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Real-Life Experiment Metrics for Evaluating Human-Robot Collaborative Navigation Tasks

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Abstract—As robots move from laboratories and industries to the real world, they must develop new abilities to collaborate with humans in various aspects, including human-robot collaborative navigation (HRCN) tasks. Then, it is required to develop general methodologies to evaluate these robots’ behaviors. These methodologies should incorporate objective and subjective measurements. Objective measurements for evaluating a robot’s behavior while navigating with others can be accomplished using social distances in conjunction with task characteristics, people-robot relationships, and physical space. Additionally, the objective evaluation of the task must consider human behavior, which is influenced by changes and the structure of their environment. Subjective evaluations of robot’s behaviors can be conducted using surveys that address various aspects of robot usability. This includes people’s perceptions of their interaction during their collaborative task with the robot, focusing on aspects such as sociability, comfort, and task-intelligence. Moreover, the communicative interaction between the agents (people and robots) involved in the collaborative task should also be evaluated. Therefore, this paper presents a comprehensive methodology for objectively and subjectively evaluating HRCN tasks.

I. INTRODUCTION

If we plan to have robotics partners in the future, these partners need to be embedded with human-like navigation behaviors. Also, these behaviors need not only to focus on accomplishing the task satisfactorily. These behaviors must include those robots move predictably and socially to increase the number of potential users for these robots and the satisfaction to use the robots [1]–[3], as well as people’s trust in robots [4], and people’s comfort [5], along with people’s perception of safety [6].

Thinking on this objective, we need to evaluate any HRCN (Examples in Fig. 1) in a way that includes the same social norms that humans use. For example, by using works like the proxemics’ rules of Hall [7] and other studies [3], [8]–[10]. Proxemic rules are related to how humans use their surrounding space. Suppose we focus only on human-human

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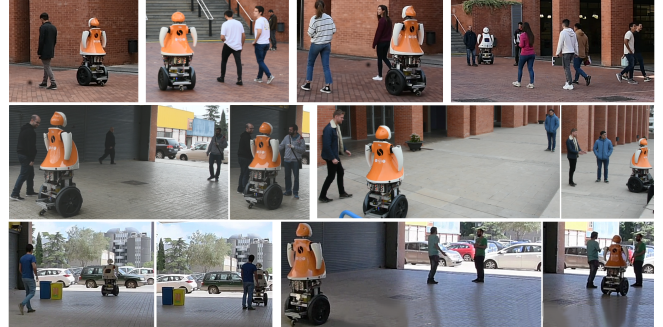


Fig. 1: Different types of HRCN tasks where authors have tested the objective and subjective metrics presented. *Up-left*: Robot Side-by-Side Accompaniment. *Up-right*: Robot V-Form Accompaniment. *Middle*: Robot Accompaniment Plus Approaching. *Bottom*: Robot Approaching.

social interactions. In that case, this use of the space is defined as several interpersonal distances to socially interact between humans depending on their level of familiarity as defined by Hall [7].

This use of the space can be translated to Human-Robot Social Interactions and, more concretely, to Human-Robot Collaborative Formations while navigating together or other types of formations to perform different tasks. For example, this work [3] includes several examples of other types of proxemics. For example, when a person is looking at a bulletin board, there are specific unwritten rules that humans respect, such as not passing between that person and the bulletin board that the person is looking at. The proxemic rules include these rules because they are related to physical distances around people. However, in this case, they refer to interactions between humans and objects, not social interactions between humans, that the robot should consider in its behavior, just like the humans do.

Many recent works in Human-robot collaborative navigation use proxemics [11]–[23]. Then, it is essential to have some guidelines to develop metrics to evaluate the robot behavior using proxemics. In addition, we can use proxemics and the following guidelines in more situations than only human-robot collaborative navigation, as several works outside this field use proxemics [20], [24]–[39]. For example, we can use them with a robot serving food at a table, Fig. {3 and 4}-left.

Furthermore, we want these robots to be helpful to the general population. In that case, we must evaluate the robot’s

behaviors regarding Usability, Social acceptance, User experience, and Societal impact (USUS) following some guidelines [40]–[45] to evaluate the everyday user experience during the HRI. Consequently, it is critical to develop methodologies to evaluate these behaviors concurrently with the robot’s behaviors. Nonetheless, it is a challenging task to create various generic metrics, which requires significant effort and time. It may take several years to engineer diverse collaborative robot navigation behaviors and corresponding metrics for each of these behaviors.

This paper presents two main contributions. Firstly, a comprehensive guide to develop objective metrics for any human-robot collaborative navigation (HRCN) using proxemics, Sec. II. To ensure an objective assessment of the robot’s behavior, the proxemic definitions should consider various factors, such as the robot’s physical appearance, the person’s social relationship with the robot, the social formations required to execute the task, and how the environment and people’s behavior affect these formations. Secondly, a general survey questionnaire is provided that can be adapted to any HRCN to evaluate the robot’s behavior concerning people’s emotional experience during interaction, Sec. III. These questions assess the perceived comfort, sociability, and intelligence of the robot’s behavior while performing the collaborative task with the person. Additionally, some questions are included to evaluate the communicative interaction between all the people and robots involved in the task, which covers both verbal and nonverbal communication, as these are formulated in a general sense.

II. OBJECTIVE METRICS

To obtain an objective evaluation of the robot’s social behavior, various studies related to proxemics, social interactions, and people’s comfort can be employed [3], [7]–[10], [46]–[48] because humans use these behaviors in their social relations between them. Then, it is logical to think that we can use an adaptation of those proxemics works in our robot’s behaviors. These robots’ proxemics rules will be slightly different from those used with humans because these areas of interaction differ depending on the robot’s type, task, and relation with it. Also, the environment can influence these interaction areas defined by proxemic rules to avoid obstacles or people. So then, these guidelines should consider these four aspects (type, task, relation, and environment) to easily adapt the proxemic rules to the robot’s behaviors. Finally, in several of our previous works, we have demonstrated that we can use and adapt these proxemic rules in different tasks of HRCN like approaching, accompaniment or both at the same time [16], [49]–[52], Fig. 1. Then, the next metrics allow evaluating the social formation to perform any robot’s collaborative navigation task.

A. Consider the robot type & relation in proxemics

Robot’s physical (or “personal”) area is determined by their size and appearance. To consider the robot’s physical size, we need to know the robot’s volume. Furthermore, for each different task, the position where the robot must

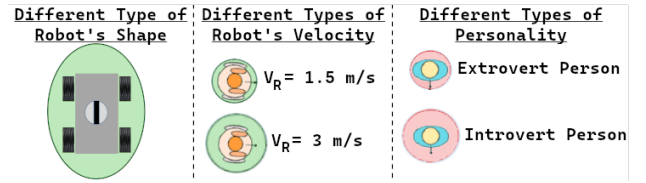


Fig. 2: Personal space plotted for robots and humans.

be placed will change taking into account the formation of said task (explained in Sec. II-B). Based on this, the robot’s personal space can be defined and located within the formation in the best area for the robot to perform the task. Additionally, if the robot’s velocity is taken into consideration, the area should be adjusted to include a safety margin of free space to ensure the robot has enough distance to stop before colliding with any obstacle. The robot’s appearance can transform this physical area into a subjective area, which will increase to make the person feel comfortable during the interaction. This fact can be similar to the relation with the robot. For people who feel familiar with the robot, their personal distances between them and the robot can be smaller, and for unfamiliar people, these distances should be greater [53]. In addition, this area can be similar to a person’s personal space considering her personality. These last cases are more subjective than robot size. Then, there is still much work to be done to know these distances. Examples of different cases of a robot’s personal area to account for its appearance and velocity can be seen in Fig. 2, as well as how people’s personal space can change depending on their personality.

Several works in the literature explore the physical space around people depending on several aspects [3], for example, different shapes of personal space, etc. Then, we recommend that the readers explore the state-of-art works and find the best person and robot’s personal space for their implementation. Also, we have explored these distances for different velocities and positions between robot and person in our previous work [47], and we confirmed through experiments these findings [16], [54].

B. Consider the robot task in proxemics

In order to tailor the metrics for a specific task, it is necessary to have an understanding of the physical formation that individuals should adopt when carrying out the task, the social relation between the members of the group, as well as their preferred personal space. Then, these proxemics include several areas with different meanings of interaction, and we need some rules to create these different areas. These areas are: the area where people can notice the interaction with the robot (Interaction area) in Sec. II-B.1, the best area where the robot should be located to perform in a good way the task (the best area to perform the task) in Sec. II-B.2, and the areas where the robot should not enter (forbidden areas) in Sec. II-B.3.

1) *Definition of the interaction area:* The robot should stay inside this area to allow people to notice that they are socially interacting. This area delimits the area of interaction between humans and robots, and it is from the human point

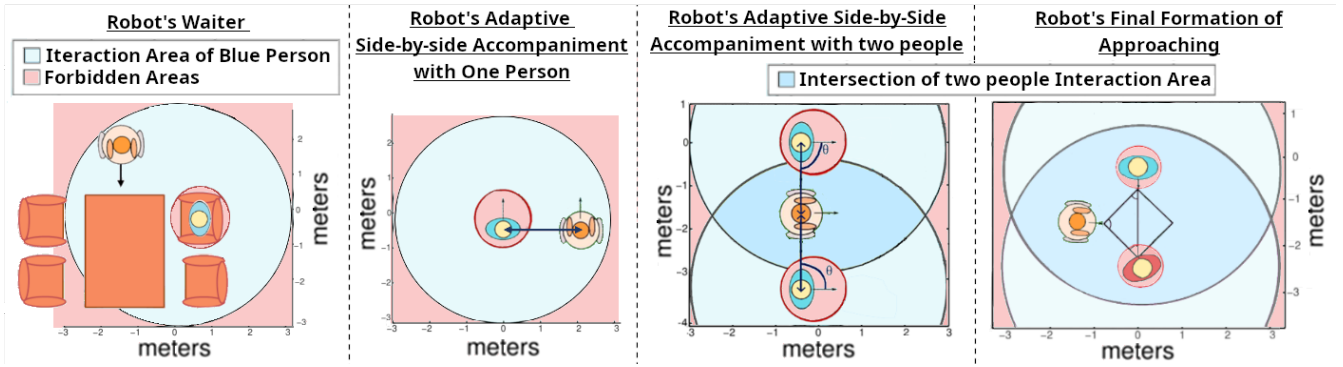


Fig. 3: People's interaction areas and forbidden areas. Also, these forbidden areas should include areas around the objects.

of view. Then, it is centered on the human position. Outside this area, people should not feel they are interacting with the robot, which corresponds to one of the two types of forbidden areas in red. However, it is not the best area for the robot to perform the task. So within this area, the value of the robot's performance will be half of any scale. The forbidden areas will be described in Sec. II-B.3, and the best area to perform the task will be described in Sec. II-B.2.

For the interaction between one robot and one person, we can look at Hall [7] studies for the social distances between two people. We focus on these studies because some researchers agree that proxemic rules between a person and a robot should be similar to the ones among people [55], and we have followed this idea among all our previous works. Then, the area best suited for people's social interactions with robots is the area of social distances, as we currently do not have an intimate or personal relationship with robots. In addition, these types of robots are called social robots because they are designed to maintain social interaction with us. Therefore, it is logical that through real-life experiments from our previous works [47], [54], we have found that the area that best adapts to these interactions is the social area defined by Hall [7].

In cases of one-person and one-robot interaction (or interactions with more than one person but without other obstacles or people between the robot and the person), this area of social distances is the best one to delimit the interaction between people and robots. For example, this is the case of the robot's one-person accompaniment, the robot's group accompaniment when the robot is at the center of the formation that can interact equally with both people, the robot's waiter for the blue person, and the approaching where the triangle formation allows the same robot's interaction with both people, see Fig. 3.

In addition, the size of this area should be enlarged depending on the number of group members, the robot's position inside this group, and the environment's elements. Then, this area should increase if there are other humans or objects between the robot and the person. For example, this is the case of the robot waiter for the different people at the table and the robot's accompaniment of a group of people when the robot is at the side of the formation. In the case of the waiter, depending on the person's position on the table, this distance is smaller or larger with respect to the robot's

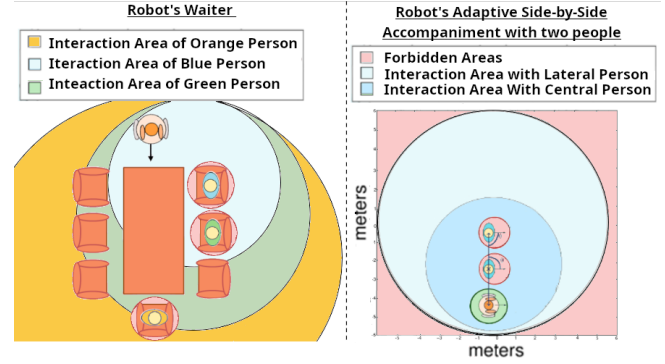


Fig. 4: Interaction areas and forbidden areas only respect people for different tasks. Also, these forbidden areas should include areas around the objects, but this is more related to the robot's collision avoidance than with the robot's sociability.

waiter position, visual examples in Fig. 4.

2) *Definition of the best area to perform the task:* The best task achievement closely relates to the formation of the group of people to develop this task, the robot's physical position inside the group, and the robot's physical space (Sec. II-A).

Regarding the physical formation to perform a task, we should know this specific formation for the case of people interactions. For example, in the case of group accompaniment, we can have two different formations to do the accompaniment: side-by-side and V-formation, as shown in Fig. 5. We have extracted these formations from studies about group people dynamics that study these people formations [56]–[58]. If more than one robot position within the group is possible, we must consider them to develop different metrics for all these cases. For example, in these two different group formations for two people accompaniment, there are two different metrics to consider depending on the two different robot's positions inside the group formation, at the lateral or the center [51], [52], see Fig. 5. As we have noticed in Fig. 5, the best robot position changes depending on these two factors: the formation to perform the task and the position of the robot inside the group formation.

Furthermore, a previous task can coerce this best area to perform the task. For example, it is the case of combining a people accompaniment with approaching a second person. In this case, the robot can select two possible positions to perform a triangle formation with both people, and the best one should be selected to have a more natural robot behavior.

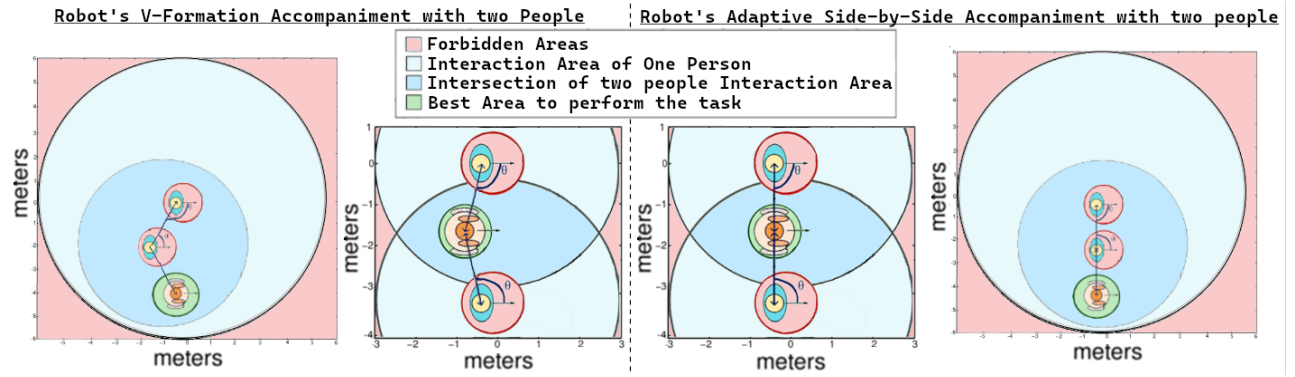


Fig. 5: Representation of how all the interaction and best robot areas change depending on the task. In this case, for the Side-by-Side and V-formation types of accompaniments.

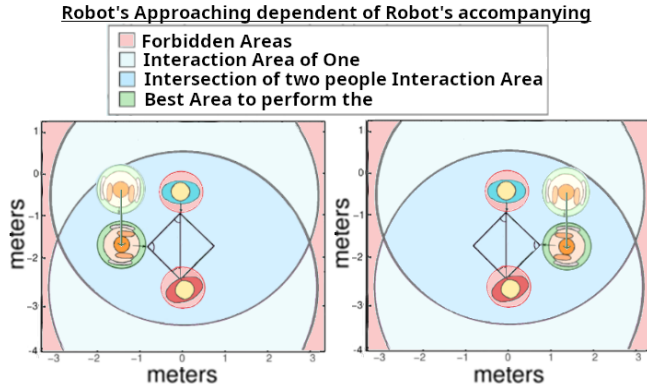


Fig. 6: The illustration demonstrates how the best robot interaction area changes depending on development of the previous task (side-by-side accompaniment).

Then, the robot should select the position of the triangle formation nearest to its previous position on one of the sides of the person it accompanies. You can see this behavior in the two left images of Fig. 6. Several previous researchers used this formation for people interaction similarly to us [3], [59], [60]. Also, this formation is sometimes generalized for more than three people as an O-shape formation.

Finally, the reader should consider the robot's physical area to set up the radius that delimits the best area to perform the task. Also, this area will be more realistic if you consider the robot's personal space. For the robot case, this space is the security distance that it needs to stop in case that any object or person interferes in its path. Regarding our robot, it is 0.3 m from its sensors, which are located at 0.5 m of its center. It is to say, the minimum area for this best area needs to be 1.3 m around the center of the robot position. This area is drawn in green in all the figures from this point until the end of this paper.

Furthermore, the reader should notice that these metrics consider the best position for humans, but we can not control them. However, to design the people's positions within the formation, we can expect people to behave similarly to how they would do with other people in that situation. We can expect this behavior because it is the most similar interaction that people know. Therefore, the robot will have the best performance value if it is located in these green areas that represent the best area to perform the task for the robot. In

the case of the scale from 0 to 1, it corresponds to the value of 1.

3) *Definition of the forbidden areas:* These metrics must consider the worst areas where the robot can not be located. When the robot is inside these areas, its performance is 0, and in some cases, we also need several security measures to prevent the robot will enter there in any case. For example, with a security system that stops the robot when any object enters inside its radius of security, 0.3 m from its sensors. Two possible cases need to be considered to find these forbidden areas:

First, the robot, in any case, should be allowed to invade any personal space of any human. Then, forbidden areas should be located surrounding humans. Also, the form of these areas can be different depending on if the human is stopping or walking, and should include the human velocity. In all our previous works, we have included human velocity using the prediction of human movement. Then, we propagate static people's forbidden areas around them using their velocity (Fig. 7-left). Consequently, our forbidden areas around humans do not include the velocity because we include it in the propagation. However, suppose other researchers do not use people's prediction and propagation of their movement. In that case, the people's velocity should be included directly in the shape of these forbidden areas, similar to the case of the robot in Fig. 2. In addition, these areas can include the level of familiarity that the person has towards the robot. For example, extroverted people that like robots should prefer near distances between them, and introverted people or afraid of robots should prefer higher distances between them, which also means more or less personal space for the person, Fig. 2 and Fig. 7-right.

Second, if the robot goes out of the area of social distance, the person can not notice that it is interacting with her. So then, this situation should be avoided by the robot. Outside the area of social distances, there is another forbidden area for the robot. However, in this case, it does not need any security measures to prevent the robot from entering there because it will not harm anyone.

C. Consider the environment in proxemics

These metrics should consider the group's environment because the people groups' formations change depending on

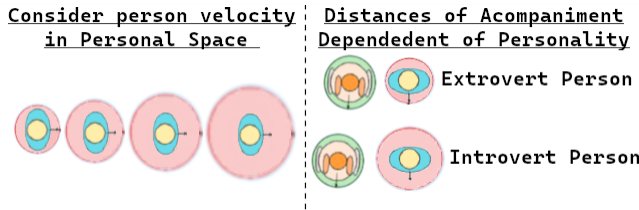


Fig. 7: *Left*: we show how the personal space of the person is propagated due to its velocity and the uncertainty of the person's movement while the time increases. *Right*: we show how the distance of accompaniment can increase due to the accompanied person's personality.

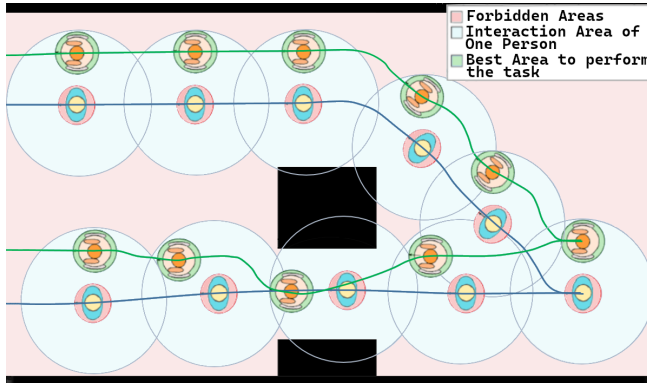


Fig. 8: Best robot's area. It depends on the formation changes due to the environment because the group of people formations should change their structure to avoid obstacles together.

it to overpass obstacles together or use the environment's elements. For example, in the example of the chairs, these areas change depending on where people are seated in the chairs, Fig. 4. This dependence on the environment can cause having infinite different performances, like in the case of side-by-side accompaniment walking through different types of corridors, Fig. 8.

Furthermore, the position of these areas depends simultaneously on the behaviors of the people interacting with the robot, for example, in the case of the side-by-side while approaching a person where there is an obstacle near the approached person. The movements and best positions of the robot to accompany the person and finally to approach the other person depend on these two people's behaviors. For example, suppose they allow enough space for the robot to move more naturally. In that case, these areas will be different that in the case of these two people prefer to make the minimum effort and induce the robot to surround the accompanied person to interact with the approached person. See Fig. 9.

So then, researchers must use methods that compute dynamic metrics that will be modified automatically, considering the task, the position of all the group members during the task performance, the environment's configuration, and the behavior of the people interacting with the robot. There are more examples in [49], [52].

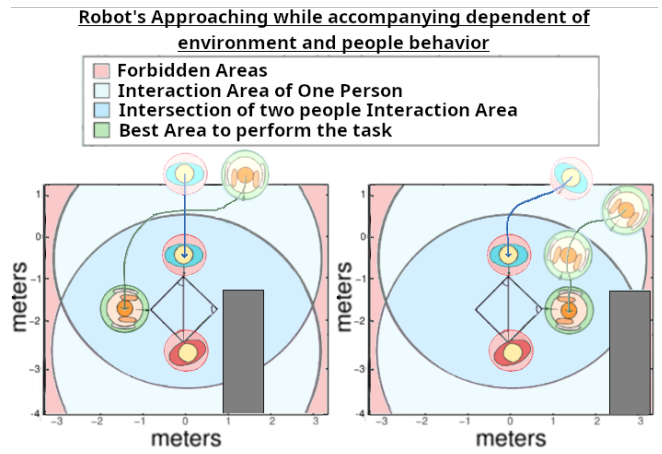


Fig. 9: Best robot interaction area. It changes depending on the position of people interacting with the robot concerning the environment.

III. SUBJECTIVE METRICS

We can use the theory of USUS questionnaires [40] to evaluate the robot behavior in a subjective way considering the user's feelings about their experience while they perform the tasks together. We have selected to evaluate the robot's sociability, comfortableness and "task-intelligence", and the group's communicative interaction. Our proposed questions can be seen in Table I. These questions can be used in any Human-Robot Collaborative task because these are presented in a general way and can also be adapted to other different tasks than navigation tasks. However, the researchers need to customize these questions for the concrete number of agents (humans and robots) involved and the tasks (accompaniment, approaching, remove together the objects from a table to a container, searching for objects or people in an environment, or other) because non-experts in robotics tend to lose focus on the task they have just completed with the robot if generic questions are used. This fact has been pointed out during several previous tests, and the presented questions have demonstrated their utility in conducting user studies in several works on HRCN [16], [51], [52], [54].

IV. EXPERIMENTAL EVALUATION

The presented objective and subjective metrics were employed in over 20.000 simulations and 600 real-life experiments to evaluate the 5 different types of robot's collaborative navigation [16], [51], [52], [54], [61], including 6 user studies. In this paper, we provide a summarized overview of all the results, which serve as experimental evidence for the effectiveness and usefulness of these metrics. The formulas for these metrics, along with two additional formulas to assess distance and angle failures, can be found in the author's PhD thesis [62]. Furthermore, these documents will be made available on the author's website¹ in the coming months, or interested readers can directly request them. Our chosen maximum velocity for the robots is 1.2 m/s, which corresponds to the typical walking speed of humans. We

¹<https://elyrepiso.wordpress.com/>

Survey's Questions
Robot's Comfortableness Scale How comfortable have you felt during the task? How safe have you felt doing the task with the robot? How comfortable have you felt with the robot's position and/or movements while you are performing the task?
Robot's Sociability Scale How natural was the robot's behavior during the task? How interactive was the robot's behavior during the task?
Robot's Intelligence Scale How intelligent did the robot behave in terms of task performance? How well did the robot anticipate to your's and other's movements during the performance of the task?
Group's Communicative Interaction How easy was the communication with your partner during the task performance? How easy was the communication with the robot during the task performance? How easy was it to see the other person during the task? How easy was it to see the robot during the task?

TABLE I: Survey questions. All questions were asked on a 7-point scale from "Not at all" to "Very much".

assume a constant acceleration over a 0.2-second iteration time that has our robot controller. Our physical robots (Tibi and Dabo) have a size of 1 meter in diameter.

Regarding the objective metrics, the results obtained in all these experiments using the proxemic metrics are shown in Tab. II. The accompanying images of real-life experiments depicted in Figure 1 demonstrate that the robot's performance in social formations closely resembles that of humans, further supported by the logical values obtained in the table of results. Additional images from simulations and real-life experiments can be found in the main author's previous papers. Thus, we can assert that these metrics have been experimentally proven effective in evaluating various types of collaborative navigation methods for robots.

In terms of subjective metrics, we employed Cronbach's Alpha to assess the internal consistency (or reliability) of our questionnaires across all user studies. All scales exhibited a reliability level exceeding the commonly used threshold of 0.7 to demonstrate a good consistency. It is worth noting that our questionnaires utilized Likert scales to transform qualitative data into quantitative data. Reliability in this context refers to the ability to reproduce results under similar conditions. For validity, we employed a test-retest approach, iterating as necessary to ensure that the questions effectively measured the desired hypotheses. Validity refers to the accuracy of a measure, it is to say, whether the results really represent what they are supposed to measure. In our experiments, we have evaluated the Robot's comfortableness, sociability, and intelligence perceived by the volunteers and also the group's communicative interaction as Tab. III shows. Our hypotheses were always to infer if volunteers consider two types of collaborative navigation as equal. Initially, the method is compared with the teleoperation to asset if

it was able to perform as similar as possible to human behavior. Remember that in the ANOVAs test plus Pairwise comparison with Bonferroni, the $p - value > 0.05$, and it means statistic difference when $p - value < 0.05$. In all cases with a $p - value > 0.05$, our hypothesis that both methods were considered equal by the volunteers was confirmed. However, we did find a statistically significant difference in the case highlighted in light red. Analyzing the mean values of robot comfort for the ASP-VG vs. ASP-SG, we observed a higher level of comfort reported for ASP-SG. Based on the volunteers' comments, we deduced that for people were more comfortable if they can see and feel the robot near them (ASP-SG case).

V. CONCLUSIONS

This paper provides a comprehensive set of guidelines for researchers seeking to develop objective and subjective metrics to evaluate a wide range of human-robot collaborative navigation (HRCN) tasks, such as solo navigation, guidance, accompaniment, approaching and so on. The objective metrics outlined in the paper take into account various social factors identified by Hall [7] and transform them to include the formation of the task, the relationship between the person and the robot, the physical appearance and personality of the agents, the positions of other people and the structure of the environment. Additionally, these metrics consider people's behavior in relation to their environment.

On the other hand, the subjective metrics are concerned with assessing people's perceptions about the robot's comfortableness, sociability, intelligence, and group communicative interaction while they interact together. Finally, the paper highlights the effectiveness of these metrics in evaluating different types of HRCN with potential users, as evidenced by previous works conducted by the authors.

The guidelines presented in the paper offer a solid foundation and a source of inspiration for other researchers who wish to develop metrics to evaluate their experiments in the field of HRCN, as well as other types of human-robot collaborative tasks. By adhering to these guidelines, researchers can ensure that their metrics are comprehensive, accurate, and reliable, thereby advancing the state of the art in human-robot collaboration.

ETHICS APPROVAL

The Ethics Review Board of Universitat Politècnica de Catalunya approved the study, with title: Navegación Robot-Humano Colaborativa en entornos con personas y predicción de movimiento humano. The Ethics Review Board decision number is: 2021-11 UPC. Then, informed consent was obtained from all individual participants included in all studies.

REFERENCES

- [1] V. Fleishman, S. Honig, T. Oron-Gilad, and Y. Edan, "Proxemic preferences when being followed by a robot," *Israeli Ministry of Science and Technology, Report*, pp. 3–12 060, 2018.
- [2] K. Wolf and L. Lischke, "Urban proxemics for public guidance," in *Proceedings of the NordiCHI Workshop on Ubicomp beyond Devices: People, Objects, Space and Meaning, ACM*, vol. 10, 2014, pp. 2 639 189–2 654 842.

Simulation experiments: Area metric extracted from the proxemic metrics						
	One Person Side-by-Side	Two Person Side-by-Side	Two Person V-form	Approaching with Splines	Approaching using line intersection	Approaching using optimal intersection
mean	0,8639	0,7813	0,7582	0,9719	0,6121	0,8163
std	($\pm 0,0293$)	($\pm 0,0976$)	($\pm 0,0685$)	($\pm 0,0722$)	($\pm 0,0086$)	($\pm 0,0111$)
Real-life experiments: Area metric extracted from the proxemic metrics						
mean	0,7764	0,8049	0,7089	0,9599	—	0,8355
std	($\pm 0,0478$)	($\pm 0,1373$)	($\pm 0,0651$)	($\pm 0,0538$)	—	($\pm 0,0168$)

TABLE II: Results of all experiments about the mean and standard deviation of the Area performance metrics extracted from the proxemic metrics of this paper. Notice this value is always between 0 and 1, as said previously. For the approaching using line intersection, real-life experiments were not done because the optimal intersection outperforms this behavior.

Simulation experiments: Area metric extracted from the proxemic metrics						
	ASP-SG vs Teleop	ASP-VG vs Teleop	ASP-VG vs ASP-SG	ASP-VG lat- eral vs central	ASP-SG lat- eral vs central	Accompaniment plus approaching
Cronbach's alpha	0,71	0,75	0,7	0,82	0,82	0,72
ANOVAs tests plus Pairwise comparison with Bonferroni						
Robot's Com- fortableness	p-value=0.2	p-value=0.2	p-value=0.02	p-value=0.2	p-value=0.91	p-value=0.01
Robot's Sociability	p-value=0.5	p-value=0.9	p-value=0.2	p-value=0.2	p-value=0.41	p-value=0.1
Robot's Intel- ligence	Not Measured	Not Measured	p-value=0.2	p-value=0.85	p-value=0.8	p-value=0.2
Group's Com- muni- cative Interaction	Not Measured	Not Measured	p-value=0.54	p-value=0.81	p-value=0.01	Not Measured

TABLE III: All user studies results using the questioners of the current paper

- [3] J. Rios-Martinez, A. Spalanzani, and C. Laugier, "From proxemics theory to socially-aware navigation: A survey," *International Journal of Social Robotics*, vol. 7, no. 2, pp. 137–153, 2015.
- [4] K. R. MacArthur, K. Stowers, and P. Hancock, "Human-robot interaction: Proximity and speed-slowly back away from the robot!" in *Advances in human factors in robots and unmanned systems*. Springer, 2017, pp. 365–374.
- [5] E. Pacchierotti, H. I. Christensen, and P. Jensfelt, "Evaluation of passing distance for social robots," in *Roman 2006-the 15th IEEE international symposium on robot and human interactive communication*. IEEE, 2006, pp. 315–320.
- [6] P. A. Lasota, T. Fong, J. A. Shah, et al., "A survey of methods for safe human-robot interaction," *Foundations and Trends® in Robotics*, vol. 5, no. 4, pp. 261–349, 2017.
- [7] E. T. Hall and T. Edward, "Hall. the hidden dimension," *Anchor Books New York*, vol. 20, p. 71, 1969.
- [8] D. Helbing and P. Molnar, "Social force model for pedestrian dynamics," *Physical review E*, vol. 51, no. 5, p. 4282, 1995.
- [9] S. Park and M. M. Trivedi, "Multi-person interaction and activity analysis: a synergistic track-and-body-level analysis framework," *Machine Vision and Applications*, vol. 18, no. 3-4, pp. 151–166, 2007.
- [10] M. Gérin-Lajoie, C. L. Richards, J. Fung, and B. J. McFadyen, "Characteristics of personal space during obstacle circumvention in physical and virtual environments," *Gait & posture*, vol. 27, no. 2, pp. 239–247, 2008.
- [11] S. Bhagya, P. Samarakoon, H. C. Sirithunge, M. V. J. Muthugala, J. Muthugala, A. Buddhika, and P. Jayasekara, "Proxemics and approach evaluation by service robot based on user behavior in domestic environment," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2018, pp. 8192–8199.
- [12] K. L. Koay, D. Syrdal, R. Bormann, J. Saunders, M. L. Walters, and K. Dautenhahn, "Initial design, implementation and technical evaluation of a context-aware proxemics planner for a social robot," in *International Conference on Social Robotics*. Springer, 2017, pp. 12–22.
- [13] A. Montanari, Z. Tian, E. Francu, B. Lucas, B. Jones, X. Zhou, and C. Mascolo, "Measuring interaction proxemics with wearable light tags," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 2, no. 1, pp. 1–30, 2018.
- [14] N. Norouzi, K. Kim, M. Lee, R. Schubert, A. Erickson, J. Bailenson, G. Bruder, and G. Welch, "Walking your virtual dog: Analysis of awareness and proxemics with simulated support animals in augmented reality," in *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, 2019, pp. 157–168.
- [15] M. Luperto, J. Monroy, J. R. Ruiz-Sarmiento, F.-A. Moreno, N. Basilico, J. Gonzalez-Jimenez, and N. A. Borghese, "Towards long-term deployment of a mobile robot for at-home ambient assisted living of the elderly," in *2019 European Conference on Mobile Robots (ECMR)*. IEEE, 2019, pp. 1–6.
- [16] E. Repiso, A. Garrell, and A. Sanfeliu, "Adaptive side-by-side social robot navigation to approach and interact with people," *International Journal of Social Robotics*, pp. 1–22, 2019.
- [17] J. Ginés, F. Martín, D. Vargas, F. J. Rodríguez, and V. Matellán, "Social navigation in a cognitive architecture using dynamic proxemic zones," *Sensors*, vol. 19, no. 23, p. 5189, 2019.
- [18] J. Ginés Clavero, F. Martín Rico, F. J. Rodríguez-Lera, J. M. Guerrero Hernández, and V. Matellán Olivera, "Defining adaptive proxemic zones for activity-aware navigation," in *Workshop of Physical Agents*. Springer, 2020, pp. 3–17.
- [19] M. Daza, D. Barrios-Aranibar, J. Diaz-Amado, Y. Cardinale, and J. Vilasboas, "An approach of social navigation based on proxemics for crowded environments of humans and robots," *Micromachines*, vol. 12, no. 2, p. 193, 2021.
- [20] G. Fernandez-Nieto, R. Martinez-Maldonado, V. Echeverria, K. Kitto, P. An, and S. Buckingham Shum, "What can analytics for teamwork

- proxemics reveal about positioning dynamics in clinical simulations?” *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW1, pp. 1–24, 2021.
- [21] 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.
 - [22] C. Millán-Arias, B. Fernandes, and F. Cruz, “Proxemic behavior in navigation tasks using reinforcement learning,” *Neural Computing and Applications*, pp. 1–16, 2022.
 - [23] H. A. Valera and M. Luštrek, “A novel human-awareness solution for person-following robot’s behavior problem based on proxemics,” in *Workshops at 18th International Conference on Intelligent Environments (IE2022)*, vol. 31. IOS Press, 2022, p. 17.
 - [24] 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*, 2011, pp. 331–338.
 - [25] N. Baba, H.-H. Huang, and Y. I. Nakano, “Addressee identification for human-human-agent multiparty conversations in different proxemics,” in *Proceedings of the 4th Workshop on Eye Gaze in Intelligent Human Machine Interaction*, 2012, pp. 1–6.
 - [26] 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*. IEEE, 2013, pp. 430–435.
 - [27] H. Overhill, “Apple pie proxemics: Edward t. hall in the kitchen work triangle,” *Design Issues*, vol. 30, no. 2, pp. 67–82, 2014.
 - [28] S. Butscher and H. Reiterer, “Proxemics-aware multi-focus visualizations to support mutual awareness during co-located collaboration,” in *Workshop on Collaboration Meets Interactive Surfaces (CMIS): Walls, Tables, Mobiles, and Wearables*, 2015.
 - [29] M. Alnusayri, G. Hu, E. Alghamdi, and D. Reilly, “Proxemicui: object-oriented middleware and event model for proxemics-aware applications on large displays,” in *Proceedings of the 8th ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, 2016, pp. 50–60.
 - [30] A. Cafaro, B. Ravenet, M. Ochs, H. H. Vilhjálmsón, and C. Pelachaud, “The effects of interpersonal attitude of a group of agents on user’s presence and proxemics behavior,” *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 6, no. 2, pp. 1–33, 2016.
 - [31] I. Podkosova and H. Kaufmann, “Co-presence and proxemics in shared walkable virtual environments with mixed colocation,” in *Proceedings of the 24th ACM Symposium on Virtual Reality Software and Technology*, 2018, pp. 1–11.
 - [32] K. Mikulski, “Proxemics in the context of the digital school,” *Cognitive Science–New Media–Education*, vol. 4, no. 1, pp. 93–108, 2018.
 - [33] S. Bhagya, P. Samarakoon, M. Viraj, J. Muthugala, A. Buddhika, P. Jayasekara, and M. R. Elara, “An exploratory study on proxemics preferences of humans in accordance with attributes of service robots,” in *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2019, pp. 1–7.
 - [34] A. Antonucci, P. Bevilacqua, L. Palopoli, M. Boldrer, and D. Fontanelli, “Motion planning in crowds: Proxemics as a base for a socially acceptable behaviour,” *I-RIM Conference*, 2019.
 - [35] R. Martínez-Maldonado, K. Mangaroska, J. Schulte, D. Elliott, C. Axisa, and S. B. Shum, “Teacher tracking with integrity: What indoor positioning can reveal about instructional proxemics,” *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 4, no. 1, pp. 1–27, 2020.
 - [36] P. Patompak, S. Jeong, I. Nilkhamhang, and N. Y. Chong, “Learning proxemics for personalized human–robot social interaction,” *International Journal of Social Robotics*, vol. 12, no. 1, pp. 267–280, 2020.
 - [37] F. Camara and C. Fox, “Space invaders: Pedestrian proxemic utility functions and trust zones for autonomous vehicle interactions,” *International Journal of Social Robotics*, pp. 1–21, 2020.
 - [38] V. Narayanan, B. M. Manoghar, V. S. Dorbala, D. Manocha, and A. Bera, “Proxemo: Gait-based emotion learning and multi-view proxemic fusion for socially-aware robot navigation,” in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2020, pp. 8200–8207.
 - [39] K. Mahadevan, M. Sousa, A. Tang, and T. Grossman, “‘grip-that-there’: An investigation of explicit and implicit task allocation techniques for human-robot collaboration,” in *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–14.
 - [40] A. Weiss, R. Bernhaupt, M. Lankes, and M. Tscheligi, “The usus evaluation framework for human-robot interaction,” in *AISB2009: proceedings of the symposium on new frontiers in human-robot interaction*, vol. 4, no. 1. Citeseer, 2009, pp. 11–26.
 - [41] A. Weiss, R. Bernhaupt, and M. Tscheligi, “The usus evaluation framework for user-centered hri,” *New Frontiers in Human–Robot Interaction*, vol. 2, pp. 89–110, 2011.
 - [42] J. Lindblom and R. Andreasson, “Current challenges for ux evaluation of human-robot interaction,” in *Advances in ergonomics of manufacturing: Managing the enterprise of the future*. Springer, 2016, pp. 267–277.
 - [43] J. Lindblom, B. Alenljung, and E. Billing, “Evaluating the user experience of human–robot interaction,” in *Human-Robot Interaction*. Springer, 2020, pp. 231–256.
 - [44] M. Qbilat, A. Iglesias, and T. Belpaeme, “A proposal of accessibility guidelines for human-robot interaction,” *Electronics*, vol. 10, no. 5, p. 561, 2021.
 - [45] P. Caleb-Solly, S. Dogramadzi, C. A. Huijnen, and H. v. d. Heuvel, “Exploiting ability for human adaptation to facilitate improved human-robot interaction and acceptance,” *The Information Society*, vol. 34, no. 3, pp. 153–165, 2018.
 - [46] K. Stubbs, P. J. Hinds, and D. Wettergreen, “Autonomy and common ground in human-robot interaction: A field study,” *IEEE Intelligent Systems*, vol. 22, no. 2, 2007.
 - [47] A. Garrell and A. Sanfeliu, “Cooperative social robots to accompany groups of people,” *The International Journal of Robotics Research*, vol. 31, no. 13, pp. 1675–1701, 2012.
 - [48] A. Garrell, M. Villamizar, F. Moreno-Noguer, and A. Sanfeliu, “Proactive behavior of an autonomous mobile robot for human-assisted learning,” in *2013 IEEE RO-MAN*. IEEE, 2013, pp. 107–113.
 - [49] E. Repiso, G. Ferrer, and A. Sanfeliu, “On-line adaptive side-by-side human robot companion in dynamic urban environments,” in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017, pp. 872–877.
 - [50] M. Galvan, E. Repiso, and A. Sanfeliu, “Robot navigation to approach people using g²-spline path planning and extended social force model,” in *Iberian Robotics conference*. Springer, 2019, pp. 15–27.
 - [51] E. Repiso, F. Zanlungo, T. Kanda, A. Garrell, and A. Sanfeliu, “People’s v-formation and side-by-side model adapted to accompany groups of people by social robots,” *IEEE/RSJ international conference on Intelligent robots and systems*, 2019.
 - [52] E. Repiso, A. Garrell, and A. Sanfeliu, “People’s adaptive side-by-side model evolved to accompany groups of people by social robots,” *IEEE Robotics and Automation Letters and IEEE/RSJ International Conference on Robotics and Automation (RA-L and ICRA)*, 2020.
 - [53] O. Castro, E. Repiso, A. Garrell, and A. Sanfeliu, “Classification of humans social relations within urban areas,” in *Iberian Robotics conference*. Springer, 2023, pp. 27–39.
 - [54] E. Repiso, A. Garrell, and A. Sanfeliu, “Adaptive social planner to accompany people in real-life dynamic environments,” *International Journal of Social Robotics*, pp. 1–33, 2022.
 - [55] K. Charalampous, I. Kostavelis, and A. Gasteratos, “Recent trends in social aware robot navigation: A survey,” *Robotics and Autonomous Systems*, vol. 93, pp. 85–104, 2017.
 - [56] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz, “The walking behaviour of pedestrian social groups and its impact on crowd dynamics,” *PloS one*, vol. 5, no. 4, p. e10047, 2010.
 - [57] I. Karamouzas and M. Overmars, “Simulating and evaluating the local behavior of small pedestrian groups,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 3, pp. 394–406, 2012.
 - [58] F. Zanlungo and T. Kanda, “A mesoscopic model for the effect of density on pedestrian group dynamics,” *EPL (Europhysics Letters)*, vol. 111, no. 3, p. 38007, 2015.
 - [59] V. K. Narayanan, A. Spalanzani, R. C. Luo, and M. Babel, “Analysis of an adaptive strategy for equitably approaching and joining human interactions,” in *25th IEEE International Symposium on Robot and Human Interactive Communication*, 2016, pp. 341–346.
 - [60] H. B. Barua, P. Pramanick, C. Sarkar, and T. H. Mg, “Let me join you! real-time f-formation recognition by a socially aware robot,” in *2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2020, pp. 371–377.
 - [61] M. Galvan, “Kinodynamic real-time motion planning for a mobile,” Master’s thesis, Universitat Politècnica de Catalunya, 2019.
 - [62] E. Repiso Polo, “Collaborative social robot navigation in accompanying and approaching tasks,” 2020.