

# How simple rules determine pedestrian behavior and crowd disasters

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With the increasing size and frequency of mass events, the study of crowd disasters and the simulation of pedestrian flows have become important research areas. However, even successful modeling approaches such as those inspired by Newtonian force models are still not fully consistent with empirical observations and are sometimes hard to calibrate. Here, a cognitive science approach is proposed, which is based on behavioral heuristics. We suggest that, guided by visual information, namely the distance of obstructions in candidate lines of sight, pedestrians apply two simple cognitive procedures to adapt their walking speeds and directions. Although simpler than previous approaches, this model predicts individual trajectories and collective patterns of motion in good quantitative agreement with a large variety of empirical and experimental data. This model predicts the emergence of self-organization phenomena, such as the spontaneous formation of unidirectional lanes or stop-and-go waves. Moreover, the combination of pedestrian heuristics with body collisions generates crowd turbulence at extreme densities—a phenomenon that has been observed during recent crowd disasters. By proposing an integrated treatment of simultaneous interactions between multiple individuals, our approach overcomes limitations of current physics-inspired pair interaction models. Understanding crowd dynamics through cognitive heuristics is therefore not only crucial for a better preparation of safe mass events. It also clears the way for a more realistic modeling of collective social behaviors, in particular of human crowds and biological swarms. Furthermore, our behavioral heuristics may serve to improve the navigation of autonomous robots.

collective behavior | decision making | individual-based model | nonlinear dynamics

Human crowds display a rich variety of self-organized behaviors that support an efficient motion under everyday conditions (1–3). One of the best-known examples is the spontaneous formation of unidirectional lanes in bidirectional pedestrian flows. At high densities, however, smooth pedestrian flows can break down, giving rise to other collective patterns of motion such as stop-and-go waves and crowd turbulence (4). The latter may cause serious trampling accidents during mass events. Finding a realistic description of collective human motion with its large degree of complexity is therefore an important issue.

Many models of pedestrian behavior have been proposed to uncover laws underlying crowd dynamics (5–8). Among these, physics-based approaches are currently very common. Well-known examples are fluid-dynamic (9) and social force models (1, 7, 8, 10), which are inspired by Newtonian mechanics. The latter describe the motion of pedestrians by a sum of attractive, repulsive, driving, and fluctuating forces reflecting various external influences and internal motivations. However, even though physics-inspired models are able to reproduce some of the observations quite well, there are still a number of problems. First, it is becoming increasingly difficult to capture the complete range of crowd behaviors in one single model. Recent observations have required extensions of previous interaction functions, which have led to quite sophisticated mathematical expressions that are

relatively hard to calibrate (10). Second, these models are based on the superposition of binary interactions. For example, in a situation where an individual A is facing three other individuals B, C, and D, the behavior of A is given by an integration of the interaction effects that the three individuals would separately have on A in the absence of the others. However, this approach raises many theoretical issues, such as how to integrate the binary interactions (e.g., to sum them up, average over them, or combine them nonlinearly), how to determine influential neighbors (e.g., the closest  $N$  individuals or those in a certain radius  $R$ ), and how to weight their influence (e.g., when located to the side of or behind the focal pedestrian) (6, 11, 12).

Here, we propose instead a cognitive science approach based on behavioral heuristics, which overcomes the above problems. Heuristics are fast and simple cognitive procedures that are often used when decisions have to be made under time pressure or overwhelming information (13, 14). Let us illustrate this by the example of a player trying to catch a ball, which may be modeled in at least two ways: either an attraction force can be used to describe the player's motion toward the estimated landing point of the ball or the process can be described by a so-called “gaze heuristic.” This heuristic consists of visually fixating on the ball and adjusting the position such that the gazing angle remains constant. Both methods predict similar behavior, but the heuristic approach is simpler and more plausible.

Heuristics have also successfully explained decision making in a variety of situations such as the investment behavior at stock markets or medical diagnosis in emergency situations (13). Modeling the *collective* dynamics of a social system with many interacting individuals through simple heuristics would be a promising approach. However, is it possible to apply a heuristics approach to pedestrian motion as well, given the wealth of different crowd dynamics patterns that have been observed?

In this work, we show that two simple heuristics based on visual information can in fact describe the motion of pedestrians well and that most properties observed at the crowd level follow naturally from them. Moreover, the combination of pedestrian heuristics with body collisions reproduces observed features of crowd disasters at extreme densities.

## Model

The elaboration of a cognitive model of pedestrian behavior requires two crucial questions to be addressed: (i) *What kind of information is used by the pedestrian?* And (ii) *how is this information processed to adapt the walking behavior?* With regard to

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the first question, past studies have shown that vision is the main source of information used by pedestrians to control their motion (15–17). Accordingly, we start with the representation of the visual information of pedestrians. To answer the second question, we propose two heuristics based on this visual information, which determine the desired walking directions  $\alpha_{\text{des}}$  and desired walking speeds  $v_{\text{des}}$  of pedestrians. Finally, we assume that pedestrians are continuously adapting their current walking behavior to match their desired behavior with a relaxation time  $\tau$  of 0.5 s (Fig. S1). This assumption has been confirmed under controlled laboratory conditions (10).

**Representation of Visual Information.** In our model, each pedestrian  $i$  is characterized by its current position  $\vec{x}_i$  and speed  $\vec{v}_i$ . For simplicity, we represent the projection of a pedestrian's body on the horizontal plane by a circle of radius  $r_i = m_i/320$ , where  $m_i$  is the mass of pedestrian  $i$  [e.g., uniformly distributed in the interval (60 kg 100 kg)]. Each pedestrian is additionally characterized by his or her comfortable walking speed  $v_i^0$  and his or her destination point  $O_i$ , namely the place in the environment he or she wants to reach, such as the exit door of a room or the end of a corridor. Finally, the vision field of pedestrian  $i$  ranges to the left and to the right by  $\phi^\circ$  with respect to the line of sight  $\vec{H}_i$ .

Past studies have shown that walking subjects can estimate the time to collision with surrounding obstacles by means of specialized neural mechanisms at the retina and brain levels (18, 19). Accordingly, we represent the pedestrian's visual information as follows: For all possible directions  $\alpha$  in  $[-\phi, \phi]$  (with a reasonable angular resolution), we compute the distance to the first collision  $f(\alpha)$ , if pedestrian  $i$  moved in direction  $\alpha$  at speed  $v_i^0$ , taking into account the other pedestrians' walking speeds and body sizes. If no collision is expected to occur in direction  $\alpha$ ,  $f(\alpha)$  is set to a default maximum value  $d_{\text{max}}$ , which represents the "horizon distance" of pedestrian  $i$  (Fig. 1).

**Formulation of the Cognitive Heuristics.** The first movement heuristic concerns the relative angle  $\alpha_{\text{des}}$  of the chosen walking direction compared with the line of sight. Empirical evidence suggests that pedestrians seek an unobstructed walking direction, but dislike deviating too much from the direct path to their

destination (16, 17). A trade-off therefore has to be found between avoiding obstacles and minimizing detours from the most direct route. Accordingly, our first heuristic is "A pedestrian chooses the direction  $\alpha_{\text{des}}$  that allows the most direct path to destination point  $O_i$ , taking into account the presence of obstacles." The chosen direction  $\alpha_{\text{des}}(t)$  is computed through the minimization of the distance  $d(\alpha)$  to the destination:

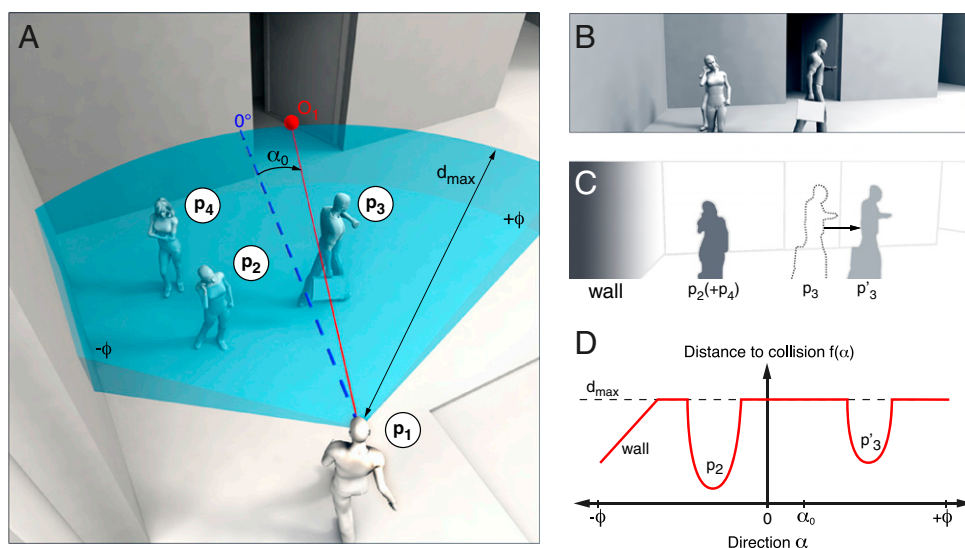
$$d(\alpha) = d_{\text{max}}^2 + f(\alpha)^2 - 2d_{\text{max}}f(\alpha)\cos(\alpha_0 - \alpha).$$

Here,  $\alpha_0$  is the direction of the destination point.

The second heuristic determines the desired walking speed  $v_{\text{des}}(t)$ . Because a time period  $\tau$  is required for the pedestrian to stop in the case of an unexpected obstacle, pedestrians should compensate for this delay by keeping a safe distance (20). Therefore, we formulate the second heuristic as follows: "A pedestrian maintains a distance from the first obstacle in the chosen walking direction that ensures a time to collision of at least  $\tau$ ." In other words, the speed  $v_{\text{des}}(t)$  is given by  $v_{\text{des}}(t) = \min(v_i^0, d_h/\tau)$ , where  $d_h$  is the distance between pedestrian  $i$  and the first obstacle in the desired direction  $\alpha_{\text{des}}$  at time  $t$ . The vector  $\vec{v}_{\text{des}}$  of the desired velocity points in direction  $\alpha_{\text{des}}$  has the norm  $\|\vec{v}_{\text{des}}\| = v_{\text{des}}$ . The change in the actual velocity  $\vec{v}_i$  at time  $t$  under normal walking conditions is given by the acceleration equation  $d\vec{v}_i/dt = (\vec{v}_{\text{des}} - \vec{v}_i)/\tau$ .

**Effect of Body Collisions.** In cases of overcrowding, physical interactions between bodies may occur, causing unintentional movements that are not determined by the above heuristics. Indeed, at extreme densities, it is necessary to distinguish between the *intentional* avoidance behavior of pedestrians adapting their motion according to perceived visual cues and *unintentional* movements resulting from interaction forces caused by collision with other bodies. We have therefore extended the above description by considering physical contact forces

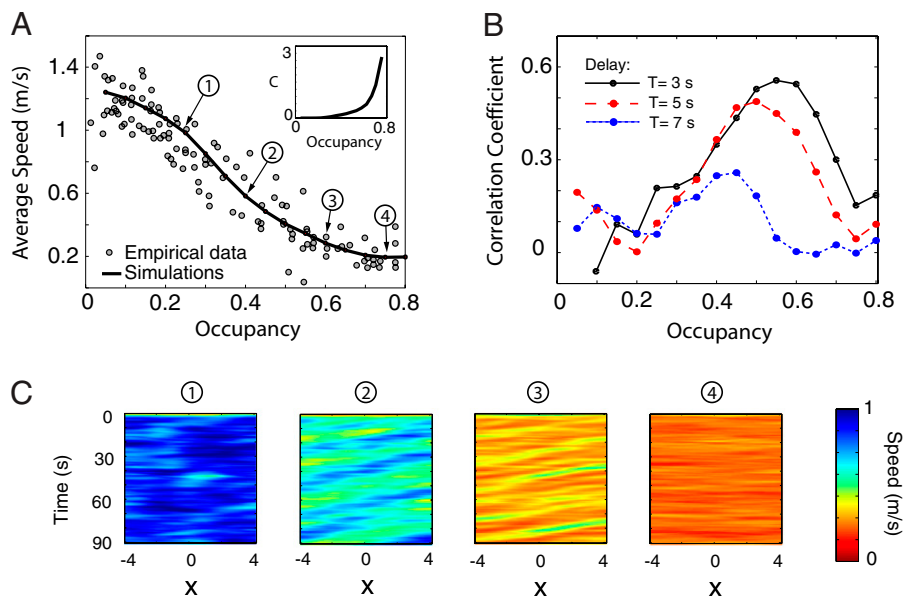
$$\vec{f}_{ij} = kg(r_i + r_j - d_{ij})\vec{n}_{ij},$$



**Fig. 1.** (A) Illustration of a pedestrian  $p_1$  facing three other subjects and trying to reach the destination point  $O_1$  marked in red. The blue dashed line corresponds to the line of sight. (B) Illustration of the same situation, as seen by pedestrian  $p_1$ . (C) Abstraction of the scene by a black and white visual field. Here, darker areas represent a shorter collision distance. (D) Graphical representation of the function  $f(\alpha)$  reflecting the distance to collision in direction  $\alpha$ . The left-hand side of the vision field is limited by a wall. Pedestrian  $p_4$  is hidden by pedestrian  $p_2$  and, therefore, not visible. Pedestrian  $p_3$  is moving away, so a collision would occur in position  $p'_3$ , but only if  $p_1$  moved toward the right-hand side.







**Fig. 3.** Evaluation of different kinds of collective dynamics resulting from unidirectional flows in a street of length  $l = 8$  m and width  $w = 3$  m. The total number of pedestrians varied from 6 to 96, assuming periodic boundary conditions. (A) Velocity–density relation, determined by averaging over the speeds of all pedestrians for 90 s of simulation. The occupancy corresponds to the fraction of area covered by pedestrian bodies. Our simulation results (black curve) are well consistent with empirical data (dots), which were collected in real-life environments (21). The *Inset* indicates the average body compression  $C = \langle C_i(t) \rangle_{i,t}$  where the brackets indicate an average over all pedestrians  $i$  and over time  $t$  (Materials and Methods). (B) Correlation coefficient between the average local speeds  $V(x,t)$  and  $V(x-X, t+T)$ , measuring the occurrence of stop-and-go waves (see Materials and Methods for the analytical definition of the local speed). Here, the value of  $X$  is set to 2 m. The increase at intermediate densities indicates that speed variations at positions  $x$  and  $x-X$  are correlated for an assumed time delay  $T$  of 3 s. Significant  $P$  values for the correlation coefficient are found for occupancies between 0.4 and 0.65, indicating the boundaries of the stop-and-go regime (Fig. S3). (C) Typical space–time diagrams at four density levels, representing different kinds of collective motion. The color coding indicates the local speed values along the street (where pedestrians move from left to right). At occupancy level 1, the diagram displays a smooth, laminar flow with occasional variations in speed. For occupancy levels 2 and 3, stop-and-go waves appear, as they have been empirically observed at high densities (figure 2a in ref. 4). At occupancy level 4, the average traffic flow is almost zero, but turbulent fluctuations in the flow occur (Fig. 4). The underlying model parameters are  $\tau = 0.5$  s,  $\phi = 45^\circ$ ,  $d_{\max} = 8$  m, and  $k = 5 \times 10^3$ . The desired speed  $v_0^i$  was chosen according to a normal distribution with mean value 1.3 m/s and SD = 0.2.

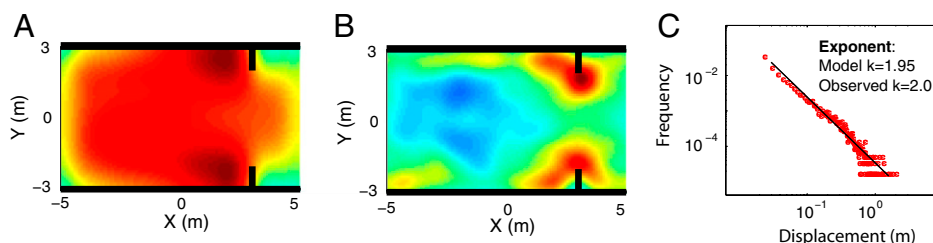
conditions with reduced visibility (e.g., escaping from a smoke-filled room) (2, 29).

In the future, further evidence for our cognitive, heuristics-based model could be collected by using eye-tracking systems (30) to determine the visual cues followed by pedestrians. Our approach also opens perspectives in other research areas. In the field of autonomous robotics, for example, the model may serve to improve navigation in complex dynamic environments, which is particularly relevant for swarms of mobile robots (31). In fact, navigation and collision-avoidance concepts of multirobot systems have often been inspired by human behavior (32, 33). The

simplicity of our approach and its visual information input will support resource-efficient designs. We also expect that our heuristics-based approach will inspire new models of collective human behavior such as group decision making (34) and certain social activity patterns (35, 36), where the occurrence of simultaneous interactions between multiple individuals matters.

## Materials and Methods

**Experimental Setup.** The controlled experiments shown in Fig. 2 were conducted in 2006 in Bordeaux (France). The experimental corridor of 7.88 m length and 1.75 m width was equipped with a 3D tracking system, which consisted of three digital cameras (SONY DCR-TRV950E) mounted at the



**Fig. 4.** Characterization of turbulent flows in front of a bottleneck for an occupancy value of 0.98. (For the analysis of a turning corridor as in the Love Parade disaster in Duisburg in 2010, see Fig. S4). (A) The local body compression  $C(\vec{x})$  reveals two critical areas of strong compression in front of the bottleneck (shown in red). (B) Analyzing the “crowd pressure” (defined as local density times the local velocity variance) (Materials and Methods) reveals areas with a high risk of falling (in red), indicating the likelihood of a crowd disaster (4). (C) Distribution of displacements (i.e., location changes between two subsequent stops, defined by speeds with  $\|\vec{v}_i\| < 0.05$  m/s). The double logarithmic representation reveals a power law with slope  $k = -1.95 \pm 0.09$ , in good agreement with empirical findings (see figure 3e in ref. 4, where the slope is  $k = -2.01 \pm 0.15$ ). The local speed, local pressure, and local compression coefficients are defined in Materials and Methods. The above results are based on simulations of 360 pedestrians during 240 s in a corridor of length  $l = 10$  m and width  $w = 6$  m, with a bottleneck of width 4 m, assuming periodic boundary conditions.

corners of the corridor. The reconstruction of the positions was made on the basis of the digital movies encoded at 12 frames/s with the help of software developed by our team. The trajectories were smoothed over a time window of 10 frames. A total of 40 participants agreed to participate in the experiment and were naive to its purpose. Pairs of pedestrians were randomly matched and performed ~20 replications of the following two conditions: (i) One subject was instructed to stand still in the middle of the corridor, while the other one was instructed to walk from one end of the corridor to the other and had to evade the standing pedestrian; (ii) starting from opposite ends of the corridor, both subjects were instructed to walk toward the other end after the starting signal. A total of 148 and 123 trajectories were reconstructed for conditions *i* and *ii*, respectively.

**Definition of Local Variables.** The simulation results presented in the main text were analyzed by measuring the local speed, local “pressure,” and local compression coefficients (4). The local speed  $V(x, t)$  at place  $x$  and time  $t$  (used in Fig. 3C) was defined as

$$V(x, t) = \frac{\sum_i \|\vec{v}_i\| f(d_{ix})}{\sum_i f(d_{ix})},$$

where  $d_{ix}$  is the distance between  $x$  and pedestrian  $i$ . In this definition,  $f(d)$  is a Gaussian distance-dependent weight function defined as:

$$f(d) = \frac{1}{\pi R^2} \exp \left( -\frac{d^2}{R^2} \right),$$

where  $R$  is a measurement parameter. The value  $R = 0.7$  m provides a reasonably precise evaluation of the local speed. The local body compression

coefficient  $C(x)$  (used in Fig. 4A) was computed in a way analogous to the local speed, setting

$$C(x, t) = \frac{\sum_i C_i(t) f(d_{ix})}{\sum_i f(d_{ix})},$$

and  $C(x) = \langle C(x, t) \rangle_t$ , where the brackets denote an average over time. The body compression  $C_i(t)$  of a pedestrian  $i$  is the sum of the contact forces  $\vec{f}_{ij}$  applied to pedestrian  $i$ :

$$C_i(t) = \sum_j \|\vec{f}_{ij}(t)\|.$$

Finally, the critical zones identified in Fig. 4B are given by the “crowd pressure”  $P(x) = p(x) \text{Var}(V(x, t))$  defined in ref. 4; i.e., the pressure corresponds to the average local density  $\rho(x) = \sum_i f(d_{ix})$  times the local speed variance at place  $x$ .

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