Expanding Robot Utility via User-Centered Adaptation

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I. Research Vision

Robots have the potential to complete a variety of tasks to aid users, from retrieving lost items in cluttered home environments to encouraging users to perform physical rehabilitation. A robot's ability to *functionally* perform these tasks is a necessary but not sufficient property that drives robot adoption [46]. Across use cases, a robot's utility depends on its ability to align with the individual needs and preferences of each user, but users can have conflicting preferences that prevent a single robot policy from benefiting all users [2, 41, 45]. A foundational goal of human-robot interaction is to develop robots that can be readily used by *any* user. However, current systems that take a one-size-fits all approach to robot deployment cannot satisfy users that have diametrically opposed preferences.

Prior work in robot learning has demonstrated the efficacy of user-collected data to allow robots to computationally reason over user preferences [4]. Users can teach robots desired behaviors through many channels such as trajectory comparisons [3, 39, 32], trajectory rankings [6, 10, 34], demonstration [27, 35, 49], corrections [1, 11, 31], language [30, 37, 44, 47], or by specifying reward values [9, 25]. An overarching limitation of these approaches is that they require conscious effort from the user to communicate over these channels. However, users naturally communicate preferences through many *embodied* channels (e.g., gaze, proxemics, or gestures) that can be computationally leveraged [29, 40].

My research establishes theoretical and algorithmic foundations to allow robots to adapt to users' individual needs and preferences through natural *embodied* interfaces. I pursue this goal by (1) learning representations from data generated during robot use and (2) encoding cognitive and structural biases into algorithms to efficiently adapt robot policies with limited data.

II. Learning from Naturally Generated Data

Internet-scale robot datasets are scarce, but users naturally emit data through several embodied channels that can be leveraged. My first research direction addresses this gap by learning robot representations from these embodied channels.

Robot Embodiment. Users automatically infer expectations from the physical design of a robot [7, 36], highlighting design as a communication channel. To understand this channel, We introduced the concept of *design metaphors* [8] as a representation of users' mental models of expected robot function [17]. We found that using these metaphors can reliably describe population-level social and functional expectations over a dataset of 165 socially interactive robots observed by over 1800 people. The semantic relationships between metaphors additionally induced corresponding measurable changes in users' expectations of robots, e.g., robots that were described as "a person" were perceived as more competent than robots described as "a toddler". We also showed that design metaphors can be used as a predictive measurement to understand expectations of unseen robot embodiments [19]. Extending design as a communication channel, we created a generative framework to modulate robot expectations through clothing design [22] and screen-based faces [23].

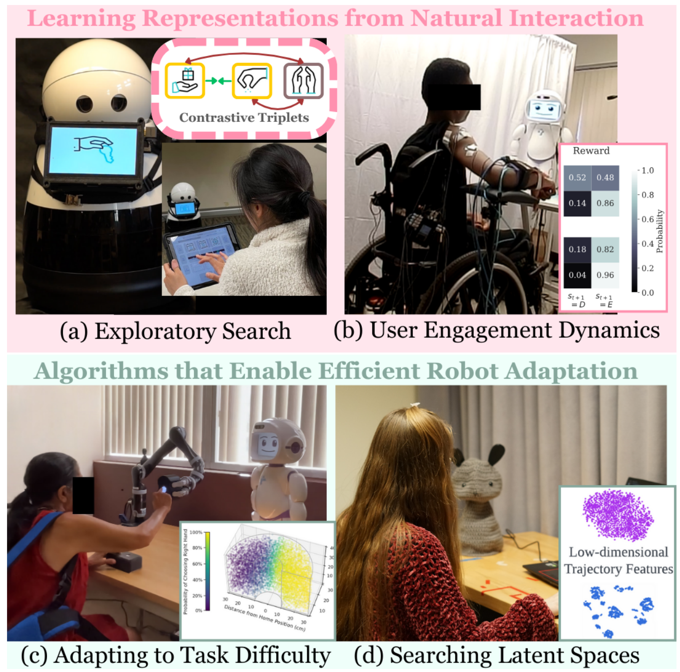

Fig. 1: Research overview. My research models natural interactions from users such as (a) exploratory search and (b) user engagement dynamics to adapt robot policies to individual users. These models facilitate adaptation in limited data domains such as (c) adjusting rehabilitation exercises and (d) finding preferred trajectories in learned representation spaces.

Exploratory Search. Design metaphors capture users' mental models of static robot designs, but preferences can also emerge through interaction. Traditional preference-learning assumes fixed preferences, but users often engage in exploratory search to jointly discover what they *prefer* the robot to do and what it *can* do [33]. We created an interface that allows users to perform exploratory search in high-dimensional robot action spaces [18]. This work learns from users' *exploratory actions*, where users selectively tested embodied actions on a physical robot that assisted users with locating and fetching items, shown in Fig 1a. The users' exploratory actions when selecting behaviors suggested their true preferences. We formulated the problem of *contrastive learning from exploratory actions* (CLEA) to learn human-aligned representations from users' natural interactions [24], without requiring explicit user labels. We found that CLEA representations captured preferences using 80% less data than self-supervised representations in down-stream preference learning tasks.

User Engagement Dynamics. Both Design Metaphors and CLEA learned population-level representations of robot behaviors before users engaged in routine interaction, however, robots can learn about users continually during use. We identified engagement is a salient embodied channel that can be used to train robot social policies. We formulated successful social interaction policies as optimizing user engagement [15]. To achieve this, we learned personal *engagement dynamics* models from facial cues, $p(s_{t+1} \mid s_t, a_t)$, rather than directly predicting reward or failure as in prior works [5, 12, 43]. We evaluated this approach in a rehabilitation exercise domain for users with cerebral palsy, shown in Fig. 1b. Robots that select actions to maximize engagement according to these dynamics models resulted in significantly increased volume of interaction with robots in our user simulations.

III. Algorithms to Efficiently Adapt Robots

Though users emit data from many channels, they also have limited time to spend adapting robots. My second research direction creates techniques to *efficiently* adapt robot behavior.

Physical Interaction. Robots have the potential to collect longitudinal and objective physical interaction data that can be used for several purposes, increasing their utility. We investigated how robots can learn personalized movement models of post-stroke participants for adaptive rehabilitation by creating the bimanual arm reaching test with robots (BARTR) [16, 20]. BARTR, shown in Fig. 1c, consisted of a physically assistive robot to position a reaching target and a socially assistive robot that provided feedback and test instructions. Using time to reach and arm choice data, we trained Gaussian Processes to model users from limited system use data. These models allowed us to developed a causal framework to calculate personalized task difficulty to facilitate rehabilitation [20]. We also used these models to derive an objective metric for *arm nonuse*, which is traditionally difficult to monitor in neurorehabilitation [26]. The BARTR metric was correlated with existing clinical standards [42], but achieved a higher test-retest reliability, enabling repeated nonuse assessment.

Generating Trajectories for Hair Care. The BARTR interaction clinically assessed post-stroke users, but the same robot can be used to augment users' ability to perform activities of daily living. To expand the robot's usefulness, we created the first robotic hair combing interface [14]. Specifying these paths manually requires a high degree of user effort to "draw" trajectories that appropriately comb hair, requiring high levels of skill and dexterity. We estimated the structural gradient of the user's hair from images to plans trajectories that follow the hair's structural gradients, requiring only one click from the user to generate combing trajectories. This technique generalizes across several hair lengths, colors, and styles. We found through a user study that this algorithm produces trajectories that are comparable to human-drawn paths and exert minimal forces. Through a collaboration, we extended this interaction to robots with dexterous soft end effectors, extending hair care to three new tasks that leverage the structural compliance of soft robots [48].

Intuitively Ranking Trajectories. Robot hair combing leverages structural priors to reduce user effort. Many robot behaviors exist in learned representation spaces that do not have such intuitive structures for users to efficiently navigate [4]. Previous approaches to eliciting preferences from rankings maximize an information gain objective to generate sets of trajectories that are easy for users to rank. Maximizing this objective does not produce trajectory sets that users perceive as improving over time. I defined a novel algorithm called CMA-ES-IG that combines an information gain objective with CMA-ES optimization to produce trajectory sets that *efficiently* converge to users' preferred trajectories in as few as ten rankings [21], compared to hundreds of pairwise comparisons. Our user studies evaluated this algorithm across robots performing social gestures and functional handover tasks, shown in Fig. 1d. Users found that CMA-ES-IG learned their preferences more quickly and easily than state-of-the-art baselines [3, 32].

IV. Future Work

Jointly Learning Function and Preference. Many preference-learning approaches in robotics conflate *preference* and *function*. Users generally rate successful policies as better than unsuccessful policies, but preferences are more likely to vary between users. In dialogue generation, functional policies are often trained from data before preference learning techniques are applied to better collect user feedback [28]. My prior work assumed access to policies that *functionally* accomplish tasks from manually engineered robot systems. My future work will leverage *quality-diversity* (QD) optimization [13] to autonomously learn sets of robot policies that maximize an objective, $f(\pi)$, that functionally performs tasks (quality), while varying along several measure functions, $m_i(\pi)$, that capture differences in user preferences (diversity). I aim to evaluate QD algorithms across several user-interactive domains, such as hair care, feeding, item retrieval, and cooking. These domains enable the collection of embodied user data and will highlight the generalization of QD-based policy learning.

Transferring Preferences Across Tasks. My work demonstrated that the same robot can perform more than one task, such as hair combing and stroke assessment, but current preference learning techniques require robots to relearn user models for each new task. I hypothesize that some elements of users' preferences may transfer across robot tasks, such as how quickly the robot moves during task execution [2] or the robot's personality [38]. My future work will learn task representations to measure preference distribution similarity across robot tasks. By computing task similarity, we can improve the efficiency of preference learning in novel tasks. This approach allows robots to first learn preferences in low-risk tasks like item retrieval, and transfer those preferences to higher-risk tasks like cooking, where preference data can be more difficult to collect, improving robots' utility for users.

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