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Extending Quantitative Proxemics and Trust to HRI

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***Abstract*— Human-robot interaction (HRI) requires quantitative models of proxemics and trust for robots to use in negotiating with people for space. Hall's theory of proxemics has been used for decades to describe social interaction distances but has lacked detailed quantitative models and generative explanations to apply to these cases. In the limited case of autonomous vehicle interactions with pedestrians crossing a road, a recent model has explained the quantitative sizes of Hall's distances to 4% error and their links to the concept of trust in human interactions. The present study extends this model by generalising several of its assumptions to cover further cases including human-human and human-robot interactions. It tightens the explanations of Hall zones from 4% to 1% error and fits several more recent empirical HRI results. This may help to further unify these disparate fields and quantify them to a level which enables real-world operational HRI applications.**

I. Introduction

Autonomous robotics including autonomous vehicles (AVs) and service robots are now a reality, spreading from research to real-world social environments around humans [40]. Such environments raise new questions about how humans can trust robots, and how they should share their physical social spaces during human-robot interactions (HRI).

Social interaction is an important factor in making humans and robots acceptable and trustworthy to the humans they assist [4], and has been identified as one of ten major robotics challenges [43]. Two major challenges within Social Robotics were defined as modelling social dynamics, and learning social and moral norms [43]. Robots may be more accepted by people if they are socially aware, i.e. able to understand and reproduce these social norms and conventions. Within these norms, trust is essential for building relationships [26], [35]. Two important factors which influence the acceptance of humans and robots and are used to assess their social abilities are proxemics (i.e. interpersonal distances) and trust.

Robots need a better understanding and models of human social behaviour, especially nonverbal communication which plays an important role in human interactions. For instance, it was shown that people have strong 'social expectations' towards robots' nonverbal cues [5]. This raises concerns: are robots' social abilities good enough to interact with humans? Are they safe? Can we trust them?

Most current models of human social behaviour are based on qualitative studies and descriptive statistics. These are appropriate for reporting scientific findings, but they cannot be easily operationalised into engineered, robotic decision-making algorithms. More quantitative and computational models are thus needed to better understand and prescribe human-robot interactions, because numerical probabilities and utilities are needed by most robotics control systems.

The present paper briefly reviews proxemics, trust, and the recent PTR model [7] which links them quantitatively in the limited case of pedestrian-autonomous vehicle interactions. It then extends the PTR model to new, generalised cases of human-human and human-robot interactions and presents new results comparing the extended model's predictions to empirical data. These links could enable research to be shared and operationalised between models of proxemics, trust, and robotic interactions for the first time.

II. Review of Previous Work

A. Review of Proxemics and Trust

This section presents a review of previous work on proxemics and trust for HRI, an extensive review of these topics was introduced in [7].

Proxemics was proposed in the 1960's by Hall [14], defining four distinct zones for human interactions: the intimate, personal, social and public zones. Psychology studies then measured these zones for human-human interactions, finding that the intimate zone goes up to 0.45m, the personal ranges from 0.45m to 1.2m, the social between 1.2m to 3.6m, and the public beyond 3.6m [21]. These numbers are sometimes inserted into costmaps for robotic interaction planning algorithms. But we have lacked a theory to generate and explain these empirical values. Social roboticists have found these proxemic zones change in size when humans interact with robots of different heights, appearances, speeds, voices, and also for different HRI activities [30]. For example, for a short, 1.35m height, humanoid robot approaching or being approached by a human, the personal zone shrinks to the range 0.4m to 0.6m [36].

Trust is commonly defined as 'trusting a person means believing that when offered the chance, he or she is not likely to behave in a way that is damaging to us' [3], [11]. A question is whether humans can build trust with robots as they do with other people and through which means. For instance, a set of questionnaire metrics was designed in [42] to assess users' acceptance and use of robots via five HRI attributes, such as team configuration, team process, context, task, and system, where trust in automation is defined as depending on the level of autonomy of a system and also on its level of intelligence. Thus most HRI trust experiments have studied only humans' qualitative acceptance of robots

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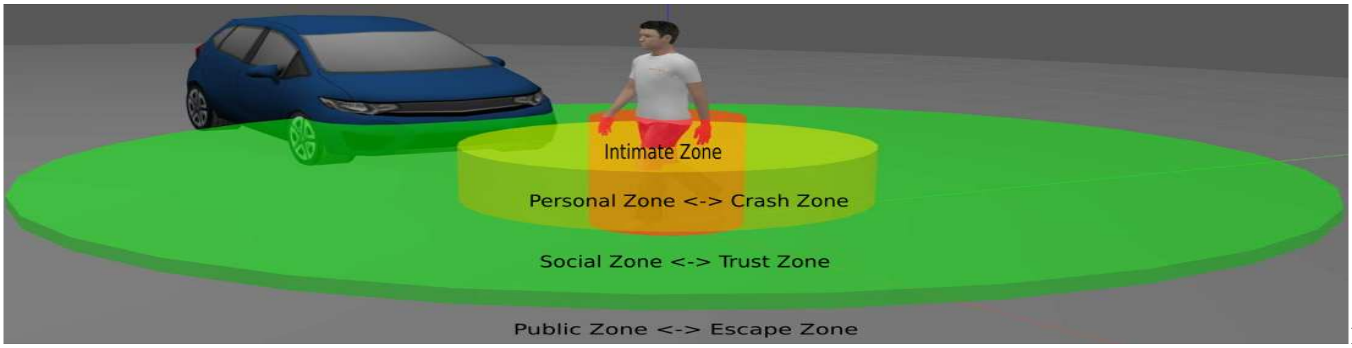

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Fig. 1: Autonomous vehicle entering pedestrian's social zone, which can also be viewed and quantified as a trust region.

[12], [25], [34]. But these qualitative models do not provide enough information to directly implement them as quantitative control systems for robotics.

B. The PTR Model: Linking Proxemics and Trust

Links between proxemics and trust have been proposed via a quantitative model, intended for use in the limited case of an autonomous vehicle, *Agent$_2$, interacting with a pedestrian,* Agent$_1$[1], crossing its path [7] as in Fig. 1. In this model, *Physical Trust Requirement (PTR)* is defined as a Boolean property of the physical state of the world (not of the psychology of the agents) with respect to Agent$_1$ during an interaction, true if and only if Agent$_1$'s future utility is affected by an immediate decision made by Agent$_2$.

The model assumes that the two agents are approaching each other at a right angle, as is the case where one crosses the other's path, as in Fig. 1. It then defines the following three zones based on the PTR:

Crash zone is the region close to Agent$_1$, $\{d : 0 < d < d_{crash}\}$,

$$d_{crash} = v_2 t_2 + \frac{v_2^2}{2\mu_2 g}, \tag{1}$$

in which a crash is guaranteed and neither party can prevent it. v_2 is Agent$_2$'s speed. The first term depends on Agent$_2$'s thinking reaction time, t_2, and the second term represents the physical braking distance, μ_2 is the coefficient of friction between Agent$_2$'s tyres and tarmac, and g is gravity [23].

Escape zone is the area where Agent$_1$ is able to choose their own action to avoid the collision, without needing to trust Agent$_2$ to behave in any particular way. If w_2 is the width of Agent$_2$, which Agent$_1$ must cross at speed v_1 if they wish to pass first, the escape zone is then $\{d : d_{escape} < d\}$ with

$$d_{escape} = v_2 t_1 + w_2 \frac{v_2}{v_1}. \tag{2}$$

Trust zone is the region $\{d : d_{crash} < d < d_{escape}\}$ where the PTR is true. Agent$_2$ can here *choose* to slow down to prevent collision, but Agent$_1$ is incapable of making any action to affect this outcome themselves. This occurs when Agent$_1$ cannot get out of Agent$_2$'s way in time to avoid collision, but Agent$_2$ is able to slow and yield to prevent the collision if it chooses to do so.

The *zone ratio* $R = d_{escape}/d_{crash}$ is a measure of how much trust (in the PTR sense) is involved in an interaction.

Zones are not symmetric between Agent$_1$ and Agent$_2$. They describe when Agent$_1$ must trust Agent$_2$. Their roles must be swapped and the zones recomputed to see when Agent$_2$ must trust Agent$_1$. The crash, escape, and trust zones were mapped to Hall's personal, public, and social zones respectively, for Agent$_1$ [7], cf. Fig 1. The trust/social zone is the region in which physical trust is required. This may be a prerequisite for some types of interactions, with physical trust being useful to enable the content of the interaction. The evidence for this mapping came from the observation that if an autonomous vehicle Agent$_2$ is set to drive at the same speed as a pedestrian Agent$_1$, the model generates Hall's proxemic social zone to within 4% quantitative accuracy. This unexpected result, found only by studying how an AV should interact with road-crossing pedestrians, is suggestive that this scenario may be a special case of a more general HRI theory of proxemics and trust.

C. Limitations of the PTR Model

The PTR model made three key assumptions which limit its application to general HRI:

Assumption 1: Agent$_2$ is a wheeled vehicle, having momentum and a braking time. These dynamics are not appropriate for other types of Agent$_2$ such as walking humans and humanoids.

Assumption 2: The width of Agent$_2$ is much larger than that of Agent$_1$, so it treated Agent$_1$ as a point and Agent$_2$ as a rectangle, because a vehicle is bigger than a pedestrian and most vehicles are rectangular. These geometric assumptions are not appropriate for two human-like agents of similar size.

Assumption 3: The pedestrian has a *goal*: to cross the road. The road crossing is orthogonal to the road. Thus the pedestrian's velocity is orthogonal to the vehicle's. This is a strong constraint which is not appropriate to general HRI scenarios. Agent$_2$ might in general approach Agent$_1$ from any direction, not just at right angles to Agent$_1$'s initial heading. We are now only interested in explaining the size

[1]*Terminology*: In the original model, Agent$_1$ was called 'the pedestrian' and Agent$_2$ called 'the vehicle'. The terms Agent$_1$ and Agent$_2$ are used throughout the present study to emphasise new generalities.

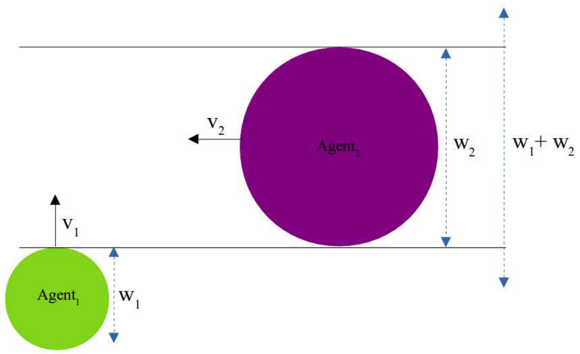


Fig. 2: New assumed geometry for the two agents.

of the trust zone which we assume is independent of any goal for Agent_1 other than avoiding a collision.

III. New Extensions to the PTR Model

The original PTR model was intended only for pedestrian road-crossing interactions with vehicles. We here expand its relevance to explain and predict new types of agents and scenarios, including human-human and human-humanoid robot interactions with approaches from arbitrary rather than orthogonal directions. We extend and generalize the model to address each of the above assumptions as follows.

Assumption 1: The second term on the right of Eq. (1) is only applicable to wheeled vehicles as it models their braking time. If Agent_2 is a walking agent, we will now assume this second term is omitted, as walkers are always in static equilibrium so can stop instantly once a decision is made. Models for running agents [20] or finer detailed models of walkers [28] could insert different braking terms here.

Assumption 2: To allow for interactions between similarly sized agents, we now modify Eq. (2) to:

$$d_{escape} = v_2 t_1 + (w_1 + w_2)\,\frac{v_2}{v_1}, \tag{3}$$

where $w_1 + w_2$ is the total distance that Agent_1 must travel in front of Agent_2 in order to avoid contact with Agent_2. These widths may now be mapped to Hall's intimate/personal zones of the agents, i.e. the ranges at which *actual* contact may occur between the agents. Justification for this modification can be seen in Fig. 2, which shows how Agent_1 must move its center point by half its own width at the start and end of the path as well as passing by the width of Agent_2, to avoid the *minimal* possible collision.

Assumption 3: As our focus is now purely on understanding proxemic and trust zones, we now drop the assumption that Agent_1 has a goal location, and consider that they simply want to avoid being hit by Agent_2. We thus want to allow Agent_2 to approach Agent_1 from any heading θ, measured relative to Agent_1's own initial heading as in Fig. 3. The previous change from rectangular to circular agents is a first step towards enabling this. We then need to consider the direction in which Agent_1 moves to escape from Agent_2. The best way to escape is *always* by moving orthogonal

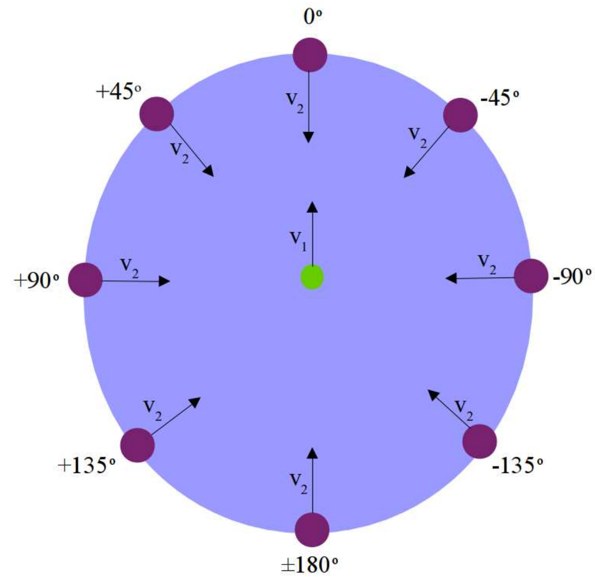


Fig. 3: Possible interaction geometries. Green=Agent_1; Purple= different possible positions and headings for Agent_2. (θ is the angle of Agent_2's approach from Agent_1's perspective.)

to the heading of Agent_2[2]. There are at least four different modelling options for whether and how this is possible:

- Option 1: Assume that Agent_1 can turn on the spot *instantly* to face any direction. In this case, the optimal strategy is to first turn to a heading orthogonal to that of Agent_2, then walk at speed v_1 to escape. This makes Agent_1's initial heading irrelevant and reduces the model back to the original assumption of orthogonal velocities.
- Option 2: Assume that Agent_1 can *only* walk in the direction of their initial heading. They cannot rotate at all. By substituting v_1 in Eq. (3) for its component orthogonal to Agent_2's heading, $v_1|\sin(\theta)|$,

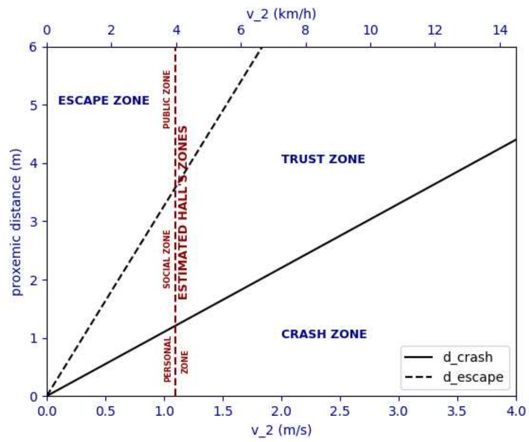
$$d_{escape} = v_2 t_1 + (w_1 + w_2)\frac{v_2}{v_1|\sin(\theta)|} \tag{4}$$

- Option 3: Assume Agent_1 can turn on the spot or twist during forward travel, where turning takes place at up to maximum angular velocity $\dot{\theta}$. If $\dot{\theta}$ is very fast then it will behave like Option 1. If $\dot{\theta}$ is very slow then it will behave like Option 2. Options 1 and 2 are thus special, limiting cases of Option 3.
- Option 4. Extending Option 3, further available motions such as sidesteps and stepping backwards could be added and optimised.

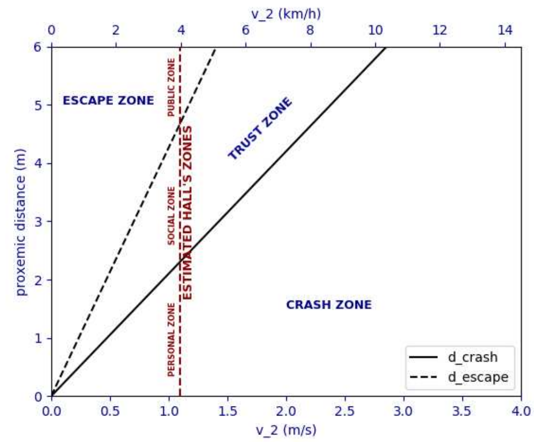
IV. Results

The present section shows some validations of the extended model by comparing its predictions to data from

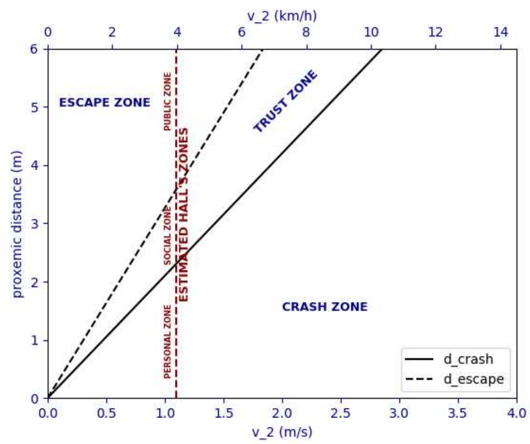
[2]Moving towards Agent_2 is obviously useless. Moving away from Agent_2 is useless if $v_1 < v_2$, but if $v_1 > v_2$ then there are no zones at all as it is trivial to escape. Any other direction is a linear combination of an optimal orthogonal escape plus one of these useless directions.



(a) No distraction: $t_1 = t_2 = 1.1$s.



(b) Both distracted: $t_1 = t_2 = 2.1$s.



(c) One distracted: $t_1 = 1.1$s and $t_2 = 2.1$s.

Fig. 4: PTR distance and zone predictions for two walking humans at normal speed with different reaction times.

a selection of previously published empirical studies of interest. Option 2 is chosen to model the direction of Agent$_1$. This is because it includes some consideration of the initial heading, unlike option 1, but without requiring a full solution of option 3 or 4 which may form extensive future work.

A. Two Walking Humans

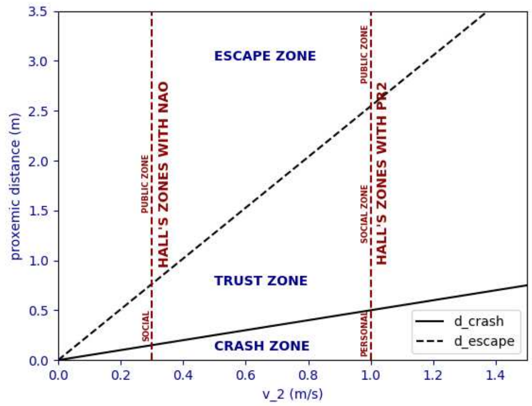
We first show that the extended model can numerically reproduce and explain Hall's original observations of proxemic zone sizes for interactions between two walking humans (unlike the previous study's [7] with a walking human and autonomous vehicle). By choosing the realistic parameters: $t_1 = t_2 = 1.1$s, $v_1 = 1.1$m/s, $w_1 = w_2 = 1.19$m, found by optimisation, the extended model then generates values $d_{crash} = 1.21$m and $d_{escape} = 3.59$m, matching Hall's data, as shown by the vertical line in Fig. 4a, where $v_1 = v_2 = 1.1$m/s [21]. This result from the extended model shows a better fit to Hall zones, with an error of less than 1% compared to the previous model's 4% error [7]. The zone ratio is found to be $R_{H-H} = 3$ [7]. This will serve as a comparator for the following experiments.

B. Distracted Walking Human Interactions

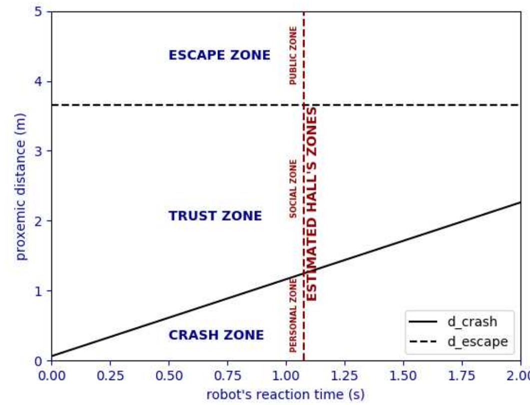
We next model the effect of distraction on the walking humans – such as attending to headphones, phones, or billboards – by increasing their reaction times in the model by 1s [10]. With both distracted, Fig. 4b shows that their crash zone size then increases from 1.21m to 2.31m and the escape zone is also increased from 3.59m to 4.69m, therefore the zone ratio R_{H-H} reduces to 2.03. With only one distracted, Fig. 4c shows that the crash zone size increases from 1.21m to 2.31m but the escape zone starts at 3.59m as in Sect. IV-A, leading to a smaller trust zone size in this case. The zone ratio, $R_{H-H} \approx 1.55$, is much smaller than the comparator. These findings are consistent with and explain empirical data that there is more distance, less trust, and hence less social interactions between distracted people [37].

C. Walking Human vs Humanoid Robot

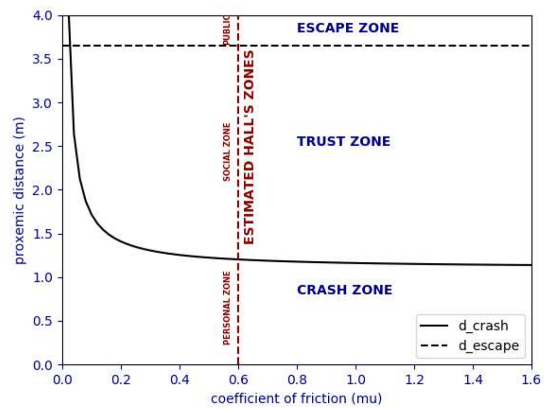
We now consider human-robot interactions. Fig. 5a shows predicted zone sizes for a human walker interacting with two different humanoids, NAO ($\sim$0.6m tall) and PR2 ($\sim$1.4m tall). The parameters used are: $t_1 = 1.1$s, $t_2 = 0.5$s, $v_1 = 1.1$m/s, $w_1 = 1.19$m, $w_2 = 0.4$m. With NAO at speed



(a) Human - Humanoid interaction.



(b) Reaction time.



(c) Coefficient of friction.

Fig. 5: Human-robot interactions. (5a) shows the PTR distance and zone predictions for a walking human interacting with humanoid robots at different speeds. (5b) and (5c) show the implied parameters for an interacting robot.

$v_2 = 0.3$m/s, the model predicts zone sizes: $d_{crash} = 0.15$m and $d_{escape} = 0.76$m. For PR2, having speed $v_2 = 1.0$m/s, zone sizes are: $d_{crash} = 0.5$m and $d_{escape} = 2.54$m. The sizes found for these human-robot interactions are much smaller than for human-human interactions, which is consistent with and matches closely results from previous empirical experiments with humanoid robots [18], [36], [39]. The zone ratios $R_{H-NAO} = 5.06$ and $R_{H-PR2} = 4.62$ are much bigger than the comparator from above. This explains existing empirical results that humans may be more sociable and friendly with humanoids than human strangers [16], and that people might not perceive robots as 'social entities' having an intimate zone [38].

D. Effects of Different Approach Headings

Fig. 6 shows the predicted escape distance for different approach headings between Agent$_1$ and Agent$_2$. In the HRI case, the prediction matches the previous result for a PR2 robot at 90° with $d_{escape} = 2.54$m, assuming the following parameters: $t_1 = 1.1$s, $t_2 = 0.5$s, $v_1 = 1.1$m/s, $v_2 = 1$m/s, $w_1 = 1.19$m and $w_2 = 0.4$m. In the HHI scenario, the parameters are as follows: $t_1 = t_2 = 1.1$s, $v_1 = v_2 = 1.1$m/s,

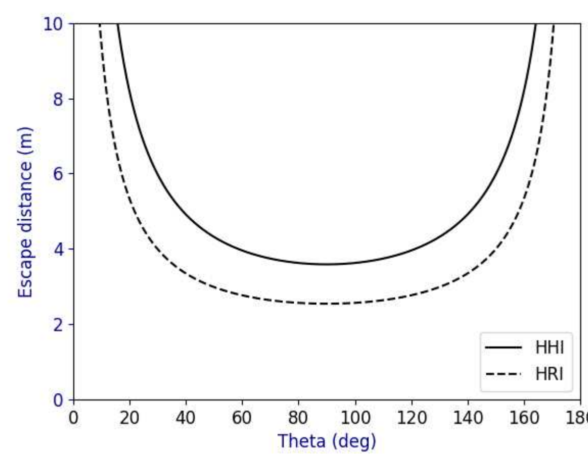


Fig. 6: Example of predicted escape distance for different interaction angles between Agent$_1$ and Agent$_2$.

= 1m/s and $w_1 = w_2 = 1.19$m, and the prediction at 90° closely matches Hall's zone, with $d_{escape} = 3.59$m. The results of this extended model match and explain recent empirical data that d_{escape} i.e. public zone may be noncircular [15] while d_{crash} i.e. personal zone is always circular [29]. This is because d_{escape} is a function of v_1 (Eq. 3) and v_2 while d_{crash} depends only on v_2 (Eq. 1). The escape distance goes to infinity as $\theta \to 0°$ and $\theta \to 180°$ because it is impossible for Agent_1 to escape if their heading is constrained to be the same as Agent_2's.

E. Measuring Human Beliefs About Robots

It is possible to measure human's beliefs about robots' proxemic behaviour via implied parameters from the model and experimental data. For example by optimising the reaction time of the robot (Fig. 5b) or its coefficient of friction (Fig. 5c) to best fit results from human interaction. Assuming $v_1 = v_2 = 1.1$m/s, $t_1 = 1.5$s, $w_1 + w_2 = 2$m, $\mu = 1.0$ and $g = 9.8\text{m/s}^2$, as in Fig. 5b, the best reaction time for this case would be $t_2 \approx 1.075$s if the robot wants to behave like a human and reproduce Hall's empirical zones. Similarly the coefficient of friction is found by keeping the previous parameters except μ which becomes unknown and by now setting $t_1 = t_2 = 1.1$s. Fig. 5c shows that the best coefficient of friction for the robot would then be $\mu = 0.6$. This should enable roboticists to learn and program their robots with the best parameters, with the possibility to vary the parameters for different people and in different environments. Current HRI proxemics results may suggest that humans have this natural ability to measure a robot's parameters and thus adapt their behaviour accordingly.

V. Discussion

The new extensions generalise the unification of proxemics and trust previously presented in the special case of AV-pedestrian interactions, to more general HRI interactions. This was achieved by modifying the assumptions to allow interactions between agents of similar sizes, approaching at arbitrary angles, and by removing the need for a goal location. The new model was validated by successfully fitting and explaining varied classical recent empirical proxemics and trust results.

We have here simulated two identical walking agents, but in the real world it is unlikely that two humans will share the same exact behavioural parameters. This new model could help to better understand proxemics and trust dynamics by simulating agents with differing parameters, without the costs or hazards associated with human experiments. The model for two walkers at normal walking speed is also valid for walkers at higher speeds e.g. 2.2m/s because the form of the equations scale, though for runners new dynamic equilibrium terms may be needed to model their stopping distance. In some cases, such as interactions with large cars, the old rectangular vehicle geometry may have to be restored and more complex equations used to compute shape overlaps and collisions. Future work should replace the use of Option 2 with a full solutions to Option 3 then 4.

Some possible applications for this work include:

Social Robotics: People are 'the big problem with self-driving cars' [6]. AVs are one case of social robots, which must understand social dynamics and norms, especially in crowded and mixed pedestrian-vehicle areas, in order to negotiate for space safely [33]. These negotiations are typically competitive rather than collaborative, with the aim of each agent being to get to their own destination quickly rather than to specifically interact with the other. Other forms of Social Robotics such as interactions with service and assistive robots may also benefit from quantitative understanding of proxemics and trust [17], [22], [24]. Unlike AVs, interaction with these robots is often cooperative.

Gaming & Extended Reality (XR) seeks to understand human proxemics in simulations of crowds, both for improving realism of video games and movie special effects, and for serious games such as simulations of evacuations, human locomotion in obstructed environments or group interactions in immersive virtual environments [1], [9], [31], [32].

Behavioural & Social Sciences: As trustors, humans are known to be more trusting (and gullible) depending on personality and environmental factors, and neuroscientific factors such as oxytocin hormones which may be physically transmitted through physical proximity [19]. As trustees, humans also maintain different reputations for trustworthiness, as studied by social network theorists [2], [41]. Hall zones are known to change in size across different human cultures [13]. Future work may need to take account of and replicate these factors for different human cultures. The Covid-19 pandemic has put a focus on human-human physical social interactions via the concept of *social distancing*. This is the encouragement or enforcement of a minimum proxemic distance between people when meeting. This requires hard numerical distance limits to be decided but there is a debate about what this distance should be. If the distance is too small, infections may be transmitted. A meta-review [8] found that 1m distance reduces transmission risk by 86%; 2m by 93%; and 3m by 96%. Others argue that if social distance is too large, trust will be harder to build [27]. An analogous debate to human-robot trust exists here, with arguments that physical proximity is sometimes needed to build human-human trust which may be jeopardized through social distancing and remote working. For example many workers are happy to hold technical meetings online but want to meet physically and closely to make contacts and deals which require trust.

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