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

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

Keywords: crowd behaviour, agent-based modelling and simulation, contagion, emotion, belief, intention.

1 Introduction

Patterns emerging in large crowds are often not easy to regulate. Various examples have shown how during big events, where many people come together, things can easily get out of control. 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, as one example 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 period of silence during the remembrance, one person started shouting, causing a large 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 here and there.

In such situations for each person involved, both cognitive and affective states and their intra-person interaction play a role. In this paper, from the cognitive side beliefs and intentions are considered, as they usually are the basis for actual behaviour; for example, running away from a place that is believed to be dangerous. From the affective side emotions are considered such as fear, but also positive emotions for certain actions that are possible; for example, to go to a place believed 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 developed, presented in [5]. For each person the model takes into account a number of parameters representing personal characteristics, for example, expressivity and openness for emotions and other mental states. This existing model is used here in an adapted form to simulate the empirical data gathered for the May 4 incident. As a first step, useful empirical data have 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 some 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. Indeed, for parameter settings indicating low or no contagion, the outcomes show higher deviations from the empirical data.

In this paper, Section 2 presents a brief overview of the model used. In Section 3 the May 4 incident is described and how empirical data were 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 some of the parameters of the model were tuned to cover the patterns shown in the empirical data. Section 6 discusses the results. Finally, Section 7 is a conclusion.

2 Overview of the Agent-Based Model used

The agent-based model used 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 agent-based model used 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).

In addition, to describe inter-agent interaction, a mirroring mechanism is used for the three different mental states considered.

- *mirroring of emotions* describes how in different individuals fear and the emotions felt about a certain considered decision option affect each other,
- *mirroring of beliefs* describes how to the strength by which different individuals believe certain information is transferred
- *mirroring of intentions* describes how the strength of intentions for certain decision options is transferred between individuals.

Below, only a brief overview is given of the central idea of the model, namely the description of the process of mirroring of any mental state. 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). In order to determine this contagion strength, a combination of three factors is taken, namely the *expressiveness* of the sender ε_{SB}, the strength of the channel between the sender *B* and the receiver A (α_{SBA}) and the *openness* of the receiver, denoted by δ_{SA}. The contagion strength itself is then calculated as follows:

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

The level q_{SA} for the particular mental state *S* of agent *A* can be calculated by first determining the overall contagion strength of all agents *B* not equal to the agent *A* which is being influenced. This is expressed as follows:

$$\gamma_{SA} = \Sigma_{B\neq A}\ \gamma_{SBA}$$

This overall contagion strength is used to calculate the weighed external impact for the mental state *S* of all the agents *B* upon agent *A*, which is called $q_{SA}*$:

$$q_{SA}* = \Sigma_{B\neq A}\ \gamma_{SBA}\ q_{SB} / \gamma_{SA}$$

Given these characteristics, the following dynamic relation is used to determine the new value of a state *S* for an agent *A*:

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

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 actual change also depends on two factors, namely the overall contagion strength γ_{SA} (i.e., the higher the total contagion strength, 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*. In this case, the combination function $f(V_1, V_2)$ is defined as follows:

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

The function used has a component for amplification (after η_{SA}) and one for absorption (after $1-\eta_{SA}$). The amplification component depends on the tendency of the agent towards more strengthening (part multiplied by $\beta_{SA}(t)$) or more weakening (part of equation multiplied by $1-\beta_{SA}(t)$). The combination function is applied to $q_{SA}*(t)$ and $q_{SA}(t)$ as follows:

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

This general model for contagion of any state S is applied to the individual levels for 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 as an effect on the personality characteristics of the agent for beliefs. In this case, the influence of a single type of emotion is modelled, namely 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 the parameters 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 emotion impact (by mirroring) 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 intention impact (by mirroring) on the intention of A for O
ω_{OEA2}	weight for the own emotion impact (by somatic marking) 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:

$3a + 2a + a + a + ba + 5oa = a(b + 5o + 7)$ parameter values

For the model specialised to the case addressed, still a few parameters will be added in Section 4.

3 Case Study: the May 4 Incident

The computational model mentioned above was applied to the May 4 incident in Amsterdam (Netherlands). In Section 3.1 the incident is described. In Section 3.2 it is explained how the empirical data were collected and formalised to function as input for the computational model. After this, Section 4 describes the extensions and specialisations that were made to the computational model to apply it to the case of the May 4 incident.

3.1 The May 4 Incident

In the evening of the 4th of May, around 20.000 people gathered on Dam Square in Amsterdam (Netherlands) for the National Remembrance of all people in the Kingdom of the Netherlands or anywhere in the world, that have been killed since the outbreak of the Second World War, in war and peace operations. At 19:58 Queen Beatrix placed a wreath at the monument and at 20.00 hrs 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 ‘WHOAAAAAA’. 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 were escorted to a safe location nearby. In total, 64 people got hurt: broken bones and scrapes, by being pushed into a certain direction, or ran over by the crowd. Especially people standing at the fences got hurt because of the crowd pushing into them, which resulted in people falling down over the fences and being ran over. 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 through a speaker, that a person had become ill and had received care. He asked everybody to take their initial place again to continue the ceremony. After Queen Beatrix returned to Dam Square from the safe location, the ceremony continued. For a short movie with images from the live broadcast on Dutch National Television, see the following URL: http://www.youtube.com/watch?v=0cEQp8OQj2Y. This shows how within two minutes the crowd starts to panic and move.

3.2 Data Extraction

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 Figure 1. The video includes the cuts and editing that were done during the live broadcast. The uncut/un-edited video material of all cameras that were filming the Remembrance could not be recovered, because this material was not saved.

Figure 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 single person on Dam Square 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 Figure 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.

A total of 130 frames, which make up the specific parts of 15 seconds in length, were analysed by hand. In an Excel file all coordinates of selected people 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, not all dots could be differentiated. 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 from the video. It turned out to be impossible to count the number of people around a certain person in the images, because the surrounding persons could simply not be distinguished. Therefore only 3 distinctions in density have been made: high, medium or low. High = people present all around target subject, medium = gaps present around target subject, low = empty space all around target subject. The size of the circle around the target subject in which density was measured, is the size of the 'roundish' opening of the entrance of a building, on the right of the big screen in the picture.

The next step was to correct for the angle the camera makes with the floor and 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 map of the Dam Square 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:

$$x_{meter} = x_{pixel} / 22$$
$$y_{meter} = y_{pixel} / 8$$

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

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

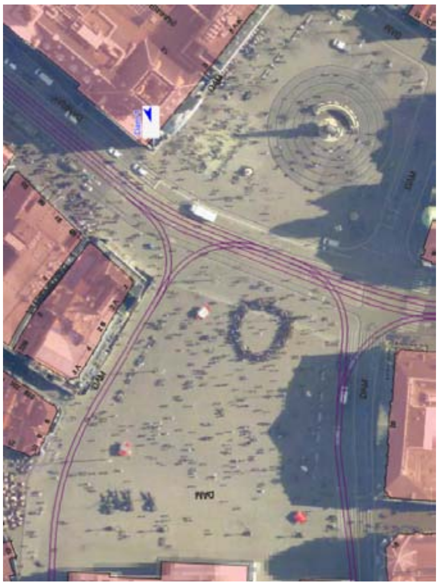

Figure 2. 600 by 800 pixels image of Dam Square

The bird's eye view perspective that was chosen to look at the Dam Square in the computational model can be seen in Figure 2. This 600 by 800 pixels figure was represented in the simulation programmed in Matlab as a grid of 300 by

[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/.

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. The ideal situation to replicate the behaviour of the crowd into the agent-based simulation would be to model the movements of 20000 people. However, obtaining all the movement data of 20000 people hand by hand is too time consuming, and seemed not possible as well. Therefore only the 35 representative persons that were annotated by hand were considered in the simulation. In future research, the possibilities will be explored to scale up these people in the simulation by 'cloning' them into multiple agents with the same behaviour.

Finally, the movements, beliefs, emotions and intentions of the 35 agents were simulated. In Section 5 it will be discussed how the simulations are fitted to the empirical data via parameter tuning. The main focus is on reproducing the movements of the people, thereby 'validating' the cognitive and emotional effects of the people only indirectly, since the cognitive (beliefs, intentions) and emotions cause the movements. Section 4 describes how the agent-model introduced before has been tailored towards this particular case.

4 Extending and Specialising the Model for the May 4 Case

In order to tailor the model as presented in Section 2 towards this domain, a number of steps have been taken.

Case specific states. First of all, the relevant states for the agents have been distinguished. There are a number of general states, about which agents have beliefs, emotions, and intentions. In this case, these states express the options that are available for the agent. There are a total of 9 options available for the agents, including an option to remain standing, and options representing all wind directions to which the agent can move (N, NE, E, SE, S, SW, W, NW). Besides these general options, there is one additional specific belief, namely the belief about the current situation. This expresses how positive people judge the current situation (0 being a negative judgment of the situation, and 1 being a positive judgment). Finally, besides the emotions for each of the individual options, also the emotion of fear is represented (which has already been mentioned in Section 2).

Channel strength. In the scenario described above, the channel strengths between the various agents are very much 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 choice has been made to create a threshold function which expresses within which reach agents still influence each other in a significant manner. The definition of the channel strength is expressed as follows:

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

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 has been made solely dependent upon the intentions the agents have. The highest feasible intention is selected (in some cases fences might obstruct certain movements which can therefore not be executed, the next highest intention is then selected). Assume that this highest feasible intention is linked with option *O* in this case (note that the options include all wind directions, and staying at the same location). For each of the options *O* available, 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:

$$x_{movement(O)} = 0 \qquad y_{movement(O)} = -1$$

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. For the current paper, as explained above, the main goal is to reproduce the movements of the people involved in the scenario. Thus, to calculate the error ε, it was decided to simply take the average (Euclidean) distance (over all agents and time points) between the actual and simulated location of the agent:

Here, *x(a, t, sim)* denotes the x-coordinate of agent *a* at time point *t* in the simulation, and *x(a, t, data)* denotes the same in the real data (similarly for the y-coordinates). Both are measured 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 simply 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, and running a simulation. For the real world data, the formalised data as described in Section 3.2 were used. Below, the results are presented for the first part of the data (i.e., seconds 11-17 of the 3-minute movie).

As discussed in Section 2 the number of parameters involved is quadratic in the number of agents (which is *35* here) and linear in the number of options (which is *8*) which provides a large number (above *10.000*). Therefore, before starting the tuning process, the settings for a large majority of the parameters were fixed at default values. For example, a number of parameters were found to have a relatively small sensitivity and were therefore 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.

To illustrate the dynamics of the tuning process, Figure 3 shows how the parameter settings for the maximum speed of all 35 agents change over the iterations. Initially, all of these values were set to *0* (i.e., a situation where the agents do not move at all), but later on more optimal values are found. For example, for some agents a maximum speed of about *2* turned out to be optimal, whereas for others the optimal speed was close to *0*. After 30 iterations, the process was stopped, since the change in parameter settings did not decrease the overall error any further.

As mentioned above, also some other parameters were tuned in addition to each agent's maximum speed. 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.

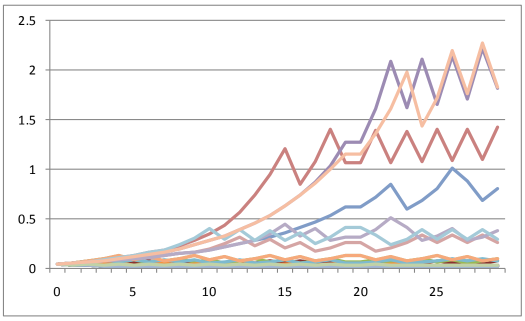

Figure 3. Change of parameter settings of all 35 agents' maximum speed during tuning.

To assess the performance of the model with these optimal settings, it was 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. Figure 4 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, obviously, the error is *0* (since all agents in the simulation start at their actual position), but over time the error increases. As shown in the figure, the error increases very quickly (and thus the overall average error becomes quite big) in the baseline case (overall average error *0.87*). Instead, the overall error in 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%*).

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						

This finding provides strong evidence for the conclusion that 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 (which means that even a model in which agents do not move at all performs fairly well); in case the steps would have been larger, the difference in performance between the three models would probably have been bigger too.

After the complete 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 a piece of visualisation software (written in Matlab), the simulation trace has been visualised in the form of a 2D animation, which can be found at http://www.few.vu.nl/~tbosse/may4/.

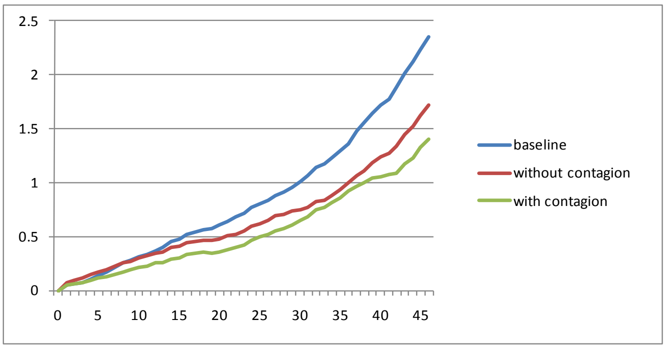

Figure 4. Development of error over the simulation for three variants of the model.

A screenshot of the animation (taken at the last time point of the scenario) is shown in Figure 5. Here, the black lines represent fences that were used to control the crowd, the large circle represents the monument on the square (see Figure 1 for the actual situation), and the big black dots represent corners of other buildings. The big red dot indicates the location of the screaming man. Most importantly, the green dots represent the actual locations of the 35 people in the crowd that were tracked, and the blue dots represent the locations of the corresponding agents in the simulation. As shown in the figure, even at the end of the simulation, the distances between the real and simulated positions are fairly small.

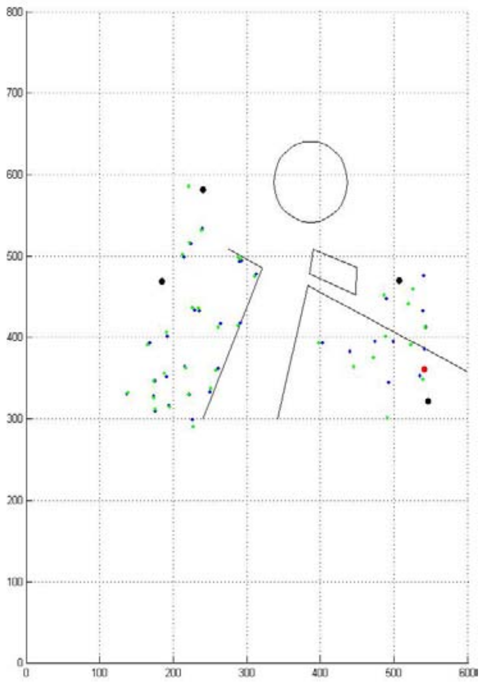

Figure 5. Screenshot of the simulation.
Note that the units displayed on the axes are in pixels, where 5.15 pixels equals 1 meter.

7 Discussion

There are two main contributions of this paper. First, it is presented 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 [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, 13]. 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.

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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