# Intention-Aware Human-Robot Collaborative Design

Doctoral Consortium

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## ABSTRACT

Robots pose unique potential partners for human designers when thought of as physical and social embodiments of computational agents. In this work, we propose the efficacy of robotic collaborative design agents and observe challenges and potential directions in an exploratory study of human collaboration with a robot on a design task. Based on these observations, we outline future studies of human-robot design collaboration and focus on the particular challenge of inferring a human partner's design intentions in order to better navigate collaborative design with a robot.

## KEYWORDS

Design Support; Human-Robot Interaction; Intention Inference

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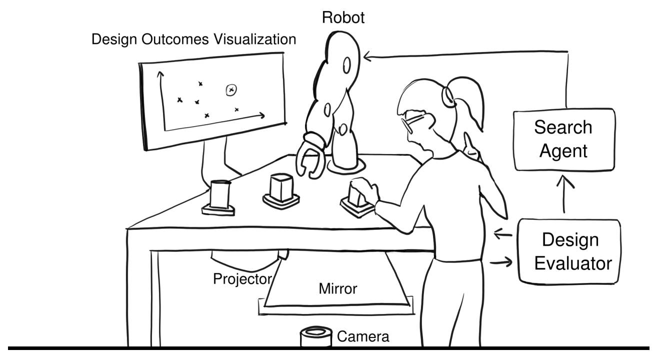


**Figure 1: Our tangible design workspace. Designs are constructed by arranging component blocks on the table surface. A search agent runs in parallel around the human designs; here, the agent suggests improvements to the design by physically rearranging the shared blocks [15].**

## 1 INTRODUCTION

We explore the potential utility of robots as teammates for human designers. Insofar as designing has elements of search and information processing [19], computation can complement human intuition in design [6]. Meanwhile, the processes of collaborative design are steeped in physical [9] and social [7, 21] interactions. Robots can physically and socially embody computational agents and have been extensively studied as teammates for humans in the human-robot interaction literature, e.g. [2]. This intersection makes robots particularly intriguing partners to explore design spaces with.

## 2 WHY DESIGN WITH A ROBOT?

In the proposed thesis, we explore the role of embodiment in bringing human and agent designers together. Design tasks are inherently ill-structured and design solution spaces tend to be complex, inviting contributions from both humanly intuition and computational scale and precision. A growing body of research has studied how to leverage both human and computational capabilities for designing, e.g. [1, 6, 22]. Davis et al. further argue that interaction between a human and an agent can itself foster creative insights [5]. Inspired by this work, we seek to discover whether and how physically embodying collaboration between a human and a design agent might create rich interactions that better approximate how humans engage with design tasks and other designers.

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Designing, particularly with others, involves strong elements of physical and social interaction. Sketching and prototyping, for example, play important roles in many design practices, mediating between concepts and the physical world [12]. Schön described designing as a "reflective conversation with the materials a of a design situation," a social process of both constructing and communicating between design worlds [18]. Gestures between designers can also evoke new ideas about a design situation [3, 10].

Robots have long been studied as physical and social actors and teammates for humans. However, despite projects that pair humans and robots in co-creative endeavors (e.g. visual art [4], or musical improvisation [11]), there is not clear precedent for how to effectively embody an agent in a robot for collaborative designing. This work aims to elucidate this design space and engage potential advantages and challenges in supporting human designers therein.

## 3 HUMAN-ROBOT COLLABORATIVE DESIGN

As a first step towards studying collaborative design between a human and a robot, we developed a physical workspace in which a human and a computer agent can construct a shared design (Fig. 1). Since then, Lin et al. have designed a co-creative robot that sketches alongside a human designer [17]; we take a more discrete approach. On our digital "sand-table", a designer arranges a set of physical blocks representing different design components. Each arrangement maps to a design configuration; the system evaluates the configuration and plots feedback for the designer, who can interact with the feedback to project historical designs into the workspace.

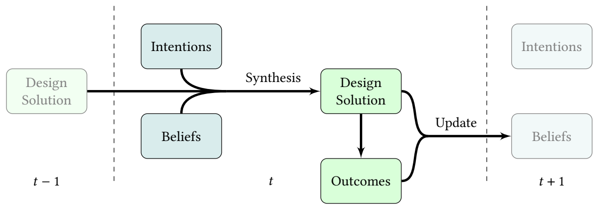


**Figure 2: Designing as a Markov process, in which design intentions and beliefs about the design space inform changes to the design itself, and observations about how the solution affects outcomes update the designer's beliefs [16].**

While the designer is working, a computer agent observes and searches locally for improvements to the design. We ran two human studies in which participants collaborated with such an agent using our system.

In our first study [14], we compared human user experience and performance designing a satellite system after exploring the design space on their own, exploring collaboratively with the agent, and observing the agent explore on its own. In all treatments, the system visualized evaluations of agent designs for the human, who could select designs to overlay on their own. The collaborative human-agent team tended to produce higher quality designs as measured by proximity to a reference Pareto front than either the human exploring alone or observing the agent. Participants reported higher positive affect and better user experience after working with the agent than observing it, although we did not observe significant effects with respect to working alone.

In a second study [15], we embodied the collaborative agent using a robotic arm, as in Figure 1. Rather than visualize design suggestions, the robot physically rearranged components in the shared workspace. This simple change introduced a myriad of collaboration challenges, from sharing access to the design representation to negotiating roles, goals, and strategies, often with human-perceived social implications. As the robot behavior in this study was not designed with social or creative negotiation in mind, much of this fell to the human participant to figure out. At times, however, the robot by chance behaved in ways that enhanced the collaboration. In the remainder of this work, we explore how to reduce the designer's burden of negotiating creative collaboration challenges and actively support the positive interactions we observed by increasing the robot's awareness, particularly of the human's design intentions.

## 4 INFERRING DESIGN INTENTIONS

The matter of grounding task-related intentions is particularly pertinent and difficult when designing, where tasks are ill-defined and open to interpretation. In our prior study, the confines of physically co-constructing a design amplified situations where the robot disregarded participants' intentions about exploring the design space. For these reasons, we believe that recognizing human design intentions is especially critical for a robot to effectively collaborate with human designers, and we sought to model these [16] to support more relevant and appropriate improvements to a shared design.

We framed designing as a Markov process, wherein designers synthesize solutions based on a set of intentions and beliefs, then update their beliefs considering the corresponding outcomes (Fig. 2). Assuming fixed intentions, we then trained a predictive model of design intentions with respect to a discrete set of design objectives, based on observed trajectories of design outcomes.

We evaluated this model in the context of voting district design in a US state, chosen for its complex objective tradeoffs. We built an interface for data collection in which a human designer partitions the state and visualizes three different fairness-related outcomes. We collected a small dataset of humans (n=4) designing for predetermined subsets of outcome intentions as a test set and generated training data by running a basic local search agent over objective functions for each combination of design intentions.

The model was implemented using an LSTM-FCN network [13], trained on the synthetic data and tested on the human data. When classifying exact subsets of intentions, we found accuracies of 0.313, 0.509, and 0.672 in the top-1, 2, and 3 predictions over seven classes, respectively. When predicting individual intentions independently, we found an average precision of 0.739 and recall of 0.700 (F1-score 0.719). In future work, we hope to evaluate the effects of using such a model to inform design choices made by a collaborative agent.

## 5 FUTURE WORK

In reality, design intentions evolve as a designer explores a task and may relate to implicit or even emergent design features. We hope to apply existing ideas on representation learning in creative tasks such as in [8, 20] to explore modeling intentions regarding features learned from designs at various stages of completion.

Further, physical and social collaborations with robots carry rich signals potentially relevant to a person's design intentions. We will explore how, for example, a human partner's pose, gaze, or expressions with respect to the robot indicate degrees of intentionality, attention, or affect, as signals for design intentions.

Finally, we need to synthesize and evaluate methods of integrating intention awareness into a robot's collaborative design behavior to explore how grounding intentions through interaction with a human partner can lead to positive design and collaboration outcomes. Additionally, we hope to revisit and rigorously validate observations from our exploratory studies where appropriate.

## 6 CONCLUSION

Robots afford unique avenues of collaboration on ill-structured design tasks. As embodied and social actors, they have the potential to bring computational capabilities to bear within the embodied and social design processes of human designers. However, physical and social interaction in the context of ill-structured tasks can foment collaboration challenges. While daunting, engaging these challenges could afford opportunities to build trust or foster new ideas, practices, or insights that benefit designs and designers. We explore modeling human design intentions as one step towards realizing such potential in human-robot collaborative design.

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