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A Rubber-sheet Transformation Model for Personalized Human-Robot Proxemics

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***Abstract*— The deployment of autonomous robots in human environments requires an understanding of social interactions and the factors that influence them. Human-robot proxemics is an important factor that impacts interactions, and modeling personalized proxemic behavior has always been a challenge, as it depends on multiple user attributes, including gender, age, and height. In this paper, we propose a novel approach that uses rubber-sheet transformation models to represent human-robot proxemics. We do this by collecting human-robot interpersonal distance data from 20 users and model it with respect to their height, age, gender, and the angle at which the robot approaches. We present an evaluation of the model, and the outcome of our results, which show a promising approximation of proxemic distances based on different user attributes. Finally, we provide a coefficient table for rubber-sheet models to lay the foundation for personalized human-robot proxemics and outline future research directions.**

I. INTRODUCTION

This work aims to contribute towards the deployment of autonomous robots in human environments in a safe and socially acceptable manner. Robots are equipped with many algorithms and models that define their surrounding world. For example, many researchers addressed robots' navigation [1], mapping [2], [3], and movements [4] to enable them to carry out their tasks. One prominent area in robotics, especially when operating in inhabited areas, is ensuring that a robot's movements are socially appropriate, meaning that it interacts with people in a way that feels acceptable [5], [6]. One of the areas that researchers focused on is human-robot proxemics [7]–[11], in which they show several factors, including gender, height, and age, that affect the interpersonal distance a robot should have when approaching people. Many studies have investigated these factors, which are crucial for effective communication and interaction. For instance, the size and shape of a robot determine how far it should stand from users, while the height and gender of the user influence our preferences regarding the robot's distance [12].

However, in the context of human-robot proxemics, it remains a challenge to determine appropriate points at which a robot should automatically stop when approaching a user for a specific task. Modeling this behavior requires not only an understanding of people's preferences but also the development of models that can be easily executed by a robot.

In this research, we explore a novel approach by utilizing rubber-sheet transformations to model human-robot proxemics. Specifically, we apply a user-defined method for collecting proxemics data (as illustrated in Fig. 1) and then develop a model that takes into account user attributes such as height, gender, and age. This paper contributes the following:

- a novel approach to modeling human-robot proxemics using a polar-form rubber-sheet model;
- the integration of users' personal attributes, such as height, age, and gender, into the model;
- a proxemic model representation and a table of coefficients for angle, height, age, and gender, which can be utilized in a social robot for real-time interactions.

To the best of our knowledge, this work is the first to demonstrate how users' gender, age, and height can be integrated into a predictive proxemics model using rubber-sheet transformation for safe and socially acceptable human-robot interactions.

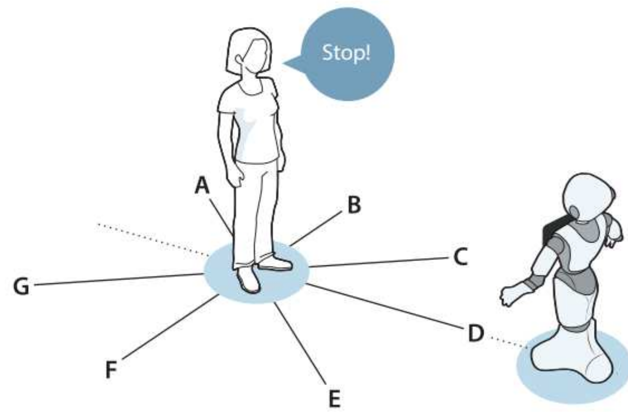

Fig. 1: Sketch of the experimental setup showing a robot approaching a human from different angles (A to G).

II. RELATED WORK

The theory of proxemics was proposed by E. T. Hall in the 1960's to describe distances that people keep away from each other based on different settings [13]. He defined four discrete spaces: the intimate, personal, social and public zones, corresponding to areas around a person where they experience a certain level of comfort or discomfort depending on who enters each zone. Subsequent empirical studies have investigated human-human and human-robot proxemics, and measured specific distances. For human-human interactions, it was found that the intimate zone corresponds to the area around a person up to 45cm, the personal zone goes from

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45cm up to 1.2m, the social zone goes from 1.2m up to 3.6m and the public is beyond 3.6m [14].

However, human-robot proxemics zones are found to be smaller [9], [11], [15], [16]. Takayama and Pantofarou [16] found empirical proxemics zones to be in the range 0.4m–0.6m (average interpersonal distances) with a robot that is 1.35m high. They also showed that robot head orientation, the gender of participants, and previous experience interacting with both pets and robots also affected people's comfortable distances. Syrdal et al. [17] studied the individual factors that affect proxemic distances, where gender and personality trait were found to be determining factors. For example, female and extrovert participants allowed the robot to approach closer from the front than male and more introvert participants. The empirical findings in [18] suggest that passing at the back of a person is more uncomfortable than at the front. Satake et al. [19] investigated robot approaching strategies from different distances towards humans. Their work using Hall concentric proxemic zones showed how a robot can begin an interaction with a human, i.e. communicate via its position its intention to start interacting with a person.

Mead et al. [20] developed an automated proxemic feature extraction method based on Schegloff's individual (e.g. shoulder pose, hip pose) [21], Mehrabian's physical (e.g. total distance, relative body orientation) [22] and Hall's psychophysical (e.g. distance, voice loudness) [13] factors identified in the social sciences. A Hidden Markov Model was trained on the physical and psychophysical features and then tested through an interaction study for the real-time annotation of proxemic features. Mead et al. [23] studied the interaction between a robot and human participants. The interactions consisted in moving the robot towards the participants and backwards several times. Their results showed that individuals' pre-interaction proxemic preference ($mean =$ 1.14m, $SD = 0.49$m) was consistent with previous studies. With a uniform performance in the robot behaviour, the proxemic preference reached a $mean = 1.39$m and a $SD =$ 0.63m. It was also found that participants adapted their distances to improve the robot's performance. Samarakoon et al. [24] developed a proxemics-based approach method for a service robot that relies on the user physical behaviour and feedback.

Despite the numerous empirical studies, the mathematical modelling of human-robot proxemics is still in its early phases. Kirby et al. [25] proposed one of the first mathematical models with the COMPANION framework for robot path planning and navigation following social conventions. The cost function for personal space was modelled as two halves of 2D Gaussian functions producing an asymmetric shape where the space in front of the person is greatest. Their approach was tested in two simulated experiments. Torta et al. [26], [27] performed two psychometric experiments with a small humanoid robot and proposed a parametric model of the personal space. The model takes into account the distance and the direction of approach, and was evaluated with a user study where subjects are sitting or standing and approached by the humanoid robot Nao. They derived a polynomial approximation based on the mean values of user preferences for different angles of approach, while the preference on the distance was modelled using a Gaussian function. Similarly, Kosinski et al. [28] investigated human perceived comfort level based on a robot approaching distance and angle via a set of rules, fuzzy sets and parameters. It was assumed that the approaching distance and angle can be described by sigmoid and bell-shaped functions and that the perceived comfort decreases as the angle changes. The authors found that the proxemic distance is linked to the angle of approach and that subjects feel more comfortable with approaches from the boundary of their field of view. Participants were more tolerant when the robot approached from the right hand side and felt least comfortable when the robot approached straight ahead.

Neggers et al. [29] investigated comfortable distances for robot Pepper passing people from different distances and sides in a hallway scenario using a 7-point comfort rating scale. They then used an inverted Gaussian to fit the average comfort rating from 32 participants and showed that comfort increases with distance. Patompak et al. [30] developed an inference method to learn human proxemic preferences. Their method is based on the social force model and reinforcement learning. They argued that proxemic spaces can be limited to two zones, the first being the quality interaction area where a robot could go without creating discomfort, and the private area which is the personal space. Camara and Fox [31] proposed a kinematic model that can generate Hall empirical proxemics zone sizes quantitatively and which also links pedestrian proxemics with trust in the context of autonomous driving. The same authors [32] extended their model by taking the angle of approach into account and generalized it to human-human and human-robot interaction scenarios, while [33] showed that the kinematic model can reproduce several empirical proxemics zone shapes.

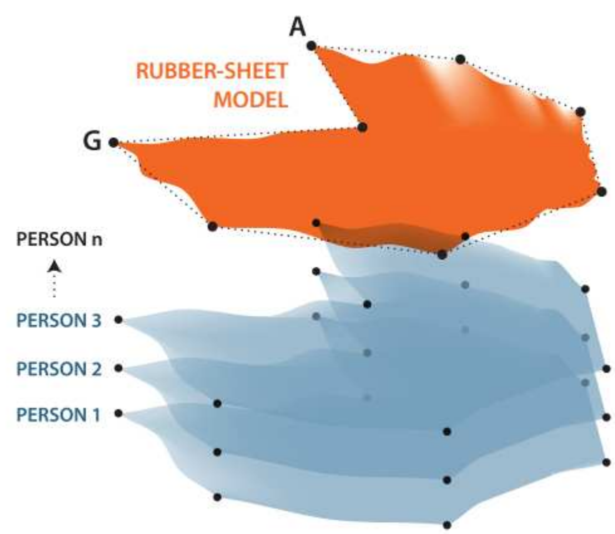


Fig. 2: Schematic of the rubber sheet model for different users.

III. Rubber-sheets in polar form

Rubber-sheet transformations use higher-order polynomials to represent shapes. The elastic property of the rubber-sheet makes it suitable for representing complex changes in shapes, such as the example in Obaid et al [34]. In our research, since we are interested in modeling a robot approaching a user from different angles, we apply rubber-sheets in a polar form, where a simple rubber-sheet with a single feature (cf. Eq. 1) or two features and an interaction term (cf. Eq. 2) can be represented in 2^{nd} order polynomials in its general form as:

$$R_i(\lambda_i) = a + b_i\lambda_i + c_i\lambda_i^2, \quad (1)$$

$$R_i(\lambda_i, \phi_i) = a + b_i\lambda_i + c_i\phi_i + d_i\lambda_i^2 + e_i(\lambda_i \times \phi_i) + f_i\phi_i^2, \quad (2)$$

where:

$$\begin{aligned} i &: \text{index ranging from 1 to } n, \\ n &: \text{number of data points}, \\ a &: \text{intercept}, \\ b, c, d, f &: \text{coefficients}, \\ \lambda, \phi &: \text{predictive features}, \\ e &: \text{interaction coefficient between } \lambda_i \text{ and } \phi_i, \\ \lambda \times \phi &: \text{interaction term}. \end{aligned}$$

To model an approximation to the distance R_i for any features λ_i and ϕ_i, we need to find the coefficients that best fit, thus we apply a least square fit to solve for the coefficients (a, b, c, d, e, f). An interaction between λ_i and ϕ_i means that the relationship between λ_i and R_i differs depending on the value of ϕ_i, thus making the model more flexible for multiple predictors and generating more coefficients. Fig. 2 presents a schematic of the rubber sheet model for different user data. Section IV provides details on the data collection.

IV. User study

We conducted a user study with 29 participants to gather proxemics data. The study was set up in a lab using the commonly used Pepper robot from SoftBank Robotics[1], which has a height of 1.20m and a width of 0.485 m. We used the Choregraphe suite to program Pepper's behavior, setting its speed to a constant 0.35m/s. Throughout the study, Pepper was set to its default idle movements to give a lively feeling. Figure 1 illustrates the in-lab setup for Pepper, where a user stands in the middle of the room while the robot moves toward the user from seven different angles, ranging from $A = 5\pi/4$ $(225°)$ to $G = -\frac{\pi}{4}$ $(-45°)$. For each angle, the robot was 2.6m away from the user before it started moving, and it was programmed to stop at a maximum distance of 2.45m (15cm away from the participants) to prevent crashes.

Participants and Data collection: The study started with two participants as pilots to verify the setup and confirm the accuracy of the speed, and positioning of the robot. Once all aspects were checked and validated, we recruited 29 participants from the Chalmers University of Technology's network. For each of the participants, we collected several demographic data points, including age, gender, height, experience with robots, pet ownership, educational background, profession, and if they are right- or left-handed. We also recorded the distance where the robot stopped away from the user (the interpersonal distance) as shown in Fig. 3. The data was then examined by two researchers, and only complete datasets were included. In some cases, participants clearly did not follow the instructions and instead tested the robot's abilities, which was not the focus of this study. Therefore, incomplete demographic data or extreme outlier measurements were removed.

[1]https://us.softbankrobotics.com/pepper

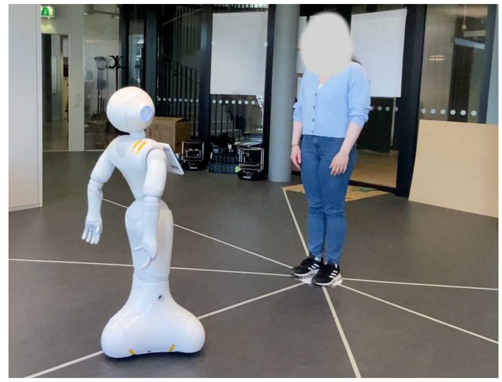


Fig. 3: Example of data collection conducted in the lab.

The final dataset included 20 participants (11 female, 9 male), aged from 19 to 53 years old, with an average age of $mean = 27.60$ and $SD = 7.9$. Overall, participant heights ranged from 155 to 187 cm ($mean = 171.75$, $SD = 10.05$), the majority did not own a pet, and most ranked that they had little prior experience with robots on a scale from 1 to 5 ($mean = 2.05$, $SD = 1.23$). Most participants were students, 15 in total, from high school to PhD level students, while 5 participants were university staff (researchers or admin).

Procedure: To start, an experimenter welcomed the participant into the lab. They were then asked to read an information and a consent form to confirm their agreement to participate. Thereafter, participants completed a demographics questionnaire before standing at a marked point in the center of the lab space, facing forward throughout the study. The experimenter then explained what the task was to the participants, in which they were told to observe Pepper moving toward them and say "stop" when they felt the robot was at a comfortable distance. The task of Pepper approaching the participant was repeated seven times, once for each of the angles A to G. To avoid an order effect, for each session, we have randomized the angle from which Pepper approaches the user. For each angle, when the participant said "stop," a measurement was recorded by the study experimenter using a measurement tape. The robot was controlled using a Wizard-of-Oz approach, where the experimenter activated the stop action when they heard the participant say "stop." Overall, the process of collecting data for one participant lasted approximately 20 minutes.

V. Data analysis

A. Feature Correlation

We first performed a correlation analysis to capture the potential relationships between the features in the whole dataset using Pearson's method, where coefficients range between -1 (strong negative) and 1 (strong positive). Fig. 4 shows some positive correlation between the proxemics distances measured from different angles of approach (noted from A to G) and a user's height, gender and age. This is consistent with previous works that have shown the effect of the angle of approach and individual features on proxemic distances [15]–[17].

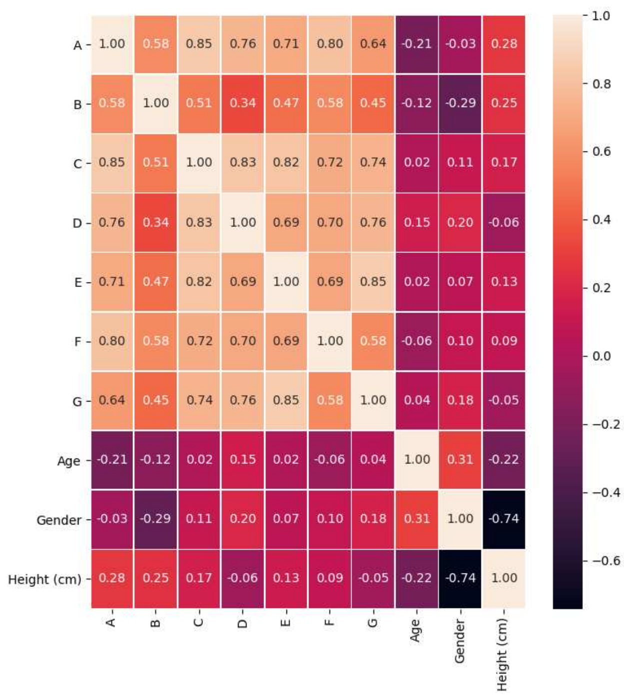


Fig. 4: Pearson's correlation matrix.

B. A Proxemic Rubber-sheet Model

Python was used to compute a rubber-sheet model on our dataset, using a set of features at a time to evaluate how they improve the model's performance. A train-test split approach (70% for training set, 30% for test set) was used for the rubber-sheet modeling and facilitate its evaluation. The model outputs coefficients of the rubber-sheet that are required for making new predictions, which can later be plugged into the robot for real-time prediction of proxemics distances based on new user data. The model's surface results were plotted using Delaunay triangulation. Figs. 5a, 5c and 5d show the model's results when the comfortable proxemic distance, R, is predicted by two features: the angle of approach, θ, and the height of the participant. Fig. 5a shows the result for the whole dataset combining both male and female participants data, while Figs. 5c and 5d show the results for female and male participants, respectively. We can see that the model adopts different shapes to fit the data depending on the gender. Shorter female participants appear to have a smaller proxemic distance in the angles of approach at the front between 0 and 180 degrees, while taller female participants have bigger proxemic distances at the same angles (Fig. 5c). For male participants, it is the opposite effect that happens (Fig. 5d). When we include the age feature into the model, similar patterns can be observed in Figs. 5e and 5f for female and male participants. We can also observe in Fig. 5b the effects of height and age on predicting R. More specifically, Fig. 5g shows how R increases with height and for younger female participants whereas in Fig. 5h younger and shorter male participants tend to have a bigger R value.

Table I provides the coefficients values (approximated to a few decimals) for all of the features modelled. We used the following units for the features: degrees (deg) for θ, centimeters (cm) for height, years for age, as a result of that, some coefficients are very large or very small for models with two features or more. As a practical example, Eqs. 3 and 4 can be directly plugged into a robot, such as Pepper that we used for validation, to predict its proxemic value with a human user based on their attributes:

$$R(\theta) = 53.87230 - 0.1124 \times \theta + 4.46 \times 10^{-4} \times \theta^2 \quad (3)$$

$$\begin{aligned} R(\theta, Height) = &- 3212.73 - 0.4901 \times \theta + 38.185 \times \text{Height} \\ &+ 3.6 \times 10^{-4} \times \theta^2 + 2.3 \times 10^{-3} \times \theta \times \text{Height} \\ &- 0.111 \times \text{Height}^2 \end{aligned} \quad (4)$$

C. Model Evaluation

We evaluated our approach using two metrics, namely the Root Mean Square Error (RMSE) and the coefficient of determination R-squared (R^2), which are standardly used for model evaluation [35], and defined respectively as:

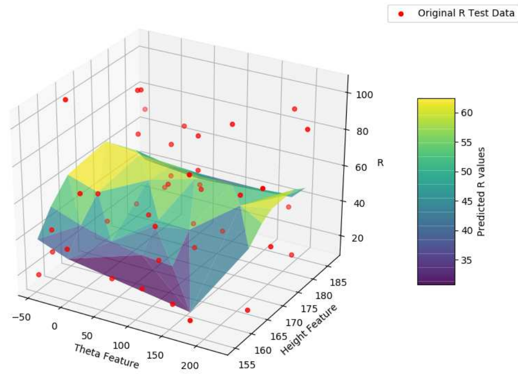
$$\text{RMSE}(y, \hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}} \quad (5)$$

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \quad (6)$$

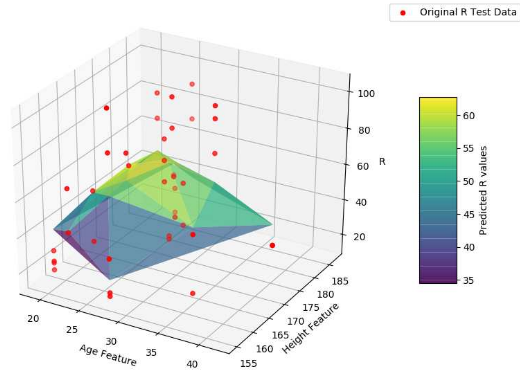
where y represents the observed value, $\hat{y}$ is the predicted value and N represents the number of data samples.

On one hand, RMSE estimates how far the predicted and the actual observations are from each other, thus the lower its value, the better the model as indicated by the downward arrow in Table I. On the other hand, the R^2 score represents the amount of the predicted value that can be attributed to the input variables, showing how well observations are reproduced by the model, hence the higher its value (up to 1), the better the model, as indicated by the upward arrow in Table I.

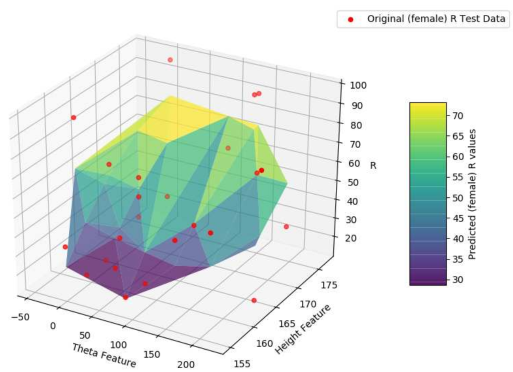
Our model performs best when trained/tested separately on female and male data, while including several features. For instance, we can see in Table I that with θ as the only predictive feature: RMSE= 27.79 and R^2 = -0.0373 for the



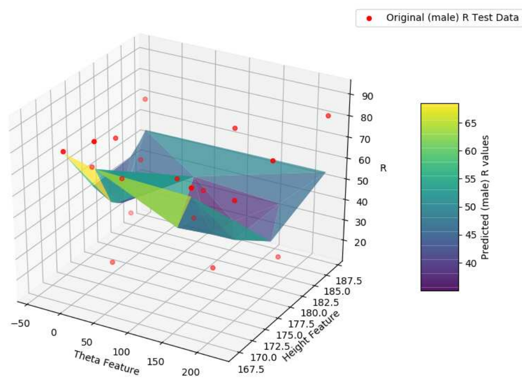
(a) Whole data (θ and height)



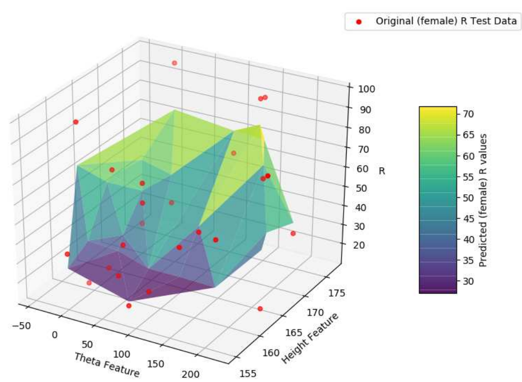
(b) Whole data (age and height)



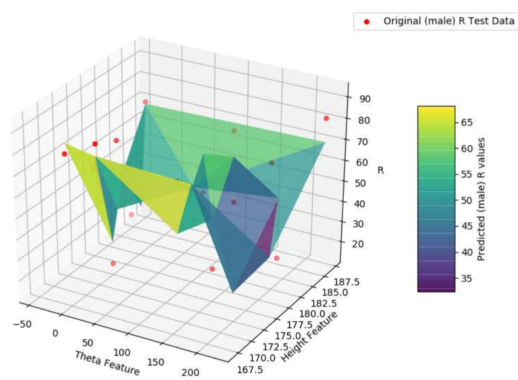
(c) Female data (θ and height)



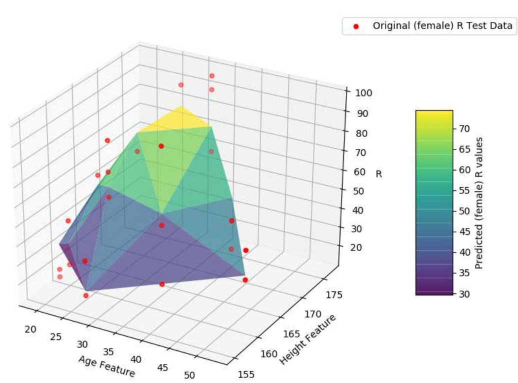
(d) Male data (θ and height)



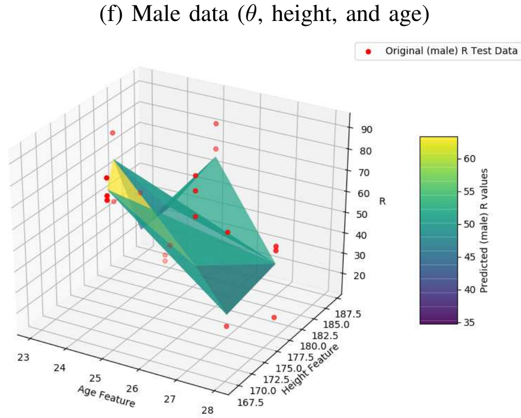
(e) Female data (θ, height, and age)



(f) Male data (θ, height, and age)



(g) Female data (age and height)



(h) Male data (age and height)

Fig. 5: Model results for different feature combinations in predicting R. The 1st row presents whole data. The 2nd and 3rd rows include θ, height, and age features per gender. The 4th row shows results for age and height features per gender.

TABLE I: Table listing the model coefficients per feature. (↓ indicates lower is best, ↑ indicates higher is best).

Model Features	**a**	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**j**	**k**	**RMSE (↓)**	R^2**(↑)**
$\{\theta\}_{\text{Whole}}$	53.87	-0.1124	4.46×10^{-4}	-	-	-	-		-	-	27.79	-0.0373
$\{\theta\text{, Age}\}_{\text{Whole}}$	10.13	-0.112	2.867	4.49×10^{-4}	1.869×10^{-6}	-0.0429	-	-	-	-	27.29	-0.0002
$\{\theta\text{, Height}\}_{\text{Whole}}$	-3212.73	-0.4901	38.185	3.6×10^{-4}	2.3×10^{-3}	-0.111	-	-	-	-	24.73	0.1787
$\{\text{Age, Height}\}_{\text{Whole}}$	-4249.33	12.85	48.30	-0.016	-0.0736	-0.134	-	-	-	-	25.07	0.1555
$\{\theta\}_{\text{Female}}$	58.33	-0.076	5.7×10^{-5}	-	-	-	-	-	-	-	26.49	-0.0945
$\{\theta\text{, Height}\}_{\text{Female}}$	-2783.62	-0.4496	32.023	1.4×10^{-4}	2.23×10^{-3}	-0.08959	-	-	-	-	21.32	0.2911
$\{\theta\text{, Height, Age}\}_{\text{Female}}$	-3616.31	-0.479	38.12	24.09	1.62×10^{-4}	2.73×10^{-3}	-1.8×10^{-3}	-0.096	-0.136	-0.029	18.98	0.4383
$\{\text{Age, Height}\}_{\text{Female}}$	-3613.43	23.82	37.78	-0.022	-0.13	-0.094	-	-	-	-	18.51	0.4654
$\{\theta\}_{\text{Male}}$	47.21	-8.47×10^{-2}	4.26×10^{-4}	-	-	-	-	-	-	-	26.87	-0.1025
$\{\theta\text{, Height}\}_{\text{Male}}$	8451.94	-0.356	-93.43	3.8×10^{-4}	1.5×10^{-3}	0.259	-	-	-	-	22.66	0.2156
$\{\theta\text{, Height, Age}\}_{\text{Male}}$	34962.36	0.165	-215.7	-1241.81	2.3×10^{-4}	1.5×10^{-3}	-0.0197	0.2228	5.42	5.3	22.14	0.2513
$\{\text{Age, Height}\}_{\text{Male}}$	33728.74	-1197.23	-207.87	4.92	5.27	0.212	-	-	-	-	21.74	0.2786

whole data, RMSE= 26.49 and R^2= -0.0945 for female data, RMSE= 26.87 and R^2= -0.1025 for male data. The model with θ as the sole feature serves as a sort of baseline with R^2 values close to zero or negative. But when θ and height are used as the predictive features, both RMSE and R^2 values improve: RMSE= 24.73 and R^2= 0.1787 for the whole data, RMSE= 21.32 and R^2 =0.2911 for female data, RMSE= 22.06 and R^2 =0.2786 for male data. Modelling with three features, θ, height and age for female and male data separately, gives even better results: RMSE= 18.51 and R^2= 0.4383 for female data, while RMSE= 22.14 and R^2 =0.2513 for male data. The best model combines age and height features and provides the lowest RMSE (18.51 for female data, 21.74 for male data) and the highest R^2 (0.4654 for female data, 0.2756 for male data) values.

VI. Discussion & Conclusion

We presented a novel approach to model human-robot proxemics using rubber-sheet polar form transformations, enabling a social robot to predict when to stop at an appropriate distance from a human user. The model is based on user data and predicts proxemics using the user's height, age, and gender, along with the robot's angle of approach. Our validations demonstrate that the proposed approach and model perform well, offering a new way to represent human-robot proxemics. Table I shows the main coefficients to form the rubber-sheet transformations for a social robot approaching a human user.

Our RMSE and R^2 values may appear too high and too low, however this was expected. Firstly, because the number of participant data is quite low, and secondly because proxemic distances are influenced by other features [16] that we did not include such as the robot's speed [36], users' culture, physical and psychophysical features [37]. For example, it was shown that recognising human speech and gestures during face-to-face social interactions can improve proxemics distances [38], and future work should consider these factors. The advantage of rubber-sheet deformation models is that, even though, they are prone to outliers but they are very flexible in modeling a variety of data features. In our models, we used $2^{nd} order$ polynomial rubber-sheets, however, with more complex data, one can trial with higher orders, for instance, if we are dealing with 3D dimensional data points, and multiple features that required modeling at the same time.

As a future direction, we aim to investigate modelling an interpersonal equilibrium for human-robot interaction, similar to the one introduced by Argyle and Dean [39] in human-human communication. In their work, they defined the equilibrium model for interpersonal distances between individuals, in which they dynamically adjust their interpersonal distance to maintain equilibrium. In this case, adaptation between the two entities (individuals) is required to achieve this balance. Argyle and Dean [39] formulated the model as follows:

$$Intimacy = \left\{ \begin{matrix} Physical\ space, \\ smile, \\ eye\ contact, \\ etc. \end{matrix} \right\} \tag{7}$$

We see this as an opportunity to adopt Eq. 7 for modeling human-robot proxemics using rubber-sheet models.

Finally, our study has some limitations that should be addressed. We used data from 20 users, while this number is sufficient to present our novel modeling approach, further research should involve a larger dataset on human-robot proxemics, to include a more demographically diverse sample in terms of age, levels of education, cultural backgrounds etc. Additionally, the robot used in our study was a social robot and possibly designed with a cute embodiment form. We anticipate that changing the robot form and type and interaction contexts can impact the human-robot proxemic behaviours [15], [40]. Future research should (i) compare the rubber-sheet model to other baselines, (ii) perform power analysis (iii) explore data collection with multiple robots, including those of different sizes and features and (iv) test in real-time robot interactions to verify whether the model predictions result in improved comfort or acceptance for participants. Another direction to consider in future research is the use of multimodal data [41], which can enrich the human-robot proxemics estimations.

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REFERENCES

[1] F. Gul, W. Rahiman, and S. S. Nazli Alhady, "A comprehensive study for robot navigation techniques," *Cogent Engineering*, vol. 6, no. 1, p. 1632046, 2019.

[2] D. Hähnel, D. Schulz, and W. Burgard, "Mobile robot mapping in populated environments," *Advanced Robotics*, vol. 17, no. 7, pp. 579–597, 2003.

[3] S. Thrun, *Robotic mapping: a survey*, p. 1–35. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2003.

[4] G. Hoffman and W. Ju, "Designing robots with movement in mind," *Journal of Human-Robot Interaction*, vol. 3, no. 1, pp. 91–122, 2014.

[5] L. Bishop, A. van Maris, S. Dogramadzi, and N. Zook, "Social robots: The influence of human and robot characteristics on acceptance," *Paladyn, Journal of Behavioral Robotics*, vol. 10, no. 1, pp. 346–358, 2019.

[6] K. Dautenhahn, "Socially intelligent robots: dimensions of human–robot interaction," *Philosophical transactions of the royal society B: Biological sciences*, vol. 362, no. 1480, pp. 679–704, 2007.

[7] J. Mumm and B. Mutlu, "Human-robot proxemics: physical and psychological distancing in human-robot interaction," in *Proceedings of the 6th international conference on Human-robot interaction*, pp. 331–338, 2011.

[8] S. B. P. Samarakoon, M. V. J. Muthugala, and A. B. P. Jayasekara, "A review on human–robot proxemics," *Electronics*, vol. 11, no. 16, p. 2490, 2022.

[9] M. Obaid, E. B. Sandoval, J. Złotowski, E. Moltchanova, C. A. Basedow, and C. Bartneck, "Stop! that is close enough. how body postures influence human-robot proximity," in *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pp. 354–361, 2016.

[10] A. Yeh, P. Ratsamee, K. Kiyokawa, Y. Uranishi, T. Mashita, H. Takemura, M. Fjeld, and M. Obaid, "Exploring proxemics for human-drone interaction," in *Proceedings of the 5th International Conference on Human Agent Interaction*, HAI '17, (New York, NY, USA), p. 81–88, Association for Computing Machinery, 2017.

[11] G. Eresha, M. Häring, B. Endrass, E. André, and M. Obaid, "Investigating the influence of culture on proxemic behaviors for humanoid robots," in *2013 IEEE RO-MAN*, pp. 430–435, 2013.

[12] J. Urakami and K. Seaborn, "Nonverbal cues in human–robot interaction: A communication studies perspective," *J. Hum.-Robot Interact.*, vol. 12, Mar. 2023.

[13] E. T. Hall, "A system for the notation of proxemic behavior 1," *American anthropologist*, vol. 65, no. 5, pp. 1003–1026, 1963.

[14] L. David and L. Diagram, *Body language*. New York: Harper Collins, 2004.

[15] M. L. Walters, K. Dautenhahn, R. Te Boekhorst, K. L. Koay, D. S. Syrdal, and C. L. Nehaniv, "An empirical framework for human-robot proxemics," in *Procs of new frontiers in human-robot interaction: symposium at the AISB09 convention*, pp. 144–149, 2009.

[16] L. Takayama and C. Pantofaru, "Influences on proxemic behaviors in human-robot interaction," in *2009 IEEE/RSJ international conference on intelligent robots and systems*, pp. 5495–5502, IEEE, 2009.

[17] D. S. Syrdal, K. L. Koay, M. L. Walters, and K. Dautenhahn, "A personalized robot companion?-the role of individual differences on spatial preferences in hri scenarios," in *RO-MAN 2007-The 16th IEEE International Symposium on Robot and Human Interactive Communication*, pp. 1143–1148, IEEE, 2007.

[18] M. M. Neggers, R. H. Cuijpers, P. A. Ruijten, and W. A. IJsselsteijn, "Determining shape and size of personal space of a human when passed by a robot," *International Journal of Social Robotics*, vol. 14, no. 2, pp. 561–572, 2022.

[19] S. Satake, T. Kanda, D. F. Glas, M. Imai, H. Ishiguro, and N. Hagita, "How to approach humans? strategies for social robots to initiate interaction," in *Proceedings of the 4th ACM/IEEE international conference on Human robot interaction*, pp. 109–116, 2009.

[20] R. Mead, A. Atrash, and M. J. Matarić, "Automated proxemic feature extraction and behavior recognition: Applications in human-robot interaction," *International Journal of Social Robotics*, vol. 5, pp. 367–378, 2013.

[21] E. A. Schegloff, "Body torque," *Social research*, pp. 535–596, 1998.

[22] A. Mehrabian, *Nonverbal communication*. Routledge, 2017.

[23] R. Mead and M. J. Mataric, "Robots have needs too: People adapt their proxemic preferences to improve autonomous robot recognition of human social signals," *New Frontiers in Human-Robot Interaction*, vol. 100, pp. 100–107, 2015.

[24] S. B. P. Samarakoon, M. V. J. Muthugala, A. B. P. Jayasekara, and M. R. Elara, "Adapting approaching proxemics of a service robot based on physical user behavior and user feedback," *User Modeling and User-Adapted Interaction*, vol. 33, no. 2, pp. 195–220, 2023.

[25] R. Kirby, R. Simmons, and J. Forlizzi, "Companion: A constraint-optimizing method for person-acceptable navigation," in *RO-MAN 2009-The 18th IEEE International Symposium on Robot and Human Interactive Communication*, pp. 607–612, IEEE, 2009.

[26] E. Torta, R. H. Cuijpers, J. F. Juola, and D. Van Der Pol, "Modeling and testing proxemic behavior for humanoid robots," *International Journal of Humanoid Robotics*, vol. 9, no. 04, p. 1250028, 2012.

[27] E. Torta, R. H. Cuijpers, and J. F. Juola, "Design of a parametric model of personal space for robotic social navigation," *International Journal of Social Robotics*, vol. 5, pp. 357–365, 2013.

[28] T. Kosiński, M. Obaid, P. W. Woźniak, M. Fjeld, and J. Kucharski, "A fuzzy data-based model for human-robot proxemics," in *2016 25th IEEE international symposium on robot and human interactive communication (RO-MAN)*, pp. 335–340, IEEE, 2016.

[29] M. M. Neggers, R. H. Cuijpers, and P. A. Ruijten, "Comfortable passing distances for robots," in *Social Robotics: 10th International Conference, ICSR 2018, Qingdao, China, November 28-30, 2018, Proceedings 10*, pp. 431–440, Springer, 2018.

[30] P. Patompak, S. Jeong, I. Nilkhamhang, and N. Y. Chong, "Learning proxemics for personalized human–robot social interaction," *International Journal of Social Robotics*, pp. 1–14, 2019.

[31] F. Camara and C. Fox, "Space invaders: Pedestrian proxemic utility functions and trust zones for autonomous vehicle interactions," *International Journal of Social Robotics*, vol. 13, no. 8, pp. 1929–1949, 2021.

[32] F. Camara and C. Fox, "Extending quantitative proxemics and trust to hri," in *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 421–427, 2022.

[33] F. Camara and C. Fox, "A kinematic model generates non-circular human proxemics zones," *Advanced Robotics*, vol. 37, no. 24, pp. 1566–1575, 2023.

[34] M. Obaid, R. Mukundan, M. Billinghurst, and M. Sagar, "Facial expression representation using a quadratic deformation model," in *2009 Sixth International Conference on Computer Graphics, Imaging and Visualization*, pp. 44–49, 2009.

[35] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination r-squared is more informative than smape, mae, mape, mse and rmse in regression analysis evaluation," *Peerj computer science*, vol. 7, p. e623, 2021.

[36] M. M. Neggers, S. Belgers, R. H. Cuijpers, P. A. Ruijten, and W. A. IJsselsteijn, "Comfortable crossing strategies for robots," *International Journal of Social Robotics*, vol. 16, no. 7, pp. 1541–1560, 2024.

[37] R. Mead and M. J. Matarić, "Perceptual models of human-robot proxemics," in *Experimental robotics: The 14th international symposium on experimental robotics*, pp. 261–276, Springer, 2016.

[38] R. Mead and M. J. Matarić, "Autonomous human–robot proxemics: socially aware navigation based on interaction potential," *Autonomous Robots*, vol. 41, no. 5, pp. 1189–1201, 2017.

[39] M. Argyle and J. Dean, "Eye-contact, distance and affiliation," *Sociometry*, vol. 28, no. 3, pp. 289–304, 1965.

[40] C. Jones, D. Reed, and F. Camara, "Who is the chameleon? a party game to explore trust and biases towards alexa, pepper and chatgpt," in *Annual Conference Towards Autonomous Robotic Systems*, pp. 182–193, Springer, 2024.

[41] H. A. Younis, N. I. R. Ruhaiyem, A. A. Badr, A. K. Abdul-Hassan, I. M. Alfadli, W. M. Binjumah, E. A. Altuwaijri, and M. Nasser, "Multimodal age and gender estimation for adaptive human-robot interaction: A systematic literature review," *Processes*, vol. 11, no. 5, p. 1488, 2023.