Agent-Based Analysis of Patterns in Crowd Behaviour Involving Contagion of Mental States

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Abstract. In this paper an agent-based analysis is made of patterns in crowd behaviour, in particular to simulate a real-life incident that took place on May 4, 2010 in Amsterdam. As a basis, an existing agent-based model is used for contagion of emotions, beliefs and intentions. From available video material and witness reports, useful empirical data were extracted. Similar patterns were achieved in simulations, whereby some of the parameters of the model were tuned to the case addressed, and most parameters were assigned default values. The results show the inclusion of contagion of belief, emotion, and intention states of agents results in better reproduction of the incident than non-inclusion.

Keywords: crowd behaviour, contagion, emotion, belief, intention.

1 Introduction

Behavioural patterns emerging in large crowds are often not easy to regulate. Various examples have shown how things can easily get out of control when many people come together during big events. Especially when in a crowd, emotion spirals (e.g., for aggression or fear) develop to high levels, the consequences can be devastating. In this paper, it is analysed what happened on Dam square in Amsterdam at the 4th of May in 2010, when large numbers gathered for the national remembrance of the dead (‘dodenherdenking’). In the middle of a two-minute period of silence, one person started shouting, causing panic to occur among the people present. What happened there, as a result of a panic spiral, was a relatively mild case in which ‘only’ a number of persons ended up in hospitals with fractures and bruises.

In such situations, for each person involved, both cognitive and affective states and their intra-person interaction play a role. In this paper, beliefs and intentions are considered from the cognitive perspective, as they usually are the basis for actual behaviour: e.g., running away from a place that is believed to be dangerous. From the affective perspective, emotions are considered, such as fear, but also positive emotions for certain actions that are possible: for example, to go to a place believed to be safe. On the one hand such internally interacting cognitive and affective states are individual, private states, but on the other hand they are easily affected via verbal and/or nonverbal inter-person interaction by similar states of other persons.

Exploiting insights from Social Neuroscience, for the dynamics of such states and their intra- and interpersonal interaction, an agent-based model was presented in [5], which we refer to as the ASCRIBE model (Agent-based Social Contagion Regarding Intentions Beliefs and Emotions). For each person the ASCRIBE model takes into account a number of parameters representing personal characteristics, for example, expressivity and openness for emotions and other mental states. This current model uses ASCRIBE in an adapted form to simulate the empirical data gathered for the May 4 incident: ASCRIBEMay4. As a first step, useful empirical data has been extracted from available video material and witness reports. In order to specialise the existing agent-based model to this case, values for most of the parameters of the model where set by hand at certain default values, whereas values of other parameters were automatically tuned by use of a parameter tuning method developed earlier; cf. [2]. By comparing different default settings for the hand-set parameters relating to contagion of emotions, beliefs and intentions, it was possible to analyse the contribution of contagion in the model: parameter settings indicating low or no contagion show higher deviations from the empirical data.

In this paper, Section 2 presents a brief overview of the ASCRIBE model. In Section 3 the May 4 incident is described and how empirical data was extracted from available material. In Section 4 it is discussed how the model was extended and specialised for the case study addressed. Section 5 describes the parameter estimation method by which parameters of the model were tuned to cover the patterns shown in the empirical data. Section 6 discusses the results and section 7 is a conclusion.

2 Overview of the Agent-Based Model used

The agent-based model ASCRIBE that was used (cf. [5]) has been inspired by some concepts and principles from Neuroscience. One of them is the concept of a *mirror neuron* (e.g., [6], [9], [10]). Such a neuron is not only active in preparation for certain actions or bodily changes but also when the person observes somebody else intending or performing the action or body change. When states of other persons are mirrored by some of the person's own states, which at the same time play a role in generating their own behaviour, then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other's mental states and behaviour. Moreover, the model exploits the concept *somatic marker* (cf. [1]), which describes how emotions felt play a central role in decision making. Each considered *decision option* induces (via an emotional response) a feeling which is used to mark the option. Such somatic markers are used as a basis to choose an option. Within the ASCRIBE model it is assumed that at the individual intra-agent level, the strength of an intention for a certain decision option depends on the agent's beliefs and emotions in relation to that option (intra-agent interaction from beliefs and emotions to intentions). Moreover, it is assumed that beliefs generate certain emotions (e.g., fear), that in turn may affect the strength of beliefs (mutual intra-agent interaction between beliefs and emotions). To describe inter-agent interaction, a mirroring mechanism is used for the three different mental states considered: *emotions* (fear, and emotions felt about a certain decision option), *beliefs* (e.g., about safe places), *intentions* (for certain decision options). Below, only a brief overview is given of the central idea of the model. For a complete overview, see [5].

The model is based upon the notion of contagion strength γ_{SBA} which is the strength with which an agent B influences agent A with respect to a certain mental state S (which, for example, can be an emotion, a belief, or an intention). It depends on the *expressiveness* (ε_{SB}) of the sender B, the strength of the *channel* (α_{SBA}) from sender B to receiver A and the *openness* (δ_{SA}) of the receiver: $\gamma_{SBA} = \varepsilon_{SB}\ \alpha_{SBA}\ \delta_{SA}$. The level q_{SA} for mental state S of agent A is updated using the overall contagion strength of all agents B not equal to agent A: $\gamma_{SA} = \Sigma_{B\neq A}\ \gamma_{SBA}$. Then the weighed external impact q_{SA}*:for the mental state S of all the agents B upon agent A, is determined by: $q_{SA}{}^* = \Sigma_{B\neq A}\ \gamma_{SBA}\ q_{SB} / \gamma_{SA}$. Given these, state S for an agent A is updated by:

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

Here ψ_{SA} is an update speed factor for S, and $f(V_1, V_2)$ a combination function. This expresses that the value for q_{SA} is defined by taking the old value, and adding the change term, which basically is based on the difference between $f(q_{SA}{}^*(t), q_{SA}(t))$ and $q_{SA}(t)$. The change also depends on two factors: the overall contagion strength γ_{SA} (i.e., the higher this γ_{SA} , the more rapid the change) and the speed factor ψ_{SA}.

Within the definition of the combination function $f(V_1, V_2)$ a number of further personality characteristics determine the precise influence of the contagion. First, a factor η_{SA} is distinguished which expresses the tendency of an agent to absorb or amplify the level of a state S, whereas another personality characteristic β_{SA} represents the bias towards reducing or increasing the value of the state S. Thus, the combination function $f(V_1, V_2)$ is defined as follows:

$$f(V_1, V_2) = \eta_{SA}\ [\ \beta_{SA}\ (1 - (1 - V_1)(1 - V_2)) + (1-\beta_{SA})\ V_1 V_2\ ] + (1 - \eta_{SA})\ V_1$$

This general model for any state S is applied to four types of states:

fear of agent A	$q_{fearA}(t)$
emotion for option O of agent A	$q_{emotion(O)A}(t)$
intention indication for option O of agent A	$q_{intention(O)A}(t)$
belief in X of agent A	$q_{belief(X)A}(t)$

The total number of such states that is available in the model depends on the number o of decision options and the number b of beliefs. It can be calculated as $1+2o+b$ types of states per agent (which amounts to actual states). When a is the number of agents, then within the whole multi-agent system $(1+2o+b)a$ types of individual states play a role. In principle all parameters ε_{SA}, δ_{SA}, η_{SA}, β_{SA}, ψ_{SA}, α_{SBA} for different states S and agents A, B may have different values. Therefore the overall number of these parameter values is quadratic in the number a of agents and linear in the number o of options and the number b of beliefs; it can be calculated as $5a\ (1+2o+b\ ) + a^2\ (1+2o+b\ ) = a\ (a+5)\ (1+2o+b\ )$ parameter values.

Furthermore, interactions between different states are considered within the agent-based model. First, the emotions have an effect on the beliefs. This influence has been modelled for the emotion of fear. The personality 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 assumed to be dynamic, depending on the fear level. In addition the opposite direction is modelled: levels of emotions being influenced by levels of beliefs. Finally, the impact of levels of beliefs and emotions related to certain options on levels of intentions for these options is modelled. For more detailed specifications of these interactions, see [5]. To model these interactions, additional person-specific parameters are involved:

$\mu_{\delta beliefA}, \mu_{\eta beliefA}, \mu_{\beta beliefA}$	adaptation speed for δ, η, β for beliefs
σ_A, τ_A	steepness and threshold values for adaptation
ζ_A	optimistic/pessimistic bias upon fear
ν_A	weight of fear against beliefs
$\omega_{X,fear,A}$	weight of information *X* for fear
ω_{OEA1}	weight of the group impact on the emotion of *A* for *O*
ω_{OBA1}	weight for the own belief impact on the emotion of *A* for *O*
ω_{OIA1}	weight for the group impact on the intention of *A* for *O*
ω_{OEA2}	weight for own emotion impact on the intention of *A* for *O*
ω_{OBA2}	weight for the own belief impact on the intention of *A* for *O*

These parameters add to the overall number of parameter values needed, providing $3a + 2a + a + a + ba + 5oa = a(b + 5o + 7)$ parameter values. The current model ASCRIBEMay4 is specialised to the May 4 case and therefore adds a few parameters, see Section 4.

3 Case Study: the May 4 Incident

The computational model mentioned above was applied to the May 4 incident in Amsterdam (Netherlands). The incident was as follows. In the evening of the 4th of May, around 20.000 people gathered on Dam Square in Amsterdam (Netherlands) for the National Remembrance of the dead. At 19:58 everybody in the Netherlands, including the crowd on Dam Square were in silence for 2 minutes to remember the dead. The 20.000 people on Dam Square were compartmented by fences and officials. At 20.01 a man in the crowd on Dam Square disturbs the silence by screaming loudly. People standing around him could see that this man looked a bit 'crazy' or 'lost', and they did not move. Other people, 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 and infected each other with their emotions and intentions to flee in a certain direction and also because of a loud 'BANG' that was heard about 3 seconds after the start of the scream. Queen Beatrix and other royal members present, were escorted to a safe location nearby. In total, 64 persons got injured: broken bones and scrapes, by being pushed into a certain direction, or ran over by the crowd. The police exported the screaming man and got control over the situation within 2 minutes. After 2½ minutes, the master of ceremony announced to the crowd, that a person had become ill and had received care. He asked everybody to take their initial place again, to continue the ceremony. After this, the ceremony continued. For a short movie with images from the live broadcast on Dutch National Television, see URL: http://www.youtube.com/watch?v=0cEQp8OQj2Y. This shows how within two minutes the crowd starts to panic and move.

The actual live broadcast of the National Remembrance on Dutch National Television has been acquired in HD-quality. In this video, one can see the crowd on Dam Square flee from the perspective shown in Fig. 1. The video includes the cuts and editing that were done during the live broadcast, because the uncut/un-edited video material of all cameras that were filming that day was not saved.

Fig. 1. Still image of the people on Dam Square starting to flee.
The circle on the right bottom indicates the location of the yelling person

From the total broadcast, a shorter 3-minute long .mpeg movie was made from the moment where the crowd was in silence and a person started to scream loudly. In this 3-minute movie there are two time slots that were processed further, namely the parts from 11-17 seconds and 20-27 seconds. In these seconds, the camera angle from Fig. 1 was visible and the direction and speed of the movements of the people could be analysed. These specific parts of 15 seconds in total length were analysed as follows. The 3-minute long .mpeg movie was cut into still images, to detect the location of people by hand. This was done with a computer program called FFmpeg.[1] Ten still images per second were chosen for the cutting, to be able to detect the movements of running people frame by frame. The location/movement detection of the crowd was done as follows: the still images were viewed in a program called IrFanView[2], where you can see the coordinates of your mouse click on the picture in the upper left corner.

The total of 130 frames were analysed by hand. In an Excel file all coordinates of selected persons in the frames were collected. Not all people in the crowd could be analysed by hand, because of the quantity, but also because it was not possible to trace every 'dot' (person) over multiple still images. In total 35 persons were traced. Persons in different positions of the crowd that have simultaneous movements as the people around them were chosen, so these target subjects can represent multiple people around them. The density of the crowd around a target subject was also acquired, which could be used to build a representative large scale simulation of ten thousands of agents.. Since the exact number of surrounding persons of a target could not be distinguished in the video, 3 distinctions in density were made: high, medium and low. The size of the circle around the target subject in which density was measured, is shown on the right in the picture.

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[1] FFmpeg is a cross-platform program to record, convert and stream audio and video. http://www.ffmpeg.org/.
[2] IrFanView is a graphic viewer, see: http://www.irfanview.com/.

The next step was to correct for the angle the camera makes with the floor ad recalculate the coordinates, into coordinates that would fit into a bird's view on the Dam Square, perpendicular to the floor. For the transformation of the pixels-coordinates in the image to the location on the map as seen from above, both the horizontal and vertical distances in pixels between corners of buildings near the center of the image were calculated. This was compared with the real distances in meters to calculate the average pixels per meter in the image for the x and y axis near the center of the image. This method results in a distortion for points further away from the center of the image, however, given the distance of the camera from the area of interest and the fact that most of the movement were in the middle horizontal band of the image, the distortion is limited. Eventually, the positions in meters from corners of the buildings were translated to the position in pixels on a 600x800 map of the area, using offsets and scaling. Specifically, the following formulae are used to translate movements in pixels to movements in meters: $x_{meter} = x_{pixel} / 22$ and $y_{meter} = y_{pixel} / 8$. This was then transformed to the map using the following formulae:

$$x_{map} = (x_{meter} * 5.15) + 136$$
$$y_{map} = (y_{meter} * 5.15) - 167$$

Fig. 2. 600 x 800 pixel image of the Dam Square

The bird's eye view perspective used in the computational model can be seen in Fig. 2. The resulting 600 by 800 pixels figure was represented in the simulation in Matlab as a grid of 300 by 400. Locations of certain obstacles, like buildings and fences, were also transformed with the formula from the camera angle into the bird's eye view.

4 Extending and Specialising the Model for the May 4 Case

To tailor the ASCRIBE model towards this domain, a number of steps were taken.

Case specific states. 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 9 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 of the options and the emotion fear is represented.

Channel strength. In the scenario described above, 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:

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

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.

Movement. The movement of the agents directly depends upon their intentions. 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 model that establishes this behaviour is 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.

5 The Parameter Tuning Method Used

As explained above, the computational 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 [12] 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 Section 3 and 4 of [2] 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 Results

This section presents the results of specialising and tuning the agent-based 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-minute movie). The number of parameters to tune was large, therefore, before starting the tuning process, the settings for a large majority of the parameters were fixed at default values (see Table 1). For example, parameters with a relatively small sensitivity were left out of consideration for the tuning process (cf. [2]). For these parameters, reasonable default settings were chosen by hand (based on experimentation). The values of the remaining parameters (among others, the maximum speed for each individual agent, the minimum distance within which agents influence each other, and the initial values of one of the beliefs, see Table 1) were initialised by hand, but were then adapted using the parameter tuning approach described in the previous section. The speed factor λ of this tuning process was set to 0.1. The initial locations of the agents involved were taken equal to the locations in the real world data. An overview of all optimal settings found for the global parameters and the initial variables involved in the model (cf. [5]) is shown in Table 1. Here, the settings shown in the first two columns were set by hand, and the settings shown in the last two columns were found after tuning. Note that all settings (except those for maximum speed) were used globally for all agents.

Table 1. Optimal parameter settings found

Global parameters (not tuned)		Initial variable settings (not tuned)		Global parameters (tuned)		Initial variables (tuned)	
#agents	35	$\varepsilon_{intention}$	0.5	$\tau_{distance}$	190	$q_{belief(nomove)}$	0.005
max_x	600	$\delta_{intention}$	0.5	sight_reach	200		
max_y	800	$\eta_{intention}$	0.5	max_speed (per agent)	see Fig.3		
Δt	0.5	$\beta_{intention}$	0.5				
$\mu_{\delta belief}$	0.5	ε_{belief}	0.5				
$\mu_{\eta belief}$	0.5	δ_{belief}	0.5				
$\mu_{\beta belief}$	0.5	η_{belief}	0.5				
ζ_{belief}	0.5	β_{belief}	0.5				
σ	100	$\varepsilon_{emotion}$	0.5				
ω_{OIA1}	0.3	$\delta_{emotion}$	0.5				
ω_{OEA2}	0.3	$\eta_{emotion}$	0.5				
ω_{OBA2}	0.3	$\beta_{emotion}$	0.5				
ω_{OEA1}	0.5						
ω_{OBA1}	0.5						
all $q_{belief(X)}$	0						
impact of event on $q_{belief(X)}$	1						
min_speed	0.01						

These optimal settings were compared to two other variants of the model: one baseline variant in which the agents do not move at all, and one variant in which all agents also make individual decisions, but do not influence each other (i.e., no contagion takes place). For the latter variant, in order to enable a fair comparison, parameter tuning was applied to find optimal settings as well. Fig. 3 shows for each of the three 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 overall average error becomes quite large (*0.87*). The overall 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%*).

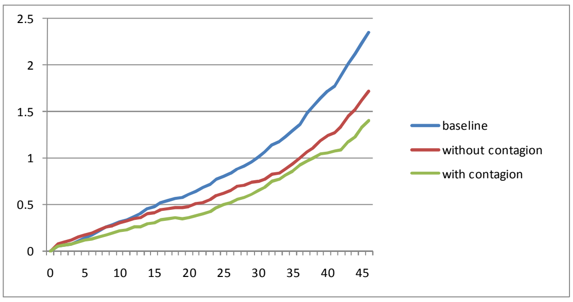

Fig. 3. Development of error over the simulation for three variants of the model.

This finding provides strong 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; in case the steps would have been larger, the difference in performance between the three models would be expected to have been bigger as well.

After the tuning process was finished, the optimal settings found for all parameters were used as input for the simulation model with contagion, to generate a simulation trace which closely resembles the real world scenario. Using visualisation software (written in Matlab), the simulation trace has been visualised in the form of a 2D animation (see http://www.few.vu.nl/~tbosse/may4/). A screenshot of the animation is shown in Fig. 4. Here, the lines represent fences that were used to control the crowd, the large circle represents the monument on the square (see Fig. 1 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. 4), the distances between the real and simulated positions are fairly small.

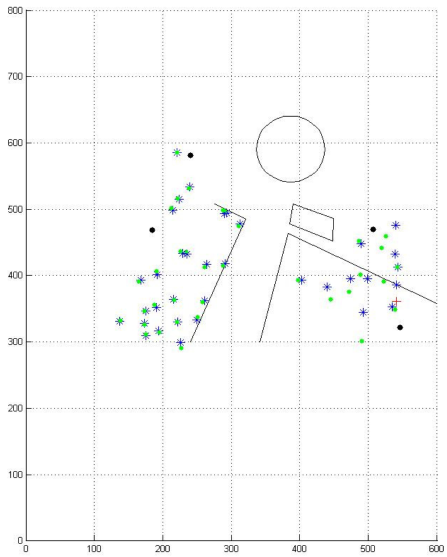

Fig. 4. Screenshot of the simulation. Units displayed on the axes are in pixels, where 5.15 pixels equals 1 meter.

7 Discussion

This paper has two main contributions. Firstly, it presents how empirical data has been extracted from available video material and witness reports of the May 4 incident in Amsterdam. Qualitative data about escape panics are rare [4]. Based on these data, it is possible to compare models for crowd behaviour with qualitative data of a real panicking event. Second, an existing agent-based model for describing group behaviour involving contagion of emotion, belief and intention, ASCRIBE [5], has been adapted to construct a model for behaviour in a crowd when a panic spiral occurs. Experiments have been performed with two variants of the model. In one variant 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 other variant, mutual influencing took place because emotions, beliefs and intentions were spreading to persons nearby. When comparing the simulations of both variants of the model with the most optimal settings for the other parameters, the variant with contagion had an *18%* lower average error rate (*0.54* instead of *0.66*). Thus, it is shown that the contagion of emotions is an essential element to model the behaviour of crowds in panic situations.

Several models for crowd behaviour have been presented by other researchers. An influential paper has been [4], 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 [11, 14]. In [3] the model of [4] 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 [7] 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 [8]. 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, no evaluation with real qualitative data has been performed. One of the most developed tools for crowd simulation, which also incorporates mental states, is ESCAPES [13]. This system, which specifically targets evacuation scenarios, has several similarities with the approach shown here. Future work will explore the possibilities to incorporate the detailed mechanisms for contagion of mental states presented here into ESCAPES.

Moreover, in the future, further parameter tuning experiments are planned to study the effect of the parameters that were fixed as default values in the current experiments. The aim is to explore whether even more realistic simulations can be achieved by exploiting the details of the model for contagion of emotions, beliefs and intentions in a more differentiated form.

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