Proxemics models for human-aware navigation in robotics: Grounding interaction and personal space models in experimental data from psychology

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Proxemics models for human-aware navigation in robotics: Grounding interaction and personal space models in experimental data from psychology*

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Abstract— **In order to navigate in a social environment, a robot must be aware of social spaces, which include proximity and interaction-based constraints. Previous models of interaction and personal spaces have been inspired by studies in social psychology but not systematically grounded and validated with respect to experimental data. We propose to implement personal and interaction space models in order to replicate a classical psychology experiment. Our robotic simulations can thus be compared with experimental data from humans. Thanks to this comparison, we first show the validity of our models, examine the necessity of the interaction and personal spaces and discuss their geometric shape. Our experiments suggest that human-like robotic behavior can be obtained by using only correctly calibrated personal spaces (i.e., without explicit representation of interaction spaces and therefore, without the need to detect interactions between humans in the environment).**

I. INTRODUCTION

Human navigation, however mundane its context and purpose, is a complex activity, subject to a large number of external constraints. Avoiding bumping into two people discussing together, and avoiding disturbing these people by interrupting their interaction, are two examples of such constraints. The first is an instance of a safety constraint, useful to prevent situations potentially harmful to the navigating agent; the second is an instance of a social constraint, useful to prevent situations potentially annoying to others. Trying and avoiding being a nuisance, both to self and to others, would therefore seem to be a basic requirement for human-like navigation.

In the context of human-aware robotic navigation, autonomous robots should respect these two types of constraints. Early robotics research have mostly focused on safety constraints [1], [2], [3]. Recent developments have investigated incorporating social constraints in navigation algorithms and space representations [4], [5], [6]. In particular, robotics research has integrated various models of personal spaces (PS) and interaction spaces (IS).

For instance, PS has been modeled by asymmetrical combinations of 2D Normal distributions, centered on the navigating agent's position [7], [5], or by considering several regions around humans in the robotic environment, assigning each region to accompanying and following tasks [8]. PS models have also been expanded, integrating explicit attraction towards interaction or, on the contrary, avoidance of interaction, in order to differentially weigh four 2D Normal distributions and obtain different PS shapes [9]. Visibility has also been considered, for instance so that robots would avoid zones that humans do not see (e.g., zones behind a corner, behind other people) [6]. Interaction space has also been modeled, for instance with Normal probability distributions, either one-dimensional or two-dimensional, according to the geometrical configuration of the interacting group [5].

Outside of robotics, experiments on animal navigation and social conventions have led to a large number of theories about personal space representation, with applications from livestock herding [10] to understanding the psychology of interaction in humans.

Hall [11], for instance, proposed the concept of proxemics to describe observations and theories of the use of space in humans. Assuming that social relationships are usually reflected in physical distances (between people), Hall defined four proxemic distances: the intimate, personal, social and public distances, which are represented by four concentric boundaries. PS conceptually matches Hall's model of personal distance.

The boundary of PS is influenced by contextual parameters (e.g., culture) or internal parameters (e.g., speed) making its direct observations difficult [12], [13]. Moreover, several authors proposed that personal space would not be concentric but would be elongated to the front [14], [15]. PS is the most studied space, but is not the only one. Indeed, more recently, psychology studies have focused on other spaces, like IS [16], either for static interactions (e.g., discussing at the water cooler) or interactions during movement (e.g., walking in group), or the affordance space [17].

So far, and to the best of our knowledge, it appears that human-aware robotics uses models of social constraints that are somewhat inspired from known representations of social spaces in humans, but not systematically grounded in experimental data from social and cognitive psychology.

This is a possible shortcoming, as it could limit the ability of robots to mimic navigation trajectories and behaviors that appear socially acceptable and natural to surrounding humans. Developing formal models of human-like social navigation could also, in turn, help social psychology identify mathematical properties of models that would be useful for understanding human behavior.

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In this paper, we present a study of several models of social space representations, grounding their comparison in experimental data from the social psychology literature. More precisely, we consider a classical experiment by Efran and Cheyne [18], where human participants had to walk down a corridor, choosing whether they would pass between two confederates involved in an interaction, or avoid them and pass behind. We then define mathematical models of personal and interaction spaces. They provide navigation costs to a cost-based trajectory planning algorithm.

Our experiment addresses three questions. Can the experiment and experimental observations be replicated using our simulated robot? We demonstrate it does, in some portions of the parameter space we explored, and it does not, elsewhere. To replicate experimental data, is it necessary to involve an interaction space representation, or are personal spaces sufficient? We demonstrate that personal spaces are sufficient, and that interaction space models may be superfluous. Finally, what geometrical shapes can personal spaces have in order to explain experimental data? We demonstrate that personal spaces need to have an asymmetrical shape, elongated to the front.

To substantiate these claims, the rest of this paper is structured as follows. We first describe Efran and Cheyne's experimental protocol and data collection, then we introduce the mathematical models for personal and interaction spaces. Our experiment, and the simulator it is implemented in, are then described, followed by the presentation and analysis of our experimental data.

II. EFRAN AND CHEYNE'S EXPERIMENTS

We summarize here the main elements and findings of the classical experiment by Efran and Cheyne [18].

Two confederates, involved in a mock discussion, stood in narrow corridors. The experiment took place in three different corridors, of widths 2.28 m, 2.49 m and 2.36 m. Confederate A was back to one wall, confederate B was facing him (or her), some distance d away. From trial to trial, distance d varied, from 0.61 m to 1.37 m. We considered 13, 15 and 15 different distances for the three corridors, respectively, for a total of 43 possible different spatial configurations. The space "outside" of the interacting pair depended on the corridor: for instance, it was only 0.21 m at its smallest (in the first corridor).

In this setting, participants were people who simply happened to walk down this corridor. They could do so either by walking outside of the interacting pair, or between confederates (see Fig. 1, top). When participants were gone from the corridor, confederates took note of the passage chosen. However, some inclusion criteria had to be met (e.g., no-one else was in the corridor during the observation). Participants were unaware that they were observed for the purpose of the experiment. There were respectively 132, 901 and 223 participants, in the three corridors. Observations were the probabilities, for each distance d, that a participant would pass between confederates: experimental data are shown in Fig. 1 (bottom).

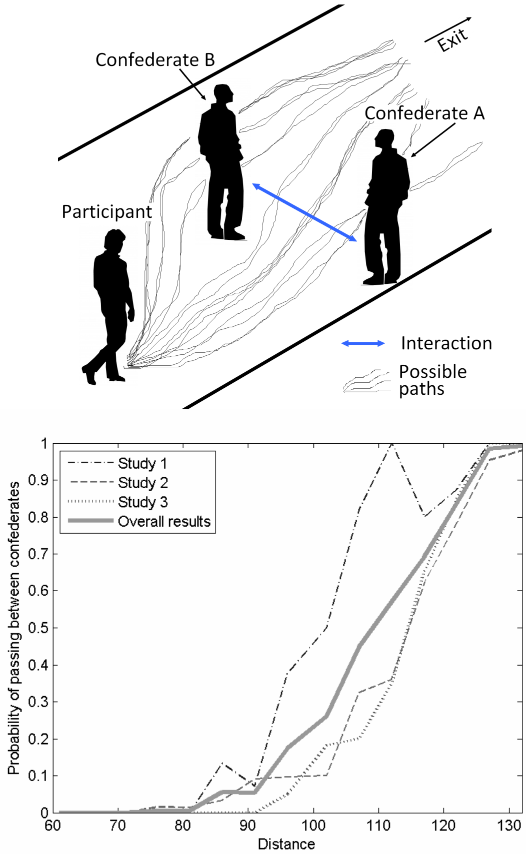

Fig. 1. Summary of Efran and Cheyne's experiment [18]. **Top:** Schema of the experimental setup. **Bottom:** Experimental data is the probability of passing between confederates, as a function of the distance d between them.

Observations indicate, of course, that a larger distance d between confederates increased the probability that participants would pass between them, and decreased the probability of passing behind confederate B. These experimental data quantify precisely how this probability varied as a function of distance d between confederates. These are the data that we aim to mathematically replicate, in our experiment.

III. PERSONAL SPACE AND INTERACTION SPACE MODELS

A. Personal space model

We model PS in the form of a real-valued cost. Its value is 0 for positions where nothing hinders the navigating agent; on the other hand, its value is 1 for positions where something maximally disturbs or hinders it (i.e., unwanted contact or collision). Between these extremes, the cost varies gradually as a function of distance and angle to the navigating agent. Following Kirby [7], this mathematically takes the form of two Normal probability distributions on the x, y plane, joined together seamlessly on the coronal plane of the navigating agent (i.e., the plane separating what is in front to what is to the rear of the navigating agent). These two 2D Normal distributions have independent front variance σ_h and rear variance σ_r, but, by construction, they have the same side variance σ_s. Their covariance matrices are Σ_h for the

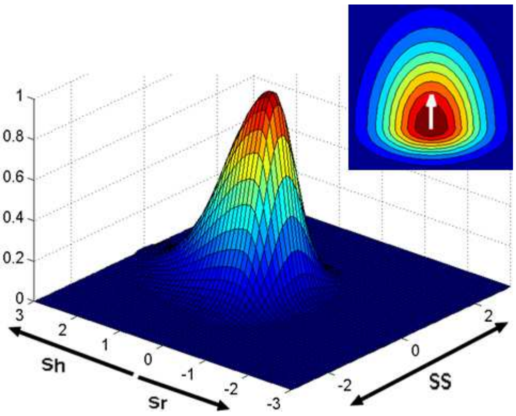

Fig. 2. Personal space model of parameters σ_h = 1.0, σ_r = 0.3, σ_s = 0.5, visualized as a real-valued function. **Inset:** The same personal space, visualized as a contour plot.

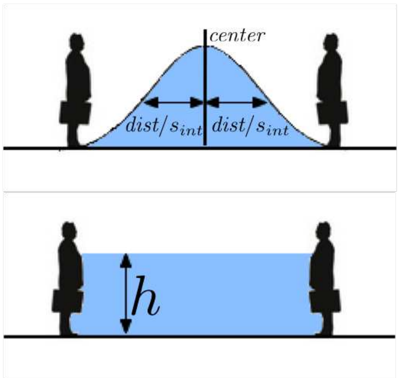

Fig. 3. Interaction space models. **Top:** Interaction space as a Normal probability distribution. **Bottom:** Interaction space as a constant function.

front 2D Normal and Σ_r for the rear 2D Normal, with:

$$\Sigma_h = \begin{pmatrix} \sigma_h & 0 \\ 0 & \sigma_s \end{pmatrix} , \; \Sigma_r = \begin{pmatrix} \sigma_r & 0 \\ 0 & \sigma_s \end{pmatrix} . \quad (1)$$

Therefore, the personal space cost at position (x, y) relative to the navigating agent, and angle $\alpha = 0$ is given by:

$$PS(x, y) \quad \propto \quad \begin{cases} \mathcal{N}(x, y \; ; \; [x_0, y_0], \Sigma_h) & \text{if } x_0 \geq 0 \\ \mathcal{N}(x, y \; ; \; [x_0, y_0], \Sigma_r) & \text{otherwise} . \end{cases} \quad (2)$$

The general formulation, for any angle α, can be found elsewhere [7]: it basically amounts to rotating the front/rear axis by angle α. An example of a personal space cost function is shown in Fig. 2.

B. Interaction space model

In this paper, we explore two mathematical definitions for the interaction space (IS) model. We only consider one-dimensional functions, because the geometry of Efran and Cheyne's experiment only provides information about passage through the "critical line", that is to say the axis crossing the corridor at the position of the interacting confederates.

The first mathematical model was already used in previous works [5], and consists in a Normal probability distribution, defined by:

$$IS_{\mathcal{N}}(x) \propto \mathcal{N}(x \; ; \; center, dist/s_{int}) \; , \quad (3)$$

with $center$ the middle position between the interacting people, $dist$ the distance between them, and s_{int} a free parameter. The proportionality coefficient is defined so that the maximum value taken by this function is 1 to represent maximum hindrance.

The second mathematical model is simply a constant value between interacting people, defined by:

$$IS_c(x) = h = \min(p_{int}/dist, 1) \; , \quad (4)$$

with h the "height" of the constant, given by the ratio between p_{int}, a free strictly positive parameter, and $dist$ the distance between the interacting people, provided it does not exceed a maximum value of 1 (for representing maximum hindrance, as previously). This model represents a constant valued hindrance between interacting people, whatever the position that would be chosen by the navigating agent to pass between them.

The two mathematical definitions of interaction space we investigate are illustrated in Fig. 3.

IV. EXPERIMENT

A. Simulation of Efran and Cheyne's experiment

We have replicated Efran and Cheyne's experiment in a robotic simulator. To do so, we have created three different environments, that are corridors of the same dimensions as described by Efran and Cheyne. Static, simulated confederates A and B, and a moving simulated participant (i.e., the simulated robot) were placed in these environments. Each was implemented as a rectangle of lengths 0.3 m from "front" to "back" and 0.4 m long from left to right.

Simulated confederates were placed as in the original experiment, with the distance d between them a controlled parameter. The simulated robot was placed, at the beginning of each simulation, at the entrance of the corridor, and was provided a navigation goal at the other end. To solve the navigation task, it would therefore have to traverse the corridor, either by passing between or behind confederates, as human participants had to.

B. Trajectory generation

We used the RiskRRT (Risk Rapid-exploring Random Tree) trajectory generation algorithm [19], which is a variant of the RRT (Rapid-exploring Random Tree) algorithm [20] adapted for dynamic environment, using partial planning. The RiskRRT trajectory generation algorithm deploys a tree of nodes with associated costs, taking into account possible collisions with static and dynamic obstacles, along with social costs, and selects the branch of lower maximal cost that also progresses toward the specified goal. A sample navigation scenario, illustrating the RiskRRT algorithm, is shown in Fig. 4.

C. Collision costs and social costs

In RiskRRT, costs associated with nodes represent risk, either of collision, or of social hindrance. This cost for a position (x, y) is therefore defined as a function of the probability that position (x, y) is collision free,

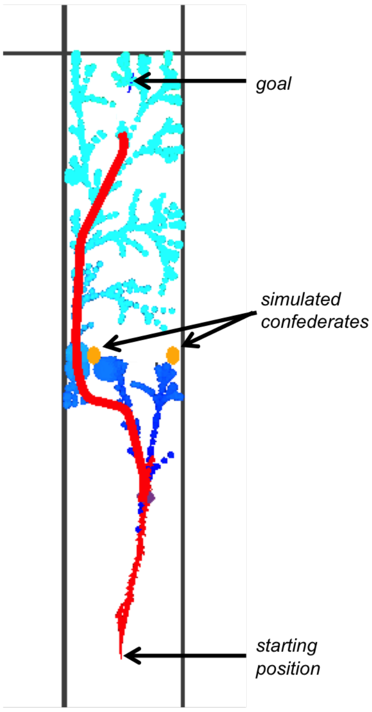

Fig. 4. Example of a navigation scenario and the possible trajectories computed by the RiskRRT algorithm. Near the simulated confederates, potential collisions and social costs increase the calculated costs of some branches of the tree. Larger costs are represented by circles of larger diameter. In this example, the simulated participant chooses to avoid passing between confederates.

$\mathit{PWithoutColl}(x, y)$, and the probability that it is "hindrance-free", $\mathit{PWithoutHind}(x, y)$, with:

$$\mathit{cost}(x, y) = 1 - (\mathit{PWithoutColl}(x, y) \cdot \mathit{PWithoutHind}(x, y)) \ . \quad (5)$$

In the simulation of Efran and Cheyne's experiment, the probability of collision involves the probability of collision with walls in the occupancy map given to the robot, $\mathit{pCollW}(x, y)$, or the confederates $\mathit{pCollC}_A(x, y)$ and $\mathit{pCollC}_B(x, y)$:

$$\mathit{PWithoutColl}(x, y) = (1 - \mathit{pCollW}(x, y)) \cdot (1 - \mathit{pCollC}_A(x, y)) \cdot (1 - \mathit{pCollC}_B(x, y)) \ . \quad (6)$$

The probability of social hindrance involves several components: the probability that the robot at position (x, y) would invade personal spaces of confederates A and B $\mathit{pHindC}_A(x, y)$ and $\mathit{pHindC}_B(x, y)$, the probability of interrupting their interaction $\mathit{pInt}(x, y)$, and the probability that outside elements would invade the personal space of the navigating agent $\mathit{pNav}(x, y)$:

$$\mathit{PWithoutHind}(x, y) = (1 - \mathit{pHindC}_A(x, y)) \cdot (1 - \mathit{pHindC}_B(x, y)) \cdot (1 - \mathit{pInt}(x, y)) \cdot (1 - \mathit{pNav}(x, y)) \ . \quad (7)$$

The first two terms refer to the PS models centered on each confederate, using the asymmetric 2D Normal model of PS

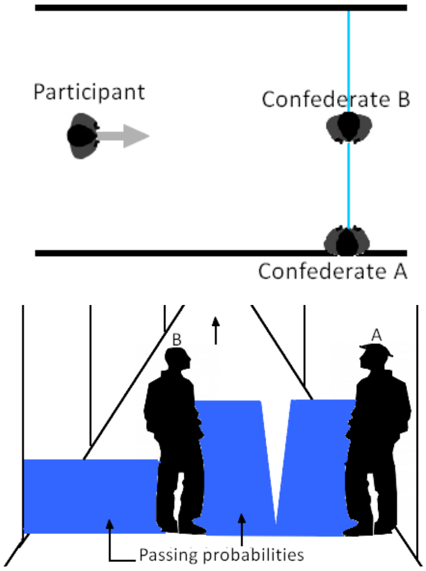

Fig. 5. **Top:** Illustration of the critical line, the only portion of interest when deciding whether to pass between or outside confederates (top view of the experimental situation). **Bottom:** Height of the critical line represents passing probabilities (perspective drawing of the experimental situation).

given by Eq. (2). $\mathit{pInt}(x, y)$ refers either to the Normal model of IS of Eq. (3), or to the constant model of IS of Eq. (4), or can be replaced by a constant zero value for testing experimental scenarios where the interaction space model is disabled. Finally, $\mathit{pNav}(x, y)$ is computed by attaching a personal space model to the navigating agent, and finding the object, in the navigating agent's neighborhood, of maximal hindrance (i.e., the navigating agent avoids being close to static or dynamic obstacles as they would invade its personal space).

Again, because of the simple geometry of the navigation scenario in Efran and Cheyne's experiment, costs only need to be computed on the "critical line" passing through confederates and crossing the corridor (see Fig. 5, top; the critical line is, because of the geometry of Efran and Cheyne's experiment, parallel with body and gaze orientations of confederates, and normal to the walls). In other words, we only used, from the RiskRRT algorithm, the cost computation for these positions of interest, ignoring the whole trajectory generation before or after the critical line, etc. We computed costs along this critical line, every 0.02 m, excepting positions occupied by confederates.

With these costs, we computed the probability of passing between or outside the confederates. Two methods have been explored, either by selecting the side of lowest average cost ("average" method), or by selecting the side containing the lowest cost overall ("minimum" method). A hypothetical situation illustrating the difference is shown in Fig. 5 (bottom). On this example, the "average" method would select passing outside of confederates (smaller average cost on the left side), whereas the "minimum" method would select passing between confederates (smaller minimum value on the right side).

Condition	Parameters	Min	Max	Step
PS Only	σ_h	0.7	1.5	0.1
	σ_r	0.1	1.3	0.1
	σ_s	0.3	1.5	0.1
PS + constant IS	σ_h	0.6	1.4	0.2
	σ_r	0.1	1.3	0.2
	σ_s	0.3	1.3	0.2
	p_{int}	0.0	0.8	0.2
PS + Normal IS	σ_h	0.4	1.6	0.2
	σ_r	0.1	1.3	0.2
	σ_s	0.3	1.5	0.2
	s_{int}	0.5	8.0	0.5
Constant IS Only	p_{int}	0.0	1.5	0.1
Normal IS Only	s_{int}	0.5	8	0.5

TABLE I

PARAMETER RANGES AND SAMPLING PRECISION FOR EACH EXPERIMENTAL CONDITION.

Experimental results showed that the "minimum" method yields similar observations (i.e., candidate models are ranked in the same order), with systematically worse model fit (i.e., there are larger discrepancies between data and model predictions) than the "average" method. Therefore, for the remainder of this paper, and because of lack of space, we only report below experiments with the "average" method.

D. Experimental conditions, parameter spaces, and model fit measure

To answer our questions about the necessity of modeling interaction spaces, we have explored several model combinations, resulting in five experimental conditions:

1) in the *"PS Only"* condition, personal spaces of the navigating agent and confederates were used in computations, but not interaction spaces (i.e., $pInt = 0$ in Eq. (8) above);
2) in the *"PS + Constant IS"* condition, personal spaces were used, along with an interaction space of constant value between confederates (i.e., $pInt = IS_c$);
3) in the *"PS + Normal IS"* condition, personal spaces were used, along with an interaction space following a Normal probability distribution between confederates (i.e., $pInt = IS_{\mathcal{N}}$);
4) in the *"Constant IS Only"* condition, personal spaces were disabled, leaving only an interaction space of constant value between confederates;
5) finally, in the *"Normal IS Only"* condition, personal spaces were disabled, leaving only an interaction space of Normal shape between confederates.

For each condition, the possible parameters dimensions were sampled at discrete values: this allows a grid search for evaluating models. Ranges and precision steps are given Table I.

Enumerating all model combinations and parameter space evaluation points yielded $8,091$ candidate models that we experimentally evaluated. Each of these candidate models was simulated in all of the 43 spatial configurations of our simulation of Efran and Cheyne's experiment (recall there were three corridors, with $13 + 15 + 15$ possible distances d between confederates). Overall, we performed $8,091 \cdot 43 = 347,913$ simulations in our experiment (and again the same number for the "minimum" method, that we discounted previously).

Each of these simulations provided the probability to pass between the confederates, *Sim_P*, for each experimental condition, parameter values, and spatial configurations at hand. We therefore measured the model fit of each simulation, by comparing our simulated data with the experimental data of Efran and Cheyne, *Obs_P*, using the root of the squared error:

$$\textit{Model fit} = \sqrt{(\textit{Sim\_P} - \textit{Obs\_P})^2} \ , \qquad (8)$$

(i.e., we measured the RMSE for a single point). Model fit is good when the measured error is small.

V. EXPERIMENTAL RESULTS

The model fit measure we presented was aggregated in various ways during data analysis. For instance, we found out that analyzing results for each of the three simulated corridors, or by averaging over corridors, had minimal impact on observations. Therefore, in the remainder of the paper, we only discuss this global analysis of data (but see Table II).

A. Can we replicate Efran and Cheyne's data?

The first data analysis we report aimed at verifying whether the proposed models and their combinations could account for the experimental data of Efran and Cheyne.

To do so, we studied, for each condition, the 200 parameter values with best and worse model fits found in the parameter space. Fig. 6 shows the results for conditions "PS Only", "PS + Constant IS" and "PS + Normal IS". We observe that, in these conditions, the best parameter values allow the simulated models to closely match experimental data, contrary to the worst parameter values, where the navigating agent passes much more frequently or less frequently between confederates.

We also studied the geometry of model fit across the parameter space, to verify whether better solutions could possibly exist outside of the chosen parameter space. We focus here on model fit in the "PS Only" condition, for all parameter values. Recall that parameter space is three-dimensional in this case, with three independent variance coefficients σ_h, σ_r and σ_s: we plot model fit against ratios σ_r/σ_h and σ_s/σ_h (Fig. 7, top) and ratios σ_r/σ_s and σ_h/σ_s (Fig. 7, bottom).

We observe flat valleys in model fit landscapes, where it is very close to its minimal value of 0.084. It is doubtful that better solutions exist outside of the parameter space we explored; examining data by Efran and Cheyne, we can hypothesize that we reached a minimal, residual value for model fit, that is due to experimental noise and small data sample (e.g., see the odd drop in passage probability around distance $d = 1.15\ m$, for corridor 1, in Fig. 1).

Overall, these results show that the chosen parameter spaces contain good solutions allowing to replicate Efran and Cheyne's data, but not trivially so, as portions of parameter

Condition	Best parameters					Best model fit			
	Parameters	Corr1	Corr2	Corr3	Overall	Corr1	Corr2	Corr3	Overall
PS Only	σ_h	1.5	1.3	1.5	0.9	0.085	0.024	0.017	0.084
	σ_r	1.1	1.0	0.6	0.1				
	σ_s	0.3	0.6	1.5	1.5				
PS + Constant IS	σ_h	1.4	1.2	1.4	0.8	0.085	0.024	0.016	0.084
	σ_r	1.3	0.9	0.7	0.1				
	σ_s	0.3	0.7	1.3	1.1				
	p_{int}	0.6	0.2	0.6	0.4				
PS + Normal IS	σ_h	1.0	1.0	1.4	0.6	0.087	0.025	0.016	0.083
	σ_r	1.1	1.3	1.3	0.1				
	σ_s	0.3	0.5	1.3	1.5				
	s_{int}	7.0	7.5	6.0	8.0				
Constant IS Only	p_{int}	1.0	0.9	1.1	1.0	0.144	0.294	0.216	0.230
Normal IS Only	s_{int}	5.5	7.0	6.0	6.5	0.179	0.325	0.308	0.283

TABLE II

SUMMARY OF THE BEST PARAMETERS AND MODEL FITS FOR EACH EXPERIMENTAL CONDITION.

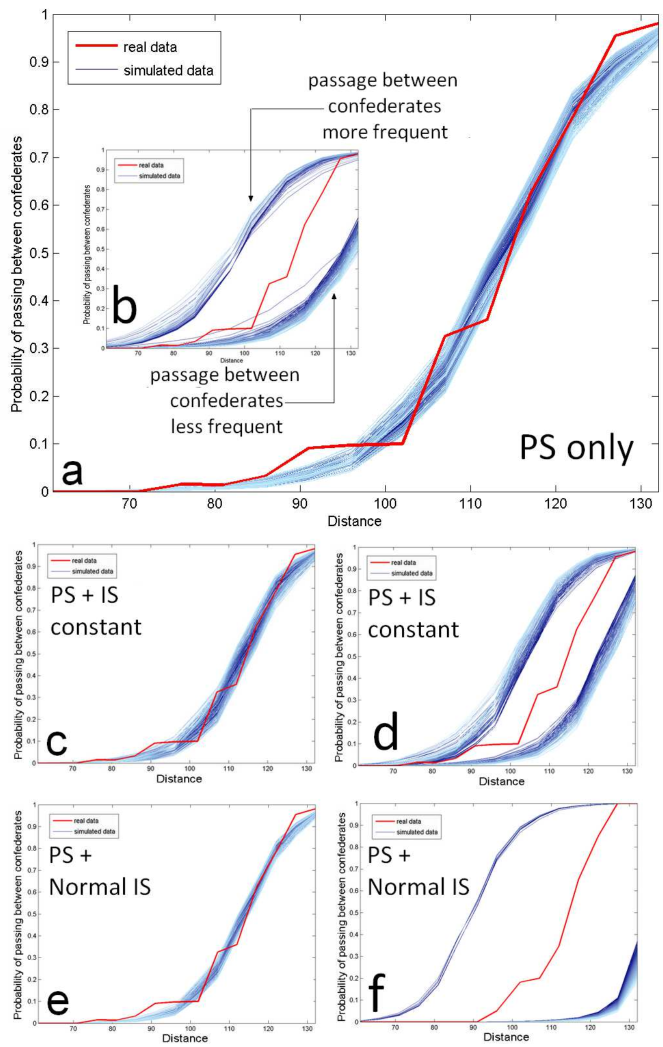

Fig. 6. Comparison of simulated passage probabilities and experimental observations by Efran and Cheyne, in corridor 2 (data are similar for other corridors). **a)** The 200 best parameter values in the "PS Only" condition replicate experimental data very well, contrary to the 200 worst (**b**). Observations are similar in the "PS + Constant IS" (**c**,**d**) and "PS + Normal IS" (**e**,**f**) conditions.

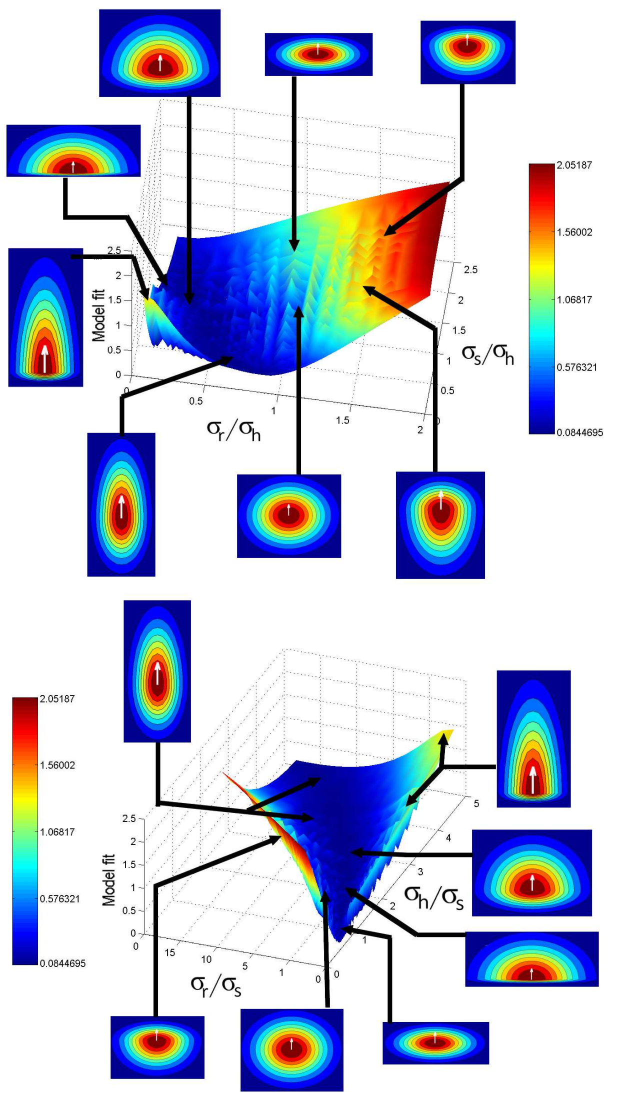

Fig. 7. Model fit in the "PS Only" condition, as a function of ratios σ_r/σ_h and σ_s/σ_h (**Top**) and as a function of ratios σ_r/σ_s and σ_h/σ_s (**Bottom**). Insets show the corresponding PS shapes for example positions in these spaces.

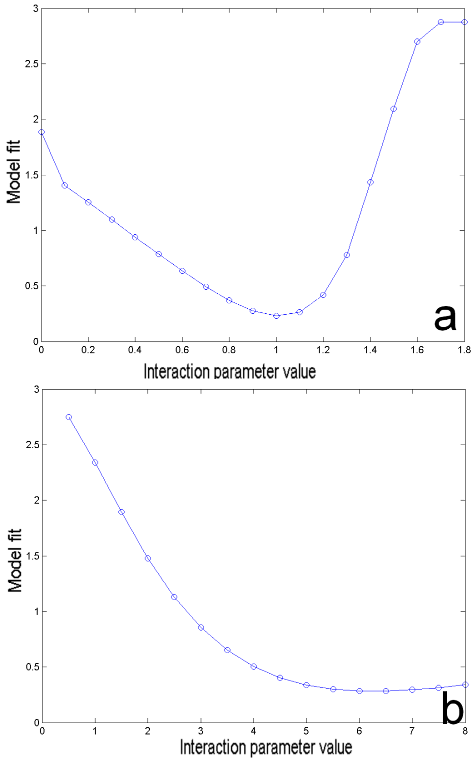

Fig. 8. Model fit as a function of the single parameter for the "Constant IS Only" (**a**) condition and the "Normal IS Only" (**b**) condition. In both cases, an optimal parameter value lies inside the explored parameter space.

spaces yield simulations that do not correspond to human behavior.

Experimental results and analyses are similar for other conditions. In particular, concerning the "Constant IS Only" and "Normal IS Only" conditions, we observe an overall worse fit, everywhere in the parameter space, compared to the "PS Only" condition (Fig. 8). These two conditions are therefore eliminated from further analysis.

B. Are interaction spaces necessary?

Previous analyses have left three conditions in competition: "PS Only", "PS + Constant IS" and "PS + Normal IS". Analysis of the best parameter values shows similar best model fits for each of the three conditions (see Table II). We have investigated this similarity and found that, for parameter values in models with IS, there was an equivalent parameter value for the personal space in the "PS Only" condition. Intuitively, this equivalent model simply replaces the IS between confederates by an increase in the front variance of the PS. We compared for instance the best parameters in the "PS Only" and the "PS + Normal IS", in the overall analysis (all three corridors combined). Removing a Normal IS with $s_{int} = 8.0$ modifies the front variance of the PS from $\sigma_h = 0.6$ to $\sigma_h = 0.9$. The situation is similar when comparing the "PS Only" and "PS + Constant IS" conditions, but with less marked increases in σ_h.

This means that models with explicit IS are equivalent to a model without IS, but with different parameters. This is both a good and a bad news. The bad news is that, in terms of scientific analysis, this leads to a negative conclusion: this shows that the data of Efran and Cheyne cannot discriminate between models with or without IS. From these data, it is impossible to know whether humans use an IS representation, or whether they only rely on a PS representation. It could also be the case that humans only use plastic PS representations, that are modified according to context, as some psychological experiments have already suggested [14], [13].

On the other hand, the good news is that using only a PS of fixed parameters yields very good results, with respect to the replication of Efran and Cheyne's experiment: notice that valleys of near optimal parameter configurations are wide (Fig. 7), indicating a robust model. We pursue the previous example: assume removing the IS from the optimal "PS + Normal IS", but not increasing σ_h. It can be verified that not increasing σ_h would only marginally affect model fit (compare, in Fig. 7 (top), the point at $\sigma_s/\sigma_h = 1.5/0.6 = 2.5$ and $\sigma_r/\sigma_h = 0.1/0.6 = 0.16$ with the point at $\sigma_s/\sigma_h = 1.5/0.9 = 1.6$ and $\sigma_r/\sigma_h = 0.1/0.9 = 0.11$: both lie in the near-optimal valley).

Taking only PS models into account, ignoring IS altogether, also would yield simpler robotic implementation. First, it reduces parameter space by one-dimension; as we showed that it would not decrease model performance, a parsimony argument supports this simplification. This observation also leads to an intriguing possibility for human-aware navigation in robotics. This suggests that detecting interactions in human populated environments, which is possibly a costly and difficult step, might be superfluous. At least for interactions when people are separated by small distances, a representation of their PS already ensures avoiding interrupting their interactions. Whether this extends to interactions on a larger spatial scale, or involving more that two people, is an open question.

C. What is the geometry of personal space?

Examining the model fit landscapes of the "PS Only" condition (Fig. 7) suggests that only some PS shapes yield adequate replication of Efran and Cheyne's data. Examples in valleys of good solutions all have similar geometries, with an asymmetrical shape, elongated to the front and short to the rear.

This result is not compatible with Hall's original proposal [11] of PS as concentric circles (a circular PS can be seen in Fig. 7 as a mediocre solution). In contrast, it strongly supports other proposals which have suggested asymmetrical shapes, similar to the ones we obtained in our experiment [14].

VI. CONCLUSION

In this paper, we have presented an experiment comparing robotic simulations of PS and IS with experimental data from psychological literature, in a corridor crossing navigation scenario involving avoiding people in interaction. We have proposed several models of IS, and a model of PS, to investigate their combinations extensively.

Our results indicate that the proposed models, with correct parameter values, can adequately replicate the experimental data of Efran and Cheyne. This could benefit future robotic applications, by providing PS parameters that were demonstrated to yield navigation strategies very close to human behavior (i.e., grounding Kirby's asymmetrical Normal model [7] in data from experimental psychology). We have also demonstrated that PS was sufficient in the navigation scenario we explored, and that omitting an explicit IS would only marginally decrease model fit. In a robotic application context, this suggests that detecting interactions might by superfluous, and only representing PS would be enough to obtain human-like group avoidance.

Finally, the analysis of PS geometry strongly suggests that human PS would be asymmetrical and elongated to the front, supporting some non-mathematical models of PS in psychological literature. However, because of the simplicity of Efran and Cheyne's experiment, some geometrical properties could not be investigated (e.g., the critical line "hides" the 2D shape of IS).

The generalizability of our results thus appears to be an interesting topic for future research. A large number of variations on Efran and Cheyne's initial experiments are easily imagined; we describe a few. For instance, if one of the confederates is not a person but a robot, would a different personal space be needed around the robotic confederate? Would it have a personal space, at all? If there is a single person in a corridor reading a poster on the wall, would a person-object interaction space be needed to correctly describe human navigation behavior? If there is a TV-set in the corridor, but no-one currently watching it, would an "enaction" space be needed?

Some of these variants would ask questions already treated experimentally in the psychological literature. For instance, in some of our previous experiments, we have studied the influence of affective variables like closeness or friendship between confederates and the navigating agent on his or her navigation behavior [21], [22]. The method we have described here could be applied to this data to refine and enrich our model of social navigation.

A more technical question concerns the generalizability of our work with respect to the choice of RiskRRT as a robotic simulator. In our simulations, it appears that computing navigation costs along the critical line was the only component of RiskRRT that was used. This suggests a certain robustness of our approach, in the sense that it is probably independent of the specificities of RiskRRT, and should extend to other cost-based social navigation method.

At the core of the experiment we presented here, lies the method we used for grounding robotic social navigation in human data. This method appears general enough to be extended to other and more complex scenarios, hopefully yielding testable predictions and helping to close the loop between robotics and experimental psychology.

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