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Simulating the effect of a social robot on moving pedestrian crowds

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***Abstract*— We investigate the interaction between a pedestrian crowd and a social robot—a relevant human-robot interaction scenario observed in train stations and entrances to public places. We use a popular agent-based social force model to simulate a pedestrian crowd as it passes near a stationary robot. The modelling framework permits analysis of difficult-to-test situations such as high density crowds and the effects of contagion whereby more people are likely to interact with the robot if it is already surrounded by an audience. Accordingly, we augment the modelling framework to account for varying crowd densities, human-robot interaction, and social influence, and inform the parameter values from empirical studies in literature. Our results show that while the rate-of-interaction, defined as the number of agents located within an interacting distance per minute, increases with flow density, the average interaction-time is independent of the same. We find that inducing social influence through contagion does not have a significant effect on the rate at which agents engage with the robot in dense crowd scenarios, and has a marginal effect at low densities. The interaction-time was found to depend on the interaction-speed at which agents engage with the robot. These results indicate that at normally witnessed flow densities crowding near the robot is unlikely to take place, and the effect of robot design choices supersede the effects of social force or contagion.**

I. INTRODUCTION

A section of social robotics focuses on the design of robots that can be used in public places to assist humans in their daily tasks [13]. Experiments with such robots include interactions—explicit and implicit—with pedestrian crowds in train stations [6], shopping malls [15], and museums [28]. The goal of these robots range from providing route guidance and information and carrying shopping merchandise to giving tours to children and groups. These tasks are achieved through social interactions that typically entail estimating the pose, identity, and behaviour of the interacting human beings [19], [24]. Depending on the level of autonomy, the robot may interact on its own, or be assisted by an off-location human in a wizard-of-oz setup [25].

Experiments with unidirectionally moving crowds in particular have shown that the level of interaction in terms of behavioural features such as "stopping to watch" a robot and "interest in the information" provided by the robot can be modulated by design choices. Examples include selecting a passive robot that randomly announces travel information over an interactive one that greets and then talks to a person only when they are within hearing range [6], or a single robot over a social setup where two robots converse between themselves while passively transmitting relevant information [6]. Other experiments in scenarios that consist of similar one-directional crowds interacting with a robot have shown that a model of engagement may require direction of motion, in addition to distance, to better explain who may interact with the robot [19], [24]. These experiments last between days and years and require tracking humans and annotating their behaviour, thus making it difficult to test a wide variety of scenarios. Further, due to reasons of safety, the robots are deployed under conditions where the crowds are relatively sparse [6].

Agent-based models provide a viable resource to recreate human crowd systems for the analysis of crowd behavior [10]. Simulations using such models further allow testing of various strategies for mitigating injuries in the event of a crowd panic [7], [18], emergent behavior such as lane formation [9] and circle pits [26], and human-aware navigation of robots [17]. Agent-based models that have been used to simulate pedestrian crowds can be broadly classified into random walk models [23], cellular automata models [11], and social force models [8]. While the primary focus of many of these models is to simulate crowd panic, we select the social force model to simulate crowd-robot interactions at it is able to reproduce emergent behaviour often seen in normal pedestrian crowds [8]. Specifically, in this paper, we adapt the social force model to simulate scenarios similar to those in [6] and [19] in order to explore the effect of robot characteristics such as interactiveness and sociality on the number of people interacting with the robot and the average interaction-time.

We model the effect of changing robot characteristics indirectly in terms of the effect it has been shown to have on pedestrian crowds [6], [19], [24]. In particular, we modify the rate-of-stopping-to-watch as an indicator of sociality in the robotic platform [6] and interacting speed as an indicator of interactiveness [6], [19]. To further investigate the effects of social contagion in terms of quorum responses [20], [27], [4], we augment the model to include the capability of including individuals that do not intend to participate initially, but then do so given that a minimum number of people are already interacting with the robot. Finally, we vary the crowd density to study both sparse and dense crowds.

We expect that crowd density will have a significant effect on the number of interacting individuals with a higher rate-of-interaction at high flow density. Similarly, we expect the rate-of-interaction to be significantly affected by rate-of-stopping-to-watch with higher values for more people deciding to engage with the robot. Conversely, the interaction-time is expected to reduce at high densities due to crowding effects. Interacting speed is expected to affect the interaction-

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time, whereby lower speeds near the robot will increase the interaction-time. Finally, contagion effects are likely to increase the rate-of-interaction at all flow densities.

The paper is organised as follows: in Section 2 we review the social force model, human-robot interaction in the context of unidirectionally moving pedestrian crowds, and contagion as flow of visual information in pedestrians; Section 3 presents our augmentation of the model including modelling the robot influence on individual direction of motion and speed and the effect of contagion; Section 4 describes the simulation experimental setup and results; we conclude with a discussion of the results and open questions that are being addressed in ongoing work.

II. Robots in human crowds

A. Modelling human crowds using social forces

The social force model is an agent-based model [8], [9], where each pedestrian, modelled as an agent, experiences three forces: a tendency to move towards the goal; an interaction force with other pedestrians; and an interaction force with the walls. The interaction forces comprise social forces, where pedestrians tend to stay away from each other as well as the wall, and physical forces that are experienced when pedestrians touch each other. For normal scenarios, where crowd densities are relatively low, physical forces may be ignored. Given N pedestrians, the social force model describes the total force experienced by pedestrian i with position and velocity $\mathbf{r}_i$ and $\mathbf{v}_i$, and mass m_i, as [8]

$$m_i\ddot{\mathbf{r}}_i = \mathbf{f}_g + \sum_{i=1,i\neq j}^{N} \mathbf{f}_{ij} + \sum_{W} \mathbf{f}_{iW} + \eta_i, \qquad (1)$$

where $\mathbf{f}_g = (s_i[0]\mathbf{e}_i[0] - \mathbf{v}_i)/\tau_i$ is the force towards the direction $\mathbf{e}_i[0]$ with adaptation time τ_i and desired speed $s_i[0]$, $\mathbf{f}_{ij}$ is the interaction force with agent j, $\mathbf{f}_{iW}$ is the interaction force with the wall W, and η_i represents the unmodeled fluctuations experienced by an agent. The interaction force $\mathbf{f}_{ij} = A_i \exp((w_{ij} - d_{ij})/B_i)\mathbf{n}_{ij}$, where A_i and B_i denote the interaction strength and the interaction range respectively, $d_{ij} = \|\mathbf{r}_i - \mathbf{r}_j\|$ is the distance between agent positions, w_{ij} is the sum of their radii, and $\mathbf{n}_{ij} = (\mathbf{r}_i - \mathbf{r}_j)/d_{ij}$ is the unit vector from j to i. Although not utilised here, the social force model can be updated to include cognitive heuristics in the form of visual information used by pedestrians such as time to collision with another pedestrian and perceptual range [21]. The social force model has also been used to design robot navigation strategies [2] and improved pedestrian flow [1].

B. Human-robot interaction in crowds

Several field studies have been conducted that focus on human-robot interaction in scenarios where pedestrian crowds interact with a robot [19], [24], [6], [25], [14]. In [19] a receptionist robot situated at the entrance of a university department is used to show that movement-based, rather than a spatial model of engagement is required to accurately capture the level of social engagement with the robot. In [6], people's reaction to the robot is observed as they approach and leave through a train station. Results from [6] show that while an interactive robot elicits a stronger feeling of being addressed by the robot, a social setup where two robots are deployed instead of a non-social setup is better in terms of engaging people, and that rate-of-stopping-to-watch is significantly affected by the type of robot design in terms of interactiveness and sociality. We use these results to inform the parameter values in our simulations.

Fig. 1. Probability of engaging with the robot as a function of distance along the normal to the direction of motion for coefficient k_d values 1.8 (solid) and 1 (dashed). P_{sw} is set to 0.2 for both cases.

C. Contagion as flow of visual information in pedestrians

Pedestrian crowds in shopping streets and train stations are also subject to socially contagious behaviours where individuals may follow the gaze or actions of others depending on the density of the crowd, and the number of the engaged audience [20], [4]. Specifically, in an experiment involving gaze following by a stimulus group of informed participants, it has been shown that gaze following is proportional to stimulus group size and that the proportion of time spent in distraction is lower at high crowd densities [4]. Following [4], we augment our crowd-robot interaction model by including a probability of engagement of a newly entered agent as a function of number of agents already interacting with the robot.

III. Modelling the effect of a robot on moving pedestrian crowds

We augment the social force model to include robot influence on pedestrian crowds, and select the model parameters based on real-world experiments from literature [19], [6], [4]. In particular, we vary the crowd flow rate as crowd density, percentage of agents who engage with the robot as rate-of-stopping-to-watch [19], [6], the level of engagement as interaction-speed [19], and propagation of engagement with the robot as socially mediated behaviour [4].

A. Crowd flow and rate-of-stopping-to-watch

We model crowd flow as a Poisson process with varying means to depict high and low density scenarios. Specifically, the probability of a person entering a pathway with the robot

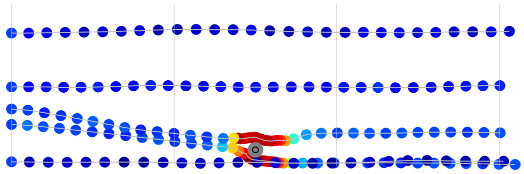

Fig. 2. Sample trajectories of agents as they pass near the robot (grey circle). Agent speed is denoted by the color (blue=fast, red=slow).

present during a timestep is $\exp(-\lambda)\lambda$, where λ is the rate parameter of the Poisson process.

Further, we assume that the willingness to engage can be captured as the rate-of-stopping-to-watch as observed in [6], where interactive social robot pairs were found to be more engaging than single non-interactive counterparts. Given an average value of rate-of-stopping-to-watch that depends on the robot design choice, we vary the probability to stop-to-watch of an individual agent in terms of the initial direction of motion and distance to the robot [19]. In particular, among the entering agents, the probability to "stop and watch" P_{sw} is a linear decreasing function of the distance between the agent and the robot along the normal to the direction of motion (capturing the tendency to steer away). The resulting probability of an entering agent to change their desired direction of motion to move towards the robot is

$$P_{i,sw} = 2(1-k_d)P_{sw}\frac{\|(\mathbf{r}_i[0]-\mathbf{r}_R)\times \mathbf{e}_i^0[0]\|}{d_n^{max}} + k_d P_{sw}, \quad (2)$$

where d_n^{max} is the maximum possible distance along the normal to the initial direction of motion, and $k_d \in [1,2]$ determines the difference in probability of engagement between the closest and the farthest agent (Fig. 1). For agents that decide to engage with the robot, the desired direction of motion is updated as

$$\mathbf{e}_i^0[k] = \begin{cases} \frac{\mathbf{r}_R-\mathbf{r}_i}{\|\mathbf{r}_R-\mathbf{r}_i\|} & \text{if } (\mathbf{r}_R-\mathbf{r}_i)^{\mathrm{T}}\mathbf{e}_i^0[0] > 1 \\ \mathbf{e}_i^0[0] & \text{otherwise,} \end{cases} \quad (3)$$

where $\mathbf{r}_R$ is the position of the robot, and the 1 m threshold is the minimum interaction distance along the initial desired direction $\mathbf{e}_i^0[0]$.

Although novelty effects have been reported in human-robot interaction studies with children [12], the same are ignored here as they were not observed in a field trial done at a train station [6], a situation more relevant to this study.

B. Robot influence on agents

The desired speed of an agent that is selected to engage is modelled as a function of robot influence. We consider the following observations on the change in desired speed: (i) the distance at which the interaction with the robot starts is constant; and (ii) the speed near the robot is a function of the robot interactiveness, i.e., individuals are likely to spend more time near an interactive robot. An interactive robot here, for example, could imply a robot design that permits limited interaction via a range sensor, which allows the robot to change gaze as a human passes by, and greet if the human

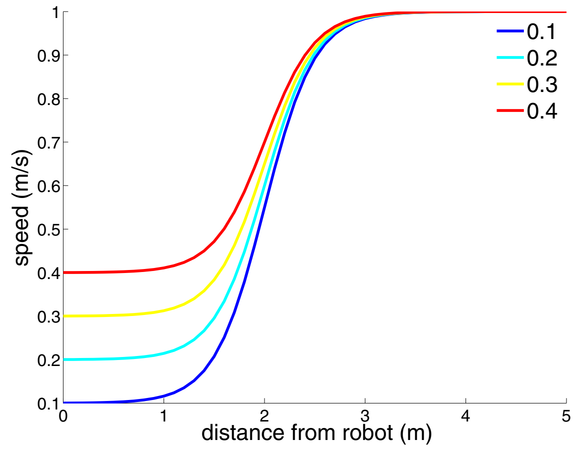

Fig. 3. Speed of an agent as a function of distance to robot for four different values of s_R. A logistic form allows different change in speeds when an agent gets close to the robot at the same interaction radius.

is within a certain distance [6], [24], [19]. Accordingly, we represent the speed $s_i[k]$ of an agent i at time k as a logistic function of the form

$$s_i[k] = s_R + \frac{(s_i[0]-s_R)}{1+\exp(-(d_{i,R}-c_1)c_2)}, \quad (4)$$

where $d_{i,R}$ is the distance between the robot and the agent, s_R is the minimum speed in the robot vicinity, and constants c_1, c_2 determine the distance of engagement and the rate of decrease in speed to it's lowest value ($c_1 = 2, c_2 = 4$ in Fig. 3). In terms of robot design choice, the value of s_R, for e.g., could be low for an interactive robot than a passive robot.

C. Social influence to engage with the robot

Following [4], [3], where social propagation of visual cues is shown to occur in pedestrian crowds, we model the behaviour of non-participating agents in terms of the size of the crowd that is assembled around the robot. In particular, the probability of engagement of an agent that is initially set to not engage (change direction and slow down) with the robot is modified as [4]

$$P_{e,i} = P_{s,i} + \frac{(m_e - P_{s,i})N_R}{T+N_R}, \quad (5)$$

where $P_{s,i}$ is the spontaneous probability of looking in the direction of the robot, N_R is the number of agents within a d_{nR} distance of the robot, m_e is the maximum proportion of agents that can engage with the robot, T is the group size at which $m_e/2$ agents will engage. Given that engagement with the robot is a different social context compared to the gaze-following [4], where $m_e = 1$, we set a lower value of m_e to be 0.5 to denote that not more than 50% of the entering agents will engage with the robot. Similarly, T is set at a higher value of 8 to denote the number of people that are needed for m_e to engage. These values justify that there is a low likelihood of more than five people interacting with the robot at a given time [24].

IV. SIMULATION EXPERIMENTS

A. Setup

The experimental platform for simulating crowd-robot interaction consists of a 30 $\times$ 10 m pathway where pedestrians move left to right with different densities. The robot is set up at the middle along the length of the pathway close to the wall. All agents (and the robot) are modelled as finite-sized circles with diameters ranging between 0.5–0.7 m. We simulate scenarios of pedestrian movement in a single direction while varying crowd density, rate-of-stopping-to-watch, interaction-speed, and the presence of social contagion. The simulation parameters are listed in Table I. The crowd density values correspond to low and high density flow of approximately 5 and 17 agents entering the pathway per minute; the rates of stopping-to-watch correspond to the values observed in a field experiment at a train station [6]; and the interaction-speeds near the robot correspond to slowing down to 10% of the original speed to 40% of the original speed.

Each simulation is initialised with four agents distributed uniformly in the pathway. All agents move left to right when viewed from top with the robot positioned stationary on one side of the pathway. Equation (1) is integrated using the fourth order Runge-Kutta method using *ode45* in MATLAB with a time step of 0.1 second. The fluctuations η_i for each agent are sampled in each direction independently from a zero-mean Gaussian distribution with standard deviation 3 N at every time-step prior to integration. For interaction with the robot, we assume that the agents that are stopping to watch experience a reduced social repulsion between themselves and with the robot. Accordingly, a reduced interaction range of $B_i/10$ is set for all agents within a distance of 2 m from the robot. Instead of using wall force, the boundary conditions are set to reflective such that upon collision with the wall, the component of velocity perpendicular to the wall is multiplied by -1. The position, velocity, and desired speed of each agent is stored in a data file for subsequent analysis. Each simulation is run for twenty four minutes; the first two minutes are ignored for analysis to overcome any initial effects.

We define the following descriptors to study the crowd-robot interaction: the rate-of-interaction is the average number of agents per minute that come within 2 m of the robot and leave; the interaction-time in seconds is the time spent within 2 m of the robot per minute per person; and rate-of-engagement is the number of agents that change direction to move towards the robot (note that this is same as rate-of-stopping-to-watch when no contagion is present).

B. Results

a) Rate-of-interaction with robot increases with flow density and is independent of interaction-speed near the robot or rate-of-stopping-to-watch: Figure 4 shows the rate-of-interaction and interaction-time without social contagion for a range of parameter values at low and high density. As expected, there is a significant difference in the rate-of-interaction between densities with 2.12 $\pm$ 0.36 agents per min at low flow density and 7.07 $\pm$ 0.53 agents at high flow density. Contrary to our expectation, the rate-of-interaction is independent of the interacting speed or rate-of-stopping-to-watch. The interaction-time ranges between 5 and 16 seconds and is independent of flow densities or the rate-of-stopping-to-watch. Across speeds (Fig. 5), statistical comparison shows that the rate-of-interaction is independent of the presence of contagion or interaction-speed at both high and low densities.

b) Effect of contagion: ANCOVA analysis of regression fits to rate-of-engagement v/s rate-of-stopping-to-watch across all interaction-speeds shows that inducing contagion does not significantly increase the rate-of-engagement at although a marginal effect is evident at low flow densities (low density: p=0.09, t=1.72; high density: p=0.43, t=0.79). There is no significant effect of social contagion on the rate-of-interaction or interaction-time (Fig. 6).

c) Interaction-time is significantly affected by the interaction-speed: Figure 7 confirms our expectation that interaction-time decreases significantly with higher interact-

TABLE I

PARAMETER VALUES USED FOR SIMULATING ONE-DIRECTIONAL PEDESTRIAN INTERACTION WITH A ROBOT UNDER SOCIAL FORCE.

Parameter	Description	Value, Range
P_{sw}	Probability of stopping to watch	[0.134 0.179]
λ	Poisson process parameter	$\{0.1, 0.5\}$
s_R	Speed near the robot	[0.1 0.4]
m	Mass of each agent	80 kg
k_d	Coefficient for probability of engagement	1.8
m_e	Max. proportion of agents that can engage	0.5
T	Group size at which $m_e/2$ will engage	8
d_{nR}	Neighbor distance of the robot	2 m
$P_{s,i}$	Probability of looking towards the robot	0.1
τ_i	Adaptation time to new goal	0.01 s
A_i	Interaction strength for agent i (for all i)	2×10^3 N
B_i	Interaction rage for agent i (for all i)	0.08 m
$s_i[0]$	Initial desired speed for agents	1 ± 0.3 m/s

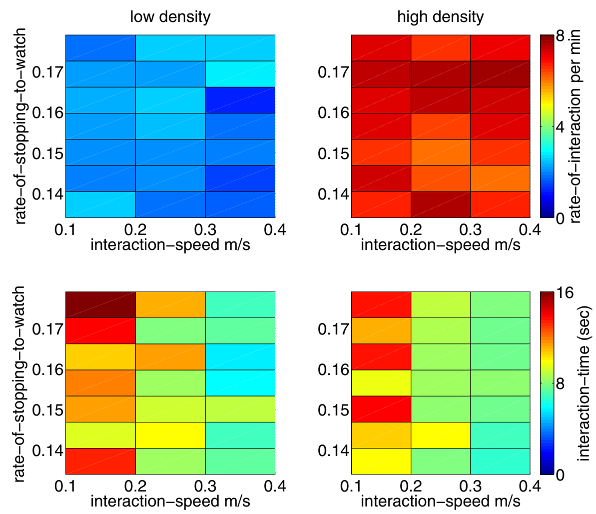

Fig. 4. rate-of-interaction and interaction-time with a stationary robot across a range of values of interacting speeds and rates of stopping to watch in the absence of social contagion.

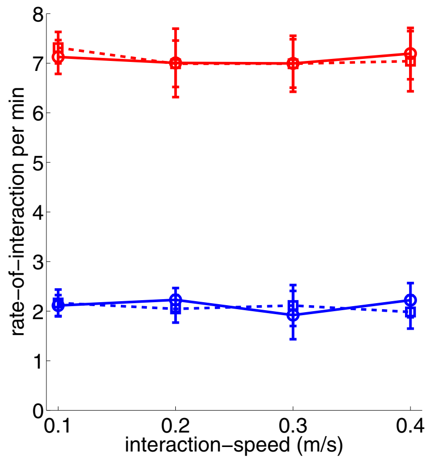

Fig. 5. rate-of-interaction v/s interacting speed in the presence (dashed) and absence (solid) of contagion for high (red) and low (blue) flow densities. Error bars denote 1 σ standard deviation across different rates of stopping to watch.

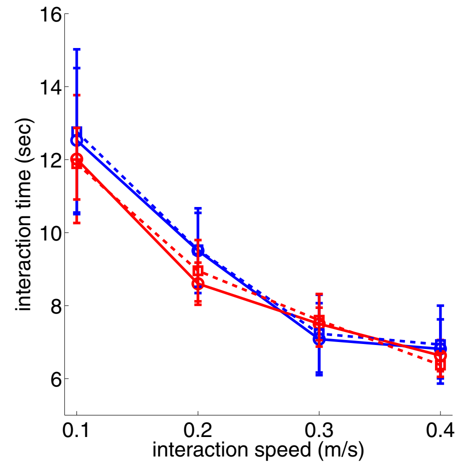

Fig. 7. The interaction-time decreased with increase in interaction-speed for high (red) and low (blue) densities both in the presence (dashed) and absence (solid) of contagion. Error bars denote 1 σ standard deviation across different rates of stopping to watch.

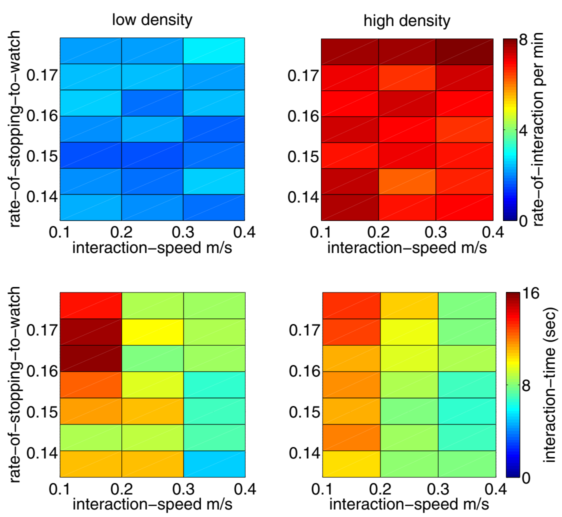

Fig. 6. rate-of-interaction and interaction-time with a stationary robot across a range of values of interacting speeds and rates of stopping to watch in the presence of social contagion.

ing speeds across all rates of stopping to watch (one-way ANOVA, independent variable: interacting speed, dependent variable: interaction-time, 8 replicates per speed, $p < 0.01$).

V. Discussion

Results from our simulations confirm the dependence of rate-of-interaction on flow density. At the same time the independence of rate-of-interaction to interaction-speed shows that the number of agents who come within the interaction range of the robot does not increase even if each agent spends less time near the robot. This is likely due to the absence of any overcrowding effects at the low speeds.

It is possible that at higher flow densities and rate-of-stopping-to-watch crowding will occur near the robot, but that would require selecting values that fall outside the range of empirical observations made in previous studies [6], [19] where no more than twenty percent of the people are found to be undecided on whether they should engage with the robot. Further, a stationary robot in a similar study rarely witnessed a crowd of more than five people [24], demonstrating that our modelling scenario is realistic at low densities where 4 or less people interact with the robot per minute (Figs. 4 and 6, rate-of-interaction per min).

Contrary to our expectation, the presence of social influence through contagion is not manifested in terms of an increase in the number of agents interacting with the robot at high flow density; at low density, we note a marginal, though non-significant increase. While the probability of engagement computed using (5) was motivated from a pedestrian study, the significance of social context and action that is propagated through the crowd will require a more careful selection of parameters. More work is needed in this direction, where the effect of an existing audience on undecided individuals is used to measure the social influence of engaging with a robot.

In the absence of crowding near the robot, the interaction-time is directly influenced by the interaction-speed, and therefore decreases significantly with increase in interaction-speed. More importantly, the interaction-time does not depend on flow density, an effect that can again be attributed to the absence of strong social forces that would otherwise be experienced were there any overcrowding near the robot. Social forces are found to dominate and give rise to emergent behaviours in densely crowded scenarios; on the other hand, here, we find that for flow densities as high up to seven agents per minute, robot design choices such as interactiveness or the presence of sociality dominate the interaction-time.

The approach presented here to simulate the social interactions between a robot and pedestrian crowd incorporates varying rates of stopping-to-watch and interaction speeds as an effect of robot interactiveness and sociality. In addition, the effect human crowding near the robot on engagement levels is modelled in the form of contagion. The combined model could be detailed further to explore changes in degrees of overt robot behaviour that are known to affect human response such as gaze following and affective interactions [22], [5], [16]. Future studies will also aim at extending this framework to analyse other scenarios such as shopping malls and museums where the robot is non stationary to study the effect of robot presence and movement [17] on the collective behaviour of casual crowds.

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References

[1] B. D. Eldridge and A. A. Maciejewski. Using genetic algorithms to optimize social robot behavior for improved pedestrian flow. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, pages 524–529, 2005.

[2] G. Ferrer, A. Garrell, and A. Sanfeliu. Robot companion: A social-force based approach with human awareness-navigation in crowded environments. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1688–1694. IEEE, 2013.

[3] A. C. Gallup, A. Chong, and I. D. Couzin. The directional flow of visual information transfer between pedestrians. *Biology Letters*, 8(4):520–522, 2012.

[4] A. C. Gallup, J. J. Hale, D. J. T. Sumpter, S. Garnier, A. Kacelnik, J. R. Krebs, and I. D. Couzin. Visual attention and the acquisition of information in human crowds. *Proceedings of the National Academy of Sciences of the United States of America*, 109(19):7245–7250, 2012.

[5] M. A. Goodrich and A. C. Schultz. Human-Robot Interaction: A Survey. *Foundations and Trends in Human-Computer Interaction*, 1(3):203–275, 2007.

[6] K. Hayashi, D. Sakamoto, T. Kanda, M. Shiomi, S. Koizumi, H. Ishiguro, T. Ogasawara, and N. Hagita. Humanoid robots as a passive-social medium-a field experiment at a train station. In *Proceedings of the ACM/IEEE International conference on Human Robot Interaction (HRI)*, pages 137–144, 2007.

[7] D. Helbing, L. Buzna, A. Johansson, and T. Werner. Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. *Transportation Science*, 39(1):1–24, 2005.

[8] D Helbing, I Farkas, and T Vicsek. Simulating dynamical features of escape panic. *Nature*, 407(6803):487–90, 2000.

[9] D. Helbing and I. J. Farkas. Simulation of pedestrian crowds in normal and evacuation situations. *Pedestrian and Evacuation Dynamics*, 21:21–58, 2002.

[10] D. Helbing and A. Johansson. Pedestrian, crowd and evacuation dynamics. In *Extreme Environmental Events*, pages 697–716. Springer, New York, 2011.

[11] C. M. Henein and T. White. Agent-based modelling of forces in crowds. In *Multi-agent and multi-agent-based simulation*. 2005.

[12] T. Kanda, T. Hirano, D. Eaton, and H. Ishiguro. Interactive robots as social partners and peer tutors for children: A field trial. *Human-computer interaction*, 19(1):61–84, 2004.

[13] T. Kanda and H. Ishiguro. *Human-robot interaction in social robotics*. CRC Press, 2012.

[14] T. Kanda, M. Shiomi, Z. Miyashita, H. Ishiguro, and N. Hagita. An affective guide robot in a shopping mall. In *Proceedings of the ACM/IEEE International conference on Human Robot Interaction (HRI)*, pages 173–180, 2009.

[15] T. Kanda, M. Shiomi, Z. Miyashita, H. Ishiguro, and N. Hagita. A communication robot in a shopping mall. *IEEE Transactions on Robotics*, 26(5):897–913, 2010.

[16] R. Kirby, J. Forlizzi, and R. Simmons. Affective social robots. *Robotics and Autonomous Systems*, 58(3):322–332, 2010.

[17] T. Kruse, A. K. Pandey, R. Alami, and A. Kirsch. Human-aware robot navigation: A survey. *Robotics and Autonomous Systems*, 61(12):1726–1743, 2013.

[18] R Mehran, A Oyama, and M Shah. Abnormal crowd behavior detection using social force model. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 935–942, 2009.

[19] M. P. Michalowski, S. Sabanovic, and R. Simmons. A spatial model of engagement for a social robot. In *Proceedings of the IEEE International Workshop on Advanced Motion Control*, pages 762–767, 2006.

[20] S. Milgram, L. Bickman, and L. Berkowitz. Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology*, 13(2):79–82, 1969.

[21] M. Moussaïd, D. Helbing, and G. Theraulaz. How simple rules determine pedestrian behavior and crowd disasters. *Proceedings of the National Academy of Sciences of the United States of America*, 108(17):6884–6888, 2011.

[22] B. Mutlu, J. Forlizzi, and J. Hodgins. A storytelling robot: modeling and evaluation of human-like gaze behavior. In *Proceedings of the IEEE-RAS International Conference on Humanoid Robot*, pages 518–523, 2006.

[23] R. Nagai, T. Nagatani, M. Isobe, and T. Adachi. Effect of exit configuration on evacuation of a room without visibility. *Physica A: Statistical Mechanics and its Applications*, 343:712–724, 2004.

[24] S. Sabanovic, M. P. Michalowski, and R. Simmons. Robots in the wild: Observing human-robot social interaction outside the lab. In *IEEE International Workshop on Advanced Motion Control*, pages 596–601, 2006.

[25] M. Shiomi, D. Sakamoto, T.akayuki Kanda, C. T. Ishi, H. Ishiguro, and N. Hagita. A semi-autonomous communication robot: a field trial at a train station. In *Proceedings of the ACM/IEEE International conference on Human Robot Interaction (HRI)*, pages 303–310, 2008.

[26] J. L. Silverberg, M. Bierbaum, J. P. Sethna, and I. Cohen. Collective Motion of Humans in Mosh and Circle Pits at Heavy Metal Concerts. *Physical Review Letters*, 110(22):228701, 2013.

[27] D. J. T. Sumpter and S. C. Pratt. Quorum responses and consensus decision making. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, 364(1518):743–53, 2009.

[28] S. Thrun, M. Bennewitz, W. Burgard, A. B. Cremers, F. Dellaert, D. Fox, D. Hahnel, C. Rosenberg, N. Roy, J. Schulte, and D. Schulz. Minerva: A second-generation museum tour-guide robot. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, 1999.