“Outside-in” Design for Interdisciplinary HRI Research

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Abstract

This paper introduces “outside-in design” as a collaborative approach to social robot design and human-robot interaction research. As an interdisciplinary group of social and computer scientists, we follow an iterative practice of collecting and analyzing data from real-world interaction, designing appropriate robotic perception and control mechanisms, developing models of interaction through automatic coding of behaviors and evaluation by human subjects, and validating the models in embodied human-robot interaction. We apply this approach in the context of shadow puppeteering, a constrained interaction space which allows us to study the foundational elements of synchronous interaction and apply them to a robot. We contribute to both social and computer sciences by combining the study of human social interaction with the design of socially responsive robot control algorithms.

Interaction with robotic technologies in the real world poses both social and technical challenges. For a robot to collaborate seamlessly with humans in an everyday activity, it has to be situationally aware, able to take advantage of the human’s knowledge of the world, and adapt its behavior accordingly. To enable a socially interactive robot to perceive and display relevant social behaviors, designers must solve complex problems in real-time perception and control involving multiple mechanical and computational systems. Designing robots for social interaction also calls for expertise in analyzing social behavior to understand the factors that make people respond to robots as social actors. The challenges of social human-robot interaction suggest that it is difficult to neatly ‘divide and conquer’ social robot design through partial solutions bounded off within social and computational disciplines.

This paper describes a collaborative practice bringing together computational and social expertise in the exploration and design of social human-robot interaction. We use an “outside-in”[1] design strategy, iterating between real-world observation, technology design, and interactive evaluation, to develop a research partnership across the traditional divide of humanities/social sciences and the natural/technological sciences. To motivate and sustain interdisciplinary collaboration, we aim to produce innovation across disciplines—social science gains the use of research technologies that allow for the reliable production of new phenomena and a rapidly moving research front (Collins 1994), while robust computational models are built and validated through behavioral observation and analysis of human-robot interaction. Our research begins with a keen appreciation for observation and reliance on existing empirical research for understanding the nuances of human interaction that can be applied to robots. Socially interactive robots, in turn, are used as test-beds for theories and models of interactivity that contribute to our understanding of human social behavior and the attribution of sociality to non-humans. We apply the outside-in design process to the design of socially interactive robots and the study of human-robot interaction in the context of shadow puppetry, which we present as a model system for studying dyadic nonverbal interaction.

In the first section, we discuss the relevance of interdisciplinary design to social robotics. We then describe shadow puppeteering as a model system for the study and design of synchronous social interaction. The next section details the iterative process of outside-in design. We conclude with a discussion of our results and suggest broader implications of our collaborative practice for advancing computational and social sciences.

Towards interdisciplinary design

Social robot design calls for approaches that can bring the social and computer sciences, along with their different scientific research practices and empirical conventions (Forsythe 2001), into productive dialogue and collaboration. Smith and Semin (Smith and Semin 2004) suggest that social robots can be used as a research tool for better understanding human psychology and social coordination. Barsalou and Breazeal (Barsalou, Breazeal, and Smith 2007) propose a research agenda in social robotics as an impetus for developing innovative approaches to mathematical model-

[1] IBM uses this term to emphasize their focus on designing from the client’s point of view, with an understanding of how the product will be used in a specific context. For us it signifies a method of constructing social robots that starts with observing and analyzing human interaction. We design from an interactor’s point of view, with the affordances of the social environment in mind.

ing of human behavior that can be implemented in social robots. Ishiguro (2005) introduces "android science" as an interdisciplinary field of research that combines expertise in cognitive science and robotics to develop human-like robots (androids) that appear and behave like humans and can be used to study human cognition.

Making robots that are able to participate in "embodied discourse" (Breazeal 2002) represents a major hurdle in the transition of robots from industrial and academic tools to daily life. Robotic problems of self-manipulation and mobility in human environments are not solved, but are well understood. Good engineering and scalable algorithms have made it possible to deal with problems that involve the robot and the physical world. In the classic control model, the agent is provided with a coarse representation of the world and must determine how its actions affect the world and their place in it; this is usually done by repeatedly thinking, acting, and sensing in a loop. These methods have led to impressive results in, for example, the DARPA grand challenge (Thrun et al. 2006) and recent advances in humanoid locomotion (Hirai et al. 1998). Unfortunately, the problem of embodied discourse is fundamentally different. For a physical task, the result of a robotic algorithm can be evaluated by its effect on the physical world. In embodied discourse, the goal is to affect the representation of another agent and, specifically, to form a shared representation with that agent. To do this, it is necessary to understand how humans perceive and process the observed behaviors of others. Of particular importance is the notion that the computational model for such a problem should be constructed from the bottom up, because the representations are constructed by the process, rather than the other way around. Methodologies and modes of analysis from the social sciences can provide insights into such questions, making social robotics an inherently multidisciplinary project.

Despite the essential multidisciplinarity of social robotics, there is little discussion of methodologies that effectively support the bridging of disciplinary divides, a task best by many challenges. Specialists in social and computational fields are often 'silo'ed into incremental advances within their own community's set of core challenges and innovations.[2] In the case of CMU's Roboceptionist, a collaborative project between the Drama Department and the Robotics Institute, the interaction between the dramatists and the roboticists is minimal and the aims defined for the two disciplines are not integrated. While this approach is successful in creating a robot that captures people's attention for entertainment, it falls short of producing a robust and adaptive research platform for the social sciences. A further challenge is posed by the difficulty of translating abstract and general theories in the social sciences into specific human-robot interaction applications. For example, Dautenhahn's sophisticated discrimination between socially situated and socially embedded robots (Dautenhahn, Ogden, and Quick 2002) has yet to be applied in the research group's more practical research focus on proxemic rules for human-robot interaction (Walters et al. 2006). Furthermore, social research in human-robot interaction is often left to the final evaluation stage of robotics projects, when the design may be too entrenched to be adaptable in response to research results; the mechanical (appearance, capabilities of interfacing with the environment) and software design (vision, navigation, grasping, etc.) have already been set. If brought in early on in the design process, social research can be used to define what kinds of interactive capabilities the robot should display and to understand the social environment it will be entering into.

In using the "outside-in design" approach, we aim to bridge the gap between the social sciences and robotics by relying on a practice of problem-based inquiry and interdisciplinary consultation throughout the research and design process. The problem of reconciling the goals, practices, and specialized languages of the collaborating disciplines[3] was solved through sustained dialogue and aided by shared readings in basic principle surveys like (Semin 2007) and previous interdisciplinary collaborations such as (Barsalou, Breazeal, and Smith 2007). Researchers from both disciplines provided input and deliberated on specifications during all phases of the study, from defining the problem, deciding what kind of observational data to gather, designing the robot's interactive capabilities, and evaluating the resulting interaction. Our process of design relies on alternating between social analysis and robotic synthesis—starting from the context of use and our technical constraints, we rely on users to evaluate interactions and our own observations to help define the robot development. In describing the outside-in design process, we focus on the considerations and discussions between computer and social scientists as we achieve a shared understanding of our research domain and methodologies.

With our project, we to aim contribute to social science research by gaining new understanding of the situated dynamics of human social behavior and by learning the fundamental behavioral patterns and cues that enable the development of social attachment and collaborative interaction. To achieve this goal, we develop computational models of rhythmic synchrony and micro-coordination that explain the underlying dynamics of human social behavior that can be applied in the design of socially interactive robots. The project also seeks to contribute to robotics research through the analysis of the fundamental aspects of interaction that give robots, as "relational artifacts," the capacity to "push certain 'Darwinian' buttons in people (making eye contact, for example) that cause people to respond as though they were in a relationship" (Turkle 2005). The achievement of this capability motivates the construction of new perception, decision-making and control algorithms.

[2]There are exceptions to this rule, such as in the disciplinary boundary-crossing work by Scassellati (Scassellatti 2000; Crick, Doniec, and Scassellati 2007), Kozima (Kozima and Nakagawa 2006), Okada (Okada and Sakamoto 2000), Dautenhahn and Nehaniv (Dautenhahn and Nehaniv 2002).

[3]Sabanovic, Michalowski, and Caporael (2007) discuss the barriers to sustained collaboration between social and computer scientists, including jargon, diverging disciplinary practices, and methodological preferences for qualitative or quantitative inquiry.

Figure 1: Interacting with the robot using shadows

Interacting through shadow puppets

Our project draws on children's shadow puppet games, where the relational movements of shadows of hands cast against a wall are used to express a story. We have developed a "shadow puppet" model system, which is limited in scope yet allows us to study the emergence of fundamental interaction patterns. As an interaction medium, shadow puppeteering allows us to observe embodied discourse between two people that is expressive enough to support the basic components of interaction while accommodating an open array of possibilities for interpretation of affect, meaning and intention that evoke human social responses. It also limits the channels of communication so that we can capture, model, and react to signals in real-time using available computational and perception tools.

Humans frequently perceive simple schematic artifacts as exhibiting a higher degree of sociality than their simple forms and actions contain (Blow et al. 2006), so such minimally designed robots can convey the essential features of affect, meaning and intention (Kozima and Nakagawa 2006). In analyzing human subjects playing shadow puppets with each other, we saw that changes in the gestures used, as well as in the speed and rhythm of the interaction, could drastically change the tenor of the encounter to express different interaction schemas such as aggression, affection, dialogue, etc. Such schemas can also be used by social robots to engage humans in affective and meaningful social interactions. Braitenberg (1986) describes how models with simple control mechanisms can generate behaviors that we might interpret as aggression, love, and foresight.

In the problem of "embodied discourse" (Breazeal 2002)—a robot that participates in interaction as an equally proficient participant—dyadic, nonverbal communication is the most basic form of human social interaction; by analyzing it we can develop knowledge and interactive capabilities that are robust building blocks for developing more complex interactive technologies. We focus on studying, modeling, and implementing nonverbal interaction, particularly its rhythmic and gestural components, to understand the emergence of co-presence and coordination within social interaction. Our research is informed by studies of the foundational nature of interactional synchrony, gesture, and imitation to social and communicative development (Condon and Sander 1974; McNeill 2005), as well as by their fundamental importance to the development of natural human-robot interaction (Breazeal 2002; Crick et al. 2006; Michalowski, Sabanovic, and Kozima 2007). In our models, rather than trying to deduce actions from goals, we focus on the temporal patterns and situated activities that drive behavior. This is in accordance with the situated perspective on cognition, which suggests that meaning is not an intrinsic to particular actions or individuals, but emerges through their active relation to other behaviors, actors, and the context of interaction.

Designing from the outside in

We approach the design and evaluation of our shadow puppet robot with a view to the affordances available in its social environment and those it can provide to the human interaction partner. We do not intend to model the high level cognition aspects of interaction and communication (such as the meaning of various gestures in context), but rather to automatically determine the parameters of the low level mechanisms (i.e. interaction synchrony, imitation,anticipation) that help to coordinate and ground interaction. The models described in (Clark and Brennan 1991; Semin 2007) highlight the difference between synchronization of content and synchronization of process and posit that the former is not possible without the latter. Our current work thus represents a foundation upon which more content-oriented models can be built.

Shadow puppetry allows us to characterize, model and create basic building blocks of gross movement as a focus for interdisciplinary research and development of expressive human-robot interaction. Gestures as a nonverbal language are a basic component of human communicative capabilities; likewise, their contextually appropriate perception and usage presents a fundamental problem in social robot design. Our first step in the process of gaining a better understanding of the dynamics of shadow puppeteering and applying them to the robot was to define the converging expressive competencies of human and robot. Human interaction was limited to using the simplest interactive shadow puppet form (see Figure 1), which was most easily replicable by the Barrett Robot hand and Whole Arm Manipulator (WAM). The next step was to use human evaluations of shadow puppet interactions to create a computational model of interaction that would fit our subjects' perceptions of interactivity. After quantifying gestural interaction through human evaluation, we modeled the interaction and used the models to generate interactive behavior. Our models were learned from observing human-human interaction and validated in an embodied human-robot interaction study. The iterative nature of our collaboration enables us to combine the study of human social cognition and behavior with the design of socially interactive robots. Following is a detailed description of the iterative steps of observation, modeling, and evaluation that comprise our outside-in design process.

Finding a common research problem

Social and computer scientists entered into the project with very different conceptions of the research process. The computer scientists wanted to start by deciding on a specific

Figure 2: Free-form shadow puppeteering

Figure 3: Still from video of shadow puppeteering

HRI-related experiment to perform. The social scientists, on the other hand, planned on starting by exploring a specific interaction space. An exploratory, observational approach would be used to define potential points of focus for more rigorous laboratory studies.

The problem domain was defined by the combined interests and previous work of the participants—anthropomorphism and the attribution of social characteristics (Caporael 1986), interaction rhythms and nonverbal HRI (Michalowski, Sabanovic, and Kozima 2007), affective responses to robots and control in HRI (Meisner, Isler, and Trinkle 2008), and manipulation (Trinkle et al. 1993). The shadow puppet domain provided an interactive context that would allow for the study of synchronous interaction and attributions of sociality to robots; at the same time the design space was constrained enough to be feasible for learning and control. A further constraint on both parties was the importance of getting publishable results in their respective fields; this multidisciplinary publication requirement could also serve as a measure of success of the collaborative project.

Real-world observation

A major obstacle in applying social theory to the design of interactive robots is the gap between the presentation of social science results, often in terms too abstract and underdetermined to be directly applied to the programming of robots, and the specifications roboticists need to develop control and perception mechanisms for robots. As we had experience using fine-grained observational data to test and challenge design assumptions (Michalowski et al. 2007), we decided to use it as a detailed quantifiable description of interaction that would allow for computational modeling. This approach also solved the problem of the "designing for me" (Forsythe 2001) approach to robot design, which relies on assumptions based on the roboticists own "conscious models" regarding human social behavior and fails to take into account the differences between commonsense narratives about social interaction and the social patterns that can be identified through detailed study.

To understand how people play shadow puppets, we invited 6 volunteers for an evening of shadow puppetry and video-recorded their interactions (Figure 2). The interactions were free-form, with the players and observers occasionally providing narrative descriptions or suggestions for what the puppets should do. Our aim with this exercise was to see what kinds of actions people commonly performed while playing shadow puppets as well as the different emotions they could express in the limited context of shadow puppeteering. The collected video (Figure 3) was analyzed to define the most commonly used gestures and characteristics by which we could distinguish between different interaction scenarios. Coding the videos with Noldus Observer software[4] allowed us to identify the "gestural primitives"—basic behavioral components—that comprise shadow puppet interactions. In analyzing the collected video data, we were also able to define categories of interaction according to the type of affective relationship and activity that was going on as "aggresive," "affectionate," "mirroring," "conversation," and "non-interactive." We found we could describe the interactive contexts by the rhythmicity of the interaction and the gestures most often employed (e.g. aggressive interactions involved faster movements and jabbing motions, affectionate interactions were slower and the two players touched each other often, conversations involved a lot of regular turn-taking and "talking" gestures—the person opening and closing their fingers repeatedly.) These observations helped us define a gesture vocabulary and interactive contexts which the robot could be taught to identify.

The gesture vocabulary we identified was composed of basic behavioral competences that converge on social science understandings of interaction and computational production of robotic expressivity. These gesture vocabularies were used in constructing the robots perception of certain human gestures as well as in the robots implementation of gesture. The robots perceptions and expressions of gesture were organized into competences on the basis of the robots desired observable behaviors. Such competences consist of sensory inputs from one or more sensors and actions through one or more actuators defined in response to specific sensor values.

Automatic gesture recognition

To participate in shadow puppet play with human interaction partners, our robot must be able to recognize and distinguish

[4]`http://www.noldus.com/`

among significant patterns in the human participant's behavior in real time. To develop a perception system that identifies the basic motions used in shadow puppet game, we used a simple colored wrist marker which allows us to automatically determine the wrist position of a player and to infer the locations of the hand center and finger tips. The behavior of the player is classified as either *Nod*, *Shake*, *Talk*, *Jerk*, *Flick*, *Touch*, or *None*, gestures defined according to the results of our initial observations of shadow puppeting interactions.

The gestures are natural separations based on points of actuation in the hand, rather than assumed circumstances of the interaction. In other words, they are an implicit property of the bodies, not the process. The same gestural vocabulary is used by the robot in interaction. Early iterations of our system used a general recognition system, but minor differences in individual hand shapes, (fingers that bend differently, for example) and in how individuals performed the gestures, caused it to be ineffective. Instead, we perform a training phase for each test subject, in which subjects are asked to perform each gesture several times. The measured parameters of these examples are used to train a classifier for the particular individual. For each behavior, we fit a multi-dimensional Gaussian distribution to the set of samples (figure 4) and use the Expectation Maximization (EM) algorithm to optimize the distribution parameters.

Quantifying gestural interactivity

One of the main aims of our project is to model the behavior patterns in shadow play sequences and define properties of these models that correlate with human evaluations. We recorded examples of people playing shadow puppets, then split the original videos into two separate video sequences—one with only the left player and one with only the right player. These processed video sequences represent our control data. We constructed our experimental data by randomly recombining left and right sides of these sequences. The resulting videos are approximately 25 seconds in length and consists of just the filled, moving outline of the players' hands.

Next, we collected evaluative feedback that allowed us to categorize the videos according to the observer's perception of interactivity.[5] We designed a website that allows people to watch our processed interaction videos and rate the interaction.[6] The survey is modeled as a game, wherein the goal is to correctly identify the videos as interactive or non-interactive. We showed a total of 24 video sequences, of which 12 were actual interactions and 12 mismatched interactions. Viewers watched a sequence of 10 unique videos, drawn uniformly at random from the set of 24 and presented in randomized order. After each video, they were asked whether or not the two participants could see each other during the interactions. Upon completing the survey, the participants are told how many videos were labeled correctly (but not which) and are invited to play again. Individual votes were tracked for each video (382 total ratings) and turned into an interaction score by dividing the number of positive votes by the total number of times the video was rated (284 correct and 98 incorrect). From this we surmise that people are able to identify when two shadow puppets are interacting. We were also able to develop a quantitative measure of interactivity for each of the videos according to an outside observer's subjective perceptions of interactivity.

Modeling interaction & developing control strategies

We define the study of social intelligence as a situated activity, which shifts the focus of our analysis and modeling from knowledge stored within the artifact to knowledge as a constructed capability-in-action, formed as part of and through physical and social performances (Clancey 1997). Our aim is to build models of interaction that can be used to generate behaviors that are coordinated with a human partner. Rather than using predictive frameworks that fully model the physical and mental states of the human to select actions, our robot uses predictive frameworks that relate its actions to the behavioral responses of a human. To develop measures of the interaction sequence that correlate well with the interaction scores assigned by the human observers, we compared three distribution properties. Based on our results, we posit that interactive behavior is strongly correlated to high "mutual information," which measures the independence of two random variables.

We then generated four interactive control strategies. The first controller (**C1**) samples from the distribution of an observed human-human interaction sequence, which has high user rating and high mutual information. The second controller (**C2**) samples from the distribution of an observed human-human interaction sequence, which has low user rating and high mutual information. The third controller (**C3**) simply imitates the human. The fourth controller tested (**C4**) is a first order Markov model. It is similar to the C1 and C2 controllers, but the robot selects a behavior based on the preceding actions of itself and the human. Our use of these controllers is based on our bottom-up approach to building sociality. In contrast to natural language processing approaches, we don't assign meaning to the gestures (i.e. we don't assume that *Nod* is possitive or that *Shake* is negative). Rather than attempt to understand the meaning of the human behaviors, these controllers are models of the process taken from empirical data. They were selected based on properties of the process that correlated highly with human evaluations of interactivity, and intended to further investigate the relationship between these properties and the signal grounding process of interaction.

Evaluation of models in human-robot interaction

Our last step is to validate our models in a human-robot interaction study where the Barrett Robot hand and Whole Arm Manipulator (WAM) replaced a player in the shadow puppetry game. The WAM is instrumented with a set of predefined gestural primitives that match those of the human player. Eight human players participated in four successive

[5] The use of outside observers to quantify interaction has precedent in experimental psychology((Bernieri, Reznick, and Rosenthal 1988), for example).

[6] See `http://www.cs.rpi.edu/~meisne/interaction`

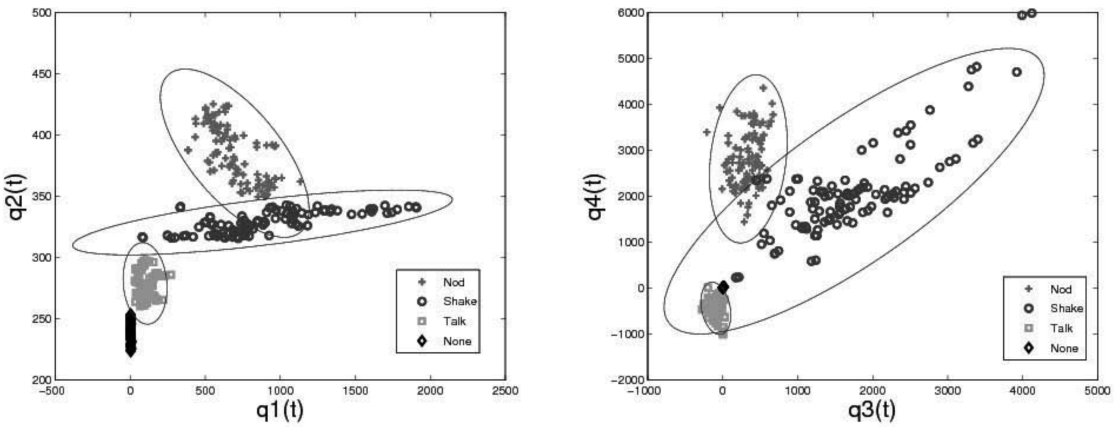

Figure 4: Gesture classifier: The gesture recognition system is trained by computing the parameters of a Gaussian mixture model. The samples in this model are represented by parameters $[q1(t), q2(t), q3(t), q4(t)]$ which are measured statistical dispersions of the hand contour over time.

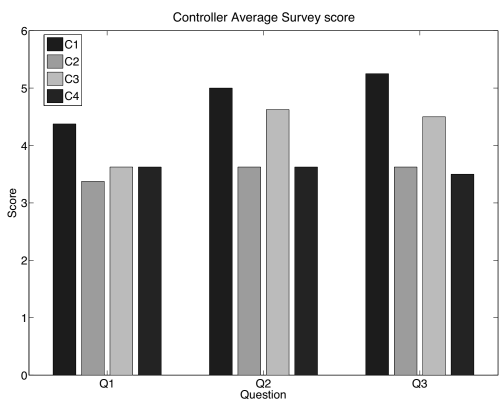

Figure 5: Average response to interaction survey questions (N=8)

two-minute sessions of interaction with the robot in which the robot implemented each control strategy once. The order of the controllers used was randomized. After each trial, subjects were asked to rate their agreement with the following three statements: **(1)** *The robot reacted appropriately to me*; **(2)** *The robot could recognize my actions*; **(3)** *The robot seemed intensely involved in the interaction.* The statements gauge the user's perception of the robot's ability to recognize gestural cues and react accordingly, as well as its social presence. The subjects rated their agreement with each question by assigning a value between 1 and 6. Our results indicate that the high mutual information controller (C1) generates the most interactive behavior, closely followed by the imitative controller (Figure 5).

By developing and validating a generative model of synchronized shadow puppet play, we demonstrated that the method of modeling interaction as a joint process rather than modeling agents separately is more closely associated with human evaluations of interactivity. We are currently running our previously described online survey method with videos of shadow puppet HRI as input to complement our results with evaluations from third person observers.

Discussion and broader applications

Using socially interactive robots as computational tools for social science research, the project helped us employ computational thinking in the study of the dynamics of social interaction. Our experiences suggest that the outside-in design approach can be applied more broadly to the following challenges in the social and computer sciences.

Building generative models of synchronous interaction: In the beginning of our project, computational modeling was being developed under a "natural language processing" metaphor, where the components of gestures (in this case called tokens) were the phonemes, the gestures themselves (such as a nod) were words, and the robot was expected to understand and construct sentences consisting of strings of actions. Through discussion and observation of humans engaged in shadow puppet play, we agreed that there was a problem with this metaphor—the robot was not making the sentence by itself, but was co-making the sentence with another actor. At this time, we were also involved in teaching the robot to understand the context of the interaction–whether the shadow puppet play it was engaged in was aggressive, affectionate, or a conversation, and to react accordingly. This proved to be too difficult of a task without a foundation in understanding and being able to respond to the basic synchrony of interaction, which is the task we have described in this paper.

Congruent with the idea that models of interaction should be built from the bottom up, we have constructed a generative model of interaction by measuring the frequency of observable behaviors in the process of interaction. We observed the actions of the participants and analyzed the process to learn about their possible objectives. The more typical alternative approach would be to model the participants as independant agents operating according to particular goals and constraints. This descriminative approach, each agent simply considers the behavior of other agents from its own perspective, as an external effect to be predicted as a posterior of its own actions. The implication is that the behavior of the other agent occurs according to some existing generative model, which contradicts the idea of emergent, shared cognition.

Gathering and analyzing data from a first-person perspective: All social interactions take place in a subjective, engaged manner. External observers of interaction, however, take a third-person view; robots are often programmed from a third-person perspective, with a focus on plans and goals rather than on active perception and co-action among the participants. In order to study interaction as an embodied phenomenon, our project suggests developing robots as tools for active data collection and the validation of theories about social behavior through interaction. Because we design the robots used in our experiments, we know the processes by which the robot is functioning, while observers can attribute goals and affective states to the robot beyond its actual abilities. Comparisons between a robot's actual capabilities and people's inferences about its intentions enable us to identify the factors that lead to the attribution of certain human characteristics to artifacts. Furthermore, by using robots as first-person data collection devices—recording the temporal, spatial, and gestural properties of the interaction that they experience as participants—we can augment the accustomed third person view of the human observer and model the interaction from the subjective, participatory perspective of an actor. From a human-robot interaction perspective, we expect robot design from a first-person perspective to produce socially embedded robots that can actively perceive and participate in dynamic patterns of social behavior, maintain engagement, and intelligently guide interactions.

Developing algorithms to automate coding of behavioral data: The identification of patterns in human behavior that are socially relevant necessitates large amounts of data produced not only in laboratory circumstances, but starting with observation and empirical research in real-world contexts. To understand the dynamics of human interaction, behavioral scientists must often categorize their observations of behavior so that the observed categories can be used in quantitative analysis. This categorization usually involves "coding" (labeling) behavior manually, which currently requires spending many hours watching, categorizing, and annotating videos. Similarly, analyzing the large data sets needed for understanding complex interactions poses challenges. The more fine-grained the data that is desired, the more time a person needs to spend isolating that data from a recording. New computational methods such as those we have started developing allow us to look for patterns in data that is more fine-grained than the human eye can be aware of and to look at data over longer periods of time with more detail. Furthermore, we are developing methods for isolating and automatically analyzing socially relevant behavioral patterns in the course of interaction as well as new methods of processing and visualizations of data in order to find patterns across interaction modalities (behaviors in space, time, relational actions among individual actors, etc.) and across different levels of analysis (e.g. fine-grained micro-behaviors, discursive phases such as greeting, conflict, etc.). We want to extend this to the research of contexts, such as the aggressive, affectionate, etc. interactions mentioned earlier.

Building and validating models through interaction: From the results of our observations, we constructed models of the interaction, which were tested by having the robot use the model to interact with people. In future work, the robot can be given the ability not only to perceive and automatically code what is going on in the course of interaction, but to continue populating the model with data constructed in interaction and to track changes in the model. Such robots can be used as controllable tools for further experimentation and in-depth study of the particular factors in social interaction, such as imitation, rhythmic entrainment, joint attention, and coordination.

Conclusion

Our goal in using an outside-in design methodology was not only to contribute to our understanding of human interaction and create an interactive robot, but also to develop an analytical practice that bridges the contributing disciplines. Through outside-in design, we developed interaction models based on real-world observation and evaluated how their interactivity was perceived by human interaction partners. Furthermore, we contributed to the study of social cognition by showing that a relational model of interaction is consistently preferred by participants in human-robot interaction. Our results show the utility of a collaborative and dialogic practice across disciplines for developing social robotics in the future. In working together, social and computer scientists become more aware of different disciplinary constraints and assumptions and are able to provide observations, data, models, theories, and results that can bridge multiple disciplines. By presenting robots as tools for the study of social behavior and cognition, this approach also opens up more possibilities for social scientists to participate in the design and evaluation of social robots.

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