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Can cooperation slow down emergency evacuations?

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ABSTRACT

We study the motion of pedestrians through obscure corridors where the lack of visibility hides the precise position of the exits. Using a lattice model, we explore the effects of cooperation on the overall exit flux (evacuation rate). More precisely, we study the effect of the buddying threshold (of no exclusion per site) on the dynamics of the crowd. In some cases, we note that if the evacuees tend to cooperate and act altruistically, then their collective action tends to favor the occurrence of disasters.

1. Introduction

This Note studies the following evacuation scenario: A large group of people needs to evacuate a subway station or a tunnel system [with complicated geometry] without visibility. The lack of visibility, or say, the heavily reduced visibility, can be imagined to be due to the breakdown of the electricity network, or due to the presence of a very dense or irritating smoke. We assume also that the evacuation audio signaling is not activated and that, in spite of all these difficulties, all pedestrians need to travel through this dark region and must find as soon as possible their way out towards the hidden exit. Additionally, we assume that all the persons are *equally fit* (i.e. they are indistinguishable) and that none of them has a priori knowledge on the location of the exit. To keep things simple, we consider that there are not spatial heterogeneities inside the region in question.

There are studies done (especially for fire evacuation scenarios) on how information and way finding systems are perceived by individuals. One of the main questions in fire safety research is whether green flashing lights can influence the evacuation (particularly, the exit choice); see e.g. [1–3] (and the fire engineering references cited therein) and [4] (partial visibility due to a non-uniform smoke concentration), [5] (partial visibility as a function of smoke's temperature), [6] (flow heterogeneity due to fire spreading). If exits are visible, then an impressive amount of literature provide proper working methodologies and efficient simulation tools. Preliminary assessment tests (cf. e.g., [7–9]) and many modeling approaches (deterministic or stochastic) succeed to capture qualitatively basic behaviors of humans (here referred to as pedestrians) walking within a given geometry towards a priori prescribed exits; see, for instance, social force/social velocity crowd dynamics models (cf. e.g. [10–13]), simple asymmetric exclusion models (see Chapters 3 and 4 from [14] as well as references cited therein), cellular automaton-type models [15,16], etc.

However, as far as we are aware, nothing seems to be known about evacuating people through regions without visibility, therefore our interest.

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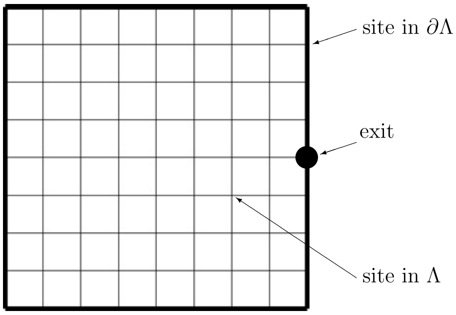

Fig. 1. Geometry of the model.

By means of a minimal model, we wish to describe how a bunch of people located inside a dark (smoky, foggy, etc.) corridor exits through an invisible door open in one of the four walls. We decide on this way (cf. Section 2) on a possible mechanism regarding how do pedestrians choose their path and speed when they are about to move through regions with no visibility. The question that triggers our attention here is the following:

Is cooperation/group formation the right strategy to choose to ensure the crowd evacuation within a reasonable time?

2. A lattice model

We use a minimal lattice model, which we name the *reverse mosca cieca game*, where we incorporate a few basic rules for pedestrian motion in the dark (see Fig. 1).

2.1. Basic assumptions on the pedestrians motion

We take into consideration the following four mechanisms:

(A1) In the core of the corridor, people move freely without constraints;
(A2) The boundary is reflecting, possibly attracting;
(A3) People are attracted by bunches of other people up to a threshold, say T;
(A4) People are blind in the sense that there is no drift (desired velocity) leading them towards the exit.

(A1)–(A4) are intended to describe the following situation:

Since, in this framework, neighbors (both individuals or groups) can not be visually identified by the individuals in motion, basic mechanisms like attraction to a group, tendency to align, or social repulsion are negligible and individuals have to live with "preferences". Essentially, their motion is more *behavioral* than *rational*. We assume that the individuals move freely inside the corridor, but they like to buddy to people they accidentally meet at a certain point (site). The more people are localized at a certain site, the stronger the preference to attach to it. However, if the number of people at a site reaches a threshold, then such site becomes not attracting for eventually new incomers. (A3), referred here as the *buddying mechanism*, is the central aspect of our research.

Once an individual touches a wall, he/she simply feels the need to stick to it at least for a while, i.e. until he/she can attach to an interesting site (having conveniently many hosts) or to a group of unevenly occupied sites or the exact location of the door is detected.

Since people have no desired velocity, their diffusion (random walk) together with the buddying are the only transport mechanisms. Can these eventually lead to evacuation? How efficient is such combination?

In the following, we study the effect of the threshold (of no-exclusion per site) on the overall dynamics of the crowd. Here we describe our results in terms of the averaged outgoing flux; see Figs. 2 and 3. In a forthcoming publication, we will investigate also other macroscopic quantities like the stationary occupation numbers and stationary correlations.

2.2. The lattice model

We start off with the construction of the lattice. Let $\Lambda \subset \mathbb{Z}^2$ be a finite square with odd side length L (Fig. 1). We refer to this generic room as the *corridor* where the dynamics is about to happen. Each element x of Λ will be called a *cell* or *site*. Two sites are said to be *nearest neighbor* if and only if their mutual Euclidean distance is equal to one. For any $x \in \Lambda$, we let $\Gamma(x)$ be the cross-shaped subset of Λ made of x and its four nearest neighbors. The *external boundary* $\partial\Lambda$ of Λ, i.e., the collections of the sites in $\mathbb{Z}^2 \setminus \Lambda$ neighboring one site in Λ, is made of four segments made of L cells each. The point at the center of one of these four sides is called *exit* and is denoted by x_{e}.

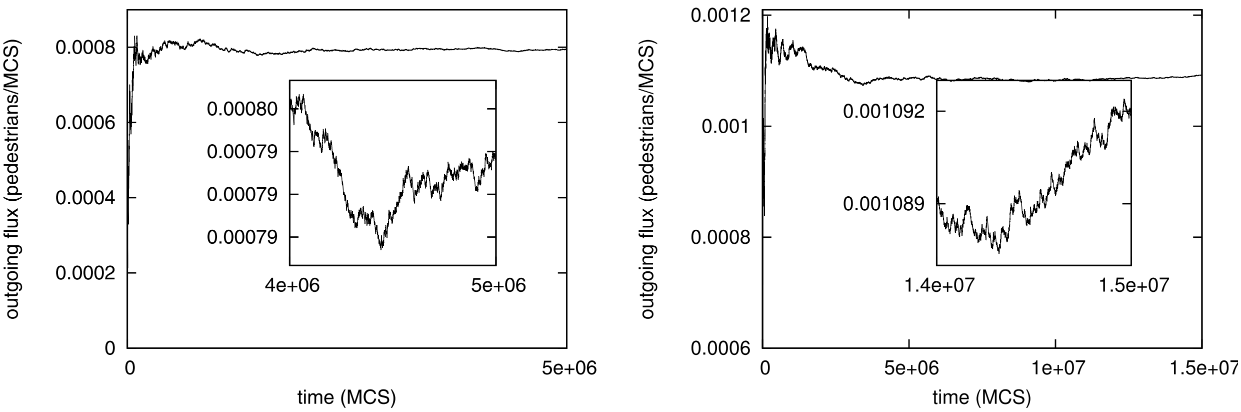

Fig. 2. Averaged outgoing flux vs. time in the case $T = 0$ and $N = 100$ on the left and $T = 100$ and $N = 100$ on the right. The inset is a zoom in the time interval $[4 \times 10^6, 5 \times 10^6]$ on the left and $[1.4 \times 10^7, 1.5 \times 10^7]$ on the right.

Let N be a positive integer denoting the (total) *number of individuals* inside the corridor Λ. We consider the state space $X := \{0, \ldots, N\}^{\Lambda}$. For any state $n \in X$, we let $n(x)$ be the *number of individuals* at cell x.

We define, now, a Markov chain n_t on the finite state space X with discrete time $t = 0, 1, \ldots$. For any $x \in \Lambda$, $n_t(x) \in \{0, 1, \ldots, N\}$ is the number of individuals at site x and at time t. At each time t, the position of all the individuals on each cell is updated according to the following rule: the individual at site $x \in \Lambda$ jumps to the site $y \in \Lambda \cup \{x_e\}$ with the probability $p(x, y)$ that will be defined below; note it can be $y = x$. If one of the individuals jumps on the exit cell a new individual is put on a cell of Λ chosen randomly with the uniform probability $1/L^2$.

The dynamics is controlled by a single integer parameter T, called *buddying threshold*, which has to be chosen in the set $\{0, 1, \ldots, N\}$. We define the function $S : \mathbb{N} \to \mathbb{N}$ such that for any $k \in \mathbb{N}$

$$S(k) = 1 \quad \text{if } k > T \quad \text{and} \quad S(k) = k + 1 \quad \text{if } k \leqslant T$$

Note that, whatever the value of T is, for $k = 0$ we have $S(0) = 1$.

Given a configuration $n \in X$, given $x \in \Lambda$ and $y \in \Lambda \cup \{x_e\}$, we define the probability $p(x, y)$ for an individual to jump from x to y as follows: We let $p(x, y) = 0$ if $y \notin \Gamma(x)$ and

$$p(x, y) := \frac{S(n(y))}{\sum_{w \in \Gamma(x) \cap \Lambda} S(n(w))}$$

for any $y \in \Gamma(x)$, where we understand $n(x_e) = T + 1$. With this choice we treat the exit as a bulk site at the threshold. It is worth stressing here that T is not a threshold in $n(x)$ – the number of individuals per cell. It is a threshold in the probability that such a cell is likely to be occupied or not.

Note that the approach we take here is very much influenced by a basic scenario described in [17,18] for randomly moving sodium ions willing to pass through a switching on–off membrane gate. The major difference here is twofold: the gate is permanently open and the buddying principle is activated.

3. Comments on cooperation effects – the buddying threshold *T*

The possible choices for the parameter T correspond to two different physical situations. The first one, for $T = 0$, the function $S(k)$ is equal to 1 (the minimal quantum) whatever the occupation numbers are. This means that each individual has the same probability to jump to one of its nearest neighbors or to stay on his site. This is resembling the independent symmetric random walk case; the only difference is that with the same probability the individuals can decide not to move. We expect that this “rest probability” just changes a little bit the time scale.

The second physical case is $T > 0$. For instance, $T = 1$ means *mild buddying*, while $T = 30, 100$ would express an *extreme buddying*. Note that $T = 100$ is not realist but we used it in the simulations to check the behavior of the model with increasing T. No simple exclusion is included in this model: on each site one can cluster as many particles (pedestrians) as one wants. The basic role of the threshold is the following: The weight associated to the jump towards the site x increases from 1 to $1 + T$ proportionally to the occupation number $n(x)$ until $n(x) = T$, after that level it drops back to 1. Note that this rule is given on weights and not on probabilities. Therefore, if one has T particles at y and T at each of its nearest neighbors, then at the very end one will have that the probability to stay or to jump to any of the nearest neighbors is the same. Differences in probability are seen only if one of the five (sitting in the core) sites involved in the jump (or some of them) has an occupation number large (but smaller than the threshold).

The main quantity of interest is the *outgoing flux*, namely, the total number of pedestrians which reached the exit in a time interval times the length of the time interval (number of Monte Carlo Steps (MCS)). In Fig. 2 we plot the outgoing flux

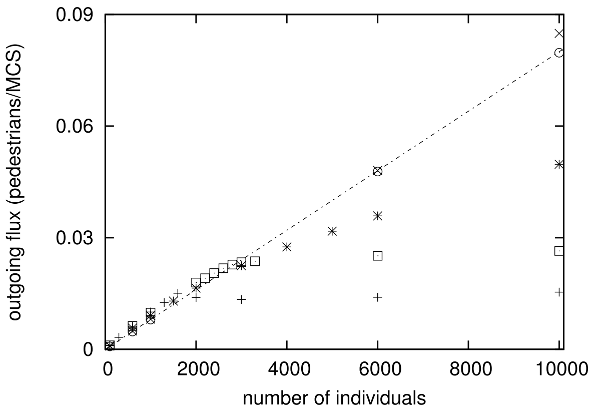

Fig. 3. Averaged outgoing flux vs. number of pedestrians. The symbols $\circ$, $\times$, $*$, $\square$, and $+$ refer respectively to the cases $T = 0, 1, 5, 30, 100$. The straight line has slope 8×10^{-6} and has been obtained by fitting the Monte Carlo data corresponding to the case $T = 0$.

as function of time: note that the measured quantities approach a reasonably stationary value after about 10^7 Monte Carlo steps. In Fig. 3, we see that the overall dynamics very much depends on both the number N of individuals and their ability to cooperate (the threshold T). In particular, this figure indicates that if N is sufficiently large, then cooperation does not seem to be the best option. Otherwise, for N sufficiently small, cooperation seems to be able to ensure a timely evacuation. This counter intuitive effect is not explaining why cooperation can, under certain circumstances, slow down emergency evacuations. More research initiatives in this direction are needed in order to shed light on this important issue.

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