Agent-Based Modelling of Social Emotional Decision Making in Emergency Situations

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1 Introduction

Decision making under stressful circumstances is a challenging type of human process. For example, in emergency evacuations of a group of persons, 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 emotions, adequate predictive capabilities, and social impact from other group members.

Mental states of individuals making a decision in a social context are not static. They often show high extents of dynamics due to social interaction. In Social Neuroscience neural mechanisms have been discovered that indeed – often in unconscious manners – account for mutual mirroring effects between mental states of different persons; e.g., [25], [34], [36]. For example, an emotion expresses itself in a smile which, when observed by another person, automatically triggers certain preparation neurons (also called mirror neurons) for smiling within this other person, and consequently generates the same emotion. Similarly, mirroring of intentions and beliefs can be considered.

In this paper group decision making in stressful circumstances is addressed. In these circumstances, emotions have an important interaction with the beliefs and intentions involved in a decision making process. The aim was to design a human-like computational model which is biological plausible by exploiting knowledge from Social Neuroscience about the relevant underlying mechanisms. Such a model

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may be useful not only for purposes of prediction, but also to obtain more insight in the dynamics of the social mechanisms and their emergent properties as described in a noncomputational manner in Social Neuroscience.

Based on modelling principles from neuroscience (Sect. 2), the computational model ASCRIBE (for Agent-based Social Contagion Regarding Intentions, Beliefs and Emotions) is introduced that not only incorporates mechanisms for mirroring emotions, intentions and beliefs between different persons (Sect. 3), but also addresses how within a person beliefs and emotions affect each other, and how they both affect the person's intentions. To illustrate the model, a number of example simulations in the context of a fictional emergency case study have been performed (Sect. 4). In the simulation scenario's agents are equipped with personal assistant devices with a tool for sharing emergency information over a short distance.

For agent-based modelling of collective phenomena individual agent behaviours can be modelled either from an agent-internal perspective, in the form of relations involving internal states of the agent, as in the ASCRIBE model, or from an agent-external, behavioural perspective, in the form of input-output relations for the agent, abstracting from internal states. Illustrated by a case study on collective decision making, this paper addresses how the two types of agent models can be related to each other by a behavioural abstraction mechanism described in Sect. 5. These relationships imply that, for example, collective behaviour patterns shown in multi-agent systems based on a behavioural agent model are shared for multi-agent systems based on corresponding cognitive agent models.

As a case study the model was evaluated based on empirical data for crowd behaviour. Behavioural patterns emerging in large crowds are often difficult to regulate. Various examples have shown how things can easily get out of control when many people come together during big events. Especially within crowds, the consequences can be devastating when emotion spirals (e.g., for aggression or fear) develop to high levels. In Sect. 6 a computational analysis is presented of the incident that happened at the Dam square in Amsterdam on the 4th of May in 2010. It is shown how the model is able to simulate an outburst of panic and its consequences. Finally, Sect. 7 concludes the paper.

2 Modelling Principles

This section briefly introduces the neurological/cognitive principles on which the models described in this chapter are based, and discusses the dynamical systems modelling approach used.

2.1 Generating Emotional Responses and Feelings

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

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

James [26] claimed a different direction of causality (see also Damasio [12], pp. 114–116):

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

The perspective of James assumes that a *body loop* via the expressed emotion is used to generate a felt emotion by sensing the own body state. Damasio made a further step by introducing the possibility of an *as-if body loop* bypassing actually expressed bodily changes (cf. Damasio [8], pp. 155–158; see also Damasio [10], pp. 79–80; Damasio [12]):

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

An as-if body loop describes an *internal simulation* of the bodily processes, without actually affecting the body, comparable to simulation in order to perform, for example, prediction, mindreading or imagination; e.g., [3], [17], [10]. Damasio [10] distinguishes an emotion (or emotional response) from a feeling (or felt emotion). The emotion and feeling in principle mutually affect each other in a bidirectional manner: an as-if body loop usually occurs in a cyclic form by assuming that the emotion felt in turn affects the prepared bodily changes; see, for example, in (Damasio [12], pp. 119–122):

emotion felt → preparation for bodily changes

A brief up-to-date survey of Damasio's ideas about emotion and feeling, and the 'tightly bound cycle' between them can be found in (Damasio [11], pp. 91–92) and (Damasio [12], pp. 108–129); for example (here the internal 'object' refers to the body state): 'The object at the origin on the one hand, and the brain map of that object on the other, can influence each other in a sort of reverberative process that is not to be found, for example, in the perception of an external object.' (Damasio [11], pp. 91–92). This essentially shows a cyclic process that (for a constant environment) can lead to equilibrium states for both emotional response (preparation) and feeling; see Fig. 1. Note that what is called stimulus s here can be taken as the sensor state sensing s. Given the cyclic nature of this process, a dynamical systems approach is a suitable modelling choice.

2.2 Mirroring

It has been found that certain preparation states for actions or for expressing body states (at the neural level called *mirror neurons*) have multiple functions, not only the function of preparing, but also the function of *mirroring* a similar state of another person; e.g., [25], [36], [15], [27], [29].

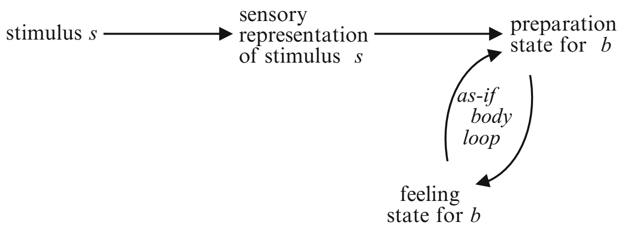


Fig. 1 Generating emotions and feelings based on an as-if body loop

Activation of mirror neurons is important not by itself, but because it plays a crucial role in an important mental function: *mirroring* mental processes of other persons by *internal simulation* using as-if body loops. From a more general viewpoint, as-if body loops as introduced above contribute:

(1) Sensory input directly affects preparation states, after which further internal processing takes place
(2) The notion of internal simulation involving body representations

Here (1) breaks with the tradition that there is a standard order of processing sensing – internal processing – preparation for action, and (2) allows for involving changing body representations in internal processes without actually having to change any body state. As mirror neurons make that some specific sensory input (an observed person) directly links to related preparation states, just like (1) above, it fits quite well in the perspective based on as-if body loops. In this way mirroring is a process that fully integrates mirror neuron activation states in the ongoing internal simulation processes based on as-if loops; see also (Damasio [12], pp. 102–104). This mirroring process is schematically shown in Fig. 2.

Here the preparation for body state *b* (e.g., some emotional response) can either be triggered by sensing an external stimulus *s* associating to *b*, or by observing somebody else performing *b* (upper part of Fig. 2). In both cases, as a first step the sensory representation affects the preparation state, after which further internal processing takes place based on the as-if body loop (lower part in Fig. 2) which in turn affects both the related feeling and the preparation state. Note that, as this mirroring process happens mostly in an unconscious manner, in a social context mirroring imposes limitations on the freedom for individuals to have their own personal emotions, beliefs, intentions, and actions.

2.3 Feelings and Valuing in the Emergence of Collective Action

Usually in the individual process of action selection, before a prepared action comes in focus to be executed, an internal simulation to predict the effects of the action takes place: the action is simulated based on prediction links, and in

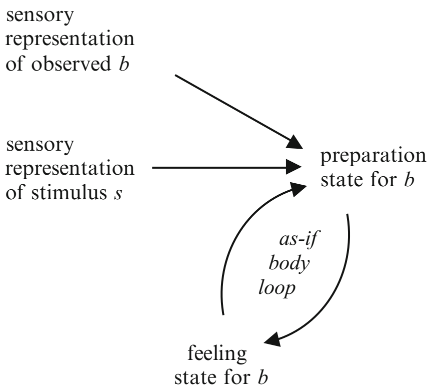


Fig. 2 Mirroring process based on mirror neuron activation and internal simulation

particular for the associated affective effects, based on as-if body loops that predict the body state which is the basis of the related feeling. Based on these predicted effects a valuation of the action takes place, which may involve or even be mainly based on the associated affective state, as, for example, described in [2], [8–12], [28], [30]. The idea here is that by an as-if body loop each option (prepared action) induces a simulated effect including a feeling which is used to value the option. For example, when a negative feeling and value is induced by a particular option, it provides a negative assessment of that option, whereas a positive feeling and value provides a positive assessment. The decision for executing a prepared action is based on the most positive assessment for it.

This simulation process for prepared actions does not only take place for preparations of self-generated actions, but also for intentions or actions from other persons that are observed. In this way by the mirroring process not only a form of action or intention recognition takes place in the form of activation of corresponding own preparation states by mirror neurons, but in addition also the (predicted) effects are simulated, including the affective effects. This provides an emotionally grounded form of understanding of the observed intention or action, including its valuing, which is shared with the observed agent; see also [12].

Given the important role of the feeling states associated to preparations of actions, it may be unrealistic to expect that a common action can be strong when the individual feelings and valuations about such an action have much variation over a group. When only the preparations for options are tuned to each other while in the meantime still the individual internal processes underlying the decision making remain a strong drive in a different direction, the overall process may result in no collectiveness at all. To achieve emergence of strong collective action, also a shared feeling and valuation for this action has to develop: also mirroring of the associated emotions has to play an important role. When this is achieved, the collective action has a solid shared emotional grounding: the group members do not only intend to perform that action collectively, but they also share a good feeling about it. In this process social media can play an important facilitating role in that (1) they dramatically strengthen the connections between large numbers of

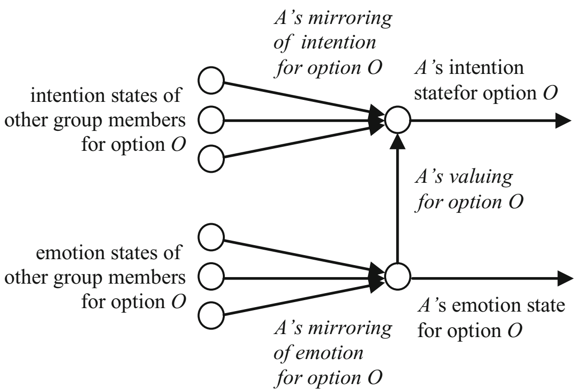


Fig. 3 Mirroring processes for both emotions and intentions and their internal interaction

individuals, and (2) they do not only support transfer of, for example, beliefs and intentions as such, but also associated emotions reinforcing them. Thus emergence of collectiveness of action is achieved by not only tuning the preparations or intentions for options to each other, but by also tuning the individual internal processes underlying the decision making for these options; see Fig. 3. This double-effective form of contagion enables both the emergence of a collective action and of a solid emotional grounding for this collective action.

2.4 Modelling Perspective

To model the types of dynamic and cyclic processes as discussed here in a neurologically inspired computational manner, a dynamical modelling perspective is needed, such as the dynamical systems perspective advocated, for example in [1], [35]. Modeling causal relations as discussed in neurological literature does not need to take specific neurons into consideration but can use more abstract mental states, relating, for example, to groups of neurons. In this way within the cognitive/affective modelling area results from the large and more and more growing amount of neurological literature can be exploited. This can be considered as lifting neurological knowledge to a mental (cognitive/affective) level considering temporal-causal relations between mental states. Nevertheless, the type of computational model that is designed can benefit by using some technical elements from the neural modelling level. In particular the approach based on small continuous-time recurrent neural networks is adopted; this approach is advocated by Beer (1995), and was inspired, for example, by earlier work in [18], [23], [24], [16]. This approach takes states as having a certain activation level (a number in the interval [0, 1]), and makes reciprocal loops and gradual adaptation possible. In [4] it is claimed that they are an obvious choice for this type of work because (1) they are the simplest nonlinear, continuous dynamical neural network model,(2) they are universal dynamics approximators in the sense that, for any finite interval of time, they can approximate the trajectories of any smooth dynamical system on a compact subset of IR^n arbitrarily well [16], and (3) they have a plausible neurobiological interpretation. This type of computational model is formulated as follows. For a state depending on multiple other states, to update its activation level, input values for incoming activation levels have to be combined to some aggregated input value. This update takes place according to the differential equation

$$\boldsymbol{d}y_i/\boldsymbol{dt} = \gamma_i[agginput_i - y_i]$$

where γ_i is the update speed of state i, $agginput_i$ is the aggregated input for i, and y_i is the activation value of i. The aggregation is created from the individual inputs $\omega_{j,i}$ y_j for all states j connected to i, where $\omega_{j,i}$ is the strength of the connection from j to i. For this aggregation a combination function $f(V_1, \ldots, V_k)$ is needed, applied to the different incoming values $V_j = \omega_{j,i}\, y_j$. It will be assumed that such a combination function satisfies:

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

A simple example of a combination function is the sum function:

$$f(V_1, \ldots, V_k) = \sum\nolimits_i V_i$$

For this function to satisfy (1), this puts strong constraints on the values $V_1, \ldots, V_k$: the sum of the inputs has to be at most 1, i.e., $\sum_{j \in s(i)} \omega_{j,i} \leq 1$, where $s(j)$ is the set of states connected as a source to state i. This dependency between connections is often not considered practical, nor biologically plausible. An often used combination function (e.g., in [4]) is based on a continuous logistic threshold function:

$$f(V_1, \ldots, V_k) = th(V_1 + \ldots + V_k)$$

with

$$th(X) = \frac{1}{1 + e^{-\sigma(X-\tau)}} \text{ or } th(X) = \left(\frac{1}{1 + e^{-\sigma(X-\tau)}} - \frac{1}{1 + e^{\sigma\tau}}\right)(1 + e^{-\sigma\tau})$$

Note that in the former variant $th(0) = \frac{1}{1+e^{\sigma\tau}}$ and this is nonzero; this is compensated in the latter variant. The former variant can be used as a suitable approximation when $\sigma\tau$ is large enough, e.g. $\sigma\tau \geq 20$. Given this, the type of computational model considered here uses $agginput_i = th(\sum_{j \in s(i)} \omega_{j,i}\, y_j)$ and provides a dynamical system of the form:

$$dy_i/dt = \gamma_i[th(\sum\nolimits_{j \in s(i)} \omega_{j,i}\, y_j) - y_i]$$

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

$$y_i(t + \Delta t) = y_i(t) + \gamma_{\mathrm{i}}[th(\sum\nolimits_{j \in s(i)} \omega_{j,i}\, y_j) - y_i]\Delta \mathrm{t}$$

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

3 ASCRIBE Model

In this section the computational model for group decision-making is introduced, which is based on the neurological principles of somatic marking and mirroring discussed in the previous section. More details on the model and its origins are addressed in. An elaborate description of the interplay of the different states can be found in [22]. In Sect. 3.1 the general model for the mirroring of mental states is introduced. Section 3.2 provides more details on the interplay between the different states of emotions, intentions and beliefs.

3.1 The General Model

The most important parameters and states within this general model will be described in this section. An overview of these parameters and states can be found in Table 1.

The model describes at an abstract level the mirroring of a mental state S (which can be, for example, an emotion, belief or intention) between agents. An important factor in determining the value of state S, is the contagion strength γ_{SBA} from agent B to agent A in a group. This denotes how much the state S of A is influenced by the state S of B. It is defined by

$$\gamma_{SBA} = \varepsilon_{SB}\alpha_{SBA}\delta_{SA} \tag{1}$$

Here, ε_{SB} is the personal characteristic *expressiveness* of the sender B for S, δ_{SA} the personal characteristic *openness* of the receiver A for S, and α_{SBA} the interaction characteristic *channel strength* for S from sender B to receiver A. In order to determine the level q_{SA} of state S in an agent A, first, the overall contagion strength γ_{SA} from the group towards agent A is calculated:

$$\gamma_{SA} = \sum\nolimits_{B \neq A} \gamma_{SBA} \tag{2}$$

This contagion strength is used to determine the weighed impact $q_{SA}{}^*$ of all the other agents upon state S of agent A:

Table 1 Parameters and states

q_{SA}	Level for state S for person A
ε_{SA}	Extent to which person A expresses state S
δ_{SA}	Extent to which person A is open to state S
η_{SA}	Tendency of person A to absorb or amplify state S
β_{SA}	Positive or negative bias of person A on state S
α_{SBA}	Channel strength for state S from sender B to receiver A
γ_{SBA}	Contagion strength for S from sender B to receiver A

$$q_{SA}{}^{*}(t) = \sum\nolimits_{B \neq A} \gamma_{SBA} \;\; q_{SB}(t)/\gamma_{SA} \tag{3}$$

The dynamics of the different mechanisms involved are modelled by dynamical relationships using the following general pattern:

$$Y_A(t + \Delta t) = Y_A(t) + \gamma < change\_expression > \Delta t$$

The change of Y is specified for a time interval between t and t + Δt; the γ represents the speed of the adjustment processes. Applied to the variable $q_{SA}(t)$ for $Y_A(t)$ the following is taken:

$$< change\_expression > = f(q_{SA}{}^{*}(t), q_{SA}(t)) - q_{SA}(t)$$

where $f(q_{SA}{}^{*}(t), q_{SA}(t))$ is a combination function. Thus the resulting update-rule for the considered states is:

$$q_{SA}(t + \Delta t) = q_{SA}(t) + \gamma_{SA}[f(q_{SA}{}^{*}(t), q_{SA}(t)) - q_{SA}(t)]\Delta t \tag{4}$$

Two additional personal characteristics determine how much this external influence actually changes state S of agent A, namely the tendency η_{SA} to absorb or to amplify the level of a state and the bias β_{SA} towards increasing (upward) or reducing (downward) impact for the value of the state. Based on this the combination function $f(q_{SA}{}^{*}(t), q_{SA}(t))$ used was taken as:

$$\begin{aligned} f(q_{SA}{}^{*}(t), q_{SA}(t)) = \eta_{SA}[&\beta_{SA}(1 - (1 - q_{SA}{}^{*}(t))(1 - q_{SA}(t))) \\ &+ (1 - \beta_{SA})\; q_{SA}{}^{*}(t)\; q_{SA}(t)] + (1 - \eta_{SA})\; q_{SA}{}^{*}(t) \end{aligned}$$

By Eq. 4 the new value for the state S at time t + Δt is calculated from the old value at t, plus the change of the value based upon the transfer by mirroring. This change is defined as the multiplication of the overall contagion strength γ_{SA} times the difference of a combination function of $q_{SA}{}^{*}$ and q_{SA} with q_{SA}. The combination function used has a component for amplification (after $\eta_{SA}(t)$) and one for absorption. The amplification component depends on the tendency of the person towards more positive (part multiplied by $\beta_{SA}(t)$ or negative part of equation multiplied by $1 - \beta_{SA}(t)$ side).

3.2 Dynamics Between Emotions, Beliefs and Intentions

When considering a computational model for group decision making, it is evident that beliefs, intentions and emotions make up a large part of this process. However, these aspects also influence each other. This section describes a computational model for the interplay of emotions, beliefs and intentions in a group of persons in the context of collective decision making. The model is extended by forming specializations of the generic model from Sect. 3.1, so as to incorporate internal interactions between the different types of states. Three different types of mental states S (as used in Eq. 4) are considered: beliefs, emotions, and intentions, indicated by *belief(X), fear, emotion(O), intention(O)* for information X and options O. In addition, interactions between these different states are modeled at the individual level; see also Table 2 for a brief explanation of all interactions in the model. In the following subsections, the specific interactions as shown in Table 2 will be addressed.

3.2.1 The Effect of Emotions on Beliefs

To model the effect of emotions on information diffusion, the personal characteristics δ_{SA}, η_{SA} and β_{SA} for a belief state S = belief(X) are not assumed constant, but are instead modeled in a dynamic manner, depending on emotions. Personal characteristics $\varepsilon_{belief(X)A}$, $\delta_{belief(X)A}$, $\eta_{belief(X)A}$, $\beta_{belief(X)A}$ and interaction characteristic $\alpha_{belief(X)BA}$ are parameters in the model as described in Sect. 3.1. One additional category is introduced here, namely informational state characteristics r_{XA} denoting how relevant, and p_{XA} denoting how positive information X is for person A. An assumption made for the model is that the intensity of the fear state of a person will affect his ability to receive information, by affecting the value of the individual person characteristics; in particular, a high level of fear affects $\beta_{belief(X)A}$, $\eta_{belief(X)A}$ and $\delta_{belief(X)A}$. First the effect of fear upon the openness for a belief belief (X) (characterized by a relevance r_{XA} of information X for A) is expressed:

$$\delta_{belief(X)A}(t+\Delta t) = \delta_{belief(X)A}(t) + \mu \cdot \left(1/1 + e^{-\sigma(q_{fear,A}(t)-\tau)}\right) \cdot \\ [(1 - \cdot (1 - r_{XA}) \cdot q_{fear,A}(t)\, \delta_{belief(X)A}(t)] \cdot \Delta t \qquad (5)$$

If $q_{fear,A}$ is lower than threshold τ (on the interval [0,1]), it will not contribute to the value of $\delta_{belief(X)A}$. If $q_{fear,A}$ has a value above τ, the openness will depend on the relevance of the information: when the relevance is high, openness will increase, while if the relevance is low, openness will decrease. In all formulae, μ is an

Table 2 The different types of processes in the model

From S	To S'	Type	Description
Belief(X)	*Fear*	Internal	Affective response on information; for example, on threats and possibilities to escape
Emotion(O)	*Emotion(O)*	Interaction	Emotion mirroring by nonverbal and verbal interaction; for example, fear contagion
Fear	*Belief(X)*	Internal	Affective biasing; for example, adapting openness, amplification extent and orientation
Belief(X)	*Belief(X)*	Interaction	Belief mirroring by nonverbal and verbal interaction; for example, of information on threats and options to escape
Belief(X)	*Intention(O)*	Internal	Cognitive response on information; for example, aiming for an exit that is believed to be reachable
Emotion(O)	*Intention(O)*	Internal	Somatic marking of intention options; for example, giving options that feel bad a low valuation
Intention(O)	*Intention(O)*	Interaction	Intention mirroring by nonverbal and verbal interaction; for example, of tendency to go in a certain direction

adaptation parameter. This proposed model corresponds to theories of emotions as frames for selective processing, as described in [14], [32]. A distinction between amplification values for different types of information is also made, depending on the emotional state fear. The dynamics for the characteristic $\eta_{belief(X)A}(t)$ modeling the amplification or absorption of *belief(X)* are described as follows:

$$\eta_{belief(X)A}(t+\Delta t) = \eta_{belief(X)A}(t) + \mu \cdot \left(1/1+e^{-\sigma(q_{fear,A}(t)-\tau)}\right) \cdot \\ [r_{XA} \cdot (1-p_{XA}) \cdot (q_{fear,A}(t)\, \eta_{belief(X)A}(t))] \cdot \Delta t \qquad (6)$$

The emotion of fear only has an influence when it is above the threshold. In that case the parameter only changes for relevant, non-positive information for which the parameter starts to move towards the value for the emotion of fear (meaning this type of information will be amplified). This property represents an interpretation of [7] on how emotion can result in selective processing of emotion-relevant information.

The bias of a person is also influenced by its emotion, but in addition depends on the content of the information, which can be either positive or negative:

$$\beta_{belief(X)A}(t+\Delta t) = \beta_{belief(X)A}(t) + \mu \cdot \left(1/\left(1+e^{\sigma(q_{fear},\, A^{(t)-\tau}}\right)\right) \cdot \left(1-q_{belief(X)A}(t)\right) \cdot \\ [(\zeta_A \cdot p_{XA} + (1-\zeta_A)\cdot(1-p_{XA})) - \beta_{belief(X)A}(t)] \cdot \Delta t \qquad (7)$$

Parameter τ is a number between 0 and 1 and represents a threshold for q_{fear}: when $q_{\mathrm{fear}} > \tau$, then $q_{fear,A}$ has an influence on the bias $\beta_{belief(X)A}(t)$. Parameter ζ_A is a personality characteristic; if $\zeta_A = 1$, represents a person who is optimistic when he/she experiences a lot of fear: positive information will be strengthened more and negative information will be weakened more. The opposite happens when $\zeta_A = 0$, this represents a person who is more ‘pessimistic’ when experiencing fear: negative information will be strengthened and positive information will be weakened. Both personality characteristics seem to exist in people: a bias towards the negative side of information in case of experiencing a high level of fear corresponds with the narrowing hypothesis from Frederickson’s broaden-and-build theory in [14]. Others have a bias towards more positive information and emotions. Leaders could use this ability motivate their followers in times of crisis, as positive information and emotions broaden people’s mindset [14], and focusing on positive information and emotions can contribute positively to individual’s mental states (including attention and cognitive capacity) and resources [14]. The dynamically changing ‘parameters’ $\delta_{belief(X)A}(t)$, $\eta_{belief(X)A}(t)$, $\beta_{belief(X)A}(t)$ are used in the equation describing the dynamics of the belief state *belief(X)*:

$$q_{belief(X)A}(t+\Delta t) = q_{belief(X)A}(t) + \gamma_{belief(X)A}(t) \cdot \left[f\left(q_{belief(X)A}{}^{*}(t), q_{belief(X)A}(t)\right) - q_{belief(X)A}(t)\right]\Delta t \tag{8}$$

Here the combination function $f(q_{SA}{}^{*}(t), q_{SA}(t))$ used is taken in a dynamic manner as:

$$\begin{aligned} f\left(q_{belief(X)A}{}^{*}(t), q_{belief(X)A}(t)\right) = \; & \eta_{belief(X)A}(t) \;\; [\beta_{belief(X)A}(t) \\ & (1-(1-q_{belief(X)A}{}^{*}(t))(1-q_{belief(X)A}(t))) \\ & + (1-\beta_{belief(X)A}(t))\; q_{belief(X)A}{}^{*}(t)\; q_{belief(X)A}(t)] \\ & + (1-\eta_{belief(X)A}(t))\; q_{belief(X)A}{}^{*}(t) \end{aligned}$$

Note that since it depends on $\delta_{belief(X)A}(t)$, also $\gamma_{belief(X)A}(t)$ becomes dynamic.

3.2.2 The Effect of Beliefs on Emotions with Respect to the Dynamics of Fear

In this subsection it is addressed how emotions are being influenced by information. This influence is modelled by altering the overall weighed impact of the contagion of the emotional state for fear:

$$q_{fear,A}{}^{*}(t) = \nu_A \cdot \left(\Sigma_{B \neq A} \gamma_{fearBA} \cdot q_{fearB} / \gamma_{fearA}\right) + (1-\nu_A) \cdot \left(\Sigma_X\; \omega_{X,fear,A} \cdot (1-p_{XA}) \cdot r_{XA} \cdot q_{belief(X)A}\right) \tag{9}$$

Here the influence depends on the impact from the emotion fear by others (the first factor, with weight ν_A) in combination with the influence of the belief present within the person. In this case, information has an increasing effect on fear if it is relevant and non-positive. This $q_{fear,A}{}^{*}(t)$ is used in the equation describing the dynamics of fear:

$$q_{fearA}(t+\Delta t) = q_{fearA}(t) + \gamma_{fearA}\left[f\left(q_{fearA}{}^{*}(t), q_{fearA}(t)\right) - q_{fearA}(t)\right]\Delta t \qquad (10)$$

with

$$f\left(q_{fearA}{}^{*}(t),\ q_{fearA}(t)\right) = \eta_{fearA}\left[\beta_{fearA}\left(1-\left(1-q_{fearA}{}^{*}(t)\right)\left(1-q_{fearA}(t)\right)\right)\right.$$
$$\left. + \left(1-\beta_{fearA}\right)\ q_{SA}{}^{*}(t)\ q_{SA}(t)\right]\ + \left(1-\eta_{fearA}\right)\ q_{fearA}{}^{*}(t)$$

3.2.3 The Effect of Beliefs and Emotions on Intentions

The abstract model for mirroring described above applies to emotion, belief and intention states S for an option O or the situation in general, but does not describe any interplay for intentions yet. Taking the Somatic Marker Hypothesis on decision making as a point of departure, not only intentions of others, but also own emotions affect the own intentions. To incorporate such an interaction, the basic model is extended as follows: to update $q_{intention(O)A}$ for an intention state S relating to an option O, both the intention states of others for O and the $q_{emotion(O)A}(t)$ values for the emotion state S' for O are taken into account. These intention and emotion states S and S' for option O are denoted by OI and OE, respectively:

Level of fear of person A:	$q_{fearA}(t)$
Level of emotion for option O of person A:	$q_{emotion(O)A}(t)$
Level of intention indication for option O of person A:	$q_{intention(O)A}(t)$
Level of belief supporting option O of person A:	$q_{beliefsfor(O)A}(t)$

Here $q_{beliefsfor(O)A}(t)$ denotes to aggregated support for option O by beliefs of A; it is defined as

$$q_{beliefsfor(O)}(t) = \Sigma_X \omega_{XOA}\ q_{belief(X)A} / \Sigma_X \omega_{XOA} \qquad (11)$$

Here ω_{XOA} indicates how supportive information X is concerning option O. The combination of the own (positive) emotion level and the rest of the group's aggregated intention is made by a weighted average of the two:

$$\begin{aligned} q_{intention(O)A}{}^{**}(t) = {} & (\omega_{OIA1}/\omega_{OIEBA})q_{intention(O)A}{}^{*}(t) \\ & + (\omega_{OEA2}/\omega_{OIEBA})q_{emotion(O)A}(t) \\ & + (\omega_{OBA2}/\omega_{OIEBA})q_{beliefsfor(O)A}(t) \end{aligned} \qquad (12)$$

$$\gamma_{intention(O)A}{}^{*} = \omega_{OIEBA}\gamma_{intention(O)A} \qquad (13)$$

ω_{OIA1},ω_{OBA2} and ω_{OEA2} are the weights for the contributions of the group intention impact (by mirroring), the own emotion impact (by somatic marking), and the own belief impact on the intention of A for O, respectively, and

$$\omega_{OIEBA} = \omega_{OIA1} + \omega_{OEA2} + \omega_{OBA2}$$

The combination of the own belief level and the rest of the group's aggregated emotion for a certain option O is made by a weighted average of the two:

$$\begin{aligned} q_{emotion(O)A}{}^{**}(t) = {} & (\omega_{OEA1}/\omega_{OEBA})\ q_{emotion(O)A}{}^{*}(t) \\ & + (\omega_{OBA1}/\omega_{OEBA}) q_{beliefsfor(O)A}(t) \end{aligned} \tag{14}$$

$$\gamma_{emotion(O)A}{}^{*} = \omega_{OEBA}\ \gamma_{emotion(O)A} \tag{15}$$

ω_{OEA1} *and* ω_{OBA1} are the weights for the contributions of the group emotion impact (by mirroring), the own belief impact on the emotion of A for O, respectively, and $\omega_{OEBA} = \omega_{OEA1} + \omega_{OBA1}$. Then the overall model for the dynamics of emotions and intentions for options becomes:

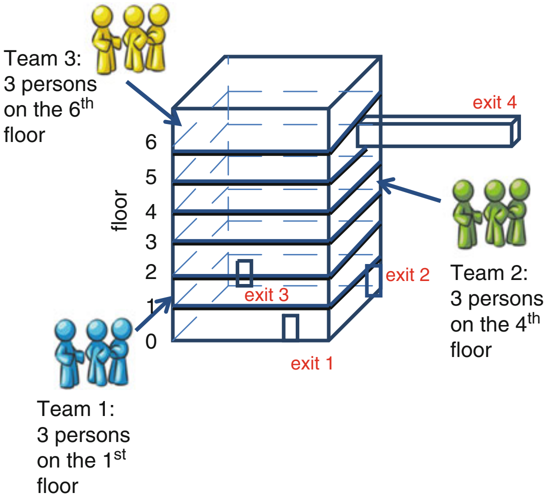
$$\begin{aligned} q_{emotion(O)A}(t+\Delta t) = {} & q_{emotion(O)A}(t) + \gamma_{intention(O)A}{}^{*} \cdot [\eta_{emotion(O)A}(\beta_{emotion(O)A} \\ & (1-(1-q_{emotion(O)A}{}^{**}(t))(1-q_{emotion(O)A}(t))) \\ & + (1-\beta_{emotion(O)A})\ q_{emotion(O)A}{}^{**}(t)\ q_{emotion(O)A}(t)) \\ & + (1-\eta_{emotion(O)A})\ q_{emotion(O)A}{}^{**}(t) - q_{emotion(O)A}(t)] \cdot \Delta t \end{aligned} \tag{16}$$

$$\begin{aligned} q_{intention(O)A}(t+\Delta t) = {} & q_{intention(O)A}(t) + \gamma_{intention(O)A}{}^{*} \cdot [\eta_{intention(O)A}(\beta_{intention(O)A} \\ & (1-(1-q_{intention(O)A}{}^{**}(t))(1-q_{intention(O)A}(t))) \\ & + (1-\beta_{intention(O)A})\ q_{intention(O)A}{}^{**}(t)\ q_{intention(O)A}(t)) \\ & + (1-\eta_{intention(O)A})\ q_{intention(O)A}{}^{**}(t) - q_{intention(O)A}(t)] \cdot \Delta t \end{aligned} \tag{17}$$

4 Simulation Studies

In this section, some example results of a small fictional case study will be presented. The goal of the case study was to investigate if the computational model can simulate the interplay of emotions, intentions and beliefs, as described in neuroscientific, social and psychological literature. The computational model was implemented in Matlab in the context of an evacuation scenario.

Fig. 4 The location of three teams in a building of six floors with four exits



The example scenario is expressed as follows: at the end of a working day in an office, the fire alarm goes off and all the persons that are in the building need to evacuate immediately. At the time of the alarm, three teams of each three people are present on different floors, as can be seen in Fig. 4. Persons can communicate with each other when they are on the same floor, or they can communicate to each other through their personal device, which is equipped with a tool for sharing emergency information over a short distance. Communication through such personal devices can only occur in case the distance is three floors or less. The building has four emergency exits, three at the ground floor and one at the 5th floor via a skyway to another building. If an exit is accessible, the information is rated as 'positive' information in the model, if not accessible then the information is rated 'not positive'. In the formalization, this leads to the following information state characteristics: $p_{ExitX} = 1$ for accessible exits and $p_{ExitX} = 0$ for blocked exists. The relevance of this information for survival is always 1, i.e. $r_{ExitX} = 1$.

4.1 An Example Scenario

In the example scenario, the three persons located at the top floor know that exit 4 is available (i.e. they have a belief of *1* in information $p_{Exit4} = 1$), whereas the three persons on the middle floor do not have any strong beliefs about any of the emergency exits. The three at the first floor know the situation of the exits 1 and 2 at the first floor, thus they have beliefs of strength *1* concerning those exists. In this case, the first exit is blocked and the second is accessible, therefore $p_{Exit1} = 0$ and $p_{Exit2} = 1$. They do not know anything about exit 3, therefore a belief of strength *0* is present concerning exit 3. Besides these values, all other values are

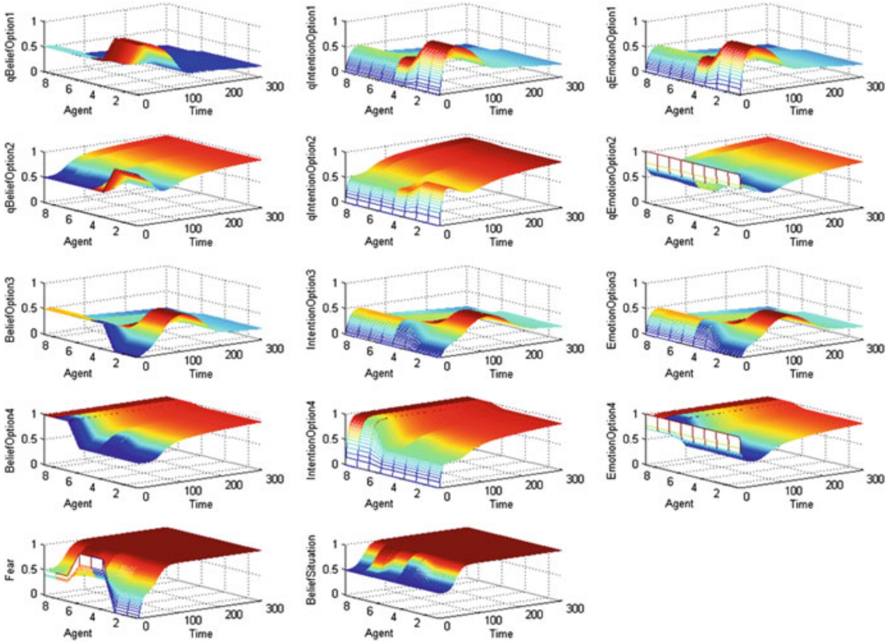


Fig. 5 Simulation results for an example scenario

set to *0.5* with respect to the beliefs to indicate that they know the exits are there but do not know specifically whether the exit is accessible or not. Moreover, the intentions of all agents are initially set to *0* (i.e. they start with not specific intention to leave the building via any of the exits) and the emotions to *0, 1, 0*, and *1* for exit 1, 2, 3, and 4 respectively (since exit 1 and exit 3 represent negative information, the emotion for that option is not positive). Finally, for the emotion of fear the agents at the first floor have no fear, at the middle floor they have maximum fear, and at the top floor medium fear is present. Furthermore, the initial belief about the situation itself is *0.5*. Furthermore, each agent has the same initial set of parameters.

Figure 5 shows the change of the values of the beliefs, intentions, and emotions. The top four rows represent the values related to the four exits. Here, the values for all agents during the simulation runs are shown. The y-axis of the graphs represents all nine persons, who have values for certain variables, stated on the z-axis. The values develop over time, which is represented by the x-axis. At the bottom row of the figure, diagrams with the amount of fear and the judgment of the entire situation are shown. It can be seen that fear spreads quickly, resulting in a very negative judgment of the situation by all agents. For exit 1 the belief about the exit being an option for evacuation eventually stabilizes at a relatively low value due to the fact that no human has a good feeling for that option (although in the beginning the emotions are slightly pulled upwards as well as the intention, due to the very strong belief of the three agents at the first floor). For exits 2 and 4 a very strong belief occurs rapidly for all agents as well as a very strong intention and the positive emotions also remain high. Finally, for exit 3 the agents at the first floor get a slightly stronger belief, intention, and emotion due to the fact that the other agents have a belief with value 0.5 about the exit. Eventually however, the values return to a rather low value again due to the fact that the others have lowered their value again. Without the ability to communicate with each other using personal devices, the beliefs, intentions, and emotions would not have been influenced by those on the other floors.

4.2 More Systematic Variations

The context of this case study was used to explore whether under a variety of parameter settings patterns emerge as expected.

4.2.1 The Effect of Information on Fear

A first prediction about the interplay of emotions, intentions and beliefs, according to the computational model is that from formula (8), it is expected that if a person experiences a situation as dangerous, then this person's fear level should increase. Simulations where the persons believed that the situation is dangerous were compared with simulations where they believed that that situation was not dangerous. The result of these simulations were that if persons believe that the situation is not dangerous ($p_{belief(s)A} = 1$), then $q_{fearA}(t)$ goes to 0, meaning that the persons will experience no fear. If the persons believe that the situation is dangerous ($p_{belief(s)A} = 0$), then $q_{fearA}(t)$ increases to 1, meaning that the persons will increase their experience of fear, when they consider the situation as dangerous. This result corresponds with our expectation.

4.2.2 The Effect of Emotion on Beliefs

According to formulas (5), (6), and (7) the level of fear that a person is experiencing, can have an effect on the way a person processes information. More precisely: it is expected that when $q_{fearA}(t)$ is above threshold τ, then the emotion fear should have an effect on the way persons process information. Multiple simulations were run to test this. In the simulations, the threshold τ was set to 0.5 and the initial value of $q_{fearA}(t)$ is below or above threshold τ, for example, 0.1 or 0.7. Whenever $q_{fearA}(t)$ is above the threshold τ (either from the start, or at a later time point), $\delta_{belief(X)A}(t)$, $\eta_{belief(X)A}(t)$ and $\beta_{belief(X)A}(t)$ start to change indeed. Here results will be briefly presented where ζ was 1.

The openness $\delta_{belief(X)A}(t)$ becomes *1* or stays *1*, this is according to the model, because when $\zeta = 1$ and $r_{belief(s)A} = 1$ (the information is relevant for survival), $\delta_{belief(X)A}(t)$ should increase.

The bias factor $\beta_{belief(X)A}(t)$ increases for the situation, exit 1 and 3 (which are not accessible), but decreases for exit 2 and 4 (which are accessible). This is what was expected, because the higher $p_{belief(s)A}$ is (meaning the more 'positive' information is), the lower $\beta_{belief(X)A}(t)$ should become (meaning information will be spread weaker by this person), the lower $p_{belief(s)A}$ is, the higher $\beta_{belief(X)A}(t)$ should become (meaning strengthening the spread of negative information).

The amplification extent $\eta_{belief(X)A}(t)$ increases differently for the situation, where exit 1 and 3 are not accessible. For this situation it goes towards *1* and it increases more, the further the agents are away from the exit. This is according to expectation, because $\eta_{belief(X)A}(t)$ should only increase if $p_{belief(s)A} =$ low and $r_{belief(s)A} =$ high, in these instances, $p_{belief(s)A} = 0$ and $r_{belief(s)A} = 1$. For exit 2 and 4, $p_{belief(s)A} = 1$ and $r_{belief(s)A} = 1$. In that case $\eta_{belief(X)A}(t)$ should not increase, and that is what is happening correctly in this evacuation scenario.

4.2.3 The Effects of a Combination of Beliefs and Emotions

In the simulations it was found that the combination of emotions and beliefs decreases the level of $q_{emotion(X)A}(t)$ more than they do separately. This effect was expected from formula (1) for $q_{emotion(X)A}(t)$**. For example, here one can see that in this situation the combination of emotions and beliefs makes $q_{emotion(X)A}(t)$ increase more, than when beliefs are not combined with emotions.

5 Model Abstraction

To obtain an agent-based social level model for group decision making, the general internal agent-based model for contagion described in Sect. 3.1 for any decision option O has been applied to both the emotion states S for O and intention or choice tendency states S' for O. In addition, an interplay between the two types of states has been modelled. To incorporate such an interaction, the general model from Sect. 3.1 was extended as follows: to update $q_{SA}(t)$ for an intention state S relating to an option O, both the intention states of others for O and the $q_{S'A}(t)$ values for the emotion state S' for O are taken into account. Note that in this model a fixed set of options was assumed that all are considered. The emotion and choice tendency states S and S' for option O are denoted by $b(O)$ and $c(O)$, respectively. Then the expressed level of emotion for option O of person A is $e_{b(O)A}(t)$, and of choice tendency or intention for O is $e_{c(O)A}(t)$. The combination of the own (positive) emotion level and the rest of the group's aggregated choice tendency for option O is made by a weighted average of the two:

$$s_{g(c(O))A}{}^{*}(t) \ = (\omega_{c(O)A}/\omega_{OA}) \ s_{g(c(O))A}(t) + (\omega_{b(O)A}/\omega_{OA}) e_{b(O)A}(t)/\varepsilon_{SA}$$
$$\gamma_{c(O)_A}{}^{*} = \omega_{OA}\gamma_{c(O)_A}$$

where $\omega_{c(O)A}$ and $\omega_{b(O)A}$ are the weights for the contributions of the group choice tendency impact and the own emotion impact on the choice tendency of A for O, respectively, and $\omega_{OA} = \omega_{c(O)A} + \omega_{b(O)A}$.

Then the behavioural agent-based model for interacting emotion and intention (choice tendency) contagion expressed in numerical format becomes:

$$s_{g(b(O))A}(t) = \Sigma_{B \neq A}\alpha_{b(O)BA} \cdot e_{b(O)B}(t)/(\Sigma_{B \neq A}\varepsilon_{b(O)B} \cdot \alpha_{b(O)BA})$$

$$\begin{aligned} e_{b(O)A}(t + \Delta t) = e_{b(O)A}(t) + \varepsilon_{b(O)A}\gamma_{b(O)A}c(s_{g(b((O))A}(t), \\ e_{b(O)A}(t)/e_{b(O)A})\,\Delta t \end{aligned}$$

with as an example

$$\begin{aligned} c(X,\ Y) = \eta_{b(O)A} \cdot [\beta_{b(O)_A} \cdot (1 - (1 - X) \cdot (1 - Y)) + (1 - \beta_{b(O)_A}) \cdot XY] \\ + (1 - \eta_{b(O)A}) \cdot X - Y \end{aligned}$$

$$s_{g(c(O))A}(t) = \Sigma_{B \neq A}\alpha_{c(O)BA} \cdot e_{c(O)B}(t)/(\Sigma_{B \neq A}\varepsilon_{c(O)B} \times \alpha_{c(O)BA})$$

$$\begin{aligned} e_{c(O)A}(t + \Delta t) = e_{c(O)A}(t) + \varepsilon_{c(O)A}\omega_{OA}\gamma_{c(O)A}d((\omega_{c(O)A}/\omega_{OA})s_{g(c(O))A}(t) \\ + (\omega_{b(O)A}/\omega_{OA})e_{b(O)A}(t)/\varepsilon_{b(O)A}, e_{c(O)A}(t)/\varepsilon_{c(O)A})\Delta t \end{aligned}$$

with as an example

$$\begin{aligned} d(X,\ Y) = \eta_{c(O)A} \cdot [\beta_{c(O)_A} \cdot (1 - (1 - X) \cdot (1 - Y)) + (1 - \beta_{c(O)_A}) \cdot XY] \\ + (1 - \eta_{c(O)A}) \cdot X - Y \end{aligned}$$

For the behavioural abstraction, the internal agent model (**IAM**) is expressed in a hybrid logical/numerical format in a straightforward manner (a graphical representation of the model, based on the principles from Sect. 2 is provided in Fig. 6):

IP1 From sensor states (SS) to sensory representations (SRS)

$$\mathrm{SS(A,\ S,\ V)} \twoheadrightarrow \mathrm{SRS(A,\ S,} \upsilon_{\mathrm{SA}}\mathrm{V)}$$

where S has instances c, g(c(O)) and g(b(O)) for options O.

IP2 Preparing for an emotion expressed in a body state (preparation state PS)

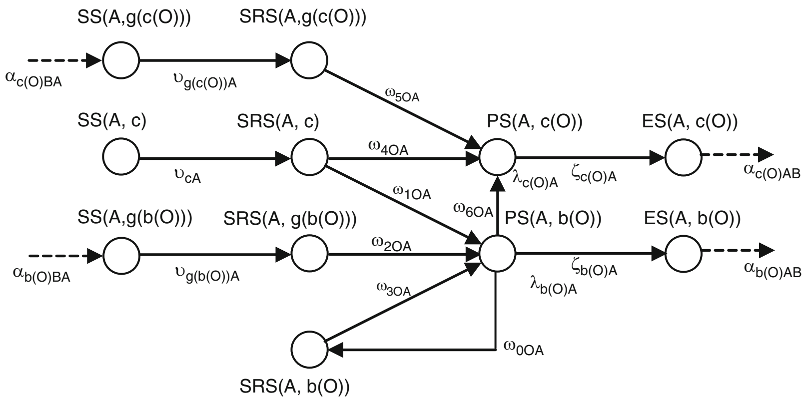


Fig. 6 Overview of the internal agent model **IAM**

$$
\begin{aligned}
&\mathrm{SRS(A,\ c,\ V_1)\ \&\ SRS(A,\ g(b(O)),\ V_2)}\\
&\mathrm{\&\ SRS(A,\ b(O),\ V_3)\ \&\ PS(A,\ b(O),\ V)}\\
&\twoheadrightarrow \mathrm{PS}\big(\mathrm{A,\ b(O),\ V} + \lambda_{\mathrm{b(O)A}}\mathrm{g}(\omega_{\mathrm{1OA}}\mathrm{V_1}, \omega_{\mathrm{2OA}}\mathrm{V_2}, \omega_{\mathrm{3OA}}\mathrm{V_3},\ \mathrm{V})\Delta\mathrm{t}\big)
\end{aligned}
$$

IP3 Preparing for an option choice (preparation state PS)

$$
\begin{aligned}
&\mathrm{SRS(A,\ c,\ V_1)\ \&\ SRS(A,\ g(c(O)),\ V_2))}\\
&\mathrm{\&\ PS(A,\ b(O),\ V_3)\ \&\ PS(A,\ c(O),\ V)}\\
&\twoheadrightarrow \mathrm{PS}\big(\mathrm{A,\ c(O),\ V} + \lambda_{\mathrm{c(O)A}}\mathrm{h}(\omega_{\mathrm{4OA}}\mathrm{V_1}, \omega_{\mathrm{5OA}}\mathrm{V_2}, \omega_{\mathrm{6OA}}\mathrm{V_3},\ \mathrm{V})\Delta\mathrm{t}\big)
\end{aligned}
$$

IP4 From preparation to effector state (ES)

$$\mathrm{PS(A,\ S,\ V)} \twoheadrightarrow \mathrm{ES(A,\ S,} \zeta_{\mathrm{SA}}\mathrm{V)}$$

where S has instances b(O) and c(O) for options O.

IP5 From preparation to sensory representation of body state (SRS)

$$\mathrm{PS(S,\ V)} \twoheadrightarrow \mathrm{SRS(S,} \omega_{\mathrm{0OA}}\mathrm{V)}$$

where S has instances b(O) for options O.

ITP Sensing aggregated group members' bodily responses and intentions

$$\wedge_{\mathrm{B}\neq\mathrm{A}}\ \mathrm{ES(B,\ S,\ V_B)} \twoheadrightarrow \mathrm{SS}\big(\mathrm{A,\ g(S),} \Sigma_{\mathrm{B}\neq\mathrm{A}}\alpha_{\mathrm{SBA}}\mathrm{V_B}/\Sigma_{\mathrm{B}\neq\mathrm{A}}\alpha_{\mathrm{SBA}}\zeta_{\mathrm{SB}}\big)$$

where S has instances b(O), c(O) for options O.

Also, the behavioural agent model **BAM** is translated in a hybrid logical/numerical format, using atoms has_value(x, V) with x a variable name and V a value. Here s(g(b((O)), A), s(g(c((O)), A), e(b(O), A) and e(c(O), A) for options O are names of the specific variables involved :

BP1 Generating a body state

$$\begin{aligned}&\text{has\_value}(s(g(b(O)),A),\ V_1)\ \&\ \text{has\_value}(e(b(O),A),\ V)\\&\twoheadrightarrow \text{has\_value}(e(b(O),A,\ V+\varepsilon_{b(O)A}\gamma_{b(O)A}\mathbf{c}(V_1,V/\varepsilon_{b(O)A})\Delta t)\end{aligned}$$

BP2 Generating an option choice intention

$$\begin{aligned}&\text{has\_value}(s(g(c(O)),A),\ V_1)\ \&\ \text{has\_value}(e(b(O),A),\ V_2)\\&\&\ \text{has\_value}(e(c(O),A),\ V)\twoheadrightarrow \text{has\_value}(e(c(O),A),\ V\\&+\varepsilon_{c(O)_A}\omega_{OA}\gamma_{c(O)_A}\mathbf{d}((\omega_{c(O)_A}/\omega_{OA})V_1\\&+(\omega_{b(O)_A}/\omega_{OA})V_2/\varepsilon_{b(O)A},V/\varepsilon_{c(O)_A})\Delta t)\end{aligned}$$

BTP Sensing aggregated group members' bodily responses and intentions

$$\wedge_{B\neq A}\ \text{has value}(e(S,B),\ V_B)\twoheadrightarrow \text{has value}\big(s(g(S),A),\Sigma_{B\neq A}\alpha_{SBA}V_B/\Sigma_{B\neq A}\alpha_{SBA}\varepsilon_{SB}\big)$$

In the following it is described how the behavioural agent model **BAM** is related to the internal agent model **IAM,** via the abstracted (from **IAM**) behavioural agent model **ABAM**. First, from the model **IAM** by a systematic transformation, an abstracted behavioural agent model **ABAM** is obtained. Then, the two behavioural agent models **ABAM** and **BAM** will be related. In [38] an automated abstraction transformation is described from a non-cyclic, stratified internal agent model to a behavioural agent model. As in the current situation the internal agent model is not assumed to be noncyclic, this existing transformation cannot be applied. The two main steps in this transformation are: elimination of sensory representation atoms, and elimination of preparation atoms.

1. Elimination of sensory representation atoms
   It is assumed that sensory representation atoms may be affected by sensor atoms, or by preparation atoms. These two cases are addressed as follows
   (a) *Replacing sensory representation atoms by sensor atoms*
      - Based on a property $SS(A,\ S,\ V)\twoheadrightarrow SRS(A,\ S,\upsilon V)$ (such as IP1), replace atoms SRS(A, S, V) in an antecedent (for example, in IP2 and IP3) by SS(A, S, V/υ).

   (b) *Replacing sensory representation atoms by preparation atoms*
      - Based on a property $PS(A,\ S,\ V)\twoheadrightarrow SRS(A,\ S,\omega V)$ (such as IP5), replace atoms SRS(A, S, V) in an antecedent (for example, in IP2) by $PS(A,\ b(O),\ V/\omega)$.

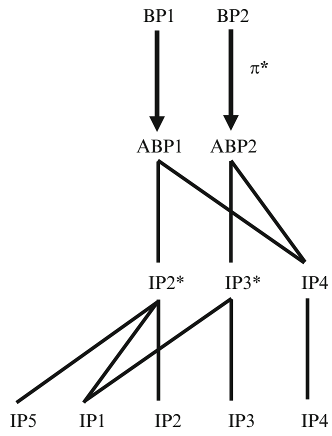


Fig. 7 Logical relations from network specification via internal agent model and abstracted behavioural model to behavioural agent model: **IAM**$\vdash$ **ABAM** = $\boldsymbol{\pi}$(**BAM**)

Note that this transformation step is similar to the principle exploited in [38]. It may introduce new occurrences of preparation atoms; therefore it should preceed the step to eliminate preparation atoms. In the case study this transformation step provides the following transformed properties (replacing IP1, IP2, IP3, and IP5; see also Fig. 7):

IP2* Preparing for a body state

$$\begin{aligned}&\mathrm{SS}(\mathrm{A},\ \mathrm{c},\ \mathrm{V}_1/\upsilon_{\mathrm{cA}})\ \&\ \ \mathrm{SS}\big(\mathrm{A},\ \mathrm{g}(\mathrm{b}(\mathrm{O})),\ \mathrm{V}_2/\upsilon_{\mathrm{g(b(O))A}}\big)\\ &\&\ \ \mathrm{PS}(\mathrm{A},\mathrm{b}(\mathrm{O}),\mathrm{V}_3/\omega_{0\mathrm{OA}})\ \&\ \ \mathrm{PS}(\mathrm{A},\ \mathrm{b}(\mathrm{O}),\ \mathrm{V})\\ &\twoheadrightarrow \mathrm{PS}\big(\mathrm{A},\ \mathrm{b}(\mathrm{O}),\mathrm{V}+\lambda_{\mathrm{b(O)A}}\mathbf{g}(\omega_{1\mathrm{OA}}\mathrm{V}_1,\omega_{2\mathrm{OA}}\mathrm{V}_2,\omega_{3\mathrm{OA}}\mathrm{V}_3,\ \mathrm{V})\Delta\mathrm{t}\big)\end{aligned}$$

IP3* Preparing for an option choice

$$\begin{aligned}&\mathrm{SS}(\mathrm{A},\ \mathrm{c},\ \mathrm{V}_1/\upsilon_{\mathrm{cA}})\ \&\ \ \mathrm{SS}\big(\mathrm{A},\ \mathrm{g}\big(\mathrm{c}(\mathrm{O})\big),\ \mathrm{V}_2/\upsilon_{\mathrm{g(c(O))A}}\big)\big)\\ &\&\ \mathrm{PS}(\mathrm{A},\ \mathrm{b}(\mathrm{O}),\ \mathrm{V}_3)\ \&\ \mathrm{PS}(\mathrm{A},\ \mathrm{c}(\mathrm{O}),\ \mathrm{V})\twoheadrightarrow \mathrm{PS}(\mathrm{A},\ \mathrm{c}(\mathrm{O}),\\ &\mathrm{V}+\lambda_{\mathrm{c(O)A}}\mathbf{h}(\omega_{4\mathrm{OA}}\mathrm{V}_1,\omega_{5\mathrm{OA}}\mathrm{V}_2,\omega_{6\mathrm{OA}}\mathrm{V}_3,\ \mathrm{V})\Delta\mathrm{t})\end{aligned}$$

2. Elimination of preparation atoms
   Preparation atoms in principle occur both in antecedents and consequents. This makes it impossible to apply the principle exploited in [38]. However, it is exploited that preparation states often have a direct relationship to effector states:

   - Based on a property $\mathrm{PS}(\mathrm{A},\ \mathrm{S},\ \mathrm{V}) \twoheadrightarrow \mathrm{ES}(\mathrm{A},\ \mathrm{S},\zeta\mathrm{V})$ (such as in IP4), replace each atom PS(A, S, V) in an antecedent or consequent by $\mathrm{ES}(\mathrm{A},\ \mathrm{S},\zeta\mathrm{V})$.

In the case study this transformation step provides the following transformed properties (replacing IP2*, IP3*, and IP4; see also Fig. 7):

IP2* Preparing for a body state

$$\begin{aligned}&SS(A,\ c,\ V_1/\upsilon_{cA})\ \&\ SS\big(A,\ g(b(O)),\ V_2/\upsilon_{g(b(O))A}\big)\\ &\&\ \ ES(A,\ b(O),\zeta_{b(O)A}V_3/\omega_{0OA})\ \&\ ES(A,\ b(O),\zeta_{b(O)A}V)\\ &\twoheadrightarrow ES\Big(A, b(O), \zeta_{b(O)A}V + \zeta_{b(O)A}\lambda_{b(O)A}\mathbf{g}(\omega_{1OA}V_1, \omega_{2OA}V_2, \omega_{3OA}V_3,\ V)\Delta t\Big)\end{aligned}$$

IP3* Preparing for an option choice

$$\begin{aligned}&SS(A,\ c,\ V_1/\upsilon_{cA})\ \&\ SS(A,\ g(c(O)),\ V_2/\upsilon_{g(c(O))A}))\\ &\&\ ES(A, b(O), \zeta_{b(O)A}V_3)\ \&\ ES(A,\ c(O), \zeta_{c(O)A}V) \twoheadrightarrow ES(A,\ c(O),\\ &\zeta_{c(O)A}V + \zeta_{c(O)A}\lambda_{c(O)A}\mathbf{h}(\omega_{4OA}V_1, \omega_{5OA}V_2, \omega_{6OA}V_3, V)\Delta t)\end{aligned}$$

By renaming V_1/υ_{cA} to V_1, $V_2/\upsilon_{g(b(O)A}$ to $V_2, \zeta_{b(O)A}\ V_3/\omega_{0OA}$ to $V_3, \zeta_{b(O)A}V$ to V (in IP2$*$), resp. $V_2/\upsilon_{g(c(O))A}$ to $V_2, \zeta_{b(O)A}V_3$ to V_3, and $\zeta_{c(O)A}V$ to V (in IP3$*$), the following is obtained:

IP2 Preparing for a body state**

$$\begin{aligned}&SS(A,\ c,\ V_1)\ \&\ SS(A,\ g(b(O)),\ V_2)\ \&\ ES\ (A,\ b(O),\ V_3)\ \&\ ES(A,\ b(O),\ V)\\ &\twoheadrightarrow ES(A,\ b(O), V + \zeta_{b(O)A}\lambda_{b(O)A}\mathbf{g}(\omega_{1OA}\upsilon_{cA}V_1, \omega_{2OA}\upsilon_{g(b(O))A}V_2,\\ &\quad \omega_{3OA}\omega_{0OA}V_3/\zeta_{b(O)A},\ V/\zeta_{b(O)A})\Delta t)\end{aligned}$$

IP3 Preparing for an option choice**

$$\begin{aligned}&SS(A,\ c,\ V_1)\ \&\ SS(A,\ g(c(O)),\ V_2)\ \&\ ES(A,\ b(O),\ V_3)\ \&\ ES(A,\ c(O),\ V)\\ &\twoheadrightarrow ES(A,\ c(O),\ V + \zeta_{c(O)A}\lambda_{c(O)A}\mathbf{h}(\omega_{4OA}\upsilon_{cA}V_1, \omega_{5OA}\upsilon_{g(c(O))A}V_2,\\ &\quad \omega_{6OA}V_3/\zeta_{b(O)A},\ V/\zeta_{c(O)A})\Delta t)\end{aligned}$$

Based on these properties derived from the internal model **IAM** the specification of the abstracted behavioural model **ABAM** can be defined; see also Fig. 7, lower part.

5.1 *Hybrid Specification of the Abstracted Behavioural Agent Model ABAM*

Note that in IP2** V_2 and V have the same value, so a slight further simplification can be made by replacing V_3 by V. After renaming of the variables according to

ABP1

V_1	$\rightarrow$	W_0
V_2	$\rightarrow$	W_1
V_3	$\rightarrow$	W
V	$\rightarrow$	W

ABP2

V_1	$\rightarrow$	W_0
V_2	$\rightarrow$	W_1
V_3	$\rightarrow$	W_2
V	$\rightarrow$	W

the following abstracted behavioural model **ABAM** for agent A is obtained:

ABP1 Generating a body state

$$\begin{aligned}&\mathrm{SS(A,\ c,\ W_0)\ \&\ SS(A,\ g(b(O)),\ W_1)\ \&\ ES(A,\ b(O),\ W)}\\&\twoheadrightarrow \mathrm{ES(A,\ b(O),\ W} + \zeta_{\mathrm{b(O)A}}\lambda_{\mathrm{b(O)A}}\mathbf{g}(\omega_{\mathrm{1OA}}\upsilon_{\mathrm{cA}}\mathrm{W}_0, \omega_{\mathrm{2OA}}\upsilon_{\mathrm{g(b(O))A}}\mathrm{W}_1,\\&\quad \omega_{\mathrm{3OA}}\omega_{\mathrm{0OA}}\mathrm{W}/\zeta_{\mathrm{b(O)A}},\ \mathrm{W}/\zeta_{\mathrm{b(O)A}})\Delta \mathrm{t})\end{aligned}$$

ABP2 Generating an option choice intention

$$\begin{aligned}&\mathrm{SS(A,\ c,\ W_0)\ \&\ SS(A,\ g(c(O)),\ W_1)\ \&\ ES(A,\ b(O),\ W_2)\ \&\ ES(A,\ c(O),\ W)}\\&\twoheadrightarrow \mathrm{ES(A,\ c(O),\ W} + \zeta_{\mathrm{c(O)A}}\lambda_{\mathrm{c(O)A}}\mathbf{h}(\omega_{\mathrm{4OA}}\upsilon_{\mathrm{cA}}\mathrm{W}_0, \omega_{\mathrm{5OA}}\upsilon_{\mathrm{g(c(O))A}}\mathrm{W}_1,\\&\quad \omega_{\mathrm{6OA}}\mathrm{W}_2/\zeta_{\mathrm{b(O)A}},\ \mathrm{W}/\zeta_{\mathrm{c(O)A}})\Delta \mathrm{t})\end{aligned}$$

ITP Sensing aggregated group members' bodily responses and intentions

$$\wedge_{\mathrm{B}\neq\mathrm{A}}\ \mathrm{ES(B,\ S,\ V_B)} \twoheadrightarrow \mathrm{SS(A,\ g(S)}, \Sigma_{\mathrm{B}\neq\mathrm{A}}\alpha_{\mathrm{SBA}}\mathrm{V_B}/\Sigma_{\mathrm{B}\neq\mathrm{A}}\alpha_{\mathrm{SBA}}\zeta_{\mathrm{SB}})$$

where S has instances b(O), c(O) for options O.

Note that as all steps made are logical derivations, it holds **IAM ⊢ ABAM**. In particular the following logical implications are valid (shown hierarchically in Fig. 7):

$$\text{IP1 \& IP5 \& IP2} \Rightarrow \text{IP2*} \qquad \text{IP4 \& IP2*} \Rightarrow \text{ABP1}$$
$$\text{IP1 \& IP3} \Rightarrow \text{IP3*} \qquad \text{IP4 \& IP3*} \Rightarrow \text{ABP2}$$

The transformation as described is based on the following of assumptions:

- Sensory representation states are affected (only) by sensor states and/or preparation states
- Preparation atoms have a direct relationship with effector atoms; there are no other ways to generate effector states than via preparation states
- The time delays for the interaction from the effector state of one agent to the sensor state of the same or another agent are small so that they can be neglected compared to the internal time delays
- The internal time delays from sensor state to sensory representation state and from preparation state to effector state within an agent are small so that they can be neglected compared to the internal time delays from sensory representation to preparation states

Now the model **BAM** is related to the behavioural agent model **ABAM**. First the notion of interpretation mapping induced by an ontology mapping is briefly introduced (e.g., [21], pp. 201–263; [40]). By a basic ontology mapping $\boldsymbol{\pi}$ atomic state properties (e.g., a_2 and b_2) in one ontology can be related to state properties (e.g., a_1 and b_1) in another (e.g., $\boldsymbol{\pi}(a_2) = a_1$ and $\boldsymbol{\pi}(b_2) = b_1$). Using compositionality a basic ontology mapping used above can be extended to an interpretation mapping for temporal expressions. As an example, when $\boldsymbol{\pi}(a_2) = a_1$, $\boldsymbol{\pi}(b_2) = b_1$, then this induces a mapping $\boldsymbol{\pi}^*$ from dynamic property $a_2 \twoheadrightarrow b_2$ to $a_1 \twoheadrightarrow b_1$ as follows: $\boldsymbol{\pi}^*(a_2 \twoheadrightarrow b_2) = \boldsymbol{\pi}^*(a_2) \twoheadrightarrow \boldsymbol{\pi}^*(b_2) = \boldsymbol{\pi}(a_2) \twoheadrightarrow \boldsymbol{\pi}(b_2) = a_1 \twoheadrightarrow b_1$. In a similar manner by compositionality a mapping for more complex temporal predicate logical relationships A and B can be defined, using

$$\boldsymbol{\pi}^*(A\&B) = \boldsymbol{\pi}^*(A)\&\boldsymbol{\pi}^*(B) \qquad \boldsymbol{\pi}^*(A \vee B) = \boldsymbol{\pi}^*(A) \vee \boldsymbol{\pi}^*(B)$$
$$\boldsymbol{\pi}^*(A \Rightarrow B) = \boldsymbol{\pi}^*(A) \Rightarrow \boldsymbol{\pi}^*(B) \qquad \boldsymbol{\pi}^*(\neg A) = \neg\boldsymbol{\pi}^*(A)$$
$$\boldsymbol{\pi}^*(\forall T\ A) = \forall T \boldsymbol{\pi}^*(A) \qquad \boldsymbol{\pi}^*(\exists T\ A) = \exists T\ \boldsymbol{\pi}^*(A)$$

o obtain a mapping the given behavioural model **BAM** onto the abstracted **ABAM**, first, consider the basic ontology mapping $\boldsymbol{\pi}$ defined by:

$$\boldsymbol{\pi}(\text{has value}(e(S, A),\ V)) = \text{ES}(A,\ S,\ V) \quad (\text{instances for S are } b(O),\ c(O) \text{ for options O})$$
$$\boldsymbol{\pi}(\text{has value}(s(S, A),\ V)) = \text{SS}(A,\ S,\ V) \quad (\text{instances for S are } g(b((O)),\ g(c((O)) \text{ for options O})$$

Next by compositionality the interpretation mapping $\boldsymbol{\pi}^*$ is defined for the specification of the behavioural model **BAM** as follows:

Mapping BP1 Generating a body state

$$\begin{aligned}
\boldsymbol{\pi}^*(\mathrm{BP1}) = {} & \boldsymbol{\pi}^*(\text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{b}(\mathrm{O})), \mathrm{A}),\ \mathrm{V}_1)\ \&\ \text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V}) \\
& \twoheadrightarrow \text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V} + \varepsilon_{\mathrm{b(O)A}}\gamma_{\mathrm{b(O)A}}\mathbf{c}(\mathrm{V}_1, \mathrm{V}/\varepsilon_{\mathrm{b(O)A}})\,\Delta \mathrm{t})) \\
= {} & \boldsymbol{\pi}(\text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{b}(\mathrm{O})), \mathrm{A}),\ \mathrm{V}_1))\ \&\ \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V})) \\
& \twoheadrightarrow \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V} + \varepsilon_{\mathrm{b(O)A}}\gamma_{\mathrm{b(O)A}}\mathbf{c}(\mathrm{V}_1, \mathrm{V}/\varepsilon_{\mathrm{b(O)A}})\,\Delta \mathrm{t})) \\
= {} & \mathrm{SS}(\mathrm{A}, \mathrm{g}(\mathrm{b}(\mathrm{O})),\ \mathrm{V}_1)\ \&\ \mathrm{ES}(\mathrm{A}, \mathrm{b}(\mathrm{O}), \mathrm{V}) \\
& \twoheadrightarrow \mathrm{ES}(\mathrm{A}, \mathrm{b}(\mathrm{O}), \mathrm{V} + \varepsilon_{\mathrm{b(O)A}}\gamma_{\mathrm{b(O)A}}\mathbf{c}(\mathrm{V}_1, \mathrm{V}/\varepsilon_{\mathrm{b(O)A}})\,\Delta \mathrm{t})
\end{aligned}$$

Mapping BP2 Generating an option choice intention

$$\begin{aligned}
\boldsymbol{\pi}^*(\mathrm{BP2}) = {} & \boldsymbol{\pi}^*(\text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{c}(\mathrm{O})), \mathrm{A}),\ \mathrm{V}_1)\ \&\ \text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V}_2) \\
& \&\ \text{has_value}(\mathrm{e}(\mathrm{c}(\mathrm{O}), \mathrm{A}),\ \mathrm{V}) \twoheadrightarrow \text{has_value}(\mathrm{e}(\mathrm{c}(\mathrm{O}), \mathrm{A}),\ \mathrm{V} \\
& + \varepsilon_{\mathrm{c(O)A}}\omega_{\mathrm{OA}}\gamma_{\mathrm{c(O)A}}\,\mathbf{d}((\omega_{\mathrm{c(O)A}}/\omega_{\mathrm{OA}})\mathrm{V}_1 \\
& + (\omega_{\mathrm{b(O)A}}/\omega_{\mathrm{OA}})\mathrm{V}_2/\varepsilon_{\mathrm{b(O)A}}, \mathrm{V}/\varepsilon_{\mathrm{c(O)A}})\,\Delta \mathrm{t})) \\
= {} & \boldsymbol{\pi}(\text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{c}(\mathrm{O})), \mathrm{A}),\ \mathrm{V}_1))\ \&\ \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{b}(\mathrm{O}), \mathrm{A}),\ \mathrm{V}_2)) \\
& \&\ \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{c}(\mathrm{O}), \mathrm{A}),\ \mathrm{V})) \twoheadrightarrow \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{c}(\mathrm{O}), \mathrm{A}),\ \mathrm{V} \\
& + \varepsilon_{\mathrm{c(O)A}}\omega_{\mathrm{OA}}\gamma_{\mathrm{c(O)A}}\,\mathbf{d}((\omega_{\mathrm{c(O)A}}/\omega_{\mathrm{OA}})\mathrm{V}_1 + (\omega_{\mathrm{b(O)A}}/\omega_{\mathrm{OA}}) \\
& \mathrm{V}_2/\varepsilon_{\mathrm{b(O)A}}, \mathrm{V}/\varepsilon_{\mathrm{c(O)A}})\,\Delta \mathrm{t})) \\
= {} & \mathrm{SS}(\mathrm{A}, \mathrm{g}(\mathrm{c}(\mathrm{O})),\ \mathrm{V}_1)\ \&\ \mathrm{ES}(\mathrm{A}, \mathrm{b}(\mathrm{O}), \mathrm{V}_2)\ \&\ \mathrm{ES}(\mathrm{A}, \mathrm{c}(\mathrm{O}), \mathrm{V}) \\
& \twoheadrightarrow \mathrm{ES}(\mathrm{A}, \mathrm{c}(\mathrm{O}), \mathrm{V} + \varepsilon_{\mathrm{c(O)A}}\omega_{\mathrm{OA}}\gamma_{\mathrm{c(O)A}}\,\mathbf{d}((\omega_{\mathrm{c(O)A}}/\omega_{\mathrm{OA}})\mathrm{V}_1 \\
& + (\omega_{\mathrm{b(O)A}}/\omega_{\mathrm{OA}})\mathrm{V}_2/\varepsilon_{\mathrm{b(O)A}}, \mathrm{V}/\varepsilon_{\mathrm{c(O)A}})\,\Delta \mathrm{t})
\end{aligned}$$

Mapping BTP Sensing aggregated group members' bodily responses and intentions

$$\begin{aligned}
\boldsymbol{\pi}^*(\mathrm{BTP}) = {} & \boldsymbol{\pi}^*(\wedge_{\mathrm{B}\neq \mathrm{A}}\ \text{has_value}(\mathrm{e}(\mathrm{S}, \mathrm{B}),\ \mathrm{V}_\mathrm{B}) \\
& \twoheadrightarrow \text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{S}), \mathrm{A}), \Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\mathrm{V}_\mathrm{B}/\Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\varepsilon_{\mathrm{SB}})) \\
= {} & \wedge_{\mathrm{B}\neq \mathrm{A}}\ \boldsymbol{\pi}(\text{has_value}(\mathrm{e}(\mathrm{S}, \mathrm{B}),\ \mathrm{V}_\mathrm{B})) \twoheadrightarrow \boldsymbol{\pi}(\text{has_value}(\mathrm{s}(\mathrm{g}(\mathrm{S}), \mathrm{A}), \\
& \Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\mathrm{V}_\mathrm{B}/\Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\varepsilon_{\mathrm{SB}})) \\
= {} & \wedge_{\mathrm{B}\neq \mathrm{A}}\ \mathrm{ES}(\mathrm{B}, \mathrm{S},\ \mathrm{V}_\mathrm{B})) \twoheadrightarrow \mathrm{SS}(\mathrm{A}, \mathrm{g}(\mathrm{S}), \Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\mathrm{V}_\mathrm{B}/\Sigma_{\mathrm{B}\neq \mathrm{A}}\ \alpha_{\mathrm{SBA}}\varepsilon_{\mathrm{SB}})
\end{aligned}$$

So to explore under which conditions the mapped behavioural model **BAM** is the abstracted model **ABAM**, it can be found out when the following identities (after unifying the variables V_i, V and W_i, W for values) hold.

$$\boldsymbol{\pi}^*(\mathrm{BP1}) = \mathrm{ABP1} \qquad \boldsymbol{\pi}^*(\mathrm{BP2}) = \mathrm{ABP2} \qquad \boldsymbol{\pi}^*(\mathrm{BTP}) = \mathrm{ITP}$$

However, the modelling scope of **ABAM** is wider than the one of **BAM**. In particular, in **ABAM** an as-if body loop is incorporated that has been left out of consideration for **BAM**. Moreover, in the behavioural model **BAM** the options O are taken from a fixed set, given at forhand and automatically considered, whereas in **ABAM** they are generated on the basis of the context c. Therefore, the modelling scope of **ABAM** is first tuned to the one of **BAM**, to get a comparable modelling scope for both models **IAM** and **ABAM**. The latter condition is achieved by taking the activation level W_0 of the sensor state for the context c and the strengths of the connections between the sensor state for context c and preparations relating to option O can be set at *1* (so $\upsilon_{cA} = \omega_{1OA} = \omega_{4OA} = 1$); thus the first argument of g and h becomes 1. The former condition is achieved by leaving out of **ABAM** the dependency on the sensed body state, i.e., by making the third argument of g zero (so $\omega_{0OA} = 0$).

Given these extra assumptions and the mapped specifications found above, when the antecedents where unified according to $V_i \leftrightarrow W_i$, $V \leftrightarrow W$ the identities are equivalent to the following identities in V, V_i

$$\varepsilon_{b(O)A}\,\gamma_{b(O)A}\;\mathbf{c}(V_1, V/\varepsilon_{b(O)A}) = \zeta_{b(O)A}\lambda_{b(O)A}\;\mathbf{g}(1, \omega_{2OA}\upsilon_{g(b(O))A}\,V_1,\; 0,\; V/\zeta_{b(O)A})$$

$$\begin{aligned}&\varepsilon_{c(O)A}\,\omega_{OA}\,\gamma_{c(O)A}\;\mathbf{d}((\omega_{c(O)A}/\omega_{OA})\,V_1 \;+ (\omega_{b(O)A}/\omega_{OA})\,V_2/\varepsilon_{b(O)A}, V/\varepsilon_{c(O)A})\\ &= \zeta_{c(O)A}\,\lambda_{c(O)A}\;\mathbf{h}(1, \omega_{5OA}\upsilon_{g(c(O))A}V_1, \omega_{6OA}\upsilon_{b(O)A}V_2/\zeta_{b(O)A},\; V/\zeta_{c(O)A})\end{aligned}$$

$$\Sigma_{B\neq A}\;\alpha_{SBA}V_B/\Sigma_{B\neq A}\;\alpha_{SBA}\varepsilon_{SB} = \Sigma_{B\neq A}\;\alpha_{SBA}V_B/\Sigma_{B\neq A}\;\alpha_{SBA}\zeta_{SB}$$

The last identity is equivalent to $\varepsilon_{SB} = \zeta_{SB}$ for all S and B with $\alpha_{SBA} > 0$ for some A. Moreover, it can be assumed that $\varepsilon_{SB} = \zeta_{SB}$ for all S and B. There may be multiple ways in which this can be satisfied for all values of V_1, U_2, U. At least one possibility is the following. Assume for all agents A

$$\lambda_{b(O)A} = \gamma_{b(O)_A} \qquad\qquad \upsilon_{b(O)A} = 1$$

$$\lambda_{c(O)A} = \omega_{OA}\gamma_{c(O)A} \qquad\qquad \upsilon_{g(S)A} = 1$$

for S is b(O) or c(O). Then the identities simplify to

$$\mathbf{c}(V_1, U) = \mathbf{g}(1, \omega_{2OA}V_1,\; 0,\; V)$$

$$\mathbf{d}((\omega_{c(O)A}/\omega_{OA})\;V_1 \;+ (\omega_{b(O)A}/\omega_{OA})\;V_2,\; V) = \mathbf{h}(1, \omega_{5OA}V_1, \omega_{6OA}V_2,\; V)$$

Furthermore, taking $\omega_{2OA} = 1, \omega_{5OA} = \omega_{c(O)A}/\omega_{OA}, \omega_{6OA} = \omega_{b(O)A}/\omega_{OA}$, the following identities result (replacing $\omega_{5OA}V_1$ by V_1 and $\omega_{6OA}V_2$ by V_2)

$$\mathbf{c}(V_1, V) = \mathbf{g}(1,\ V_1,\ 0,\ V) \qquad\qquad \mathbf{d}(V_1\ + V_2, V) = \mathbf{h}(1,\ V_1,\ V_2,\ V)$$

There are many possibilities to fulfill these identities. For any given functions $\mathbf{c}(X, Y), \mathbf{d}(X, Y)$ in the model **BAM** the functions **g**, **h** in the model **IAM** defined by

$$\mathbf{g}(W,\ X,\ Y,\ Z) = \mathbf{c}(W - 1 + X + Y, Z)$$
$$\mathbf{h}(W,\ X,\ Y,\ Z) = \mathbf{d}(W - 1 + X + Y, Z)$$

fulfill the identities $\mathbf{g}(1, X, 0, Z) = \mathbf{c}(X, Z)$ and $\mathbf{h}(1, X, Y, Z) = \mathbf{d}(X + Y, Z)$. It turns out that for given functions $\mathbf{c}(X, Y)$, $\mathbf{d}(X, Y)$ in the model **BAM** functions **g**, **h** in the model **IAM** exist so that the interpretation mapping $\boldsymbol{\pi}$ maps the behavioural model **BAM** onto the model **ABAM**, which is a behavioural abstraction of the internal agent model **IAM** (see also Fig. 7): $\boldsymbol{\pi}^*(\mathrm{BP1}) = \mathrm{ABP1}$, $\boldsymbol{\pi}^*(\mathrm{BP2}) = \mathrm{ABP2}$, $\boldsymbol{\pi}^*(\mathrm{BTP}) = \mathrm{ITP}$. As an example direction, when for $\mathbf{c}(X, Y)$ a threshold function th is used, for example, defined as $\mathbf{c}(X, Y) = \mathrm{th}(\sigma, \tau, X + Y) - Y$ with $\mathrm{th}(\sigma, t, V) = 1/\left(1 + e^{-\sigma(V-\tau)}\right)$, then for $\tau' = \tau + 1$ the function $\mathbf{g}(W, X, Y, Z) = \mathrm{th}(\sigma, \tau', W + X + Y + Z) - Z$ fulfils $\mathbf{g}(1, X, 0, Z) = \mathbf{c}(X, Z)$. Another example of a function $\mathbf{g}(V, W, X, Y)$ that fulfills the identity when $\mathbf{c}(X, Z) = 1 - (1 - X)(1 - Z) - Z$ is $\mathbf{g}(W, X, Y, Z) = W\,[1 - (1 - W)(1 - X)(1 - Z)] - Z$. As the properties specifying **ABAM** were derived from the properties specifying **IAM**, it holds **IAM** $\vdash$ **ABAM**, and as a compositional interpretation mapping $\boldsymbol{\pi}$ preserves derivation relations, the following relationships holds for any temporal pattern expressed as a hybrid logical/numerical property A in the ontology of **BAM**:

$$\mathbf{BAM} \mid\!- A \;\Rightarrow\; \boldsymbol{\pi}(\mathbf{BAM}) \mid\!- \boldsymbol{\pi}(A) \;\Rightarrow\; \mathbf{ABAM} \mid\!- \boldsymbol{\pi}(A) \;\Rightarrow\; \mathbf{IAM} \mid\!- \boldsymbol{\pi}(A)$$

Such a property A may specify certain (common) patterns in behaviour; the above relationships show that the internal agent model **IAM** shares the common behavioural patterns of the behavioural model **BAM**. An example of such a property A expresses a pattern that under certain conditions after some point in time there is one option O for which both b(O) and c(O) have the highest value for each of the agents (joint decision).

The precision of the abstracted model **ABAM** is evaluated by calculating the root mean squared error:

$$err = \sqrt{\frac{\sum_{i=1}^{N} (f_i - y_i)^2}{N}}$$

where N is the number of time points, f_i is the value of an output of an abstracted model at time point t_i, and y_i is the value of the corresponding output of the model **IAM**.

The root mean squared errors for the model outputs ES(b(O)) and ES(c(O)) are 0.017 and 0.026 correspondingly.

6 Model Analysis: A Real World Case Study

The computational model introduced in Sect. 3 has been tested by applying it to a real world case study. A description of this case study is provided in Sect. 6.1. Next, Sect. 6.2 describes how the model was extended and instantiated for the case study. Section 6.3 explains how the parameters of the model were tuned to reproduce the real world scenario, and Sect. 6.4 presents the results. More details of this case study can be found in.

6.1 Case Study: The May 4 Incident

The case study addressed is the May 4 incident in Amsterdam (The Netherlands). The incident took place in the evening of May 4th 2010, when approximately 20.000 people gathered on Dam Square in Amsterdam for the National Remembrance of the dead. What follows is a short description of the events.

At 20:00 h everyone in the Netherlands, including the crowd on Dam Square, was silent for 2 min to remember the dead. Fences and officials compartmented the 20,000 people on Dam Square. At 20:01 a man in the crowd on Dam Square disturbed the silence by screaming loudly. People standing directly near him could see that this man looked a bit ‘crazy’ or ‘lost’, and they did not move. Those not within a few meters of the screaming source, started to panic and ran away from the man that screamed. The panic spread through the people that were running away who infected each other with their emotions and intentions to flee. This panic was fuelled by a loud ‘BANG’ that was heard about 3 s after the man started screaming. Queen Beatrix and other royal members present were escorted to a safe location nearby. In total, 64 persons got injured: they got broken bones and scrapes by being pushed, or got run over by the crowd. The police exported the screaming man and got control over the situation within 2 min. After 2½ min, the master of ceremony announced to the crowd that a person had become ill and had received care. He asked everybody to take his or her initial place again, and to continue the ceremony. After this, the ceremony continued.[1]

[1] A short movie with images from the live broadcast on Dutch National Television, can be found at: http://www.youtube.com/watch?v=0cEQp8OQj2Y. This shows how, within two minutes, the crowd starts to panic and move.

Fig. 8 Still image of the people on Dam Square starting to flee. The circle on the *right* bottom indicates the location of the yelling person

The live broadcast of the National Remembrance on Dutch National Television has been acquired in HD-quality.[2] In this video, one can see the crowd on Dam Square flee from the perspective shown in Fig. 8. The video includes the cuts and editing that were done during the live broadcast, because the un-edited video material of all cameras that were filming that day was not saved.

From the total broadcast, a shorter 3-min movie was made, starting the moment when the crowd was silent and the person started to scream loudly. In this 3-min movie there are two time slots that were further processed (11–17 s and 20–27 s), because (i) they showed the clear camera angle like the one that can be seen in Fig. 8, and (ii) the direction and speed of the movements of people could be clearly analysed. They were analysed as follows. The movie was cut into still images, to detect the location of people by hand. Ten still images per second were chosen in order to be able to detect the movements of running people frame by frame. By keeping track of the coordinates of mouse-clicks on the locations of people in the crowd while they were moving, their trace of movement could be detected.

A total of 130 frames were analysed by hand. Not all people could be analysed, both because of the quantity, and the impossibility to trace every 'dot' (person) over multiple still images. Persons in different positions of the crowd with simultaneous movements to the people around them were chosen, such that these target subjects were able to represent multiple people around them. In total 35 persons were traced.

The next step was to correct for the angle the camera makes with the floor by recalculating the coordinates into coordinates that would fit into a bird's-eye view on the Dam Square, perpendicular to the floor. People's distance in meters from

[2] Permission granted for educational and research purposes by The Netherlands Institute for Sound and Vision.

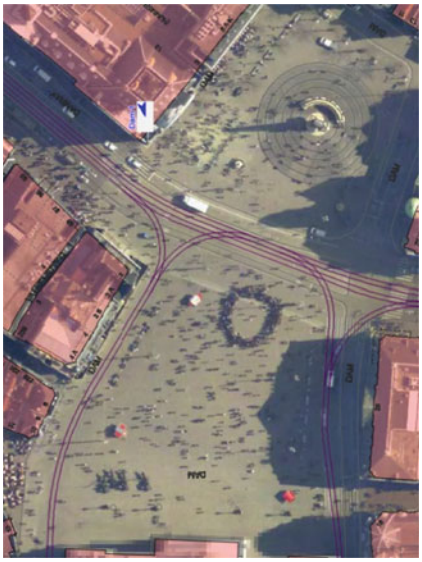


Fig. 9 600 x 800 pixel image of Dam Square

corners of the buildings were translated to the position in pixels on a 600 × 800 map of the area, using offsets and scaling. Specifically, the following formulae are used to translate movements in pixels to movements in meters:

$$x_{meter} = x_{pixel} / \ 22$$

$$y_{meter} = y_{pixel} / \ 8$$

This was then transformed to the map using the following formulae:

$$x_{map} = (x_{meter} {}^{*} \ 5.15) + 136$$

$$y_{map} = (y_{meter} {}^{*} \ 5.15) - 167$$

The bird's eye view perspective used in the computational model can be seen in Fig. 9. The resulting figure was represented in the simulation in Matlab. Locations of certain obstacles, like buildings and fences, were also transformed into the bird's-eye view.

6.2 *Instantiating the Model for the Case Study*

To tailor the ASCRIBE model towards the case study, a number of steps were taken.

First of all, the relevant states for the agents have been distinguished. In this case, the emotion, belief and intention states relate to the options for each agent. A total of nine options are available including ‘remain standing’, and moving in any wind direction (N, NE, E, SE, S, SW, W, NW). Besides these, there is an additional belief about the current situation. This expresses how positive a person judges the current situation (*0* a negative judgment, and *1* a positive judgment). Finally, the emotions for each option and the emotion *fear* are represented.

In the case study, the channel strengths between the various agents are dependent on the physical location of the agents. If other agents are close, the channel strength is high, whereas it is low or *0* in case agents are far apart. Therefore, a threshold function was used expressing within which reach agents still influence each other in a significant manner:

$$\alpha_{SBA}(t) = 1 - \left(1/1 + e^{-\sigma(distance_{BA}(t) - ^{\tau}distance)}\right)$$

Here σ and $\tau_{distance}$ are global parameters and $distance_{BA}$ is the Euclidean distance between the positions $(x_A(t),\ y_A(t))$ and $(x_B(t),\ y_B(t))$ of A and B at t.

The movement of the agents directly depends upon their intentions. Recall that the strength of the intention is determined by the intentions of others (see Sect. 3), and the agent’s own personality characteristics and mental states, such as beliefs and emotions (see Sect. 4). The highest feasible intention is selected (in cases where certain movements are obstructed, the next highest intention is selected). For each of the selected options O, the movement $x_{movement(O)}$ on the x-axis and $y_{movement(O)}$ on the y-axis is specified; e.g., the option for going south means -1 step on the y-axis and none on the x-axis: $x_{movement(O)} = 0$ and $y_{movement(O)} = -1$. The actual point to which the agent will move is then calculated by taking the previous point and adding the movement of the agent during a certain period to that. The movement of the agent depends upon the strength of the intention for the selected option and the maximum speed with which the agent can move. If the intention is maximal (i.e., *1*) the agent will move with the maximum speed. In case the intention is minimal (i.e., *0*) the agent will not move. The dependency between mental states and speed of movement has been described, e.g., in [19]. The model that establishes this relationship is expressed as follows:

$$x_A(t + \Delta t) = x_A(t) + max\_speed_A \cdot q_{intention(O)A}(t) \cdot x_{movement(O)} \cdot \Delta t$$

$$y_A(t + \Delta t) = y_A(t) + max\_speed_A \cdot q_{intention(O)A}(t) \cdot y_{movement(O)} \cdot \Delta t$$

Here the maximum speeds max_speed_A are agent-specific parameters.

6.3 Parameter Tuning

As explained above, the ASCRIBE model contains a large number of parameters; these parameters address various aspects of the agents involved, including their personality characteristics (e.g., expressiveness, openness, and tendency to absorb or amplify mental states), physical properties (e.g., minimum and maximum speed, and limit of their sight), and characteristics of their mutual interactions (e.g., channel strength between sender and receiver). The accuracy of the model (i.e., its ability to reproduce the real world data as closely as possible) heavily depends on the settings of these parameters. Therefore, parameter estimation techniques [39] have been applied to learn the optimal values for the parameters involved.

In order to determine what is 'optimal', first an error measure needs to be defined. The main goal is to reproduce the movements of the people involved in the scenario; thus it was decided to take the average (Euclidean) distance (over all agents and time points) between the actual and simulated location:

$$\varepsilon = \sum_{agents\ a}\ \sum_{timepoints\ t} \frac{\sqrt{(x(a,t,sim) - x(a,t,data))^2 + (y(a,t,sim) - y(a,t,data))^2}}{\#agents \cdot \#timepoints}$$

Here, *x(a, t, sim)* is the x-coordinate of agent *a* at time point *t* in the simulation, and *x(a, t, data)* the same in the real data (similarly the y-coordinates). Both are in meters.

Next, the relevant parameters were tuned to reduce this error. To this end, the approach described in detail in Sects. 3 and 4 of [5] was used. This approach makes use of the notion of *sensitivity* of variables for certain parameter changes. Roughly spoken, for a given set of parameter settings, the idea is to make small changes in one of the parameters involved, and to observe how such a change influences the change of the variable of interest (in this case the error). Here, 'observing' means running the simulation twice, i.e., once with the original parameter settings, and once with the same settings were one parameter has slightly changed. Formally, the sensitivity $S_{X,P}$ of changes ΔX in a variable X to changes ΔP in a parameter P is defined as follows (note that this sensitivity is in fact the partial derivative $\partial X / \partial P$): $S_{X,P} = \Delta X / \Delta P$. Based on this notion of sensitivity, the adaptation process as a whole, is an iterative process, which roughly consists of: (1) calculating sensitivities for all parameters under consideration, and (2) using these sensitivities to calculate new values for all parameters. This second step is done by changing each parameter with a certain amount ΔP, which is determined as follows: $\Delta P = -\lambda * \Delta X / S_{X,P}$. Here, ΔX is the deviation found between actual and simulated value of variable X, and λ is a speed factor. Note that, since in the current case X represents the error, the 'actual value' of X is of course *0*, so ΔX simply equals ε in the simulation.

6.4 Results

This section presents the results of specialising and tuning the ASCRIBE model with 35 agents, to the real world data of the May 4 incident. The results are presented for the first part of the data (i.e., seconds 11–17 of the 3-min movie). To assess the performance of the ASCRIBE model, it was compared to three other models. First, one baseline model was developed in which the agents do not move at all. Second, the model was compared to an implementation of the model by Helbing and colleagues [20], which is currently one of the most influential models in the area of crowd simulation. Third, a variant of ASCRIBE was developed in which all agents also make individual decisions, but do not influence each other (i.e., no contagion takes place). This was done to assess whether the idea and implementation of contagion of mental states is useful at all. This resulted in three different models (in addition to our own ASCRIBE model with contagion of mental states), to which we refer below as *baseline*, *Helbing*, and *without contagion*, respectively. To enable a fair comparison, parameter tuning was applied for all models (except for the baseline model, since it did not contain any parameters to tune) in order to find optimal settings; see for details.

Figure 10 shows for each of the four variants how the average error (over all agents) increases during the simulation. Note that the error is expressed in meters. At the first time point, the error is *0* (all agents start at their actual position), but over time the error increases very quickly in the baseline case, so that the error at the last time step of the simulation becomes quite large (2.35 m). For this model, the average error per time step is 0.87 m. The average error found for the tuned model without contagion is much lower (*0.66*, i.e., an improvement of *24 %*), and is even lower for the tuned model with contagion (*0.54*, i.e., an improvement of *38 %*). This finding provides evidence for the conclusion that incorporating the contagion makes the model more accurate, even when it is based on default settings for the parameters. Note that in the current scenario, the agents' movements involve relatively small steps, compared to the size of the grid; the total distance that the agents travel during the 7 s of analysis is only 2.35 m. Therefore, the relative errors found (i.e., the percentages of improvement mentioned above) are more insightful that the absolute errors. In case the total distance travelled would have been larger, the absolute difference in performance between the four models would be expected to have been bigger as well.

As for the Helbing model, the average error of this model per time step was found to be *0.59* (i.e., an improvement of *32 %* w.r.t. the baseline model). As can be observed from Fig. 10, this model performs better than the model without contagion, but worse than the model with contagion (at least, in this particular scenario). One of the main reasons for this is that the model with contagion seems to be better able to deal with the fact that some agents only start moving half way the scenario. This phenomenon, which is also well visible in the video of the event, is caused by the fact that the crowd is separated by fences (see also Fig. 8), and especially the people that are located on the left hand side of the area wait a couple of seconds

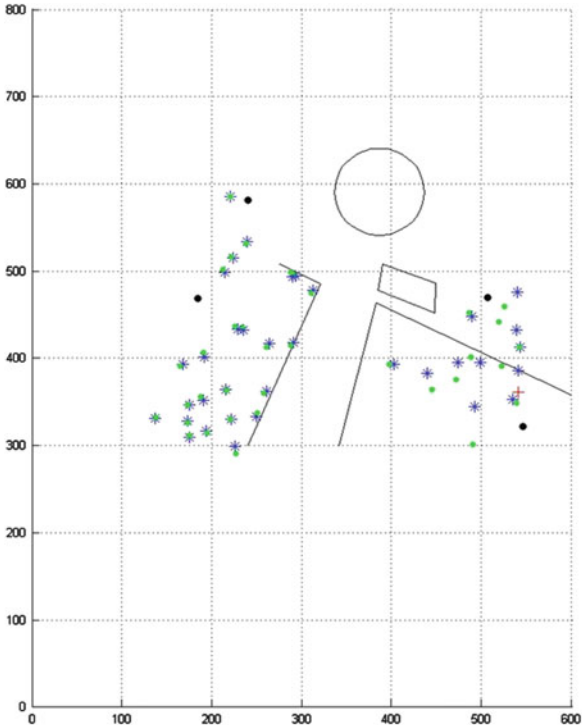


Fig. 10 Screenshot of the simulation. Units displayed on the axes are in pixels, where 5.15 pixels equals 1 m

before they start moving, whereas other people start moving right after the scream. In the model with contagion, this phenomenon can be reproduced quite accurately by means of the contagion mechanism: the agents at the left hand side of the area initially have a low level of fear (since they are not directly affected by the screaming man), but only when they observe other agents panicking and trying to escape, they are influenced by them and attempt to get away as well. Since the Helbing model does not include an explicit mechanism for contagion of mental states, it has more difficulties in reproducing this particular effect (because in this model, the speed by which the agents move is more stable – although not completely constant – over time). Therefore, for the Helbing model, the parameter tuning resulted in an optimal situation where some agents on the left hand side hardly move at all. This is reflected by the fact that the error for this model (compared to the model with contagion) only increases in the last eight time steps.

When comparing the Helbing model with the model without emotion, one can observe that, although the errors of both models at time point 45 are comparable, the Helbing model performs slightly better when taking the overall average error over all time points. This can in part be explained by the fact that the Helbing model has more freedom when it comes to selecting the direction in which the agents move. In our model (both with and without contagion), selection of actions has been implemented in such a way that the agents can only pick one out of eight wind directions (see Sect. 6.2), whereas the Helbing model uses a continuous scale for this. We speculate that the performance of our model (both with and without contagion) may be further improved by changing this discrete mechanism for action selection into a continuous mechanism.

After the tuning process was finished, the optimal settings found for all parameters were used as input for the four simulation models, to generate simulation traces which closely resemble the real world scenario. Using visualisation software (written in Matlab), these simulation traces have been visualised in the form of a 2D animation.[3] A screenshot of the animation of the ASCRIBE model with contagion is shown in Fig. 10.

Here, the lines represent fences that were used to control the crowd, the large circle represents the monument on the square (see Fig. 8 for the actual situation), and the big dots represent corners of other buildings. The plus sign on the right indicates the location of the screaming man. The small dots represent the actual locations of the 35 people in the crowd that were tracked, and the stars represent the locations of the corresponding agents in the simulation. Even at the end of the simulation (see Fig. 10), the distances between the real and simulated positions are fairly small for this model.

7 Conclusions and Discussion

In this paper a computational model for collective decision making based on neural mechanisms revealed by recent developments in Social Neuroscience is proposed; e.g., [5], [6], [9], [12], [14], [34].

These mechanisms explain how mutual adaptation of individual mental states can be realised by social interaction. They not only enable intentions to converge to an emerging common decision, but at the same time enable to achieve shared underlying individual beliefs and emotions. Therefore a situation can be achieved in which a common decision is made that for each individual is considered in agreement with the own beliefs and feelings. More specifically, this model for collective design making involves on the one hand individual beliefs, emotions and intentions, and on the other hand interaction with others involving mirroring of such mental states; e.g., [20], [32], [33]. The model involves seven types of interactions: three types of mirroring interactions between different persons, and within each person four types of interactions between the individual mental states.

The ASCRIBE model has been adapted to construct a model for behaviour in a crowd when a panic spiral occurs. Experiments have been performed in which the model was compared to three other models, namely (1) a baseline model where the

[3] See http://www.few.vu.nl/~tbosse/may4/. This URL contains two animations: one in which only the result of the model with contagion is shown, and one in which the results of all four models are shown together.

agents do not move at all, (2) a model by Helbing and colleagues [20], and (3) a variant of the model where parameters related to contagion were set in such a way that there was no contagion at all; in this case the movement of individuals is only determined by their individual state. In the full ASCRIBE model, mutual influencing took place because emotions, beliefs and intentions were spreading to persons nearby. When comparing the simulations of the four models with the most optimal settings for certain parameters, the variant with contagion had the lowest average error rate per time step. Thus, it is shown that the contagion of mental states is an essential element to model the behaviour of crowds in panic situations.

The paper addressed also how internal agent models and behavioural agent models for collective decision making can be related to each other. The relationships presented were expressed for specifications of the agent models in a hybrid logical/numerical format. It was shown how the internal agent model IAM can be systematically transformed into an abstracted behavioural model ABAM, where the internal states were abstracted away, and such that IAM $\vdash$ ABAM. Moreover, it was shown that under certain conditions the obtained agent model ABAM can be related to the behavioural agent model BAM by an interpretation mapping π, i.e., such that π(BAM) = ABAM. In this way hybrid logical/numerical relations where obtained between the different agent models according to:

$$\mathbf{IAM} \ |\!- \ \mathbf{ABAM} \text{ and } \mathbf{ABAM} = \boldsymbol{\pi}(\mathbf{BAM})$$

These relationships imply that, for example, collective behaviour patterns shown in multi-agent systems based on the behavioural agent model BAM are shared (in the form of patterns corresponding via **π**) for multi-agent systems based on the models ABAM and IAM.

Previous works have presented several models for crowd behaviour. As mentioned above, an influential paper has been written by Helbing and colleagues [20], in which a mathematical model for crowd behaviour in a panic situation is presented, based on physics theories and socio-psychological literature. This model is based on the principle of particle systems, in which forces and collision preventions between particles are important. This approach is often used for simulating crowd behaviour in virtual environments [37], [41]. In [6] the model of [20] is extended by adding individual characteristics to agents, such as the need for help and family membership. In both models, there are no individual emotion, belief and intention states that play a role. In contrast, in [31] an agent has an 'emotional status', which determines whether agents walk together (i.e. it influences group formation). The emotional status of an agent can change when to agents meet. An even further elaborated role of emotional and psychological aspects in a crowd behaviour model can be found in [33]. In this model, several psychological aspects influence the decision making of individual agents, for example, motivation, stress, coping, personality and culture. In none of the models presented above, there is contagion of emotional or other mental states between people. Also, in contrast to the analysis results presented in this paper, no evaluation with real qualitative data has been performed in these previous studies.

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