Adaptive Modelling of Social Decision Making by Affective Agents Integrating Simulated Behaviour and Perception Chains

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Abstract. It is widely recognized that both cognitive and affective aspects play an important role in human decision making. In most recent approaches for computational modelling of affective agents emotions have a cognitive origin. In contrast to these approaches, the computational social decision making model proposed in this paper is grounded on neurological principles and theories, thus providing a deeper level of understanding of decision making. The proposed approach integrates existing neurological and cognitive theories of emotion in a decision model based on evaluation of simulated behaviour chains. The application of the proposed model is demonstrated in the context of an emergency scenario.

Keywords: Social decision making, affective, cognitive, simulated behavioural chains, neurological modelling.

1 Introduction

Traditionally, human decision making has been modelled as the problem of rational choice from a number of options using economic utility-based theories [17, 18]. In the last decades such approaches were criticized by many authors [18] for the lack of realism and limited applicability. In particular, it is imputed to the traditional decision making modelling methods that the role of human cognitive heuristics and biases, and affective states is totally neglected. Much evidence exist [1, 4, 5, 10] that affective states have a significant impact on a human's decision making. However, computational models to explain this evidence are rare. In this paper the focus is on the integration of cognitive and affective aspects in a computational social decision making model which is grounded in neurological theories.

In the areas of Artificial Intelligence and Cognitive Science a number of computational models of decision making with emotions have been developed [9, 21, 22], which use variants of the OCC model developed by Ortony, Clore and Collins [19] as a basis. The OCC model postulates that emotions are valenced reactions to events, agents, and objects, where valuations are based on similarities between achieved states and goal states; thus emotions in this model have a cognitive origin.

The model proposed in this paper exploits some of the principles underlying the OCC model but embeds them in a neurological context that includes theories that cover other aspects as well, thus providing a deeper and wider level of understanding of social decision making. More specifically, options in decision making involving sequences of actions are modelled using the neurological theory of simulated behaviour (and perception) chains proposed by Hesslow [13]. Moreover, the emergence of emotional states in these behavioural chains is modelled using emotion generation principles described by Damasio [4-8]. Evaluation of sensory consequences of actions in behavioural chains, also uses elements borrowed from the OCC model. Different types of emotions can be distinguished and their roles in the decision making clarified. The social aspect comes in by processes of emotion and intention contagion between different persons.

Evaluation and the emotions involved in it usually have a strong impact from the human's earlier experiences. For example, an option that in the past ended up in feeling good may easily generate positive emotions when it is considered in the present. Therefore, in a decision process usually such elements involving what is often called 'intuition' or 'experience' play a role as well. In the proposed model for social decision making, this form of adaptivity to past experiences is also incorporated based on neurological principles. In such a way elements from neurological, affective and cognitive theories were integrated in the adaptive agent model proposed.

In some more neurological detail, generation and differentiation of emotion-loaded options for sequences of actions is modelled from a neurological perspective using Damasio's principles of (as-if) body loops and somatic marking [1, 6, 10]. The influence of the social context on the individual decision making is modelled based on *the mirroring function* of preparation neurons in humans. Such neurons, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror similar states of other persons. This mirroring function in social decision making is realised in two forms: (1) by *mirroring of emotions*, which indicates how emotional responses in different agents about a decision option mutually affect each other, and (2) by *mirroring of intentions* or *action preparations* of individuals for a decision option. Finally, the adaptivity in the agent model is based on the neurological principle of Hebbian learning [2, 11, 12].

The paper is organised as follows. The general modelling principles on which the proposed computational model is based are described in Section 2. A detailed formalisation of the proposed model is provided in Section 3. In Section 4 it is demonstrated how the proposed social decision making model is applied in an emergency scenario. Finally, Section 5 concludes the paper.

2 Neurological Principles Adopted

Considering options and evaluating them is viewed as a central process in human decision making. In this paper options are not single actions but sequences of actions, as in planning. To model considering such sequences, from the neurological literature the *simulation hypothesis* proposed by Hesslow [13] was adopted. This hypothesis rests on the following assumptions described in [13]:

(1) *Simulation of actions.* We can activate pre-motor areas in the frontal lobes in a way that resembles activity during a normal action but does not cause any overt movement.
(2) *Simulation of perception*. Imagining that one perceives something is essentially the same as actually perceiving it, but the perceptual activity is generated by the brain itself rather than by external stimuli.
(3) *Anticipation*. There are associative mechanisms that enable both behavioural and perceptual activity to elicit other perceptual activity in the sensory areas of the brain. Most importantly, a simulated action can elicit perceptual activity that resembles the activity that would have occurred if the action had actually been performed.

Based on anticipation mechanisms of the hypothesis, chains of behaviour can be simulated as shown in Fig. 1. Here some situation elicits activation of s1 in the sensory cortex that leads to preparation for action r1. Then, according to the simulation hypothesis, associations are used such that r1 will generate s2, which is the most connected sensory consequence of the action for which r1 was generated. This sensory state may serve as a stimulus for a new response, and so on. In such a way long chains of simulated responses and perceptions representing plans of action can be formed. These chains are being simulated by an agent internally as follows:

> 'An anticipation mechanism will enable an organism to simulate the behavioural chain by performing covert responses and the perceptual activity elicited by the anticipation mechanism. Even if no overt movements and no sensory consequences occur, a large part of what goes on inside the organism will resemble the events arising during actual interaction with the environment.' ([13])

As reported in [13], behavioural experiments have demonstrated a number of striking similarities between simulated and actual behaviour.

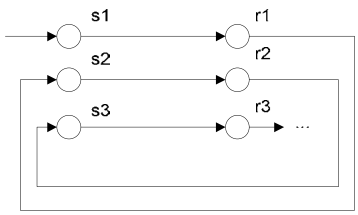

Fig. 1. Simulation of a behavioural chain proposed by Hesslow [13]

Hesslow argues in [13] that the simulated sensory states elicit emotions, which can guide future behaviour either by reinforcing or punishing simulated actions. However, specific mechanisms for emotion elicitation are not provided. This gap can be filled by combining the simulation hypothesis with a second source of knowledge from the neurological area: Damasio's emotion generation principles based on *(as-if) body loops*, and the principle of *somatic marking* [1, 6]. These principles were adopted to model evaluation of options.

Damasio [4, 5, 7] argues that sensory or other representation states of a person often induce emotions felt within this person, according to a *body loop* described by the following causal chain:

sensory state $\rightarrow$ preparation for the induced bodily response $\rightarrow$ induced bodily response $\rightarrow$ sensing the bodily response $\rightarrow$ sensory representation of the bodily response $\rightarrow$ induced feeling

As a variation, an *as if body loop* uses a direct causal relation as a shortcut in the causal chain: preparation for the induced bodily response $\rightarrow$ sensory representation of the induced bodily response. 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 as an additional causal relation: feeling $\rightarrow$ preparation for the bodily response. Thus, agent emotions are modelled based on reciprocal causation relations between emotion felt and body states. Following these emotion generation principles, an 'as if body' loop can be incorporated in a simulated behavioural chain as shown in Fig.2 (left). Note that based on the sensory states different types of emotions may be generated.

In the *OCC model* [19] a number of cognitive structures for different types of emotions are described. By evaluating sensory consequences of actions s1, s2, …, sn from Fig. 2 using cognitive structures from the OCC model, different types of emotions can be distinguished. More specifically, the emergence of hope and fear in agent decision making in an emergency scenario will be considered in Section 4.

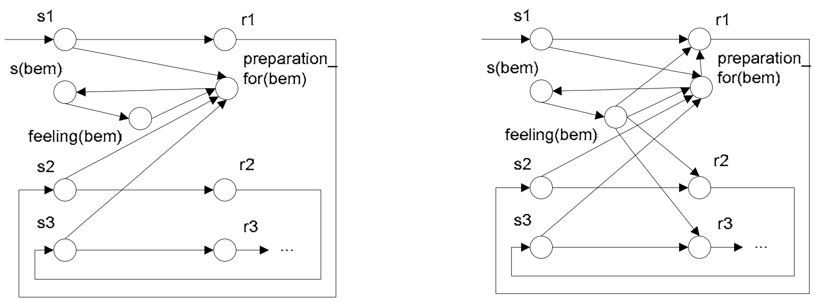

Fig. 2. Simulation of a behavioural chain extended with an 'as if body' loop with emotional state bem (left) and with emotional influences on preparation states (right)

Hesslow argues in [13] that emotions may reinforce or punish simulated actions, which may transfer to overt actions, or serve as discriminative stimuli. Again, specific mechanisms are not provided. To fill this gap the Damasio's *Somatic Marker Hypothesis* was adopted. This hypothesis provides a central role in decision making to emotions felt. Within a given context, each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly negative somatic marker linked to a particular option occurs as a strongly negative feeling for that option. Similarly, a positive somatic marker occurs as a positive feeling for that option. Damasio describes the use of somatic markers in the following way:

> 'the somatic marker (..) forces attention on the negative outcome to which a given action may lead, and functions as an automated alarm signal which says: beware of danger ahead if you choose the

option which leads to this outcome. The signal may lead you to reject, *immediately*, the negative course of action and thus make you choose among other alternatives. (…) When a positive somatic marker is juxtaposed instead, it becomes a beacon of incentive.' ([7], pp. 173-174)

To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 2 (right). Through these connections emotions influence the agent's readiness to choose the option. From a neurological perspective, the impact of a sensory state to an action preparation state via the connection between them in a behavioural chain will depend on how the consequences of the action are felt emotionally.

As neurons involved in these states and in the associated 'as if body' loop will often be activated simultaneously, such a connection from the sensory state to the preparation to action state may be strengthened based on a general *Hebbian learning* principle ([2, 11, 12]) that was adopted as well. It describes how connections between neurons that are activated simultaneously are strengthened, similar to what has been proposed for the emergence of mirror neurons; e.g., [8, 16, 20].

Thus, by these processes an agent differentiates options to act based on the strength of the connection between the sensory state of an option and the corresponding preparation to an action state, influenced by its emotions. The option with the highest activation of preparation is chosen to be performed by the agent.

As also used as an inspiration in [14], in a social context, the idea of somatic marking can be combined with recent neurological findings on the *mirroring function* of certain neurons (e.g., [8, 16, 20]). Mirror neurons are neurons which, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror similar states of other persons. They are active not only when a person intends to perform a specific action or body change, but also when the person observes somebody else intending or performing this action or body change. This includes expressing emotions in body states, such as facial expressions. The mirroring function relates to decision making in two different ways. In the first place *mirroring of emotions* indicates how emotions felt in different individuals about a certain considered decision option mutually affect each other, and, assuming a context of somatic marking, in this way affect how by individuals decision options are valuated in relation to how they feel about them. A second way in which a mirroring function relates to decision making is by applying it to the *mirroring of intentions or action tendencies* of individuals (i.e., preparation states for an action) for the respective decision options. This may work when by verbal and/or nonverbal behaviour individuals show in how far they tend to choose for a certain option. In the computational model introduced below in Section 3 both of these (emotion and preparation) mirroring effects are incorporated.

3 A Computational Model for Decision Making with Emotions

First, in Section 3.1 a modelling language is described used for the formalisation of the decision making model proposed. Then, the formal model is provided in Section 3.2.

3.1 Modeling language

To specify dynamic properties of a system, the order-sorted predicate logic-based language called LEADSTO is used [3]. Dynamics in LEADSTO is represented as evolution of states over time. A state is characterized by a set of properties that do or do not hold at a certain point in time. To specify state properties for system components, ontologies are used which are defined by a number of sorts, sorted constants, variables, functions and predicates (i.e., a signature). For every system component A a number of ontologies can be distinguished: the ontologies IntOnt(A), InOnt(A), OutOnt(A), and ExtOnt(A) are used to express respectively internal, input, output and external state properties of the component A. Input ontologies contain elements for describing perceptions of an agent from the external world, whereas output ontologies describe actions and communications of agents. For a given ontology Ont, the propositional language signature consisting of all state ground atoms based on Ont is denoted by APROP(Ont). State properties are specified based on such ontology by propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Then, a *state* S is an indication of which atomic state properties are true and which are false: S: APROP(Ont) $\rightarrow$ {true, false}.

LEADSTO enables modeling of direct temporal dependencies between two state properties in successive states, also called *dynamic properties*. A specification of dynamic properties in LEADSTO is executable and can be depicted graphically. The format is defined as follows. Let α and β be state properties of the form 'conjunction of atoms or negations of atoms', and e, f, g, h non-negative real numbers. In the LEADSTO language the notation $\alpha \twoheadrightarrow_{e,\, f,\, g,\, h} \beta$ means: if state property α holds for a certain time interval with duration g, then after some delay (between e and f) state property β will hold for a certain time interval of length h. When e = f = 0 and g = h = 1, called standard time parameters, we shall write $\alpha \twoheadrightarrow \beta$. To indicate the type of a state property in a LEADSTO property we shall use prefixes input(c), internal(c) and output(c), where c is the name of a component. Consider an example dynamic property:

input(A)|observation_result(fire) $\twoheadrightarrow$ output(A)| performed(runs_away_from_fire)

Informally, this example expresses that if agent A observes fire during some time unit, then after that A will run away from the fire during the following time unit.

In addition, LEADSTO allows expressing mathematical operations, e.g. has_value(x, v) $\twoheadrightarrow_{e,\, f,\, g,\, h}$ has_value(x, v*0.25).

3.2 The computational model

Depending on a situational context an agent determines a set of applicable options to satisfy a goal at hand. In the model proposed here the applicable options are generated via connections from activated sensory states reflecting this situational context to preparation states for the relevant actions related to an option. The issue of how precisely the strengths of these connections from a particular context to relevant action preparations have come into existence is out of scope of this paper; some related research can be found in [18]. An option is represented by a (partially) ordered sequence of actions (i.e., a plan) to satisfy the agent's goals. Computationally, alternative options considered by an agent are being generated and evaluated in parallel. The evaluation of options is based on the simulation of a behavioural chain as described in Section 2 (see Figure 3). The social context in which decision making is performed is represented by a group of agents interacting (verbally, nonverbally) on the relevant options. It is assumed that the preparation states of an agent for the actions constituting options and for emotional responses for the options are body states that can be observed with a certain intensity or strength by other agents from the group. The *contagion strength* of the interaction from agent A_2 to agent A_2 for a preparation state p is defined as follows:

$$\gamma_{pA_2A_1} = \varepsilon_{pA_2} \cdot \alpha_{pA_2A_1} \cdot \delta_{pA_1} \qquad (1)$$

Here ε_{pA_2} is the personal characteristic expressiveness of the sender (agent A_2) for p, δ_{pA_1} is the personal characteristic openness of the receiver (agent A_1) for p, and $\alpha_{pA_2A_1}$ is the interaction characteristic channel strength for p from sender A_2 to receiver A_1.

By aggregating such input, an agent A_i 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 proper, 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_j}, $\alpha_{pA_jA_i}$ and δ_{pA_i} introduced above.

(a) the aggregated group preparation to (i.e., the externally observable intention to perform) each action p constituting the option. This is expressed by the following dynamic property:

$$\wedge_{j\neq i} \text{ internal}(A_j) \mid \text{preparation\_for}(p, V_j) \twoheadrightarrow \text{internal}(A_i) \mid \text{srs}(G(p), \Sigma_{j\neq i}\ \gamma_{pA_jA_i} V_j \,/\, \Sigma_{j\neq i}\ \gamma_{pA_jA_i}\varepsilon_{pA_j}) \qquad (2)$$

(b) the aggregated group preparation to an emotional response (body state) be for each option. In general an option may induce different types of emotions (e.g., fear, hope, joy). For each of them a separate preparation state is introduced. Formally:

$$\wedge_{j\neq i} \text{ internal}(A_j) \mid \text{preparation\_for}(be, V_j) \twoheadrightarrow \text{internal}(A_i) \mid \text{srs}(G(be), \Sigma_{j\neq i}\ \gamma_{beA_jA_i} V_j \,/\, \Sigma_{j\neq i}\ \gamma_{beA_jA_i}\varepsilon_{beA_j}) \qquad (3)$$

Furthermore, the emotional responses induced by options affect preparation states for the actions from options via 'as-if body' loops as described in Section 2. Thus, the preparation state for the first action from an option is affected by the sensory representations of the option, of the perceived group preparation for the action and of the emotion felt towards the option. Formally[1]:

$$\text{srs}(O, V1)\ \&\ \text{srs}(be, V2)\ \&\ \text{srs}(G(a1), V3)\ \&\ \text{preparation\_for}(a1, V4) \twoheadrightarrow \text{preparation\_for}(a1, V4 + \gamma(h(V1, V2, V3) - V4)\Delta t), \qquad (4)$$

[1] Here and in the rest of the formulae in this section all internal states assume to belong to an agent A; the prefix internal(A) is omitted for a better readability.

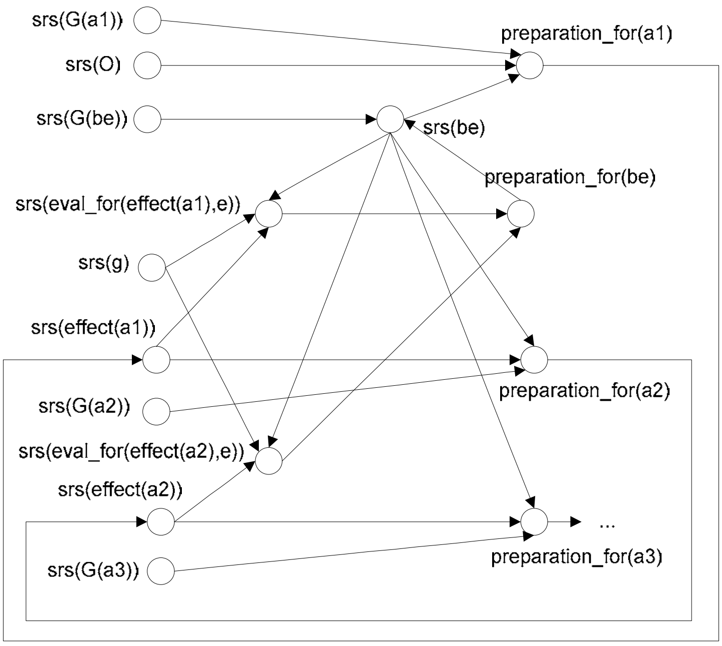

Fig. 3. A graphical representation of the emotional decision making model in the social context.

where O is an option, be is an emotional response state, Ga1 is the aggregated group preparation to action a1, h(V1, V2, V3) is a combination function:

$$h(V1, V2, V3) = \beta\ (1\text{-}(1\text{-}\ V1)(1\text{-}\ V2)(1\text{-}\ V3)) + (1\text{-}\beta)\ V1\ V2\ V3.$$

The simulated perception of the effect of an action from a plan in a simulated behavioural chain is modelled by the following property:

preparation_for(a, V) $\twoheadrightarrow$ srs(effect(a), V) (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 preparation state for each following action a from the behavioural chain is specified by:

srs(effect(a), V1) & srs(be, V2) & srs(G(a), V3) & preparation_for(a, V4) (6)
$\twoheadrightarrow$ preparation_for(a, V4 + γ(h(V1, V2, V3) – V4) Δt),

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 [19] 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 [19] are particularly relevant for the evaluation process. Such structures can be represented formally as evaluation properties. Examples of such properties for the emotions fear and hope are provided in the following section 4. As indicated in [19], 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 is specified formally as:

srs(g, V1) & srs(effect(a), V2) & srs(be, V3) & connection_between_strength(preparation_for(a), srs(effect(a)), V4) & srs(eval_for(effect(a), be), V5)
$\twoheadrightarrow$ srs(eval_for(effect(a), be), V5 + γ(h(V4*f(g, effect(a)), V3) – V5) Δt), (7)

where f(g, effect(a)) 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:

$\wedge_{i=1..n}$ srs(eval_for(effect(a_i), be), V_i) & srs(G(be), V3) (8)
$\twoheadrightarrow$ preparation_for(be, f(V_1, …, V_n)),
where bem is a particular type of the emotional response.

The agent perceives its own emotional response and creates the sensory representation state for it:

preparation_for(be, V) $\twoheadrightarrow$ srs(be, V) (9)

The Hebbian learning principle for links connecting the sensory representation of options, and effects of the actions from these options, with preparation states for subsequent actions in the simulation of a behavioural chain is formalised as follows (cf. [11]):

connection_between_strength(O, preparation_for(a1), V1) & srs(O, V2) & preparation_for(a1, V3)
$\twoheadrightarrow$ connection_between_strength(O, preparation_for(a1), V1 + (η V2 V3 (1 – V1) - ξV1)Δt), (10)

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

connection_between_strength(srs(effect(a_i)), preparation_for(a_{i+1}), V1) & srs(effect(a_i), V2) & preparation_for(a_{i+1}, V3)
$\twoheadrightarrow$ connection_between_strength(srs(effect(a_i)),
preparation_for(a_{i+1}), V1 + (η V2 V3 (1 – V1) - ξ V1)Δt) (11)

4 Decision Making in Emergency Situations: a Case Study

In this section it is demonstrated how decision making in an evacuation scenario can be modelled using the proposed approach (see Fig. 4). In this scenario a group of agents considers different options (paths) to move outside of a burning building. Each option is generated based on the agent's beliefs about the accessibility of locations in the building. Each option is represented by a sequence of locations with an exit as the last location, specified by follows_after(move_from_to(p1, p2), move_from_to(p2, p3)). 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 preparation_for(move_from_to(p2, p1)) and srs(is_at_location(p1)) is also ω.

Considered options (i.e., activation of the preparations for the actions involved) evoke two types of emotions - fear and hope, which are often considered in the emergency context [17]. According to [19], 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

$$\omega V1 + (1-\omega)/(1+ \lambda e^{-\varphi V2}), \qquad (12)$$

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 (12): $(1-\omega)/(1+ \lambda)$.

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

srs(g, V1) & srs(effect(a), V2) & srs(bfear, V3) &
connection_between_strength(preparation_for(a), srs(effect(a)), V4) &
srs(eval_for(effect(a), bfear), V5)
$\twoheadrightarrow$ srs(eval_for(effect(a1), bfear), V5 + γ(h(V4*f(g, effect(a)), V3) – V5) Δt),

where f(g, effect(a)) = |V1-V6|, and V6 is calculated by (12) for state effect(a).

srs(g, V1) & srs(effect(a), V2) & srs(bhope, V3) &
connection_between_strength(preparation_for(a), srs(effect(a)), V4) &
srs(eval_for(effect(a), bhope), V5)
$\twoheadrightarrow$ srs(eval_for(effect(a), bhope), V5 + γ(h(V4* f(g, effect(a)), V3) – V5) Δt),
where f(g, effect(a))=1-|V1-V6|, and V6 is calculated by (12) for state effect(a).

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

Using the developed model a number of simulations have been performed. In particular, social decision making in a group of 6 agents with 3 agents of type 1 (see Table 1) and 3 agents of type 2 has been modelled.

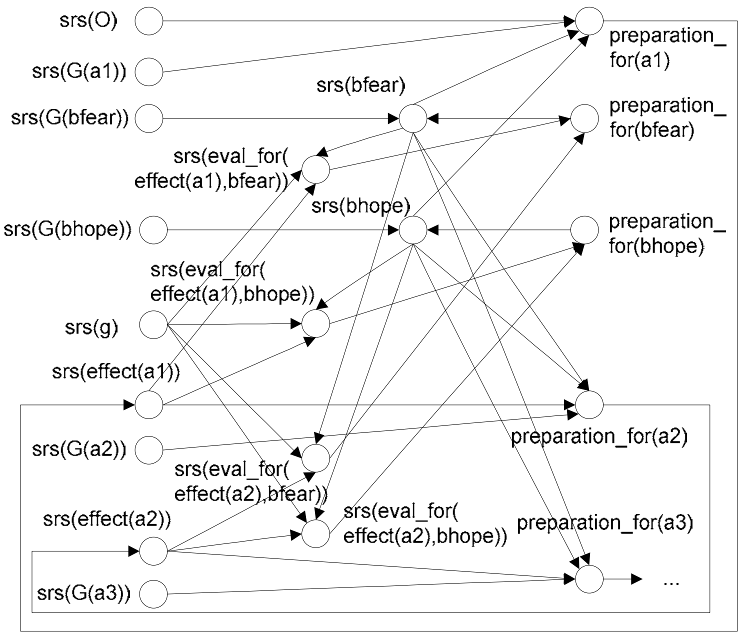

Fig. 4. A graphical representation of the emotional decision making model for an emergency scenario.

Table 1. Two types of agents used in the simulation.

Agent type	**ε for all states to all agents**	**δ for all states from all agents**	α	β	γ	η	ξ
Type 1: Extravert with a positive thinking attitude	*0.8*	*0.8*	*1*	*0.7*	*0.7*	*0.6*	*0.1*
Type 2: Introvert with a negative thinking attitude	*0.4*	*0.4*	*1*	*0.3*	*0.7*	*0.6*	*0.1*

The agents in the group are making choice among two options (paths) to move out of the building. For this example simulation it is assumed that all agents have the same beliefs about the availability of locations in the building and the degree of danger of each location. Path 1 considered by each agent is short, but also is more dangerous (i.e., has a higher concentration of fire and smoke at some locations); whereas the alternative path 2 is much longer, but is considered to be more safe. The dynamics of spread of fire and smoke is taken into account in the internal processing of the agents.

In Fig. 5 the change of the strength of the links over time between the sensory representations of both options and the corresponding preparation states to start the option execution is depicted. As one can see from the graphs all agents are more inclined to choose the second option. Furthermore, as the group reaches the consensus, the difference in the strength of the link for option 2 for both types of agents decreases over time. The agents of type 2 are consistently lower in their estimation of the options than the agents of type 1. This can be explained by their personal characteristics from Table 1.

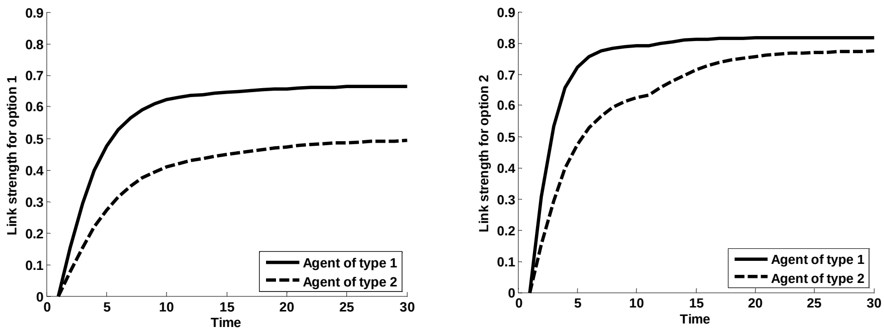

Fig. 5. The change of the strength of the link over time between the sensory representations of option1 (left) and option 2 (right) and their corresponding preparation states to start the option execution.

In Fig. 6 the change of fear and hope over time for option 1 for both types of agents is depicted.

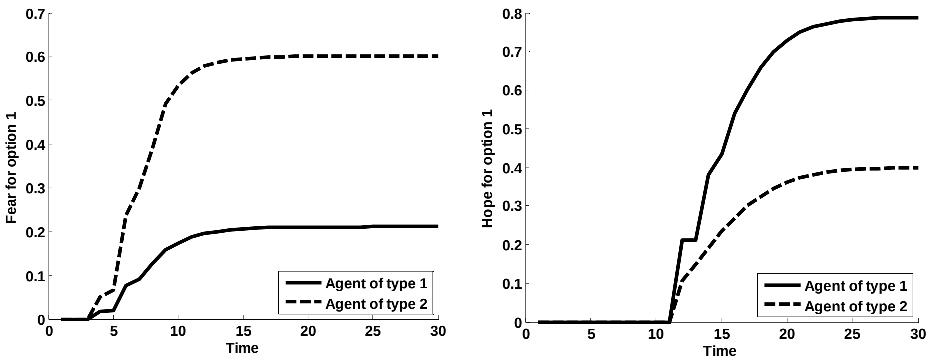

Fig. 6. The change of fear (left) and hope (right) for option 1 for both types of agents.

As can be seen from the graphs, the agents of type 1 have much more hope and much less fear than the agents of type 2, even though option 1 is not the most promising option. Such dynamics is largely accounted for by the settings of the individual parameters of agents from Table 1.

5 Conclusion

In this paper a computational approach for modelling adaptive decision making of individuals in a group is proposed. The approach is based on a number of neurological theories and principles supplementing each other in a consistent manner. By taking a neurological perspective and incorporating cognitive and affective elements in one integrated model, a more realistic and deeper and wider understanding of the internal processing underlying human decision making in social situations has been achieved. This gives a richer type of model than models purely at the cognitive level (and ignoring affective aspects), or diffusion or contagion models at the social level abstracting from internal processing, for example, as addressed in [14].

Although the neurological theories and principles used as a basis for the model proposed have been validated to a certain extent, in the future a large-scale validation study for the model in the frames of the EU-project SOCIONICAL is planned (http://www.socionical.eu).

Previously, a number of computational models for human decision making including different types of cognitive biases and heuristics have been developed, also in LEADSTO language [15]. Such models can be readily integrated with the model proposed in this paper. More specifically, models of cognitive biases can be used for the generation of effect of action states and for the evaluation of these states for the generation of emotions.

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