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Simulating Virtual Humans Crowds in Facilities

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***Abstract*—The area of crowd simulation has been widely explored in several contexts from entertainment to safety purposes. In this paper we present an approach to simulate the evacuation of crowds in facilities such as hospitals, geriatric clinics, orphanages and etc, where agents adopt different profiles, e.g. workers, patients and families. We use Snook tables to parametrize the effort of people to push patients impacting the people speed when evacuating in this specific context. This model can be applied in games, although our main goal is to contribute with safety systems by computing evacuation times and finding out the number of trained people needed in different scenarios. To control the motion of people in crowds and to avoid collisions we use BioCrowds, but any other crowd simulator could be used as well. Results indicate that the total evacuation time is reduced by having more trained workers, smaller hospital floors and an approximately similar number of rescuers and dependents number of patients and rescuers. In addition, we compare our method with another simulation in a hospital and obtained results were coherent.**

***Keywords*-Crowd simulation; rescue method; injured people motion;**

I. Introduction

In real life, during emergency scenarios in crowded environments, there is a probability of human lives being lost. Earthquakes, tsunamis, fires and many other phenomena can occur and lead to panic evacuation situations. Therefore, this type of situation can be even more dangerous to human lives if a fraction of the population depends on the help of others to evacuate, like in facilities as hospitals. In this case, it is important to study the space and the impact of dependent people in a hazardous scenario as to find out the ideal number of trained people, the recommended number of patients and best routes to be used in the evacuation process, etc.

Years of research in crowd simulation area has been key to understanding human behavior in these situations, so that an optimal solution can be elaborated. One of the first studies in the behavior of crowds was proposed by Reynolds [18]. He described an approach for simulating a flock of birds and schools of fish in a polarized, non colliding group motion. Many other works have been conducted in this area, as the case of the Implicit Crowds model [10]. This model uses an energy-based model that takes into account the expected future state of agents as well as their current state to reach an integration scheme for simulations. Although many methods were proposed to simulate crowds [5, 7, 16, 20, 21], few of them have been specifically proposed in in the context of this work. Paravisi et al. [15] proposed a method to rescue agents by carrying them during a certain time, using NIOSH equations [22]. In this work we are interested about pushing people, instead of carrying them, simulating what normally happens in hospital evacuations, when using wheelchair and stretchers.

One of the simulators present in literature is BioCrowds [4], a free-of-collision method to simulate many infinitesimal agents. As used by Paravisi [15], in his work, we adapted the idea of pushing agents to provide evacuation in facilities using BioCrowds [4]. The main contribution of this paper is to use Snook tables [19] (responsible for data definition about push/pull/carry weight in literature) in the context of crowd simulations. As a consequence, our agents can be tired when they rescue others, impacting their speed. In addition, we create different profiles and behaviors for altruist (including trained staff) and dependents agents and integrated it in a crowd simulator to provide evacuation in facilities.

This paper is organized as follows. Related works are discussed in Section II. The method we propose is presented and described in Section III. Simulation results will be shown and evaluated in Section IV, while conclusions and possible directions this work may take in the future are addressed in Section V.

II. Related Works

Helbing and Molnár [8] created a physical particle system model, for crowd simulation, based on the idea that pedestrians are subjected to social forces, that is, a measure of the motivation to perform actions, which is also influenced by the rest of the crowd. Later on, Helbing et al. [9] expanded the model by adding escape panic features to the social force equation based on socio-psychological studies [3, 11, 17] and reports video analysis of simulations in these types of situations. From this study they summarized escape panic characteristics as follows:

- People try to move faster than normal;

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- Interactions between individuals become physical in nature;
- Moving and passing through bottlenecks becomes uncoordinated;
- Jams build up;
- Arc formations and clogging on the exits;
- The physical interactions during jams cause dangerous pressures;
- Escape is slowed down by fallen or injured people; and
- There's tendency towards mass behavior.

This model was later used by Braun et al. [1, 2] to simulate rescue situations by giving agents levels of altruism and dependency, that is, agents with a high level of altruism rescue the highly dependent ones. Therefore, using those parameters the authors are capable of model heterogeneous crowds, where individuals have following attributes:

- Id_i - Identifier of the agent;
- $IdFamily_i$ - Identifier of the family agent i is part of. A family is a predefined group formed by some agents who know each other;
- DE_i - Dependence level of the agent represented by a value in the interval $[0, 1]$, which mimics the need for help of agent i.
- AL_i Altruism level of the individual represented by a value in the interval $[0, 1]$. It represents the tendency of helping other agents.

The work of Braun [1, 2] has been an inspiration for this paper, where we also modeled agents with different profiles in the context of evacuations in a rescue method. However, in Braun's work, agents are not impacted by the fact they are rescuing others.

Paravisi et al.[15] expanded BioCrowds by using the altruism and dependency levels, as proposed by [1] integrated with revised NIOSH equations [22]. This last one is responsible by establishing a relation between the maximum weight that an altruist can carry, as well as how many agents are needed to carry a dependent one, with the NIOSH lifting equations.

Zehrouni et al. [24] and Masoud et al. [12] model hospital evacuations on a macroscopic level, i.e. people should be evacuated from one facility and reach another one. Zehrouni et al. [24] presents a simulation of evacuation plans in the region of Ile-de-France in case of severe flooding. This study combines health care processes in a regional level with a Markov chain flood model to investigate the flow of patients from affected hospitals towards receiving hospitals. The results of the simulations were then used to estimate the impact of future floods in the infrastructure of the region. Masoud et al. [12] describes an objective programming model of hospital evacuation under uncertainties. The study categorizes evacuating hospitals according to their ability to be reached by vehicles and patients according to their need of specialized care. The aim of this work is to more accurately evaluate evacuation plans given the uncertain state of the infrastructure in case of a disaster. The study showed probabilistic approaches and can be used to solve large-scale problems.

Yokouchi et al. [23] proposed a model of horizontal evacuation in a hospital based on crowd density. The study describes three types of patients, according to their mobility capabilities, transferable by sheets, transferable by wheelchairs or able to walk without help. This model was utilized to simulate the evacuation of an existing hospital and investigate how the area occupied by different types of patient locomotion would affect the evacuation process. min Jiang et al. [14] modeled the evacuation of a large hospital in the region of Shenyang. The model was built based on video and camera observations and questionnaires carried out in the hospital. The behavior characteristics of the crowd as well as their walking speed were based on the collected data. The study then simulated the produced model utilizing the FDS+Evac fire simulation software developed by NIST, USA [13]. The study has concluded that pedestrians walk slower in hospitals and a third of the pedestrians do not know where to go when hearing a fire alarm. The simulations found out the usual exit methods were a significant risk in the evacuation of the simulated hospital.

The main contribution of this paper is a model for simulating crowds with different evacuation profiles and considering Snook tables [19] to simulate people pushing others with wheelchair and stretchers, and how it impacts the individual speeds.

III. The Model

This section describes our model to provide agents endowed with various profiles relevant to simulate crowd evacuation in facilities (e.g. hospitals, geriatric clinics, orphanages and etc). Firstly we present some details about original BioCrowds (Section III-A) and then we detail our re-parametrization in BioCrowds. Our main goal is to simulate the rescuing process of dependent agents by workers in the facility, to consider various agents profile that behave differently and its impact in the evacuation efficiency.

A. Original BioCrowds

The BioCrowds method proposes the space discretization populating the environment with uniformly distributed markers. Agents in the environment compete for these markers, based on proximity criteria, and use them to determine their movement vectors. Indeed, each agent i, located at position $\vec{x}_i$ accesses the markers inside its personal space R_i to search for markers that are closest to i than any other agent j. So, a marker is only available to the closest agent. In original BioCrowds all agents know how to reach the goals and are homogeneous, i.e. they have same abilities, same maximum speeds, same personal space and all other

For a given agent i, with a set of N available markers $S = \{a_1, a_2, \cdots, a_N\}$, we calculate it's movement vector $\vec{m}$ using Equation 1:

$$\vec{m} = \sum_{k=1}^{N} w_k(\vec{a}_k - \vec{x}), \tag{1}$$

where $\vec{a}_k$ is the marker's position and $\vec{x}$ is the agent's position. w_k is the marker's weight, calculated from Equation 2:

$$w_k = \frac{f(\vec{g} - \vec{x}, \vec{a}_k - \vec{x})}{\sum_{l=1}^{N} f(\vec{g} - \vec{x}, \vec{a}_l - \vec{x})}, \tag{2}$$

where $\vec{g}$ is the position of agent i goal.

To determine function f, let us first assume that all markers $\vec{a}_k$ affecting agent i are at the same distance $\vec{a}_k - \vec{x}$ from this agent. Such function should prioritize markers that lead the agent directly to its goal, i.e., it should (i) reach its maximum when the (non-directed) angle θ between $\vec{g} - \vec{x}$ and $\vec{a}_k - \vec{x}$ is equal to $0°$; (ii) reach its minimum when $\theta = 180°$; and (iii) decrease monotonically as θ increases from 0 to $180°$. Also, if the distances $\vec{a}_k - \vec{x}$ differ, the markers further from the agent should have relatively smaller weights, to prevent them from dominating the computation of the tentative motion vector $\vec{m}$. A possible choice for f that satisfies these assumptions is defined in Equation 4:

$$f(x, y) = \frac{1 + cos\theta}{1 + ||y||}, \tag{3}$$

where θ is the angle between x and y. Please refer to BioCrowds original paper [4] for further details about the method.

The weights will cause the agent to move towards their goal as long as there are markers available along the way. An agent's movement will be blocked by the absence of markers. Indeed, vector $\vec{m}$ is a good candidate for specifying next step movement of the agent while guaranteeing a collision free trajectory and capturing the increase of speed in larger spaces. However, in calculating the actual displacement, we have to also consider the maximum speed s_{max} (displacement per simulation step) which is related to the distance traveled by the agent at each time step. Consequently, we calculate the actual displacement v as:

$$\vec{v} = s\frac{\vec{m}}{||m||}, \tag{4}$$

where $s = min(\vec{m}, s_{max})$. So that the position of the agent is updated through: $\vec{x}(t + 1) = \vec{x}(t) + \vec{v}$.

B. BioCrowds Extension

Our BioCrowds extension uses different agent classes to define the hospital heterogeneous crowd. Agents are defined through the following attributes:

- i: Identifier of the agent;
- P_i: The percentile of agent i that determines its ability to push weight. Possible definitions are: $90, 75, 50, 25, 10$, according to Table I. It is going to be detailed later;
- G_i: Identifier of the group which agent i is part of. A group is formed by an agent rescuing and the one being rescued;
- $\vec{v}_{i,t}$: agent i velocity at frame t;
- $\vec{x}_{i,t}$: agent i position at frame t.
- $td_{i,t}$: traveled distance of agent i from the beginning of simulation until frame t, described as Equation 5:

  $$td_{i,t} = \sum_{f=1}^{t} d(\vec{x}_{i,(f+1)} - \vec{x}_{i,f}), \tag{5}$$

  where d states for the Euclidean distance between two points.
- τ_i: The class that the agent belongs to can be either altruist, dependent or trained. The altruist class is assigned to the population which will try to rescue the dependent agents, however once one altruist agent saves one dependent agent, it does not enter in the facility again. The dependent is the class given to agents who need rescue and cannot rescue others. In fact, this type of agent only move if someone is rescuing it. The trained class is assigned to trained agents. They rescue others and can go back in the facility to keep rescuing, while they have health (energy) to do that. Further details about how this process happens is later described.
- D_i: this parameter is determined using Snook Tables [19]. This factor determines the maximum distance that a given weight can be pushed by agent i.

Reviewing Snook Tables

Snook and Ciriello [19] made a set of empirical observations and generated the Snook tables. Basically, such tables define the maximum acceptable weights, for a set of tasks, that a population should follow in order to not injure themselves. These tables are based on controlled experiments and can be used to find the percent of an industrial population capable of sustaining the efforts tabulated in lifting, lowering, pushing, pulling, and carrying. Indeed, they state for a more general model than the Revised NIOSH Lifting Equation [22] because they apply to a broader variety of tasks. While the NIOSH equation establishes a recommended weight limit for lifting, the Snook tables provide guidance as a regular part of daily work to assist in jobs involving lifting, lowering, pushing, pulling and carrying.

In this work, we use tables on push weights proposed by Snook and Ciriello [19]. These tables define values of weight that a certain population can push for a certain distance. Table I shown some data contained in such tables and used in this work.

Table I

THIS TABLE CONTAINS A SET OF EXPERIMENTS CONDUCTED BY SNOOK [19]. THE DATA IS HOW MANY kg A CERTAIN % OF POPULATION PUSH IN A CERTAIN *height* DURING A A CERTAIN *distance*. WE CONSIDERED ONLY THE TABLE OBSERVED WITH MALES AND THE CONSIDERED HEIGHT OF OBJECT TO BE PUSHED IS $95cm$.

% of population	2.1m	7.6m	15.2m	30.5m	45.7m	61.0m
90	34	30	28	27	23	20
75	44	39	36	35	30	26
50	54	48	45	44	37	32
25	65	58	54	52	45	38
10	75	66	62	60	52	44

Calibrating BioCrowds based on Snook Tables

We used the presented Snook table [19] for $95cm$ height mark based on the height of the handle on the wheelchair. The observed population presented data in the following discretized distance values: 2, 7, 15, 30, 45 and 61 meters, as illustrated in Table I. So, for each population percentile, we interpolate between the discretized points getting an approximate curve to be able to estimate the distance that any agent can move while pushing an object of $95cm$ height. We can easily calibrate the population of the hospital with female characters and use other tables as reference. This can be done, e.g. when we are going to simulate a specific facility.

Regarding data contained in Snook and Ciriello [19] tables that recommend maximum weights to not generate injuries in industrial workers, we hypothesize that it should not be the maximum weight to be pushed by people, in panic situations or evacuation scenarios. We proposed to expand the agents behavior to support panic situations, so when the agent is pushing a wheelchair at the maximum distance allowed for a given weight (i.e the agent is probably very tired), Equation 6 decreases the agent velocity $\vec{v'}_{i,t}$ in the same proportion than the traveled distance increases in relation to the maximum recommended. Important to notice that agent i velocity will never be equal to zero, as shown in next equation:

$$\vec{v'}_{i,t} = \begin{cases} \vec{v}_{i,t}, & \text{if } td_{i,t} < D_i \\ \frac{\vec{v}_{i,t}}{\frac{td_{i,t}}{D_i}}, & otherwise. \end{cases} \qquad (6)$$

This updated velocity is true for altruist and trained agents. Dependent agents share the velocity of the rescuer agent, that can be altruist or a trained one. When a trained/altruist agent rescues a dependent one, a group is formed and the second one inherits attributes from the first. It is defined as Equation 7:

$$\vec{v'}_{i,t} = \vec{v'}_{j,t}, \qquad (7)$$

where i is a dependent agent and j is an altruistic or trained agent.

Since the trained agents can enter into the building again to keep rescuing others, their velocity can be very impacted as a function of the distance they move while pushing and saving others, as seen in Equation 6. With that being said we included a possibility of ”recovering” for the trained agents, between carrying two different dependents. It is defined by recovering some fraction of their maximum speed after rescuing a dependent agent (simulating that the agent rested between the two routes). We implemented this by a simple mean between the maximum speed (attributed to all agents at the beginning of the simulation) and the current speed of each agent i:

$$\vec{v}_{i,t+1} = avg(s_{max}, \vec{v}_{i,t+1})$$

, where $t+1$ is the time that trained agent i is going back to the facility to rescue another agent. Next section discusses experimental results obtained with our model.

IV. EXPERIMENTAL RESULTS

We modeled three hospitals in accordance to District Hospitals presented in Guidelines for Development [6], by the World Health Organization. For a ”one bed patient rooms”, it specifies a width of 3.3 meters and length of 3.9 meters, width the entrance being 1.25 meters wide. The corridors should be 2-3 meters in width, we opted for 3 meters to provide a better flow of the crowd. The 3 hospitals modeled have the same width of 72m but vary in length and capacity:

- Hospital 1, length of 20 m and capacity for 28 dependents or patients (Figure 1);
- Hospital 2, length of 40 m and capacity for 56 dependents or patients (Figure 2);
- Hospital 3, length of 60 m and capacity for 84 patients or dependents (Figure 3).

Our experiments vary four parameters:

- total Population size: varies in 40, 50, 80, 100, 160 and 200;
- proportion of dependents and altruists for the same size population: we tested 80% to 20% and 50% to 50%;
- percentage of altruists that are trained for the same population: we tested 0%, 20%, 50% or 100%; and
- the hospital size, as illustrated in Figures 1, 2 and 3.

Each of the cases was executed 5 times so we could average the results, in order to minimize the random effects. At the beginning of the simulation, dependent agents are randomly assigned to rooms (each room has maximum one dependent), then an emergency situation starts. Both classes of altruists (altruists and trained) are randomly positioned inside the building to be simulated, so that they can be either visiting a room or walking in the corridors.

The main goal of our experiments is to investigate the impact of the population composition, that is the percentage of each class, and hospital sizes in the evacuation time. In addition, we compared our results with a case study presented by Yokouchi et al. [23], as discussed in Section IV-C.

In section IV-A we discuss the results of experiments where we maintain constant population and vary the agent classes. In Section IV-B we discuss the results of experiments where we maintain constant the agent classes and vary the hospital capacity.

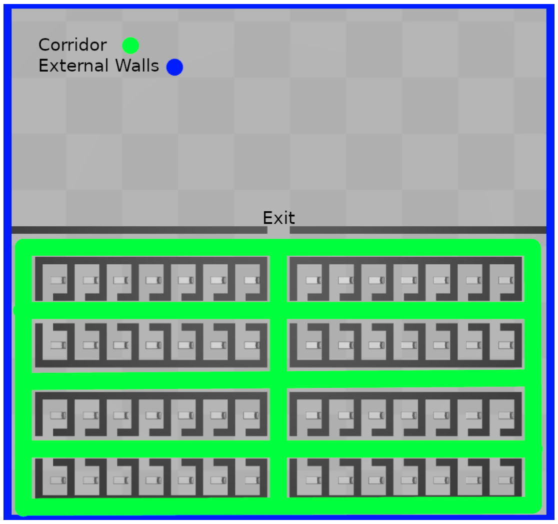

Figure 1. Layout of the Hospital 1 model.

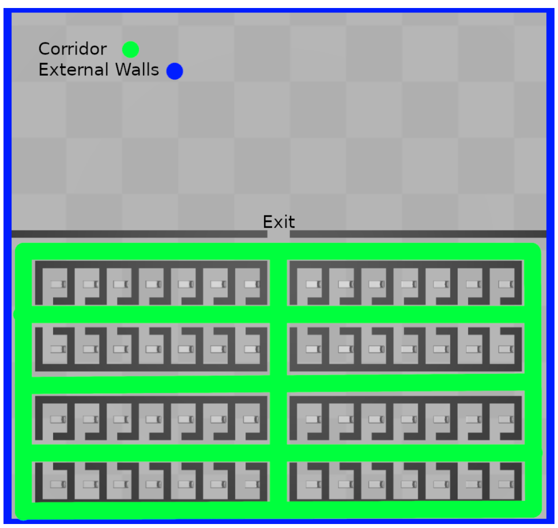

Figure 2. Layout of the Hospital 2 model.

A. The Impact of Trained Agents

In this section we aim to discuss the impact of trained agents in the simulation. We executed 12 experiments as seen in Table II. Experiments 1 to 9 vary the agent classes in the simulation. That is, given a fixed population, each experiment changes the % of dependents, altruists and trained agents. Figure 4 shows simulation 1, 2, 3 and 4, as defied in Table II. In these experiments Hospital 3 is simulated

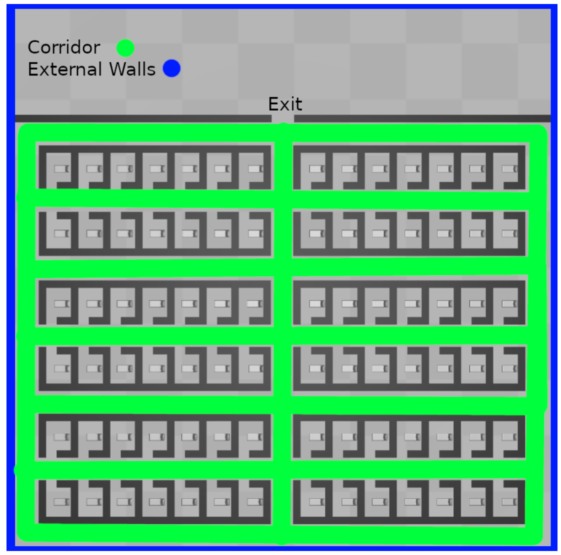

Figure 3. Layout of the Hospital 3 model.

Table II
SIMULATIONS PARAMETERS FOR TRAINED IMPACT CASES.

Sim	Hospital	Number of of altruist	Number of dependents	Percentage Trained
1	3	16	84	0
2	3	16	84	20
3	3	16	84	50
4	3	16	84	100
5	2	44	56	0
6	2	44	56	20
7	2	44	56	50
8	2	44	56	100
9	1	22	28	0
10	1	22	28	20
11	1	22	28	50
12	1	22	28	100

with 84 dependents, which is the maximum capacity, and 16 altruists making the total population 100 agents. It is possible to see that the evacuation time is smaller with higher trained percentages of agents in order to evacuate more agents.

Similarly, Figure 5 presents experiments 5, 6, 7 and 8 from Table II. Hospital 2 is simulated with 100 agents, from which 56 are dependents, so that all the rooms are filled with one patient, and 44 altruists. Again we can observe that increasing trained percentages of agents reduce the evacuation time. It is possible to notice in Figures 4 and 5 that when there are 0% of trained agents, some of dependent ones are not saved.

Figure 6 shows experiments 9, 10, 11 and 12 from Table II. Hospital 1 is simulated with a population of 50 agents, where 28 are dependents and 22 are altruists, shows that a higher percentage of trained altruists enables faster evacuations. After analyzing these results we can conclude that trained altruists are more effective reducing the evacuation time.

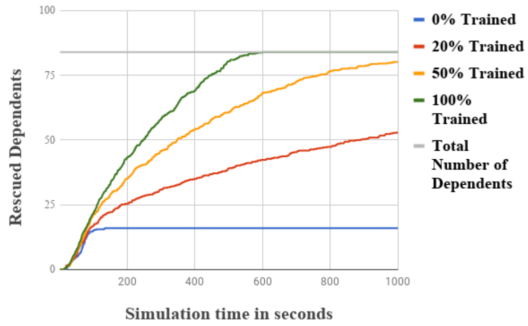

Figure 4. Simulating 100 agents in Hospital 3 changing the percentage of trained altruists with 84 dependents and 16 altruists.

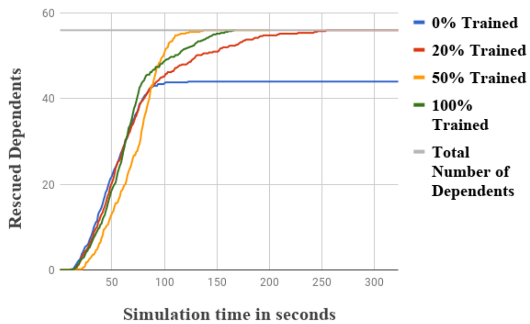

Figure 5. Simulating 100 agents in Hospital 2 changing the percentage of trained altruists with 56 dependents and 44 altruists.

B. Impact of hospital size

In this section we discuss the impact of changing the hospital size int the simulation. We executed 12 experiments (enumerated from 13 to 24 to avoid confusions with simulations from last section) which can be seen in Table III.

Figure 7 shows experiments 13, 14 and 15. Hospital 3 is simulated with 50, 100 and 200 agents and 22, 72 and 172 altruists respectively. In addition, all 3 experiments had 28 dependents. This graphic shows that having a number of altruists closer to the number of dependents leads to shorter

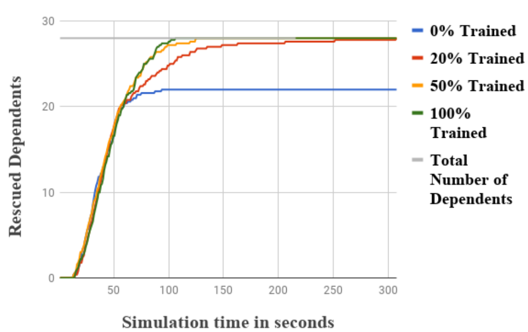

Figure 6. Simulating 50 agents in Hospital 1 changing the percentage of trained altruists with 28 dependents and 22 altruists.

Table III
SIMULATIONS PARAMETERS FOR HOSPITAL SIZE IMPACT CASES.

Sim	Hospital	Number of of altruist	Number of dependents	Percentage Trained
13	3	22	28	20
14	3	72	28	20
15	3	172	28	20
16	2	22	28	20
17	2	72	28	20
18	2	172	28	20
19	1	22	28	20
20	1	72	28	20
21	1	172	28	20
22	3	20	20	0
23	3	40	40	0
24	3	80	80	0

evacuation times. It can be noticed that more altruists, without dependent to be rescued, generate more flow in the facility, maybe disturbing the motion of crowd.

Figure 8 shows experiments 16, 17 and 18. Populations are the same as experiments 13, 14 and 15, but in the hospital 2 and similarly to those experiments, it is possible to ascertain that a number of altruists closer to the number of dependents makes the evacuation faster.

Figure 9 shows experiments 19, 20, 21. They are performed with the same populations that experiments 13 to 18, but simulated in Hospital 1. If we compare the Figures 7, 8 and 9 we can see that the evacuation of the Hospital 1 is faster and that Hospital 3 simulation is the slowest. This result was expected because Hospital 1 is smaller and so the time for agents to exit the facility is reduced, in comparison to the other hospitals.

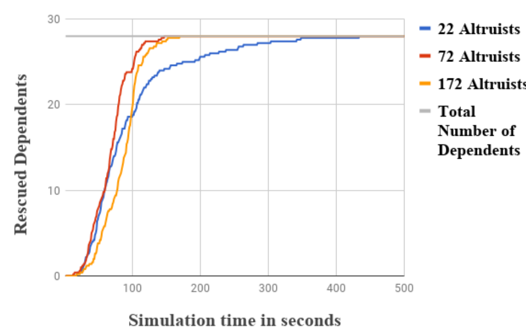

Figure 7. Simulating agents in hospital 3 changing the number of altruists.

Figure 10 shows experiments 22, 23 and 24. Hospital 3 is simulated with different crowds, each with the same proportion of altruists and dependents, but different agent quantities. From this graph we can observe that the more agents in the hospital the slower the evacuation will be because of the collision between agents and the rescue process.

Concluding, this section presents data to validate the hypothesis that how bigger is the hospital, greater is the

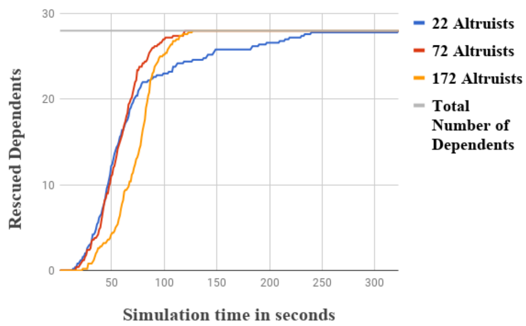

Figure 8. Simulating agents in hospital 2 changing the number of altruists.

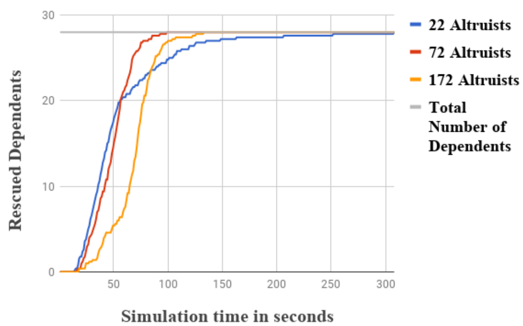

Figure 9. Simulating agents in hospital 1 changing the number of altruists.

evacuation time. In addition, the impact of agents classes in the simulation provide results as expected, i.e. the number of trained agents should be similar to the number of dependents for a more efficient evacuation time. Too much agents, in the facility, can create more flow problems, increasing the evacuation time. Once all these aspects are validated in our model, as expected, we pursue with a simulation to compare with a real study case, as discussed in next section.

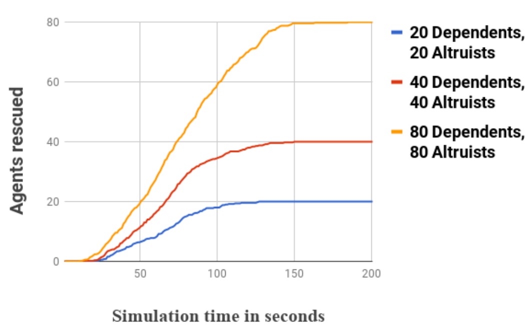

Figure 10. Simulating different crowds with the same number of altruists and dependents in hospital 3.

C. Comparison with a Real Case study

We compare our approach with some results described in Yokouchi et al. [23], where a simulation of crowd evacuation in Iwasa Hospital and Maternity was performed. We build a simplified model of the hospital, described in their work, illustrated in Figure 11. [1] Yokouchi's model has three different profiles for patients, carried by sheets or blankets, pushed by wheelchair or move unassisted. These profiles have some predefined percentiles in the total population as well as velocities. Since our interest here is to compare with our method to push agents, we only used the 56% for the patients being pushed on wheelchair with 2.34 m/s for velocity (as described by Yokouchi et al. [23]). Others are 23% of autonomous, with 1.2 m/s speed and 21% that need assistance with blankets, with a velocity of 1.6 m/s. For their 60 patients experiment that is a total of 36 patients on wheelchairs, so that is the population we simulated in our case study. They also have nurses which are rescuers, in our model they are comparable to the trained agents. The total number of nurses is 12 and one patient using wheelchair requires only one nurse, while for the blankets profile, more than one nurse is needed. So, in our experiment we have 36 patients (instead of 60) and 7 nurses (instead of 12) to rescue the wheelchair dependents. To calculate the number of nurses dedicated to wheelchairs profiles, in our simulation, we simply used the proportional nurses for each type of population, as described by the authors.

In Yokouchi et al. [23] the authors present results of simulations regarding 60 patients and 12 nurses. However we selected from their work only the data concerned with the profile we are interested in this work, i.e. information about patients who needs wheelchairs being saved per time. For the one floor simulation in their hospital it takes a mean of 4.66 minutes to evacuate, and for the wheelchair profile a mean of 2.29 minutes. Considering our method, we obtained a mean of 3.6 minutes (running 5 simulations to eliminate the random effect) using only wheelchairs, in which we utilized the same velocity for the wheelchair profile of their method.

So, the total simulation time in the both simulations are 2.29 mins in Yokouchi et al. [23] and 3.6 mins in our simulation. It is important to notice that such difference can be reasonably explained by some reasons: Firstly, the fact that we simulated the fatigue, that is the reduction of the maximum speed of the altruist agents based on Snook Table, which reduces considerably the ability to rescue. This characteristic is still more important in this case where trained agents should perform multiple rescues in the same simulation. In addition, we modeled a recovery equation that can be better calibrated if adequate reference is found [2]. Secondly, we are not aware of details about the geometry of the hospital simulated in their case, so size could also somewhat impact the evacuation time. Finally, the missing

[1] Indeed, we did not find accurate information (concerning dimensions) about their hospital model, so we provide an approximation using metrics of WHO.

[2] We did not find information about how this process happens in panic situations

details about the hospital model can bring some artifacts in the environment that can help or not the collision avoidance in the evacuation scenarios. Yet, one can say that we could re-simulate more cases having other patients profiles, but since we are not aware of details about other patients, we prefer to compare only the main focus of this work, i.e. wheelchairs profiles.

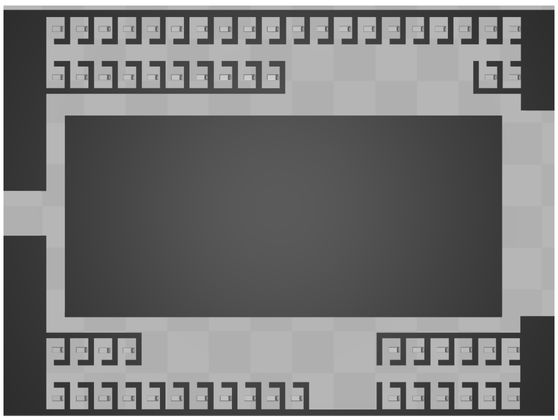

Figure 11. Concept of the hospital depicted in Yokouchi et al. [23] experiment.

V. Final Considerations

This paper presents a BioCrowds extension for simulating emergency evacuation scenarios in hospitals. Our contribution is to propose a method for pushing patients, based on real life observations from Snook tables [19]. Also we propose a fatigue model for the rescuers, where their velocities decreased while pushing a patient based on his/her weight. We show our results with these methods and finally compare them to a similar case study.

In future works we could add the different dependent profiles as the work of Yokouchi et al. [23], so that we can cover different scenarios such as pulling or carrying, which is already covered in the Snook Tables. We also plan to expand our model to support multiple floors of a hospital so we can see the fatigue working over longer periods of time. Finally, we intend to simulate a complex situation with dynamic obstacles so we can get approximated results with reality and simulate a real hospital.

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