Behavior Adaptation for Robot-assisted Neurorehabilitation

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ABSTRACT

11% of adults report experiencing cognitive decline which can impact memory, behavior, and physical abilities. Robots have great potential to support people with cognitive impairments, their caregivers, and clinicians by facilitating treatments such as cognitive neurorehabilitation. Personalizing these treatments to individual preferences and goals is critical to improving engagement and adherence, which helps improve treatment efficacy. In our work, we explore the efficacy of robot-assisted neurorehabilitation and aim to enable robots to adapt their behavior to people with cognitive impairments, a unique population whose preferences and abilities may change dramatically during treatment. Our work aims to enable more engaging and personalized interactions between people and robots, which can profoundly impact robot-assisted treatment, how people receive care, and improve their everyday lives.

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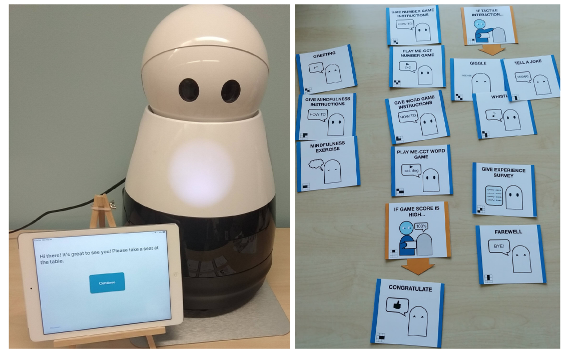

Figure 1: JESSIE enables clinicians, caregivers, and other stakeholders to create customized programs for cognitive neurorehabilitation to help maximize and determine the efficacy of treatment administered by a robot, *Left:* The Kuri robot platform. *Right:* A program created by a clinician.

1 INTRODUCTION

As the world's population grows older, more people are likely to develop age-related health conditions, such as cognitive impairments, which can severely impact their independence and quality of life [4, 6, 10]. Furthermore, people with cognitive impairments may experience drastic cognitive and physical changes during the course of treatment, and often require highly personalized and unique interventions to support their health and independence [3–5].

However, this population is quickly outpacing the resources and availability of full-time care providers. Informal caregivers, such as family members, often shoulder the responsibility of care which can adversely affect their relationship with the care receiver and lead to stress and burnout [12].

Socially assistive robots present exciting opportunities for supporting people's health and prolonging their independence in numerous ways such as assisting with activities of daily living and providing emotional support [7, 13, 16]. Robots can also administer cognitive training and other behavioral treatments to enhance neurorehabilitation treatment for people with cognitive impairments and extend treatment to a person's home [8, 15, 19]. Similar robots have been shown to improve task adherence and engagement in other applications such as education and stroke rehabilitation [20].

To maximize the efficacy of behavioral treatments administered by robots, it is critical to personalize the treatment to suit a person's preferences and abilities [1, 6]. Personalization can improve a person's engagement with training, which can ultimately improve their retention of the material and long-term adherence to treatment [1, 6]. But while there are numerous approaches to enabling robots to adapt their behavior to a user, existing approaches assume a person's preferences stay constant throughout an interaction, or do not take preferences into account at all.

Our work aims to enable robots to adapt their behavior longitudinally to a person with cognitive impairment while considering their dynamic preferences and abilities. Our research has the following objectives: a) explore the efficacy of cognitive training administered via a social robot for a person with cognitive impairment, b) investigate appropriate user features for modeling user preferences and abilities, c) develop novel algorithms for adapting robot behavior to a person with cognitive impairment throughout treatment, and d) implement these algorithms on physical robot systems and evaluate their efficacy, usability, and acceptance in neurorehabilitation.

2 RELATED WORK

Robots for Neurorehabilitation. There are many existing technologies to support neurorehabilitation, though robots have been shown to improve patient compliance and engagement as compared to virtual systems [20]. Robots such as NAO have been used to assist clinicians during cognitive training sessions [15]. These robots augment a session led by a human clinician, and have been shown to increase engagement and decrease depressive symptoms among people with mild cognitive impairment (MCI) [15]. Other robots,

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such as Bandit [19], can lead a training session without a clinician present. Bandit could automatically modify the difficulty based on a person's performance, which increased engagement and improved performance at higher difficulties for people with dementia [19].

While many existing systems consider user behavior or preferences for longitudinal interactions [11], few have been developed for people with cognitive impairments. Managing robot behavior in response to these preferences is particularly challenging when working with people with progressive conditions such as dementia, as their preferences and abilities may change quickly [8, 22].

Behavior Adaptation. Behavior adaptation is the ability for an agent to modify its behavior in response to certain stimuli. In our case, a robot would modify its behavior in response to a person's behavior, preferences, or abilities. A key element for behavior adaptation is interpreting how user data can inform a robot's actions, as well as how users respond to those actions. Researchers have used countless methods to imbue social robots with this ability in numerous contexts, including neurorehabilitation [9].

Among the most widely used methods for behavior adaptation are reinforcement learning (RL) approaches. For instance, many researchers model the behavior adaptation problem as a Markov Decision Process (MDP) to enable robots to try different actions, observe the results, and then modify their behavior during a cognitive training session [2, 14, 15, 17, 21]. Approaches such as inverse RL enable an agent to learn optimal behavior from an expert, such as a robot observing a human therapist leading a treatment in order to learn how to respond to a patient in future interactions [18, 23].

3 OUR WORK TO DATE

In applications such as neurorehabilitation, integrating domain knowledge from experts such as a therapist, or personal knowledge from a caregiver, can help personalize treatment and maximize its efficacy. Thus, in order to determine the efficacy of treatment administered by a social robot and personalize these treatments to individuals, it is crucial to give these stakeholders control over a robot's behavior. However, they often have low technology literacy [24], which can serve as a barrier to effectively reprogramming a robot. Existing frameworks to support novice programmers are almost entirely procedural, require understanding code structure, and do not allow high-level specification of desired behavior.

Methodology: Our system JESSIE (see Fig. 1) couples control synthesis methods with an accessible tangible specification interface to enable novice programmers to quickly and easily specify complex robot behavior. Users specify the desired robot behavior using our tangible specification interface, and JESSIE automatically generates the associated robot control. Thus, clinicians can customize robot behavior and reactions for personalized cognitive training regimens in order to keep people engaged and focused on overarching goals, rather than concerning themselves with specific implementation details or individual robot actions [8].

Evaluation: We evaluated JESSIE in the context of enabling users to develop cognitive training regimens for people with MCI. We conducted a study with six neuropsychologists to assess the system's usability, specifically for clinicians with no programming experience. We taught them how to use our specification interface to create a program, allowed them to design their own sessions for a person with MCI to complete with a Kuri robot, and concluded the session with an open interview. We used a grounded theory approach to identify overarching themes among participants [8].

Results and Discussion: We found that clinicians, who had no prior experience programming robots, were able to use JESSIE to program cognitive therapy sessions with personalized activities, reactions, and constraints after little time or training. They reported positive comments regarding its usability and gave suggestions for improvement including increased support for personalization, varying the robot's status throughout treatment, and collaborative goal setting. Our observations also suggest that JESSIE enables novice programmers to leverage control synthesis techniques to create complex, interactive sessions on a social robot, which would take more time to write and test with procedural programming languages. Thus, this system will enable the robotics community to customize social robot behavior, adapt to end-user preferences, and promote longitudinal HRI in numerous domains, extending the scalability, accessibility, and personalization of social robots [8].

4 ONGOING AND REMAINING WORK

Moving forward, we will continue to work closely with neuropsychologists and people with cognitive impairments while implementing cognitive therapy sessions on a robot. By enabling these stakeholders to create personalized therapy sessions using our system JESSIE, we will further explore how to best consider their expertise while adapting to user preferences to improve robot-assisted treatment. In our discussions and explorations with stakeholders, we will determine factors such as: a) ethical and design considerations for designing technology for people with cognitive impairments, b) appropriate features for modeling their preferences and abilities, particularly those that might differ from people without cognitive impairments, and c) appropriate behaviors for a robot to exhibit in response to various preferences and abilities.

We will then extend JESSIE by implementing these behaviors on a Kuri robot to perform pilot studies with people without cognitive impairments. Thus, we can ascertain the robustness of our system while minimizing risk to people with cognitive impairments. We will ask participants to complete cognitive training sessions with a robot over eight weeks to reflect a traditional training regimen. During this time, the robot will gather interaction and performance data as informed by our discussions with stakeholders.

We will use this data to develop novel behavior adaptation methods for longitudinal interactions with people with cognitive impairments. We will first explore approaches such as RL and inverse RL which have shown promise in other applications [2, 14, 15, 17, 18, 21, 23]. This will serve as a basis for our new methods that can leverage expert knowledge and are suitable for the dynamic preferences and abilities of people with cognitive impairments.

We will then implement these methods on physical robot systems and perform longitudinal studies with people with cognitive impairments to evaluate their efficacy, usability, and acceptance for cognitive neurorehabilitation. By applying principles of inclusive design and working closely with stakeholders throughout the development process, we aim to design robots that have the potential to profoundly impact the way people manage their impairments, receive care, and improve their everyday lives.

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