Side-by-side Human-Computer Design using a Tangible User Interface

Matthew V. Law, Nikhil Dhawan, Hyunseung Bang, So-Yeon Yoon, Daniel Selva, and Guy Hoffman
Cornell University, Ithaca, NY, USA

We present a digital-physical system to support human-computer collaborative design. The system consists of a sensor-instrumented "sand table" functioning as a tangible space for exploring early-stage design decisions. Using our system, human designers generate physical representations of design solutions, while monitoring a visualization of the solutions' objective space. Concurrently, an AI system uses the vicinity of the human's exploration point to continuously seed its search and suggest design alternatives. We present an experimental study comparing this side-by-side design space exploration to human-only design exploration and to AI-only optimization. We find that side-by-side collaboration of a human and computer significantly improves design outcomes and offers benefits in terms of user experience. However, side-by-side human-computer design also leads to more narrow design space exploration and to less diverse solutions when compared to both human-only and computer-only search. This has important implications for future human-computer collaborative design systems.

Introduction

A useful formulation of early-stage design is viewing it as an exploration of the space of possible designs [5]. This can be formalized as a *search* through the solution space, proposing and evaluating solutions in pursuit of some possible world [44]. This is a particularly tractable model of design in symbolically represented state spaces [16]. Given that search is also a core capacity of Artificial Intelligence (AI) [33] and [48], researchers were

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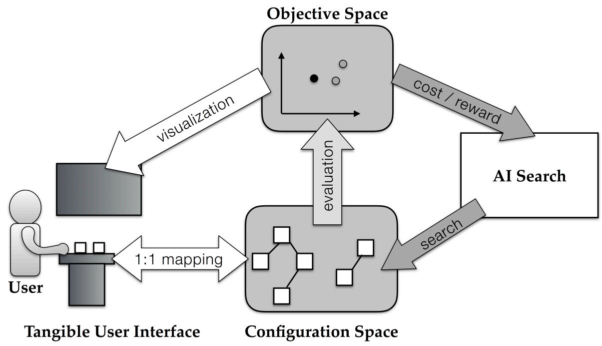


Fig 1. Conceptual schematic of side-by-side human-computer collaborative design using a tangible interface. The human designer and AI search algorithm explore different designs simultaneously and affect each other's position in the solution space. The human generates tangible physical representations of design solutions, while monitoring a visualization of the objective space. The AI search uses the human's exploration to continuously seed its search and suggest design alternatives.

able to develop intelligent tools to aid in design problems through a variety of computational search methods [45] and [31]. In most cases of design-as-search, both when a human designer and when a computer design tool is employed, the process is modeled as one of an individual designer [18]. Some researchers, however, have suggested that exploring a design space can be more powerful when designers work with others. Fischer calls design social by nature [15]. Indeed, collaborative design can transcend the capacity of the individual, leveraging specialized expertise across "symmetries of ignorance" to enable designs that address complex problems and spaces [2]. The usefulness of collaboration in design has engendered a strong interest in systems and tools that support collaborative design, precipitating the field of computer-supported collaborative design (CSCD) [42].

Beyond CSCD, the potential of design as a collaborative activity also suggests human-computer collaborative design, which is the focus of this paper. While many approaches to human-computer collaborative design either pose agents as support tools for humans [31], [37], and [14] or position humans as inputs to a computational process [13], [7], [26], and [4], research in human-computer teamwork suggests merit in a more balanced partnership between human and computer designers, modeling the interaction as a true collaboration [17].

In this paper, we present a system to support a side-by-side model of human-computer collaborative design using a digital-tangible "sand table" interface in combination with an AI search agent and a visualization of the design problem's objective space (Fig. 1). In our model, the user searches the design space using a physical one-to-one mapping of the solution space, while the AI search algorithm uses the user's designs as seeds to search the design space alongside the human designer, and subsequently presents the human with a visualization of the search process.

Our motivation to use a tangible user interface (TUI) stems from the fact that tangible and tabletop interfaces have been found to be particularly well-suited for collaborative exploration of design spaces. On its own, a TUI affords designers the ability to employ senses and manipulations they are familiar with in the physical world to interact with virtual models [21]. TUIs have been found to promote learning [6] and [47], and interaction with physical media to drive innovative exploration in design spaces [28], [46], and [32]. Tangible interfaces can also impact the nature of collaborative design processes and hence outcomes, e.g. the effect of a TUI on spatial cognition in groups can increase "problem-finding", leading to higher creativity [28].

TUI's have been extensively evaluated vis-a-vis graphical or screen-based interfaces [52], [49], and [35], including with respect to design tasks [27], so this is not the focus of this work. We instead set out to use the TUI as a collaborative platform for evaluating side-by-side exploration with an agent in a design space.

In this vein, we present an experimental study that compares side-by-side human-computer collaborative design with two baseline conditions: human-only design search, and human observation of computer-only search. Dependent variables include the quality of the generated designs and user experience. The design problem we use to illustrate our approach is the *EOSS Sensor-Orbit Design Problem*, a real-world space mission design problem with multiple competing objectives.

The core contributions of this work are: (a) a digital-physical system that supports side-by-side human-computer collaborative exploration of a design space; (b) support for our hypothesis that this system results in better designs than either the human or the computer working alone; (c) insights into the user-experience benefits of side-by-side human-computer collaborative design; and (d) limitations and design implications related to the effects of side-by-side exploration on the coverage and diversity of the design solutions explored.

The EOSS Sensor-Orbit Design Problem

Designing sensor configurations for Earth-observing satellite systems (EOSS) is a real-world multi-objective design problem in Aerospace Engineering. The design of such systems has become increasingly difficult and important to space organizations planning satellite missions due to increasingly stringent mission requirements without the necessary budget increases to fully meet the increased demands [40].

Specifically, we engage the problem of deploying sensors on a climate-monitoring satellite constellation to optimally satisfy 371 measurement requirements (e.g. air temperature, cloud cover, atmospheric chemistry) defined by the World Meteorological Organization (www.wmo-sat.info/oscar) at minimal cost [19]. A design in this space consists of assigning up to 12 different kinds of sensors to satellites in five different orbits around the Earth. Each sensor has different capabilities that address different measurement requirements to varying degrees, dependent on the orbit in which it is deployed. The cost of deploying various sensors is also highly orbit-dependent, insofar as it affects the choice of launch vehicle and supporting subsystems, among other considerations. The cost and scientific benefit of a specific sensor configuration is further complicated by synergistic or deleterious effects that sensors deployed together can exert on each other.

Research Questions

The described system and study are elements of an ongoing project to both understand and realize novel forms of human-computer collaboration in physical design spaces. In this particular work, we explore the following research questions:

- **RQ1**: How do design solutions produced by a human and design agent working side-by-side compare to either human-only or algorithm-only generated solutions?
- **RQ2:** How does collaborating side-by-side with an intelligent agent affect user experience while exploring a design space?

Fig 2. A user working collaboratively with an AI design agent using the presented digital-tangible sand table interface.

The Collaborative Design Sand Table Tangible User Interface

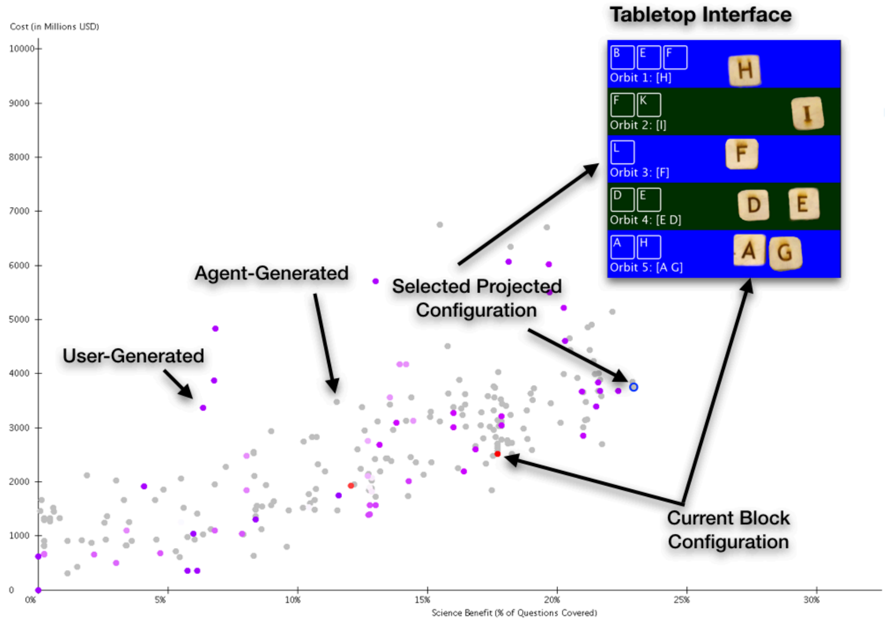


Fig 3. This figure illustrates the tabletop (top right) and visualization interfaces. As users arrange sensor blocks into orbits, the system evaluates and plots the corresponding total cost and science benefit of the design on the scatterplot. The current design (in this case instrument H in Orbit 1, I in Orbit 2, etc.) is plotted in red, the next most recent in pink. All other user-generated designs are plotted in a purple that fades over time. When a design agent generates a configuration, the system plots the corresponding output in gray. Finally, users can select an outcome to project its configuration on the table (in this case, instruments B,E,F in Orbit 1, etc.).

Overview

Inspired by the affordances of TUIs for design and collaboration, we developed a tangible sand table interface to study collaborative design (Fig. 2).

Our mixed-reality system consists of an interactive tabletop, a visualization, and a set of blocks. The blocks, which are mapped to sensors from the design problem, can be placed in regions designated as different orbits on the tabletop. The science benefit and cost associated with a particular block configuration is calculated using a custom simulation engine [41] and plotted on a visualization above the table. Points on the visualization are color-coded to indicate recency and whether they are user or agent generated.

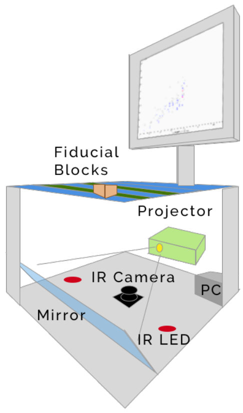


Fig 4. The sand table projected a workspace onto a surface where a camera tracked blocks identified by fiducial markers. As the blocks move between regions on the surface, a simulation engine evaluates the associated configurations and plots them on a screen. All plotted points in the objective space can be selected and projected back onto the tabletop surface.

The most recent point is plotted in red, the second most recent in pink and all other points in various shades of purple such that a dark shade indicated a more recently generated point. All points on the plot are user-selectable; the configuration used to generate any selected point is overlaid on the orbits in the tabletop workspace (Fig. 3).

Independent and Collaborative Design Agents

We developed two computational design agents to explore the sensor-orbit configuration design space, one that operates independently without user input, and one that explores the design space collaboratively with a human.

The "independent" design agent employs a Non-dominated Sorting Genetic Algorithm (NSGA-II) [9] to explore the design space. Evolutionary and genetic algorithms have long been associated with design exploration and NSGA-II is a conventional approach to exploring both design and multi-objective optimization spaces [38], [25], [8], [22], [10], and [30].

Inspired by recent work demonstrating the effect of simple local behavior on global outcomes in collaboration [43], the second, "collaborative", design agent employs a simplistic version of local search modified to continuously orient its search space around the sensor-orbit configurations being explored by the human user. It does so by evaluating random one-block perturbations of the current table configuration. This allows the human and design agent to monitor one another while exploring the space in parallel, with the user choosing when to interact and cross search paths (Fig. 1).

Technical Specifications

Our tabletop TUI (Fig. 4) is designed in the tradition of the reacTable [23]. An internally housed projector displays images on the 36"x30" tabletop where an infrared camera detects objects placed on the surface. Blocks representing sensors are fitted with unique fiducial markers and tracked across the table surface using the camera and reacTIVision [24]. The NSGA-II agent was implemented via the jMetal optimization library [12].

Experimental Setup

We compare our side-by-side approach with two baseline methods, which are effectively “subsets” of the proposed approach. We ran a three-condition, within-user study which asked participants to explore the EOSS design problem on their own, by passively observing the NSGA-II agent, and side-by-side with the collaborative local-search design agent (Fig. 5).

Each study lasted roughly an hour and involved three treatment sessions. During each session, participants were asked to explore the design space through our interface, after which they were given up to thirty seconds to construct what they considered the “best” design based on what they had learned during exploration. They then completed a questionnaire assessing affect and user experience for that round. Following the study, users completed a post-survey ranking the conditions and reflecting on their choices.

In the following we describe the three conditions in detail:

1. *HUMAN-ONLY (HUM)*: Participants were instructed to explore the design space through the sand table interface on their own. They were given a set of blocks for each instrument and explored using the tabletop and visualization without any assistance from a design agent. As described in the system description, participants could click on previously generated designs of their own to reflect on their design exploration at any time.
2. *OBSERVE-AGENT (OBS)*: Participants followed along as the NSGA-II design agent explored the space in real-time, with all evaluated configurations plotted on the screen. Again, participants were able to select cost points as they were explored to see the corresponding configurations on the tabletop, and we allowed them to move around blocks on the table as well, although the system did not evaluate any block configurations.
3. *SIDE-BY-SIDE (SBS)*: Participants worked alongside the local-search design agent. As in the HUM condition, the system would evaluate and plot evaluations for the block configurations that users placed on the table. The local search agent would continuously explore minor variations of the current block configuration, which the system would evaluate and visualize for

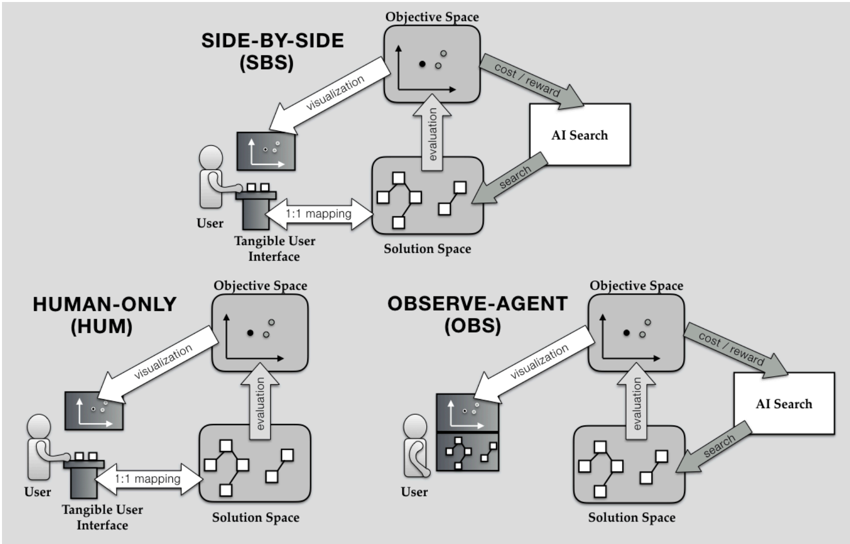


Fig 5. The three design-space search interactions studied: human-only search, human-observation of agent search (NSGA-II), and side-by-side collaborative search.

the user as well. For simplicity, we defined the local search neighborhood as any configuration at an edit distance of one from the current configuration (e.g. add, remove, substitute, or move one instrument in any orbit). Users were free to monitor the agent's search path and adjust their own.

The instruments and orbits were randomly remapped between conditions with users informed in order to prevent knowledge carryover. The conditions were also randomly and uniformly counterbalanced against ordering effects due to fatigue or increased familiarity with the interface or task.

Hypotheses

Through our study, we examined the following hypotheses[1]:

- **H1: Design Quality:** The user-agent collaboration (SBS) will generate better designs than the user (HUM) or computer alone (OBS) will generate. While "better" is often difficult to quantify in a design problem, in this case we will evaluate designs relative to a baseline Pareto front generated by a conventional genetic algorithm used in this domain—NSGA-II.
- **H2: User Experience:** Users have a better experience when collaboratively exploring with an agent (SBS) compared to exploring on their own (HUM) or following the agent as it explores (OBS).

[1] We initially intended to explore a third hypothesis addressing learning outcomes but were unable to do so due to an error in data collection.

Results

31 subjects (13 female, ages 18–37) participated in our study. To attain a more diverse population sample, we recruited participants from a large city both through mailing lists and flyers at local universities and via ads on related social media groups and online bulletin boards. The resulting participant set came from a varied educational background: six had completed high school or a GED, 18 had a bachelor's degree, and 7 had a master's degree, advanced graduate work, or a PhD. We describe our findings with regard to our hypotheses around Design Quality and User Experience.

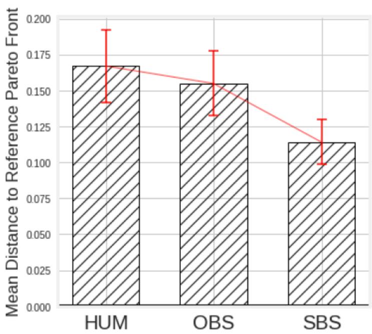
Design Quality

Given the multi-objective nature of the sensor-orbit problem, there is no clear single metric to objectively compare designs, a matter complicated by the unknown nature of the true Pareto frontier in this real-world problem.

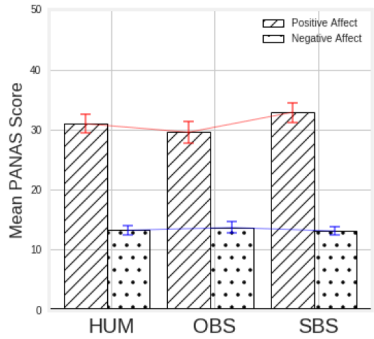
For each participant and condition, we had a single design solution produced from a blank slate at the conclusion of the condition to compare within-user. Following [20], [50], and [36], we calculated the *generational distance* for each of the designs using their normalized Euclidean distance from a reference, empirically-derived Pareto frontier. We constructed this reference Pareto frontier from the configurations generated by running NSGA-II over 80 iterations with a population size of 200 (Fig. 7). For reference, the NSGA-II agents in OBS evaluated an average of 267.6 unique designs in addition to the initial population of 200 over the course of the treatment. User designs were then compared relative to their distance from this reference frontier[2].

One-tailed paired-sample t-tests were conducted to evaluate the difference in quality of designs produced in the SBS condition, compared to each of the baseline conditions, HUM and OBS. The SBS condition produced significantly closer designs ($M=0.114,\ SD=0.086$) in comparison to both HUM ($M=0.167,\ SD=0.138,\ t=-1.920,\ p=0.032$) and OBS ($M=0.155,\ SD=0.124,\ t=-1.827,\ p=0.039$), see Fig. 6(a). These results suggest that participants tended to produce better designs after exploring the space with the collaborative agent, relative to the reference Pareto-optimal front, supporting **H1**.

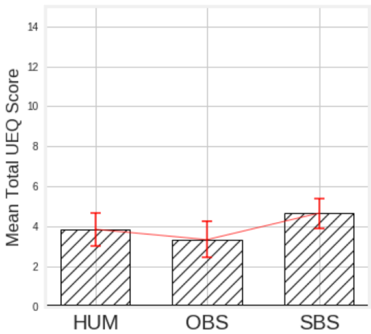
[2] In the case that user-generated designs dominated any configurations on the reference frontier they were assigned the negation of this distance. Overall, we acknowledge that this choice of reference may limit the validity of our finding to a small time or a small number of function evaluations



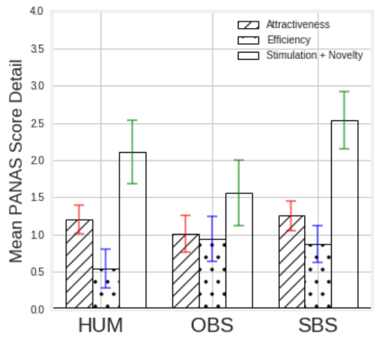
(a) Mean distance of user-produced designs to the reference Pareto front from each treatment. The reference Pareto front was generated by running NSGA-II.



(b) Mean positive and negative affect scores via PANAS measured immediately after each treatment.



(c) Mean User Experience Questionnaire scores measured immediately after each treatment.



(d) The UEQ scale used was a subset composed of metrics for attractiveness, efficiency, stimulation, and novelty.

Fig 6. Mean design quality and user experience scores across the three conditions.

User Experience

Participants' enjoyment was measured using the Positive and Negative Affect Schedule (PANAS) [51], and user experience via the User Experience Questionnaire (UEQ) [29]. Following the study, participants also ranked the treatments in order of helpfulness and enjoyment, and provided qualitative comparisons of the treatments in terms of helpfulness and enjoyment.

Participants displayed stronger positive affect in the SBS condition (*M=32.85, SD=8.964*) compared to HUM (*M=30.97, SD=8.677, t=1.455, p=0.078*), and compared to OBS (*M=29.56, SD=8.677, t=3.117, p=0.002*). One-tailed paired-sample t-tests indicate that only the latter difference is significant, thus only partially supporting **H2**. No significant difference was found in participants' negative affect after the SBS condition (*M=13.13, SD=3.784*) compared to either HUM (*M=13.26, SD=3.838, t=−0.295, p=0.385*) or OBS (*M=13.71, SD=5.172, t=−0.668, p=0.255*) (Fig 6(b)).

Table 1 Participants ranked and reflected on the three treatments at the conclusion of the study in terms of helpfulness and enjoyment. The rankings were aggregated using an extended Borda system (scores listed next to rank in parentheses). Four users did not respond for the enjoyment ranking.

Treat-ment	**Helpfulness Rank(Score) n=31**	**Enjoyment Rank(Score) n=27**	**Comments**	
SBS	1 (81)	1 (70)	Positive	I liked the fact that I was being assisted along [...] It felt like as if two brains were working simultaneously.
			Negative	It was distracting to see the agent coming up with points around me that weren't always improvements, and this made me feel less productive.
OBS	2 (55)	3 (43)	Positive	It felt like watching the agent exploring by itself allowed me to see different trends without having to move the blocks myself [...] I was arriving at a better solution more quickly.
			Negative	Observing the agent exploring was dreadful. Way too much information, and I couldn't control the variances in sequences to help myself understand the impacts of various instruments.
HUM	3 (50)	2 (49)	Positive	Exploring alone makes it easier and enjoyable because it allows me to follow my own logic of exploration.
			Negative	Exploring with blocks is too inefficient and make me feel frustrated. I felt lost without help from the computer.

Participants scored the system more positively via aggregate UEQ scores after SBS design (*M=4.664, SD=4.117*) than either HUM (*M=3.858, SD=4.553, t=1.301, p=0.102*) or OBS (*M=3.339, SD=4.929, t=1.717, p=0.048*), although one-tailed paired-sample t-tests indicate that only the first was barely significant and effect sizes were small (Fig. 6(c)). We employed a subset of the full UEQ scale, including the complete scales for attractiveness, efficiency, stimulation, and novelty. Interestingly, users rated OBS higher than HUM or SBS in terms of efficiency, but lower than the others in terms of attractiveness and the hedonistic scales of stimulation and novelty (Fig. 6(d)).

Finally, users overall ranked the treatments as (1. SBS, 2. OBS, 3. HUM) in terms of helpfulness and (1. SBS, 2. HUM, and 3. OBS) in terms of enjoyment (Table 1). The rankings were aggregated using an extended Borda system [3] whereby each user's ranking was scored with three points for their first choice, two for their second, and one for their third choice.

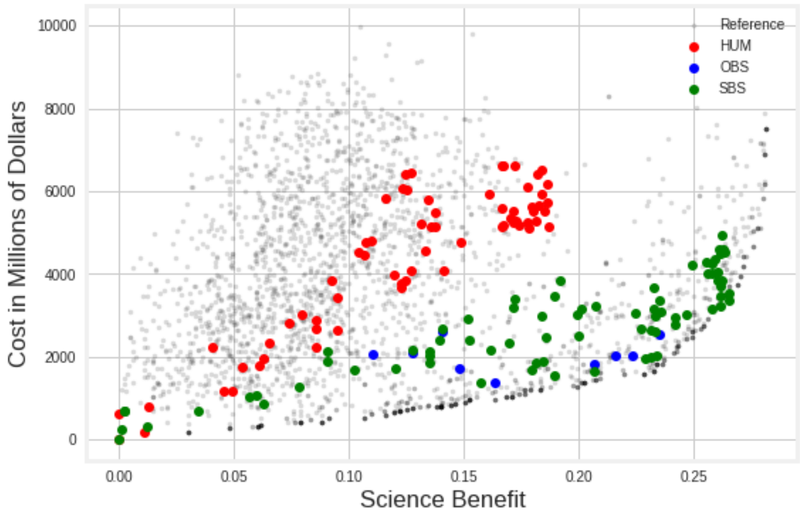


Fig 7. This figure shows an example of all the evaluated configurations explored by a single user during the exploration phase in each study condition. The outputs used to generate the reference Pareto front are plotted in the background in gray.

Discussion

To summarize, we found that participants produced better designs after exploring the design space side-by-side with the collaborative design agent than after exploring on their own or observing and querying the NSGA-II algorithm visualization. Participants exhibited marginally higher affect and user experience when working side-by-side than either of the other modes. They also overwhelmingly rated this design method higher than the other two. In the following, we discuss implications of our findings, qualitative insights from user comments, and possible explanations that could lead to tradeoffs when constructing collaborative design agents.

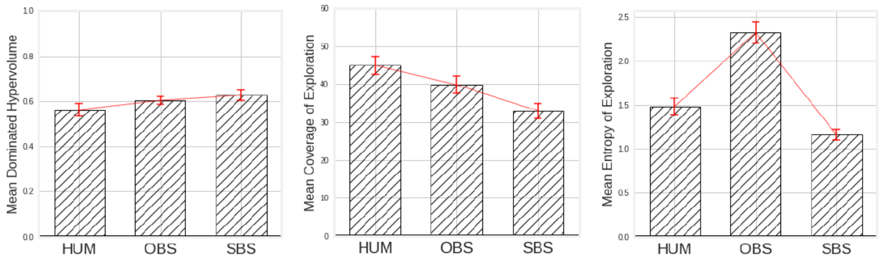
Qualitative Insights on Designing Side-by-side

Participants' post-study reflections provide some insight on why so many preferred exploring with the collaborative design agent (abbreviated as DA below) and how they perceived the DA. Several users pointed out complementary advantages they inferred in the DA, from speed to the ability to explore with more blocks at the same time. Others simply appreciated the experience of working together: *"Exploring with the DA felt more like a collaborative effort, rather than working alone or watching someone else work on something"* or saw the back-and-forth with the design agent as a way to reduce the randomness of their search. Some participants derived confidence from working with the design agent: *"It felt like as if two brains were working simultaneously and there was a hope to achieve optimal configuration"*.

On the other hand, some expressed annoyance with the agent: *"It would have been better if the computer gave better suggestions alongside working with me..."*. At least one user saw the design agent as a playful antagonist: *"I enjoyed exploring with the DA at the same time because I almost felt like I was competing against the DA"*. Several developed ad-hoc strategies for collaboration, e.g. splitting up the objectives: *"After DA determined points from my selection, I rearranged the blocks to the DA point with the highest benefit. Then, I switched blocks to determine the lower cost"*. The experiences described by participants in the side-by-side condition, whether positive or negative, suggest that users are capable of seeing such agents as collaborators and not just tools. In particular, the variety of implicit choices and ad-hoc strategies users made in interacting with the design assistant while exploring the design space mirror observations prior work has made about human to human collaboration using TUIs, e.g. [52], including turn-taking, dominant-submissive pairs, and independent, parallel exploration. This supports the potential of intelligent agents acting as true collaborators in the design search process.

Does Working Side-by-side Lead to Broader Search?

In order to gain intuition about why users generated better designs after SBS exploration, we examined the solutions they encountered during search under the different conditions. Using one conventional way to compare sets of solutions, we found that the set of configurations considered by participants in the SBS condition tended to dominate more of the objective space, in terms of hypervolume [53] (*M=0.626, SD=0.134*), than those explored in HUM (*M=0.561, SD=0.145*), (Fig. 8(a)). This difference was significant via a one-tailed paired t-test (*t=2.45, p=0.010*). Designs explored by participants in the OBS condition also tended to dominate less hypervolume than in SBS (*M=0.603, SD=0.091*), although this difference was not significant (*t=1.07, p=0.146*).



(a) (b) (c)

Fig 8. In the SBS condition, participants tended to consider more Pareto-optimal designs as measured by the overall hypervolume dominated by the non-dominated Pareto frontiers in each condition (a). Nonetheless, the search spaces explored by human participants when collaboratively exploring in the SBS condition tended to cover fewer possible sensor-orbit pairings (b) and exhibit lower information entropy (c) than in the other two conditions.

To our surprise, however, users appeared to explore less broadly in the SBS condition than in either the HUM or OBS conditions. To quantify this, we define the *coverage* of the exploration as the number of possible sensor-orbit pairings that appeared in at least one evaluated configuration during the exploration. Similarly to [34], we also use the normalized entropy of explored configurations as a measure of *diversity*. We calculate entropy as:

$$H(X) = -\frac{1}{logN}\sum_{i}^{n} p(x_i)logp(x_i)$$

where *X* is the configurations explored, *N* is the number of configurations in *X*, x_i is a possible sensor-orbit pair, $p(x_i)$ is the probability of x_i appearing in a configuration in *X*, and *n* is the number of possible sensor-orbit pairs.

We find that participants tended to cover more of the orbit-sensor pairings when searching the solution space in the HUM condition (*M=44.93, SD=13.03*) and the OBS condition (*M=39.89, SD=12.79*) than in the SBS condition (*M=32.97, SD=10.53*). Both of these differences were significant via paired one-tail t-tests (*t=5.357, p<0.001* and *t=2.428, p=0.011* for HUM and OBS respectively). We also find that the human's search tended to be more disordered when either exploring alone (*M=1.482, SD=0.502*) or passively observing (*M=2.326, SD=0.672*), again both significant via paired one-tail t-tests (*t=3.093, p=0.002* and *t=8.414, p<0.001* respectively).

Participants' post-study reflections suggest that working with the design agent encouraged them to converge more confidently and quickly to a more focused region of the configuration space. For example, *"I could immediately see some sort of direction to move in instead of randomly guessing"*, *and "when we both (computer and I) are exploring together, less time is wasted, and productive results are easier to discover"*. Indeed, as one user put it, *"I felt lost without help from the computer"*.

However, as others observed, collaboration *"might have led to a bias in what order to use and I resulted in a lower science benefit than I had on my own" and "exploring on my own gave me more freedom to try something completely different, and potentially get a more helpful combination"*. Participants appreciated this freedom, saying, *"it was really useful learning through trial and error"*, and *"exploring alone makes it easier and enjoyable because it allows me to follow my own logic of exploration"*.

This raises an important conundrum for the design of collaborative agents, insofar as the processes for achieving better designs through collaboration may not coincide with those that best encourage broader exploration of the design space or generate more creative designs. Some work with TUIs found similarly that rapid design exploration enabled by physical interfaces could actually reduce the degree to which users reflect in the design process [11]. This result also evokes prior work suggesting conversely that leveraging humans as a search heuristic can reduce the diversity of algorithmically generated solutions [39]. Insofar as a key benefit of collaborative design is its potential to foster broader exploration and emergence, future research should explore how interactions with collaborative design agents might expand, rather than contract, human designers' exploration.

Limitations and Future Work

Our findings are somewhat constrained by the complexity and domain-specific nature of the design problem we chose in contrast with the relevant sophistication and expertise of our users. The resultant abstractness of the problem made it very demanding for our users, and could have added to the variance in our results, although we attempted to account for this with a within-user design.

TUIs are especially useful for co-present collaboration in a shared physical workspace. Although our agent interacted with the user through the tabletop interface and display, it did not do so physically. This study is part of an ongoing project in which we plan to study collaborative exploration between a human and a physically embodied design agent in a shared workspace. Observing interactions between a virtual agent and a human through our TUI sand table is a first step towards this end.

This work also does not empirically compare the human-agent collaborative exploration to collaboration between humans. While some participants reported interacting with the agent in similar ways to what we see in the literature on co-present human-computer collaborations, future work should directly examine these similarities in order to lay the groundwork for designing better collaborative agents in this vein.

Finally, while we adapted a design-as-search model, there are other potentially richer formulations (e.g. design-as-exploration) that may better model real-world design processes. Future work should consider other formulations of design which allow for important processes like problem reframing.

Conclusion

Humans and algorithms have different strengths and limitations in searching design spaces. Algorithms can quickly explore a large space and precisely compare solutions, while humans are adept at fast pattern recognition, generalization, and context integration. Egan and Cagan note the importance of both human intuition to handle difficult-to-translate qualitative processes and the objectivity and consistency of computation at scale [13]. This suggests benefits to be reaped by systems that model the human-machine interaction as a collaborative activity, building on the complementary skills of each agent, e.g. flexible and conversational mixed initiative collaborations or adjustable autonomy for different contexts [1].

In this paper, we described a new tabletop tangible sand box interface in order to study real-time collaboration between humans and design-search algorithms. Such side-by-side human-computer collaborative exploration of a design space via a physical one-to-one mapping of the solution space has not been studied before, despite the potential it offers designers to capitalize on benefits of both collaborative and AI-supported design.

In an experiment we find that the proposed model of side-by-side design collaboration can lead a human designer to generate better designs than when working alone or observing an agent, both in terms of the distance from the Pareto front of the user-selected final design, and the hypervolume dominance of all explored designs. We also find marginal benefits to user positive affect and user experience. In particular, side-by-side design positively overcomes some of the trade-off between efficiency and stimulation that exists when weighing human-only and computer-only design.

However, we also find that this sort of collaboration might lead to lower solution space coverage and less diversity in the solutions explored. As we do not want human-machine collaborative design to reduce the creativity and open-ended exploration that early-stage design requires, these concerns should be considered in the development of such agents and future research.

This caveat notwithstanding, our work supports the feasibility of treating design agents not just as tools, but as peer collaborators in the exploration of possible solutions during early-stage design.

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