A Neurologically Inspired Network Model for Graziano's Attention Schema Theory for Consciousness

Erik van den Boogaard(✉), Jan Treur, and Maxim Turpijn

Behavioural Informatics Group, Vrije Universiteit Amsterdam, Amsterdam, Netherlands
evandenboogaard@hotmail.com, j.treur@vu.nl, maxim.turpijn@gmail.com

Abstract. This paper describes a network-oriented model based on the neuroscientist Graziano's Attention Schema Theory for consciousness. This theory describes an *attention schema* as an internal model of the attention process supporting the control of attention, similar to how our mind uses a *body schema* as an internal model of the body to control its movements. The Attention Schema Theory comes with a number of testable predictions. After designing a neurologically inspired temporal-causal network model for the Attention schema Theory, a few simulations were conducted to verify some of these predictions. One prediction is that a noticeable attention control deficit occurs when using attention without awareness. Another is that a noticeable attention control deficit occurs when using only bottom-up influence (from the sensory representations) without any top-down influence (for example, from goal or control states). The presented model is illustrated by a scenario where a hunter imagines (using internal simulation) a prey which he wants to attend to and catch, but shortly after he or she imagines a predator which he then wants to attend to and avoid. The outcomes of the simulations support the predictions that were made.

1 Introduction

Understanding and modeling consciousness has been a challenge since a long time. Several theories have been put forward over time, often with involvement of neuroscientists or at least essential knowledge from neuroscience; see, for example, [1,2,5,6,11–13] to name just a few. Some of the themes that often recur in such theories are:

– A winner takes it all competition between unconscious processes in order to achieve a selection of what is to reach consciousness; e.g., [1,2,6]
– Internal simulation of the own mental and bodily processes, other persons' mental and bodily processes, and other external processes; e.g., [5,7,11–13]
– By becoming conscious certain aspects are more explicitly presented to (other parts of) the brain and thus become more accessible to the brain; e.g. [1,2,6]
– The relation between attention and consciousness; e.g., [16]

© Springer International Publishing AG 2017
J.M. Ferrández Vicente et al. (Eds.): IWINAC 2017, Part I, LNCS 10337, pp. 10–21, 2017.
DOI: 10.1007/978-3-319-59740-9_2

– The extent to which consciousness fulfils a functional role in behaviour, or instead is only an epiphenomenon

A recent theory which addresses the above five themes is the Attention Schema Theory for consciousness of the neuroscientist Graziano; see, for example, [8–10,23]. It is claimed that this theory explains the brain basis of subjective awareness in a mechanistic and scientifically testable manner. The theory starts with attention which is a process by which signals compete for the brain's limited computing resources. This internal competition is partly under bottom-up influence of sensory representations and partly under top-down control of other mental states such as goal states or control states. According to this theory the top-down control of attention is improved when the brain has access to an (simplified) internal model of attention itself that can be used for internal simulation of the attention process. The brain therefore constructs a schematic model of the process of attention, called the *Attention Schema*. This is similar to the brain's construct of a schematic model of the body, the *Body Schema*, with its role in body movements. The presence of this internal model for attention leads a brain to concluding that it has a subjective experience.

An advantage of the Attention Schema Theory is that it explains how we can be aware of both internal and external events. The brain can apply attention to many types of information including external sensory information and internal information about, for example, affective and cognitive states. If awareness is based on a model of attention, then this model will pertain to the same domains of information to which attention pertains. A further advantage of this theory is that it has a neurological basis and provides testable predictions. If awareness is based on an internal model of attention, used to help control attention (see Fig. 1), then without awareness, attention should still be possible but could show deficits in control.

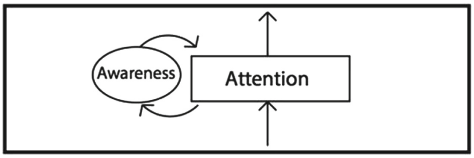

Fig. 1. Awareness as an internal model of attention supporting control of attention

This paper introduces a neurologically inspired computational model for the Attention Schema Theory. The model was designed by a Network-Oriented Modeling approach based on temporal-causal networks [19,20], taking into account causal relations assumed in the Attention Schema Theory. The model addresses all of the five themes mentioned above. It has been used to perform simulation experiments and it was verified by mathematical analysis. Model parameters such as connection weights, update speed factors, and steepness, threshold were estimated to fulfil the requirements that reflect the expected internal behavioural patterns based on the Attention Schema Theory.

2 The Neurologically Inspired Network Model

In this section, the Network-Oriented Modeling approach used is briefly introduced, and the conceptual and numerical representation of the developed network model are described. The Network-Oriented Modeling approach based on temporal-causal networks described in more detail in [19,20] is a generic and declarative dynamic modeling approach based on networks of causal relations. Dynamics is addressed by incorporating a continuous time dimension. This temporal dimension enables modelling by networks that inherently contain cycles, such as networks modeling mental or brain processes, or social interaction processes, and also enables to address the timing of the processes in a differentiated manner. The modeling perspective covers (adaptive) recurrent neural network models and (adaptive) social network models. It is more generic than each of these methods in the sense that a much wider variety of modeling elements are provided, enabling the modeling of many types of dynamical systems, as described by many examples in [19] and confirmed by a formal analysis in [22].

The Network-Oriented Modeling approach is supported by dedicated modeling environments (e.g., in Matlab, or in Pyhon) that can be used to model at a conceptual level. The obtained temporal-causal network models are based on states and connections between them; they can be represented at two levels: by a conceptual representation and by a numerical representation. A conceptual representation of a temporal-causal network model can have a (labeled) graphical form with (states as nodes and connections as edges) or a matrix form (with states on the axes and connections in the cells). More specifically, the following three model parameters define a temporal-causal network, and are part of a conceptual representation of such a network model:

- **connection weight** $\omega_{X,Y}$ Each connection from a state X to a state Y has a *connection weight* $\omega_{X,Y}$ representing the strength of the connection, often between 0 and 1, but sometimes also below 0 (negative effect).
- **combination function** $\mathbf{c}_Y(..)$ For each state Y (a reference to) a *combination function* $\mathbf{c}_Y(..)$ to aggregate the causal impacts of other states on state Y. This can be a standard function from a library (e.g., a scaled sum or logistic function) or an own-defined function.
- **speed factor** η_Y For each state Y a *speed factor* η_Y is used to represent how fast a state is changing upon causal impact, usually in the [0, 1] interval.

Each state Y is assumed to have an (activation) level in the [0, 1] interval that varies over time, indicated in the numerical representation by a real number $Y(t)$. Combination functions can have different forms. The applicability of a specific combination rule may depend much on the type of application addressed, and even on the type of states within an application. Therefore, for the Network-Oriented Modeling approach based on temporal-causal networks a number of standard combination functions are available as options and a number of relevant properties of such combination functions have been identified; e.g., see [19], Chap. 2, Table 2.10. Some of these standard combination functions are scaled sum, max, min, and simple and advanced logistic sum functions. These options cover elements from different existing approaches, varying from approaches based on neural networks to approaches considered for social network modeling, or reasoning with uncertainty or vagueness.

A *conceptual representation* of the designed network model is shown in Fig. 2. The legend shown in Table 1 explains the different states in the model. Nodes outside the box called *Mind* represent external states. For the scenario considered here the model only incorporates two different stimuli; it represents a situation where a human hunter first spots a prey and then is confronted with a predator. This should result in a shift of attention from the prey to the predator and eventually result in the hunter fleeing from the predator instead of going after the prey. An arrow between two nodes means that there is a temporal-causal relation from one state to the pointed state. Such a relation means that one state has either an strengthening (positive connection weight) or a suppressing (negative connection weight) effect on the other state.

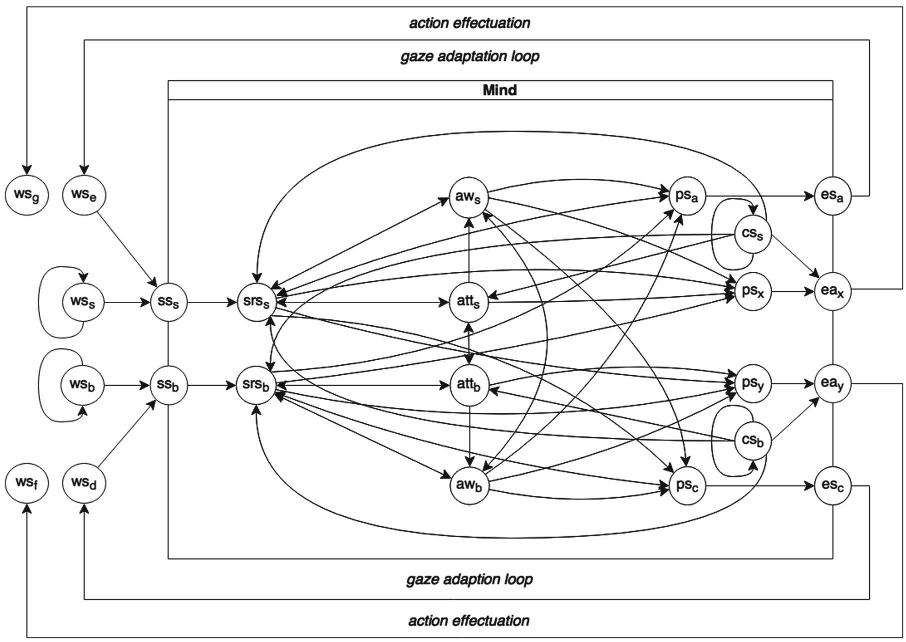

Fig. 2. A graphical conceptual representation of the temporal-causal network model

In the hunter and prey scenario, the external world states ws_s and ws_b respectively represent the prey and predator. The world states ws_e and ws_d represent the output of the *gaze adaptation loop*, which leads to control of the sensor states ss_s and ss_b. This can be interpreted as directing and sharpening of the senses (for example, eyes or ears), as a result of focusing of the attention. The world states ws_f and ws_g represent approaching or distancing behavior with regard to the prey and predator, modelled as *action effectuation*. Specific attention and awareness states were modelled for prey (att_s and aw_s) and predator (att_b and aw_b). These states are affected via both top-down and bottom-up influences. The bottom-up influences occur via the sensory input, which leads to a sensory representation which in turn affect attention and awareness for that input. Top-down influence comes from two control states: cs_s for the prey and cs_b for the predator; for example this can relate to goals.

Besides bottom-up and top-down influence there is also a mutually suppressing effect. For example, a high value of the attention state att_b for the predator will have a suppressing (inhibiting) effect on the attention state att_s for the prey, and conversely. Similarly the awareness states aw_b and aw_s mutually suppress each other. This can work as a winner takes it all competition, in order to obtain a single attention and awareness focus.

Also action execution states are included in the model, with their corresponding preparation states. These can perform gaze adaptation by the *gaze adaptation loop* and actual execution of actions (e.g., escape from the predator) by the *action effectuation loop*. But the preparation states (without activating the corresponding execution states) also play an important role in internal simulation. Internal simulation takes place by using internal *as-if loops* as a kind of shortcuts for the gaze adaptation loop and the action effectuation loop. These as-if loops are modeled by direct (predictive) connections from preparation states to the sensory representation states of the effects of the prepared actions. Via these internal as-if loops, so-called *simulated action and perception chains* are generated [11–13], through which the preparation states directly affect the sensory representation states of the action effects, instead of through the external loop via action execution, action effectuation, and sensing.

The conceptual representation of the model can be transformed into a numerical representation in a systematic manner. The *impact* of state X_i on state Y at time point t can be determined by multiplying the state value $X_i(t)$ of each state X_i $(i = 1, 2, .., k)$ with impact on Y by the weight $\omega_{X_i,Y}$ of the connection from X_i to Y:

$$\mathbf{impact}_{X_i,Y}(t) = \omega_{X_i,Y}\, X(t) \tag{1}$$

The aggregated impact is a combination of multiple impact values $V_{X_i,Y} = \mathbf{impact}_{X_i,Y}(t)$ for the states X_i and is calculated using combination function $\mathbf{c}_Y(..)$:

$$\mathbf{aggimpact}_Y = \mathbf{c}_Y(V_{X_1,Y}, \ldots, V_{X_k,Y}) = \mathbf{c}_Y(\omega_{X_1,Y} X_1, \ldots, \omega_{X_k,Y} X_k) \tag{2}$$

Table 1. Legend of the state labels in the model

ws_s	World state for prey	ps_a	Preparation state for action a
ws_b	World state for predator	ps_c	Preparation state for action c
ss_s	Sensor state for prey	ps_x	Preparation state for action x
ss_b	Sensor state for predator	ps_y	Preparation state for action y
srs_s	Sensory representation state for prey	es_a	Execution state for action a
srs_b	Sensory representation state for predator	es_c	Execution state for action c
aw_s	Awareness state for prey	ea_x	Execution of action x
aw_b	Awareness state for predator	ea_y	Execution of action y
att_s	Attention state for prey	ws_d	World state for d
att_b	Attention state for predator	ws_e	World state for e
cs_s	Control state for prey	ws_f	World state for f
cs_b	Control state for predator	ws_g	World state for g

The speed of the influence of $\mathbf{aggimpact}_Y(t)$ on Y depends on the speed factors η_Y. Thus the following *difference* and *differential* equations are obtained for each state Y:

$$\begin{aligned} T(t+\Delta t) &= Y(t) + \eta_Y\,[\mathbf{aggimpact}_Y(t) - Y(t)]\,\Delta t \\ &= Y(t) + \eta_Y\,[\mathbf{c}_T\,(\omega_{X_1,Y}X_1(t), \ldots, \omega_{X_k,Y}X_k(t)) - Y(t)]\,\Delta t \\ \mathrm{d}Y(t)/\mathrm{d}t &= \eta_Y\,[\mathbf{c}_T\,(\omega_{X_1,Y}X_1(t), \ldots, \omega_{X_k,Y}X_k(t)) - Y(t)] \end{aligned} \tag{3}$$

The current model consists of 24 states and about 50 connections. Note that not all connections are active during a specific scenario, for example, as discussed in the next section. For the combination functions for the control states in the presented model the *identity function* **id(..)** was used:

$$\mathbf{c}_Y(V) = \mathbf{id}(V) = V \tag{4}$$

The identity function was used here as in the scenario illustrated here the control states have only a single impact, from themselves. The other states use the *scaled sum combination function* $\mathbf{ssum}\lambda(\ldots)$ with scaling factor λ:

$$\mathbf{c}_Y(V_1, .., V_k) = \mathbf{ssum}_\lambda(V_1, .., Vk) = (V_1 + .. + V_k)/\lambda \tag{5}$$

To avoid negative state values a prevention is applied: if the outcome of $(V_1 + .. + V_k)/\lambda$ is negative, the value 0 is taken for $\mathbf{ssum}_\lambda(V_1, .., V_k)$ instead; so in fact the following is used: $\mathbf{ssum}_\lambda(V_1, .., V_k) = \max(0, (V_1 + .. + V_k)/\lambda)$. This is important for cases in which negative connection weights are involved to model suppression. Note that in the Network-Oriented Modeling approach followed, also alternative combination functions can be used, for example logistic sum functions. A change of combination function is similar to and as simple as a change of a parameter value.

3 Simulation Experiments

Several scenarios were simulated, based on the literature on the Attention Schema Theory, with a hunter first hunting for a spotted prey and later fleeing from a spotted predator. Figure 3 shows an internal simulation scenario. In this scenario the external stimuli (ws_s and ws_b) are inactive and the internal states are triggered internally by the control states (cs_s and cs_b). All parameter values of this example simulation can be found in the Appendix.

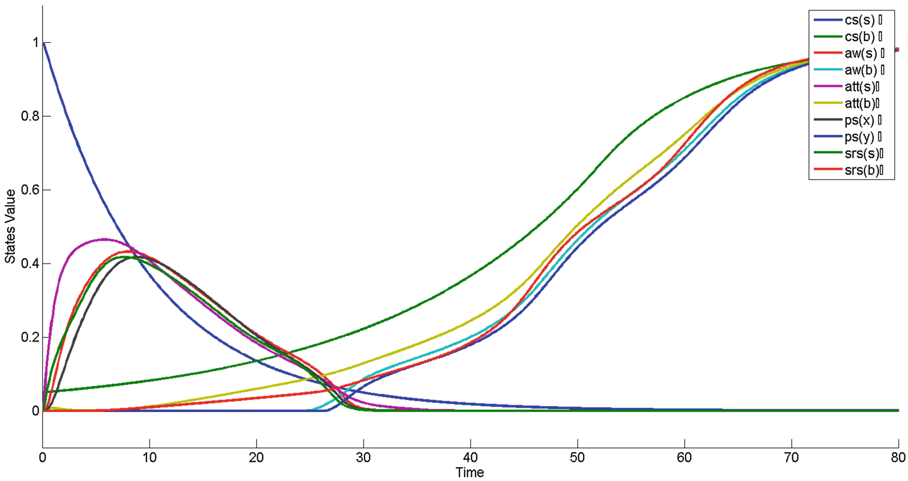

Fig. 3. Example simulation: internal simulation

The hunter first visualizes (constructs a mental image of) a prey and attention to it and then visualizes a predator and attention to it. This will cause a shift in (simulated) attention from the prey to the predator. For this scenario, the attention state att_s for the prey initially increases, which also leads to an increase in awareness state aw_s of the prey. As soon as the predator is visualized, the attention shifts from the prey to the predator which is shown as a *decrease* in the activation level of the attention state att_s for the prey and an *increase* in the level of the attention state att_b for the predator. This effect also occurs for the awareness states aw_s and aw_b for prey and predator. The sensory representation states and preparation states for action execution also follow the same trend, but no action is executed, because as it only concerns internal simulation, these states are suppressed by the control states.

4 Verification by Mathematical Analysis

In order to verify the model a general method for verification of temporal-causal networks was followed. It is based on substitution of values from a simulation in stationary point equations; see [21] or [19] Chap. 12. A state Y has a *stationary point* at time point t if $\mathrm{d}Y(t)/\mathrm{d}t = 0$. A stationary point is usually a local maximum or a local minimum. Using the simulations by the model, several stationary points can be found. Using the difference or differential Eq. (3) mentioned earlier and a scaled sum combination function it can be deduced that a state Y has a stationary point at t if and only if:

$$\begin{aligned} &\mathbf{aggimpact}_Y(t) = Y(t) \\ &\mathbf{c}_Y\left(\omega_{X_1,Y}X_1(t), \ldots, \omega_{X_k,Y}X_k(t)\right) = Y(t) \\ &\left(\omega_{X_1,Y}X_1(t) + \cdots + \omega_{X_k,Y}X_k(t)\right)/\lambda = Y(t) \end{aligned} \tag{6}$$

Three stationary points were selected:

1. a local maximum for state att_s (attention for the prey)
2. a local minimum for state ps_y (preparation state *before* attention shifts from prey to predator)
3. a local minimum for state srs_s (sensory representation state *after* attention shifts from prey to predator)

According to this verification method, the model is verified by using for each of the stationary points mentioned above the state values from the simulation and substituting them into the equation above (6). As an example, the equation expressing that att_s is stationary at time t is as follows:

$$\begin{aligned} &\mathbf{aggimpact}_{\mathbf{att}_s}(t) = \mathrm{att}_s(t) \\ &\max\left(0, \left(\omega_{\mathbf{cs}_s,\mathbf{att}_s}\mathrm{cs}_s(t) + \omega_{\mathbf{srs}_s,\mathbf{att}_s}\mathrm{srs}_s(t) + \omega_{\mathbf{att}_b,\mathbf{att}_s}\mathrm{att}_b(t)\right)/\lambda\right) \\ &= \mathrm{att}_s(t) \end{aligned} \tag{7}$$

In the simulation results shown in Fig. 3 a maximum for state att_s is found at $t = 5.8$. For att_s, the scaling factor is $\lambda = 1.7$. This provides the equation

$$\begin{aligned} &\max\left(0, \left(\omega_{\mathbf{cs}_s,\mathbf{att}_s}\mathrm{cs}_s(5.8) + \omega_{\mathbf{srs}_s,\mathbf{att}_s}\mathrm{srs}_s(5.8) + \omega_{\mathbf{att}_b,\mathbf{att}_s}\mathrm{att}_b(5)\right)/1.7\right) \\ &= \mathrm{att}_s(5.8) \end{aligned} \tag{8}$$

From the simulation data it was found that the state value for att_s at this time point is 0.4651, while the state value for cs_s is 0.5639 at $t = 5.8$, srs_s had a state value of 0.3954, and att_b had a state value of 0. The weight $\omega_{\mathbf{cs}_s,\mathbf{att},s}$ was 0.7, the weight $\omega_{\mathbf{srs}_s,\mathbf{att},s}$ was 1 and the weight $\omega_{\mathbf{att}_b,\mathbf{att},s}$ was -0.1. Substituting these values into the equation above (7) results in the following

$$\begin{gathered} \max(0, (0.7 * 0.5639 + 1 * 0.3954 - 0.1 * 0)/1.7) = 0.4651 \\ 0.4648 = 0.4651 \end{gathered}$$

So the equation for this stationary point holds with an accuracy <0.001. Next stationary points verified are a minimum for ps_y that can be found at $t = 20$ and a minimum for srs_s found at $t = 60$. The same method was used as above and this resulted in the following equations:

$$\begin{aligned} &\max(0, (\omega_{\mathbf{aw}_b,\mathbf{ps}_y}\mathrm{aw}_b(20) + \omega_{\mathbf{srs}_s,\mathbf{ps}_y}\mathrm{srs}_s(20) + \omega_{\mathbf{att}_b,\mathbf{ps}_y}\mathrm{att}_b(20) + \\ &\omega_{\mathbf{srs}_b,\mathbf{ps}_y}\mathrm{srs}_b(20))/\lambda) = \mathrm{ps}_y(20) \end{aligned} \tag{9}$$

Substitution of the values provides

$$\begin{gathered}\max(0, (1 * 0 - 1 * 0.1932 + 0 * 0.0596 + 1 * 0.0343)/2) = 0\\ \max(0, -0.0794) = 0\\ 0 = 0\end{gathered}$$

So, the equation for this stationary point holds with accuracy 0. Finally

$$\begin{aligned}&\max(0, (\omega_{\mathbf{ss}_s,\mathbf{srs}_s}\mathrm{ss}_s(60) + \omega_{\mathbf{cs}_s,\mathbf{srs}_s}\mathrm{cs}_s(60) + \omega_{\mathbf{aw}_s,\mathbf{srs}_s}\mathrm{aw}_s(60)\\ &+ \omega_{\mathbf{att}_s,\mathbf{srs}_s}\mathrm{att}_s(60) + \omega_{\mathbf{ps}_a,\mathbf{srs}_s}\mathrm{ps}_a(60)\omega_{\mathbf{cs}_b,\mathbf{srs}_s}\mathrm{cs}_b(60))/\lambda) = \mathrm{srs}_s(60)\end{aligned} \tag{10}$$

Substitution provides:

$$\begin{gathered}\max(0, (1 * 0.0017 + 1 * 0.0024 + 1 * 0 + 1 * 0 + 1 * 0 - 3 * 0.8503)/5) = 0\\ \max(0, -0.5094) = 0\\ 0 = 0\end{gathered}$$

The equation for this stationary point also holds with a very small accuracy 0. These verification results provide some evidence that the implemented model is correct.

5 Discussion

The presented neurologically inspired temporal-causal network model, designed following the Network-Oreinted Modeling approacvh put forward in [19,20], is based on the Attention Schema Theory for consciousness recently developed by neuroscientist Michael S.A. Graziano and others; e.g. [8–10,23]. The model was illustrated for a relatively simple scenario in which an attention shift takes place in relation to two different stimuli. For reasons of presentation the incorporated model of attention was kept simple. However, the network model can also incorporate a more complex model for attention involving multiple stimuli, for example, as described in [4].

A number of conclusions can be drawn from the different simulation experiments that have been performed using the developed model, among which the one shown in Sect. 3. These simulation experiments show a functional role of awareness in evolutionary perspective as theorized by, for example, [6]. Given the temporal-causal loop between attention and awareness, it turns out that the impact on attention grows faster and higher than without this loop being active. Based on the results of simulation scenarios such as the one shown in Fig. 3, support was found for a positive effect of visualizing a scenario by internal simulation to the flow of attention and awareness. With an amplifying effect of the (bottom-up) sensory representation states, the effect on both attention and awareness is prolonged with an amplifying effect on attention to the predator which may lead to a faster response to the occurrence of the predator, because a preparation state threshold is exceeded sooner. This suggests a potential faster response to, for example, an encounter with a predator or prey which implies an increased survival chance and therefore an evolutionary advantage. So, it seems that the developed model based on the Attention Schema Theory, connects well to some theories about the functional role of awareness; see also [23]. These theories also provide an answer to the question of whether or not subjective awareness serves a useful purpose or whether it is merely an epiphenomenon with no clear purpose. This suggests that an attention schema may be of great utility, at least, in the top-down control of attention.

Future research can be done to test the model more extensively, by simulating more scenarios, in relation to claims made in literature such as [8–10,23]. Although these scenarios at the time of writing were not all tested yet, it is however likely that the model will also work with these scenario's, because they mostly largely rely on the same internal connections and patterns generated by them. The following additional example scenarios are some of the relevant ones:

1. *Simulation with external stimuli* of a prey and a predator.
   Based on previous results with the model using control states to trigger internal simulation (visualization) of stimuli (prey and predator), similar results using real world external stimuli (world states for prey and predator) can be expected. The only real difference is that in this case the sensory representation states are activated by the sensor states instead of by the control states; the rest of the processes will be similar.
2. Simulation with external stimuli (visible prey and predator) and external reactions (eye gaze, approaching, fleeing) using *attention without awareness*
   In this scenario first the hunter attends to the prey which he does *not* become aware of (achieved by disconnecting those parts of the model), and soon after the predator comes into sight his attention shifts from the prey to the predator and there is no shift in awareness from the prey to the predator. It can be predicted that the attention level - *without* awareness - will not rise as fast and as high as *with* awareness, as there are less causal impacts on the attention states; see also [23]. If this indeed is the case, then this confirms that awareness can play a crucial role in attention such that *without* awareness a reaction to spotting a prey or a predator may be too late or even absent which leads to an increased existential risk for the hunter.
3. A *mirroring scenario* where an individual spots another hunter reacting to a prey and a predator.
   In this case the trigger is not from internal control states or from external stimuli concerning prey or predator, but from external stimuli concerning observation of another hunter addressing prey and predator. By way of modeling a mirroring mechanism, the sensory representations corresponding to these observations are connected to the own preparation states (with mirror function) as if the hunter him or herself would be in the situation. These preparation states trigger the whole internal simulation process (mental imagination) as shown in Sect. 3. Based on the results of the presented model, for this case similar results can be expected compared to the case of using real external stimuli (for prey and predator) for the hunter him or herself. In addition, a self-other distinction control state can be incorporated, so that the hunter is able to know that in this case it is not his or her own process

that is internally simulated but somebody else's. This is a basis for generating empathy with somebody else: having and feeling the same mental states, but at the same time knowing that they are relating to states of somebody else; e.g., [18]. This scenario relates to an angle on consciousness as related to social interaction; see also [9], Chap. 10 on more elaboration on the relation of the Attention Schema Theory to social theories of consciousness, and [14] to how this may relate to attributing awareness to somebody else.

Appendix Parameter Values Used in the Example Simulation Shown in Sect. 3

	states and connections	1 ws_s	2 ws_b	3 ss_s	4 ss_b	5 srs_s	6 srs_b	7 aw_s	8 aw_b	9 att_s	10 att_b	11 ps_a	12 ps_c	13 ps_x	14 ps_y	15 es_a	16 es_c	17 cs_s	18 ea_x	19 cs_b	20 ea_y	21 ws_d	22 ws_e	23 ws_f	24 ws_g
1	ws_s	**0.9**	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	ws_b	0	**1.5**	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	ss_s	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	ss_b	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	srs_s	0	0	0	0	0	0	1	0	1	0	1	-1	1	-1	0	0	0	0	0	0	0	0	0	0
6	srs_b	0	0	0	0	0	0	0	1	0	1	-1	1	-1	1	0	0	0	0	0	0	0	0	0	0
7	aw_s	0	0	0	0	1	0	0	-1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
8	aw_b	0	0	0	0	0	1	-1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
9	att_s	0	0	0	0	1	0	1	0	0	-0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	att_b	0	0	0	0	0	1	0	1	-0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	ps_a	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
12	ps_c	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
13	ps_x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
14	ps_y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
15	es_a	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
16	es_c	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
17	cs_s	0	0	0	0	1	-0.1	0	0	0.7	0	0	0	0	0	0	0	-2	-1	0	0	0	0	0	0
18	ea_x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
19	cs_b	0	0	0	0	-3	1	0	0	0	0.7	0	0	0	0	0	0	0	0	1.5	-1	0	0	0	0
20	ea_y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
21	ws_d	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	ws_e	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	ws_f	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	ws_g	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
speed factors	**0.3**	**0.3**	1	1	1	1	1	1	1	1	1	1	1	1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0	0
initial values	**0**	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0.05	0	0	0	0	0
combination functions																								
id(.)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	**1**	**1**
ssum(..)	0	0	0	0	1	1	1	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0
factor λ	0	0	0	0	5	5	2	2	1.7	1.7	0	0	2	2	0	0	0	0	0	0	0	0	0	0
slogistic(..)	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
steepness σ	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
threshold τ	0.6	0.368	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
alogistic(..)	0	0	1	1	0	0	0	0	0	0	1	1	0	0	1	1	0	1	0	1	1	1	0	0
steepness σ	**0**	**0**	10	10	0	0	0	0	0	0	10	10	0	0	10	10	0	10	0	10	10	10	0	0
threshold τ	**0**	**0**	0.5	0.5	0	0	0	0	0	0	0.5	0.5	0	0	0.5	0.5	0	0.5	0	0.5	0.5	0.5	0	0

References

1. Baars, B.J.: In the Theater of Consciousness: The Workspace of the Mind. Oxford University Press, Oxford (1997)

2. Baars, B.J.: The conscious access hypothesis: origins and recent evidence. Trends Cogn. Sci. **6**, 47–52 (2002)
3. Bosse, T., Jonker, C.M., Treur, J.: Formalisation of Damasio's theory of emotion, feeling and core consciousness. Conscious. Cogn. **17**, 94–113 (2008)
4. Bosse, T., van Maanen, P.-P., Treur, J.: Simulation and formal analysis of visual attention. Web Intell. Agent Syst. **7**, 89–105 (2009)
5. Damasio, A.R.: The Feeling of What Happens. Body and Emotion in the Making of Consciousness. Harcourt Brace, New York (1999)
6. Dennett, D.C.: Consciousness Explained. Little Brown, Boston (1991)
7. Goldman, A.I.: Simulating Minds: The Philosophy, Psychology, and Neuroscience of Mindreading. Oxford University Press, New York (2006)
8. Graziano, M.S.A., Webb, T.W.: The attention schema theory: a mechanistic account of subjective awareness. Front. Psychol. **6**, 1–11 (2015)
9. Graziano, M.S.A.: Consciousness and the Social Brain. Oxford University Press, New York (2013)
10. Graziano, M.S.A., Webb, T.W.: A mechanistic theory of consciousness. Int. J. Mach. Conscious. **6**, 163–176 (2014)
11. Hesslow, G.: Will neuroscience explain conscious-ness? J. Theoret. Biol. **171**, 29–39 (1994)
12. Hesslow, G.: Conscious thought as simulation of behaviour and perception. Trends Cogn. Sci. **6**, 242–247 (2002)
13. Hesslow, G.: The current status of the simulation theory of cognition. Brain Res. **1428**, 71–79 (2012)
14. Kelly, Y.T., Webb, T.W., Meier, J.D., Arcaro, M.J., Graziano, M.S.A.: Attributing awareness to oneself and to others. In: Proceedings of the National Academy of Sciences, U.S.A., vol. 111, pp. 5012–5017 (2014)
15. Kim, J.: Philosophy of Mind. Westview Press, Boulder (1996)
16. Koch, C., Tsuchiya, N.: Attention and consciousness: two distinct brain processes. Trends Cogn. Sci. **11**, 16–22 (2007)
17. Port, R.F., van Gelder, T.: Mind as Motion: Explorations in the Dynamics of Cognition. MIT Press, Cambridge (1995)
18. Singer, T., Leiberg, S.: Sharing the emotions of others: the neural bases of empathy. In: Gazzaniga, M.S. (ed.), pp. 973–986. MIT Press (2009)
19. Treur, J.: Network-Oriented Modeling: Addressing Complexity of Cognitive, Affective and Social Interactions. Springer, Heidelberg (2016)
20. Treur, J.: Dynamic modeling based on a temporal-causal network modeling approach. Biologically Inspired Cogn. Architectures **16**, 131–168 (2016)
21. Treur, J.: Verification of temporal-causal network models by mathematical analysis. Vietnam J. Comput. Sci. **3**, 207–221 (2016)
22. Treur, J.: On the applicability of network-oriented modeling based on temporal-causal networks: why network models do not just model networks. J. Inf. Telecommun. **1**, 23–40 (2017)
23. Webb, T.W., Kean, H.H., Graziano, M.S.A.: Effects of awareness on the control of attention. J. Cogn. Neurosci. **28**(6), 842–885 (2016)

http://www.springer.com/978-3-319-59739-3

Natural and Artificial Computation for Biomedicine and Neuroscience
International Work-Conference on the Interplay Between Natural and Artificial Computation, IWINAC 2017, Corunna, Spain, June 19-23, 2017, Proceedings, Part I
Ferrández, J.M.; Álvarez-Sánchez, J.R.; de la Paz, F.; Toledo Moreo, J.; Adeli, H. (Eds.)
2017, XXII, 476 p. 160 illus., Softcover
ISBN: 978-3-319-59739-3