An Adaptive Model for Dynamics of Desiring and Feeling based on Hebbian Learning

Tibor Bosse[1], Mark Hoogendoorn[1], Zulfiqar A. Memon[1,2],
Jan Treur[1], Muhammad Umair[1,3]

[1]VU University Amsterdam, Department of AI
De Boelelaan 1081, 1081 HV Amsterdam, The Netherlands
[2]Sukkur Ins. of Business Administration (Sukkur IBA)
Air Port Road Sukkur, Sindh, Pakistan
[3]COMSATS Institute of Information Technology, Dept. of Computer Science
Lahore, Pakistan
Email: {tbosse, mhoogen, zamemon, treur, mumair}@few.vu.nl
URL: http://www.few.vu.nl/~{tbosse, mhoogen, zamemon, treur, mumair}

Abstract. Within cognitive models, desires are often considered as functional concepts that play a role in efficient focusing of behaviour. In practice a desire often goes hand in hand with having certain feelings. In this paper by adopting neurological theories a model is introduced incorporating both cognitive and affective aspects in the dynamics of desiring and feeling. Example simulations are presented, and both a mathematical and logical analysis is included.

1. Introduction

Desires play an important role in human functioning. To provide automated support for human functioning in various domains [2], it may be important to also monitor the humans states of desiring. Desires [13] are often considered cognitive states with the function of focusing the behaviour by constraining or indicating the options for actions to be chosen. Yet, there is much more to the concept of desire, especially concerning associated affective aspects. Cognitive functioning is often strongly related to affective processes, as has been shown more in general in empirical work as described in, for example, [9, 19]. In this paper a model is introduced that addresses both cognitive and affective aspects related to desires, adopting neurological theories as described in, for example, [3, 6, 7, 8, 19]. The aim of developing such a model is both to analyse adaptive dynamics of interacting cognitive and affective processes, and to provide a basis for an ambient agent that supports a person; cf. [14, 16, 2]. Evaluation criteria include in how far the model shows emerging patterns that are considered plausible, and the possibility to use the model in model-based reasoning within an ambient agent; cf. [2].

Within the presented model an activated desire induces a set of responses in the form of preparations for actions to fulfil the desire, and involving changing body states. By a *recursive as-if body* loop each of these preparations generates a level of feeling [18] that in turn can strengthen the level of the related preparation. These loops result in equilibria for both the strength of the preparation and of the feeling, and when these are strong enough, the action is actually activated. The specific strengths of the connections from the desire to the preparations, and within the recursive as-if body loops can be innate, or are acquired during lifetime. The computational model is based on neurological notions such as somatic marking, body loop and as-if body loop. The adaptivity in the model is based on Hebbian learning.

Any mental state in a person induces emotions felt by this person, as described in [7, 8]; e.g., [8], p. 93: '… few if any exceptions of any object or event, actually present or recalled from memory, are ever neutral in emotional terms. Through either innate design or by learning, we react to most, perhaps all, objects with emotions, however weak, and subsequent feelings, however feeble.' More specifically, in this paper it is assumed that responses in relation to a mental state of desiring roughly proceed according to the following causal chain for a *body loop*, based on elements from [3, 7, 8]:

desire $\rightarrow$ preparation for bodily response $\rightarrow$ body state modification $\rightarrow$ sensing body state $\rightarrow$ sensory representation of body state $\rightarrow$ induced feeling

In addition, an *as-if body loop* uses a direct causal relation

preparation for bodily response $\rightarrow$ sensory representation of body state

as a shortcut in the causal chain; cf. [7]. The body loop (or 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 $\rightarrow$ preparation for the bodily response

Such recursion is suggested in [8], pp. 91-92, noticing that what is felt is a body state under the person's control: 'The brain has a direct means to respond to the object as feelings unfold because the object at the origin is inside the body, rather than external to it. The brain can act directly on the very object it is perceiving. (…) The object at the origin on the one hand, and the brain map of that object on the other, can influence each other in a sort of reverberative process that is not to be found, for example, in the perception of an external object.'

Within the model presented in this paper, both the bodily response and the feeling are assigned a level (or gradation), expressed by a number. The causal cycle is triggered by an activation of the desire and converges to certain activation levels of feeling and preparation for a body state. The activation of a specific action preparation is based on both the activation level of the desire and of the feeling associated to this action. This illustrates Damasio's theory on decision making by *somatic marking*, called the Somatic Marker Hypothesis; cf. [1, 6, 8].

The strengths of the connections from feeling to preparation may be subject to learning. Especially when a specific action is performed and it leads to a strong effect in feeling, by *Hebbian learning* [10, 12] this may give a positive effect on the strength of this connection and consequently on future activations of the preparation of this specific action. Through such a mechanism experiences in the past may have their effect on behavioural choices made in the future, as also described as part of Damasio's Somatic Marker Hypothesis [6]. In the computational model described below, this is applied in the form of a Hebbian learning rule realising that actions induced by a certain desire which result in stronger experiences of satisfaction felt will be chosen more often to fulfil this desire.

In Section 2 the computational model for the dynamics of desiring and feeling is described. Section 3 presents some simulation results. In Section 4, formal analysis of the model is addressed, both by mathematical analysis of equilibria and automated logical verification of properties. Finally, Section 5 is a discussion.

2. Modelling Desiring and Feeling

In this section the computational model for desiring and feeling is presented; for an overview see Fig. 1. This picture also shows representations from the detailed specifications explained below. The precise numerical relations between the indicated variables V shown are not expressed in this picture, but in the detailed specifications of properties below, which are labelled by LP0 to LP9 (where LP stands for Local Property), as also shown in the picture. The detailed specification (both informally and formally) of the computational model is presented below. Here capitals are used for (assumed universally quantified) variables. The model was specified in LEADSTO [4], where the temporal relation a ↠ b denotes that when a state property a occurs, then after a certain time delay (which can be specified as any positive real number), state property b will occur. In LEADSTO both logical and numerical relations can be specified.

Generating a desire by sensing a bodily unbalance

The desire considered in the example scenario is assumed to be generated by sensing an unbalance in a body state *b*, according to the principle that organisms aim at maintaining homeostasis of their internal milieu. The first dynamic property addresses how body states are sensed.

LP0 Sensing a body state

If body state property *B* has level *V*, then the sensor state for *B* will have level *V*.
body_state(B, V) ↠ sensor_state(B, V)

For the example scenario this dynamic property is used by the person to sense the body state *b* from which the desire originates (e.g., a state of being hungry), and the body states b_i involved in feeling satisfaction with specific ways in which the desire is being fulfilled. From sensor states, sensory representations are generated as follows.

LP1 Generating a sensory representation for a sensed body state

If a sensor state for *B* has level *V*, then the sensory representation for *B* will have level *V*.
sensor_state(B, V) ↠ srs(B, V)

Next the dynamic property for the process for desire generation is described, from the sensory representation of the body state unbalance.

LP2 Generating a desire based on a sensory representation

If a sensory representation for *B* has level *V*, then the desire to address *B* will have level *V*.
srs(B, V) ↠ desire(B, V)

Inducing preparations

It is assumed that activation of a desire, together with a feeling, induces preparations for a number of action options: those actions considered relevant to satisfy the desire, for example based on earlier experiences. Dynamic property LP3 describes such responses in the form of the preparation for specific actions. It combines the activation levels V and V_i of two states (desire and feeling) through connection strengths ω_{1i} and ω_{2i} respectively. This specifies part of the recursive as-if loop between feeling and body state. This dynamic property uses a combination model based on a function $g(\sigma, \tau, V, V_i, \omega_{1i}, \omega_{2i})$ which includes a sigmoid threshold function

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

with steepness σ and threshold τ. For this model $g(\sigma, \tau, V, V_i, \omega_{1i}, \omega_{2i})$ is defined as

$$g(\sigma, \tau, V, V_i, \omega_{1i}, \omega_{2i}) = th(\sigma, \tau, \omega_{1i}V + \omega_{2i}V_i)$$

with V, V_i activation levels and ω_{1i}, ω_{2i} weights of the connections to the preparation state. Note that alternative combination functions g could be used as well, for example quadratic functions such as used in [15]. Property LP3 is formalised in LEADSTO as:

LP3 From desire and feeling to preparation

If the desire for b has level V
and feeling the associated body state b_i has level V_i
and the preparation state for b_i has level U_i
and ω_{1i} is the strength of the connection from desire for b to preparation for b_i
and ω_{2i} is the strength of the connection from feeling of b_i to preparation for b_i
and σ_i is the steepness value for the preparation for b_i
and τ_i is the threshold value for the preparation for b_i
and γ_1 is the person's flexibility for bodily responses
then the preparation state for b_i will have level $U_i + \gamma_1(g(\sigma_i, \tau_i, V, V_i, \omega_{1i}, \omega_{2i}) - U_i) \Delta t$.

desire(b, V) & feeling(b_i, V_i) & prep_state(b_i, U_i) &
has_steepness(prep_state(b_i), σ_i) & has_threshold(prep_state(b_i), τ_i)
→ prep_state(b_i, $U_i + \gamma_1 (g(\sigma_i, \tau_i, V, V_i, \omega_{1i}, \omega_{2i}) - U_i) \Delta t$)

From preparation to feeling

Dynamic properties LP4 and LP5 describe how the as-if body loop together with the body loop affects the feeling.

LP4 From preparation and sensor state to sensory representation of body state

If the preparation state for body state B has level V_1
and the sensor state for B has level V_2
and the sensory representation for B has level U
and σ is the steepness value for the sensory representation of B
and τ is the threshold value for the sensory representation of B
and γ_2 is the person's flexibility for bodily responses
then the sensory representation for body state B will have level level $U + \gamma_2 (g(\sigma, \tau, V_1, V_2, 1, 1) - U) \Delta t$.

prep_state(B, V_1) & sensor_state(B, V_2) & srs(B, U) & has_steepness(srs(B), σ) &
has_threshold(srs(B), τ)
→ srs(B, $U + \gamma_2 (g(\sigma, \tau, V_1, V_2, 1, 1) - U) \Delta t$)

Dynamic properties LP5 describes the remaining part of the as-if body loop.

LP5 From sensory representation of body state to feeling

If a sensory representation for body state B has level V,
then B will be felt with level V.
srs(B, V) → feeling(B, V)

Action performance and effects on body states

Temporal relationships LP6 and LP7 below describe the preparations of body states b_i and their effects on body states b and b_i. The idea is that the actions performed by body states b_i are different means to satisfy the desire related to b, by having an impact on the body state that decreases the activation level V (indicating the extent of unbalance) of body state b. In addition, when performed, each of them involves an effect on a specific body state b_i which can be interpreted as a basis for a form of satisfaction felt for the specific way in which b was satisfied. So, an action performance involving b_i has an effect on both body state b, by decreasing the level of unbalance entailed by b, and on body state b_i by increasing the specific level of satisfaction. This specific level of satisfaction may or may not be proportional to the extent to which the unbalance is reduced.

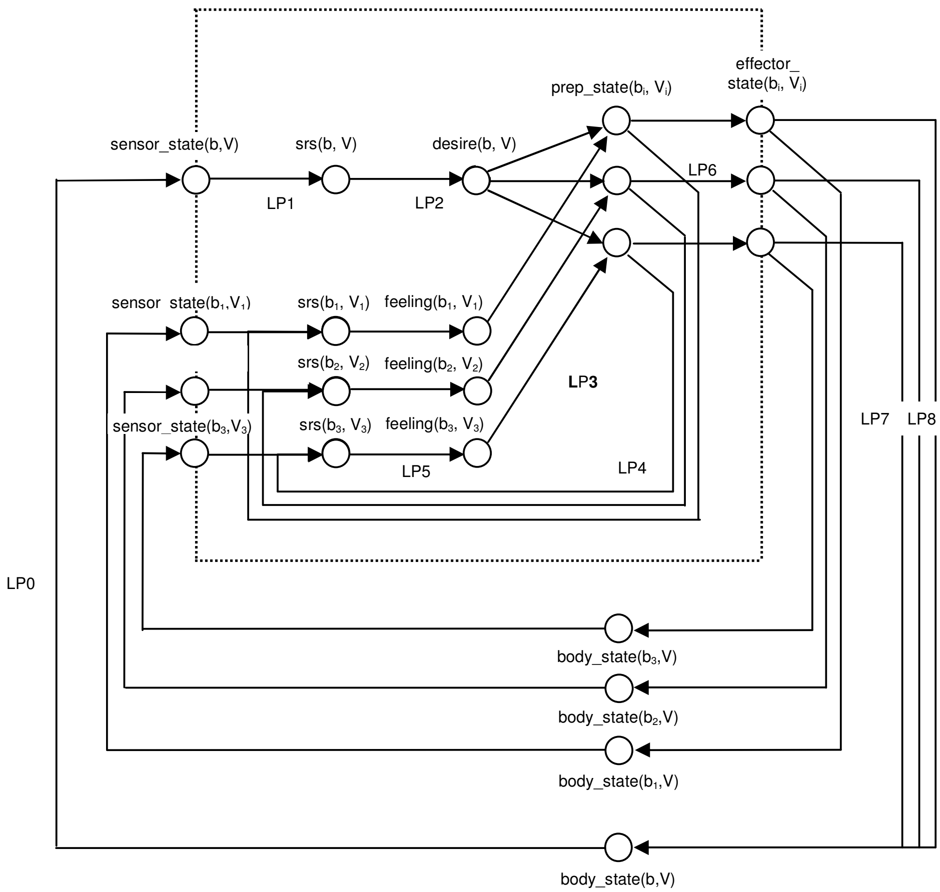

Fig. 1. Overview of the computational model for desiring and feeling

As the possible actions to fulfil a desire are considered different, they differ in the extents of their effects on these two types of body states, according to an effectiveness rate α_i between *0* and *1* for *b*, and an effectiveness rate β_i between *0* and *1* for b_i. The effectiveness rates α_i and β_i can be considered a kind of connection strengths from the effector state to the body states *b* and b_i, respectively. In common situations for each action these two rates may be equal (i.e., $\alpha_i = \beta_i$), but especially in more pathological cases they may also have different values where the satisfaction felt based on rate β_i for b_i may be disproportionally higher or lower in comparison to the effect on *b* based on rate α_i (i.e., $\beta_i > \alpha_i$ or $\beta_i < \alpha_i$). An example of this situation would be a case of addiction for one of the actions. To express the extent of disproportionality between β_i and α_i, a parameter λ_i, called *satisfaction disproportion rate*, between *-1* and *1* is used; here: $\lambda_i = (\beta_i - \alpha_i) / (1-\alpha_i)$ if $\beta_i \geq \alpha_i$; $\lambda_i = (\beta_i - \alpha_i) / \alpha_i$ if $\beta_i \leq \alpha_i$. This parameter can also be used to relate β_i to α_i using a function: $\beta_i = f(\lambda_i, \alpha_i)$. Here $f(\lambda, \alpha)$ satisfies

$f(0, \alpha) = \alpha$ $f(-1, \alpha) = 0$ $f(1, \alpha) = 1$

The piecewise linear function $f(\lambda, \alpha)$ can be defined in a continuous manner as:

$f(\lambda, \alpha) = \alpha + \lambda(1-\alpha)$ if $\lambda \geq 0;$ $f(\lambda, \alpha) = (1+\lambda)\alpha$ if $\lambda \leq 0$

Using this, for normal cases $\lambda_i = 0$ is taken, for cases were satisfaction is higher $0 < \lambda_i \leq 1$ and for cases where satisfaction is lower $-1 \leq \lambda_i < 0$.

LP6 From preparation to effector state

If preparation state for B has level V, then the effector state for body state B will have level V.

prep_state(B, V) → effector_state(B, V)

LP7 From effector state to modified body state b_i

If the effector state for b_i has level V_i,
and for each i the effectivity of b_i for b is α_i
and the satisfaction disproportion rate for b_i for b is λ_i
then body state b_i will have level $f(\lambda_i, \alpha_i)V_i$.

effector_state(b_i, V_i) & is_effectivity_for(α_i, b_i, b) &
is_disproportion_rate_for(λ_i, b_i) → body_state(b_i, f(λ_i, α_i)V_i)

LP8 From effector state to modified body state b

If the effector states for b_i have levels V_i,
and body state b has level V,
and for each i the effectivity of b_i for b is α_i
then body state b will have level

$$V + (\vartheta * (1-V) - \rho * (1 - ((1 - \alpha_1 * V_1) * (1 - \alpha_2 * V_2) * (1 - \alpha_3 * V_3))) * V) \Delta t.$$

effector_state(b_i, V_i) & body_state(b, V) & is_effectivity_for(α_i, b_i, b)
→ body_state(b, V + (ϑ * (1-V) – ρ * (1 – ((1 - α_1*V_1) * (1 - α_2*V_2) * (1 - α_3*V_3))) * V) Δt

Note that in case only one action is performed (i.e., $V_j = 0$ for all $j \neq i$), the formula in LP8 above reduces to $V + (\vartheta * (1-V) - \rho*\alpha_i*V_i * V) \Delta t$. In the formula ϑ is a rate of developing unbalance over time (for example, getting hungry), and ρ a general rate of compensating for this unbalance. Note that the specific formula used here to adapt the level of b is meant as just an example. As no assumptions on body state b are made, this formula is meant as a stand-in for more realistic formulae that could be used for specific body states b.

Learning of the connections from desire to preparation

The strengths ω_{2i} of the connections from feeling b_i to preparation of b_i are considered to be subjected to learning. When an action involving b_i is performed and leads to a strong effect on b_i, by Hebbian learning [10, 12] this increases the strength of this connection. This is an adaptive mechanism that models how experiences in the past may have their effect on behavioural choices made in the future, as also described in Damasio's Somatic Marker Hypothesis [6]. Within the model the strength ω_{2i} of the connection from feeling to preparation 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.

LP9 Hebbian learning for the connection from feeling to preparation

If the connection from feeling b_i to preparation of b_i has strength ω_{2i}
and the feeling b_i has level V_{1i}
and the preparation of b_i has level V_{2i}
and the learning rate from feeling b_i to preparation of b_i is η
and the extinction rate from feeling b_i to preparation of b_i is ζ
then after Δt the connection strength from feeling b_i to preparation of b_i will be

$\omega_{2i} + (\eta V_{1i} V_{2i} (1 - \omega_{2i}) - \zeta\omega_{2i}) \Delta t.$

has_connection_strength(feeling(b_i), preparation(b_i), ω_{2i}) & feeling(b_i, V_{1i}) & preparation(b_i, V_{2i}) & has_learning_rate(feeling(b_i), preparation(b_i), η) & has_extinction_rate(feeling(b_i), preparation(b_i), ζ)
$\rightarrow$ has_connection_strength(feeling(b_i), preparation(b_i), $\omega_{2i} + (\eta V_{1i} V_{2i} (1 - \omega_{2i}) - \zeta\omega_{2i}) \Delta t$)

3. Example Simulation Results

Based on the model described in the previous section, a number of simulations have been performed. A first example simulation trace included in this section as an illustration is shown in Fig. 2; in all traces, the time delays within the temporal LEADSTO relations were taken 1 time unit. Note that only a selection of the relevant nodes (represented as state properties) is shown. In all of the figures time is on the horizontal axis, and the activation levels of state properties on the vertical axis.

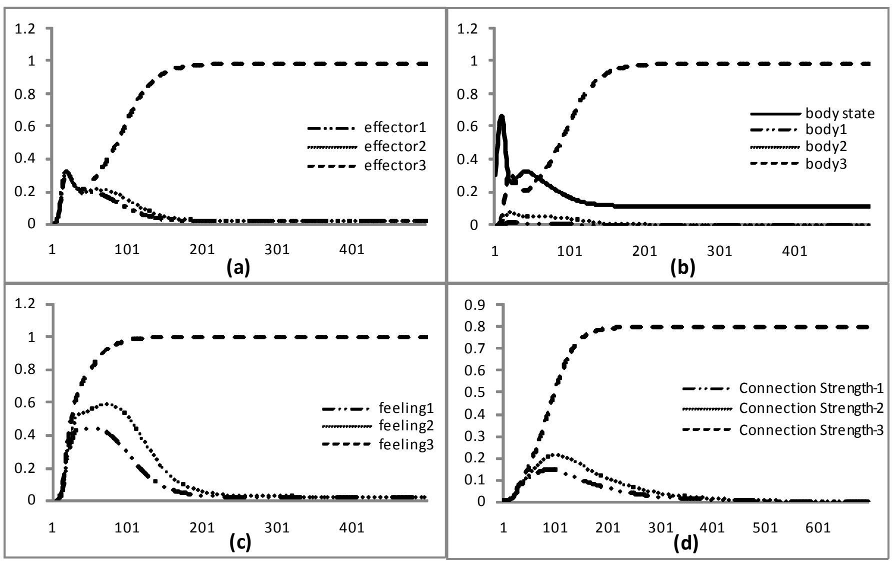

Fig. 2: Simulation Trace 1 – Normal behaviour
($\sigma_1=\sigma_2=10$, $\tau_1=\tau_2=0.5$, $\gamma_1=\gamma_2=0.05$, $\alpha_1=\beta_1=0.05$, $\alpha_2=\beta_2=0.25$, $\alpha_3=\beta_3=1$, $\rho=0.8$, $\vartheta=0.1$, $\eta=0.04$, $\zeta=0.01$)

For the example shown in Fig. 2, for each i it was taken $\lambda_i = 0$, so satisfaction felt is in proportion with fulfilment of the desire. Action option 3 has the highest effectiveness rate, i.e. $\alpha_3 = 1$. Its value is higher as compared to the other two action options. This effect has been propagated to their respective body states as shown in Fig. 2(b). All these body states has a positive effect on body state b, decreasing the level of unbalance, as shown in Fig. 2(b), where the value of body state b (which was set initially to 0.3) decreases over time until it reaches an equilibrium state. Each of these body states generates feelings by a recursive as-if body loop, as shown in Fig. 2(c). Furthermore it gives a strong effect on the strength of the connection from feeling to preparation. The connection strength keeps on increasing over time until it reaches an equilibrium state, as shown in Fig. 2(d). As the extinction rate (ζ*=0.01*) is smaller compared to the learning rate (η*=0.04*), the connection strength becomes *0.8*, which is closer to *1*, as confirmed by the mathematical analysis in Section 4. Fig. 3, shows the simulation of an example scenario where the person is addicted to a particular action, in this case to action option 1, λ_1 = 1. But because the effectiveness rate α_1 for this option is very low (0.05), the addiction makes that the person is not very effective in fulfilling the desire: the level of unbalance remains around *0.3*; the person mainly selects action option 1 because of its higher satisfaction.

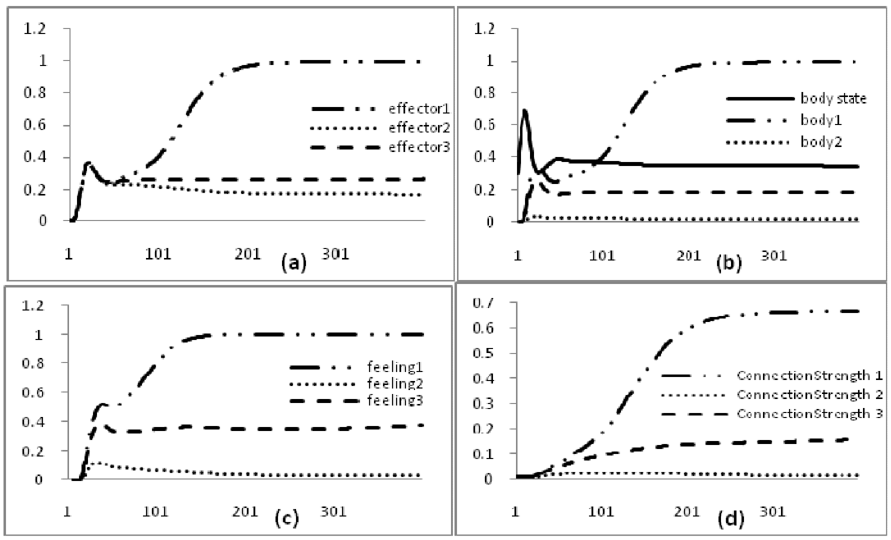

Fig. 3: Simulation Trace 2 – Addiction-like behaviour
($\sigma_1=\sigma_2=10$, $\tau_1=\tau_2=0.5$, $\gamma_1=\gamma_2=0.05$, $\alpha_1=0.05$, $\alpha_2=\beta_2=0.1$, $\alpha_3=\beta_3=0.7$,
$\rho=0.8$, $\vartheta=0.1$, $\eta=0.02$, $\zeta=0.01$)

In the next trace (see Fig. 4), the effectiveness rates for the different action options have been given a distinct pattern, i.e. after some time α_1 has been gradually increased with a term of 0.009, starting with an initial value of 0.05 until it reaches the value of 1, thereafter it has been kept constant to 1. In the same period the effectiveness rate α_3 has been gradually decreased with 0.009, starting with an initial value of 1, until it reaches the value of 0.05, thereafter it has been kept constant to 0.05, showing an exact opposite pattern of α_1. Effectiveness rate α_2 is being kept constant to 0.15 for all the time points. As can be seen in Fig. 4, first the person selects action option 3 as the most effective one, but after a change in circumstances the person shows adaptation by selecting action option 1, which has now a higher effectiveness rate.

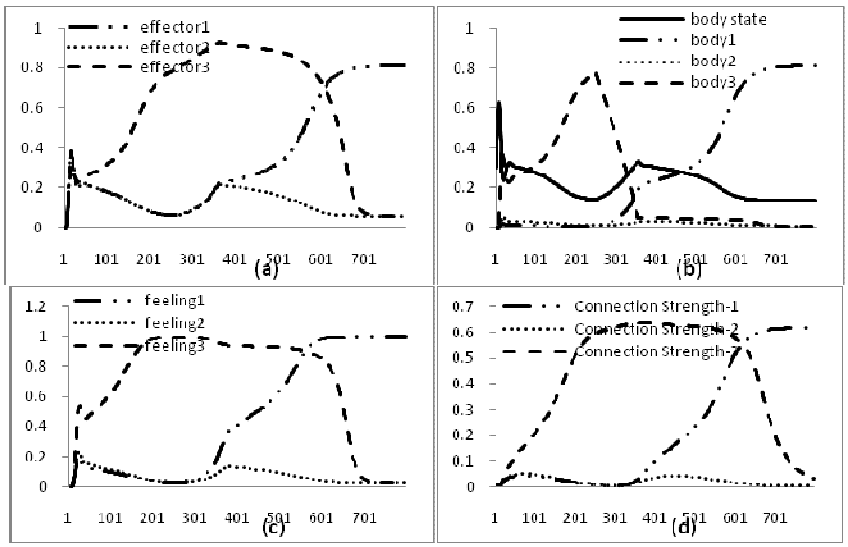

Fig. 4: Simulation Trace 3 – Adapting to changing circumstances
($\sigma_1=\sigma_2=6$, $\tau_1=\tau_2=0.5$, $\gamma_1=\gamma_2=0.1$, $\alpha_1=\beta_1$ increasing from 0.05 to 1, $\alpha_2=\beta_2=0.15$, $\alpha_3=\beta_3$ decreasing from 1 to 0.05, $\rho=0.8$, $\vartheta=0.1$, $\eta=0.04$, $\zeta=0.02$)

4. Formal Analysis of the Model

This section addresses formal analysis of the model and the simulation results as presented above. First a mathematical analysis of the equilibria is made. Next, a number of more globally emerging dynamic properties are verified for a set of simulation traces.

Mathematical analysis of equilibria

For an equilibrium of the strength of the connection from feeling b_i to preparation of b_i, by LP9 it holds $\eta V_{1i}V_{2i}(1 - \omega_{2i}) - \zeta\omega_{2i} = 0$ with values V_{1i} for feeling level and V_{2i} for preparation level for b_i. This can be rewritten into

$$\omega_{2i} = \frac{\eta V_{1i}V_{2i}}{\eta V_{1i}V_{2i} + \zeta} = \frac{1}{1 + \zeta/(\eta V_{1i}V_{2i})}$$

Using $V_{1i}, V_{2i} \leq 1$ from this it follows that

$$\omega_{2i} \leq \frac{1}{1 + \zeta/\eta}$$

gives a maximal connection strength that can be obtained. 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 small compared to the learning rate. For example, for the trace shown in Fig. 2 with $\zeta = 0.01$ and $\eta=0.04$, this bound is 0.8, which indeed is reached for option 3. For the traces in Fig. 3 and 4 with $\zeta/\eta = ½$ this maximum is $^2/_3$, which is indeed reached for option 1 in Fig. 3 and option 3, resp. 1 in Fig. 4. Whether or not this maximally possible value for ω_{2i} is approximated for a certain option, also depends on the equilibrium values for feeling level V_{1i} and preparation level V_{2i} for b_i. For values of V_{1i} and V_{2i} that are 1 or close to 1, the maximal possible value of ω_{2i} is approximated. When in contrast these values are very low, also the equilibrium value for ω_{2i} will be low, since:

$$\omega_{2i} = \frac{\eta V_{1i} V_{2i}}{\eta V_{1i} V_{2i} + \zeta} \leq \eta V_{1i} V_{2i} / \zeta$$

So, when one of V_{1i} and V_{2i} is 0 then also $\omega_{2i} = 0$ (and conversely). This is illustrated by the options 1 and 2 in Fig. 2, and option 2 in Fig. 3.

Given the sigmoid combination functions it is not possible to analytically solve the equilibrium equations in general. Therefore the patterns emerging in the simulations cannot be derived mathematically in a precise manner. However, as the combination functions are monotonic, some relationships between inequalities can be found:

(1) $V_{1j}V_{2j} \leq V_{1k}V_{2k} \Rightarrow \omega_{2j} \leq \omega_{2k}$
(2) $\omega_{2j} < \omega_{2k} \Rightarrow V_{1j}V_{2j} < V_{1k}V_{2k}$
(3) $\omega_{2j} \leq \omega_{2k}$ & $V_{1j} \leq V_{1k} \Rightarrow \omega_{2j} V_{1j} \leq \omega_{2k} V_{1k} \Rightarrow V_{2j} \leq V_{2k}$
(4) $V_{2j} < V_{2k} \Rightarrow \omega_{2j} V_{1j} < \omega_{2k} V_{1k}$
(5) $\beta_j \leq \beta_k$ & $V_{2j} \leq V_{2k} \Rightarrow (1+\beta_j) V_{2j} \leq (1+\beta_k) V_{2k} \Rightarrow V_{1j} \leq V_{1k}$
(6) $V_{1j} < V_{1k} \Rightarrow (1+\beta_j) V_{2j} < (1+\beta_k) V_{2k}$

Here (1) and (2) follow from the above expressions based on LP9. Moreover, (3) and (4) follow from LP3, and (5) and (6) from the properties LP4, LP5, LP6, LP7, LP0 and LP1 describing the body loop and as-if body loop.

For the case that one action dominates exclusively, i.e., $V_{2k} = 0$ and $\omega_{2k} = 0$ for all $k \neq i$, and $V_{2i} > 0$, by LP8 it holds

$$\vartheta * (1-V) - \rho * \alpha_i * V_{2i} * V = 0$$

where V is the level of body state b. Therefore for $\vartheta > 0$ it holds

$$V = \frac{1}{1+(\rho\alpha_i / \vartheta) V_{2i}} \geq \frac{1}{1+(\rho/\vartheta)\alpha_i}$$

As $V_{2i} > 0$ is assumed, this shows that if ϑ is close to 0 (almost no development of unbalance), and $\rho > 0$ and $\alpha_i > 0$, the value V can be close to 0 as well. If, in contrast, the value of ϑ is high (strong development of unbalance) compared to ρ and α_i, then the equilibrium value V will be close to 1. For the example traces in Fig. 2, 3 and 4, $\rho = 0.8$ and $\vartheta = 0.1$, so $\rho/\vartheta = 8$. Therefore for a dominating option with $\alpha_i = 1$, it holds $V \geq 0.11$, which can be seen in Fig. 2 and 4. In Fig. 3 the effectiveness of option 1 is very low ($\alpha_1 = 0.05$), and therefore the potential of this option to decrease V is low: $V \geq 0.7$. However, as in Fig. 3 also option 3 is partially active, V reaches values around 0.35. Note that for the special case $\vartheta = 0$ (no development of unbalance) it follows that $\rho * \alpha_i * V_{2i} * V = 0$ which shows that $V = 0$. Values for V at or close to 0 confirm that in such an equilibrium state the desire is fulfilled or is close to being fulfilled (via LP0, LP1 and LP2 which show that the same value V occurs for the desire).

Logical verification of properties on simulation traces

In order to investigate particular patterns in the processes shown in the simulation runs, a number of properties have been formulated. Formal specification of the properties, enabled automatic verification of them against simulation traces, using the logical language and verification tool TTL (cf. [5]). The purpose of this type of verification is to check whether the simulation model behaves as it should. A typical example of a property that may be checked is whether certain equilibria occur, or whether the appropriate actions are selected.

The temporal predicate logical language TTL supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to *states* of the world, *time points* and *traces*, i.e. trajectories of states over time. *Dynamic properties* are temporal statements formulated with respect to traces based on the state ontology Ont in the following manner. Given a trace γ over state ontology Ont, the state in γ at time point t is denoted by state(γ, t). These states are related to state properties via the infix predicate |=, where state(γ, t) |= p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties are formulated in a sorted predicate logic, using quantifiers over time and traces and the usual logical connectives such as ¬, ∧, ∨, ⇒, ∀, ∃. For more details on TTL, see [5].

A number of properties have been identified for the processes modelled. Note that not all properties are expected to always hold for all traces. The first property, GP1 (short for Global Property 1), expresses that eventually the preparation state with respect to an action will stabilise.

GP1(d): Equilibrium of preparation state

Eventually, the preparation state for each b_i will stabilise at a certain value (i.e., not deviate more than a value d).

∀γ:TRACE, B:BODY_STATE [∃t1:TIME [∀t2:TIME > t1, V1, V2 :VALUE
[state(γ, t1) |= prep_state(B, V1) & state(γ, t2) |= prep_state(B, V2)
⇒ V2 ≥ (1 – d) * V1 & V2 ≤ (1 + d) * V1]]]

Next, in property GP2 it is expressed that eventually the action which has the most positive feeling associated with it will have the highest preparation state value.

GP2: Action with best feeling is eventually selected

For all traces there exists a time point such that the bi with the highest value for feeling eventually also has the highest activation level.

∀γ:TRACE, B:BODY_STATE, t1:TIME<end_time, V:VALUE
[[state(γ, t1) |= feeling(B, V) & ∀B2:BODY_STATE, V2:VALUE [state(γ, t1) |= feeling(B2, V2)
⇒ V2 ≤ V]
⇒ [∃t2:TIME > t1, V1:VALUE [state(γ, t2) |= prep_state(B, V1) &
∀B3:BODY_STATE, V3:VALUE [state(γ, t2) |= prep_state(B3, V3) ⇒ V3 ≤ V1]]]]

Property GP3 expresses that if the accumulated positive feelings experienced in the past are higher compared to another time point, and the number of negative experiences is lower or equal, then the weight through Hebbian learning will be higher.

GP3: Accumulation of positive experiences

If at time point t1 the accumulated feeling for bi is higher than the accumulated feeling at time point t2, then the weight of the connection from bi is higher than at t1 compared to t2.

∀γ:TRACE, B:BODY_STATE, a:ACTION, t1, t2:TIME<end_time, V1, V2:VALUE
[[state(γ, t1) |= accumulated_feeling(B, V1) & state(γ, t2) |= accumulated_feeling(B, V2) & V1>V2]
⇒ ∃W1, W2:VALUE [state(γ, t1) |= has_connection_strength(feeling(B), preparation(B), W1) &
state(γ, t2) |= has_connection_strength(feeling(B), preparation(B), W2) & W1 ≥ W2]]

Next, property GP4 specifies a monotonicity property where two traces are compared. It expresses that strictly higher feeling levels result in a higher weight of the connection between the feeling and the preparation state.

GP4: High feelings lead to high connection strength

If at time point t1 in a trace γ1 the feelings have been strictly higher level compared to another trace γ2, then the weight of the connection between the feeling and the preparation state will also be strictly higher.

∀γ1, γ2:TRACE, B:BODY_STATE, t1:TIME<end_time, W1, W2:VALUE
[∀t' < t1:TIME, V1, V2:VALUE
[[state(γ1, t') |= feeling(B, V1) & state(γ2, t') |= feeling(B, V2)] ⇒ V1 > V2] &
state(γ1, t1) |= has_connection_strength(feeling(B), preparation(B), W1) &
state(γ2, t1) |= has_connection_strength(feeling(B), preparation(B), W2) ⇒ W1 ≥ W2]

Finally, property GP5 analyses traces that address cases of addiction. In particular, it checks whether it is the case that if a person is addicted to a certain action (i.e., has a high value for the satisfaction disproportion rate λ for this action), this results in a situation of unbalance (i.e., a situation in which the feeling caused by this action stays higher than the overall body state). An example of such a situation is found in simulation trace 2 (in Fig. 3).

GP5: Addiction leads to unbalance between feeling and body state

For all traces, if a certain action has λ > 0, then there will be a time point t1 after which the feeling caused by this action stays higher than the overall body state.

∀γ:TRACE, B1:BODY_STATE, L1:VALUE [state(γ, 0) |= has_lambda(B1,L1) & L1 > 0
⇒ [∃t1:TIME < last_time
∀t2:TIME>t1 X,X1:VALUE [state(γ, t2) |= body_state(b, X) & body_state(B1, X1) ⇒ X < X1]]]

An overview of the results of the verification process is shown in Table 1 for the three traces that have been considered in Section 4. The results show that several expected global properties of the model were confirmed. For example, the first row indicates that for all traces, eventually an equilibrium occurs in which the values of the preparation states never deviate more than 0.0005 (this number can still be decreased by running the simulation for a longer time period). Also, the checks indicate that some properties do not hold. In such cases, the TTL checker software provides a counter example, i.e., a situation in which the property does not hold. This way, it could be concluded, for example, that property GP1 only holds for the generated traces if d is not chosen too small.

Table 1. Results of verification

property	trace 1	trace 2	trace 3
GP1(X)	X≥0.0001	X≥0.0005	X≥0.0001
GP2	satisfied	satisfied	satisfied
GP3	satisfied	satisfied	Satisfied
GP4	satisfied for all pairs of traces		
GP5	satisfied	satisfied	satisfied

5. Discussion

In this paper an adaptive computational model was introduced for dynamics of cognitive and affective aspects of desiring, based on neurological theories involving (as-if) body loops, somatic marking, and Hebbian learning. The introduced model describes more specifically how a desire induces (as a response) a set of preparations for a number of possible actions, involving certain body states, which each affect sensory representations of the body states involved and thus provide associated feelings. On their turn these feelings affect the preparations, for example, by amplifying them. In this way an model is obtained for desiring which integrates both cognitive and affective aspects of mental functioning. For the interaction between feeling and preparation of responses, a converging recursive body loop is included in the model, based on elements taken from [3, 7, 8]. Both the strength of the preparation and of the feeling emerge as a result of the dynamic pattern generated by this loop. The model is adaptive in the sense that within these loops the connection strengths from feelings to preparations are adapted over time by Hebbian learning. By this adaptation mechanism, in principle the person achieves that the most effective action to fulfill a desire is chosen. However, the model can also be used to cover persons for whom satisfaction for an action is not in proportion with the fulfilment of the desire, as occurs, e.g., in certain cases of temptation and addiction, such as illustrated in [14].

Despite growing interest in integrating cognitive and affective aspects of mental functioning in recent years, both in informally described approaches [9, 19] and in formal and computational approaches [11, 15], the relation of affective and cognitive aspects of desires has received less than adequate attention. Moreover, most existing formal models that integrate cognitive and affective aspects in mental functioning adopt the BDI (belief-desire-intention) paradigm and/or are based on appraisal theory (e.g., [11]). The proposed model is the first to show the effect of desire on feeling in a formalised computational manner and is based on neurological theories given in the literature as opposed to the BDI paradigm or appraisal-based theories. An interesting contrasting proposal of representing feelings as *resistance to variance* is put forward by [17]; this model is however not computational.

The computational model was specified in the hybrid dynamic modelling language LEADSTO, and simulations were performed in its software environment; cf. [4]. The computational model was analysed through a number of simulations for a variety of different settings and scenarios, and by formal analyses both by mathematical methods and by automated logical verification of dynamic properties on a set of simulation traces. Several expected global properties, such as the occurrence of equilibria and the selection of appropriate actions, were confirmed for the generated traces. Although this is not an exhaustive proof, it is an important indication that the model behaves as expected. Currently the model is generic in a sense that it does not address any specific desire or feeling. It would be an interesting future work to parameterise the model to analyse desire relating to different types of feeling. Future work will also focus on a more extensive validation of the model.

It was shown that under normal circumstances indeed over time the behaviour of the person is more and more focusing on actions that provide higher levels of desire fulfilment and stronger feelings of satisfaction, thus improving effectiveness of desire fulfilment. Also less standard circumstances have been analysed: particular cases in which the fulfilment of the desire and the feeling of satisfaction are out of proportion, as, for example, shown in some types of addictive behaviour. Indeed also such cases are covered well by the model as it shows over time a stronger focus on the action for which the satisfaction is unreasonably high, thereby reducing the effectiveness to fulfil the desire. In [14] it is reported how this model can be used as a basis for an ambient agent performing model-based reasoning and supporting addictive persons in order to avoid temptations.

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