An Integrative Dynamical Systems Perspective on Emotions

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Abstract. Within cognitive, affective and social neuroscience more and more mechanisms are found that suggest how emotions relate in a bidirectional manner to many other mental processes and behaviour. Based on this, in this paper a neurologically inspired dynamical systems approach on the dynamics and interaction of emotions is discussed. Thus an integrative perspective is obtained that can be used to describe, for example, how emotions relate to feelings, beliefs, desires, experiences, decision making, and to emotions of others. It is pointed out how this perspective can be used to obtain integrated computational models of such mental processes incorporating emotions.

Introduction

From the beginning Artificial Intelligence has addressed the modelling of cognitive processes behind intelligence. The original practice was that emotions were not taken into account in such models (for example, see Feigenbaum, 1969). Presumably they were avoided since intelligence was aimed to be modelled in an idealised manner, and emotions were assumed to disturb that ideal. However, even in that time from the cognitive area it was pointed out that this was a serious omission when human intelligence is aimed at. For example, Neisser (1963) and Simon (1967) formulate this as follows:

> 'Needs and emotions do not merely set the stage for cognitive activity and then retire. They continue to operate throughout the course of development. Moreover, they do not remain constant but undergo growth and change of their own, with substantial effects on intellectual activities.' (Neisser, 1963, p. 196.)
> 'Information processing theories, however, have generally been silent on the interaction of cognition with affect. Since in actual human behavior motive and emotion are major influences on the course of cognitive behavior, a general theory of thinking and problem solving must incorporate such influences' (Simon, 1967, p. 29)

This situation in Artificial Intelligence has substantially changed in recent years. Currently, in conferences on AI or agent system modelling, often modelling of emotions is one of the topics mentioned in their calls. One of the reasons for this change is the need for human-like models, for example as a basis for virtual agents, or in Ambient Intelligence applications. Another reason for this change is the growing awareness fed by the strong development of neuroscience that in human-like models emotions cannot be neglected, as they play a role in most human processes, and this role often provides a constructive, and not a disturbing contribution. This widened scope of AI and agent system modelling provides a multitude of new types of research questions that can be explored using computational modelling methods. Examples of such questions are:

- Does a feeling affect an expressed emotion or the other way around?
- In which way is it possible to control emotion?
- How does desiring relate to feeling?
- In how far do sensing and believing relate to feeling?
- How does having experiences over time relate to experiencing emotions?
- Can you make an adequate decision without feeling good about it?
- In how far is an individual in a group free in having own emotions?
- Why do groups with individuals with initially different preferences often come to common decisions and all members feel good with these decisions?

It turns out that to address this new area, different views on causality and modelling are required compared to the traditional views in cognitive modelling. For example, Scherer (2009) states:

> 'What is the role of causality in the mechanisms suggested here? Because of the constant recursivity of the process, the widespread notion of linear causality (a single cause for a single effect) cannot be applied to these mechanisms. Appraisal is a process with constantly changing results over very short periods of time and, in turn, constantly changing driving effects on subsystem synchronization (and, consequently, on the type of emotion). (…) Thus, as is generally the case in self-organizing systems, there is no simple, unidirectional sense of causality (see also Lewis 1996).' (Scherer, 2009, p. 3470)

More generally, structures and mechanisms found in neuroscience suggest that many parts in the brain are connected by cyclic connections, and such connections may be assumed to play an important role in many of the brain's processes (e.g., Bell, 1999; Crick and Koch, 1998; Potter, 2007). Moreover, these connections can change over time (plasticity). In particular, traditionally assumed linear patterns such as 'sensing → sensory processing → preparing → action' have to be reconsidered, as due to mutual, cyclic connections, for example, between preparation and sensory states, the processing may be intertwined, as will be discussed in this paper in more detail. The modelling perspective on emotions considered here takes this into account. It views emotions and feelings as being part of a number of interrelated adaptive and regulatory cycles, and based on these cycles emotional states emerge over time, and affect many other human processes. Examples of such types of cycles are emotional response – feeling cycles (e.g., Damasio, 1999, 2010), emotion regulation cycles (e.g., Gross, 1998, Goldin *et al.*, 2008), cognitive-affective cycles (e.g., Phelps, 2006; Pessoa, 2008), and social contagion cycles (e.g., Iacoboni, 2008; Hatfield *et al*., 2009). More advanced models for emotions and their role in mental functioning may involve a multiple of such types of cycles, that have to be integrated. One example of this further integration is described in (Aziz et al., 2011) where an emotion regulation cycle is integrated with a social interaction cycle. As another example, in (Hoogendoorn et al., 2011) and (Bosse et al., 2012) cognitive-affective cycles are integrated with social interaction cycles.

To address modelling of the type of integrated cyclic processes discussed above, in this paper an integrative dynamical systems perspective is put forward and illustrated. The presented perspective covers qualitative conceptual modelling based on graphs with temporal-causal relations in which cycles are allowed, and quantitative computational modelling based on the (numerical) dynamical systems perspective described, for example, in (Ashby, 1952; Port and van Gelder, 1995). Moreover, it is shown how from such qualitative conceptual models in a systematic manner corresponding quantitative computational models can be obtained. The paper provides a unifying survey of a perspective for which different instances can be found in specific applications in the literature.

In the paper, first the general modelling perspective used is discussed. Next, the cycle between emotional response and feeling is addressed, after which emotion regulation is discussed. Furthermore, the interaction between cognitive and affective states is discussed, and the role of emotion-related valuing in decision making. Moreover, emotions in social contagion processes are addressed. Finally it is discussed how Hebbian learning can be used for adaptive processes. The paper closes with a discussion.

Modelling Perspective

To model the types of highly cyclic processes involving emotions as discussed here in a neurologically inspired computational manner, a dynamical modelling perspective is needed that can handle such cycles. In the current paper modelling is done at two levels: a qualitative, conceptual level, and at a quantitative, computational level. For the first level graphs are used that are allowed to have cycles, and for the second level the dynamical systems perspective as advocated, for example, in (Ashby, 1952; Port and van Gelder, 1995), is used.

Modeling causal relations as discussed in neurological literature does not need to take specific neurons into consideration but can use more abstract mental states, relating, for example, to groups of neurons. In this way within the cognitive/affective modelling area results from the large and more and more growing amount of neurological literature can be exploited. This can be considered as lifting neurological knowledge to a mental (cognitive/affective) level considering temporal-causal dynamic relations between mental states. Such dynamic relations can be found in neuroscientific literature and can be specified at a qualitative, conceptual level by graphs consisting of nodes and directed connections between them where cycles are allowed, as shown, for example, in Figures 1 to 7.

To build a quantitative, computational model based on such a graph in a systematic manner, some technical elements from the neural modelling level are useful. In particular, in the current paper a systematic approach is used based on states as having certain activation levels (numbers in the interval [*0*, *1*]) over time, and temporal relations which make reciprocal loops and gradual adaptation possible. This type of computational model is suitable to model temporal-causal relations between states by dynamical relations for the activation levels of these states in a mathematical manner as in (Ashby, 1952; Port and van Gelder, 1995), and is formulated as follows. For a state depending on multiple other states, to update its activation level, input values for incoming activation levels are to be combined to some aggregated input value $agginput_i$. This update itself then takes place according to a differential equation

$$\mathbf{d}y_i/\mathbf{d}t \;=\; \gamma_i\;[agginput_i\; - y_i\,] \tag{1}$$

where γ_i is the update speed for state i, $agginput_i$ is the aggregated input for i, and y_i is the activation level of state i. The aggregation is created from the individual inputs $\omega_{j,i}\, y_j$ for all states j connected toward state i, where $\omega_{j,i}$ is the strength of the connection from j to i (a number between -1 and 1). For this aggregation a combination function $f(V_1,\, ...,\, V_k)$ is needed, applied to the different incoming values $V_j = \omega_{j,i}\, y_j$. Using this, (1) can be expressed as:

$$\mathbf{d}y_i/\mathbf{d}t \;=\; \gamma_i\;[f(\omega_{1,i}\, y_1,\; ...,\; \omega_{k,i}\, y_k) - y_i\,] \tag{2}$$

Here only for states j connected to state i the value of $\omega_{j,i}$ can be nonzero, for not connected states they are trivially set 0; for simplicity of notation, often the arguments for not connected states are left out of the function f. It will be assumed that such a combination function f satisfies the following conditions:

(a) $0 \leq f(V_1,\, ...,\, V_k) \leq 1$ whenever $V_1,\, ...,\, V_k \leq 1$
(b) f is monotonous: $f(V_1,\, ...,\, V_k) \leq f(W_1,\, ...,\, W_k)$ whenever $V_i \leq W_i$ for all i

A simple example of a combination function used in (1) is the sum function:

$$f(V_1,\; ...,\; V_k) = \Sigma_i\, V_i \tag{3}$$

For this function to satisfy (a), this puts strong constraints on the values $V_1,\, ...,\, V_k$ and therefore on the connection strengths $\omega_{j,i}$: the sum of the inputs has to be at most 1, i.e., $\Sigma_{j\in s(i)}\, \omega_{j,i} \leq 1$, where $s(j)$ is the set of states connected as a source to state i. This dependency between connections is often not considered practical, nor biologically plausible. Moreover, for negative $\omega_{j,i}$ also (a) and (b) may not be fulfilled. An often used alternative combination function (e.g., in (Beer, 1995)) in (1) is based on a continuous logistic threshold function:

$$f(V_1,\, ...,\, V_k) \;=\; th(V_1 + ... + V_k) \tag{4}$$

with

$$th(X) \;=\; 1/(1{+}\mathrm{e}^{-\sigma(W-\tau)}) \tag{5}$$

or

$$th(X) \;=\; ((1/(1{+}\mathrm{e}^{-\sigma(W-\tau)}))\; - (1/(1{+}\mathrm{e}^{\sigma\tau})))\,(1{+}\mathrm{e}^{-\sigma\tau}) \tag{6}$$

Note that in variant (5) it holds $th(0) = 1/(1{+}\mathrm{e}^{\sigma\tau})$, and this is nonzero, which may be considered an artifact of the model which lacks biological plausibility. This flaw is compensated in variant (6). Note that for variant (6), $th(X)$ is set 0 whenever $X< 0$ (which may occur when negative weights $\omega_{j,i}$ are used). Variant (5) can be used as a suitable approximation of (6) when $\sigma\tau$ is large enough, e.g. $\sigma\tau \geq 20$. Given this, the type of computational model considered here uses $agginput_i \;=\; th(\Sigma_{j\in s(i)}\;\, \omega_{j,i}\;\, y_j)$ and filling this in (2) provides a dynamical system of the form:

$$\mathbf{d}y_i/\mathbf{d}t \;=\; \gamma_i\;[\; th(\Sigma_{j\in s(i)}\;\, \omega_{j,i}\;\, y_j) - y_i\,] \tag{7}$$

Note that the type of model can be described in difference equation format as follows:

$$y_i(t+\Delta t) = y_i(t) + \gamma_i \, [\, th(\Sigma_{j\in s(i)} \; \omega_{j,i} \; y_j) - y_i \,] \, \Delta t \qquad (8)$$

This difference equation can be directly used for simulation, or more dedicated numerical approximation methods can be used.

In subsequent sections, for a number of processes in which emotions play a role it is discussed how this modelling perspective can be applied. Note that the example computational models below are given in the general format of (2) above, so that still a choice can be made for a specific combination function *f*, for example, one of the forms specified in (3) or (4) with (5) or (6) above, which can be considered as available building blocks.

The quantitative computational modelling approach adopted here fits in the scope of small continuous-time recurrent neural networks; this approach is advocated by Beer (1995), and was inspired, for example, by earlier work in (Grossberg, 1969; Hopfield, 1982, 1984; Funahashi and Nakamura, 1993). In (Beer, 1995) it is claimed that they are an obvious choice for modelling because (1) they are the simplest nonlinear, continuous dynamical neural network model, (2) they are universal dynamics approximators in the sense that, for any finite interval of time, they can approximate the trajectories of any smooth dynamical system on a compact subset of IR^n arbitrarily well (Funahashi and Nakamura, 1993), and (3) they have a plausible neurobiological interpretation. The following is a summary of the assumptions that are adopted for the modelling perspective as discussed.

Conceptual and computational modelling assumptions

- Cyclic connections play a role in many brain processes; often no linear patterns such as 'sensing → sensory processing → preparing → action' are followed
- Emotions relate bidirectionally to practically all mental processes and behavior
- Processes can be described at a qualitative conceptual modelling level and at a quantitative computational modelling level
- Given a description at a qualitative conceptual modelling level, this can be transformed in a systematic manner into a description at a quantitative computational modelling level
- In a description at a quantitative computational modelling level at each time point states have a strength or activation level that can be expressed by a number in [*0*, *1*]
- During processing at each point in time the activation level of a state affects the activation levels of states connected to it for next points in time (temporal-causal relation)
- The dynamical computational models considered at a quantitative computational modelling level are specified by temporal relations between the strengths of the states considered

Generating Emotional Responses and Feelings

The question on the direction of causality between feeling and emotional response has a long history. A classical view on emotions is that based on some sensory input, due to internal processing emotions are felt, and based on this they are expressed in some emotional response (e.g., a body state such as a face expression):

stimulus → sensory representation → felt emotion → preparation for bodily changes → expressed emotion

James (1884) claimed a different direction of causality (see also Damasio, 2010, pp. 114-116):

stimulus → sensory representation → preparation for bodily changes → expressed emotion → felt emotion

The perspective of James assumes that a *body loop* via the expressed emotion is used to generate a felt emotion by sensing the own body state. Damasio made a further step by introducing the possibility of an *as-if body loop* bypassing actually expressed bodily changes (cf. Damasio, 1994, pp. 155-158; see also Damasio, 1999, pp. 79-80; Damasio, 2010):

stimulus → sensory representation → preparation for bodily changes → felt emotion

An as-if body loop describes an *internal simulation* of the bodily processes, without actually affecting the body, comparable to simulation in order to perform, for example, prediction, mindreading or imagination; e.g., Becker and Fuchs, 1985; Goldman, 2006; Hesslow, 2002. Damasio (1999) distinguishes an emotion (or emotional response) from a feeling (or felt emotion); see for example:

> 'Seen from a neural perspective, the emotion-feeling cycle begins in the brain, with the perception and appraisal of a stimulus potentially capable of causing an emotion and the subsequent triggering of an emotion. The process then spreads elsewhere in the brain and in the body proper, building up the emotional state. In closing, the process

returns to the brain for the feeling part of the cycle, although the return involves brain regions different from those in which it all started.' (Damasio, 2010, p. 111)

The emotion and feeling in principle mutually affect each other in a bidirectional manner: an as-if body loop usually occurs in a cyclic form by assuming that the emotion felt in turn affects the prepared bodily changes; see, for example, in (Damasio, 2010, pp. 119-122):

emotion felt $\rightarrow$ preparation for bodily changes

A brief up-to-date survey of Damasio's ideas about emotion and feeling, and the 'tightly bound cycle' between them can be found in (Damasio, 2003, pp. 91-92) and (Damasio, 2010, pp. 108-129); for example:

'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 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.' (Damasio, 2003, pp. 91-92)

This essentially shows a cyclic process that (for a constant environment) can lead to equilibrium states for both emotional response (preparation) and feeling. These biological mechanisms as briefly sketched have been used to obtain a qualitative conceptual description depicted as a graph in Figure 1. Here *b* is a label indicating a specific body state corresponding to the considered emotion. Note that what is called stimulus *s* here can be taken as the sensor state sensing *s*. This answers the question on the direction of the causality between feeling and emotional response in the sense that both emotional response affects feeling and feeling affects emotional response, in a cyclic manner. Note that for stimuli *s* and body states *b* indicate abstract states which by themselves may be characterised by multiple aspects; see also, for example, (Damasio, 1999; Lazarus, 1991; Roseman, 1996; Scherer, 1999; Scherer, 2009). For example preparation for a specific emotional response *b* can involve different aspects of the body such as heart rate, skin, and specific chemicals in the blood. In many cases these abstract states can be related to vectors of values for such multiple aspects (see also Bosse, Jonker and Treur, 2008). Moreover, in more complex models more than one stimulus *s* and more than one body state *b* can be modelled as abstract states, for example, as s_1, s_2, .. and b_1, b_2, … Then for each combination of an s_i and a b_j relations as depicted in Figure 1 can be covered by the model (multiple stimuli have a combined effect on each preparation state). Note that the perspective presented here uses explicitly represented feeling states, which contrasts to approaches that consider emotions to be not explicitly represented as states having a causal effect; see, for example, (Peck and Kozloski, 2011).

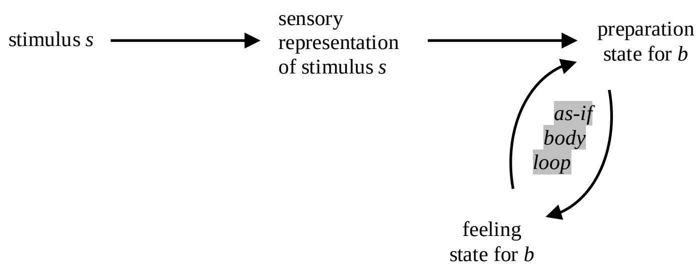

Fig. 1. Generating emotions and feelings based on a cyclic as-if body loop

The graph depicted in Figure 1 has been used to obtain a quantitative computational model according to the systematic approach described in the Modelling Perspective section above, resulting in the model as shown in Box 1. Here each of the states has an associated differential equation for the update of its activation level, and connection strengths are nonnegative: $\omega_{X,Y} \geq 0$. Note that in Box 1 (and similarly for all boxes later on) the symbols such as *sr*, *p* and *ef* denote activation levels of sensory representation, preparation and feeling, respectively, not the notions sensory representation, preparation and feeling themselves. To avoid possible misunderstanding, these activation levels might have been denoted by y_{sr}, y_p and y_{ef} respectively, but for the sake of notational simplicity this more complex notation has not been used. Moreover, note that due to monotonicity of the combination function *f*, it holds that the higher the value of $\omega_{p,ef}$, the stronger the level of the response state affects the level of the feeling state *ef*, and the higher the value of $\omega_{ef,p}$, the stronger the feeling level affects the emotional response level *p*. Due to the cyclic nature of the model this effect propagates back and forth between the two states.

The following is a summary of the assumptions that are adopted to model emotional response and feeling, as discussed.

Assumptions on emotional response and feeling

- Emotions and feelings can be labeled in an abstracted form by body states, which themselves can relate to a vector for a number of aspects or dimensions
- At each time point emotions, feeling, sensory representation and preparation states have a strength (or activation level) that can be expressed by a number in [*0, 1*], indicating the strength of this state
- Mutual, cyclic interactions take place between preparation and sensory states
- From sensory representations preparations for emotional responses are triggered
- The level of preparation for an emotional response affects the level of the corresponding feeling
- A feeling level affects the corresponding emotional response preparation level

$$\mathbf{d}sr/\mathbf{d}t \;=\; \gamma_{sr}\;[\,f(\omega_{s,sr}\,s) - sr\,]$$
$$\mathbf{d}p/\mathbf{d}t \;=\; \gamma_{p}\;[\,f(\omega_{sr,p}\,sr,\;\omega_{ef,p}\,ef) - p\,]$$
$$\mathbf{d}ef/\mathbf{d}t \;=\; \gamma_{ef}\;[\,f(\omega_{p,ef}\,p) - ef\,]$$

The symbols are explained as follows:

s	activation level of the stimulus
sr	activation level of the sensory representation of the stimulus
p	activation level of the preparation state (for the emotional response)
ef	activation level of the feeling state (emotion felt)
γ_X	update speed parameter for state X
$\omega_{X,Y}$	strength of the connection from state X to state Y

Box 1 Example computational model for emotion-feeling cycle

The biological mechanisms briefly sketched above have been used as inspiration for computational mechanisms in earlier work as well, for example, described in (Bosse *et al.*, 2008; Bosse *et al.* 2012). Here in (Bosse et al., 2008) a qualitative model without cycles is described; the connection from feeling to preparation was not covered. In (Bosse et al., 2012) the focus is on emotion reading in a social context. A more complex model is presented of which the cycle shown in Figure 1 is part. The computational model specification in both cases (Bosse *et al.*, 2008; Bosse *et al.* 2012) is not in terms of differential equations, but in terms of the hybrid temporal-causal LEADSTO format; cf. (Bosse, Jonker, Meij, and Treur, 2007).

Emotion Regulation

Controlling or regulating your emotion is often associated to suppressing an emotional response, for example, expressing a neutral poker face. This type of controlling emotions is sometimes considered not very healthy, and a risk for developing serious medical problems. However, it has been found that the mechanisms to regulate emotions form a much wider variety. For example, closing or covering your eyes when a movie is felt as too scary, or avoiding an aggressive person are different forms of control. Emotion regulation mechanisms (e.g., Gross, 1998; Goldin *et al.*, 2008) cover *antecedent-focused regulation* (e.g., selection and modification of the situation, attentional deployment, and reappraisal) and *response-focused regulation* (suppression of a response). Examples of antecedent-focused mechanisms are closing your eyes or turning away your gaze from stimuli that trigger too high levels of emotions, redirecting attention, or changing the cognitive interpretation of the situation. Response-focused emotion regulation mechanisms suppress the emotional responses without taking away or modulating the triggers. Expressing a poker face or fighting against tears are examples of such mechanisms. Emotion regulation mechanisms are processes with a cyclic character. In modelling emotion regulation, in the first place a control state is needed to detect whether an undesired level of emotion occurs. This is assumed to be realised in the prefrontal cortex (Goldin *et al.*, 2008). When this control state has a high activation level (for example, indicating too high levels of an undesired emotion), this can affect a number of other states. Response-focused mechanisms can be modelled by suppressing connections (with negative weight factors) from the control state to preparation and/or effector states. Antecedent-focused mechanisms can be modelled by suppressing connections from the control state to sensor states, sensory representation states or feeling states. In Figure 2 some of these possibilities are depicted.

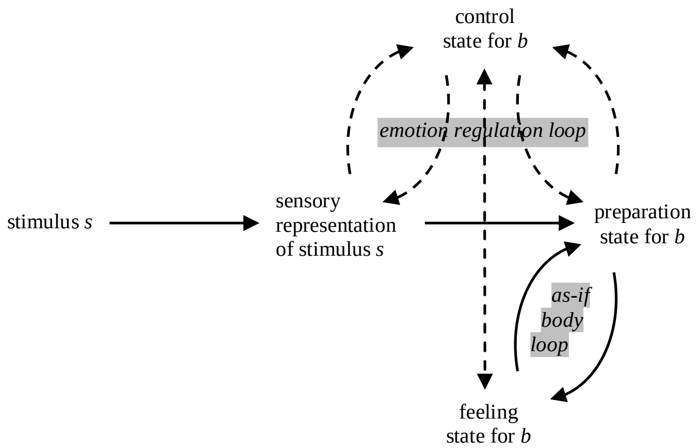

Fig. 2. Cyclic mechanisms for emotion regulation

The graph for emotion regulation depicted in Figure 2 has been used to obtain a quantitative computational model according to the systematic approach described in the Modelling Perspective section above, resulting in the model as shown in Box 2. Note that here the connection strengths $\omega_{cs,X}$ from the control state cs to other states have a negative value: $\omega_{X,Y} \leq 0$. These connections suppress the activation levels of the destination nodes. The more negative these connection strengths are, the stronger the suppression. The following is a summary of the assumptions that were adopted for emotion regulation, as discussed.

Assumptions on emotion regulation

- The activation levels of emotional response preparation, feeling and sensory representation affect the activation level of a control state for emotion regulation
- In turn the activation level of such a control state affects in a negative manner the activation levels of emotional response preparation, feeling and sensory representation

$$\mathbf{d}cs/\mathbf{d}t = \gamma_{cs}\,[f(\omega_{sr,cs}\, sr,\ \omega_{p,cs}\, p,\ \omega_{ef,cs}\, ef) - cs\,]$$
$$\mathbf{d}p/\mathbf{d}t = \gamma_{p}\,[\,f(\omega_{sr,p}\, sr,\ \omega_{ef,p}\, ef,\ \omega_{cs,p}\, cs) - p\,]$$
$$\mathbf{d}ef/\mathbf{d}t = \gamma_{ef}\,[f(\omega_{p,ef}\, p,\ \omega_{cs,ef}\, cs) - ef]$$
$$\mathbf{d}sr/\mathbf{d}t = \gamma_{sr}\,[\,f(\omega_{s,sr}\, s,\ \omega_{cs,sr}\, cs) - sr]$$

The symbols are explained as follows:

cs	activation level of the control state
p	activation level of the preparation state (for the emotional response)
s	activation level of the stimulus
sr	activation level of the sensory representation of the stimulus
ef	activation level of the feeling state (emotion felt)
γ_X	update speed parameter for state X
$\omega_{X,Y}$	strength of the connection from state X to state Y

Box 2 Example computational model for emotion regulation

Biological mechanisms for emotion regulation as discussed also have been the inspiration for computational mechanisms, for example, in (Chow, Ram, Boker, Fujita, Clore, 2005), which takes homeostatic principles as a point of departure to address emotion regulation computationally. Also in (Bosse et al., 2010) such principles are the underlying assumptions, and they are applied to the different phases considered by Gross (1998): situation selection, situation modification, attention deployment, reappraisal, response suppression. Here a different type of specification is used, in LEADSTO format (cf. Bosse et al., 2007). In (Treur, 2011a) a computational model for (reduced) social interaction is presented in which emotion regulation is used for cases of enhanced sensory processing sensitivity to avoid stimuli that are felt as having a too strong impact. This model uses a similar computational mechanism as used here, but for a specific type of regulation. The same applies to the computational model for dreaming discussed in (Treur, 2011); here emotion regulation is used to downregulate fear in dream episodes.

Interaction between Cognitive and Affective States

Usually it is assumed that behaviour can be described in relation to cognitive states such as beliefs and desires, while leaving affective states aside. The latter types of states are considered as being part of a separate line of (affective) processes that produce their own output, for example, in the sense of emotions and expressions of them. However, this assumed separation between cognitive and affective processes is questioned more and more. Specific examples of questions about such interactions are: how does desiring relate to feeling, and in how far do sensing and believing relate to feeling? Recent neurological findings suggest that this separation may not be a fruitful way to go. For example, Phelps (2006) states:

> 'The mechanisms of emotion and cognition appear to be intertwined at all stages of stimulus processing and their distinction can be difficult. (..) Adding the complexity of emotion to the study of cognition can be daunting, but investigations of the neural mechanisms underlying these behaviors can help clarify the structure and mechanisms'. (Phelps, 2006, pp. 46-47)

Similar claims have been made recently by Pessoa (2008), and others. In experimental contexts different types of effects of affective states on cognitive states have indeed been found; see, for example, (Eich, Kihlstrom, Bower, Forgas, and Niedenthal, 2000; Forgas, Goldenberg, and Unkelbach, 2009; Winkielman, Niedenthal, and Oberman, 2009). Moreover, in the rapidly developing area of cognitive neuroscience (e.g., Purves, Brannon, Cabeza, Huettel, LaBar, Platt, and Woldorff, 2008; Gazzaniga, 2009) more in general knowledge has been contributed on mechanisms for the interaction or intertwining of affective and cognitive states and processes (for example, involving emotion, mood, beliefs or memory); see, for example, (Dolan, 2002; LaBar and Cabeza, 2006; Pessoa, 2008; Phelps, 2006; Storbeck and Clore, 2007).

To become a more specific, the interaction between beliefs and emotions is discussed in a bit more detail. For example, in (Damasio, 1999; 2003) it is described how in a person a belief state induces emotions felt within this person:

> 'Even when we somewhat misuse the notion of feeling – as in "I feel I am right about this" or "I feel I cannot agree with you" – we are referring, at least vaguely, to the feeling that accompanies the idea of believing a certain fact or endorsing a certain view. This is because believing and endorsing *cause* a certain emotion to happen. (..) Through either innate design or by learning, we react to most, perhaps all, objects with emotions, however weak, and subsequent feelings, however feeble.' (Damasio, 2003, p. 93)

For the sake of simplicity it is assumed that beliefs are cognitive states representing knowledge about the world and generated (mainly) on the basis of sensing. So, for the case of beliefs as cognitive states, during the process that they are generated, beliefs trigger emotional responses that result in certain feelings. However, the process of generation of a cognitive state such as a belief is not fully independent of such associated feelings, as also put forward by Frijda (1993), Lewis (1996), and Frijda, Manstead, and Bem (2000b), and Spinoza (1677):

> 'Beliefs thus are regarded as one of major determinants of emotion, and therefore an important part of the study of emotion can properly be seen as falling under the umbrella of cognitive psychology. Oddly enough, however, the reverse direction of influence in the relation between emotion and cognition has received scant attention. (...) Indeed, such an influence has traditionally been considered to be one of the most important things to be said about emotions. Spinoza (1677/1989) defined emotions as "states that make the mind inclined to think one thing rather than another". (...) The general proposal thus is that emotions can awaken, intrude into, and shape beliefs, by creating them, by amplifying or altering them, and by making them resistant to change.' (Frijda, Manstead, and Bem, 2000b, p. 1, 5)

Support for a connection from feeling to belief can be found as well in Damasio's Somatic Marker Hypothesis; cf. (Damasio, 1994; 2003; Bechara and Damasio, 2005). This is a theory on decision making which provides a central role to emotions felt. Each decision option induces (via an emotional response) a feeling which is used to mark the option. A negative marker has a weakening effect and a positive marker a strengthening effect for the option. Usually the Somatic Marker Hypothesis is applied to provide endorsements or valuations for options for a person's actions. However, it may be considered plausible that such a mechanism is applicable to valuations of internal states such as beliefs as well. In summary, some indications can be found for the assumption that a belief generates emotional responses and related feelings, and these feelings in turn affect the belief. This provides a pattern based on two cycles as depicted in Figure 3. Note that the diagram shown in Figure 3 applies as well to multiple cognitive states active at the same time and multiple emotional responses and feelings. In such a case the level of a given emotion can be affected by the levels of more than one cognitive state by some combination function and similarly a the level of given cognitive state can be affected by the levels of more than one emotion.

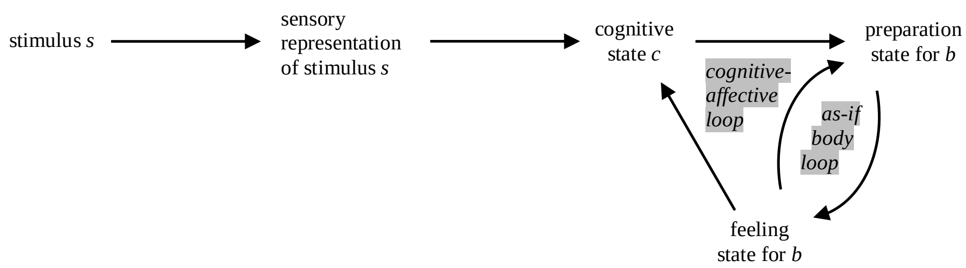

Fig. 3. Cyclic process of mutual interaction between cognitive and affective states

Similar analyses can be made for other types of cognitive states. For example, desires 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 process of ‘desiring’, especially concerning the feelings associated to it. Desires lead to activations for responses in the form of preparations for certain actions (to fulfill the desire) and their related emotions. Such responses in turn relate in a reciprocal manner to feelings, via cyclic as-if body loops as discussed above. For example, a desire to have some food may trigger a preparation to take some chocolate, which by an as-if body loop in a cyclic manner goes hand in hand with activation of some feeling. This feeling can strengthen both the desire and the preparation. The two cycles shown in Figure 3 model these processes.

A third type of cognitive state considered is a sensory representation. Such a state is closely related to a sensor state and at least this type of state may be believed not to be affected by affective states. However, even here recently findings have been reported suggesting that this independence of affective states cannot be claimed. In particular, in (Gazzola et al., 2012) it is reported how for heterosexual men one and the same stimulus (a leg being touched in an invisible manner, by a woman) leads to different sensory activation levels depending on a presented video of either a woman or a man. Such findings suggest that in a diagram as depicted in Figure 3, also an arrow from feeling to sensory representation state can be drawn.

The following is a summary of the assumptions that are adopted for interaction between cognitive and affective states, as discussed.

Assumptions on interaction between cognitive and affective states

- Affective states and cognitive states can be distinguished
- By mutually affecting each other’s states affective and cognitive processes are intertwined and overlapping
- The activation level of a cognitive state affects the activation level of an associated emotional response and through this the activation level of a feeling
- The activation level of the feeling affects the activation level of the cognitive state

A generic version of such computational models for the interaction between (activation levels of) cognitive and affective states can be found in Box 3. Here the connection strengths $\omega_{X,Y}$ are assumed ≥ 0. Note that the higher the values $\omega_{c,p}$ and $\omega_{ef,c}$ of the strengths of the connections from and to the cognitive state *c*, and the values $\omega_{ef,p}$ *and* $\omega_{p,ef}$ for the connections between the emotional response and feeling state, the higher the activation value of the cognitive state *c*.

$$\mathbf{d}sr/\mathbf{d}t = \gamma_{sr} \; [\, f(\omega_{s,sr}\, s) - sr \,]$$
$$\mathbf{d}c/\mathbf{d}t = \gamma_c \; [\, f((\omega_{sr,c}\, sr,\; \omega_{ef,c}\, ef) - c \,]$$
$$\mathbf{d}p/\mathbf{d}t = \gamma_p \; [\, f(\omega_{c,p}\, c,\; \omega_{ef,p}\, ef) - p \,]$$
$$\mathbf{d}ef/\mathbf{d}t = \gamma_{ef} \; [f(\omega_{p,ef}\, p) - ef]$$

The symbols are explained as follows:

s	activation level of the stimulus
sr	activation level of the sensory representation of the stimulus
p	activation level of the preparation state (for the emotional response)
ef	activation level of the feeling state (emotion felt)
c	activation level of the cognitive state
γ_X	update speed parameter for state X
$\omega_{X,Y}$	strength of the connection from state X to state Y

Box 3 Computational model for cognitive-affective interaction

The interaction between belief and feeling has also been addressed in (Memon and Treur, 2010), using a computational model specified in LEADSTO format (Bosse *et al.*, 2007), which is a difference with the model discussed above. Moreover the connection to the belief is adaptive. The interaction between desire and feeling as discussed here has been worked out in more detail in a computational model in (Bosse *et al.*, 2010). Here also the adaptivity based on feedback of actual execution is part of the model. Also this model was specified in LEADSTO format.

Emotion-Related Valuing in Decision-Making

In the area of decision making the role of emotions has been discussed since long. From an idealised rationality perspective it has long been assumed that emotions can only disturb proper rational decision making and should be left out of the process in order to come up with adequate decisions. However, this has been questioned in more recent times. For example, in (Loewenstein and Lerner, 2003) it is stated:

> ‘Throughout recorded human intellectual history there has been active debate about the nature of the role of emotions or ‘passions’ in human behavior, with the dominant view being that passions are a negative force in human behavior (…). By contrast, some of the latest research has been characterized by a new appreciation of the positive functions served by emotions’ (Loewenstein and Lerner, 2003, p. 619)

Can you make an adequate decision without feeling good about it? If you make a decision with a bad feeling this may cast doubt on how robust the decision is: at any occasion in the (near) future you may be tempted to change it into a different decision. The area of decision making is another specific area in which affective elements play an important role. The focus in decision making is on how to perform valuing of situations or options for actions to be decided for. More specifically, feelings generated in relation to an observed situation and prepared action option play an important role in valuing predicted or imagined effects of such an action in the situation. Such valuations have been related to amygdala activations (see, e.g., Morrison and Salzman, 2010; Murray, 2007; Salzman and Fusi, 2010). Although traditionally an important function attributed to the amygdala concerns the context of fear, in recent years much evidence on the amygdala in humans has been collected showing a function beyond this fear context.

Emotional responses are triggered by stimuli for which (by internal simulation) a prediction is made of a consequence. Feeling these emotions represents a way of experiencing the value of such a prediction: to which extent it is positive or negative. This valuation in turn affects the activation of the concerning option. The pattern involves two cycles, as depicted in Figure 4. Note that these cycles are active in parallel for all options a (partially) triggered by s, and result in specific valuation values for each of the options, which, depending on their value, strengthen the options. In this way the valuing process strengthens some of these option preparations more due to higher values of the connections involved in the two cycles, such as the connection from valuation to preparation, or the connections involved in prediction and in the as-if body loop.

Note that this pattern is similar to what is considered in Damasio's Somatic Marker Hypothesis discussed above. Moreover, note that this provides a (circular) causal role of feelings in decisions for actions, which has some parallel to the discussion on the causal role of qualia; e.g., (Kim, 1996).

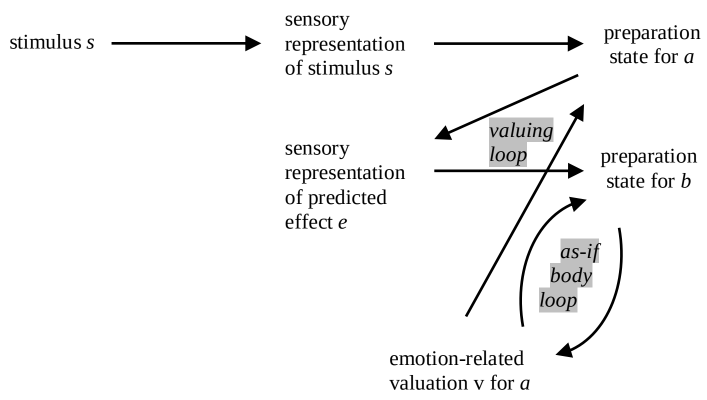

Fig. 4. A cycle for decision making based on emotion-related valuing

The following is a summary of the assumptions that are adopted for the role of emotions in decision making, as discussed.

Assumptions on emotions in decision making

- For a given context activation levels of preparations for a number of decision options are increased
- For these options sensory representations for predictions get increased activation levels
- These predictions affect the activation levels of associated emotional responses and feelings
- The feelings affect the levels of the option preparations and in this manner play a role of valuing the option

An example of such a computational model is shown in Box 4, with connection strengths $\omega_{X,Y} \geq 0$. Note that the connection strengths determine the valuation *ve* generated for a given option *a*. For example, when in a special case for a given option *a* all of $\omega_{s,pa}$, $\omega_{pa,se}$, $\omega_{se,pb}$, $\omega_{pb,ve}$, $\omega_{ve,pb}$, and $\omega_{ve,pa}$ are higher than those for all other options, then this option *a* will get the highest valuation *ve* and activation level *pa*. On the other hand, it may well be the case that some option *a* has the highest $\omega_{s,pa}$, but still gets the lowest valuation *ve* and as a consequence lowest activation level *pa*, due to lower values for other connections involved in the cycles for this option. In such a case, although at forehand there are good indications for *a* as a response for the given stimulus *s*, still because of negative valuation of the predicted effect it is not pursued.

$$\mathbf{d}sr/\mathbf{d}t = \gamma_{sr} \; [\, f(\omega_{s,sr}\, s) - sr \,]$$
$$\mathbf{d}pa/\mathbf{d}t = \gamma_{pa} \; [\, f(\omega_{sr,pa}\, sr,\ \omega_{ve,pa}\, ve) - pa \,]$$
$$\mathbf{d}pb/\mathbf{d}t = \gamma_{pb} \; [\, f(\omega_{se,pb}\, se,\ \omega_{ve,pb}\, ve) - pb \,]$$
$$\mathbf{d}se/\mathbf{d}t = \gamma_{se} \; [f(\omega_{pa,se}\, pa) - se]$$
$$\mathbf{d}ve/\mathbf{d}t = \gamma_{ve} \; [f(\omega_{pb,ve}\, pb) - ve]$$

The symbols are explained as follows:

s	activation level of the stimulus
sr	activation level of the sensory representation of the stimulus
pa	activation level of the preparation state for decision option a
pb	activation level of the preparation state for emotional response *b*
se	activation level of the predicted effect representation
ve	activation level of the emotion-related valuing state
γ_X	update speed parameter for state *X*
$\omega_{X,Y}$	strength of the connection from state *X* to state *Y*

Box 4 Computational model for decision making based on emotion-related valuing

A similar computational model as the one described here has been discussed in (Treur and Umair, 2011). In particular, it has been analysed how adaptivity can be added and in how far this makes the model behave rationally for a given environment.

Emotions and Social Contagion

Emotions also play an important role in mutual social interactions. In a social context usually emotions of different individuals affect each other (emotion contagion). The question that may arise, for example, in how far an individual in a group free is in having own his or her emotions. Moreover, the role of emotion contagion may be considered for the miracle that groups with individuals with initially different preferences often come to coherent common decisions and all members feel good with these decisions. Viewed from a distance, an emotion contagion cycle can be described as depicted in Figure 5. Here the preparation states are not only affected by stimuli from the (non-human) environment, but also by sensing other individuals' emotional responses. The mechanisms underlying emotion contagion can be considered in a more detail manner. From the area of Social Neuroscience it has been found that mirror neurons and internal simulation are key elements in these mechanisms. Mirror neurons are neurons that do not only have the function to prepare for a certain action or body change (e.g., a face expression), but are also activated upon observing somebody else who is performing this action or body change. They have been found both in monkeys and humans; e.g., (Rizzolatti and Sinigaglia, 2008; Iacoboni, 2008; Mukamel, Ekstrom, Kaplan, Iacoboni, and Fried, 2010). Mirror neurons make that some specific sensory input (an observed person) directly links to activation of related preparation states. This mechanism of mirror neuron activation upon observation is modelled in Figure 5 by the arrows from sensory representation of observed *b* to preparation state for *b*.

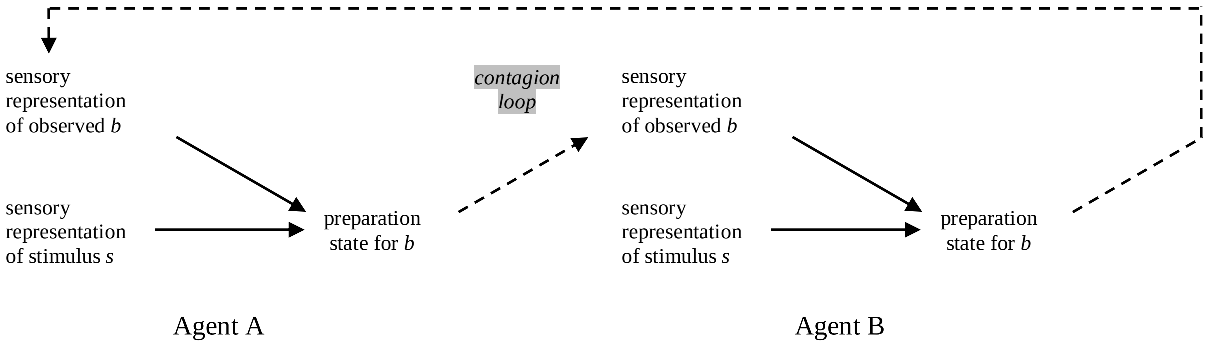

Fig. 5. Emotion contagion cycle

The following is a summary of the assumptions that are adopted for emotions in social contagion, as discussed.

Assumptions on emotions in social interaction

- An emotion with a certain strength expressed by one person affects the strength of the preparation of a similar emotional response in another person
- In combination with as-if body loops the level of a feeling of one person affects the level of a similar feeling by another person

A computational model at this level of abstraction is shown in Box 5, with connection strengths $\omega_{X,Y} \geq 0$. Note that the connection strength $\omega_{p_B, so_{A,B}}$ represents the aspects of the relation between agent *A* and *B* that determine how well *B* is observed by *A*. For example, when *B* is not observed at all by *A*, the value is *0*. Moreover, the connection strength $\omega_{so_{A,B}, p_A}$ represents how responsive *A* is for *B*. Persons with a poor mirroring function have a low value for this. Note that the connections $\omega_{so_{A,B}, p_A}$ and ω_{sr_A, p_A} determine a balance between the effect of the stimulus in the emotional response in comparison to the effect of the observed emotion from others. Persons with high $\omega_{so_{A,B}, p_A}$ compared to ω_{sr_A, p_A} will easily adapt to other persons, whereas persons with high ω_{sr_A, p_A} compared to $\omega_{so_{A,B}, p_A}$ will be more difficult to affect. Furthermore, note that these processes can occur for multiple emotions *b* (e.g., some *b1* and *b2*) at the same time. For such cases extra indices (for *b1* and *b2*) can be used in the computational model specification. For example, person *A* can be angry (with high activation level $p_{A,b1}$)

because person B did something wrong and see that person B feels bad about this (high activation level $p_{B,b2}$), and therefore at the same time person A starts to feel bad as well (high activation level $p_{A,b2}$).

As these emotion contagion processes happen mostly in an unconscious manner, mirroring imposes limitations on the freedom for individuals to have their own personal emotions, beliefs, intentions, and actions in a group. Simulations by computational models similar to the one described here show that often the emotions in a group converge to each other, except for persons with very low incoming connection strength, openness or responsiveness (here modelled by $\omega_{p_B,so_{A,B}}$ and $\omega_{so_{A,B},p_A}$). Persons A with high impact on the emotions in a group are those who have low values for these parameters $\omega_{p_B,so_{A,B}}$ and $\omega_{so_{A,B},p_A}$ but high values for $\omega_{p_A,so_{B,A}}$. Persons A who easily adapt to others without having much impact are those who have the opposite pattern: high values for $\omega_{p_B,so_{A,B}}$ and $\omega_{so_{A,B},p_A}$ and low values for $\omega_{p_A,so_{B,A}}$. For more details, for example, see (Bosse, Duell, Memon, Treur, and Wal, 2009).

$$\boldsymbol{d}sr_A/\boldsymbol{d}t = \gamma_{sr_A}\ [\ f(\omega_{s_A,sr_A}\ s_A) - sr_A\ ]$$
$$\boldsymbol{d}sr_B/\boldsymbol{d}t = \gamma_{sr_B}\ [\ f(\omega_{s_B,sr_B}\ s_B) - sr_B\ ]$$
$$\boldsymbol{d}p_A/\boldsymbol{d}t = \gamma_{p_A}\ [\ f(\omega_{sr_A,p_A}\ sr_A,\ \omega_{so_{A,B},p_A}\ so_{A,B}) - p_A\ ]$$
$$\boldsymbol{d}p_B/\boldsymbol{d}t = \gamma_{p_B}\ [\ f(\omega_{sr_B,p_B}\ sr_B,\ \omega_{so_{B,A},p_B}\ so_{B,A}) - p_B]$$
$$\boldsymbol{d}so_{A,B}/\boldsymbol{d}t = \gamma_{so_{A,B}}\ [\ f(\omega_{p_B,so_{A,B}}\ p_B) - so_{A,B}\ ]$$
$$\boldsymbol{d}so_{B,A}/\boldsymbol{d}t = \gamma_{so_{B,A}}\ [\ f(\omega_{p_A,so_{B,A}}\ p_A) - so_{B,A}\ ]$$

The symbols are explained as follows:

p_X	activation level of the preparation state of agent X (for X's emotional response)
$so_{X,Y}$	sensory representation of agent X observing agent Y's response
s_X	activation level of the stimulus for agent X
sr_X	activation level of the sensory representation of the stimulus by agent X
γ_X	update speed parameter for state X
$\omega_{X,Y}$	strength of the connection from state X to state Y

Box 5 Abstracted computational model for emotion contagion

The fact that mirror neurons make that sensory input from an observed person directly links to preparation states, makes that they fit quite well in Damasio (1994, 2010)'s perspective on internal simulation involving as-if body loops. In this way mirroring can be modelled in a more detailed manner as a process that fully integrates mirror neuron activation states and the ongoing internal processes based on as-if loops (e.g., Damasio, 2010, pp. 102-104). This more refined description of a mirroring process is schematically shown in Fig. 6.

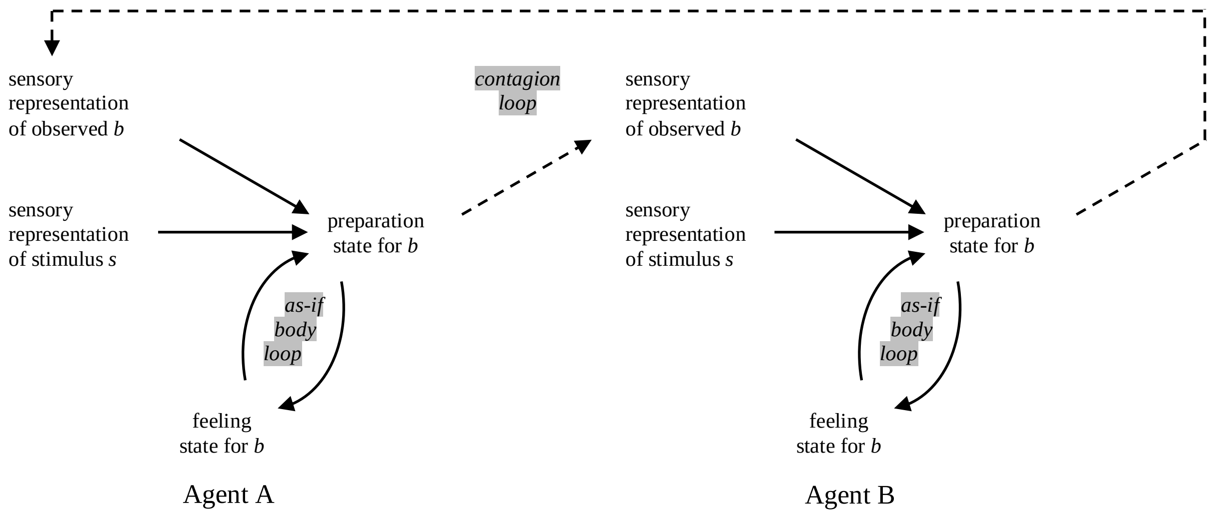

Fig. 6. Cycles integrating emotion contagion and internal generation of emotion and feeling

A computational model for this more refined perspective is shown in Box 6, again with connection strengths $\omega_{X,Y} \geq 0$. This is a combination of the models in Box 1 and Box 5.

$$\mathbf{d}sr_A/\mathbf{d}t = \gamma_{sr_A} \; [\, f(\omega_{s_A,sr_A}\, s_A) - sr_A \,]$$
$$\mathbf{d}sr_B/\mathbf{d}t = \gamma_{sr_B} \; [\, f(\omega_{s_B,sr_B}\, s_B) - sr_B \,]$$
$$\mathbf{d}p_A/\mathbf{d}t = \gamma_{p_A} \; [\, f(\omega_{sr_A,p_A}\, sr_A,\ \omega_{so_{A,B},p_A}\, so_{A,B},\ \omega_{ef_A,p_A}\, ef_A) - p_A \,]$$
$$\mathbf{d}p_B/\mathbf{d}t = \gamma_{p_B} \; [\, f(\omega_{sr_B,p_B}\, sr_B,\ \omega_{so_{B,A},p_B}\, so_{B,A},\ \omega_{ef_B,p_B}\, ef_B) - p_B \,]$$
$$\mathbf{d}ef_A/\mathbf{d}t = \gamma_{ef_A} \; [\, f(\omega_{p_A,\, ef_A}\, p_A) - ef_A \,]$$
$$\mathbf{d}ef_B/\mathbf{d}t = \gamma_{ef_B} \; [\, f(\omega_{p_B,\, ef_B}\, p_B) - ef_B \,]$$
$$\mathbf{d}so_{A,B}/\mathbf{d}t = \gamma_{so_{A,B}} \; [\, f(\omega_{p_B,so_{A,B}}\, p_B) - so_{A,B} \,]$$
$$\mathbf{d}so_{B,A}/\mathbf{d}t = \gamma_{so_{B,A}} \; [\, f(\omega_{p_A,so_{B,A}}\, p_A) - so_{B,A} \,]$$

The symbols are explained as follows:

p_X	activation level of the preparation state of agent *X* (for *X*'s emotional response)
$so_{X,Y}$	sensory representation of agent *X* observing agent *Y*'s response
ef_X	activation level of the feeling state (emotion felt) of agent *X*
s_X	activation level of the stimulus for agent *X*
sr_X	activation level of the sensory representation of the stimulus by agent *X*
γ_X	update speed parameter for state *X*
$\omega_{X,Y}$	strength of the connection from state *X* to state *Y*.

Box 6 More detailed computational model for emotion contagion integrating as-if body loops

More complex variations of social contagion models involving both beliefs and emotions or intentions and emotions have been addressed in (Hoogendoorn, Treur, Wal, Wissen, 2011), using similar mechanisms as discussed here. Moreover, in (Bosse, Hoogendoorn, Klein, Treur, Wal, and Wissen, 2012) the model ASCRIBE is presented (for Agent-based Social Contagion Regarding Intentions Belief and Emotions), in which internal dynamics involving emotions, beliefs and intentions and the social contagion of these states are integrated in a similar manner.

Learning

In the models discussed above, the values of the connection strengths were not specified. In principle, they can be assumed constant, keeping their initial value over time. However, they can also be adaptive over time and provide a mechanism for learning. A well-known type of learning based on adaptive strengths for connections is *Hebbian learning*. This is based on the principle that connected neurons that are frequently activated simultaneously strengthen their connecting synapse ('neurons that fire together, wire together'); see Figure 7. The principle goes back to Hebb (1949), but has recently gained enhanced interest by more extensive empirical support (e.g., Bi and Poo, 2001), and more advanced mathematical formulations (e.g., Gerstner and Kistler, 2002).

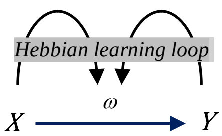

Fig. 7. Cycles between states and connections: Hebbian learning

The following is a summary of the main assumption that is adopted for learning, as discussed.

Assumptions on learning

- The activation levels of two connected states affect the strength of their connection

In Box 7 an example computational model for this learning principle is shown for two connected states *X* and *Y*.

$$\mathbf{d}\omega_{X,Y}/\mathbf{d}t \;=\; \eta_{X,Y}\,[\,XY\,(1 - \omega_{X,Y}) - \zeta_{X,Y}\,\omega_{X,Y}\,]$$

The symbols are explained as follows:

$\omega_{X,Y}$	strength of the connection from state X to state Y
$\eta_{X,Y}$	learning rate for the connection from X to Y
$\zeta_{X,Y}$	extinction rate for the connection from X to Y

Box 7 Computational model for Hebbian learning

For lower values of $\omega_{X,Y}$ and low extinction rate the speed of change is proportional to both activation values X and Y, and to the learning rate. For higher values of $\omega_{X,Y}$ it is bounded by 1 due to the factor $(1 - \omega_{X,Y})$. This type of learning mechanism has been applied in different computational models. For example, emotion regulation mechanisms can be subject of learning: they are strengthened over time when they are intensively used. An example of this is the function of dreams to handle stressful experiences (e.g., Levin and Nielsen, 2007). The idea is that in dreams fearful situations are generated in which the regulation mechanisms are exercised and doing so they are strengthened: fear extinction learning. This has been addressed computationally in a manner similar to the computational model above in (Treur, 2011a). Moreover, in decision making, often the consequences of a decision made are monitored and based on that the valuation for the chosen option is adapted. This has been addressed to analyse rationality of decision making for specific environments based on emotion-related valuing in (Treur and Umair, 2011), using a similar computational model.

Discussion

In this paper a unifying neurologically inspired perspective on the dynamics and interaction of emotions was discussed, making use of knowledge of mechanisms from cognitive, affective and social neuroscience. It was discussed how many cyclic connections in the brain can be found and assumably play an important role in brain processes (see also, Bell, 1999; Crick and Koch, 1998; Potter, 2007; Sporns, Tononi, and Edelman, 2000), and in particular how affective states can have bidirectional associations to many other types of mental states and behaviour (e.g., Critchley, 2005; Damasio, 2003; Frijda, Manstead, and Bem, 2000b; Scherer, 2009). It was indicated how the type of processes considered can be described in a qualitative conceptual manner by graphs with cycles, and in a quantitative computational manner using the dynamical systems approach advocated, for example, in (Ashby, 1952; Port and van Gelder, 1995). It was discussed how a dynamical systems perspective applied to numbers indicating activation levels or strengths of these mental states, provides a suitable approach to model such cyclic processes (see also, for example, Scherer, 2009). Moreover, it was discussed how from such a qualitative conceptual description in a systematic manner a quantitative computational description can be obtained based on the approach also put forward in (Beer, 1995). Thus a unifying integrative dynamical perspective is obtained that can be used to model how emotions relate to a variety of other mental states and processes such as feelings, beliefs, desires, experiences, and valuations in decision making. Moreover, the approach covers how emotions of different persons affect each other (emotion contagion). It was pointed out how this perspective can be used to obtain integrated computational models incorporating emotions, for a number of single agent and multi-agent cases.

The types of examples of cycles discussed here can be and actually have been integrated further. More advanced dynamical system models for emotions and their role in mental functioning may involve different types of cycles that have to be integrated. Examples of this further integration are integration of an emotion regulation cycle with a social interaction cycle as described in (Aziz et al., 2011), or the integration of cognitive-affective cycles with social interaction cycles as described in (Bosse et al., 2012; Hoogendoorn et al., 2011). Furthermore, in a number of models mechanisms for adaptivity and emotional response-feeling cycles have been integrated with other types of cycles (e.g., Bosse et al., 2010; Bosse, Memon, and Treur, 2012; Memon and Treur, 2010).

The presented modelling perspective aims at a cognitive/affective modelling level, but takes inspiration from the underlying mechanisms as described at a biological or neurological level. Modeling causal relations discussed in neurological literature in a cognitive/affective level model does not take specific neurons into consideration but uses more abstract mental states. This is a way to use results from the large and more and more growing amount of neurological literature for the cognitive/affective modelling level. This method can be considered as lifting neurological knowledge to a higher level of description. In a more detailed manner, in (Bickle, 1998, pp. 205-208), such a perspective is discussed:

> '… we can expect that injection of some neurobiological details back into folk psychology would fruitfully enrich the latter, and thus allow development of a more fine-grained folk-psychological account that better matches the detailed functional profiles that neurobiology assigns to its representational states.' (Bickle, 1998, pp. 207-208)

Here Bickle suggests that by relating a (folk) psychological to a neurobiological account, the former can be enriched based on the more detailed description provided by the latter. The type of higher level model that results from adopting principles from the neurological level may inherit some characteristics (in the technical and/or conceptual sense) from the neurological level. For example, it takes mental states as having a certain strength or activation level, instead of binary (to occur or not to occur). This is needed to be able to model gradual adaptation processes and loops, which both are essential for the processes addressed here. As a consequence, for a mental state depending on multiple other states, values for such activation levels have to be combined, to obtain an activation level for this state; this explains why combination functions are needed.

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