Interface-Aware Robotic Assistance

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I. Motivation and Problem Statement

For a human to issue control signals to any robot, whether for teleoperation or shared control, they must use some form of interface to communicate with the robotic device [4, 1]. The human-issued control signal may also be used for instruction, correction, or feedback [30, 14, 16]. Deviations in timing, magnitude, or direction between the true signal intended by the human and that measured through the interface can thus have rippling effects throughout the human-robot interaction (HRI) system. Despite being the oldest application of HRI, teleoperation still remains challenging and in many cases inaccessible, especially for non-expert users controlling complex robotic systems [26]. The challenges are compounded for people with motor deficits, given their control signals can be sparse, noisy, and limited in dimensionality. Although research has made impressive strides in exploring novel interfaces [7, 27], broadening autonomous robot capabilities [23, 34], and exploring shared-control strategies [13, 18], complex robot teleoperation remains the domain of skilled and competent users [17].

Probabilistic robotics techniques are designed to capture the uncertainties in robot interactions to provide robustness in the face of sensor and model limitations. In these techniques—which were first developed for autonomous robots transitioning from factories to the real world—two fundamental sources of noise are modeled: (1) uncertainty in the robot sensor measurements and (2) noise in actuation, which leads to uncertainty in the state transition models [32]. *I propose that for human-robot systems which also involve human control signals, a third source of uncertainty and noise is imperative to model: (3) human interaction with the control interface* [19].

Historically, the *source* of the human signal and its characteristics have been largely ignored. For example, trajectory data is treated the same by an imitation learning algorithm whether it was collected via kinesthetic or teleoperated demonstrations. Many of the sources of variance are accentuated within the domain of assistive devices for persons with motor impairments. Within the clinical domain of assistive devices, the physical mechanism for activating the interface is designed and chosen by considering the available human mobility [5]. Many are prohibited from using an assistive devices independently due to their inability to *reliably* control an interface [11]. Assistive autonomy is generally *interface agnostic*. The specific operational characteristics of the interface may not be explicitly taken into consideration when the human command is utilized by the autonomous system. For instance, once the teleoperation signal is measured,

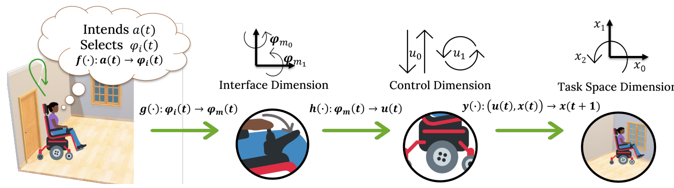

Fig. 1. Teleoperation signal mappings. Typically only $y(\cdot)$ is modeled, though $h(\cdot)$ might be known. Our contributed framework explicitly represents $g(\cdot)$ and $h(\cdot)$. a^t, u^t, x^t: robot task-space action and associated control command, and robot state. ϕ_i^t, ϕ_m^t: intended versus measured interface action.

the autonomy pipeline treats velocity commands similarly, regardless of their source. My prior work has identified this as a major gap in the domain of assistive devices for people with motor impairments [19, 21, 20]. **My goal is to design algorithms that maximize the human's autonomy by leveraging robotics autonomy.** My approach is to develop algorithms that reason about the source of the human's signal and how it might be filtered and altered through the control interface prior to using the signal for any further actions, decision making or assistance. I call this *interface-aware robot assistance*.

II. Formalizing Interface-Aware Assistive Robots

We introduced the framework of interface awareness in robot teleoperation and shared control [8]. Consider the mappings involved in teleoperation, as shown in Fig 1. Let a^t denote the action primitives defined in the physically assistive robotic device task space (e.g., move forward, turn left) that the human desires to be executed by the robot. The dynamics of the robotic device dictates that action a^t is achieved through robot control command u^t. Typically, teleoperation is modeled simply as $a^t \mapsto u^t$; i.e. the human will execute the control command for their intended robot action. The output of the interface device is the *human input*, or user command $\mathbf{u}_h$—which can take the form of a high-level goal, mid-level motion primitive, or lower level velocity commands. Although it is common knowledge that humans are noisy, the human input is tacitly interpreted as a source of ground-truth or high-confidence information in many uncertain robotic settings [3, 10, 25]. Even in situations where the human operator is known to be a non-expert—such as LfD frameworks that treat demonstration examples as sub-optimal—there is an implicit assumption that the provided human input was precisely what they *intended* [28, 9]. Our approach to interface-aware signal interpretation is to explicitly consider the human's physical interaction with the control interface by modeling how the physical actions are mapped to task-level actions through the interface ($f(\cdot)$ in Fig 1) and how the user

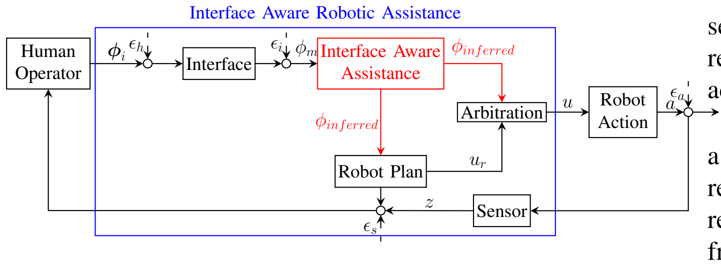

Fig. 2. Interface-aware assistance pipeline.

signal is stochastically altered through the interface ($g(\cdot)$ in Fig 1). Let $\phi_i^t \in \Phi$ denote the unobservable *intended* interface level action initiated by the user that aims to achieve a^t. The measured interface level action $\phi_m^t \in \Phi$ is fully observed. The mapping $g(\cdot) : \phi_i^t \mapsto \phi_m^t$ captures the translation from intended to measured interface-level physical actions. This mapping is dictated by the manner of interface activation but is user-specific. In an ideal noise-free setting, ϕ_i^t and ϕ_m^t are equivalent. However, in practice, ϕ_m^t may deviate from ϕ_i^t due to biases resulting from motor impairments, interface malfunctions, fatigue, or mental distractions, to name a few. We call $g(\cdot)$ the *human input distortion model*. The mapping $h(\cdot) : \phi_m^t \mapsto u_h^t$ defines how the measured interface level actions are translated into control signals for the robot platform. This mapping is typically fixed and dictated by both the mechanics of the interface and the robot device control space. In selecting the interface-level action ϕ_i^t that achieves a^t, the human makes use of an inverse controller $f(\cdot) : a^t \mapsto \phi_i^t$ which is an internal model they learn [22]. The mapping $f(\cdot)$ represents the human's understanding of how the interface output maps to the robot's inverse kinematics and dynamics. It is often incorrectly assumed that $f(\cdot)$ is the inverse of the mapping $h(\cdot)$; which as discussed above, is fixed and dictated by the mechanics of the interface. This amounts to falsely implying a perfect understanding of the robot platform and interface on the part of the human. The complexity of a robot platform and intuitiveness of its motions, all impact the efficacy of the learned mapping $f(\cdot)$. Even when an appropriate mapping is learned, faulty memory retrieval due to time pressure, mental fatigue, attention deficit, or mental rotation is an additional potential confound [31, 15, 24, 29].

Modeling $f(\cdot)$ and $g(\cdot)$ is important because the user desires ϕ_i^t to cause the transitions in the world state, whereas in reality ϕ_m^t causes the transition, potentially into undesirable world states. Moreover, a-priori explicit modeling of $f(\cdot)$ and $g(\cdot)$ provides additional sources of context to use for robotic assistance during teleoperation and shared control HRI without any additional real-time on-board sensors.

III. Interface-Aware and Task Agnostic Assistance

Figure 2 shows our contributed interface-aware assistance pipeline, where assistance happens earlier than is typical in shared-control systems. The human-robot assistance system becomes interface-aware by using the inferred signal $\phi_{inferred}$ instead of the measured human signal ϕ_m for direct teleoperation, planning, or shared-control. ϵ_h is the sensorimotor noise in the human input, ϵ_i is the noise pattern resulting from the interfacing system, and ϵ_a and ϵ_s are actuation and sensor measurement noise, respectively.

We validated our framework both in simulation and in a user study with 10 control participants. The experimental results showed that our interface-aware pipeline significantly reduced task completion time, cognitive workload, and user frustration. The assistance system was shown to be most useful for people who have a good understanding of the control mapping but have difficulties providing their intended input [8]. Subsequently, I investigated a task-agnostic evolution to the interface-aware algorithm in a manipulation task that includes features present in many Activities of Daily Living [6]. I was motivated by the hypothesis that, by leveraging known models of the user's stochastic interface interaction and internal mapping, which are not specific to a particular task, providing assistance at the interface-level actions, even without a known policy $p(\mathbf{a}|\mathbf{x})$ for the given state x, could enhance overall task performance. While having knowledge of a policy can further enhance interface-aware assistance, it is not a prerequisite for providing assistance. In a case study with Spinal Cord Injured participants controlling a 7DOF Kinova Jaco robotic arm with a 1D sip/puff interface, we demonstrated the ability to leverage $f(\cdot)$ and $g(\cdot)$ to provide safety-aware and task-agnostic inference and corrections at the interface-signal level, eliminating the need for complex planners. Our method offers the advantage of not requiring intense computations for assistance, unlike previous approaches [2].

IV. Future Research Directions

For future work, I am motivated by a desire to further generalize my algorithmic interface-aware inference work, perform rigorous evaluations with end-user subject studies, and contribute interface-aware policy learning algorithms. I will also explore efficient methods for modeling $f(\cdot)$ and $g(\cdot)$.

One of the simplifying assumptions of our original framework was that both the subject's internal mapping $f(\cdot)$ and the stochastic deviations of human input $g(\cdot)$ remain stationary; however, they are in fact non-static. The human's understanding of the robot and interface evolves the more they interact, as does the human's ability to operate the robot and the interface—hopefully due to successful rehabilitation, but also possibly due to a degenerative disease [33, 12]. My prior work has shown that in a simulated ablation study, different levels of inaccuracy in the noise models can affect the prediction accuracy of the interface-aware inference and by extension the utility of the interface-aware assistance. I plan to use active learning strategies to update the model parameters by tracking the variability in the difference between ϕ_m and $\phi_{inferred}$ as well as tracking inference uncertainty over varying interaction period lengths to design an interface-aware shared control framework that is adaptive with respect to time. I aim to conduct extensive end-user studies to evaluate how interface-awareness affects user perception of autonomy assistance compared to an interface-agnostic algorithm in control sharing.

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