Emotional Decision Making in Large Crowds

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Abstract Currently it is widely recognised that emotions of people influence their decisions. In this paper the role of emotions in social decision making in large technically assisted crowds is investigated. For this a formal, computational model is proposed, which integrates existing neurological and cognitive theories of affective decision making. Based on this model several variants of a large scale crowd evacuation scenario were simulated. By analysis of the simulation results it was established that spread of emotions in a crowd increases resistance of agent groups to opinion changes and supports continuity of decision making in a group.

1 Introduction

Currently it is widely recognised that emotions of people influence their decisions [1,3]. Previously human decision making has been considered as entirely rational and has been modelled using economic utility-based theories [7,8]. Purely rational decision making models were disapproved by many empirical studies (see e.g. [15]). However, devising a better alternative addressing the limitations of these models by combining cognitive and affective aspects still remains a big challenge.

To address this challenge several computational models were proposed [4,13,14], which use variants of the OCC model developed by Ortony, Clore and Collins [11] 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. In contrast to these approaches, we employ a neurological fundament comprising several theories, based on which a model of emotional decision making is built. All these theories were validated empirically. The theories complement each other in the proposed model in a consistent manner by supplying each other with technical details used for refinement of abstract principles, as described in Section 2.

In Social Science literature [9,10] empirical evidences exist indicating that emotions increase a group's cohesion. In this paper we examine two hypotheses related to these findings by simulation based on the developed model:

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Hypothesis 1: Emotions increase the continuity of social decision making in a group and the robustness of a group against external perturbations (e.g., receipt of inconsistent information from strangers).

Hypothesis 2: Emotions arising in social decision making increase the cohesiveness of a group.

The hypotheses were verified on simulation data of a large scale crowd evacuation scenario, in which agents considered several options (exits) to escape from a burning train station. The obtained simulation results are discussed in Section 3. Section 4 concludes the paper.

2 Emotional Decision Making Model

Options in decision making involving sequences of actions are modelled using the neurological theory of *simulated behaviour (and perception) chains* proposed by Hesslow [6]. Based on this hypothesis, chains of behaviour can be simulated as follows: some situation elicits activation of sensory state *s1* in the sensory cortex that leads to preparation for action *r1*. Then, 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 serves 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 considered in decision making can be formed.

In the case study evacuation options are represented internally in agents by one-step simulated behavioural chains (see Fig.1). In Fig.1 the burning station situation elicits activation of sensory representation state *srs(evacuation_required)* in the agent that leads to preparation for action *preparation_for(move_to(E))*. Here *E* is one of the exits of the burning station.

Hesslow argues in [6] that emotions may reinforce or punish simulated actions, which may transfer to overt actions, or serve as discriminative stimuli. However no specific mechanism for this is provided. To fill this gap we adopt the Damasio's *Somatic Marker Hypothesis* [1,3]. This hypothesis postulates that 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 positive somatic marker occurs as a positive feeling for that option. To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 1. Through these connections emotions influence the agent's readiness to choose the option. In Fig.1 the preparation state for action *move_to(E)* is marked by two emotions, relevant for the emergency context – hope and fear. The dynamics of this state is formally specified by:

$$\boldsymbol{d}\, prep_{move\_to(E)}(t)/\boldsymbol{d}t =$$
$$\gamma[\, h(srs_{evacuation\_required}(t),\ srs_{fear}(t),\ srs_{hope}(t),\ srs_{G(move\_to(E))}(t)) - prep_{move\_to(E)}(t)\,] \qquad (1)$$

where *G(move_to(E))* is the aggregated preparation of the neighbouring agents to action *move_to(E),* γ indicates the speed of change of state $prep_{move\_to(E)}(t)$,

h(V1, V2, V3, V5) is a combination function:

$$h(V1, V2, V3, V5) = \beta (1-(1-V1)V2(1-V3)(1-V5)) + (1-\beta)\, V1\, V3\, V5(1-V2),$$

here β indicates optimistic $(\beta>0.5)$, neutral $(\beta=0.5)$, or pessimistic$(\beta<0.5)$ attitude of the agent to the option evaluation.

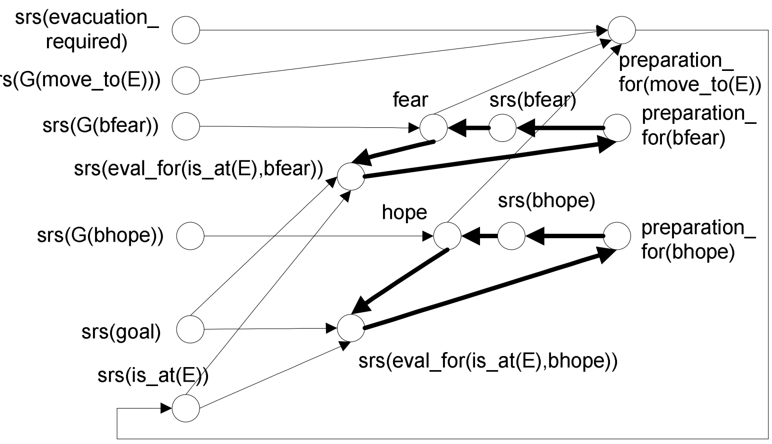


Fig. 1. The emotional decision making model for the option to move to exit E.

Note that if more than one exit is known to the agent, then in each option representation the preparation state corresponding to the option's exit is generated. Computationally, alternative options considered by an agent are being generated and evaluated in parallel. The option with the highest activation of preparation is chosen to be performed by the agent.

In the model associations are used such that *preparation_for(move_to(E))* will generate *srs(is_at(E))*, which is the most connected sensory consequence of the action *move_to(E)*. The strength of the link between a preparation for an action and a sensory representation of the effect of the action (see Fig.1) is used to represent the confidence value of the agent's belief that the action leads to the effect.

According to Hesslow [6], the simulated sensory states elicit emotions, which can guide future behaviour. However, specific mechanisms for emotion elicitation are not provided. This gap can be filled by combining the simulation hypothesis with the Damasio's emotion generation principles based on '*as if' body loops* [3]. In these loops sensory or other representation states of a person induce emotions felt within this person described by the following causal chain:

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

In the *OCC model* [11] a number of cognitive structures for different types of emotions are described, which can be used for specialization of the generic 'as if' body loop described above. For example, cognitive structures for emotions *hope* and *fear* from the case study were identified as follows. According to [11], 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 action from an option and the agent's goal state, which corresponds to *sensory state* in the generic 'as if' body loop above. The evaluation function for hope in the evacuation scenario can be specified as:

$eval(g, is\_at(E)) = \omega,$

where ω is the confidence value for the belief about the accessibility of exit E, which is an aggregate of the agent's estimation of the distance to the exit and the degree of clogging of the exit.

The evaluation property for fear (similarly for *hope*) of the effect of action *move_to(E)* compared with the goal state *goal* is specified formally as:

$$\begin{aligned} \mathbf{d}\, srs_{eval\_for(is\_at(E)),bfear}(t)/\mathbf{d}t = \\ \gamma[h(\omega(prep_{move\_to(E)}(t), srs_{is\_at(E)}(t)) \cdot f(srs_{goal}(t), srs_{is\_at(E)}(t)), \\ srs_{bfear}(t)) - srs_{eval\_for(is\_at(E)),bfear}(t)] \end{aligned} \quad (2)$$

where

$f(srs_{goal}(t), srs_{is\_at(E)}(t)) = |srs_{goal}(t) - eval(goal, is\_at(E))|$

Based on the evaluation function for fear, the dynamics of the emotional state *fear* (similarly for *hope*), which is *induced feeling* in the generic 'as if' body loop above is formalised by:

$$\mathbf{d}\, fear(t)/\mathbf{d}t = \gamma[h(srs_{G(bfear)}(t), f(srs_{goal}(t), srs_{is\_at(E)}(t))) - fear(t)] \quad (3)$$

where $G(bfear)$ is the aggregated fear state of the neighbouring agents.

The 'as if' body loops for hope and fear emotions from the case study are depicted in Fig. 1 by thick solid arrows.

The social influence of a group on the individual decision making is modelled based on the mirroring function [12] of preparation neurons in humans. It is assumed that the preparation states of an agent for the actions 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 neighbourhood. Furthermore, it is assumed that an agent is able to observe preparation states of other agents in its neighbourhood specified by radius r. Note that the agent's neighbourhood changes while the agent moves.

The *contagion strength* of the interaction from agent A_2 to agent A_1 for a preparation state p is defined as follows:

$\gamma_{pA_2A_1} = \varepsilon_{pA_2} \cdot trust_{A1,A2}(t) \cdot \alpha_{pA_2A_1} \cdot \delta_{pA_1}$

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.

Trust is an attitude of an agent towards an information source that determines the extent to which information received by the agent from the source influences agent's belief(s). The trust to a source builds up over time based on the agent's experience with the source. In particular, when the agent has a positive (negative) experience with the source, the agent's trust to the source increases (decreases). Currently experiences are restricted to information experiences only. An information experience with a source is evaluated by comparing the information provided by the source with the agent's beliefs about the content of the information provided. The experience is evaluated as positive (negative), when the information provided by the source is confirmed by (disagree with) the agent's beliefs. The following property describes the update of trust of agent A_i to agent A_j based on information communicated by A_j to A_i about the degree of clogging of exit E:

$\boldsymbol{d}\ trust_{Ai,\ Aj}(t)/\boldsymbol{dt} = \gamma_{tr}\cdot(comm_{Aj,\ Ai,clogging(E)}(t)\ /(1 + e^{\alpha}) - trust_{Ai,\ Aj}(t)),$

here $\alpha = -\omega 1 * (1 - |\ comm_{Aj,\ Ai,clogging(E)}(t) - belief_{Ai,clogging(E)}(t)|),$

$comm_{Aj,\ Ai,clogging(E)}$ is the degree of clogging of exit E communicated by agent A_j to agent A_j, $belief_{Ai,clogging(E)}(t)$ is the agent A_i's belief about the degree of clogging of exit E at time point t, $\omega 1$ indicates the steepness of the threshold function, i.e., the speed of change of trust after positive or negative experiences.

An agent B perceives the joint attitude of the crowd towards each option by aggregating the input from all agents in its neighbourhood $\aleph$:

(a) the aggregated neighbourhood's preparation to each action p is expressed by:

$$G(p) = \Sigma_{A\neq B,\ A\in\aleph}\ \gamma_{pAB}\, prep_{move\_to(E)}{}^{A}(t) / \Sigma_{A\neq B}\ \gamma_{pAB}\, \varepsilon_{pA} \quad (2)$$

(b) the aggregated neighbourhood's preparation to the emotional response (hope and fear) for each option:

$$G(bfear) = \Sigma_{A\neq B,\ A\in\aleph}\ \gamma_{beAB}\ prep_{fear}{}^{A}(t) / \Sigma_{A\neq B}\ \gamma_{beAB}\, \varepsilon_{beA}$$

3 Simulation Results

To ensure that the simulation setting is a true representative of reality, a real CAD design of an existing Austrian main railway station was incorporated to generate the space along with observed population statistics. The station was populated randomly with 1000 agents representing humans, from which 50 agents were equipped with personal assistants.

All personal assistants receive constantly from a global 'evacuation control unit' information about the degree of clogging of each exit. This information is assumed to be measured by a technology mounted on each exit. Furthermore, it is assumed that the global control unit provides reliable, up-to-date information to all personal assistants without any noise.

Each personal assistant has a location map used to transform the coordinates of an exit to the desired orientation to move. Thus, agents with personal assistants have direct access to information essential for successful evacuation, which they could propagate further by interaction with other agents.

Agents can interact with each other *non-verbally* by spreading emotions and intentions to choose particular exits, and *verbally* by communicating information about the states of the exits. The agents without devices are free to decide whether to follow agents with personal assistants or to rely on their own beliefs and exit choices. It is important to stress that the grouping effect is not encoded in our model explicitly, but emerges as a result of complex decision making by agents.

The model was implemented in the Netlogo simulation tool [15] by cellular automata. In this tool the environment is represented by a set of connected cells, where moveable agents (turtles) reside. Cells can be walkable (open space and exits) and not-walkable (concrete, partitions, walls). Each cell of the environment is accessible from all the exits.

To verify the hypotheses formulated in the introduction, three variants of the model described in Section 2 were implemented as 3 simulation conditions:

Condition 1: Agents generate and exchange both information and emotions during the social decision making.

Condition 2: Agents generate both emotions and information, but exchange only information.

Condition 3: Agents generate and exchange only information.

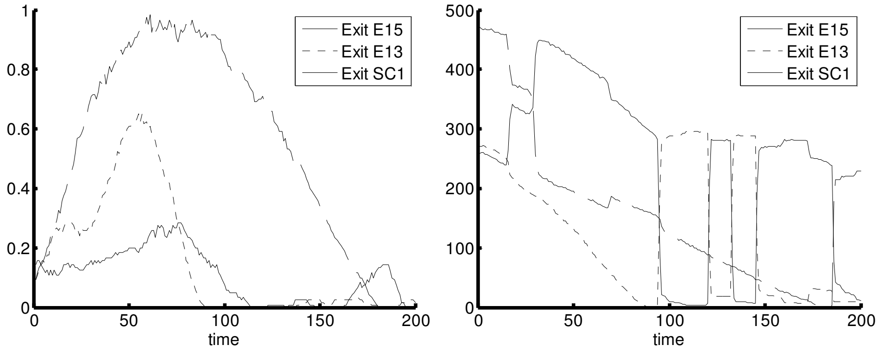
Since the model contains stochastic elements, 10 trials were performed for each simulation setting with 1000 heterogeneous agents with the parameters drawn from the ranges of uniformly distributed values as indicated in Table 1 below. The agents are assumed to have a varying positive attitude towards the option evaluation (β), they are fairly expressive (ε) and open (δ) to each other, and change their states rather quickly (γ). The agents are assumed to be strangers with low initial trust to each other, and with a gradual (not abrupt) increase or decrease of trust depending on experiences ($\omega 1$).

Table 1. Ranges and values of the agent parameters used in the simulation.

ε for all states from all agents	**δ for all states from all agents**	**β**	**γ**	**Δt**	**r**	**ω1**	**Initial trust to all agents**
[0.7,1]	*[0.7,1]*	*[0.55,0.7]*	*[0.7,1]*	*1*	*10 cells*	*9*	*[0.1,0.3]*

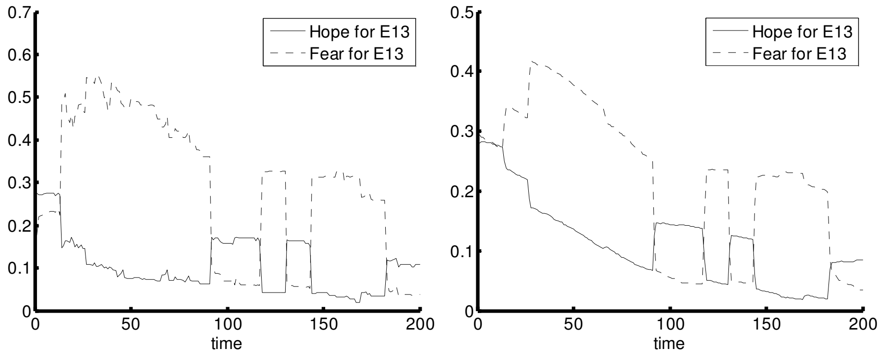
In the following some simulation results are discussed.

In *Condition 1* the most clogged exit throughout the simulation is Exit SC1, as it is the closest exit to most of the agents (Fig. 2a). As information about clogging of other exits spreads through the population of agents, the clogging of Exit SC1 decreases, but still remains higher than the clogging of other exits. Agents react to the change of clogging of the exits by changing their preferred exits (Fig. 2b). The amount of agents aiming at exit SC1 decreases throughout the simulation, whereas the numbers of agents choosing E15 and E13 fluctuate depending on the situation around these exits.



(a) *(b)*

Fig. 2. (a) The change of the degree of clogging of each exit over time in *Condition 1*; (b) The change of numbers of agents heading to each exit in *Condition 1*.



(a) *(b)*

Fig. 3. The emotional response toward the option to follow exit E13 averaged over technology-assisted agents (a) and over the agents without devices (b).

Information about the exits received by agents influences their emotional states (Fig 3). Technology-assisted agents, who receive first information about exits, change their emotions more rapidly (Fig.3a) than the agents without devices (Fig.3b). In such an information-scarce environment, information provided by agents with ambient devices spreads rapidly and is readily accepted by other agents.

To test the hypotheses formulated in Section 1, the simulation traces generated for each condition were analysed using the TTL Checker Tool [2]. To verify the first hypothesis, a smoothness degree of the preparation for each action (i.e., move to exit E) averaged over all agents is determined in each simulation trial (*smoothness index* (si_E)):

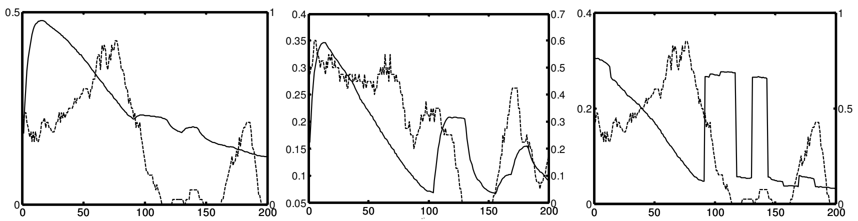
$$si_E = \Sigma_{t=1..t\_last-1}\, p_{t,E}/|N|, \quad \text{with}$$

$$p_{t,E} = \begin{cases} |prep_{move\_to(E)}(t+\Delta t) - prep_{move\_to(E)}(t)|, & when\ |prep_{move\_to(E)}(t+\Delta t) - prep_{move\_to(E)}(t)| \geq \varepsilon \\ 0, & when\ |prep_{move\_to(E)}(t+\Delta t) - prep_{move\_to(E)}(t)| < \varepsilon \end{cases}$$

Here N is the set of all agents, $prep_{move\_to(E)}$ is the preparation state to move to exit E, ε is a threshold for distinguishing small changes from large changes; ε is taken 0.1 for the analysis.

Thus, the smoothness index depends on the rate of change of the agent's opinion based on incoming information. This index indicates the robustness of a group of agents to messages provided by agents outside the group, which support a decision option different from the one currently supported by the group. The greater the smoothness index, the less robust is a group. Thus, to support *Hypothesis 1* by simulation data, the smoothness indexes for agents in condition 1 should be smaller than the indexes for the agents in condition 3.

Note that a group is defined by a set of human agents, supporting the same decision option and located closely to each other in the physical space. In the evacuation scenario this occurs when the situation around an exit(s) changes. Then, the agents with personal assistants receive new information, based on which they may change their decisions. Further, these agents spread new information to other agents in their neighbourhood. If besides information also emotions are being spread (see Table 2, condition 1 and Fig. 4a), the population of agents change their decisions gradually. When emotions are generated, but are not being spread, the group becomes less robust to changes and reacts more abruptly to incoming messages (see Table 2, condition 2 and Fig.4b). In the situation when emotions are not generated, the agents in a group change their decisions frequently, rapidly and drastically (see Table 2, condition 2 and Fig.4b). Such a form of behaviour is highly unrealistic for human beings.



(a) (b) (c)

Fig. 4. The change of the preparation to move to exit E15 averaged over the whole population of agents (solid line; left vertical axis), and the change of the degree of clogging of exit E15 (dotted line; right vertical axis) in condition 1(a), condition 2(b) and condition 3(c); the horizontal line is time.

Thus, the outcomes of the simulation (see Table 2 and Fig.4) support *Hypothesis 1* that generation and spread of emotions increase the continuity and robustness of social decision making.

To verify *Hypothesis 2* the metrics called *change index* (ci), reflecting the frequency of group change by an agent during the simulation, was introduced.

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

Coefficient	Condition 1	Condition 2	Condition 3
si_{exit1}	0.12 (0.03)	0.32 (0.04)	0.65 (0.07)
si_{exit2}	0.12 (0.04)	0.23 (0.05)	0.45 (0.08)
si_{exit3}	0.13 (0.04)	0.21 (0.07)	0.29 (0.07)
ci	1.5 (0.4)	1.9 (0.7)	7.1 (0.7)

It is defined by:

$ci_L = 1/|N| \sum_{A \in N} |S_{A,L}|$, $\quad ci = \sum_{i \in LEAD} ci_i/|LEAD|$,

where $LEAD$ is the set of all agents with personal assistants,

$S_{A,L} = \{ t \mid (t \in F_{A,L} \ \& \ (t+1) \notin F_{A,L}) \ \text{OR} \ ((t+1) \in F_{A,L} \ \& \ t \notin F_{A,L}) \}$, and

$F_{A,L} = \{ t \mid t \geq t\_first_A \ \& \ \exists d1,d2{:}DECISION \ at(has\_preference\_for\_option(A, d1), t) \ \& \ at(has\_preference\_for(L, d2), t) \ \& \ d1=d2 \ \& \ at(distance\_between(A, L) < dist\_threshold, t) \}$,

$at(X,t)$ denotes that X holds at time point t, and

t_first_A is such that $\exists o1{:}INFO \ at(communicated\_from\_to(L, A, inform, o1), t\_first_A) \ \& \ \forall t{:}TIME, o{:}INFO \ t < t\_first_A \ \& \ \neg at(communicated\_from\_to(L, A, inform, o), t)$, and

$N = \{a \mid t\_first_A \text{ is defined}\}$.

The average change index in *Condition 3* was 4.7 and 3.7 times higher than in *Conditions 1* and *2* respectively (Table 2, ci row). Thus, when emotions are not generated, agents are significantly less attached to their group than in the case when emotions are generated and being spread. Therefore, the generation and spread of emotions increase the cohesiveness of groups in the simulation. This confirms *Hypothesis 2*.

4 Conclusion

Many empirical studies indicated [3,5,7, 10] that emotions play an important role in social decision making. In this paper the role of emotions in supporting continuity and robustness of social decision making and of cohesiveness of groups in large crowds has been investigated. To this end two hypotheses were formulated.

To verify the hypotheses a computational model for social decision making was developed. This model is based on a number of neurological theories on human decision making developed in recent years. By taking a neurological perspective and incorporating cognitive and affective elements in one integrated model, more insights into human decision making can be obtained than by merely cognitive modelling. By simulation based on the developed model both hypotheses were confirmed. Spread of emotions in a crowd increases resistance of agent groups to opinion changes. Acceptance of a different decision option occurs gradually, as also described in the literature [9,10]. Furthermore, spread of emotions in a group increases its cohesiveness. This result is also supported by the literature [10].

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