capabilities can lead to reduced retrospective ownership states for self but higher retrospective ownership states for a (fictitious) other agent, for whom also a mental image is generated, as happens in persons suffering from Schizophrenia.

As discussed in [17] mirroring is a process from an observed action or body state of another person to a person's own preparation states, which involves a mental rotation mapping sensory representations of observed actions of other agents onto the representational structures for self-generated actions. This mental rotation realises a change of perspective from another agent (third-person) to a perspective from oneself (first-person). Attribution a self-generated action to another agent involves a reverse mental rotation, realising a change of perspective from oneself (first-person) to another agent (third-person) perspective. When such a reverse mental rotation is made, a self-generated action is perceived as observed from a third person perspective. The human-like agent model presented in this paper uses such a mechanism, based on inverse mirroring, as introduced in [23]. This mechanism can develop based on Hebbian learning [12], [2], [11]. The adaptive inverse mirroring mechanism adopted from [23] has been integrated in the agent model for ownership states adopted from [22] to obtain the model presented here.

The modelling format used to formally specify the agent model is based on the executable hybrid dynamical modelling language LEADSTO [4]. This hybrid language combines executable temporal logical elements [1] and numerical dynamical system elements [19].

The obtained human-like agent model can be used as a basis for the design of virtual agents in simulation-based training or in gaming. For example, a virtual patient mpdel can be developed based on the presented model so that, for example, a psychiatrist or psycho-therapist (e.g., during his or her education) can gain insight in the processes in certain types of patients, or it can be used by a therapist to analyse how a certain form of therapy can have its effect on these processes. Another type of application may be to design a system for agent-based virtual stories in which, for example, persons with deviations in ownership states play a role (e.g., characters suffering from schizophrenia, attributing their own actions to other real or imaginary persons).

References

1. Barringer, H., Fisher, M., Gabbay, D., Owens, R., Reynolds, M.: The Imperative Future: Principles of Executable Temporal Logic, John Wiley & Sons (1996)
2. Bi, G.Q., and, Poo, M.M.: Synaptic Modifications by Correlated Activity: Hebb's Postulate Revisited. Ann Rev Neurosci 24, 139-166 (2001)
3. Blakemore, S.-J., Wolpert, D.M., and Frith, C.D.: Why can't you tickle yourself? *Neuroreport* 11, 11-16 (2000)
4. Bosse, T., Jonker, C.M., Meij, L. van der, Treur, J.: A Language and Environment for Analysis of Dynamics by Simulation. Intern. J. of AI Tools 16, 435-464 (2007)
5. Damasio, A., and Meyer, K.: Behind the looking-glass. Nature 454, 167-168 (2008)
6. Farrer, C., and Franck, N.: Self-monitoring in schizophrenia. Curr Psychiatry Rev 3, 243-251 (2007)
7. Feinberg, I.: Efference copy and corollary discharge: Implications for thinking and its disorders. Schizophrenia Bulletin 4, 636-640 (1978)
8. Fourneret, P. , de Vignemont, F. , Franck, N. , Slachevsky, A. , Dubois, B., and Jeannerod, M.: Perception of self-generated action in schizophrenia, Cogn. Neuropsych. 7, 139-156 (2002)
9. Frith, C.D., Blakemore, S., & Wolpert, D.: Explaining the symptoms of schizophrenia: Abnormalities in the awareness of action. Brain Research Rev. 31, 357-363 (2000)
10. Frith, C.D.: The cognitive neuropsychology of schizophrenia. Hove: Lawrence Erlbaum Associates Ltd (1992)
11. Gerstner, W., and Kistler, W.M.: Mathematical formulations of Hebbian learning. Biol. Cybern. 87, 404-415 (2002)
12. Hebb, D.O.: The Organization of Behaviour. New York: John Wiley & Sons (1949)
13. Hendriks, M., and Treur, J.: Modeling Super Mirroring Functionality in Action Execution, Imagination, Mirroring, and Imitation. In: Pan, J.-S., et al. (eds.), Computational Collective Intelligence, Proc. ICCCI'10, Part I. LNAI, vol. 6421, pp. 330-342. Springer (2010)
14. Hurley, S.: The shared circuits model: How control, mirroring, and simulation can enable imitation, deliberation, and mind reading. Behavioral and Brain Sciences 31, 1-22 (2008)
15. Iacoboni, M.: Mirroring People: the New Science of How We Connect with Others. Farrar, Straus & Giroux (2008)
16. Jeannerod, M.: The sense of agency and its disturbances in schizophrenia: a reappraisal. Exp Brain Res 192, 527-532 (2009)
17. Jeannerod, M., and Anquetil, T.: Putting oneself in the perspective of the other: A framework for self-other differentiation. Social Neuroscience 3, 356-367 (2008)
18. Moore, J., and Haggard, P.: Awareness of action: Inference and prediction. *Consciousness and Cognition* 17, 136–144 (2008)
19. Port, R.F., Gelder, T. van (eds.): Mind as Motion: Explorations in the Dynamics of Cognition. MIT Press (1995)
20. Rizzolatti, G, and Sinigaglia, C.: Mirrors in the Brain: How Our Minds Share Actions and Emotions. Oxford Univ. Press (2008)
21. Synofzik, M., Thier, P., Leube, D.T., Schlotterbeck, P., and Lindner, A., Misattributions of agency in schizophrenia are based on imprecise predictions about the sensory consequences of one's actions. *Brain* 133, 262–271 (2010)
22. Treur, J.: A Cognitive Agent Model Incorporating Prior and Retrospective Ownership States for Actions. In: Walsh, T. (ed.), *Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence, IJCAI'11*, pp. 1743-1749 (2011)
23. Treur, J., and Umair, M.: A Cognitive Agent Model Using Inverse Mirroring for False Attribution of Own Actions to Other Agents. In: K.G. Mehrotra et al. (eds.): *Proceedings of the 24th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE'11, Part II*. Lecture Notes in Artificial Intelligence, vol. 6704, pp. 109-119. Springer Verlag, Heidelberg-Berlin (2011)
24. Voss, M., Moore, J., Hauser, M., Gallinat, J., Heinz, A., and Haggard, P.: Altered awareness of action in schizophrenia: a specific deficit in predicting action consequences. *Brain* 133, 3104–3112 (2010)