A Neural Model for Adaptive Emotion Reading Based on Mirror Neurons and Hebbian Learning

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Abstract

This paper addresses the use of Hebbian learning principles to model in an adaptive manner capabilities to interpret somebody else's emotions. First a non-adaptive neural model for emotion reading is described involving (preparatory) mirror neurons and a recursive body loop: a converging positive feedback loop based on reciprocal causation between mirror neuron activations and neuron activations underlying emotions felt. Thus emotion reading is modelled taking into account the Simulation Theory perspective as known from the literature, involving the own emotions in reading somebody else's emotions. Next the neural model is extended to an adaptive neural model based on Hebbian learning within which a direct connection between a sensed stimulus concerning another person's body state (e.g., face expression) and the emotion recognition state is strengthened.

Introduction

In the Simulation Theory perspective on emotion reading (or Theory of Mind) it is assumed that a person uses the facilities involving the own mental states that are counterparts of the mental states attributed to another person; e.g., (Goldman, 2006). For example, the state of feeling pain oneself is used in the process to determine whether the other person has pain. More and more neurological evidence supports this perspective, in particular the recent discovery of mirror neurons that are activated both when preparing for an action (including a change in body state) and when observing somebody else performing a similar action.; e.g., (Rizzolatti, Fogassi, and Gallese, 2001; Wohlschlager and Bekkering, 2002; Kohler, Keysers, Umilta, Fogassi, Gallese, and Rizzolatti, 2002; Ferrari, Gallese, Rizzolatti, and Fogassi, 2003; Rizzolatti, 2004; Rizzolatti and Craighero, 2004; Iacoboni, 2008).

Mirror neurons usually concern neurons involved in the preparation of actions or body states. By Damasio (1999) such preparation neurons are attributed a crucial role in generating and feeling emotional responses. In particular, using a 'body loop' or 'as if body loop', a connection between such neurons and the feeling of emotions by sensing the own body state is obtained; see (Damasio, 1999) or the formalisation presented in (Bosse, Jonker and Treur, 2008). Taken together, the existence of mirror neurons and Damasio's theory on feeling emotions based on (as if) body loops provides strong neurological support for the Simulation Theory perspective on emotion reading.

An extension of this idea was adopted by assuming that the (as if) body loop is processed in a recursive manner: a positive feedback loop based on reciprocal causation between feeling state (with gradually more feeling) and body state (with gradually stronger expression). This cycle is triggered by the stimulus and ends up in an equilibrium for both states. In (Bosse, Memon, and Treur, 2008; Memon and Treur, 2008) it was shown how a cognitive emotion reading model based on a recursive body loop can be obtained based on causal modelling using the hybrid modelling language LEADSTO (Bosse, Jonker, Meij and Treur, 2007). In (Bosse, Memon, and Treur, 2009) it was shown how this hybrid causal model can be extended to obtain an adaptive cognitive emotion reading model. The adaptation creates a shortcut connection from the sensed stimulus (observed facial expression) to the imputed emotion, bypassing the own emotional states.

In the current paper a different model is presented for similar mind reading phenomena. This time, instead of a causal modelling approach, a more neurological point of departure is chosen by using a neural network structure which is processed in a purely numerical manner using generic principles for neural activation and Hebbian learning. In this way the obtained model stays more close to the neurological source of evidence and inspiration.

The structure of this paper is as follows. First, the basic neural emotion reading model is introduced. Next, it is shown how the model can be made adaptive, by adopting a Hebbian learning principle that enables the model to strengthen the connections between neurons. For both the basic model and the adaptive model, some simulation results are shown, and different variations are discussed. The paper is concluded with a discussion.

A Neural Emotion Reading Model

In this and the next section the model to generate emotional states for a given stimulus is introduced. It adopts three important concepts from Damasio (1999)'s theory of consciousness: an *emotion* is defined as 'an (unconscious) neural reaction to a certain stimulus, realised by a complex ensemble of neural activations in the brain', a *feeling* is 'the (still unconscious) sensing of this body state', and a *conscious feeling* is what emerges when 'the organism detects that its representation of its own body state has been changed by the occurrence of the stimulus' (Damasio, 1999). Moreover, the model adopts his idea of a 'body loop' and 'as if body loop', but extends this by making these loops recursive. According to the original idea, from a neurological perspective emotion generation roughly proceeds according to the following causal chain; see (Bosse, Jonker and Treur, 2008; Damasio, 1999) (in the case of a body loop):

sensing a stimulus →
sensory representation of stimulus →
(preparation for) bodily response →
sensing the bodily response →
sensory representation of the bodily response →
feeling the emotion

As a variation, an 'as if body loop' uses a causal relation

preparation for bodily response →
sensory representation of the bodily response

as a shortcut in the neurological chain. In the model used here an essential addition is that the body loop (or as if body loop) is extended to a recursive body loop (or recursive as if body loop) by assuming that the preparation of the bodily response is also affected by the state of feeling the emotion (also called emotional feeling):

feeling the emotion → preparation for bodily response

as an additional causal relation. Damasio (2004) also assumes such recursively used reciprocal causal connections:

'… feelings are not a passive perception or a flash in time, especially not in the case of feelings of joy and sorrow. For a while after an occasion of such feelings begins – for seconds or for minutes – there is a dynamic engagement of the body, almost certainly in a repeated fashion, and a subsequent dynamic variation of the perception. We perceive a series of transitions. We sense an interplay, a give and take.' (Damasio, 2004, p. 92)

Within the neural model presented here both the neural states for preparation of bodily response and the feeling are assigned a level of activation, expressed by a number, which is assumed dynamic. The cycle is modelled as a positive feedback loop, triggered by the stimulus and converging to a certain level of feeling and body state. Here in each round of the cycle the next body state has a level that is affected by both the level of the stimulus and of the emotional feeling state, and the next level of the emotional feeling is based on the level of the body state.

This neural model refers to activation states of (groups of) neurons and the body. An overall picture of the connection for this model is shown in Figure 1. Here each node stands for a group of one or more neurons, or for an effector, sensor or body state. The nodes can be interpreted as shown in Table 1.

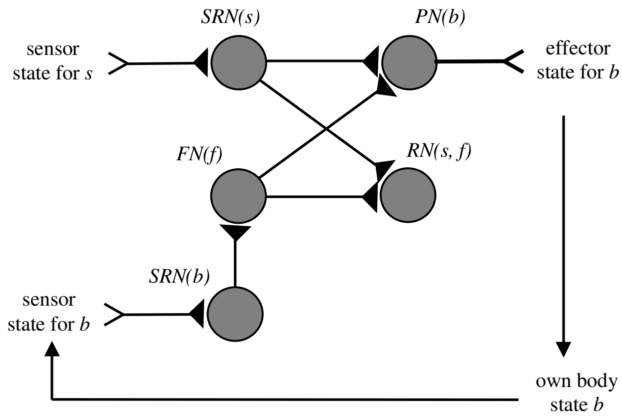

Figure 1: Neural network structure of the model with body loop

In the neural activation state of *RN(s, f)*, the experienced emotion *f* is related to the stimulus *s*, which triggers the emotion generation process. Note that the more this neuron is strongly related to *SRN(s)*, the more it may be considered to represent a level of awareness of what causes the feeling *f*; this may be related to what by Damasio (1999) is called a state of conscious feeling. This state that relates an emotion felt *f* to any triggering stimulus *s* can play an important role in the conscious attribution of the feeling to any stimulus *s*.

node nr	*denoted by*	*description*
0	*s*	stimulus; for example, another person's body state b'
1	*SS(s)*	sensor state for stimulus *s*
2	*SRN(s)*	sensory representation neuron for *s*
3	*PN(b)*	preparation neuron for own body state *b*
4	*ES(b)*	effector state for own body state *b*
5	*BS(b)*	own body state *b*
6	*SS(b)*	sensor state for own body state *b*
7	*SRN(b)*	sensory representation neuron for own body state *b*
8	*FN(f)*	neuron for feeling state *f*
9	*RN(s, f)*	neuron representing that *s* induces feeling *f*

Table 1 Overview of the nodes involved

According to the Simulation Theory perspective a neural model for emotion reading should essentially be based on a neural model to generate the own emotions as induced by any stimulus *s*. Indeed, the neural model introduced above can be specialised in a quite straightforward manner to enable emotion reading. The main step is that the stimulus *s* that triggers the emotional process, which until now was left open, is instantiated with the body state *b'* of another person, for example a facial expression of another person. Indeed, more and more evidence is available that (already from an age of 1 hour), as an example of the functioning of the mirror neuron system (Rizzolatti, 2005), sensing somebody else's facial expression leads (within about 300 milliseconds) to preparing for and showing the same facial expression

(Goldman and Sripada, 2004, pp. 129-130). Within the network in Figure 1 this leads (via activation of the sensory representation state *SRN(b')*) to activation of the preparation state *PN(b)* where *b* is the own body state corresponding to the other person's body state *b'*. This pattern shows how this preparation state *PN(b)* functions as a mirror neuron. Next, via the recursive body loop gradually higher and higher activation levels of the own feeling state *f* are generated.

To formally specify the neural model, the mathematical concepts listed in Table 2 are used.

concept	*description*
N	set of node numbers (as listed in Table 1); variables indicating elements of this set are i, j, k
N'	$N \backslash \{0\}$ the set of node numbers except the node for the stimulus s
$w_{ij}(t)$	strength of the connection from node i to node j at time t; this is taken 0 when no connection exists or when $i=j$
$y_i(t)$	activation level of node i at time t
$net_i(t)$	net input to node i at time t
g	function to determine activation level from net input
γ	change rate for activation level
η	learning rate for weights

Table 2 Mathematical concepts used

The function g can take different forms, varying from the identity function $g(v) = v$ for the linear case, to a discontinuous threshold (indicated by β) step function with $g(v) = 0$ for $v<\beta$ and $g(v) = 1$ for $v \geq \beta$, or a continuous logistic threshold function based on $1/(1+exp(-\alpha(v-\beta))$ with steepness α. For the connections between nodes of which at least one is not a neuron the connections have been made simple: weights 1 and g the identity function; so $w_{12} = w_{34} = w_{45} = w_{56} = w_{67} = 1$

The activation levels are determined for step size Δt for all $i \in N'$ as follows:

$$net_i(t) = \Sigma_{j \in N}\ w_{ji}(t)\, y_j(t)$$
$$\Delta y_i(t) = \gamma(g(net_i(t)) - y_i(t))\, \Delta t$$

Note that for step size $\Delta t = 1$ and change rate $\gamma = 1$, the latter difference equation can be rewritten to

$$y_i(t+1) = g(net_i(t))$$

which is a wellknown formula in the literature addressing simulation with neural models.

The model description in the form of a system of differential equations can be used for an analysis of equilibria that can occur. Here the external stimulus level for s is assumed constant. Moreover, it is assumed that $\gamma > 0$. In general putting $\Delta y_i(t) = 0$ provides the following set of equations for $i \in N'$:

$$y_i = g(\Sigma_{j \in N}\ w_{ji}\, y_j)$$

For the given network structure these equilibrium equations are:

$$y_1 = g(w_{01}\, y_0)$$
$$y_2 = g(w_{12}\, y_1)$$
$$y_4 = g(w_{34}\, y_3)$$
$$y_5 = g(w_{45}\, y_4)$$
$$y_6 = g(w_{56}\, y_5)$$
$$y_7 = g(w_{67}\, y_6)$$
$$y_8 = g(w_{78}\, y_7)$$
$$y_3 = g(w_{23}\, y_2 + w_{83}\, y_8)$$
$$y_9 = g(w_{29}\, y_2 + w_{89}\, y_8)$$

Taking into account that connections between nodes among which at least one is not a neuron have weight 1 and g the identity function, it follows that the equilibrium equations are:

$$y_2 = y_1 = y_0$$
$$y_7 = y_6 = y_5 = y_4 = y_3$$
$$y_8 = g(w_{78}\, y_7)$$
$$y_3 = g(w_{23}\, y_2 + w_{83}\, y_8)$$
$$y_9 = g(w_{29}\, y_2 + w_{89}\, y_8)$$

Example Simulations: Non-Adaptive Case

The numerical software environment Matlab has been used to obtain simulation traces for the model described above. An example simulation trace that results from this model with the function g the identity function is shown in Figure 2. Here, time is on the horizontal axis, and the activation levels of three of the neurons *SRN(s)*, *FN(f)*, and *RN(s,f)* are shown on the vertical axis. As shown in this picture, the sensory representation of a certain stimulus s quickly results in a feeling state f, and a representation that s induces f. When the stimulus s is not present anymore, the activations of *FN(f)* and *RN(s, f)* quickly decrease to 0. The weight factors taken are: $w_{23} = w_{83} = w_{89} = 0.1$, $w_{78} = 0.5$ and $w_{29} = 0$. Moreover, $\gamma = 1$, and a logistic threshold function was used with threshold 0.1 and steepness 40.

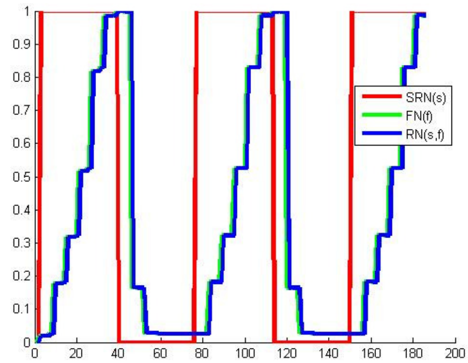

Figure 2: Example simulation for non-adaptive emotion reading

For the values taken in the simulation above, the equilibrium equations are:

$$y_2 = y_1 = y_0$$
$$y_7 = y_6 = y_5 = y_4 = y_3$$
$$y_8 = g(0.5\, y_7)$$
$$y_3 = g(0.1\, y_2 + 0.1\, y_8)$$
$$y_9 = g(0.1 y_8)$$

As the threshold was taken *0.1* it follows from the equations that for stimulus level $y_0 = 0$ all values for y_i are (almost) *0*, and for stimulus level $y_0 = 1$ that all values for y_i are *1*, which is also shown by the simulation in Figure 2.

An Adaptive Neural Emotion Reading Model

As a next step, the neural model for emotion reading is extended by a facility to strengthen the direct connection between the neuron *SRN(s)* for the sensory representation of the stimulus (the other person's face expression) and the neuron *RN(s, f)*. A strengthening of this connection over time creates a different emotion reading process that in principle can bypass the generation of the own feeling. The learning principle to achieve such an adaptation process is based on the Hebbian learning principle that connected neurons that are frequently activated simultaneously strengthen their connecting synapse e.g., (Hebb, 1949; Bi and Poo, 2001; Gerstner and Kistler, 2002; Wasserman, 1989). The change in strength for the connection w_{ij} between nodes $i, j \in N$ is determined (for step size Δt) as follows:

$$\Delta w_{ij}(t) = \eta\, y_i(t) y_j(t)(1 - w_{ij}(t))\, \Delta t$$

Here η is the learning rate. Note that this Hebbian learning rule is applied only to those pairs of nodes $i, j \in N$ for which a connection already exists.

Also for the adaptive case equilibrium equations can be found. Here it is assumed that $\gamma, \eta > 0$. In general putting both $\Delta y_i(t) = 0$ and $\Delta w_{ij}(t) = 0$ provides the following set of equations for $i, j \in N'$:

$$y_i = g(\Sigma_{j\in N}\ w_{ji}\, y_j)$$
$$y_i y_j(1 - w_{ij}) = 0$$

From the latter set of equations (second line) it immediately follows that for any pair $i, j \in N'$ it holds:

either $y_i = 0$
or $y_j = 0$
or $w_{ij} = 1$

In particular, when for an equilibrium state both y_i and y_j are nonzero, then $w_{ij} = 1$.

Example Simulations: Adaptive Case

Based on the neural model for adaptive emotion reading obtained in this way, a number of simulations have been performed; for an example, see Figure 3. As seen in this figure, the strength of the connection between *SRN(s)* and *RN(s, f)* (indicated by *b* which is in fact w_{29}) is initially *0* (i.e., initially, when observing the other person's face, the person does not impute feeling to this). However, during an adaptation phase of two trials, the connection strength goes up as soon as the person imputes feeling *f* to the target stimulus s (the observation of the other person's face), in accordance with the temporal relationship described above.

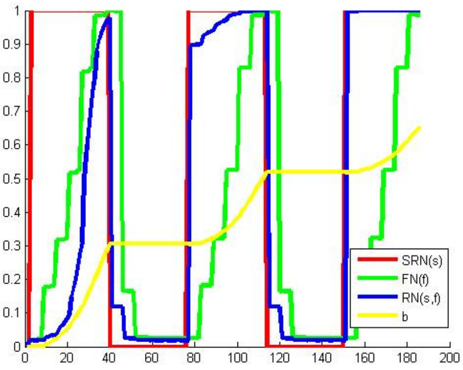

Figure 3: Example simulation for adaptive emotion reading

Note that, as in Figure 2, the activation values of other neurons gradually increase as the person observes the stimulus, following the recursive feedback loop discussed. These values sharply decrease as the person stops observing the stimulus as shown in Figure 3, e.g. from time point 40 to 76, from time point 112 to 148, and so on. Note that at these time points the strength of the connection between *SRN(s)* and *RN(s, f)* (indicated by *b*) remains stable. After the adaptation phase, and with the imputation sensitivity at high, the person imputes feeling *f* to the target stimulus directly after occurrence of the sensory representation of the stimulus, as shown in the third trial in Figure 3. Note here that even though the person has adapted to impute feeling *f* to the target directly after the stimulus, the other state property values continue to increase in the third trial as the person receives the stimulus; this is because the adaptation phase creates a connection between the sensory representation of the stimulus and emotion imputation without eliminating the recursive feedback loop altogether. Note that when a constant stimulus level *1* is taken, an equilibrium state is reached in which $b = 1$, and all y_i are *1*.

The learning rate η used in the simulation shown in Figure 3 is *0.02*. In Figure 4 a similar simulation is shown for a lower learning rate: *0.005*.

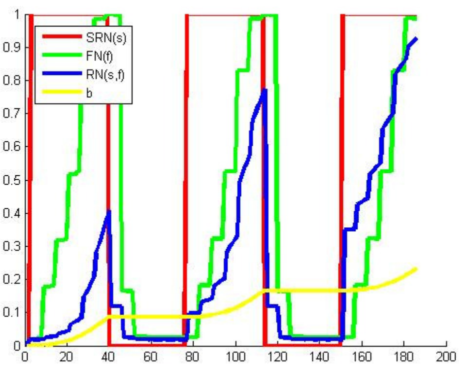

Figure 4: Adaptive emotion reading with lower learning rate

Discussion

In recent years, an increasing amount of neurological evidence is found that supports the 'Simulation Theory' perspective on emotion reading, e.g., (Rizzolatti, Fogassi, and Gallese, 2001; Wohlschlager and Bekkering, 2002; Kohler, Keysers, Umilta, Fogassi, Gallese, and Rizzolatti, 2002; Ferrari, Gallese, Rizzolatti, and Fogassi, 2003; Rizzolatti, 2004; Rizzolatti and Craighero, 2004; Iacoboni, 2005, 2008). That is, in order to recognise emotions of other persons, humans exploit observations of these other persons' body states as well as counterparts within their own body. The current paper introduces a numerical model to simulate this process. This model is based on the notions of (preparatory) mirror neurons and a recursive body loop (cf. Damasio, 1999, 2004): a converging positive feedback loop based on reciprocal causation between mirror neuron activations and neuron activations underlying emotions felt. In addition, this model was extended to an adaptive neural model based on Hebbian learning, where neurons that are frequently activated simultaneously strengthen their connecting synapse (cf. Hebb, 1949; Bi and Poo, 2001; Gerstner and Kistler, 2002; Wasserman, 1989). Based on this adaptive model, a direct connection between a sensed stimulus (for example, another person's face expression) and the emotion recognition can be strengthened.

The simulation model has been implemented in Matlab, in a generic manner. That is, the model basically consists of only 2 types of rules: one for propagation of activation levels between connected neurons, and one for strengthening of connections between neurons that are active simultaneously. These rules are then applied to all nodes in the network. To perform a particular simulation, only the initial activation levels and connection strengths have to be specified. Both for the non-adaptive and for the adaptive model, a number of simulations have been performed. These simulations indicated that the model is indeed sufficiently generic to simulate various patterns of adaptive emotion reading. An interesting question for further research is to what extent the model can simulate other neural processes as well. Another challenge for the future is to extend the model such that it can cope with multiple qualitatively different emotional stimuli (e.g., related to joy, anger, or fear), and their interaction.

Validation of the presented model is not trivial. At least, this paper has indicated that it is possible to integrate Damasio's idea of body loop with the notion of mirror neurons and Hebbian learning, and that the resulting patterns are very plausible according to the literature. In this sense the model has been validated positively. However, this is a relative validation, only with respect to the literature that forms the basis of the model. A more extensive empirical evaluation is left for future work.

By other approaches found in the literature, a specific emotion recognition process is often modelled in the form of a prespecified classification process of facial expressions in terms of a set of possible emotions; see, for example, (Cohen, Garg, and Huang, 2000; Malle, Moses, and Baldwin, 2001; Pantic and Rothkrantz, 1997, 2000). Although a model based on such a classification procedure is able to perform emotion recognition, the imputed emotions have no relationship to a person's own emotions. The neural model for emotion reading presented in the current paper uses a person's own feelings in the emotion reading process as also claimed by the Simulation Theory perspective, e.g., (Goldman, 2006; Goldman and Sripada, 2004). Besides, in the neural model presented here a direct classification is learnt by the adaptivity model based on a Hebbian learning rule. A remarkable issue here is that such a direct connection is faster (it may take place within hundreds of milliseconds) than a connection via a body loop (which usually takes seconds). This time difference implies that first the emotion is recognised without feeling the corresponding own emotion, but within seconds the corresponding own emotion is in a sense added to the recognition. When an as if body loop is used instead of a body loop, the time difference will be smaller, but still present. An interesting question is whether it is possible to design experiments that show this time difference as predicted by the neural model.

Some other computational models related to mirror neurons are available in literature; for instance: a genetic algorithm model which develops networks for imitation while yielding mirror neurons as a byproduct of the evolutionary process (Borenstein and Ruppin, 2005); the mirror neuron system (MNS) model that can learn to 'mirror' via self-observation of grasp actions (Oztop and Arbib, 2002); the mental state inference (MSI) model that builds on the forward model hypothesis of mirror neurons (Oztop, Wolpert, and Kawato, 2005), etc. A comprehensive review of these computational studies can be found in (Oztop, Kawato, and Arbib, 2006). All of the above listed computational models and many others available in the literature are targeted to imitation, whereas the neural model presented here specifically targets to interpret somebody else's emotions.

The approach adopted in the current paper has drawn some inspiration from the four models sketched (but not formalised) in (Goldman, 2006, pp. 124-132). The recursive body loop (or as if body loop) introduced here addresses the problems of model 1, as it can be viewed as an efficient and converging way of generating and testing hypotheses for the emotional states. Moreover, it solves the problems of models 2 and 3, as the causal chain from facial expression to emotional state is not a reverse simulation, but just the causal chain via the body state which is used for generating the own emotional feelings as well. Finally, compared to model 4, the models put forward here can be viewed as an efficient manner to obtain a mirroring process between the emotional state of the other person on the own emotional state, based on the machinery available for the own emotional states.

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