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A dynamic state-based model of crowds

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ABSTRACT

We consider the problem of categorising, describing and generating the dynamic properties and behaviours of crowds over time. Previous work has tended to focus on a relatively static "typology"-based approach, which does not account for the fact that crowds can *change*, often quite rapidly. Moreover, the labels attached to crowd behaviours are often subjective and/or value-laden. Here, we present an alternative approach which uses relatively "agnostic" labels. This means that we do not prescribe the behaviour of an individual, but provide a *context* within which an individual might behave. This naturally describes the time-series evolution of a crowd, and allows for the dynamic handling of an arbitrary number of "sub-crowds". Apart from its *descriptive* power (capturing, in a standardised manner, descriptions of known events), our model may also be used *generatively* to produce plausible patterns of crowd dynamics and as a component of machine learning-based approaches to investigating behaviour and interventions.

1. Introduction

As a discipline, crowd science has acknowledged the need to understand the *nature* of human collective phenomena before trying to *explain* them, and a number of attempts have been made to specify and classify different *crowd types and behaviours*. However, these *typologies* are often partial, over-fitted to a specific crowd type, or use arbitrary and/or subjective labels for behaviours of complex origin (for example, "panic"). Moreover, they tend to be relatively inflexible, and do not reflect the fluid nature of crowd behaviour (and how this might influence the crowd's structure and impact over time). For example, a static typology might not capture a situation in which a peaceful demonstration can quickly turn into a riot, or how a physical crowd moving around a shopping mall can suddenly become united into a psychological crowd in response to a shared grievance or an external threat. In this paper, we present an alternative to the typology approach; a *dynamic, state-based model of crowds*, inspired by an existing *assembly-action-dispersal* framework.

Our approach is relatively objective, can capture the dynamic evolution of a crowd over time, and (unlike existing typologies, which are relatively static) allows for the natural description of how sub-groups emerge within a crowd. This new model may be useful for describing the evolution of incidents such as riots (Dezecache et al., 2021) or emergencies (Sidiropoulos et al., 2020), but it is equally well-suited to the study of expected, "normal" crowds (Helbing et al., 2002). Importantly, our model focuses largely on *observable* features of crowds (Haghani and Sarvi, 2018), makes no subjective assumptions about underlying psychological factors or individual motivations (Wijermans et al., 2013), and lends itself to codification in computer simulations (Helbing et al., 2000). The model is sufficiently rich to capture macro-level *descriptions* of crowds, but may also be used to *generate* plausible crowd dynamics (Amos and Webster, 2022; Webster and Amos, 2020). Our overall goal is to provide a standardised and objective framework for the description of crowds (in terms of both behaviours and properties, and how these dynamically change over time), in the hope that it might find applications in reporting on real crowds and informing future simulation studies.

The rest of the paper is structured as follows: in Section 2 we describe previous related work; in Section 3 we describe the abstract model and explain its operation, and in Section 4 we illustrate its application with an imagined real-world scenario. In Section 5, we then present a formalisation of our model, and show how it might be applied to the example scenario. We conclude in Section 6 with a consideration of the limitations of our model, as well as suggestions for future work.

2. Previous work

The study of human crowds and their associated dynamics dates back to the late 19th Century (De Tarde, 1903; Hobsbawm, 2010;

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Le Bon, 1897; Sighele, 1892) (see also Nye, 1975), but the field of "crowd science" (as it would later be referred to) only achieved a degree of methodological rigour around the 1970s (McPhail, 1971; Tajfel and Turner, 1979; Turner and Killian, 1972) (see also McPhail, 1991). Since then, crowd studies have sought to better understand the complex dynamics of crowds, to predict their behaviour, and to suggest mechanisms by which they may be influenced or even managed (often, but not exclusively, with the aim of trying to ensure the safety of individuals) (Challenger and Clegg, 2011; Drury et al., 2009; Sime, 1995; Still, 2014).

McPhail argues that rigorously capturing the *nature* of collective behaviour must preface any attempt to *explain* it; "It is misguided to debate the pros and cons of competing explanations before the phenomena to be explained have first been examined, specified and described" (McPhail, 1991). In order to motivate what follows, we therefore provide a brief overview of previous attempts to specify and classify crowds and collective behaviour(s). Perhaps the most well-known (in the popular sense) and lyrical codification of crowds comes in Canetti's *Crowds and Power* (Canetti, 1962), in which the author uses metaphorical images of fire, water and swarms to describe different types of gathering, and provides an extensive catalogue of crowd types and attributes. Although influential, Canetti's work has also been criticised as lacking traditional academic rigour (Phillips, 1963).

Prior to Canetti, Blumer (1939) initially introduced the notion of‘ "acting", "expressive", "casual" and "conventional" crowds, each instance of a crowd being distinguished by their perceived purpose and dynamics. This framework was modified by Swanson (1953) (with specific reference to "acting" crowds) and adopted by Turner and Killian (1972) with the addition of‘ "individualistic" and "solidaristic" crowds. Their typology matrix places "symbolising tendencies" (acting and expressive) on one axis, and"coordinating tendencies" (solidaristic and individualistic) on the other, and locates instances of crowds within this two-dimensional space. However, this framework fails to capture attributes or *forms* of behaviour, and is not amenable to dynamic reconfiguration.

McPhail's subsequent work on codifying elementary forms of collective behaviour within gatherings (summarised in McPhail, 1991) lists 40 different "actions" that may be performed by one or more people (e.g., "booing", "bowing"). These have commonly been used by observers to record crowd behaviours, although there are two main arguments against this approach: (a) they are too fine-grained to be able to capture *general* attributes of a crowd, and (b) McPhail's work is largely focussed on *protest* crowds, and may not be easily modified to capture other forms of gathering.

A relatively influential (and more recent) attempt to characterise crowds is described in Berlonghi (1995), where eleven different crowd types (from "ambulatory" to "violent") are specified. However, these types are somewhat arbitrary, and some focus on the "objective" of the crowd (e.g."looting") while others describe its physical attributes (e.g., "dense"), with no distinction made between the two categories. Recent work has focused on the detection of crowd types for the purposes of safety management; a taxonomy constructed to aid the automatic labelling of crowd videos (Cheung et al., 2016) uses relatively arbitrary definitions (e.g., the difference between "Assertive" and "Aggressive" behaviour may not always be clear), and a related paper (Wei et al., 2020) also makes a number of assumptions that are perhaps difficult to justify (and relies on the now-discredited theories of Le Bon, 1897). A design-based approach to crowd categorisation (Lie et al., 2014) uses a diagrammatic methodology to capture the purpose, structure, "emotional arousal" and movement of crowds, but this provides only a static snapshot (however, the use of a participant *timeline*, using different crowd phases, is perhaps instructive for our purposes).

A report prepared for the UK government Cabinet Office (Challenger et al., 2011) highlights the relative scarcity of research into types of crowd (and members of crowds). The authors cite (Berlonghi, 1995), but emphasise that "...there is a real need for future research to focus on identifying different types of crowds – categorised according to a broad range of dimensions – along with the characteristics and behaviours they are likely to exhibit. Ultimately, this should assist event planners and managers with their preparation for, and management of, a particular crowd event with a particular type of crowd comprised of particular types of crowd member." The report proposes a crowd typology, which includes categorisation dimensions such as crowd purpose, duration, start time, individual locations, event atmosphere, and so on. Each category is then subdivided into subclasses (for example, "purpose" is divided into "sport/entertainment", "travel", "religious meeting/political demo", "spontaneous", and "mixed"). The authors state that such a typology "...could be used as a framework to help think through the numerous characteristic and likely behaviours which different types of crowd may have and, consequently, should help to guide event preparation".

While this typology is an advance on what went before, it still imposes a "top down" structure on crowd characteristics, and it is difficult to see how it easily admits the possibility of *emergent* (or unexpected) behaviours. Typologies such as this, arranged into a hierarchical, tree-like structure, view the crowd as essentially unchanging, without understanding where behaviours stem from. However, in reality, the behaviour of a crowd is inherently *dynamic* and *complex*, and is influenced by a number of factors (including, but not limited to, heterogeneity of its composition, size and density, physical location and space, emotions, communication, group dynamics, and other external and contextual factors) (Haghani et al., 2023).

We therefore believe that a dynamic, *transitional* model is needed, which captures the changing behaviour and attributes of a crowd *over time*. Moreover, existing typologies still use relatively arbitrary labels for crowd types (e.g., "Religious meeting/political demo"), which may not capture all possible purposes. In what follows, we describe a new, more general model of crowds that captures a wide range of different gatherings, allows for dynamic crowd reconfiguration, is easily extensible, and offers the possibility of more formal encoding at a later date. This model is particularly well-suited to capturing the *evolution* of a crowd over time, and imposes relatively few arbitrary or subjective labels on participant behaviour.

Fundamentally, what we seek is a way of *conceptualising* the crowd that allows for dynamic reconfiguration and the incorporation of important concepts such as social identity (Seitz et al., 2017; Templeton and Neville, 2020), and which supports a move away from the "masses" model of crowds to embrace a more nuanced group-based approach (Templeton et al., 2015). Our model is partly inspired by the early work of Sime, who presented his *decomposition diagram* for domestic fires in Sime (1984). This work codified multiple verbal/written incident reports into a general descriptive framework for "act sequence analysis". Using this model, it is possible to describe different individual sequences of behaviours in a consistent manner, as well as capturing common patterns of behaviour. Another relevant paper (Kielar et al., 2014) presents an pedestrian decision-making model based on concurrent hierarchical finite state machines, which can generate goal-directed behavioural tendencies in simulated individuals.

3. Our dynamic state-based model

In this Section we present an abstract version of our model, introducing and illustrating its core components, and in Section 5 we give a formalisation of it. Our model is sufficiently general that it can be applied to both *physical* (Degond et al., 2013; Moussaid et al., 2009) and *psychological crowds* (Drury et al., 2009; Reicher, 2001; Templeton et al., 2018). The physical crowd is made up of people who simply happen to be in the same place at the same time, while the psychological crowd exhibits some form of common social identity (a sense of connectivity or feeling of being part of the same group) (Hornsey, 2008). With that in mind, we use the sub-definition of "crowd" given in Adrian et al. (2019):

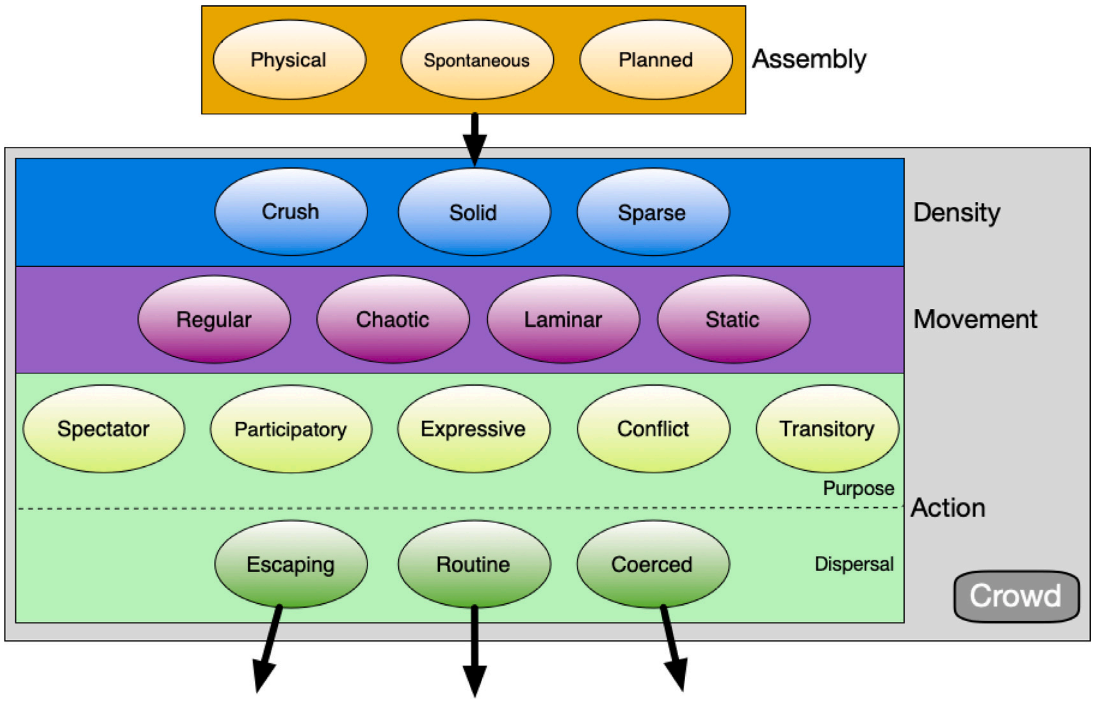

Fig. 1. High-level description of our model, showing variables and the possible values for each. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

"A (typically large) number of people in one place at the same time. It is possible that a physical crowd contains one or more psychological crowds (e.g. football fans in a transport hub with commuters)".

Importantly, in what follows, we assume a crowd has three main *attributes* (or variables); (1) a level of **density**, (2) a form (or lack) of **movement**, and (3) **action**, which corresponds to the crowd's "purpose". Each of these attributes may be assigned a value from a fixed set of states.

Our model is loosely inspired by the three-phase "convergence-task-divergence" life cycle framework (Adang, 2016) . By entering the **assembly** phase (corresponding to "convergence" in that framework), a crowd is essentially created, and a state is selected that describes the initial formation of a crowd. Once a crowd is in existence, we may dynamically (and repeatedly) assign values to the **density**, **movement** and *action* variables (the "task" phase), depending on both its internal operation and any external triggers or stimuli. The "divergence" phase is modelled by the "dispersal" subset of states in the **action** variable. This separation into different attributes avoids issues such as the conflation of rationale and structure, whilst giving the flexibility to capture a full range of interactions and dynamic behaviours. As in Sime (1984), within our model the evolution of a crowd is captured as a sequence of states and the transitions between them, which essentially describes a time series of events and crowd attributes. We now describe these in detail.

3.1. Assembly

Assembly is depicted by the yellow states; we necessarily select an arbitrary "start point" for consideration of the crowd event. After that time, a crowd may assemble in one of three basic ways:

- **physical**, where individuals congregate or move through a specific area, but *without common purpose* (e.g., a shopping street or transport hub). Such assemblies are also referred to as "casual" crowds, as there is no real shared identity present.
- **spontaneous**, where individuals form a crowd (or sub-crowd) *in response to a specific "trigger" event* (e.g., to watch a street performance, to act as bystanders at an incident (emergency or otherwise), or as a result of some external intervention.
- **planned**, where individuals gather for a *specific purpose* (e.g., a concert, sporting event). Crowds assembling in such a way are sometimes referred to as "conventional" (if the event is spectator-based, like a concert) or "expressive" (if the event is largely characterised by the expression of opinion, as in a political rally).

3.2. Density

Once a crowd is assembled, we might then consider its physical configuration, represented by the blue **density** states. By separating structure from "purpose", we address a significant flaw in previous typology-based approaches. Berlonghi (1995), for example, conflates the *purpose* of a crowd with its *physical characteristics*: examples of different crowd types within this typology include "spectator" and "dense/suffocating", implying that these crowd types are somehow disjoint. In fact, as many incidents have shown (e.g., fatal crowd crushes that occurred at Hillsborough Nicholson and Roebuck, 1995 and the Love Parade Helbing and Mukerji, 2012), crowds as whole should be able to simultaneously exhibit *more than one crowd type* under the typology model (for example, a dense/suffocating spectator crowd), and it is not immediately clear how this may be represented using a static typology. However, our model easily admits this by allowing for transitions between states and state values, as well as the formation of sub-groups.

We specify three **density** values that a crowd may take; **crush** (high density, no space between individuals, individuals are very tightly packed), **solid** (medium density, few gaps exist between individuals), and **sparse** (low density, identifiable gaps exist between individuals) (Still, 2014). Of course, any implementation of the model may apply its own density thresholds for each of these states.

3.3. Movement

Movement may be **regular** (essentially similar to that generated by standard movement models, without the existence of significant internal structure), **chaotic** (little, if any, coordination between individuals; movement is characterised by turbulence), **laminar** (layers or "streams" exist) (Helbing et al., 2007) or **static** (movement level is zero).

3.4. Action

Once the crowd has assembled, and we have assigned it values for **density** and **movement**, we consider its **action** variable, (depicted in Fig. 1 as the green cluster of states). This is conceptually sub-divided into two subsets of states; the "purpose" values determine the rationale of the crowd, and the "dispersal" states represent how the crowd dissipates. We now consider each in turn:

- **spectator**: the primary purpose of such crowds is to *watch or observe* a specific event (e.g., concert/cinema audience). Of course, we admit the possibility of audience participation in the event (e.g., applause, singing along), but this is not the *primary* rationale for the crowd's existence.
- **participatory**: these crowds display *active involvement* from individuals (e.g., a religious procession), without necessarily being characterised by expressions of opinion (see below).
- **transitory**: these crowds are generally characterised by *movement of individuals*, such as may be found in a busy street, or commuters moving through a transportation hub.
- **conflict**: these crowds are characterised by *hostility* or violence beyond the level of "expression", which may be expressed internally (e.g., a fight between members of the crowd), towards the environment (e.g., the destruction of property) or in relation to another group (e.g., police).
- **expressive**: such crowds largely exist for the purposes of *expression* (e.g., chanting at a political rally, or taking part in a celebration). Of course, there may be significant intersection with the "spectator" or "participatory" states.
- **escaping**: the crowd willingly leaves an area in response to a threat or other emergency, perhaps (but certainly not always) in response to information given or requests issued by the authorities. This state may include situations in which members of the crowd are *rescued* or similarly removed (e.g., from a crush).
- **routine**: the crowd disperses naturally in a "normal" fashion (this includes being "merged" into another crowd).
- **coerced**: the crowd is *forcibly* dispersed (against the will of its members) by the authorities (or even, perhaps, by another group).

4. Example scenario

In this Section we illustrate the application of our model by way of an imagined scenario - a city-centre rally taking place in a square (inspired, in part, by Drury and Reicher, 1999). We first describe the evolution of the incident, using the traditional form of text-based narrative and diagrams, and then show how this form of description might be mapped onto our model. By illustrating the mapping, we show how such informal descriptions may be *codified* in a consistent manner, as well as potentially allowing for integration with algorithmic analysis. In Fig. 2 we show the evolution of the scenario as a series of events, as follows:

a The crowd is assembling in the square. We identify two main clusters; one is made up of streams of people heading for the square, and the other is comprised of the people who are waiting for the rally to begin.
b The crowd has largely assembled, and is listening to a number of speakers (event 1).
c A section of the crowd begins to loudly chant anti-government slogans (event 2).
d In response to this, the police deploy a cordon of officers to contain and/or disperse the crowd, which creates a state of conflict with the protestors (possibly also increasing the size of the protesting group) (event 3).
e The protesting group is now engaged in violent confrontation with the police, while other members of the crowd are escaping the scene (event 4).
f The protestors are dispersed by the police (event 5).

In Fig. 3 we show how this description might be informally represented within our model. We begin with an **assembly: planned crowd**, which has **density: sparse** and **movement: regular** (to represent people converging on a central point), and **action: transitory**, transitioning to **action: routine** to represent that the crowd is routinely absorbed at the meeting point. When enough people have accumulated at the meeting point and the rally has begun, we reach event 1 (the effective starting event), which is **assembly: planned**, **density: solid**, **movement: static** and **action: spectator** (listening to speakers).

Eventually, the protesting group emerges (event 2), which is **assembly: spontaneous**, **action: expressive** (but still **density: solid**, **movement: static**). An external event is triggered (the police intervention, denoted by the magenta cloud, event 3), acting on this group, which causes a "fork" (that is, the creation of two new groups). One group (the "conflict" group) has **movement: chaotic** and **action: conflict**, while the other "escaping" group has **movement: regular** and **dispersal: escaping**. Eventually the "conflict" group is dispersed by the police (event 5), so it adopts **movement:regular** and **dispersal:coerced**.

5. Model formalisation

In this Section we present a formal version of our model, using a discrete transition system to model the state and transitions of multiple crowds, and represent individual crowds as sets with corresponding dynamics operations. The aim is to capture our model within a standardised framework that may be used to both describe historical events and be integrated into existing software simulations to produce plausible patterns of crowd dynamics.

5.1. Preliminaries

Given a set of people $\mathcal{P}$, a *crowd* $C[a]$ is a subset of $\mathcal{P}$ that assembles in some manner a, where a is either $\mathbf{assembly}:\mathsf{physical}$, $\mathbf{assembly}:\mathsf{spontaneous}$, or $\mathbf{assembly}:\mathsf{planned}$. For convenience we will sometimes omit the manner of assembly and simply use C. We define the *state* of a crowd to be the behaviour and physical configuration of that crowd at some moment in time, and define it as a tuple in $Action \times Density \times Movement$, where

$$Action = \left\{ \begin{array}{ll} \mathbf{purpose}:\mathsf{spectating}, & \mathbf{purpose}:\mathsf{participating}, \\ \mathbf{purpose}:\mathsf{transitory}, & \mathbf{purpose}:\mathsf{conflict}, \\ \mathbf{purpose}:\mathsf{expressive}, & \mathbf{dispersal}:\mathsf{routine}, \\ \mathbf{dispersal}:\mathsf{escaping}, & \mathbf{dispersal}:\mathsf{coerced} \end{array} \right\},$$

$$Density = \left\{ \begin{array}{ll} \mathbf{density}:\mathsf{crush}, & \mathbf{density}:\mathsf{solid}, \\ \mathbf{density}:\mathsf{sparse} & \end{array} \right\},$$

$$Movement = \left\{ \begin{array}{ll} \mathbf{movement}:\mathsf{chaotic}, & \mathbf{movement}:\mathsf{laminar}, \\ \mathbf{movement}:\mathsf{regular}, & \mathbf{movement}:\mathsf{static} \end{array} \right\}.$$

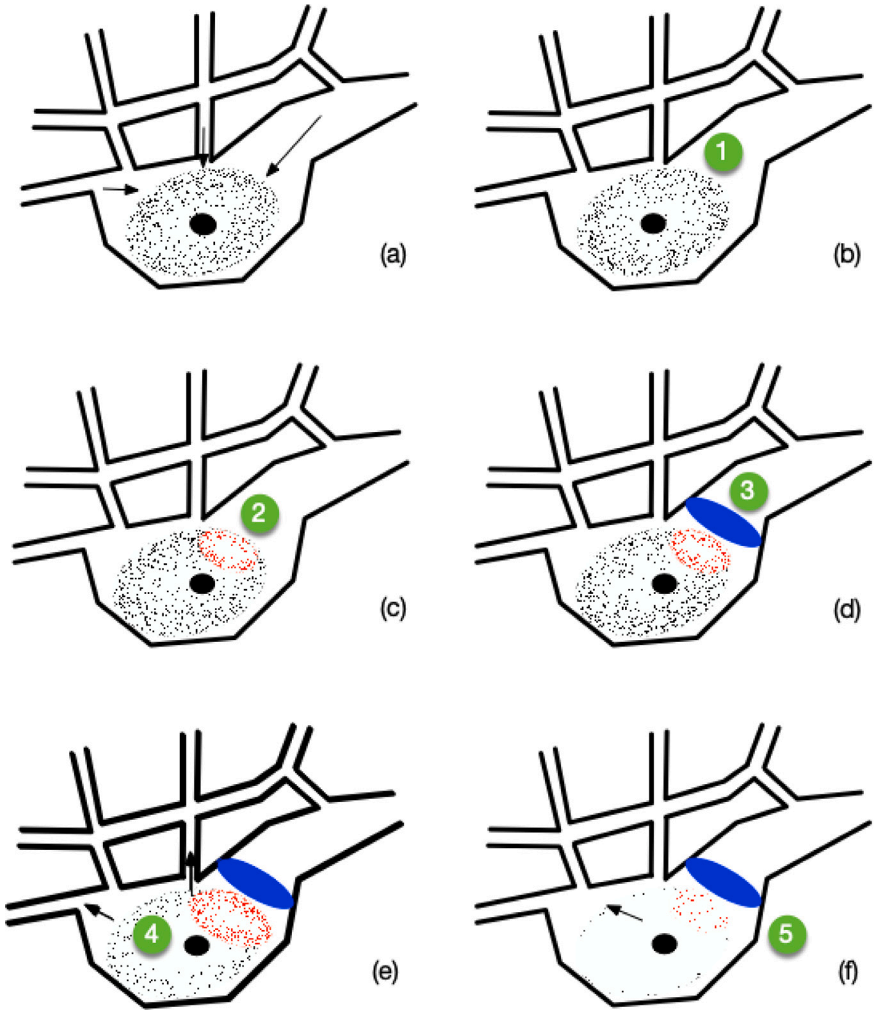

Fig. 2. Evolution of an imagined crowd incident. (a) Crowd gathers in square, with two main groups — the mobile "streams" and those already assembled. (b) The audience has assembled: (event 1). (c) A sub-group begins to demonstrate (event 2). (d) The police respond with a cordon (event 3). (e) This creates conflict with the sub-group, some other members of the crowd leave in response (event 4). (f) The remainder of the crowd is dispersed by the police (event 5).

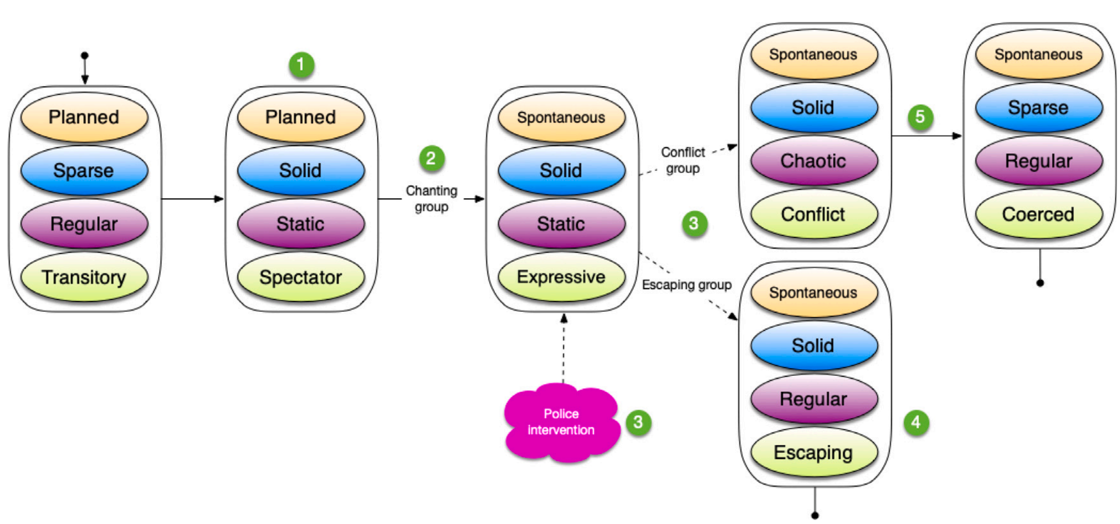

Fig. 3. Mapping of the incident onto our model. Specific events are labelled in green. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

5.2. Dynamics operations

Over time crowds may split into smaller groups, merge with other crowds, and increase or decrease in size. To model these changes we define the following *dynamics operations*:

1. *Aggregation*, where two or more crowds merge to form a single larger crowd.

   example $:\{C_1, C_2\} \rightsquigarrow C_3$
2. *Disaggregation*, where a crowd is partitioned into two or more smaller crowds.

   example $:C_1 \rightsquigarrow \{C_2, C_3\}$
3. *Transferal*, where members of one crowd leave and join another.

   example $:C_1 \curvearrowright C_2$
4. *Expansion*, where people who are not in a crowd join one.

   example $:\mathcal{P} \curvearrowright C_1$
5. *Contraction*, where existing members of a crowd leave (but do not join another crowd).

   example $:C_1 \curvearrowright \mathcal{P}$

5.3. Scenarios

A *scenario* models the event-driven dynamics of a set of N crowds over a finite sequence of T consecutive events. Formally, we define a scenario as a tuple $\mathfrak{S} = (\mathcal{P}, \mathcal{C}, \mathcal{E}, \Delta, \mathbf{S})$. The set $\mathcal{P}$ represents all people modelled by the scenario and $\mathcal{C}$ is the set of N crowds $C_1[a_1], C_2[a_2], \ldots, C_N[a_N]$ where each $C_i[a_i]$ is a subset of $\mathcal{P}$, any two crowds $C_i[a_i]$ and $C_j[a_j]$ are required to be mutually exclusive, and the union of all crowds is not necessarily equal to $\mathcal{P}$. Events that denote or induce some change in the behaviour or physical configuration of one or more crowds are represented by labels in the ordered *event set* $\mathcal{E}$. We use the notation $\mathcal{E}[k]$ to denote the kth element of this set. For each event in $\mathcal{E}$ there is a corresponding set of dynamics operations in the ordered set Δ. We use the notation $\Delta[k]$ to denote the kth set in Δ that defines changes to crowds after event $\mathcal{E}[k]$. The *state function* $\mathbf{S} : \{0 \ldots T\} \times \mathcal{C} \to Action \times Density \times Movement$ maps crowds to states at different moments in time, where $\mathbf{S}(k, C)$ is the state of crowd C after the kth event and $\mathbf{S}(0, C)$ denotes the *initial state* of that crowd. We use the notation $\mathbf{S}(k, C) = —$ to indicate that the state of crowd C is not defined after the kth event. A crowd that has no defined state either has not yet assembled, has fragmented into two or more other crowds, has merged into a larger crowd, or has dispersed.

5.4. Traces

A *global state* σ_k represents the behaviour and physical configuration of all N crowds after the kth event and is defined as the product of individual crowd states $\sigma_k = \times_{1 \le i \le N} \mathbf{S}(k, C_i)$. The *trace* of the scenario is then represented as a sequence of transitions between global states

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \ldots \xrightarrow{E[T-1],\Delta[T-1]} \sigma_{T-1} \xrightarrow{E[T],\Delta[T]} \sigma_T.$$

5.5. Application

We now show how the description of the scenario from Section 4 may be formalised. Let $\mathfrak{S} = (\mathcal{P}, \mathcal{C}, \mathcal{E}, \Delta, \mathbf{S})$ be the scenario, where:

$$\mathcal{C} = \begin{Bmatrix} C_1[\textbf{assembly}:\text{planned}], & C_2[\textbf{assembly}:\text{planned}], \\ C_3[\textbf{assembly}:\text{planned}], & C_4[\textbf{assembly}:\text{spontaneous}], \\ C_5[\textbf{assembly}:\text{spontaneous}] & \end{Bmatrix},$$

$$\mathcal{E} = \begin{pmatrix} \texttt{the crowd has largely assembled,} \\ \texttt{a section of the crowd begins to loudly chant,} \\ \texttt{the police deploy a cordon of officers,} \\ \texttt{the protesting group violently engages the police,} \\ \texttt{the protesters are dispersed by the police} \end{pmatrix},$$

$$\Delta = \begin{pmatrix} \{\{C_1, C_2\} \rightsquigarrow C_3\}, \\ \{C_3 \rightsquigarrow \{C_4, C_5\}\}, \\ \{C_4 \curvearrowright C_5\}, \\ \emptyset, \\ \emptyset \end{pmatrix}.$$

Trace The state function $\mathbf{S}$ will be defined as we iterate over the trace of the scenario.:

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5.$$

Note that we do not model '*the crowd is assembling in the square*' as an event, as it is actually a description of the initial global state σ_0 defined as:

$$\sigma_0 = \times \begin{pmatrix} (\textbf{purpose}:\text{transitory}, & \textbf{density}:\text{sparse}, & \textbf{movement}:\text{regular}), \\ (\textbf{purpose}:\text{spectating}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}), \\ & —, & \\ & —, & \\ & — & \end{pmatrix} \begin{matrix} \mathbf{S}(0, C_1) \\ \mathbf{S}(0, C_2) \\ \mathbf{S}(0, C_3) \\ \mathbf{S}(0, C_4) \\ \mathbf{S}(0, C_5) \end{matrix}$$

event $\mathcal{E}[1]$*:* `the crowd has largely assembled`. We transition to global state σ_1 observing that $\Delta[1] = \{\{C_1, C_2\} \rightsquigarrow C_3\}$, and hence that crowds C_1 and C_2 have merged to form the new crowd C_3.

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5$$

$$\sigma_1 = \times \begin{pmatrix} & —, & \\ & —, & \\ (\textbf{purpose}:\text{spectating}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}), \\ & —, & \\ & —, & \end{pmatrix} \begin{matrix} \mathbf{S}(1, C_1) \\ \mathbf{S}(1, C_2) \\ \mathbf{S}(1, C_3) \\ \mathbf{S}(1, C_4) \\ \mathbf{S}(1, C_5) \end{matrix}$$

event $\mathcal{E}[2]$*:* `a section of the crowd begins to loudly chant`. We transition to global state σ_2 observing that $\Delta[2] = \{C_3 \rightsquigarrow \{C_4, C_5\}\}$, and hence that crowd C_3 splits into two new crowds C_4 and C_5.

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5$$

$$\sigma_2 = \times \begin{pmatrix} & —, & \\ & —, & \\ & —, & \\ (\textbf{purpose}:\text{spectating}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}). \\ (\textbf{purpose}:\text{expressive}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}) \end{pmatrix} \begin{matrix} \mathbf{S}(2, C_1) \\ \mathbf{S}(2, C_2) \\ \mathbf{S}(2, C_3) \\ \mathbf{S}(2, C_4) \\ \mathbf{S}(2, C_5) \end{matrix}$$

event $\mathcal{E}[3]$*:* `the police deploy a cordon of officers`. In order to illustrate features of the model, we assume that the size of the protesting crowd *does* increase. We transition to global state σ_3 observing that $\Delta[3] = \{C_4 \curvearrowright C_5\}$, and hence that members of crowd C_4 have left that crowd and joined C_5. We do not explicitly model the cardinality of sets in this formalism, but this is a feature that could be added or defined elsewhere.

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5$$

$$\sigma_3 = \times \left(\begin{array}{ccc} & -, & \\ & -, & \\ & -, & \\ (\textbf{purpose}:\text{spectating}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}), \\ (\textbf{purpose}:\text{conflict}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{static}) \end{array}\right) \begin{array}{l} S(3,C_1)\\ S(3,C_2)\\ S(3,C_3)\\ S(3,C_4)\\ S(3,C_5) \end{array}$$

event $\mathcal{E}[4]$: `the protesting group violently engages the police`. We transition to global state σ_4. This time $\Delta[4]$ is the empty set, and we have no dynamics operations for the crowds.

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5$$

$$\sigma_4 = \times \left(\begin{array}{ccc} & -, & \\ & -, & \\ & -, & \\ (\textbf{dispersal}:\text{escaping}, & \textbf{density}:\text{sparse}, & \textbf{movement}:\text{regular}), \\ (\textbf{purpose}:\text{conflict}, & \textbf{density}:\text{solid}, & \textbf{movement}:\text{chaotic}) \end{array}\right) \begin{array}{l} S(4,C_1)\\ S(4,C_2)\\ S(4,C_3)\\ S(4,C_4)\\ S(4,C_5) \end{array}$$

event $\mathcal{E}[5]$: `the protesters are dispersed by the police`. We transition to global state σ_5. Again, $\Delta[5]$ is the empty set, and we have no dynamics operations for the crowds. Crowd C_4 dispersed in the previous state.

$$\sigma_0 \xrightarrow{E[1],\Delta[1]} \sigma_1 \xrightarrow{E[2],\Delta[2]} \sigma_2 \xrightarrow{E[3],\Delta[3]} \sigma_3 \xrightarrow{E[4],\Delta[4]} \sigma_4 \xrightarrow{E[5],\Delta[5]} \sigma_5$$

$$\sigma_5 = \times \left(\begin{array}{ccc} & -, & \\ & -, & \\ & -, & \\ & -, & \\ (\textbf{dispersal}:\text{coerced}, & \textbf{density}:\text{sparse}, & \textbf{movement}:\text{regular}) \end{array}\right) \begin{array}{l} S(5,C_1)\\ S(5,C_2)\\ S(5,C_3)\\ S(5,C_4)\\ S(5,C_5) \end{array}$$

This "worked example" raises a number of important issues/ considerations. While the dynamics operators define when crowds change, they do not "enforce" any such changes in the model. For example, there is nothing in the formalism to state that after an aggregation operation the state of all crowds that have merged should be equal to the null value — in all successive states. Similarly, there is no defined restriction in the model to enforce a crowd to have a null value for its state in the next global state after it has been dispersed. We assume that it might be the case that an event could occur during the dispersal of one or more crowds, so that they might be dispersing across more than one state.

We additionally observe that the sequence of sets of dynamics operators Δ could also be used to construct some form of tree structure that can be used for downstream analysis. For example, if our model for the example above formed the basis for a more advanced simulation we might be interested in determining the likelihood that a person in C_5 being dispersed in global state σ_5 was originally a member of C_1 in the initial state σ_0. Tracing back through such a tree might be useful to determine this. In addition, such a tree might be useful as an illustration tool to show how a scenario evolves, since it could be represented as a sequence of (possibly disjoint) Venn diagrams.

5.6. Generative version of the model

We now discuss how our model can be formulated as a discrete-time Markovian stochastic process that can be used to capture the *high-level* behaviours and dynamics of a population of simulated individuals and crowds (Sunshine-Hill et al., 2007; Gainer, 2020). We are interested in the behavioural and physical dynamics of (1) a population of individuals and (2) the crowds that they can form. Here, we show how high-level representations of such systems may be conceptualised as discrete-time Markov processes. In the case of the former, we formalise our model as a discrete-time Markov chain, and argue that such macroscopic representations can be useful when used in conjunction with microscopic numerical simulations. In the latter, we extend our models to Markov Decision Processes, which are formal representations of decision problems in stochastic environments, and discuss how they can be used for downstream tasks to learn interventional strategies for crowds.

5.6.1. Discrete-time Markov chain

Given a population of individuals $\mathcal{P}$ that can be members of a set of crowds $\mathcal{C}$ our model is a tuple $(\mathcal{S}, \mathcal{A}, \mathbf{P})$, where $\mathcal{S}$ is the set of all possible global states for the crowds in $\mathcal{C}$. The set of all possible *actions* in the environment is denoted by $\mathcal{A}$. An action may refer to a direct intervention made by some agent or agency (for example, `the police deploying a cordon of officers` in the example in Section 4), a change in the behaviour or structure of a crowd (for example `a section of the crowd begins to chant loudly`), stochastic environmental effects arising from other models forming part of complex composite simulations (for example, adverse weather conditions), or any other external intervention that results in a change in state for one or more crowds. Each action is a tuple in $\mathcal{E}\times\mathbb{P}(\Delta_C)$ where $\mathcal{E}$ is a set of labels describing an intervention that denotes or induces some change in the behaviour or physical configuration of one or more crowds, Δ_C is the set of all possible dynamics operations (see Section 5) expressible over crowds in $\mathcal{C}$, and $\mathbb{P}$ denotes the powerset. The function $\mathbf{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0,1]$ gives the likelihood of one state transitioning to another, where $\mathbf{P}(\sigma_1, a, \sigma_2)$ is the conditional probability $P(\sigma_2 \mid a, \sigma_1)$ that the model transitions to state σ_2 given that the environment takes action a in state σ_1.

The construction of the distribution over successor states lies outside the scope of this work. This we defer to the human expert designing the underlying microscopic simulation. While we do not directly refer to the size of crowds in our basic model, it is clear that by labelling such sets (crowds) with their respective cardinalities our model can provide a succinct 'snapshot' of a microscopic model at some point in time. Furthermore, we postulate that more complex couplings between the high- and low-level models may yield more rich representations than when using simulations alone, as macroscopic crowd states may in turn be perceived by individual crowd members, influencing their behaviour and creating a feedback process.

5.6.2. A framework for learning

We may often be interested in *learning* appropriate interventional strategies to influence the dynamics of crowds over time. For example, given our example from Section 4 we might be interested in learning which actions the police may take in order to minimise the likelihood of reaching a state of conflict. To achieve this we may extend our model from Section 5 to a Markov Decision Process (MDP) (Bellman, 1957), a mathematical framework for modelling sequential decision problems under uncertainty which has already been successfully applied to crowd simulation (Ruiz and Hernández, 2015). We extend the model from Section 5 with *rewards* to the tuple $(\mathcal{S}, \mathcal{A}, \mathbf{P}, \mathbf{R})$. The function $\mathbf{R} : \mathcal{S}\times\mathcal{A}\times\mathcal{S} \to \mathbb{R}$ maps state transitions to real valued rewards, where $\mathbf{R}(\sigma_1, a, \sigma_2)$ is the reward obtained for reaching σ_2 when taking action a in state σ_1. Accumulating a reward along the trace of the model yields a weight that can be used to modulate the efficacy of the sequence of actions that were taken with respect to achieving some defined objective. Well-established methodologies such as Reinforcement Learning (Sutton and Barto, 2018) (RL) can then be used to obtain optimum strategies (known as *policies* in the RL literature) by learning the distribution over actions conditioned on the current state of the model. For example, if we are interested in learning a strategy that the police should follow to minimise the risk of reaching a state of conflict, as in the previous example, then we should accordingly assign higher rewards to actions that resulted in transitions to states where no conflict occurs. We note that determining appropriate rewards is the task of the human expert defining both the system and the learning objective.

6. Summary and further work

In this paper we have described a dynamic state-based model of crowds that is capable of dealing with changes in assembly, rationale, physical structure and dispersal over time. It is sufficiently general to encompass a wide variety of crowds, and is particularly well-suited to handling the formation of sub-groups. Importantly, we present this simply as a starting point, in a descriptive (rather than prescriptive) fashion. The model may be easily augmented or modified to suit a particular purpose — what we propose here is a general conceptual architecture for thinking about the evolution of crowds over time, rather than a rigid typology. We acknowledge a number of limitations of our model. We still make some relatively subjective decompositions (e.g., in terms of the physical states, which may not capture specific structures in sufficient detail). The issue of *granularity* is still relatively fuzzy (e.g., at what point do we decide to create a new crowd to represent the emergence of a new group, area of differential density, etc?). We also note that the transitions between discrete states are not always sharp; rather, crowds/groups may exist on a *continuum* between states. However, we believe that this model offers a new framework for thinking about and representing the types of dynamic macroscopic outcomes that emerge from the interactions between individuals and their environment (Gwynne and Hunt, 2018).

The need for a dynamic model is particularly important with the growth in reliance on simulation tools within crowd science and the practice of crowd management (Haghani, 2021). As noted in Challenger et al. (2011), ''The next generation of simulation tools should be able to accommodate multiple environments and multiple crowd events in the same simulation model, rather than solely modelling one particular event in one particular environment''. This is precisely what our model offers, and future work will focus on both investigating how it might be incorporated into crowd simulation platforms, and using it to analyse historical footage and accounts of crowd-incidents, in order to compile a set of case studies. We believe that this will be particularly valuable in terms of capturing and codifying complex event narratives (perhaps, in future work, using an algorithmic or AI-based approach), where multiple events occur in parallel, external factors are significant, and the emergence and behaviour of sub-crowds is highly dynamic (e.g., the Hillsborough and Love Parade disasters).

CRediT authorship contribution statement

Martyn Amos: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Paul Gainer:** Writing – review & editing, Methodology. **Steve Gwynne:** Writing – review & editing, Methodology. **Anne Templeton:** Writing – review & editing, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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