Crowd Simulation with Deliberative-reactive Agents

Cristian Berceanu[1], Ionuț Banu[1], Bettina S. Husebo[2,3] and Monica Patrascu[1,2,3,*]

[1]Complex Systems Laboratory, University Politehnica of Bucharest, Romania
[2]Centre for Elderly and Nursing Home Medicine, University of Bergen, Norway
[3]Neuro-SysMed Center, University of Bergen, Norway

Abstract
Crowd dynamics are emergent processes caused by local pedestrian interactions. In this work, we describe a decentralized crowd simulation model based on deliberative-reactive agents. The model simulates fire evacuation scenarios and includes specific behaviors such as collisions, panic, bottleneck and cluster formation. The environment interactions are passive (fire alarms) or active (adaptive guidance indicators). Results show that the model is able to generate higher level dynamics through emergence. An analysis based on psychological reaction time shows that the crowd behaves like an organic whole, aligning with observations of real-world human crowds. This paper is a summary of "Predictive Agent-Based Crowd Model Design Using Decentralized Control Systems" published in IEEE Systems Journal (2022).

Keywords
agent-based modeling, complex systems, simulation model, emergence, human behavior modeling

1. Introduction

Emergency evacuation of buildings is a challenging crowd behavior problem [1], suitable for complex multi-agent modeling [2, 3]. This paper is a summary of "Predictive Agent-Based Crowd Model Design Using Decentralized Control Systems" published in IEEE Systems Journal (2022) [4], in which we design a predictive agent-based crowd model, with the purpose of analyzing the outcomes of emergency evacuation, while taking into account pedestrian collisions, the effect of smoke, and environment artefacts such as fire sprinklers, alarms, and exit indicators.

The dynamics of a crowd must consider the heterogeneous behaviors of individuals and their social interactions [5, 6]. As a *complex system*, the dynamics of a crowd emerge from local interactions between component systems (i.e. the human participants). Evacuation dynamics show special stress conditions, which propagate along the crowd through mechanical and social interactions. From the three main categories of pedestrian simulation models [7], microscopic models consist of a large number of interacting agents with specific behaviors [8, 9]. To track the movement of people, we propose a microscopic modeling approach.

Current crowd modeling studies [10, 11, 12] reduce the crowd participants to particles without dynamics or inference. In real-life situations, each person makes individual decisions that are influenced by the environment, other participants, psychological and physiological properties,

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*Corresponding author.
0000-0003-3210-5977 (C. Berceanu); 0000-0001-9475-9189 (I. Banu); 0000-0002-6037-2864 (B. S. Husebo); 0000-0003-2201-2312 (M. Patrascu)

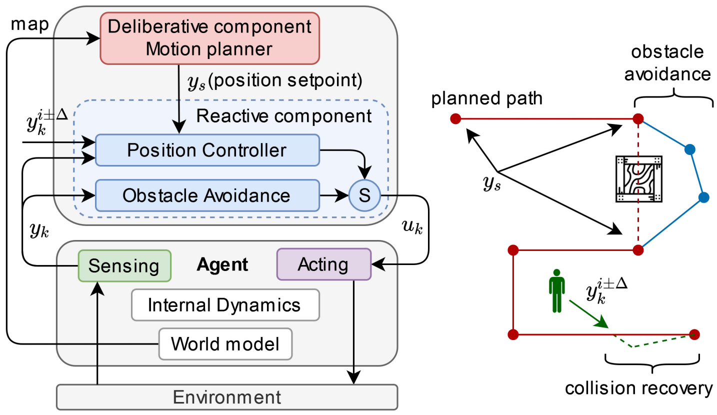


Figure 1: Deliberative-reactive control architecture for the pedestrian agent (left) and example (right).

etc. Thus, modeling of each participant should include a level of autonomy and agency. In this study, we combine agents with decentralized control principles [13]: each agent is sensitive and reacts only to factors or agents within a vicinity of itself [14], while the global behavior of the crowd is obtained through emergence [15]. With this approach, we bring the crowd model closer to a real-world structure comprised of autonomous systems with agency [16].

The three main contributions of our study [4] cover a crowd modeling method based on agent autonomy and emergence, a deliberative-reactive agent model for the crowd participants, and a routing-based system for dynamic guided evacuation.

2. Concept

The aim of the model is to obtain the crowd behavior during fire evacuation. The design is bottom-up, in which agents representing persons generate high-level behaviors of the crowd through local interactions, resulting in an agent-based simulation model (ABSM). Beside modeling individual agent dynamics, the problem of constructing an ABSM is centered around designing the local interaction rules so that observable patterns emerge. Rules are often at least partly known *a priori* in illustrative models, whereas this paper deals with a predictive ABSM: known agents are placed in a known environment and allowed to interact with the purpose of analysing their emergent behavior [17]. For simple interactions, e.g. in herding or flocking, all agents have the same easy to design rules. These are not suitable for humans with reasoning capabilities [3]. Panicked people make decisions based on uncontrolled personal interests, social and cultural constraints, leading to social disfigurement (e.g. following the decisions of others). In an agent network, collective panic is an emergent behavior resulting from individual internal decision-making and interaction rules in locally observable vicinities.

Thus, we propose equipping each agent with its own decision-making inference module; in our case, a controller. This approach sustains the autonomy of agents as crowd participants and allows crowd patterns to emerge organically from the local individual autonomous decision of each agent. From the environment, the agent receives inputs modeling the the presence of obstacles, e.g., walls or smoke inhalation, as well as signals from the evacuation systems, e.g.,

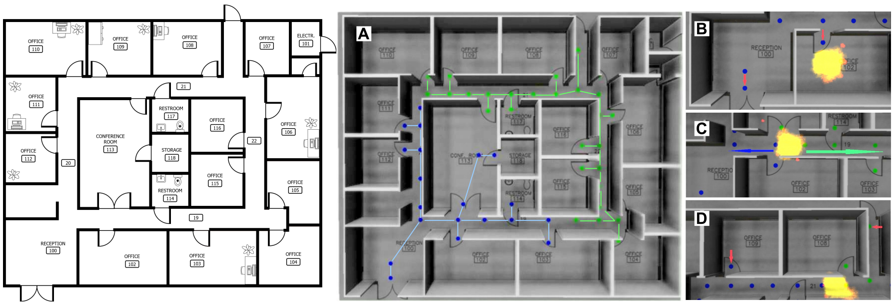


Figure 2: Floor plan [20] (left) and guidance indicators (right): A. visibility graph for fire drill case; B. office routes for fire in office; C. hallway routes for fire in hallway; D. office routes for fire in hallway.

alarms and indicators. The output is the trajectory of the agent through the environment. The network of agents with controllers form a decentralized control system (DCS). Here, the DCS is non-cooperative. This means that each agent has a locally and independently defined objective, which for a person in a crowd, is to reach an exit as fast as possible.

Figure 1 shows the architecture of the agent. We choose a deliberative-reactive controller structure [18] for humans moving through a physical space. The reactive component performs path following with collision avoidance [19], while the deliberative component performs motion planning (calculates point-based trajectories) and responds to environmental stimuli (smoke and alarms). For agent i in a crowd of n agents, at step k, the target points on the planned path become the setpoint y_s, while y_k is the position of the agent in the environment, u_k is the movement decision, and $y_k^{i\pm\Delta}$ contains the interactions with obstacles or humans within a vicinity Δ. The movement between two trajectory points is adjusted through the subsumption module S to locally avoid obstacles (walls and humans). For instance, rounding corners or pushing through a dense cluster require recovery to the trajectory.

3. Environment Structure and Building Components

In [4], we perform the design of an agent-based simulation model for crowd evacuation in case of fire. For the fire suppression and alarm system, and for guided evacuation, we employ static agents [21], which, from the point-of-view of the crowd, are part of the environment. All agents are implemented in JADE (JAVA Agent Development Framework) [22] and for ABSM visualisation we use the jMonkeyEngine [23] 3D graphic engine.

The environment has a floor plan with different types of rooms connected through 4 hallways and has two exits: one through the reception hall, and one situated in the diagonally opposite corner of the plan [20]. Figure 2 shows model of the floor plan. We also model the smoke diffusion, which affects walking speed [24] or the exit pedestrians choose.

The protection control system is part of the environment. Its purpose is to respond to fire events with two controllers: one for fire suppression and one for evacuation guidance. In real-world buildings, this system works alongside HVAC and other internal structural automation. The aim of the fire suppression and alarm control system is to reduce damage caused by fire, while the guidance controller aids the evacuation of occupants. It is comprised of sensing, acting, and controller agents, which emulate the smoke detectors, the alarms, the sprinkler system, and the occupant monitor. In the graphic engine, the alarms become visible as red elements when active, while sprinkler activation is a burst of blue particles.

The guidance control system we design in [4] that computes the shortest and *safest* routes in case of emergency based on fire location and displays them using a series of visual indicators. Each of the two routes (blue or green) begins in each room on the floor plan and ends in one of the exits (figure 2). Safe route computation is case-based (fire vs. exit locations) [4] and shortest paths are obtained via Dijkstra's algorithm, weighted to favor routes with less smoke. The safety and visibility graph are formed by guidance indicators (setpoints for the agent).

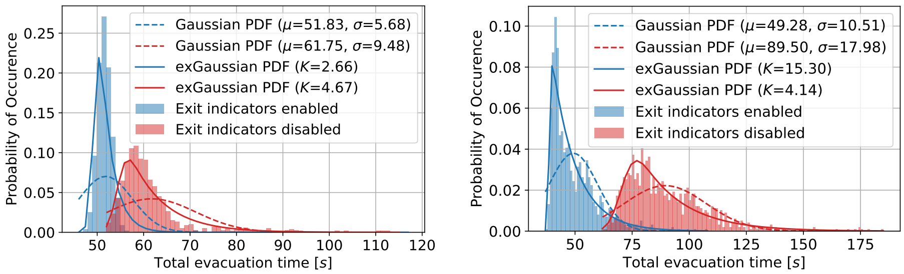
4. Modeling the Crowd

The user interface of the simulation model allows setting the number of human agents, while their initial placement on the floor plan is randomized. Agent diversity is ensured by probability-based decisions and internal state updates, thus obtaining behaviors of people who walk faster or slower, have different responses to smoke inhalation, knowledge of exit positions or levels of spatial orientation within the floor plan. Some, under the stress of evacuation, make decisions to rush to the exit farthest from them.

The human agent is represented by an entity that, in the graphic engine, can display physical properties akin to real life. For an agent, the inputs are: smoke quantity in room, state (on/off) of alarms, state (on/off) and color (green/blue) of guidance indicators, wall collision-generated forces, distance to fire, and collision-generated forces from other human agents. The internal states are: inhaled smoke, agent position, walking direction, speed, life status. The agent output is comprised of the walking direction and speed to be processed for the representation of movement on the graphical interface. The ABSM is discrete and all dynamics are computed in discrete time. The world model or knowledge base of the agent contains the location of exits and the visibility graph (world map). The internal state of the agent is updated based on previous states and inputs. Smoke inhalation affects the life status and movement speed, alarms trigger the evacuation behavior, while the controller updates the movement direction.

Motion planner: the deliberative component. During regular operation, the agent moves randomly, with self-generated directions and speeds. During drills or emergencies, the agent moves between points of the visibility graph. When the guidance system is not active, the agent makes a choice for an exit and generates its evacuation route accordingly (Dijkstra). However, pedestrians do not always choose the optimal path. A probability-based accuracy parameter models this choice. The probability of misjudgment in a semi-panic situation is up to 40% for residents without disabilities and up to 50% for persons with low stamina [25].

The reactive component is formed of a position controller subsumed with a collision avoidance behavior. The *position controller* governs the movement in a specified direction with a specified speed. *Collision avoidance*: when another agent, wall, or door frame is detected on or close to the agent direct path, a new direction is computed, followed by the recovery either toward the initial target or the next node. This behavior emulates the inattentional blindness of weaving through a crowd while influenced by emergency anxiety and panic modes, i.e. making decisions on direction under pressure [26, 27, 28, 29].



(a) With agent delayed reaction.

(b) Without delayed reaction.

Figure 3: Cumulative histograms and fitted distributions (maximum likelihood estimation).

5. Results and Discussion

To analyze the resulting emergent crowd behavior and to validate the ABSM we first perform the overall crowd assessment during evacuation with 142 total human agents.

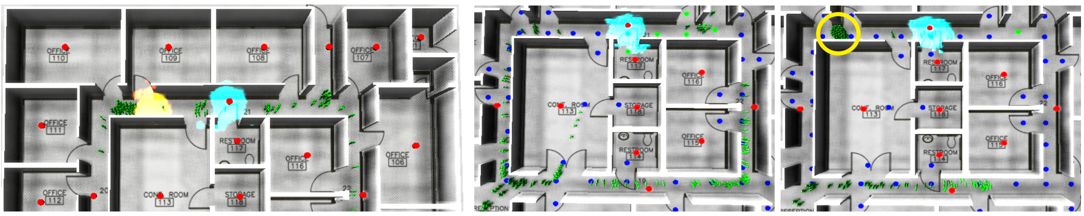
Fire drill and active fire. We analyze the impact of the closest exit estimation accuracy for pedestrians (figures and table are included in [4]). The case with 100% accuracy is ideal, in which every human agent does not panic and knows exactly the closest exit when the alarm starts. Results show that this case is comparable with the one when the exit indicators are enabled, illustrating the usefulness of the guidance controller.

Crowd reaction time. In psychology, *reaction time* (RT) is the duration between the appearance of an exogen stimulus and the occurrence of a specific response to that stimulus [30]. RT is usually measured and modeled as an ex-Gaussian probability density function (PDF) [31]. We introduce *crowd reaction time* (CRT): the duration between the activation of alarms and the finalized evacuation. We ran 1000 simulations for each of four scenarios: indicators enabled or disabled (25% accuracy for inefficient decisions in panic mode), with or without human agent reaction delay. Figure 3 shows the CRT distribution is an ex-Gaussian PDF, mirroring the individual RT. The crowd behaves as an organic whole: *an emergent, complex systems-of-systems.*

Bottleneck formation is likely scenario is when building occupants do not have information on the location of the fire (figure 4). The **effect of the pedestrian agent movement speed** is illustrated in figure 4) in three cases: (a) nominal base speed for agents; (b) 40% increase; and (c) 40% decrease. We observe a change in crowd cohesion, in which panicked running leads to large clusters and trampling.

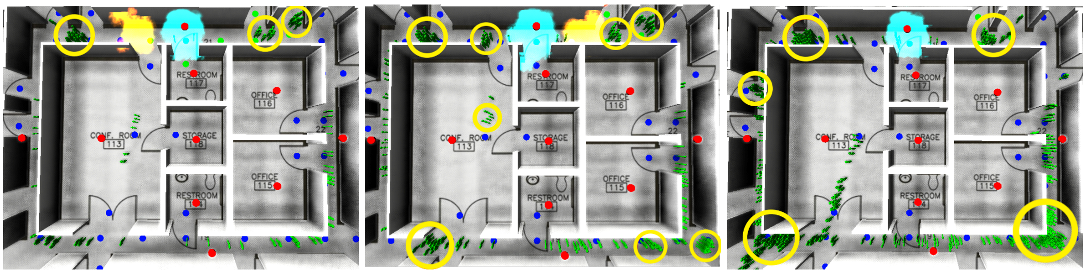
Cluster formations can be observed for various crowd sizes. Figure 5 shows frames with 80, 142, and 284 pedestrian agents in the model. These clusters emerge naturally due to collisions, different speeds, and common goals. The **guidance controller has an effect on the crowd dynamics** by enabling pedestrians to easily find the nearest exit, thus offering external knowledge to incorporate into their own reasoning process. Otherwise, pedestrians estimate the nearest exit, resulting in the formation of collision points (figure 6).

In [4] we include an analysis vs. other crowd models in terms of behaviors and computational efficiency. The overall result of our design is a crowd model with realistic behaviors, scalable to crowds of different sizes and that allows for more human-specific behaviors to be modeled.



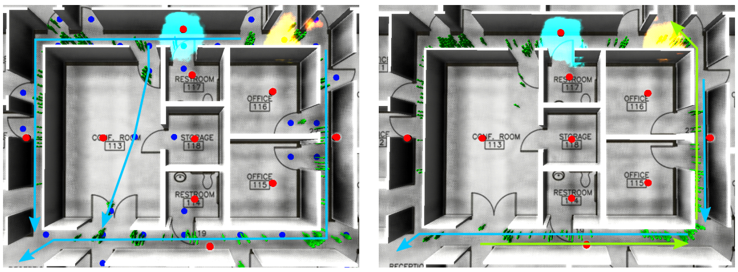
(a) Nominal base speed. (b) 40% speed decrease. (c) 40% speed increase.

Figure 4: Bottleneck formation depending on pedestrian speed.



(a) With 80 agents. (b) With 142 agents. (c) With 284 agents.

Figure 5: Cluster formation for different crowd sizes.



(a) With routing. (b) Without routing.

Figure 6: Collision point formation from intersecting flows: right-bottom corner of case (b).

6. Conclusion

In this study we propose a decentralized deliberative-reactive agent-based crowd model, which we simulate during fire drills and evacuation. We also design a fire suppression system and a guidance controller. Results show that the model based on agent autonomy and local interactions is able to generate higher level dynamics through emergence.

Acknowledgments

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