Furthering an agent-based modeling approach introducing affective states based on real data

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Abstract

Modeling new agent-based simulation systems focused on pedestrian and crowd management that include information regarding affective states, in order to involve agents replicating human behaviour more closely, is to this day an open challenge in pedestrian simulation. Taking into consideration how human perception and decision-making processes work, being them heavily influenced not only by a person's environment but also by his/her personal psychological and physiological aspects, is of vital importance in the perspective of trying and introduce agents with more realistic behaviour inside simulations. In this regard, following up on a recent work, this paper presents further steps operated in a research effort aimed at utilizing quantitative data recorded through an online experiment to proceed with the modeling of *affective agents*. The presented approach leads then to some preliminary simulations, showing the impact and effect of the newly introduced information on pedestrian's proxemic distances and movement choices when moving in different situations among other people influencing them with their behaviour as well.

Keywords

affective agents, agent modeling, proxemics, pedestrian simulation

1. Introduction

The simulation of human agents displaying a more and more realistic behaviour is still an open topic in the agent-based simulation research, tackled by all kinds of approaches in which researchers try to include new parameters inside the agents' design whose purpose is to influence the way they move around the environment and interact with each others. Moreover, in the era of COVID-19 pandemic, investigating crowd dynamics has become an even more topical theme, especially when considering the pandemic-related issues to be addressed in crowd research [1].

Given how human behaviour is incredibly complex, seeing how both internal and external factors guide humans' decisions on how to act in certain environments and situations, it is difficult to try and include this complexity inside agent models. This is especially true for emotions and affects, which play a very important part in reacting and regulating the interaction

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a person has with his/her surroundings and with other people, and that also manifest themselves differently depending on the person. This can be easily seen, for example, when observing different behaviours and physiological reactions in men and women [2], or when comparing younger and older people in their reactions to tasks [3, 4].

In our approach to the matter, that we already started exploring in [5], we try to take into account those influencing factors in order to proceed with the proposition of an "affective agent model", namely an Affective Multiagent System. In particular, we introduce as an extension to our initial model new parameters involving sociality levels and fear of contagion, proceeding then to report some preliminary trials performed through two different agent-based simulation relying on the designed model and on the data gathered through an online experiment. Given the data we are basing the model on, the core idea of our work is to define an agent that describes the behaviour of different types of people, with different genders and belonging to different age groups, while interacting with strangers under the conditions given by the global COVID-19 pandemic. This particular situation, in fact, allowed us to consider even more factors that could condition the subjects' behaviour, such as fear of infection and government's regulation among others. More specifically, we focus on how these factors influenced the distance from others that the participants deemed to be safe under these conditions, a behaviour related to the concept of *Proxemics* and human distances as studied by Edward Hall [6].

The paper is organized as follows: Section 2 presents a brief state of the art review regarding agent-based simulations involving the introduction of an affective aspect in the model and, given the origin of our data and the simulations we show, basic concepts about proxemics and interpersonal differences; Section 3 presents the experiment we gathered our data from; Section 4 shows then the agent model we designed to introduce affectivity, and in Section 5 the simulations using that same model are introduced; Section 6 then shows some preliminary results obtained by observing the simulations given different initial conditions; finally, conclusion are drawn in Section 7.

2. Background

2.1. Emotion in agent-based modeling

In the case of agent-based simulations, the design of new agent models that take well into consideration emotions and affects represents a research frontier in constant expansion. Numerous researchers have already been facing this issue, working to include new factors and parameters into agent modeling to reach the design of more plausible and realistic agent simulations.

An usual approach often found in the literature already present about this topic is how emotions and affects are parameterized inside the model. A good majority of the works focusing on introducing this kind of information mainly base themselves on well-known and established emotional models [7, 8], utilizing them to as base on which to build the agents on [9], or mainly following emotional theory to craft functions to regulate the emotional aspects of the agents [10]. Another important point in research dealing with agent simulation involving emotion is in what kind of emotion is portrayed, which sometimes is even accompanied by parameters describing personality [11], and is often *fear*. Especially in evacuation simulations, in fact, fear is widely used as a parameter apt to influence pedestrian behaviour, modeled in different

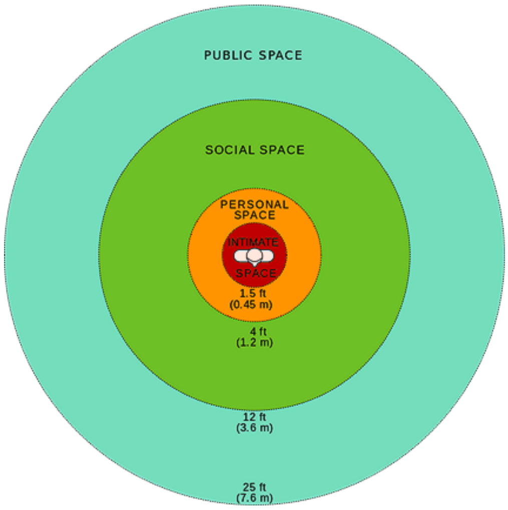

Figure 1: The four different spaces identified by Hall.

ways and used differently depending on the types of agents involved in the simulations [12]. It is also one of the emotions usually investigated when studying emotion propagation, given its relevance in emergency situations [13]. What emerges from these works, though, is how emotion is usually dealt with, highlighting how information about the emotions to be modeled are gathered from literature and models often used in psychology, parameterized into formulas for the agents to use. Very few works actually base themselves on data coming from an actual human population, making use of information coming from observing the behaviour of people in real life situations [14]. Others, also, given how difficult it is to carry on evacuation studies contemplating an emotional factor, rely on data gathered from animal population to model pedestrian crowds despite the caveats such an approach brings with it [15].

2.2. The concept of Proxemics

Proxemics, already contemplated in some agent modeling works [16, 17], studies the human use of space and the effects of population density on behaviour, communication, and social interaction. Cultural anthropologist Edward Twitched Hall in 1963 was the one to coin the term [6] and, in his work, he tried to identify some basic characteristics common to all people when dealing with interpersonal distances. The majority of studies on proxemic distances and behaviours relates to the theory brought by Hall's research and, in particular, to the definition he gave when investigating interpersonal distances of four distinct zones for interaction, each with its own scope and finality (Figure 1).

There are many factors that influence how humans approach proxemic distances. Gender proved to be one of these factors, with studies highlighting how, for example, women tend to show a lower tendency to engage in physical contact as opposed to men [18, 19]. Age was also found to be another important influence, especially considering how proxemic behaviour seems to change with growth [20, 21]. Also, perceived safety is another factor affecting distances from others, making them vary also depending on the environment in which people are interacting.

People are more in favour of an eventual personal space invasion when it is justified by small or overcrowded spaces [22], while an unjustified invasion could cause discomfort and even fear [23]. In these cases, having a chance to escape could help in perceiving the uncomfortable situation as more bearable [24]. Nowadays, given the ongoing COVID-19 pandemic, perceived safety can also be linked to the fear of infection induced by the virus' presence and diffusion [25, 26]. As an inevitable consequence of this impact, different intensities of fear, anxiety and stress inevitably end up influencing how people approach interpersonal distances in these new and disorienting conditions.

3. Online Experiment

As briefly mentioned before, in order to parametrize affective states inside an agent model according to real data we decided to start from data coming from a previously executed online experiment, presented here in a summarized version but extensively illustrated in [5]. The main goal of the performed experiment was to study how distances perceived as comfortable varied in COVID-19 times, observing the participants' responses in different conditions.

The experiment was opened and made publicly available from 27/12/2020 to 18/01/2021, and it involved 80 Italian subjects aged between 16 and 92 years old (44 women; 25 people aged 65 or older). The only requirement that was taken into consideration for the study was for the participants not to have previously contracted COVID-19, because of how different the responses of already infected people could have been in comparison to the ones of who managed not to catch the disease.

Figure 2: Example of the figure-stop activities presented to the participants.

The experimental procedure was composed of two main phases, the first focused information gathering and the second focused on tasks actively involving the participants. The information gathering phase revolved around questionnaires designed to obtain personal information regarding the subject, while the active task phase consisted in a *figure-stop activity*, as inspired by previous studies [27].

The figure-stop activity started with presenting subjects an avatar, personalized by looking at the demographic information they submitted, positioned on the left side of a given environment. The participants were then asked to move their character to the right, towards another figure positioned at the opposite side of the environment. In particular, this second figure was of the opposite gender and age group with respect to the ones indicated by the subject. The request was to move the indicated avatar closer to the other figure and stop when the participants perceived that shortening the distance any further could make them uncomfortable (Figure 2).

This activity was proposed for a total of eight time during the experiment with different conditions. What changed in the different configurations were the environment in which the avatar was to be moved, which could be an outdoor park or an indoor restaurant, and the mask condition, which brought four different combinations: (1) both figures had a mask on, (2) only the main avatar had a mask on, (3) only the other figure had a mask on, (4) no figure had a mask on.

4. Agent model

As for our adopted Agent model, we follow up the framework we already designed in [5] in order to include the factors that we had yet to adjust during our first approach to the issue. In this extended formulation, in fact, we have explicitly formalized the addition of parameters regarding internal and external sociality, fear of contagion and the mood they produce, with the aim of make the simulation more realistic. The Multiagent System (MAS) integrating affectivity is described hereafter.

Definition 1. An *Affective Multiagent System (AMAS)* is a MAS $\langle n, S, \{f_1, \dots, f_n\}\rangle$ with a certain set of states $S = X \times G \times M \times R \times A \times IS \times ES \times CF \times MD \times H \times D$, where

- $X \subseteq \mathbb{R}^d$ is the d-dimensional space that contains all the possible spatial positions the agents can be in;
- G, M, and R are the sets of the binary values g, m, and r, respectively, that when associated with any agent i state if i is male ($g = 1$) or female ($g = 0$), if i has a mask on ($m = 1$) or not ($m = 0$), and if i can move around the environment ($r = 1$) or not ($r = 0$), respectively;
- $A = \{y, ya, a, e\}$ is the set of the age groups an agent can belong to (y = young, ya = young-adult, a = adult, e = elderly);
- IS and ES are two sets of four values each which indicate the agent levels of internal and external sociability, ranging from 0, indicating low sociability, to 3, indicating high sociability;
- $CF = \{0, 1, ..., 8\}$ is the set of the level of contagion fear the agent could have that ranges from 0, absent fear, to 8, severe fear;
- $MD = \{neutral, scared\}$ is the set of the two possible moods a person could adopt, and is derived from combining the parameters about sociality and fear described before;
- $H = \{in, pr, sc, pb\}$ is the set of zones coming from Hall's interpersonal distances an agent can embrace (in = intimate, pr = private, sc = social, pb = public); The agent's Hall space is determined by all the factors listed above it, and this choice influences the d value that follow, given how every Hall space has its upper and lower bounds that define it;

- $D \subseteq \mathbb{R}^+$ is the set of values for the **minimum** distance an agent can have from any other agent; This minimum distance, in fact, is randomly chosen between the upper and lower bound of the selected Hall's space.

To define the two levels of *MD*, i.e. the mood of the agents, we applied the following procedure. Firstly we proposed a mood measure that is a linear combination of the three measures *IS*, *ES* and *CF*.

$$moodMeasure = \alpha * IS + \beta * ES + \gamma * CF \tag{1}$$

To obtain the proper coefficients of this combination, we have applied a Particle Swarm Optimization (PSO) technique [28]. The chosen fitness function is the Pearson Correlation Coefficient (PCC) between the distances chosen by the subjects and the *moodMeasure* defined by Eq. 4, previously transformed using a polynomial monotonic function to take into account the eventual non linear mapping between distances and fear. Then we have applied a threshold to binarize the *moodMeasure* to obtain the two levels *neutral* and *scared*. This process was performed separately for males and females.

For the selection of Hall's space, on the other hand, the process is the following: every combination of gender, age, mask condition and mood leads to a different set of weights influencing the probability of each Hall's space being picked. Once these weights have been identified, one of the Hall's spaces is selected.

5. Simulations

As we wanted to evaluate the effect of the affective state on the agents' behaviour, we decided to focus on the difference between genders where we found, by looking at the results of the online experiment, the highest differences in the distances to be maintained from others. Every other parameter contemplated inside the model presented above, with the exception of the age group, was then considered alongside the gender information.

Moreover, we specify that, in our models, one time step corresponds to 0.33s. This parameter, in addition to also considering 40cm sided cells, leads to an agent walking speed of about 1.2 metres per second, in line with typically observed values in pedestrian movement [29]. We give these measurements considering that an agent fully occupies a cell of the environment.

5.1. First model: Multiple agents free roaming

The first model here presented regards the simulation of multiple agents moving around in a two-dimensional environment, with their behaviour and their chosen proxemic distances influenced by the factors composing their affective state.

The model allows the user to set a small set of parameters, which controls different aspects of the simulation and allows to observe the agents' behaviour given different initial conditions. The user can, in fact, select the *environment* to be used during the simulation, choosing from an indoor one and an outdoor one as proposed in the online experiment, to then set the initial densities for two different agent populations. The first one is composed of agents modeling *pedestrians*, while the second one is composed of agents modeling *obstacles*. Obstacles are, in

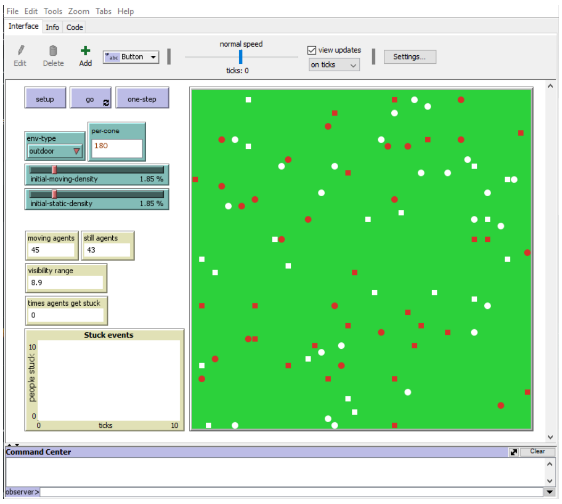

Figure 3: The user interface of the first model used for *multiple agents free roaming* simulations. *Circles* represent pedestrians, while *squares* represent obstacles. Masked agents are coloured in *white*, while non-masked agents are coloured in *red*.

our case, agents that do not follow the model shown in 4, as their only instantiated parameter is the presence or absence of the mask and they do not have an active behaviour in the simulation. The maximum density that can be set for both type of agents is 10%, so that the total population density in the environment will never exceed 20% in order to maintain a low total population density for our trials. Another parameter the user can set is the angle of what is here called a *perception cone*. This measure is used to decide how much to restrict the agent's movement directions when finding another agent that is deemed too close, thus removing all the values in that cone from the agent's set of possible directions for movement. This modelling choice intuitively reflects actual human perception, and it is also in line with previous approaches found in the literature [30].

The pedestrians inside the simulation (shown in Figure 3) have been designed to walk inside the given environment, modeled with periodic boundary conditions as to follow the shape of a two-dimensional discrete torus, by *random walk*[1], which was chosen since random walk is often used as baseline and reference for comparison and since it is already a well established practice to use it in agent simulation [31]. Also, given that the online experiment highlighted how the distances selected by the participants were not only influenced by their own personal parameters but also by the mask configuration of the two figures, every pedestrian computes two different preferred distances: one to be maintained from people who wear a mask, and the other to be maintained from people who do not.

5.2. Second model: Single agent goal oriented

The second model here presented aims at simulating one single agent having the goal of crossing a room full of people in order to reach the other side of the environment, observing then how

[1]Brownian motion that has the agents change direction at every passing turn.

the agent moves to reach its objective given the affective component influencing its behaviour.

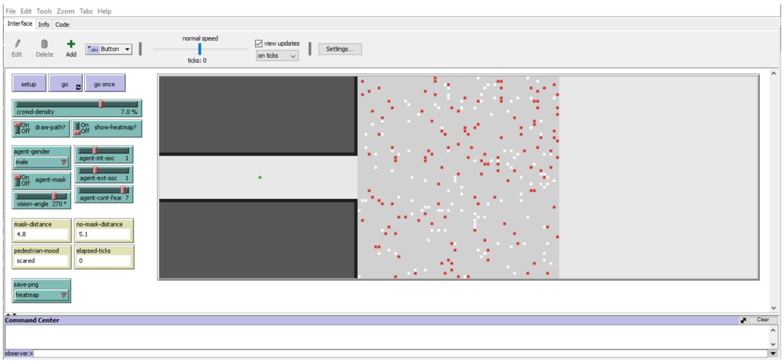

Figure 4: The user interface of the second model used for *single agent goal oriented* simulations. The *circle* represents the main moving agent, while *squares* represent the crowd. Masked agents are coloured in *white*, or in *green* in the case of the main agent, while non-masked agents are coloured in *red*, or in *orange* in the case of the main agent.

This time, the model presents an environment with a specific structure: on the left side of the space there is a corridor where the *main moving agent* we intend to observe is going to be instantiated; in the middle of the environment there is a big room in which the agents composing a *crowd* move by *random walk* inside its limits; lastly, on the right side of the space there is the empty room the main moving agent intend to get to, reaching its far right edge to reach its goal. The model allows to set different parameters regarding the main moving agent, in order to observe different types of agents tackle the same task. It is in fact possible to decide the gender, mask usage, sociality levels and contagion fear for the agent, and to also set a *visibility angle*, which is a parameter used to understand how much the agent looks around itself and of which other people it concerns itself with when deciding how to correct its course to reach its goal. Other than the parameters for the main agent, it is also possible to set the density for the *crowd* occupying the middle section of the environment which, in this case also, is capped at 10% to observe the simulated situation with limited population density.

6. Experiments and Achieved Results

6.1. First model

Table 1 shows some preliminary results obtained by making the first model simulation run 25 times for 100 timesteps at a time, in different combination of environments, visibility ranges and total crowd density. We previously showed how the densities of moving people and non-moving people can be set separately, in order to set them differently for different trials, but in this case we kept them equal so that, summed up, they could reach the population densities that are reported into the table in terms of $\frac{pedestrians}{m^2}$. The different numbers of people are derived from the way the environment is set up, since every empty patch randomly chooses a number than, if smaller than the density set through the slider, allows them to spawn an agent representing a person. We also decided to try and perform the trials with different perception angles for the pedestrian, given how there could be differences in how people anticipate the others' movements [32], to simulate and see if it could bring interesting differences in the results.

		Outdoor Environment			*Indoor Environment*		
Percept. Angle	**Total Density ($\frac{ped}{m^2}$)**	**Moving (mean)**	**Still (mean)**	**Pedestrian stuck per timestep (mean)**	**Moving (mean)**	**Still (mean)**	**Pedestrian stuck per timestep (mean)**
90°	0.31	63.32	67	9.24 (14.59%)	62.48	64.8	8.89 (14.22%)
	0.61	122.36	131.76	52.86 (43.20%)	123.32	129.08	52.01 (42.17%)
	0.90	176.52	198.2	100.77 (57.09%)	178.96	197.76	100.96 (56.41%)
	1.20	230.04	264.64	153.79 (66.85%)	240.68	262.08	159.27 (66.18%)
180°	0.31	62.4	65.96	33.05 (52.96%)	62.44	68.08	30.84 (49.39%)
	0.61	125.4	133.16	90.39 (72.08%)	121.52	130.24	88.27 (72.64%)
	0.90	181.48	195.44	148.44 (81.79%)	183.16	190.48	148.11 (80.86%)
	1.20	238.92	264.24	209.52 (87.69%)	231.84	255.84	201.42 (86.88%)

Table 1
Table showing the percentage of pedestrians remaining stuck for each timestep performed with different initial densities and visibility ranges in the two contemplated environments.

As we can see from these results, as the pedestrian density inside the environment grows, the number of events recording the moments a pedestrian agent finds itself stuck grows rather quickly, and this is clearly visible when observing the percentages indicating the mean of pedestrians recorded as stuck per timestep.

The percentages reached even with a total density of only $1.20\frac{ped}{m^2}$, which corresponds to a selected 15% density, indicates how, despite the environment not being too crowded for people to move around into, the distances set by the affective states of every person prevent them from moving around when others are perceived as too close to allow a comfortable movement. Also, the perception angle adopted seems to have a visible impact regarding pedestrian behaviour in this sense. The differences between the results in indoor or outdoor environments are not very accentuated, but this could be because of how people tended to maintain caution in approaching others regardless of the place they were navigating.

6.2. Second model

Table 2 reports the results obtained by performing trials of our second model. Utilizing always a 270° visibility angle, so that agents disregard people behind their back, we performed 50 trials for each combination of parameters shown.

The times to exit observed during the trials show how the pedestrians naturally moved more easily in a less crowded space, with times rising up whenever we consider both the comparison between neutral and scared agents and between male and female agents. This allows us to conclude that scared people navigate increasingly crowded spaces with less ease in comparison to neutral agents, and the same happens when considering how female agents take longer to reach the other end of the room as opposed to male agents. This can be due to a higher tendency, of both scared and female agents,to select wider distances to be maintained from others.

Gender	Mood	Mask	Crowd density ($\frac{ped}{m^2}$)	Time to exit (mean)
Male	Scared	Yes	0.12	383 s
			0.43	926 s
		No	0.12	632 s
			0.43	1326 s
	Neutral	Yes	0.12	218 s
			0.43	588 s
		No	0.12	319 s
			0.43	995 s
Female	Scared	Yes	0.12	521 s
			0.43	1543 s
		No	0.12	898 s
			0.43	1650 s
	Neutral	Yes	0.12	274 s
			0.43	820 s
		No	0.12	948 s
			0.43	1559 s

Table 2
Table showing an example of how much time agents with different parameters and with facing different crowd densities use in order to reach the other side of the environment.

7. Conclusions

In this paper, we followed up to the first steps we made in formalizing an Affective Multiagent System integrating the notion of affective state, here related to proxemics and safety perception in interpersonal distances. The formal agent model obtained was then implemented into two different simulations, depicting two different situations in which to observe the effect the affective state had on the agents' behaviours.

Even if stemming from a preliminary work, the results here obtained are quite interesting, since the simulations observation makes clear enough how much the introduction of interpersonal spaces can impact agents' movement inside a certain environment, especially as crowd density increases. They represent another good step in investigating this particular research area, especially given the current importance of the topic [1], but of course there are still limitations and simplistic assumptions to deal with as future work is concerned.

Firstly, we would like to propose the online experiment once again in order to gain more data: the analysis we performed in order to obtain the parametrization hereby introduced was quite simple given the limited amount of entries we gathered from the questionnaire, and having a much larger dataset would allow us to expand our view on the matter and to consider a different path for the parametrization itself.

Then, in an extended version of this work, we aim at further investigating the simulations here presented, the second one in particular, to have a better look at the agent's movements with path drawing and heatmaps. We would also like to use the model to observe other situations in which proxemic distances could play an important part, like evacuation simulations, and to generalize it in order to take into consideration data coming from other experiments concerned with different types of interactions (obstacles, vehicles, etc.).

Finally, we also aim at proposing the same experiment here presented in a real-life environment: observing the participants during an actual execution of the tasks could provide other useful insights on their behaviour. Moreover, proposing the online experiment in a real-life setting could also allow us to gain data that could help in validating the behaviours we observed in the simulations.

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