Grouping behaviour in AmI-enabled crowd evacuation

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Abstract Grouping behaviour occurs often in crowd evacuation. On the one hand, groups are needed for efficient evacuation. On the other hand, large uncontrolled groups (herds) may cause clogging and increase panic. The mechanisms of emergence of leaders and groups in complex socio-technical systems with intelligent technical components are not well understood. This paper presents the first attempt to unveil the role of AmI technology in formation of spontaneous groups in crowd evacuation. To this end several hypotheses were formulated, which were tested by simulation experiments based on a cognitive agent model. The checking of the hypotheses was done in the context of a train station evacuation scenario. The general outcome is that in a system with scarce and uncertain information, AmI technology can be used to stimulate emergence of leaders and groups to increase the efficiency of evacuation. Furthermore, a large penetration rate of ambient devices may be unnecessary and even not appropriate for fluent evacuation.

1 Introduction

In the literature [1, 9, 10, 13] it is indicated that people often form spontaneous groups during evacuation. On the one hand, dynamic formation of groups is recognised as a prerequisite for efficient evacuation [1,13]. On the other hand, large uncontrolled groups, sometimes called herds, may cause clogging of paths and increase panic [1, 9]. In examples of efficient evacuation emergent leaders played a prominent role in guiding of and sustaining a steady emotional state in groups [1]. In social psychology several sources of power of informal (or emergent) leaders are recognised, among which knowledge and physical traits are the most essential ones [2]. AmI technology can be used to discover and propagate knowledge in

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socio-technical systems. Although much research has been done on emergent leadership in social systems [2], the mechanisms of emergence of leaders and groups in complex socio-technical systems with intelligent technical components are less clear. This paper presents the first attempt to unveil the role of AmI-technology in formation of spontaneous groups in crowd evacuation. For this several hypotheses were formulated.

Hypothesis 1: *AmI-equipped humans, who obtain up-to-date information about the environment, are recognised as leaders in emergent groups in organisations with scarce and uncertain information.*

Previous studies showed that in general humans have a loyal attitude to information provided by (intelligent) technology. The validation of this statement for crowd evacuation is necessary, but also problematic, as such experiments cannot be organised easily. To address this issue, we examined three conditions: (a) humans have high initial trust to technology and distrust it slowly after negative experiences; (b) humans trust technology in the same manner as to human strangers; (c) humans have high initial trust to technology (initial bias), but distrust it rapidly after negative experiences. Note that trust to technology is dynamic and depends on the human's experiences with technology. In relation to these conditions the following hypotheses are formulated:

Hypothesis 2: *More grouping behaviour is observed under (a) and (c) conditions than under (b) condition.*

Hypothesis 3: *Humans under (c) change groups more frequently than under (a).*

To quantify these hypotheses the measures *following index*, *change index* and *group size* are introduced in section 4. One more hypothesis to be tested in the paper is related to *the large group effect* known for social emergency systems [1]:

Hypothesis 4: *Evacuation with larger groups proceeds more slowly (less efficiently) than with smaller groups.*

The hypotheses were tested in the frames of an emergency case study introduced in Section 2. For formal verification of the hypotheses a cognitive agent-based model was developed, in which humans and AmI devices were represented by agents. This model is based on a number of theories from Neuropsychology, Social Science and Psychology, many of which were empirically validated. The model is described in Section 3.The verification results for the hypotheses are presented in Section 4. Section 5 concludes the paper.

2 Case Study

Since it is nearly impossible to perform an evacuation trial to validate an emergency egress strategy at a mass place, an agent-based social simulation approach was taken instead. In this simulation study we focussed on evacuation of a train station. To ensure that the simulation setting is a true representative of reality, we incorporated real CAD design of an existing Austrian main railway station to generate the space along with observed population statistics.

The station in the simulation model had 3 exits with different flow capacities. The station was populated randomly with 500 agents representing humans, from which 10 agents were equipped with AmI technology.

The AmI technology in focus is the LifeBelt, specially designed for emergency situations [4]. Particularly, it exploits the unused information transmission capability of sense of touch instead of usual visual and auditory perception to deliver the message. In this way, it does not deviate and frustrate the human already overwhelmed with the visual and auditory perceptual overload. The LifeBelt system exploits the position and variation of vibro-tactile stimuli to indicate both orientation (intended direction) as well as urgency (intended speed) through tactor-elements embedded into a hip worn belt. The controller activates the vibrator switches according to commands received wirelessly from a global control unit, in this case a global ‘evacuation control unit’.

The recommendation for an exit is generated by evacuation control unit under the influence of exit area dynamics (e.g. flow, density), which are assumed to be measured by a technology mounted on the exit. The exit choice would then be communicated to all the LifeBelts. Each LifeBelt has a location map used to transform the coordinates of an exit to the desired orientation to move.

Agents interact with each other *non-verbally* by spreading emotions and intentions to choose particular exits, and *verbally* by communicating information about the states of the exits. As the agents with LifeBelts possess information about the exits not available to the agents without LifeBelts, the AmI-equipped agents hold one of the most important sources of power identified in social studies on emergent leadership [2]. However, the agents without devices are still free to decide whether to follow AmI-equipped agents or to rely on their own beliefs and exit choices. It is important to stress that the grouping effect is not encoded in our model explicitly, but emerges as a result of complex decision making by agents.

3 Cognitive Agent Model

To model cognitive processes of an agent a general affective decision making model from [11] was instantiated for the case study. The model is formalised using a temporal state transition system format [12].

Depending on a situational context an agent determines a set of applicable options to satisfy its goal. In the case study the goal of each agent is to get outside of the building in the fast possible way. This is achieved by an agent by moving towards the exit that provides for fastest evacuation as it perceived by the agent. Evacuation options are represented internally in agents by one-step simulated behavioural chains, based on the neurological theory by Hesslow [5] (see Fig.1). In Fig. 1 the burning station situation elicits activation of the state srs(evacuation_required) in the agent's sensory cortex that leads to preparation for action preparation_for(move_to(E)). Here E is one of the exits of the station. Note that if more than one exit is known to the agent, then in each option representation the preparation state corresponding to the option's exit is generated. Then, associations are used such that preparation_for(move_to(E)) will generate srs(is_at(E)), which is the most connected sensory consequence of the action move_to(E).

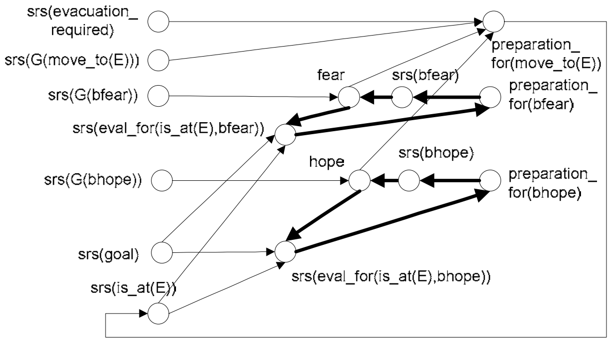

Fig. 1. The emotional decision making model for the option to move to exit E.

The strength of the link between a preparation for an action and a sensory representation of the effect of the action (see Fig.1) is used to represent the confidence value of the agent's belief that the action leads to the effect.

The simulated sensory states elicit emotions, which guide agent behaviour either by reinforcing or punishing simulated actions. By evaluating sensory consequences of actions in simulated behavioural chains using cognitive structures from the OCC model [8], different types of emotions can be distinguished. In the example two types of emotions - fear and hope – are distinguished, which are often considered in the emergency domain. According to [8], the intensity of fear induced by an event depends on the degree to which the event is undesirable and on the likelihood of the event. The intensity of hope induced by an event depends on the degree to which the event is desirable and on the likelihood of the event. Thus, both emotions are generated based on the evaluation of a distance between the effect states for the action from an option and the agent's goal state.

In particular, the evaluation function for hope in the evacuation scenario is specified as $eval(g, is\_at(E)) = \omega$, where ω is the confidence value for the belief about the accessibility of exit E, which is an aggregate of the agent's estimation of the distance to the exit and the degree of clogging of the exit. Although it is assumed that the distances to the exits are known to the agents, the information about the degree of clogging of the exits is known only to AmI-equipped agents.

Emotions emerge and develop in dynamics of reciprocal relations between cognitive and body states of a human [3]. These relations, omitted in the OCC model, are modelled from a neurological perspective using Damasio's principles of 'as-if body' loops and somatic marking [3]. The as-if body loops for hope and fear emotions are depicted in Fig. 1 by thick solid arrows. The following rules describe the evolution of the emotional states:

srs(eval_for(is_at(E),bhope),V2) & srs(G(bhope),V1)
$\twoheadrightarrow$ hope(o, (β_h- β_h *(1-V1)*(1-a1) + (1-β_h)*V1*a2)/(1- β_h*(1-V1)*a1 - (1-β_h)*V1*a1)),
where a1 = β_h - 2*β_h*V2 + V2, a2 = β_h – β_h*(1-V2)
srs(eval_for(is_at(E),bfear),V2) & srs(G(bfear),V1)
$\twoheadrightarrow$ fear(o, (β_f - β_f *(1-V1)*(1-a3) + (1-β_f)*V1*a4)/ (1- β_f*(1-V1)*a3 - (1-β_f)*V1*a3)),
where a3 = β_f*V2+1-V2-β_f*(1-V2), a4 = β_f – β_f*V2

here β_h is the degree of extraversion (i.e., tendency to experience positive emotions) of the agent; β_f is the degree of neuroticism (i.e., a tendency to experience negative emotions) of the agent; G(bhope) is the aggregated preparation to the emotional response (body state) of the agent's social neighbourhood.

The social influence on the individual decision making is modelled based on *the mirroring function* [6] of preparation neurons in humans. Such neurons, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror similar states of other persons. This mirroring function in social decision making is realised in two forms: (1) by *mirroring of emotions*, which indicates how emotional responses in different agents about a decision option mutually affect each other, and (2) by *mirroring of intentions* or *action preparations* of individuals for a decision option. Furthermore, the social influence includes spread of beliefs of agents supporting or prohibiting options (e.g., the belief about the accessibility of an exit).

The mirroring is realised through information and emotion contagion processes. The contagion strength of the interaction from agent B to agent A is defined as follows: $\gamma_{BA}=\varepsilon_B\cdot$ trust(A, B) $\cdot\ \delta_A$, here ε_B is the personal characteristic expressiveness of the sender (agent B), δ_A is the personal characteristic openness of the receiver (agent A).

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

trust(A_i, A_j, V1) & communicated_from_to(A_j, A_i, congestion(e, V2)) & belief(A_i, congestion(e, V3)) $\rightarrow$ trust(i, j, V1+ γ_{tr}*(V3/(1 + e^{α}) – V1)), here α=-ω1*(1-|V2-V3|) + 4.

According to the Somatic Marker Hypothesis [3], each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly positive somatic marker linked to a particular option occurs as a strongly positive feeling for that option. To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 1. Through these connections emotions influence the agent's readiness to choose the option.

4 Experiments and Results

The model was implemented in the Netlogo simulation tool [14]. In this tool the environment is represented by a set of connected cells, where moveable agents (turtles) reside. Cells can be walkable (open space and exits) and not-walkable (concrete, partitions, walls). Each cell of the environment is accessible from all the exits. Based on the conditions (a)-(c) identified in the introduction, three simulation settings S1-S3 were determined (see Table 1, the upper part). To test the hypothesis 4, setting S4 was identified, in which AmI-equipped agents were able to propagate information in a large range. Since the model contains stochastic elements, 10 trials were performed for each simulation setting with 500 agents.

To evaluate the hypotheses three evaluation metrics were introduced: *following index (fi)*, which reflects the degree of following of AmI-equipped agents by other agents, *change index (ci)*, reflecting the frequency of group change by agents, and *group size* (*gs*). As shown below, the metrics are defined per an AmI-enabled agent L (i.e, fi_L, ci_L, gs_L) and by taking the mean over all AmI-equipped agents (i.e., fi, ci, gs):

$fi_L = 1/|N| \cdot \sum_{A \in N} |F_{A,L}|/(t\_last - t\_first_A)$, $fi = \sum_{i \in LEAD} fi_i/|LEAD|$,

where t_first_A is such that $\exists o1$:INFO at(communicated_from_to(L, A, inform, o1), t_first_A) & $\forall t$:TIME, o:INFO $t < t\_first_A$ & $\neg$at(communicated_from_to(L, A, inform, o), t); $N = \{a \mid t\_first_A$ is defined$\}$; $F_{A,L} = \{ t \mid t \geq t\_first_A$ & $\exists$d1,d2: DECISION at(has_preference_for(A, d1), t) & at(has_preference_for(L, d2), t) & d1=d2 & at(distance_between(A, L) < dist_threshold, t) }, t_last is the time point when L is evacuated, LEAD is the set of all technology-equipped agents, |LEAD|=10 in all experiments.

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

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

$gs_L = \sum_{t=1..t\_last} FT_{L,t}/t\_last$, $gs = \sum_{i \in LEAD} gs_L/|LEAD|$,

where $FT_{L,t} = \{ ag \mid t \geq t\_first_{ag}$ & $\exists$d1,d2: DECISION at(has_preference_for(ag, d1), t) & at(has_preference_for(L, d2), t) & d1=d2 & at(distance_between(A, L) < dist_threshold, t) }.

The obtained results are summarised at Table 1 (in the lower part).

As one can see from the table, the emergence of groups with AmI equipped agents as guiding leaders occurs in all settings ($fi > 0$), thus, the hypothesis 1 is confirmed. The high standard deviation values for fi and gs in S2 indicate that in some trials persistent groups emerged, whereas in other trials almost no grouping occurred. This is in contrast to the other simulation settings, in which notable grouping behaviour emerged in every trial. The highest fi is observed in settings S1 and S4, in which the agents were biased positively towards technology.

Table 1. The parameters used in the simulation settings S1-S4 (the upper part) and the corresponding results for 10 simulation trials for each setting (lower part)

Simulation setting Parameter	S1	S2	S3	S4
Initial trust value to an AmI-enabled agent	0.9	0.1	0.9	0.9
Initial trust value to an agent without AmI	0.1	0.1	0.1	0.1
$\omega 1$ in the update of trust to an AmI-enabled agent	39	9	9	39
$\omega 1$ in the update of trust to an agent without AmI	9	9	9	9
Interaction range (in cells)	10	10	10	25
Evaluation metrics	**S1**	**S2**	**S3**	**S4**
Mean overall evacuation time (standard deviation)	147.7 (10.7)	174.4 (16.9)	150.1 (9.7)	170.3 (21.3)
Mean following index fi (standard deviation)	0.46 (0.09)	0.27 (0.12)	0.43 (0,07)	0.5 (0.09)
Mean change index ci (standard deviation)	0.48 (0.05)	0.25 (0.07)	0.92 (0.21)	0.17 (0.03)
Mean group size gs (standard deviation)	26 (8.7)	29 (19.8)	27 (8.3)	81 (14.2)

Hypothesis 2 is also confirmed, as the fi's for settings S1 and S3 are significantly higher than fi for setting S2. From the comparison of the ci's for settings S1 and S3 the confirmation of hypothesis 3 follows. For the hypothesis 4, first it can be observed in table 1 that the groups formed in S4 are in average 3 times larger than the groups formed in S1. Note that the only distinction between S1 and S4 is the interaction range (penetration rate) of the AmI-enabled agents. Thus, settings S1 and S4 are adequate for checking hypothesis 4. As can be seen from the table, the overall evacuation time for S1 is lower than for S4. Thus, hypothesis 4 is confirmed as well. Also, as can be seen from the results, AmI-enabled evacuation with relatively small groups (settings S1 and S3) proceeds the fastest.

5 Conclusions

Dynamic formation of groups and emergence of leaders have a significant impact on the efficiency of evacuation [1]. However, governing principles behind these phenomena in socio-technical systems are not clearly understood. In this paper we made the first step towards understanding how AmI technology influences grouping behaviour in large-scale socio-technical systems. For this, four hypotheses were formulated, a cognitive agent model was developed, and agent-based social simulation tools were used to verify the hypotheses. Although the obtained results still require empirical validation, some of them correlate well with findings from Social Science (cf [1, 13]). Furthermore, the simulation model developed relies strongly on a theoretical basis comprising theories from Social Science, Psychology and Neuropsychology, many of which were empirically validated.

Previously, grouping (or herding) behaviour of humans in evacuation was modelled using diverse computational techniques [7, 9, 10]. However, this work largely ignores the (intelligent) technological component. Also, the human behaviour is modelled in a very simplistic way, often using classical contagion models or lattice gas principles.

In the future, in collaboration with social psychologists more realistic mechanisms of emergent leadership (e.g., physiological and behavioural cues) and group formation will be integrated in the existing model.

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