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Dynamics of Social Positioning Patterns in Group-Robot Interactions*

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***Abstract*— When a mobile robot interacts with a group of people, it has to consider its position and orientation. We introduce a novel study aimed at generating hypotheses on suitable behavior for such social positioning, explicitly focusing on interaction with small groups of users and allowing for the temporal and social dynamics inherent in most interactions. In particular, the interactions we look at are approach, converse and retreat. In this study, groups of three participants and a telepresence robot (controlled remotely by a fourth participant) solved a task together while we collected quantitative and qualitative data, including tracking of positioning/orientation and ratings of the behaviors used. In the data we observed a variety of patterns that can be extrapolated to hypotheses using inductive reasoning. One such pattern/hypothesis is that a (telepresence) robot could pass through a group when retreating, without this affecting how comfortable that retreat is for the group members. Another is that a group will rate the position/orientation of a (telepresence) robot as more comfortable when it is aimed more at the center of that group.**

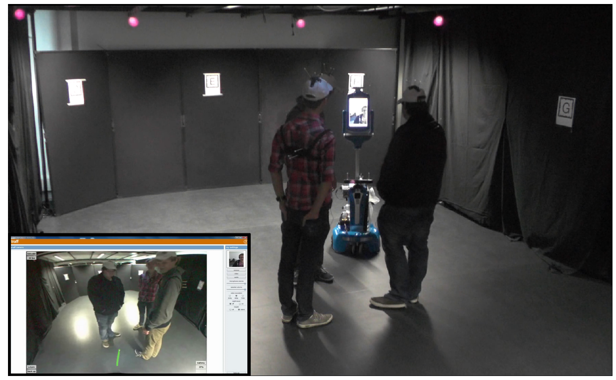

Fig. 1. Example of the interactions described in the paper. A group of four participants discuss a murder mystery. One of them is remotely present through a robot, and has to go through several approach/converse/retreat cycles. The inset shows the interface as seen by this participant.

I. INTRODUCTION

As robots are slowly making their way into situations where they interact with groups of people, it becomes more and more important that we understand which robot behaviors are suitable for such interactions. At the same time, interactions with people can involve a very wide range of different behaviors that may all be more or less appropriate. In other words; being social can pose a very complex, highly dynamic interactive challenge.

Since many robots have the capacity to move around, one important aspect of being social are the behaviors required to be positioned and oriented in a social way (**social positioning**). Social positioning plays a role during many of the different phases that could be entailed in an interaction, such as approach, converse, and retreat. As such, it has a very direct relevance to several settings, for example (semi-autonomous) telepresence robots[1] and robots giving people information at a mall, airport[2], or museum. As these examples show, many of these settings can involve (small) groups of users.

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Another aspect of social positioning are two interaction dynamics that play an important role. First, there are the **temporal dynamics**; interactions take place over time, which implies that (social positioning) requirements can change and that movements rather than static positions should be taken into account [1]. Second, there are **social dynamics**; participants in an interaction respond and adapt to each other [2]. This means on the one hand that people could adapt to the robot and on the other that they might expect the robot to adapt to them. Obviously, these dynamics become more complex as more entities become involved in the interaction (e.g., a robot interacting with a group).

This paper introduces a study aimed at collecting quantitative and qualitative data that can be used to inductively generate hypotheses on suitable social positioning behavior for a robot interacting with a group that can move and respond dynamically (see Figure 1). In particular, the study looks at the interactions involved in approaching a group, conversing with it, and retreating from it – since those elements are common in many of the previously mentioned settings in which mobile robots are used.

There are two reasons this aim is challenging. First, to allow for the dynamics, there should not be many constraints on the behavior of the participants, which reduces the control we have over the study. Second, it still is a challenge to implement temporally and the socially dynamic behaviors. We have here resolved this by using a telepresence robot controlled by one of the participants, though it should be noted that this may limit the generalizability of the found hypotheses to other kinds of robots.

The contribution of this paper is twofold. First, we will introduce the method of the study in more detail as well as the data collected with it. Second, we will present social positioning patterns we found in the data, from which hypotheses can be derived. Note that though the data allows for a more extensive analysis, we consider this to be out of the scope (and size) of this paper.

II. THEORETICAL BACKGROUND

Much of the work in social positioning for robots is based on two theories from sociology on social positioning in humans. Proxemics, first introduced by Hall [3], focuses on the distances people keep to each other. F-formations, as introduced by Kendon [1], describe the different spatial arrangements people can use in social interactions. It has been shown that, as these theories would predict, many different social situations can be distinguished based on only position and orientation information (e.g. [4], [5]).

We will give an overview of the existing work in social positioning for robots, including work which demonstrates how the behaviors displayed by participants controlling a telepresence robot can be used to investigate the suitability of different (telepresence) robot behaviors (Section II-A). We will further discuss work that focuses on the different interaction dynamics (Section II-B).

A. Social positioning in robotics

Previous work has applied and investigated proxemics and F-formations in the context of robotics. Significant effects have been found in various settings; in different contexts [6], with different properties of the robot [7], with relation to the background of the participants [8], and for different cultures [9]. These findings show that taking proxemics and F-formations into account can have a positive effect on the perceived appropriateness of the displayed robot behavior. To our knowledge, there is no work on social positioning for robots specific for interaction with small groups.

Social positioning has also been approached by having participants control the robot. By definition, this approach involves some form of telepresence, and often uses robots that are equipped with a video connection as well. The approach can be used to have participants experience the possibilities and limitations of the robot [10] or to inform design decisions [11]. Of particular relevance in the context of this paper is the research of Kristoffersson et al. [12] and van Oosterhout & Visser [13], since they actively observed the displayed behaviors. Both used manual annotations of visual data (video/photo), to investigate relevant patterns in the behavior. Van Oosterhout & Visser [13] found that people generally position themselves within Hall's personal space zone. Kristoffersson et al. [12] found that when talking through a telepresence robot about a disembodied topic (here a remote control) participants tend to assume a L-shape arrangement, as Kendon's F-formations would predict [1]. Actively observing the behaviors used by participants controlling a robot thus seems a fruitful approach to investigate suitable social positioning of (telepresence) robots.

B. Temporal and social dynamics of interaction

One factor that makes it hard to study human robot interaction is that it is a dynamic process. Or, as Hüttenrauch et al. [14] put it when investigating the applicability of proxemics and F-formations to the field of robotics, "The dynamic changes and transitions from one interaction episode state into the another one are difficult to express in terms of Hall's interpersonal distances and Kendon's F-formations arrangements when tried in a HRI scenario" *([14], p.5058)*.

There are two sides to these interaction dynamics. First, there are the temporal dynamics of movements and changing requirements. There is a limited set of papers that explicitly look into the temporal dynamics of social positioning for interactions between people and a robot [12], [14], [15], [16]. Second, there are the social dynamics of people adapting to a robot and other people, as well as expecting adaptation. Complex as they are, these dynamics allow for many interesting applications. For example, by relying on people to get out of the way for a navigating robot [17], to signal approachability with a group of virtual agents [18], or to influence the formation of people interacting with a robot [19]. As evidenced by these papers, the temporal and social dynamics are relevant and can have a strong influence on what happens in the interaction.

III. METHOD

The aim of this study was to collect data that can be used to generate hypotheses on (dynamic) features that could be taken into account when designing social positioning robot behavior for interaction with a small group. To achieve this, we created a setting in which groups of four people would go through several cycles of approach/converse/retreat behavior. One of the participants was present through a telepresence robot (the **Visitor**), and used the robot to interact with the rest of the group (the **Interaction Targets**).

One of the challenges to our aim was that to allow for the dynamics to arise we wanted to leave our participants as free as possible. At the same time, we wanted to keep the different cycles comparable, to make the comparison of the acquired quantitative data easier. Therefore, we created a somewhat controlled setting where we 'reset' the position of the Interaction Targets *between* the cycles, while allowing them to move *during* the cycles.

Another challenge was to automatically generate robot behaviors that are sufficiently dynamic and appropriate. As discussed in the introduction and theoretical background, we have here resolved this by having one participant control the telepresence robot used in the study.

A. Task

The task had to motivate the participants to have a conversation in which the Visitor had to go through several cycles of approach/converse/retreat behavior. We thus asked our participants to solve a murder mystery, where the Visitor had to go and collect eight clues, and return to the group in order to share the clues. To eliminate effects of the specifics of the murder mystery, groups were randomly assigned to one of three murder mysteries. Preliminary analysis did not indicate any effect of the different murder mysteries, so this variable has been excluded from the analysis.

Each of the clues had to be picked up at different markers positioned around the interaction area (see Figure 2). The location of the marker for the next clue was provided to the Visitor 75 seconds after the previous clue was presented, which gave ample time for both approach and conversation (we confirmed this in a pilot study).

Each group of participants was thus part of a total of eight approach/converse/retreat cycles, separated by the Visitor having to go to a marker to collect the next clue. After these, rather than a ninth clue, the Visitor was given the instruction to decide as a group on a primary suspect. This resulted in one last approach, and a discussion that was ended by the experimenter when consensus was reached.

B. Procedure

The study took place in a controlled laboratory setting. For the study, we used a Giraff (www.giraff.org) telepresence robot equipped with the hardware required for the data collection (Section III-C.1). The robot was located in a room with the Interaction Targets (**interaction area**). The Visitor controlled the robot from a separate room using the standard Giraff software (Figure 1).

After a briefing, participants were randomly assigned to either be the Visitor (1 participant) or be an Interaction Target (3 participants). This was followed by task-specific instructions from the experimenter. The Interaction Targets were equipped with everything required for the data collection (Section III-C.1) while the Visitor was given a brief training on controlling the Giraff (changing position, orientation and head tilt).

The Visitor approached the Interaction Targets for a total of 9 times. The first eight times the Visitor approached the Interaction Target from one of the eight markers shown in Figure 2. The final approach was from the same marker as the first approach. To eliminate possible ordering effects, the Visitor had to go to the different markers in one of eight randomly assigned counterbalanced orders[3].

At the end of each cycle, before being given the next clue, we asked participants (individually) to fill in a brief questionnaire on the robot behavior during that cycle (Section III-C.2.a). The next clue was presented after all participants had finished filling in the questionnaire.

While filling in the questionnaire at the end of each cycle, the Interaction Targets were asked to stand in a fixed formation which was temporarily projected on the floor. The projections were not shown during the cycles and we explicitly told our participants that they were allowed to move around during the cycles. We used two formations; a circular formation, with every participant occupying an equal amount of space, and a semi-circular formation featuring an open space [18]. Groups were randomly assigned to one of

[3]We used a balanced latin square design for this, controlling for regularities in the order in which positions close-by and further to the previous position would be chosen.

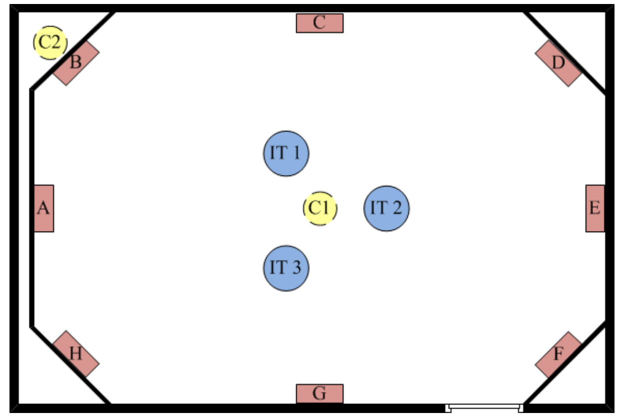


Fig. 2. Overview of the interaction area (approximately 6 by 4 meters). On the circle in the middle the positions of the Interaction Targets are indicated (IT1, IT2, IT3), these were projected using a projector mounted to the ceiling, but only in between the approach/converse/retreat cycles. The rectangles near the border of the interaction area indicate the positions of the markers A-H. C1 and C2 indicate the positions of the cameras.

the formations. This was not a condition, as it would have been in deductive research, but instead intended to cover some of the variations that might naturally occur.

At the end of the interaction part of the study, after the group had reached a consensus on their primary suspect, we asked all participants individually to fill in a post-experiment questionnaire (See Section III-C.2.b).

C. Data collection

During the study, a variety of data has been collected. Here we will describe the methods we used for collecting objective data with various sensors (III-C.1) and subjective data with questionnaires (III-C.2). The tracking and questionnaire data is available from the first author upon request.

1) Objective measures: All three Interaction Targets were equipped with uniquely identifiable markers (one on the back of the chest, one on a cap), which were tracked by an OptiTrack (www.naturalpoint.com/optitrack/) motion capture system using 8 infrared cameras. The robot was similarly equipped. The system used allows sub-centimeter level precision tracking of both position and orientation of each marker. We optimized tracking for the center of the interaction area, to make sure we could properly capture the interaction. Markers near the edges of the interaction area could often not be tracked. To ensure proper tracking of the actual interaction, we informed the Interaction Targets about this and asked them to not get too close to the edges of the interaction area. In the analysis here presented, we will take the marker on the cap worn by the Interaction Targets to represent their position.

Speech of the Interaction Targets was recorded by equipping them with microphones for close talk recordings. The robot was equipped with a microphone array to record audio and a Kinect sensor.

Two cameras recorded the interaction area. One camera provided a side view, the other a (fish eye) top down view. All interactions of the Visitor with the interface were recorded with screen capture software.

2) Subjective measures: After each approach/converse/retreat cycle (i.e. 9 times), all participants were given an in-between questionnaire. After the interaction part of the study a post-experiment questionnaire was administered.

a) In-between questionnaire: The in-between questionnaire consisted of five questions; two related to the usefulness of the clue and task progress. The remaining questions measured comfortability with the robot operators' driving behavior during approach and retreat, and the distance to the robot during conversation. For the robot operator, we instead used three questions assessing work load (based on [20]).

b) Post-experiment questionnaire: The post-experiment questionnaire consisted of 49 items. Among others we measured co-presence and attentional engagement [21]. Furthermore we measured the participants' attitude towards robots [22] and workload [20].

D. Participants

A total of 56 participants participated, divided into 14 groups of 4 persons. Of these, 13 (23.2%) were female, 43 (76.8%) male. All were students, aged between 18 and 32 years with a mean of 20 (SD=2.2). Most participants had the Dutch nationality (85.7%).

E. Data synchronization and segmentation

After the experiment, we synchronized the data from the various sources in Elan[4] using points that were visually/auditory/motion-wise salient. We used the tracking data to determine when the robot was moving or not[5] and then used that information to segment the collected data. **Approaches** are defined as the set of movements (and enclosed non-movements) between the Visitor being given a clue and the Visitor starting to (verbally) share that clue with the Interaction Targets. Likewise, **Retreats** are the set of movements (and enclosed non-movements) between the buzzer indicating that the next clue could be collected and the end of the recorded movement to the marker. The segment in between Approach and Retreat is a **Converse**.

In the segment between each Retreat and the next Approach the participants were filling in the questionnaires, we did not use this segment in our analysis. After the ninth Approach, the task of the participants changed, so we excluded that data from our analysis as well.

IV. FINDINGS

We will present first findings from the (quantified) observations (IV-A) and the investigation of the relations between features of the dynamics of the motion patterns and the ratings of the Interaction Targets (IV-B). A more extensive analysis is out of the scope of this paper.

[4]Annotation tool developed by the Max Planck Institute for Psycholinguistics (The Language Archive, Nijmegen, The Netherlands), available from tla.mpi.nl/tools/tla-tools/elan/

[5]We defined the robot to be moving if the position of the marker placed on its base, smoothed over 50 frames, changed more than 0.02cm between frames (2.4cm/s). This yielded some false positives.

A. Observed patterns of behavior

Under the assumption that the participants all tried to display suitable social positioning, suitable behaviors would likely be more common. Thus, patterns that are commonly observed in the interactions can be generalized to hypotheses for suitable behavior with inductive reasoning. We will here introduce some of such patterns, organized by the phase of the interaction (Approach/Converse/Retreat) in which they occurred. Where applicable, we will quantify these patterns and use the tracking data to calculate how common they were.

1) Approach: During the Approach, most Visitors drove the robot towards the Interaction Targets (Table I-1,4). Only in one of the groups we observed that the Visitor only turned the robot to face the Interaction Targets without driving to them.

When approaching, Visitors commonly aimed for the closest-by opening between the Interaction Targets they could see, rather than taking a larger detour to approach the group from another angle (Table I-3). We only observed one Visitor taking multiple such detours; for this Visitor, the Interaction Targets were in the semi-circular formation and the detours seemed aimed at the large opening in that formation.

In some cases we saw that the Interaction Targets actively changed their position to accommodate for the approaching Visitor – e.g. by making the opening the Visitor was aiming at larger and/or by moving a little towards the Visitor. However, this pattern was only moderately common (Table I-5).

2) Converse: During conversation, many Interaction Targets changed their position between the beginning and the end of the Converse segment, while movement of the Visitor was very rare (Table I-6,7). When the Visitor did move, these movements were rotations that increased the visibility of the Interaction Targets.

3) Retreat: In 38 out of the 112 Retreats (33.9%) we observed, to our surprise, that Visitors passed straight through the group. This was always done to reach a marker located directly behind the group. In 42% of these situations the Visitors communicated this beforehand. Only in rare cases (9 cases, 8% of total Retreats) we observed that the Visitor backed up from the group and took a detour instead. The Interaction Targets actively assisted the Visitor, by pointing out the position of markers, by moving out of the way and even by actively inviting the Visitor to pass through the group.

B. Relating motion patterns with ratings

The ratings provided by the Interaction Targets during the in-between questionnaire give additional information on whether the displayed behavior was actually perceived as more or less comfortable. Patterns in the relation between this information and (dynamical) aspects of the recorded behavior can be used as further hypotheses for suitable behaviors.

	Quantified pattern	min	Q25	Q50	Q75	max
1	Distance between robot and center of the group at end of Approach	7cm	91cm	113cm	134cm	315cm
2	Angle (in degrees) between robot viewing direction and center of the group at the end of the Approach	0deg	5deg	10deg	18deg	133deg
3	Angle (in degrees) between the actual position of the robot at the end of the Approach and the position it would have had if it had moved in a straight line from the marker to the center of the group.	0deg	9deg	18deg	34deg	135deg
4	Distance between first and last detected position of robot during Approach	0cm	111cm	176cm	211cm	293cm
5	Distance between first and last detected position of Interaction Targets during Approach (averaged)	1cm	9cm	13cm	21cm	84cm
6	Distance between first and last detected position of robot during Converse	0cm	0cm	0cm	1cm	233cm
7	Distance between first and last detected position of Interaction Targets during Converse (averaged)	5cm	13cm	20cm	37cm	122cm

TABLE I

QUANTIFIED PATTERNS OF BEHAVIOR WITH A FIVE-NUMBER SUMMARY (MINIMUM (MIN), LOWER QUARTILE (Q25), MEDIAN (Q50), UPPER QUARTILE (Q75), AND MAXIMUM (MAX)) OF THEIR DISTRIBUTION IN THE COLLECTED DATA

There were large individual differences in how the different Interaction Targets answered the in-between questionnaires, which makes it harder to reliably extract this information. To compensate for this, we used Gaussian normalization (normalizing the scores of an Interaction Target by subtracting the mean of those scores and dividing by their standard deviation), averaged over the three Interaction Targets in a group.

We will first describe some informal findings acquired by looking for patterns in the Approaches/Converses/Retreats that had the ten highest and ten lowest average normalized ratings (IV-B.1). Then we will discuss more quantified ways for looking at these findings (IV-B.2).

1) Motion patterns with the highest/lowest ratings: Driving the robot with a smooth and steady path seems to be important for the average normalized ratings, since we observed this in most of the ten Approaches and Retreats that scored highest, while observing more 'wobbly' robot motion in many that scored lowest.

In most of the highest rated Approaches we additionally observed that the Visitor stopped at on average 1.25 meter from and aimed at the center of the group, and changed the head tilt of the robot to face the group even better (see Figure 3a). In some of the lowest rated Approaches the Visitor did not approach at all, or got so close to the Interaction Targets that they stepped away (see Figure 3b).

In nine out of the ten highest rated Retreats we saw that the Visitors explicitly communicated their goals (verbally) before driving. The pattern we observed before, in which the Visitor passed straight through the group while retreating, was observed in both the highest and the lowest rated ten Retreats and thus seems to have had no strong influence of itself on the given ratings.

We did not observe any particularly salient patterns in the ten highest rated Converses, but in the ten lowest rated the robot was usually far away from the group center or relatively close to at least one of the Interaction Targets.

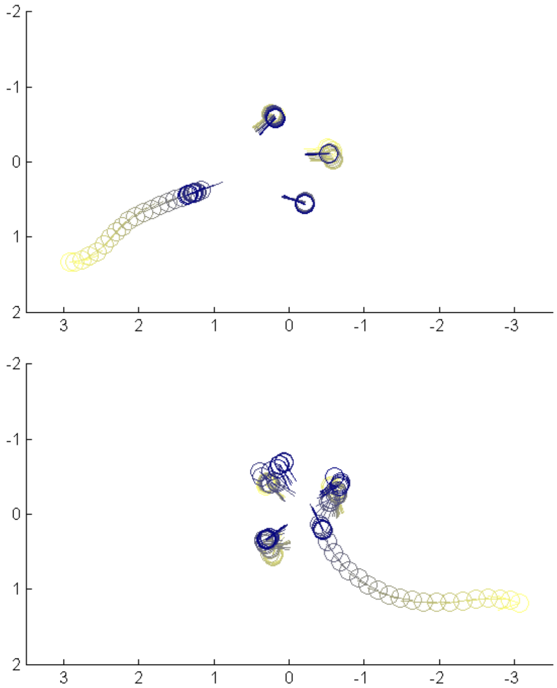
2) Quantified relations with ratings: We wanted to quantify the relation between the ratings and several aspects of the used motions. To do so, we here used Spearman's rank correlation since it is robust against outliers and non-normally distributed data (the average normalized ratings were not normally distributed, p=0.0306 in a Kolmogorov-Smirnov test). We did not find a significant correlation for distance between the robot and the center of the group at the end of the Approach (ρ = 0.109, p = 0.220), nor for the speed used during the Approach (ρ = -0.008, p = 0.929). We did, however, find a significant correlation for angle between the direction of the robot and the center of the group at the end of the Approach (ρ = -0.218, p = 0.014). This indicates a positive relation between how well the robot faces the center of the group and the ratings.

These are only first results, to illustrate how this data could be used. Though it does not fit the size and scope of this paper, further analysis, for example based on mutual information, will likely reveal even more measurable relations. Different aspects of the motion of the robot and its behavior in general are still open for investigation, and may well reveal subtle yet strong indicators of proper robot behavior.

V. CONCLUSIONS AND DISCUSSION

In this paper, we have introduced a study in which a Visitor controlling a telepresence robot went through several approach/converse/retreat cycles with a group of three Interaction Targets. During these cycles, they together attempted to solve a murder mystery, with the Visitor leaving repeatedly to collect clues. We then identified various qualitative and quantitative patterns in the data we recorded in these interactions; common behaviors, regularities in the behaviors that were rated as most/least comfortable, and a correlation between these ratings and a particular positioning.

Using inductive reasoning, all these patterns can be used as hypotheses for more general settings. These could be settings with a different task, different people, and a different robot. One of the limitations of inductive reasoning is that it is impossible to know beforehand if such a generalization is justified. For example, since our patterns were found in a setting with a telepresence robot, there is no guarantee they a



b

Fig. 3. Representation of head tracking data from two Approaches, one with a high average normalized rating (a) and one with a low average normalized rating (b). The circles with lines show the positions and orientations of the Visitor and Interaction targets in the interaction area. Indicators near the end of the Approach are darker. Axes indicate distance (in meter) from the center of the interaction area in the horizontal and vertical direction.

will translate to other types of robots. It is for this limitation of inductive reasoning that it is important to realize that our findings are hypotheses only.

To demonstrate the use of our method, we have used this inductive reasoning to generate a variety of hypotheses on social positioning. These include, in line with what proxemics would pose [3], the hypothesis that a (telepresence) robot should make an approach motion to get within approximately 1.25 meter of the individual interaction targets it wants to interact with. Based on our findings we can also hypothesize a relation between how well a robot faces the center of a group and how comfortable the group rates that positioning. In addition we found that dynamics indeed play a role in these interactions, since both the Visitor and the Interaction Target adapted their position and orientation to each other in various ways. This for example led to the hypothesis that a robot could pass through a group when retreating without this effecting how comfortable that retreat is.

Given the rich data that we collected, there are many opportunities for further analysis, in particular into the relation between aspects of the motion of the robot and how comfortable it is rated to be.

Overall, we have introduced a quantitative inductive study to robotics research and used it to generate various hypotheses that can guide the design of social positioning robot behavior. Our findings furthermore show that the temporal and social dynamics can play a role in the interaction between a (telepresence) robot and a group.

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