Learning to Believe by Feeling: an Agent Model for an Emergent Effect of Feelings on Beliefs

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Abstract. An agent's beliefs usually depend on cognitive factors, but also affective factors may play a role. This paper presents an agent model that shows how such affective effects on beliefs can emerge and become stronger over time due to experiences obtained. In this way an effect of judgment by 'experience' or 'gut feeling' can be obtained. It is shown how based on Hebbian learning a connection from feeling to belief can develop. Some example simulation results and a mathematical analysis of the equilibria are presented.

Keywords: agent model, emergent effect, believing, feeling, Hebbian learning

1 Introduction

Beliefs that are activated usually trigger emotional responses that result in certain feelings. Conversely, emotions felt can also have an effect on beliefs, as discussed in empirical work such as [11], [12], [13], [20], [21] and [22]. Connections from feelings to beliefs might be assumed given a priori (innate), but in this paper it is shown how it such connections can emerge by a Hebbian learning mechanism; cf. [2], [14], [15]. To this end, elements from neurological theories on emotion and feeling were adopted, following lines as described in [5], [9], [10] and [22].

A main focus here is on how the effect of the feeling on the belief can emerge over time. To model this, it is assumed that due to a Hebbian learning mechanism over time the connection from feeling to belief gets nonzero strength: the agent learns to strengthen its belief based on a supporting feeling. As a consequence, when such a feeling would be absent, the agent's belief would develop less strength; the feeling gives it its full strength. This principle models the idea that over time persons build up certain intuitions or gut feelings, and let these play an important role in what to (fully) believe and what not to believe.

In this paper, first in Section 2 a dynamical agent model for the generation of feelings based on a recursive as-if body loop is introduced. In Section 3, the Hebbian learning model is described. Section 4 presents some simulation results. In Section 5 a mathematical analysis of the equilibria of the model is presented. Finally, Section 6 is a discussion.

2 An Agent Model for the Dynamics of Believing and Feeling

As mental states in a person usually do, any belief state induces emotions felt within this person, as described by Damasio in [9] and [10]. In some more detail, emotion generation via an as-if body loop roughly proceeds according to the following causal chain; see [9] and [10]: belief → preparation for body state → sensory representation of body state → feeling. The as-if body loop is extended to a recursive as-if body loop by assuming that the preparation of the bodily response is also affected by the state of feeling the emotion: feeling → preparation for the body state; as an additional causal relation. Such recursiveness is also assumed by [10], p. 91. Thus the obtained model for emotion generation is based on reciprocal causation relations between emotion felt and preparations for body states. Within the model used both the preparation for the bodily response and the feeling are assigned an (activation) level or gradation, expressed by a number, which is assumed dynamic; for example, the strength of a smile and the extent of happiness. The cycle is modelled as a positive feedback loop, triggered by a belief and converging to a certain level of feeling and preparation for body state. An overview of this dynamical model for the agent's believing and feeling is depicted in Figure 1. In this picture states represent groups of neurons, indicated by circle icons, labeled with representations from the detailed specifications explained below. However, note that the precise numerical relations between the indicated variables V representing activation levels, are not expressed in this picture, but below in the detailed specifications of dynamic properties for the temporal relations between these states (labeled by LP1 to LP6 as shown in the picture). Note that the sensor and effector state for body states and the dashed arrows connecting them to internal states are not used in the model.

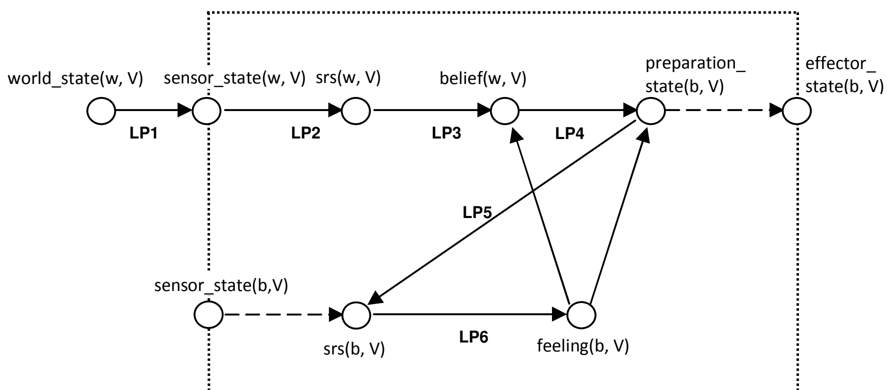

Fig 1: Overview of the agent model for the dynamics of believing and feeling

Informally described theories in, for example, biological or neurological disciplines, often are formulated in terms of causal relationships or in terms of dynamical systems. To adequately formalise such a theory the hybrid dynamic modelling language LEADSTO has been developed that subsumes qualitative and quantitative causal relationships, and dynamical systems; cf. [3]. This language has been proven successful to obtain agent models in a number of contexts, varying from biochemical processes that make up the dynamics of cell behaviour (cf. [16]) to neurological and cognitive processes (e.g., [4], [5] and [6]). Within LEADSTO the *dynamic property* or temporal relation a $\twoheadrightarrow_D$ b denotes that when a state property a occurs, then after a certain time delay (which for each relation instance can be specified as any positive real number D), state property b will occur. Below, this D will be taken as the time step Δt, and usually not be mentioned explicitly. In LEADSTO both logical and numerical calculations can be specified in an integrated manner, and a dedicated software environment is available to support specification and simulation. In the dynamic properties below capitals are used for variables (assumed universally quantified). First the part is presented that describes the basic mechanisms to generate a belief state and the associated feeling. The first dynamic property addresses how properties of the world state are sensed. Note that first a semiformal and next a formal representation is shown.

LP1 Sensing a world state

If world state property W occurs of strength V
then the sensor state for W will have strength V.

world_state(W, V) $\twoheadrightarrow$ sensor_state(W, V)

From the sensor states, sensory representations are generated according to LP2.

LP2 Generating a sensory representation for a sensed world state

If the sensor state for world state property W has strength V,
then the sensory representation for W with have strength V.

sensor_state(W, V) $\twoheadrightarrow$ srs(W, V)

Next the property is described that relates a sensory representation and a feeling to a belief strength. Here a connection strength ω_1 from sensory representation to belief and ω_2 from feeling to belief is assumed. In Section 4 it will be discussed how the connection strength ω_2 is adapted by a Hebbian learning principle. A function $g(\beta_1, \omega_1, \omega_2, V_1, V_2)$ is used for the way in which activation levels V_1 and V_2 of sensory representation and feeling are combined taking into account the connection strengths. Here β_1 is a parameter called the person's orientation for believing; value 0 indicates that the person is reluctant to believe and 1 that the person is willing to believe.

LP3 Generating a belief state for a feeling and a sensory representation

If a sensory representation for w with strength V_1 occurs,
and the associated feeling of b has strength V_2
and the belief for w has strength V_3
and the connection from sensory representation to belief of w has strength ω_1
and the connection from feeling b to belief of w has strength ω_2
and β_1 is the person's orientation for believing
and γ_1 is the person's flexibility for beliefs
then after Δt the belief for w will have strength $V_3 + \gamma_1(g(\beta_1, \omega_1, \omega_2, V_1, V_2)-V_3)\,\Delta t$.

srs(w, V_1) & feeling(b, V_2) & belief(w, V_3) & has_connection_strength(srs(w), belief(w), ω_1)
& has_connection_strength(feeling(b), belief(w), ω_2)
$\twoheadrightarrow$ belief(w, $V_3 + \gamma_1$ (g(β_1, ω_1, ω_2, V_1,V_2) - V_3) Δt)

For the function $g(\beta_1, \omega_1, \omega_2, V_1, V_2)$ the following was taken:

$$g(\beta_1, \omega_1, \omega_2, V_1, V_2) = \beta_1(1-(1-\omega_1 V_1)(1-\omega_2 V_2)) + (1-\beta_1)\, \omega_1 \omega_2 V_1 V_2$$

This function $g(\beta_1, \omega_1, \omega_2, V_1, V_2)$ can be considered to play the role of a quadratic threshold function, parameterised by β_1. Note that for connection strength $\omega_2 = 0$ (no effect of feeling on belief) the formula reduces to following:

$$g(\beta_1, \omega_1, 0, V_1, V_2) = \beta_1(1-(1-\omega_1 V_1)) = \beta_1 \omega_1 V_1$$

In the example simulations discussed in Section 4 the connection strength ω_1 was 1.

Dynamic property LP4 describes the emotional response to a belief in the form of the preparation for a specific bodily reaction. The resulting level for the preparation is calculated based on a function $h(\beta_2, \omega_3, \omega_4, V_1, V_2)$ of the original levels. Here ω_3 is the connection strength from belief to preparation and ω_4 from feeling to preparation.

LP4 From belief and feeling to preparation of a body state

If belief w with strength V_1 occurs
and feeling the associated body state b has strength V_2
and the preparation state for b has strength V_3
and the connection from belief of w to preparation for b has strength ω_3
and the connection from feeling b to preparation for b has strength ω_4
and β_2 is the person's orientation for emotional response
and γ_2 is the person's flexibility for bodily responses
then after Δt the preparation state for body state b will have strength $V_3 + \gamma_2(h(\beta_2, \omega_3, \omega_4, V_1, V_2)-V_3)\,\Delta t$.

belief(w, V_1) & feeling(b, V_2) & preparation_state(b, V_3) &
has_connection_strength(belief(w), preparation(b), ω_3) &
has_connection_strength(feeling(b), preparation(b), ω_4)
→ preparation_state(b, $V_3+\gamma_2(h(\beta_2, \omega_3, \omega_4, V_1, V_2)-V_3)\,\Delta t$)

For the function $h(\beta_2, \omega_3, \omega_4, V_1, V_2)$ the following has been taken:

$$h(\beta_2, \omega_3, \omega_4, V_1, V_2) = \beta_2\,(1-(1-\omega_3 V_1)(1-\omega_4 V_2)) + (1-\beta_2)\,\omega_3\omega_4 V_1 V_2$$

In the example simulations discussed in Section 4 the connection strengths ω_3 and ω_4 have been set on 1. Dynamic properties LP5 and LP6 describe the as-if body loop.

LP5 From preparation to sensory representation of a body state

If preparation state for body state B occurs with strength V,
then the sensory representation for body state B with have strength V.

preparation_state(B, V) → srs(B, V)

LP6 From sensory representation of body state to feeling

If a sensory representation for body state B with strength V occurs,
then B will be felt with strength V.

srs(B, V) → feeling(B, V)

3 How the Agent Learns to Believe by Feeling

This far it was discussed how via a converging loop activated beliefs lead to certain feelings. Conversely, persons may affect the strength of their beliefs by their feelings in the sense that, for example, an optimist person strengthens beliefs that have a positive feeling associated and a pessimistic person strengthens beliefs with a negative associated feeling. Thus the strengths of beliefs may depend on noninformational aspects of mental processes and related personal characteristics. To model this for the case of feelings a connection from feeling to belief is used; see Figure 1. Support for a connection from feeling to belief from a neurological theory can be found in Damasio's Somatic Marker Hypothesis; cf. [1], [7], [8] and [10]. This is a theory on decision making with a central role for emotions felt. Each decision option induces (via an emotional response) a feeling which is used to mark the option. For example, when a negative somatic marker is linked to a particular option, it provides a negative feeling for that option. Similarly, a positive somatic marker provides a positive feeling for that option. Damasio describes the use of somatic markers in the following way: 'the somatic marker (...) forces attention on the negative outcome to which a given action may lead, and functions as an automated alarm signal (…) When a positive somatic marker is juxtaposed instead, it becomes a beacon of incentive. (…) on occasion somatic markers may operate covertly (without coming to consciousness) and may utilize an 'as-if-loop'.' ([7], pp. 173-174). Usually the Somatic Marker Hypothesis is applied to provide endorsements or valuations for options for a person's decisions on actions. However, it may be considered plausible that such a mechanism is applicable to valuations of internal states such as beliefs as well.

One of the elements of the Somatic Marker Hypothesis is that somatic markers depend on past experiences of the person. Within the agent model introduced above this element is incorporated by making the connection strength from feeling to believing adaptive, dependent on beliefs and feelings experienced over time. From a Hebbian neurological perspective [15], strengthening of a connection from feeling to belief over time may be considered plausible, as neurons involved in the belief and in the associated feeling will often be activated simultaneously. Therefore such a connection from feeling to belief may be developed and adapted based on a Hebbian learning mechanism [2], [14] and [15]: connections between neurons that are activated simultaneously are strengthened, similar to what has been proposed for the emergence of mirror neurons in, e.g., [17] and [18].

Based on these considerations, in the agent model the connection strength ω is adapted using the following Hebbian learning rule. It takes into account a maximal connection strength *1*, a learning rate η, and an extinction rate ζ. A similar Hebbian learning rule can be found in ([14], p. 406). By the factor $(1 - \omega)$ the learning rule keeps the level of ω bounded by *1* (which could be replaced by any number), as Hebbian learning without such a bound usually provides instability. When extinction is neglected, the upward changes during learning are proportional to both V_1 and V_2, which in particular means that no learning takes place whenever one of them is *0*, and maximal learning takes place when both are *1*.

LP8 Hebbian learning rule

If the belief for w has strength V_1
and the feeling of b has strength V_2
and the connection from feeling b to belief of w has strength ω
and the learning rate from feeling b to belief of w is η
and the extinction rate from feeling b to belief of w is ζ
then after Δt the connection from feeling b to belief of w will have strength $\omega + (\eta V_1 V_2 (1 - \omega) - \zeta\omega)\, \Delta t$.

feeling(b, V_1) & belief(w, V_2) & has_connection_strength(b, w, ω) &
has_learning_rate(b, w, η) & has_extinction_rate(b, w, ζ)
$\twoheadrightarrow$ has_connection_strength(b, w, $\omega + (\eta V_1 V_2 (1 - \omega) - \zeta\omega)\, \Delta t$)

4 Example Simulation Results

Based on the agent model described in the previous section, a number of simulations have been performed. Some example simulation traces are included in this section as an illustration; see Figure 2, Figure 3 and Figure 4 (the time delays within the LEADSTO relations were taken 1 time unit). Here the connection strengths ω_1, ω_3 and ω_4 have been set on *1*.

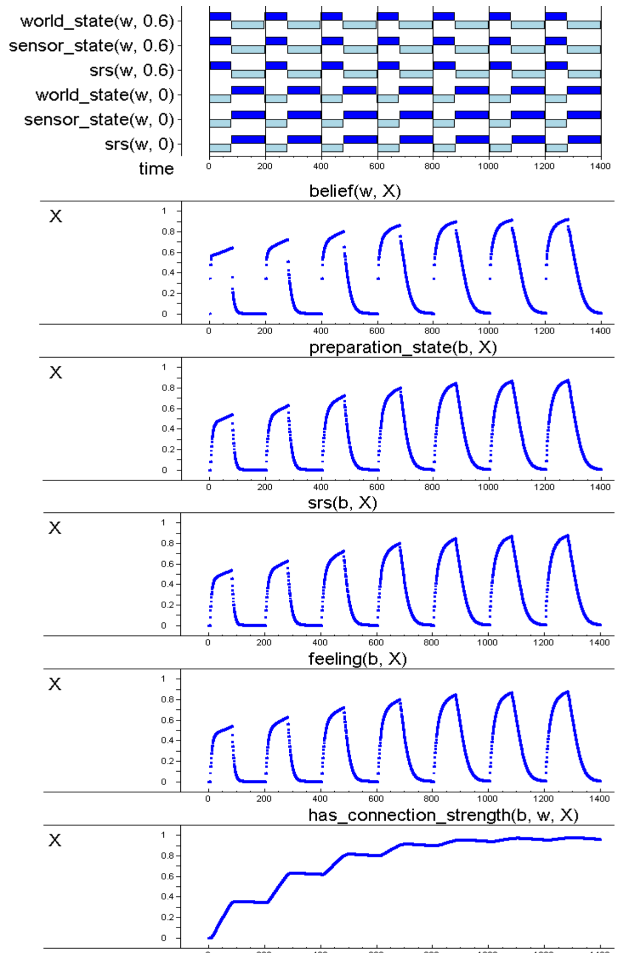

Fig 2: Example trace with a number of learning phases

In Figure 2, $\beta_1 = 0.95$, $\beta_2 = 0.4$, $\eta = 0.02$ and the extinction rate ζ is *0.0002*. The example trace in Figure 2 shows how after learning of the connection from feeling to belief, the strength of the belief substantially exceeds the strength of the incoming stimulus (*0.9* vs *0.6*).

In Figure 3 and Figure 4 some example simulation traces are showing how equilibria are reached for a constant environment with settings as indicated in the upper part of the figures. These traces illustrate the outcomes of the mathematical analysis of equilibria presented in Section 5.

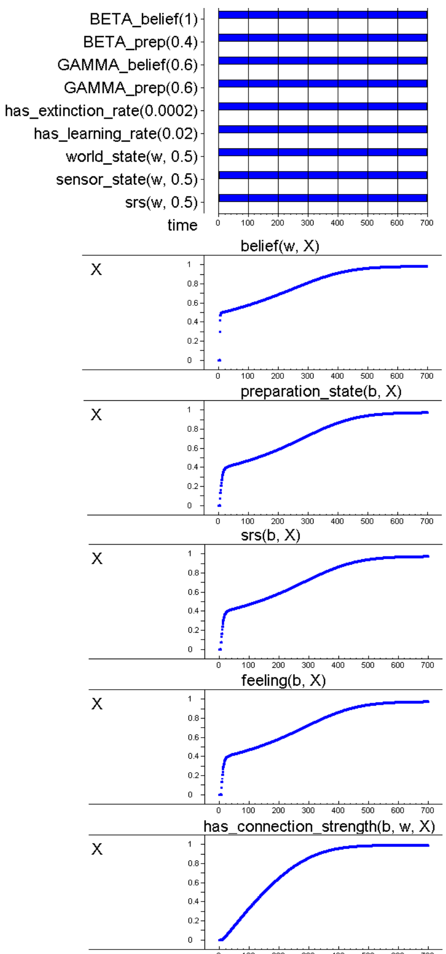

Fig 3. Approximated equilibrium for $\beta_1 = 1$, $\beta_2 = 0.4$

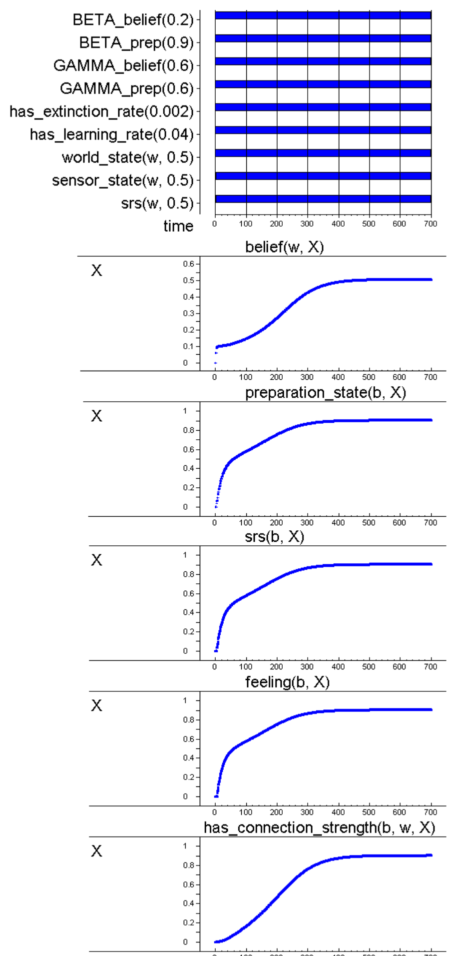

Fig 4. Approximated equilibrium for $\beta_1 = 0.2$, $\beta_2 = 0.9$

5 Mathematical Analysis

The example simulations in Figure 3 and Figure 4 show how for a time period with a constant environment with strength *0.5*, the strengths of beliefs, body states and feelings and connection between feeling and belief reach a stable equilibrium. By a mathematical analysis it can be addressed which types of equilibria are possible. To this end equations for equilibria can be determined from the dynamical model equations for the belief and the preparation state level, which (assuming ω_1, ω_3 and ω_4 constant) can be expressed as differential equations as follows (with *b(t)* the level of the belief, *s(t)* of the stimulus, *f(t)* of the feeling, and *p(t)* of the preparation for the body state at time *t*).

$$db(t)/dt = \gamma_1 (\beta_1(1-(1-\omega_1 s(t))(1-\omega_2(t)f(t))) + (1-\beta_1)\ \omega_1\omega_2(t)s(t)f(t) - b(t))$$
$$dp(t)/dt = \gamma_2 (\beta_2(1-(1-\omega_3 b(t))(1-\omega_4 f(t))) + (1-\beta_2)\ \omega_3\omega_4 b(t)f(t) - p(t))$$
$$d\omega_2(t)/dt = (\eta\, b(t)f(t)(1 - \omega_2(t)) - \zeta\omega_2(t))$$

Note that below, as in Section 4 the connection strenghts ω_1, ω_3 and ω_4 are taken *1*. Moreover, ω_2 is denoted as ω. To obtain equations for equilibria, constant values for all variables are assumed (also the ones used as inputs such as the stimuli). Then in all of the equations the reference to time *t* can be left out, and in addition the derivatives *dp(t)/dt* and *db(t)/dt* can be replaced by *0*. As for an equilibrium it also holds that $f = p$ assuming γ_1, γ_2, ζ and η nonzero, this leads the following equations in b, f, ω, s:

$$\beta_1(1-(1-s)(1-\omega f)) + (1-\beta_1)\omega s f - b = 0 \qquad (1)$$
$$\beta_2(1-(1-b)(1-f)) + (1-\beta_2)bf - f = 0 \qquad (2)$$
$$\eta bf(1 - \omega) - \zeta\omega = 0 \qquad (3)$$

Note that as an extreme case $b = f = s = 0$ satisfies (1), (2) and (3). For the general case, first, equation (3) can be rewritten into $\eta bf - \omega\eta bf - \zeta\omega = 0$, providing

$$\omega = \eta bf/(\eta bf + \zeta)$$
$$\omega = 1/(1 + \zeta/\eta bf)$$

where the last step only applies when $b, f \neq 0$. Using $b, f \leq 1$ from this it follows that $\omega \leq 1/(1 + (\zeta/\eta)) < 1$. For small ζ/η this can be rewritten into $\omega \leq 1 - (\zeta/\eta)$. This shows that given the extinction, the maximal connection strength will be lower than *1*, but may be close to *1* when the extinction rate is very small compared to the learning rate. However, it also depends on the equilibrium values for *f* and *b*. For values of *f* and *b* that close to *1*, this maximal value of ω can be approximated. When in contrast these values are low, also the equilibrium value for ω will be low, since: $\omega = \eta bf/(\eta bf + \zeta) \leq \eta bf/\zeta$. In particular, when one of *b* and *f* is *0* then also ω is *0*.

For the general case equation (1) can directly be used to express *b* in f, ω, s and β_1. Using this, in (2) *b* can be replaced by this expression in f, ω, s and β_1, which transforms (2) into a quadratic equation in *f* with coefficients in terms of s, ω and the parameters β_1 and β_2. Solving this quadratic equation algebraically provides a complex expression for *f* in terms of s, ω, β_1 and β_2. Using this, by (1) also an expression for *b* in terms of s, ω, β_1 and β_2 can be found. As the expressions for the general case become rather complex, only an overview for a number of special cases is shown in Table 1 (for *9* combinations of values *0*, *0.5* and *1* for both β_1 and β_2). For these cases the equations (1) and (2) can be substantially simplified as shown in the second column (for equation (1)) and second row (for equation (2)). As can be seen in Table 1, persons that have a low orientation for believing ($\beta_1 = 0$) and a low profile in generating emotional responses ($\beta_2 = 0$), have an equilibrium for which both the belief and the feeling have level 0, and also $\omega = 0$. The case where both $\beta_1 = 0.5$ and $\beta_2 = 0.5$ indicates an equilibrium with $b = f = s$, and $\omega = 1/(1 + \zeta/\eta s^2)$. Note that in Table 1 for $\beta_1 = 1$ and β_2 nonzero two equations in ω and b occur, which can be solved further to obtain more complex explicit expressions for each of them.

Table 1. Overview of equilibria for 9 cases of parameter settings for β_1 and β_2.

	β_2	0		0.5	1	
β_1	**eq. (1)** / **eq. (2)**	$f = 0$	$b = 1$	$b = f$	$f = 1$	$b = 0$
0	$b = \omega s f$	$b = f = \omega = 0$	-	$b = f = \omega = 0$	$b = \omega s$ $f = 1$ $\omega = 0$ or $\omega = 1 - \zeta/\eta s$	$b = \omega = 0$
0.5	$b = (s + f)/2$	$b = s/2$ $f = \omega = 0$	$b = f = s = 1$ $\omega = 1/(1+(\zeta/\eta))$	$b = f = s$ $\omega = 1/(1 + \zeta/\eta s^2)$	$b = (s + 1)/2$ $f = 1$ $\omega = 1/(1+(\zeta/\eta(s + 1)/2))$	$b = f = s = \omega = 0$
1	$1 - b = (1-s)(1-\omega f)$	$b = s$ $f = \omega = 0$	$b = f = \omega = 1$ — $b = s = 1$ $\omega = 1/(1+(\zeta/\eta f))$	$b = f$ $\omega = 1/(1 + (\zeta/\eta b^2))$; $\omega = (1-(s/b))/(1-s)$	$f = 1$ $\omega = (b-s)/(1-s)$ $\omega = 1/(1+(\zeta/\eta b))$	$b = s = \omega = 0$

6 Discussion

In this paper an adaptive agent model was introduced for the emerging effect of feeling on belief. The introduced agent model on the one hand describes more specifically how a belief generates an emotional response that is felt, and on the other hand how a connection can emerge enabling that the emotion that is felt affects the strength of the belief. For feeling the emotion, a converging recursive body loop is used, based on elements taken from [5], [9] and [10]. A relation from feeling to belief is developed based on a Hebbian learning rule (cf. [2], [14], [15]). After developing a connection from feeling to belief, the strength of a belief does no only depend on the strength of a stimulus, but also on the strength of the induced emotional response and feeling. A mathematical analysis of the equilibria of the model was discussed. The agent model was specified in the hybrid dynamic modelling language LEADSTO, and simulations were performed in its software environment; cf. [3].

In [19] a nonadaptive model for interaction between belief and feeling was presented, where a priori a connection from feeling to belief is assumed given. The agent model presented in the current paper is different in three respects. Firstly, it uses an as-if body loop instead of a body loop as was used in [19]. Secondly, in the agent model presented here, the connections between different mental states have weights that can be numbers between 0 and 1. Thirdly, here the connection from feeling to belief is not given a priori as in [19] but emerges over time, what can be considered as a major difference.

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