An Adaptive Affective Social Decision Making Model

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Abstract. Social decision making under stressful circumstances may involve strong emotions and contagion from others, and requires adequate prediction and valuation capabilities. In this paper based on principles from Neuroscience an adaptive agent-based computational model is proposed to address these aspects in an integrative manner. Using this model adaptive decision making of an agent in an emergency evacuation scenario is explored. By means of formal analysis and simulation, computational learning mechanisms are identified required for effective decision making of agents.

Keywords: social decision making, neurological modelling, adaptation

1 Introduction

Decision making under stressful circumstances is a challenging type of human process. For example, in emergency evacuations the quality of such decision making processes may make a difference between surviving or not. Decision making under stress involves a number of aspects that have to be dealt with, such as high levels of fear and/or hope, adequate predictive capabilities, for example, related to available information and earlier experiences, and social impact from other group members. In recent cognitive and neurological literature such decision making processes have been addressed. Elements that play an important role in deciding for certain options are the predicted effects of the options (determined by internal simulation), the valuing of these effects, and the emotions felt in relation to this valuing (based on as-if body loops). These elements affect each other by cyclic internal cognitive/affective processes. The connections used in these processes are adapted based on experiences.

Prediction of the (expected) effects of a decision option, based on internal simulation starting from the preparation of the action has been analysed, for example, in [30, 21]. Moreover, in [17, 18] it is pointed out how such predictions can be repeated, thus generating simulated behaviour and perception chains. The predictions of action effects are not taken as neutral or objective, but are valued in a subjective and emotion-related manner according to the importance of the predicted effect for the agent, in a positive (hope) or negative (fear) sense; e.g., [24]. If the predicted effects are valued as (most) positive, this may entail a positive decision for the option. In a social context, these processes of prediction and valuing within individuals are mutually affecting each other, so that joint group decisions may develop.

In this paper based on principles from literature as indicated, an adaptive agent-based computational model is proposed to address these aspects in an integrative manner. In contrast to the existing agent-based decision-making models designed from a software engineering perspective (cf [6]), by employing theoretical principles from Neuroscience and Social Science, we strive to create a more biologically plausible model of human decision making. In the scenario used as illustration an agent considers three decision options (paths) to move outside of a burning building. The path to the first exit (option 1) is short, but eventually becomes dangerous. The path to the second exit (option 2) is known to be dangerous (e.g., contains locations with high smoke and fire concentration). The path to the third exit (option 3) is long, but remains safe. By means of formal analysis and simulation, computational learning mechanisms are identified required for effective decision making of agents.

The paper is organised as follows. A background for the model is considered in Section 2. In Section 3 the model proposed is described. In Section 4 agent learning mechanisms are considered. Simulation results based on the model are described in Section 5. Formal analysis of the model is provided in Section 6. Section 7 concludes the paper.

2 Background

The computational decision making model proposed in this paper is based on neurological findings and principles considered in this section.

2.1 Emotions and Valuing

In decision making tasks different options are compared in order to make a reasonable choice out of them. Options usually have emotional responses associated to them relating to a prediction of a rewarding and/or aversive consequence. In decisions such an emotional valuing of predicted consequences often plays an important role. In recent neurological literature such a notion of value is suggested to be represented in the amygdala [2,3,15, 22,20,27]. Traditionally an important function attributed to the amygdala concerns representing emotions, in particular in the context of fear. However, in recent years much evidence on the amygdala in humans has been collected showing a function beyond this fear context. In humans many parts of the prefrontal cortex (PFC) and other brain areas such as hippocampus, basal ganglia, and hypothalamus have extensive, often bidirectional connections with the amygdala [13,28,22]. A role of amygdala activation has been found in various tasks involving emotional aspects [24]. Usually emotional responses are triggered by stimuli for which a prediction is possible of a rewarding or aversive consequence. Feeling these emotions represents a way of experiencing the value of such a prediction: to which extent it is positive or negative. This idea of positive and negative value is also the basis of work on the neural basis of economic choice in neuroeconomics. In particular in decision-making tasks where different options are compared, choices have been related to a notion of value as represented the amygdala [2,3,22,23,20,27,29].

2.2 Internal Simulation

The notion of *internal simulation* was put forward, among others, by Hesslow [17,18] and Damasio [7,8]. The idea of internal simulation is that sensory representation states are activated (e.g., mental images), which in response trigger associated preparation states for actions or bodily changes, which, by prediction links, in turn activate other sensory representation states.

sensory representation states → *preparation states* → *sensory representation states*

The latter states represent the effects of the prepared actions or bodily changes, without actually having executed them. Being inherently cyclic, the simulation process can go on indefinitely, and may, for example, be used to evaluate the effects of plans before they are executed. In Figure 1 these dynamical relationships are depicted by the arrows from the upper plane to the middle plane and back. In Section 3 these relationships are formalised in (4), (5) and (6). Internal simulation has been used, for example, to describe (imagined) processes in the external world (e.g., prediction of effects of own actions [4]), or processes in a person's own body (e.g., [7]).

The idea of internal simulation has been exploited in particular by applying it to bodily changes expressing emotions, using the notion of *as-if body loop* bypassing (the need for) actually expressed bodily changes (cf. [7], pp. 155-158; [8], pp. 79-80):

sensory representation → *preparation for bodily changes = emotional response* → *emotion felt = based on sensory representation of (simulated) bodily changes*

An as-if body loop describes an inner simulation of bodily processes, without actually affecting the body. Note that [7] distinguishes an emotion (or emotional response) from a feeling (or felt emotion). In Figure 1 these dynamical relationships are depicted by the arrows in the lower plane, and the arrow from the lower to the upper plane. In Section (3) these relationships have been formalised in (8) and (9).

An as-if body loop usually occurs in an extended, cyclic form by assuming that the emotion felt in turn also affects the preparation states, as it is pointed out, for example, in ([9], pp. 91-92; [10], pp. 119-122). This can be viewed as a way to incorporate emotion integration in the preparation of actions. In Figure 1 this relationship is depicted via the arrows in the upper plane.

2.3 Social contagion

When decision making takes place in a social context of a group of agents interacting (verbally, nonverbally) on the relevant options, mutual contagion occurs. It is assumed that the preparation states of an agent for the actions constituting options and for emotional responses for the options are reflected in body states that are observed with a certain intensity or strength by other agents from the group. The *contagion strength* γ of the interaction from an agent A to an agent B for a preparation state p depends on the personal characteristic *expressiveness* ε of the sender (agent A) for p, the personal characteristic *openness* δ of the receiver (agent B) for p, and an interaction characteristic α (*channel strength*) for p from sender A to receiver B. The effects of contagion are integrated within the internal processes. In Section 3 these relations are formalised in (1), (2), and (3).

3 An Affective Social Decision Making Model

Based on the neurological findings and principles from Section 2 a computational affective social decision making model has been developed. This model is described in this section.

Depending on a situational context an agent determines a set of applicable options to satisfy a goal at hand. In the model proposed the applicable options are generated in a cyclic manner, via connections from activated sensory states reflecting this situational context to preparation states for the relevant actions related to an option, and valuations of sensory states. An option is represented by a (partially) ordered sequence of actions (i.e., a plan) to satisfy the agent's goals. For example, in the evacuation scenario under investigation each option is represented by a sequence of locations with an exit as the last location.

Computationally, alternative options considered by an agent are being generated and evaluated in parallel. The evaluation of options is based on internal simulation as described in Section 2. The process is depicted in Figure 1. In the vertical plane it is shown how in the overall process options for actions are considered (action preparations in the upper horizontal plane), for which by prediction links sensory representations of effects are generated (internal simulation, middle horizontal plane), which are evaluated (emotion-related valuing, lower horizontal plane). The notations used in the model are summarized in Table 1.

3.1 The Social Contagion Impact

The social context in which decision making is performed is represented by a group of agents interacting (verbally, nonverbally) on the relevant options. The *contagion strength* of the interaction from agent A to agent B for a preparation state p is modelled as follows:

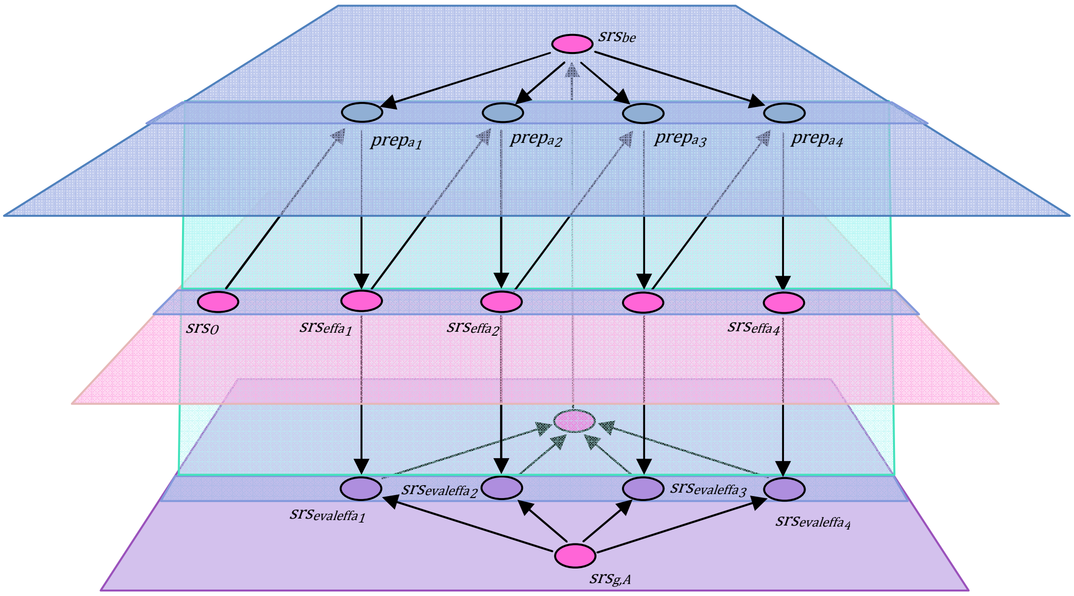

Figure 1. A graphical representation of the model for a given agent and option O.
Circles represent neural states and links represent connections between the states.
Upperplane: the preparation states for the subsequent actions related to the option O
Middleplane: the predicted effects of the subsequent actions
Lower plane: the emotion-related valuing of the predicted action effects

Table 1 Notations used

Notation	Explanation
ε_{SA}	expressiveness of agent *A* for mental state *S*
α_{SAB}	channel strength for *S* from agent *A* to agent *B*
δ_{SB}	openness of agent *B* for *S*
γ_{SAB}	contagion strength for state *S* in the interaction from agent *A* to agent *B*
G(S, B)	aggregated group state for *S* as impact for *B*
$prep_{a,O,A}$	Preparation of agent *A* for action *a* in option *O*
$srs_{E,O,A}$	Feeling emotion *E* by agent *A* for option *O*
$srs_{G(a,O,A)}$	Group preparation for *a* in *O* perceived by *A*
$srs_{effect(a,O),A}$	*A*'s representation of the effect of *a* in *O*
$srs_{eval\_for(effect(a,O),E),A}$	*A*'s valuation by *E* of the effect of *a* in *O*
$srs_{g,A}$	*A*'s goal *g*
$prep_{E,O,A}$	Preparation for *E* of agent *A* for option *O*
$srs_{dist(effect(a,O)),A}$	Representation of *A*'s distance to exit by *a* and *O*

$$\gamma_{pAB} = \varepsilon_{pA} \cdot \alpha_{pAB} \cdot \delta_{pB} \qquad (1)$$

Here ε_{pA} is the personal characteristic expressiveness of the sender (agent A) for p, δ_{pB} is the personal characteristic openness of the receiver (agent B) for p, and

α_{pAB} is the interaction characteristic channel strength for p from sender A to receiver B.

By aggregating such input, an agent B perceives the group's joint attitude towards each option, which comprises the following dynamic properties. Note that for the sake of simplicity no intermediate states for this process have been included, such as effector states, body states, or sensor states; the process from internal states to external expression, transfer and receipt is characterised at once by using parameters such as ε_{pA}, α_{pAB} and δ_{pB} introduced above.

(a) The aggregated group preparation to (i.e., the externally observable intention to perform) each action p constituting the option for agent B:

$$G(p, B) = \Sigma_{A \neq B} \ \gamma_{pAB}\, q_{p,A} \ / \Sigma_{A \neq B} \ \gamma_{pAB}\, \varepsilon_{pA} \qquad (2)$$

(b) The aggregated group preparation to an emotional response (body state) be for each option. A predicted consequence for an option may induce different types of emotions (e.g., fear, hope, joy) with separate preparation states. Formally:

$$G(be, B) = \Sigma_{A \neq B} \ \gamma_{beAB}\, q_{be,A} \ / \Sigma_{A \neq B} \ \gamma_{beAB}\, \varepsilon_{beA} \qquad (3)$$

Note that in Figure 1 for reasons of transparency only one agent is depicted. The contagion received by this agent can be visualised as incoming arrows to the preparation states of the action options in the upper horizontal plane, and to the preparation state of the emotional response in the lower horizontal plane. The contagion from the depicted agent to other agents can be visualised as outgoing arrows from the same preparation states.

3.2 Internal simulation

The preparation state $prep_{a1}$ for the first action from an option is affected by the sensory representations srs_{Oi} of the option, of the perceived group preparation $srs_{G(a1,Oi,A)}$ for the action and of the emotion srs_{be} felt towards the option which functions as valuing the option (Figure 1, upper horizontal plane). Formally:

$$\mathbf{d}\, prep_{a_1,O_i,A}(t)/\mathbf{d}t =$$
$$\gamma [\ h(srs_{O_i,A}(t),\ srs_{be,O_i,A}(t),\ srs_{G(a_1,O_i,A)}(t)) - prep_{a_1,O_i,A}(t)\ ] \qquad (4)$$

where A is any agent, O_i is an option, be is an emotional response state, $G(a1,O_i,A)$ is the aggregated group preparation to action a_1 of agent A, $h(V_1, V_2, V_3)$ is a combination function. In general, different forms of combination functions are possible. For example:

$$h(V_1, V_2, V_3) = \beta\,(1\text{-}(1\text{-}\ V_1)(1\text{-}\ V_2)(1\text{-}\ V_3)) + (1\text{-}\beta)\ V_1\ V_2\ V_3$$

Another possibility is a logistic combination function:

$$h(V_1, V_2, V_3) = 1/(1+e^{-\beta 2(V-\beta 2)}),\ with\ V = \omega_1 \cdot V_1 + \omega_2 \cdot V_2 + \omega_3 \cdot V_3$$

The simulated perception of the effect of an action a (Figure 1, middle plane) in a simulated behavioural chain, based on prediction links (the arrows from the upper to the middle plain in Figure 1) is modelled by the following property:

$$\boldsymbol{d}\ srs_{effect(a,O_i),A}(t)\ /\boldsymbol{dt}\ =$$
$$\gamma[\ \omega(prep_{a,O_i,A}(t),srs_{effect(a,O_i),A}(t))\cdot prep_{a,O_i,A}(t)\ -\ srs_{effect(a,O_i),A}(t)]\ (5)$$

The confidence that an action will result in a particular effect is specified as the strength of the link between the preparation for the action state and the sensory representation of the corresponding effect state (the vertical arrows from the upper plane to the middle plane in Figure 1). In the evacuation scenario the strength of a link between a preparation for a movement action and a sensory representation of the effect of the action is used to represent confidence values of the agent's beliefs about the accessibility of locations. For example, if the agent's confidence of the belief that location *p1* is accessible from location *p2* is ω, then the strength of the link between the states described by $prep_{move\_from\_to(p2,p1)}$ and $srs_{is\_at\_location(p1)}$ is put on ω.

Similar to the first action *a1*, the preparation state for each subsequent action *a* from the behavioural chain is specified by:

$$\boldsymbol{d}\ prep_{a,O_i,A}(t)/\boldsymbol{dt} =$$
$$\gamma[h(srs_{effect(a,O_i),A}(t),\ srs_{be,O_i,A}(t),\ srs_{G(a,O_i,A)}(t)) - prep_{a,O_i,A}(t)] \quad (6)$$

Note that here the effects of the arrows pointing towards the preparation states in the upper plane in Figure 1 are combined using the chosen combination function. The option with the highest value for the preparation state for the first action is chosen for the execution by the agent.

3.3 Emotion-related valuing

In the lower horizontal plane in Figure 1 emotion-related valuing of the action options takes place.

An emotional response is generated based on an evaluation of the effects of each action of the option. In such an evaluation the effect state for each action is compared to a goal state(s) of the agent. Note that for different types of emotions different aspects of a goal state or different types of goals may be used. In [25] a number of cognitive structures eliciting particular types of emotions are described. As a simulated behavioural chain is a kind of a behavioural projection, cognitive structures of prospect-based emotions (e.g., fear, hope, satisfaction, disappointment) from [25] are particularly relevant for the evaluation process. Such structures can be represented formally as evaluation properties. As indicated in [25], the intensity of prospect-based emotions depends on the likelihood (confidence) that a prospect state will occur. Thus, the strength of the link between the preparation state for an action and the sensory representation of its effect state is taken into account as a factor in the evaluation property. The generic evaluation property of the effect of the action a compared with the goal state g (in the lower plane in Figure 1) is specified formally as:

$$\boldsymbol{d}\ srs_{eval\_for(effect(a,O_i),be),A}(t)/\boldsymbol{dt} =$$

$\gamma[h(\omega(prep_{a,O_i,A}(t), srs_{effect(a,O_i),A}(t))\cdot f(srs_{g,A}(t), srs_{effect(a,O_i),A}(t)), \quad srs_{be,O_i,A}(t)) \quad - srs_{eval\_for(effect(a,O_i),be),A}(t)\ ],$ (7)

where $f(srs_{g,A}(t), srs_{effect(a,O_i),A}(t)), srs_{be,O_i,A}(t))$ is an evaluation function depending on the cognitive structure used for the evaluation.

The evaluation of the effects of the actions for a particular emotional response to an option together with the aggregated group preparation to the emotional response determine the intensity of the emotional response:

$$prep_{be,O_i,A}(t) = f(srs_{eval\_for(effect(a_1,O_i),be),A}(t), \ldots, srs_{eval\_for(effect(a_n,O_i),be,A}(t)) \quad (8)$$

where *be* is a particular type of the emotional response.

By the as-if body loop, the agent perceives its own emotional response preparation and creates the sensory representation state for it (in Figure 1 the arrow from the lower plane to the upper plane):

$$\mathbf{d}\, srs_{be,O_i,A}(t)\ /\mathbf{d}t = \gamma\ [\ prep_{be,O_i,A}(t) - srs_{be,O_i,A}(t)\ ] \quad (9)$$

The options in the evacuation scenario evoke two types of emotions: fear and hope, which are often considered in the emergency context. According to [25], the intensity of fear induced by an event depends on the degree to which the event is undesirable and on the likelihood of the event. The intensity of hope induced by an event depends on the degree to which the event is desirable and on the likelihood of the event. Thus, both emotions are generated based on the evaluation of a distance between the effect states for the actions from an option and the agent's goal states. In this example each agent in the group has two goal states '*be outside*' and '*be safe*'. The evaluation functions for both emotions include two aspects: (1) how far is the agent's location from the nearest reachable exit; (2) how dangerous is the agent's location (i.e., the amount of smoke and fire). Formally these two aspects are combined in the evaluation function from (7) using the formula

$$\omega V1 + (1-\omega)/(1+ \lambda e^{-\varphi V2}) \quad (10)$$

where $V1$ is the degree of danger of the location, $V2$ is the distance in number of actions that need to be executed to reach the nearest accessible exit, λ and φ are parameters of the threshold function, ω is a weight. The goal value in (7) is obtained by setting $V1$=0 and $V2$=0 in (10): $(1-\omega)/(1+ \lambda)$.

According to the two emotions considered in the example, (7) is refined into two specialized evaluation properties – one for fear and one for hope:

$$\mathbf{d}\, srs_{eval\_for(effect(a,O_i),bfear),A}(t)/\mathbf{d}t =$$
$$\gamma[h(\omega(prep_{a,O_i,A}(t), srs_{effect(a,O_i),A}(t))\cdot f(srs_{g,A}(t), srs_{effect(a,O_i),A}(t)), srs_{bfear,O_i,A}(t)) - srs_{eval\_for(effect(a,O_i),bfear,A}(t)] \quad (11)$$

where

$f(srs_{g,A}(t), srs_{effect(a,O_i),A}(t))=$

$|srs_{g,A}(t) - \omega\cdot srs_{danger(effect(a,O_i)),O_i,A}(t) - (1-\omega)/(1+ \lambda e^{-\varphi\, srs_{dist(effect(a,O_i)),A(t)}})|$

and

$$d\, srs_{eval\_for(effect(a,O_i),bhope),A}(t)/dt =$$

$$\gamma[h(\omega(prep_{a,Oi,A}(t),srs_{effect(a,Oi),A}(t))\cdot f(srs_{g,A}(t),srs_{effect(a,O_i),A}(t)),$$
$$srs_{bhope,O_i,A}(t)) - srs_{eval\_for(effect(a,A),bhope),A}(t)] \quad (12)$$

where

$$f(srs_{g,A}(t),srs_{effect(a,O_i),A}(t))=$$
$$1- |srs_{g,A}(t) - \omega\cdot srs_{danger(effect(a,O_i)),O_i,A}(t) - (1-\omega)/(1+ \lambda e^{-\varphi f1(a,O_i,A)})|$$

Also specialized versions of other generic properties 3-9 are defined by replacing the generic state be in them by specific emotional response states *bfear* and *bhope*.

4 Agent Learning

Decision making in ongoing real life processes is adaptive in the sense that decisions made lead to new information and valuations based on which future decisions may be different. In this process a central role is played by how the experienced emotion-related information and valuations lead to adaptations. Such adaptations may concern, for example, (1) altered action effect prediction links, (2) altered links by which input from the other group members is incorporated, or (3) altered emotion-related valuation links. These three types of links are addressed in the approach put forward here.

In the model presented in this paper, a Hebbian learning principle [16] is exploited to obtain this form of adaptivity for the three types of links mentioned: roughly spoken this principle states that connections between neurons that are activated simultaneously are strengthened. From a Hebbian perspective, strengthening of connections as mentioned in case of positive valuation may be reasonable, as due to feedback cycles in the model structure, neurons involved will be activated simultaneously. Therefore such a connection may be developed and adapted based on a Hebbian learning mechanism. Originally proposed in [16], in recent years more support has been found for the biological plausibility of this principle; e.g., [5]. In [12] a more in depth treatment of different variations of the principle from a mathematical perspective can be found, including the variation used here. The Hebbian learning of the three types of links considered above is formalised as follows (and similarly for state *bhope*).

For link (1):

$$d\, \omega(prep_{a_i,O_j,A}(t),\ srs_{effect(a_{i+1},O_j),A}(t))/dt =$$
$$\eta\, srs_{effect(a_{i+1},O_j),A}(t)\ prep_{a_i,O_j,A}(t)\ (1 - \omega(prep_{a_i,O_j,A}(t),$$
$$srs_{effect(a_{i+1},O_j),A}(t))) - \xi\, \omega(prep_{a_i,O_j,A}(t),\ srs_{effect(a_{i+1},O_j),A}(t)) \quad (13)$$

where η is a learning rate and ξ is an extinction rate.

In the presence of actual observation of an agent of an effect of its action, $\omega(prep_{a_i,O_j,A}(t),\ srs_{effect(a_{i+1},O_j),A}(t))$ may be updated differently. For example, its value may be set to *0* in the absence of the effect, and to *1* in the presence of the effect. Another alternative is to apply a Bayesian update rule [26] or a probabilistic update based on the weighting function from the Prospect Theory [19].

For link (2):

$$d\,\alpha_{prep(a_i,O_j)A_2A_1}(t)/dt = \eta\, prep_{a_i,O_j,A_1}(t)\, prep_{a_i,O_j,A_2}(t)\, (1 - \alpha_{prep(a_i,O_j)A_2A_1}(t)) - \xi\, \alpha_{prep(a_i,Oj)A_2A_1}(t)) \quad (14)$$

For link (3): $d\omega(prep_{bfear,O_i,A}(t),\ srs_{bfear,O_i,A}(t))/dt =$

$$\eta\, srs_{bfear,O_i,A}(t)\, prep_{bfear,O_i,A}(t)\, (1 - \omega(prep_{bfear,O_j,A}(t),\ srs_{bfear,O_j,A}(t))) - \xi\, \omega(prep_{bfear,O_j,A}(t),\ srs_{bfear,O_j,A}(t)) \quad (15)$$

5 Simulation Results

Based on the model described in Section 3 and the variations in types of links being learned considered in Section 4, simulation has been performed in the Matlab environment. The aim of the simulation was to investigate systematically how different mechanisms of learning considered in Section 4 influence the dynamics of the agent decision making. The simulation model included a group of 10 agents at some location in the building with the parameters drawn from the ranges of uniformly distributed values as indicated in Table 2 below. The agents were deliberating about three decision options (paths) to move outside of a burning building. Furthermore, information sources placed at each location in the building were providing information to the agents about the degree of danger of the locations.

Table 2. Ranges and values of the agent parameters used in the simulation

Parameter	γ	η	ζ	ε_{pA}	δ_{pA}	β	$\alpha_{pA_iA_j}$
Range/value	[0.7,1]	0.8	0.1	[0.7,1]	[0.7,1]	[0.55, 0.7]	1

First, simulation of the agent system without learning was performed; see Figure 2. In this simulation the agents did not adapt to changing conditions of the environment, e.g., emergence and spread of fire. The agents did not have the ability to store information received from the information sources. Thus, the danger of fire was taken into consideration by an agent only at the moment when it received the corresponding information. Because of this shortsightedness, the agents preferred options 1 and 2 (shorter, but dangerous paths) to option 3 (a longer, but safer path) (Figure 2).

After that different variations in learning of the three types of links considered in Section 4 have been explored in a systematic manner by simulation. A partial simulation trace for the case of learning of the emotion-related links (3) in the model for option 1 of Agent1 is provided in Table 3.

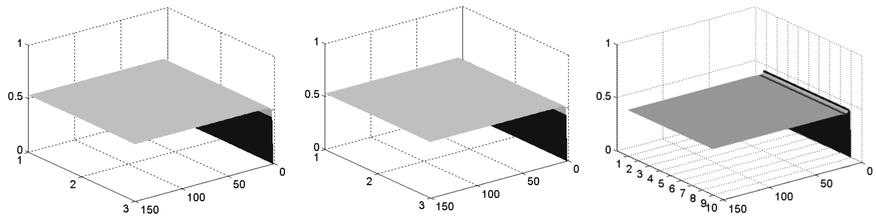

Figure 2. Change of the Agent1's preparation for execution of options 1 (left), 2 (center), 3 (right) without learning; the x-axis is the time scale (0-150), on the y-axis are the ordered numbers of actions in each options

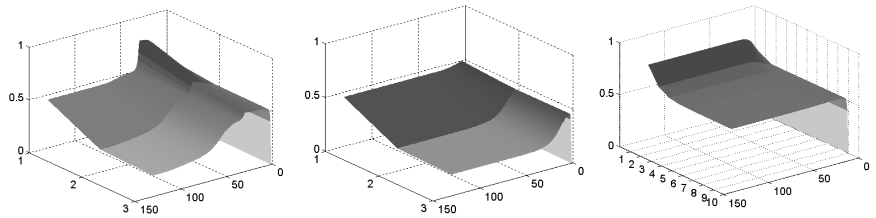

Figure 3. Change of the Agent1's preparation for execution of options 1 (left), 2 (center), 3 (right) with the Hebbian learning of links (1), (2) and (3); the x-axis is the time scale (0-150), on the y-axis are the ordered numbers of actions in each option.

Table 3. A partial simulation trace for the case of learning of the emotion-related links (3) in the model for option 1 of Agent1

Time point	**10**	**30**	**50**	**70**	**100**
Preparation to move to loc2 from loc1	*0.73*	*0.88*	*0.55*	*0.55*	*0.55*
Preparation to move to loc3 from loc2	*0.67*	*0.82*	*0.52*	*0.45*	*0.44*
Preparation to move to exit1 from loc3	*0.66*	*0.8*	*0.52*	*0.43*	*0.40*

Option 1 consists of three movement actions between locations loc1, loc2 and loc3. During the time period [0, 29) the path corresponding to option 1 was safe. Thus, option 1 was valuated highly by the agent, and was chosen for execution. During the execution of option 1, at time point 29, the agent received information about fire, which occurred at location loc 2 along the path of option 1. This observation caused a rapid devaluation of all action steps constituting option 1 by the agent, which eventually stabilized (time point 100). Other simulation results are summarized in Table 4 and depicted in Figure 3.

In comparison with the case without learning, learning of links (1) and (3) results into a noticeable increase in discrimination of the decision options in favour of option 3 (i.e., a longer and safer path). Learning of links (3) has the greatest effect on decision making. On the contrary, learning of links (2) has a negligible effect on the evaluation of options in this simulation study (Table 4). A close similarity of the preparation states of the agents observed in simulation is the main cause of a limited effect of learning of link (2) on decision making. In situations in which agents with radically conflicting opinions participate in social decision making, the effect of learning of links (2) would be much higher. A combination of learning of all links (1), (2) and (3) results in the strongest discrimination between the options (Figure 3, Table 4).

Table 4. Preparation for the first action of each option and the average preparation (over all actions) for each option per learning case

Learning links	Option 1 1st action	Option 1 (average)	Option 2 1st action	Option 2 (average)	Option 3 1st action	Option 3 (average)
(1)	*0.53*	*0.50*	*0.53*	*0.50*	*0.63*	*0.59*
(1), (2)	*0.53*	*0.49*	*0.53*	*0.49*	*0.63*	*0.57*
(3)	*0.55*	*0.46*	*0.55*	*0.46*	*0.88*	*0.77*
(1), (3)	*0.49*	*0.36*	*0.49*	*0.36*	*0.8*	*0.69*
(1), (2), (3)	*0.49*	*0.31*	*0.49*	*0.31*	*0.8*	*0.65*

6 Formal Analysis

The behaviour of the agent's adaptation process can also be investigated by formal analysis, based on the specification for the connection strength $\omega = \omega_{ij}$ from node i to node j.

$$\frac{d\omega(t)}{dt} + \gamma\,(\eta a_i(t)a_j(t) + \zeta)\,\omega(t) = \gamma\eta a_i(t)a_j(t)$$

This is a first-order linear differential equation with time-dependent coefficients: a_i and a_j are functions of t which are considered unknown external input in the equation for ω. An analysis can be made for when equilibria occur:

$$\frac{d\omega(t)}{dt} = 0 \Leftrightarrow (\eta a_i a_j + \zeta)\,\omega = \eta a_i a_j \quad \Leftrightarrow \quad \omega = \frac{\eta a_i a_j}{\eta a_i a_j + \zeta}$$

Indeed this relation was confirmed up to an accuracy of 0.01 for ω by the example simulations. One case here is that $\omega = 0$ and one of a_i and a_j is 0. When a_i and a_j are nonzero, it can be rewritten as (since $a_i a_j \leq 1$): $\omega = 1/(1 + \zeta/\eta a_i a_j) \leq 1/(1 + \zeta/\eta)$. This shows that when no extinction takes place ($\zeta = 0$), an equilibrium for ω of 1 is possible, but if extinction is nonzero, only an equilibrium < 1 is possible, as is also shown in the example simulations.

Further analysis can be made by obtaining an explicit analytic solution of the differential equation in terms of the functions a_i and a_j. This can be done as follows. Take $W(t) = \int_{t_0}^{t} a_i(u)a_j(u)\,du$ the accumulation of $a_i(t)a_j(t)$ over time from t_0 to t; then $\frac{dW(t)}{dt} = a_i(t)a_j(t)$. Given this, the differential equation for ω can be solved by using $e^{\gamma(\eta W(t)+\zeta(t-t_0))}$ as an integrating factor obtaining:

$$\omega(t) = \omega(t_0)\, e^{-\gamma(\eta W(t)+\zeta(t-t_0))} + \gamma\eta \int_{t_0}^{t} a_i(u)a_j(u)\; e^{-\gamma(\eta(W(t)-W(u))+\zeta(t-u))}\,du$$

For the special case of constant $a_i a_j = c$, explicit expressions can be obtained, using $W(t) = c(t-t_0)$ and $W(t)-W(u) = c(t-u)$:

$$\int_{t_0}^{t} a_i(u)a_j(u)\; e^{-\gamma(\eta(W(t)-W(u))+\zeta(t-u))}\,du =$$

$$\int_{t_0}^{t} c\, e^{-\gamma(\eta c+\zeta)(t-u))} du = \frac{1}{\gamma(\eta c+\zeta))} [1 - e^{-\gamma(\eta c+\zeta)(t-t_0))}]$$

Although in a simulation usually $a_i a_j$ will not be constant, these expressions may still be useful in a comparative manner. When $a_i a_j \geq c$ on some time interval, then by monotonicity the above expressions for ω with $a_i a_j = c$ provide a lower bound for ω. Thus it can be found that

$$\eta c/(\eta c+\zeta) - \omega(t) = [\eta c/(\eta c+\zeta) - \omega(0)]\ e^{-\gamma(\eta c+\zeta)t}$$

which shows the convergence rate to an equilibrium for constant $a_i a_j = c$, provides an upper bound for the deviation from the equilibrium. This has half-value time $\ln(2)/\gamma(\eta c+\zeta) = 0.7/\gamma(\eta c+\zeta)$. When $a_i a_j \geq c$ on some time interval, then by the monotonicity mentioned earlier, the upward trend will be at least as fast as described by this expression. In the example simulations these relations roughly have been confirmed as a way of approximation of the actual convergence speed (with deviations varying from less than *15%* to *50%*).

7 Conclusion

Effectiveness of human reasoning and decision making is determined largely by learning and adaptation mechanisms. In this paper effects of learning of different types of links in a social affective decision making model based on neurological principles are explored. Learning of the emotion-related links has the strongest effect on discrimination of decision making options, which can be seen as in line with recent perspectives addressing the role of the Amygdala in valuing, described, for example, in [13, 24, 23, 24]. The adaptation of action effect prediction links has a smaller, but still noticeable effect on social decision making. Next to learning of action effect prediction links, adaptation of effect-next action prediction links in simulated chains was investigated by simulation. It was established that the learning effect of the latter links on decision making is the same as of the former links. Thus, employing learning of both types of links in simulated decision chains does not have any added value for discrimination of the decision options. The Hebbian learning of external information provision links did not result in a significant discrimination between the decision options. This is explained by a high mutual influence of the agents and the similarity of their states. In conclusion, in societies of homogeneous and/or pervious to influence agents, employing Hebbian learning of action-effect prediction and emotion-related links would result in an efficient social decision making process. When agents express strong opposing opinions in decision making, learning of external information provision links may also need to be employed.

Previously, the Prospect Theory model of human decision making was proposed [19], which is often used for representing human decision making in Cognitive Science (see e.g., [11]). The theory is developed for simple probabilistic options (actions) with monetary outcomes, however can be extended to more involved options. In the model individuals subjectively transform probabilities p_i into decision weights $w(p_i)$ and outcomes x_i into values $v(x_i)$, relative to a reference point, which depends on the individual's expectation and situation. The utility of an option in its simplest form is calculated as $\sum_{i=1..N} w(p_i)\cdot v(x_i)$, where N is the number of outcomes of an option. The decision weighting function may have different forms, e.g. as in [11]: $w(p)=p^{\delta}/(p^{\delta} + (1-p)^{\delta})^{1/\delta}$. In the proposed model such a function could be incorporated into (13) for updating the strength values of links from preparation to sensory representation of action effect states.

The value function for an option in the Prospect Theory model is often defined as a power function of deviations of outcomes of actions from the agent's reference point. In [1] a computational decision making model is proposed, in which parameters of a prospect theory value function change with emotions. Similarly, in the proposed model, emotions, which play a crucial role in the evaluation of options, arise based on a difference between sensory representation of action effect states (the reference point) and the agent's desired state (a goal) (equation (7)). In contrast to the standard prospect model with atomic actions, options in our model are composite (i.e., represented by chains). Furthermore, in contrast to a linear (non-cyclic) evaluation of options in the prospect model, in the proposed model the evaluation of later states in a chain has an effect through an emotional influence on the evaluation of earlier states in a cyclic manner. This assumption is in line with psychological evidences [14], submitting that emotions influence not only the final outcome (action selection), but the processing dynamics of the whole system.

In the literature [11] it is recognized that humans often employ diverse emotion regulation mechanisms (e.g., to cope with fear and stress). These mechanisms involve interplay between cognitive and affective processes. In the future the proposed model will be extended with an emotion regulation component.

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