The microscopic model and the panicking ball-bearing

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Summary. Prominent microscopic models simulate panic (which has been described as a myth) allowing unwarranted simplifying assumptions that people are irrational, non-deliberative and interchangeable. While these assumptions can be remedied by increasing the behavioural repertoire of modelled individuals, large cognitive architectures would stifle a model's power to explain emergent crowd effects. We propose the microscopic human factor (MHF) approach that increases behavioural repertoire without compromise to the elegant simplicity from which the models derive their explanatory power.

1 Introduction

Jonathan Sime once admonished building designers for creating *ball-bearing designs* that treat people "as if they are nonthinking objects rather like the elements of a building structure" [1]. He argued that such designs neglect the important interactions between people and spaces. Sime also touched on evacuation simulations, suggesting that human cognition, decision making and social behaviours were excluded from models for practical reasons of modelling difficulty [2].

Since that time microscopic models have been developed. These models can, in principle, incorporate individuality. Yet, because of a continued focus on irrational "panic" behaviours, these models largely simulate homogenous crowds and ignore human factors. They still model ball-bearings.

The purpose of this paper is to argue that microscopic models must leave panic behind by modelling people rather than ball-bearings, and furthermore that this improvement is both possible and practical. In aid of this position, we begin by briefly reviewing the case against panic in crowds. We then turn to a consideration of two prominent microscopic models, their foundations in panic as a description of human behaviour and the problems introduced by the panic assumption. We will then describe our *microscopic human factor* (MHF) approach that moves a microscopic model away from panic by increasing behavioural repertoire – without jettisoning the benefits of microscopic modelling in the process. Finally, as a demonstration of the utility of the MHF approach, we will discuss our experience in using MHF techniques to expand the repertoire of the floor field model [3].

2 Panic

People are generally familiar with the concept of panic. Informed only by attention-seeking media reports and the emotionally-appealing images of Hollywood action blockbusters, it is easy to believe that people in large

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crowds are prone to mindless flight and irrational behaviour on the one hand, and deliberate violence and uncontrolled aggression on the other. Dictionary definitions of panic support this populist view, emphasizing uncontrolled flight with an accompanying state of emotional arousal and unreasoned behaviour [4]. Johnson's sociological investigation found that the concept of panic includes "selfish competition uncontrolled by social and cultural constraints" [5]. In our view, the hallmark of panic, then, is irrational and asocial or anti-social behaviour.

The question is: do people really panic in crowd situations? The academic view opposes the pop-psychological irrationalist view just described. It is the academic perspective that the behaviour of people in emergency situations (such as fire and crowd disasters) is not irrational – rather, making sense in the context of the information available at the time [2,6]. Additionally, sociologists tell us that social norms continue to be important in these situations and that incidences of injuries in crowds are seldom deliberate acts by violent people [5,7]. Although competitive evacuations do occur, irrational panic (despite its media-driven allure) is at best non-explanatory and is at worst seen as a myth [8].

3 Panic in microscopic models

Panic is such a compelling concept, however, that it continues to crop up in non-behavioural disciplines modelling crowd behaviour, particularly in microscopic models (see below). Although these disciplines may be less familiar with the evidence from the social sciences against panic, there is another reason why panic is compelling for crowd modellers. Because panicked individuals are assumed to exhibit behaviour that is irrational and free of social constraints the modeller is relieved of the responsibility to simulate cognitive/psychological/behavioural factors in crowd dynamics. The result is agents (modelled individuals) that are non-cognitive; specifically they are non-rational (taking actions that do not make sense), non-deliberative (containing no mental state or processing) and interchangeable. This in turn reduces the complexity of the model, and encourages techniques used traditionally to model inanimate objects.

Although the panic assumption may be convenient in that it reduces complexity, it means that the behaviour modelled is at odds with our concept of human behaviour. This opens the model to the criticism that its results cannot be meaningfully applied to people because it is not a model of people. Let us consider the human behaviour simulation in two prominent microscopic models that use different modelling approaches.

The social force model is explicitly presented as a model for investigating panic [9]. This explains why its agents are reactive rather than deliberative, and why they have homogenous behaviour; its agents are interchangeable, operating on the same information to the same ends. This sets the stage for a particle-dynamics-based numerical simulation. We note that this model incorporates a simulation of personal space within the numerical simulation (the social force). Although this is a positive aspect of the model, it is overshadowed by the continued focus on panic as a predictor of behaviour.

The floor field model [3], born from a vehicular cellular automaton, has been used to study several different pedestrian phenomena (notably bottlenecks at an exit during evacuation [10]). The authors, while unfortunately following [9] in identifying panic as a likely outcome of some situations, take the positive step of modelling “normal” conditions as well. The normal conditions in the model, however, still resonate with Sime’s ball-bearing metaphor. The agents lack facilities for the heterogeneity that comes from human cognition and behaviour – the authors state their desire to keep the model simple by avoiding agent intelligence.

Although we are concerned about the applicability of these models to general human behaviour, we do not wish to imply that these models have no value. The great value of microscopic models, in our view, is that they simulate emergent macro-level crowd effects through simple local rules evaluated from the perspective of each agent. By analysing these micro-level rules it is possible to determine the conditions under which the macro-level effects will be produced, enhanced or moderated. Notwithstanding this, we argue that there is an opportunity to improve the microscopic explanatory power of the models by moving away from the unwarranted assumption of panic.

4 Microscopic Human Factors

The way to improve these microscopic models, in short, is to make the agents behave more like people. Currently, for example, the agents have one fixed goal, they do not change their goals based on information obtained from the environment, they do not communicate information amongst themselves, they queue indefinitely at bottlenecks, they do not intentionally originate any forces, etc. Humans, by contrast, are cognitive with a rich behavioural repertoire available for deployment. Ultimately it is this behavioural repertoire that is denied by the panic assumption and which is therefore not represented in the microscopic models. It is the lack of these behaviours – even more than the precise cognitive process that underlies them – that calls into question these models’ applicability to human crowds.

The question we are left with, then, is how to (a) improve microscopic models’ treatment of human behaviour without (b) losing the benefits of these models. One approach to (a) is to import large-scale cognitive architectures such as ACT-R [11], which aim to simulate complex cognitive processes including perception, memory, attention, planning, etc. Although this approach may improve relevance to people, it negates one of the key benefits of microscopic models: the establishment of causal connections between emergent macro-level crowd effects and their origins in individual behaviour. Simple agent rules give way to a complex cognitive simulation that tends to be analytically opaque (as cognitive architectures are emergent systems themselves). The microscopic model becomes little more than an arena, simulating the physics and movement of agents, but divorced from the real action unfolding within the cognitive simulators. This disconnection breaks the causal chain and it becomes difficult to explain the macro-level crowd effects by reference to processes within the individual.

The key to maintaining the benefits inherent in microscopic models is to respect the simplicity and elegance that is their nature. Any model is, by definition, an abstraction that discards detail through simplification in favour of explanatory power. We can simplify and abstract behavioural characteristics in order to bring them within the framework of the microscopic model. Our approach is to simulate cognitive behaviour and structures at the same level of abstraction at which the microscopic models currently simulate movement behaviours. We can then increase behavioural repertoire by expressing human characteristics as simple local rules, fusing them with the simple local rules of the microscopic model. We call these simple local rules *microscopic human factors* (MHFs). This technique ensures that the causal connection between emergent crowd behaviours and the local agent rules is not broken.

5 Microscopic Human Factors in the Floor Field model

In order to demonstrate the potential of the MHF technique, we now turn to an example: a discovery and communication simulation [12]. This is one of several extensions we have made to the floor field model. (For other examples, see the voluntary pushing in our force model [13] and our model of front-to-back communication [14].)

We have found the floor field model to be particularly amenable to extension because its simple cellular automaton rules are both defined and evaluated from the perspective of the individual. These rules are easily expressed within the context of a multi-agent system (MAS), our preferred tool for modelling emergent effects and studying collective behaviour. In a MAS, agents are considered to be autonomous, with internal rules and the possibility for internal state; this allows for the possibility that agents with different sets of rules can be simulated together, for agent memory and consequently for behaviours that unfold over time. By implementing the rules of the floor field model in a multi-agent system we gain the opportunity to specify more internal behaviour for the agents.

We have noted above that the agents in the floor field model are homogenous with respect to their movement goals. Case studies of fire events (e.g. [15]) indicate that people can be reasonably expected to have different experience, goals and behaviours in a fire, that not everyone will move to the same exit and that communication (e.g. of exit locations) can change people's goals. Our goal in introducing this MHF was to reduce agent homogeneity through discovery and communication of exit locations in the physical environment. We will proceed by outlining the relevant parts of the floor field model, summarizing our changes to the basic model, and discussing our results.

In the classic floor field model (see [3] for complete details) an agent's behaviour is driven by two floor fields. These fields are like maps in that they store information in the context of its location; when making movement decisions, agents make reference only to their immediate surroundings. The *static field, S,* provides, for each location, a distance to points of interest (e.g. the closest exit). The *dynamic field, D,* provides, for each location, a measure of the number of agents that have recently moved through. Agents' use of these fields is further altered by the use of sensitivity parameters that can decrease sensitivity to a field (e.g. decreased sensitivity to the static field implies poor knowledge of the space) or increase sensitivity to a field (e.g. increased sensitivity to the dynamic field promotes following behaviours). In our model, an agent considers movement from its current cell to the four cardinal neighbours rating each neighbouring cell according to the following (slightly simplified) formula in which k_D and k_S are the sensitivity parameters and i and j identify the cell being rated.

$$desirability = \exp(k_D D_{ij}) \exp(k_S S_{ij}) \tag{1}$$

Each neighbour cell is evaluated for desirability according to this formula, and a probabilistic decision is made in which better-rated neighbour cells are more likely to be selected as a desired destination. Each agent undertakes this desirability calculation at the same time. Movement is then done in parallel, and agents may or may not get to complete their movement depending on whether they collide with or are blocked by others.

We used the MHF approach to add evolving goals by introducing additional static fields into the floor field model. As static fields underlie an agent's navigational ability – representing knowledge of the space – replacing an agent's static field with a more elaborated one is analogous to the agent integrating new information into its mental map. We fused this new behavioural concept with the model done microscopically at the level of the desirability calculation (eq. 1). The agent now considers one of a set of static fields by changing the S_{ij} term to $S_{n_{ij}}$, n indicating the index into the set. We also added two ways that an agent's static field change can be triggered: discovery and communication. The discovery method involves the addition of a new floor field, the *discovery field*[1]. This field simply encodes a number on each cell indicating the static field that should be consulted. If the agent moves to a cell with a higher number, it is assumed to gain the information available there, and switches to the corresponding static field. Regarding communication, if an agent is blocked in movement (because another agent is occupying its desired cell) then the blocked agent communicates its static field number. The blocking agent, hearing a (higher-numbered) static field, incorporates this information by switching to the indicated static field.

Let us consider an application of these changes to the model. Consider an egress scenario in which there are two well-known exits from a space, but one is blocked. In a real life we expect that people who approach a blocked exit change their goal, moving to an alternate exit. The classic floor field model cannot simulate this because agent goals are determined by the modeller at the outset and are fixed. Our discovery and communication MHF handles the scenario using two static fields: the first, in which there are two exits, and the second, in which the blocked exit does not appear. At the outset, all agents use the first static field. The discovery field causes agents who approach the blocked exit to change to the second static field. These agents can communicate news of the blocked exits to others.

There are two patterns of agent behaviour when the model is run. Some of the agents use the good exit directly, never learning of the exit blockage. Others move to the blocked exit, discover the new information, change their mental map, and start moving toward the good exit, potentially alerting naïve agents along the way.

Because this is a microscopic model with very simple rules, the MHF approach allows us to study the emergent effects of communication and information. For example, if communication is prevented, large numbers of naïve agents trying to reach the blocked exit can pin knowledgeable agents in place, preventing them from reaching the open exit and creating an impasse (see figure 1).

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[1] We originally called this the *information field* but this name was confusing because all fields carry information. We have renamed it the *discovery field*.

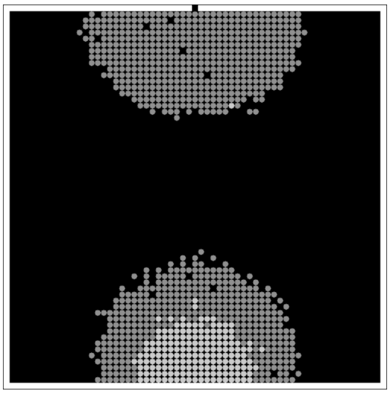

Figure 1 Knowledgeable agents (light gray) know the lower exit is blocked, but are pinned in place by naïve agents (dark gray)

6 Conclusion

While behavioural researchers have exposed the myth of panic, microscopic models continue to be panic-based. By leaving panic behind we can begin, as Sime suggested, to model people rather than ball-bearings. The Microscopic Human Factors (MHF) approach can improve the behavioural repertoire of microscopic models, and hence reduce their focus on irrational, homogenous, interchangeable agents. This approach simulates cognitive behaviour and structures at the same level of abstraction at which the microscopic models currently simulate movement behaviour. This allows behavioural rules to be fused with existing model rules and preserves the causal connection between agent rules and emergent crowd-level effects – ultimately allowing for a study of the emergent consequences of human behaviour in agents. The MHF approach helps to distance microscopic models from panic simulation by increasing the models' relevance to human crowds – without compromise to the simplicity from which the models derive their explanatory power.

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