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# Interface Operation and Implications for Shared-Control Assistive Robots

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***Abstract*— Shared-control for assistive devices can increase the independence of individuals with motor impairments. However, each person is unique in their level of injury and physical constraints. Consequently, a plethora of interfaces are used to control the assistive device, depending on the individual. In order to be effective, the shared-autonomy assistance should be aware of the usage characteristics of the interface and adjust to varying performance characteristics of the person. To that end, we conduct a 23 person (9 spinal cord injured and 14 uninjured) study using three commercial interfaces used to operate powered wheelchairs, and establish performance measures to characterize interface usage. The analyses of our performance measures unveil key aspects of the interface operation that can inform features of a customizable and interface-aware control sharing framework.**

## I. Introduction

Assistive devices such as powered wheelchairs are designed to provide independence to people living with various motor impairments. When a person with a particular impairment is fitted for an assistive device such as a powered wheelchair, the seating clinician will take the unique abilities and physical constraints of the individual into account. This is particularly true when choosing the control interface the person will use to operate their assistive device. The chosen interface can affect how a person operates their device and what operational challenges they may face. For example, a person using a head array interface can experience a limited visual field while maneuvering as a result of trying to avoid head motions that lead to an unwanted control command. They also may experience elevated levels of fatigue in their neck and torso during lengthy maneuvers and trips due to the repetitive activation of these muscles.

Commercially available interfaces employed for controlling assistive devices can be either proportional—where the user has control over both *which* control signal to generate and its *magnitude*—or non-proportional—where the user only has control over the selection of *which* signal to turn on or off. Common interfaces can be one, two, or three dimensional. For example, a person with high cervical-level spinal cord injury who does not have upper-limb motor function and uses a powered wheelchair may be fitted with a sip/puff device. The powered wheelchair operates in $SE(2)$ configuration space, whereas through a sip/puff interface, the human can only provide a limited subset of commands $[\mathbf{u}_t, \mathbf{u}_r] \in SE(2)$ at a time; either $\mathbf{u}_t \in \mathcal{R}^1$ (translation) or $\mathbf{u}_r \in \mathcal{S}^1$ (rotation). This can make the control of the powered wheelchair more challenging as the human will need to now *switch* between the different subsets of the control space in order to fully maneuver the wheelchair.

Robotics autonomy can help mitigate the burden of control mode switching as well as other challenges that exist in operating an assistive device. When formulating *assistive autonomy*, however, it is important to complement the human's residual abilities rather than supersede them to ensure operator satisfaction, empowerment, and acceptance [1], [2]. The concept of *shared-control* fits neatly within this domain. Considerable research has gone into the design of different aspects of shared-control that can affect joint human-robot performance. These aspects, among others, include features in a shared-control paradigm such as adaptation and personalization of assistance [3], situation- and context-awareness [1], intent inference [4], implicit or explicit cues for when autonomy should step in and how to arbitrate between autonomy and human commands [5].

When designing *shared-control for assistive robotics*, an important observation is that users who are most severely impaired (and therefore can benefit the most from a shared-control paradigm) often have their input filtered through a low-dimension and low-information interface. Custom interfaces, such as body machine interfaces (BMI) [6] have been designed to make assistive devices accessible to those with severe impairments who cannot operate typical commercial interfaces. These devices are heavily researched and, therefore, often characterized. This characterization has shown to improve the design of customized control sharing methods [7]. Unfortunately, this research has not extended to common interfaces available outside of research, where a large population could benefit from this type of work. Reasons for this gap may be a lack of a generic testing framework and performance measures for evaluating wheelchair interface operation.

To fill this gap, we designed command-following and trajectory-following tasks to experimentally evaluate interface usage characteristics of end-users in a controlled setting. Our contribution is five-fold:

1) We define measures for evaluating interface usage.
2) We quantitatively compare usage characteristics across three common powered wheelchair interfaces, by persons with and without spinal cord injury.
3) We demonstrate that these measures correlate and can predict usage characteristics.
4) We present insights that inform decisions for formulating features of shared-control.

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5) We contribute an open source software package for evaluating interface operation performance.

We first cover a brief background on relevant literature in Section II. We then provide a detailed description of our study design in Section III followed by our performance measures and the results of our experimental study in Sections IV and V. A discussion of these results and the implications for the design of adaptable autonomy is provided in Section VI. We conclude with our proposal for future work in Section VII.

## II. Background

Shared-control offers many benefits to human-robot teams by leveraging the advantages of both robotics autonomy and humans. However, the interface through which the human and robot interact can affect team performance. Thus, it may be useful to consider properties of the interface as parameters that modulate the joint performance of a shared-control strategy. To that end, our work draws from two categories of research: (1) interface usage characterization and (2) shared-control. We also discuss literature on interface-aware shared-control.

### A. Interface Characterization

Prior work uses video games to understand an interface's influence on human-robot team performance [8]. The authors classify interfaces based on their inputs and outputs and use the information to create a framework for systematically evaluating interfaces in the human robot interaction (HRI) domain; however, this framework does not provide sufficient information to inform an adaptable autonomy algorithm. In the domain of assistive technology, clinicians are surveyed about the usefulness and adequacy of powered wheelchair control interfaces for their patients [9]. Their results provide subjective evidence for a need to integrate robot autonomy into conventional powered wheelchairs. However, their results do not provide quantitative information on how interfaces affect powered wheelchair usage which could be exploited by assistive autonomy. Novel interface technologies have been developed for those with severe motor impairments, including an isometric joystick [10]. The authors compared task completion time and accuracy of the novel interface against a conventional joystick within a control population but not an end-user population. In another work, the authors introduce a novel BMI interface and compare user accuracy and performance between the target spinal cord injured (SCI) group and an uninjured control group, but do not compare the performance against any conventional interfaces [6].

### B. Shared-Control

Shared-control distributes control between the human and autonomous partner to improve overall team performance and safety [11]. However, the specific shared-control paradigm is often domain and application specific [12]. Some work aims at general principles for designing the correct paradigm or level of autonomy, but does not adapt to features of the human-robot team [5].

Designing autonomous controllers that adjusts to the user is common in social robotics [13]. In this domain, adaptability is particularly useful since each person exhibits unique emotional characteristics. The field of shared-control, however, contains less work in adaptability, despite the fact that users tend to prefer different shared-control paradigms [14]. Some work uses knowledge of the interface to improve aspects of the autonomy, such as path planning [15], which is an integral aspect of autonomous assistance, but does not alter the interaction mechanism of the shared-control paradigm.

Adaptable shared-control paradigms show promise in their ability to improve human-robot team performance and safety. Some work utilize the user's control behavior to vary parameters of the shared-control paradigm [11]. For instance, distance to obstacles is a common metric for allocating control between the human and robot [16], as is notions of trust [17] or the discretion of the user [18]. Other work uses a combination of smoothness, directness and safety to define user efficiency and skill for weighting the user's input [3].

### C. Interface-Aware Shared-Control

Prior work proposes an adaptable autonomy framework that takes into account interface and time-delay [19]. Another work develops sliding autonomy where the assistance specifically incorporates knowledge of interfaces [20]. In all of these, the hardware characteristics are considered, but not the usage characteristics which may be used as parameters for an adaptive shared-autonomy strategy.

More recently, a probabilistic control-blending framework for wheelchair control is proposed and the performance is compared against a baseline linear blending strategy using three common wheelchair interfaces in a population of controls [7]. They use a model of the interface velocities to improve inference of the user's intended velocity. In a similar vein, a probabilistic framework is proposed for discerning the most probable intended goal from noisy joystick input when driving similar paths [21].

Previous work utilizes knowledge of the interface and user population as a stimulus for designing sufficient autonomy and control sharing. However, there is a gap in research where a shared-control paradigm can adapt to various features of interface usage and expertise. In this paper, we begin to fill this gap with an experimental interface characterization methodology to inform a customizable autonomy algorithm.

## III. Experimental Methods

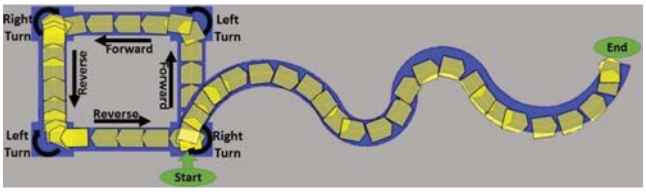
This section provides a detailed description of the research design and procedures used in the experiment.

### A. Hardware

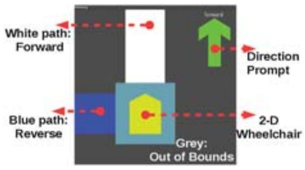
The study was conducted using three interfaces and two computer game tasks*. The three interfaces for this study

*Source code: https://github.com/argallab/interface_assessments
Game engine: godotengine.org

Fig. 1: Control interfaces used in this study. *From left to right:* 3-axis joystick, head array system, sip/puff switch.




(a)

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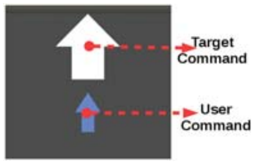



(c)

Fig. 2: Study tasks. (a) The square and curve path portions of the trajectory following task. (b) Trajectory following task. (c) Command following task.

(Fig. 1) were particularly selected since they are the most common types of interfaces employed by SCI users of powered wheelchairs [9]. The selection used in this study were (1) an ASL 533 Compact joystick (ASL, TX, USA), (2) 105 electronic head array system (ASL, TX, USA), and (3) sip/puff switch (Origin Instruments, TX, USA), which were two dimensional proportional, two dimensional non-proportional, and one dimensional non-proportional, respectively. The range for all three interfaces were normalized to be between -1 and 1.

### *B. Participants*

The study consisted of 23 participants: 9 with spinal cord injury (41.6 $\pm$ 13.9 years, levels C3-C6, complete and incomplete) and 14 uninjured (31.6 $\pm$ 9.1 years). The experiment was approved by the Northwestern University Institutional Review Board (STU00207312) and informed consent was obtained from all subjects.

### *C. Tasks*

The experiment consisted of a command following and trajectory following task. The tasks were designed in a simulated environment so that uncertainties from real world dynamics did not corrupt the performance measures.

*1) Command Following:* The command following task was designed to uncover a subject's ability to respond to a visual command stimulus in terms of accuracy of response, response time, and how steadily they issued a specific command (Fig. 2c). In this task, a white arrow—the command prompt $\hat{\mathbf{u}}$—appeared on the screen pointing in different directions in a randomly balanced sequence. The directions included the four cardinal and four inter-cardinal angles. The subject was instructed to issue a command for the same direction as soon as they saw the command prompt and to continue issuing the command uninterrupted for the duration of the prompt ($T$). The blue arrow was the feedback of the actual command issued by the user. In our implementation of the command following analyses, we evaluate only one dimension of $\hat{\mathbf{u}}$—the heading—and ignore magnitudes since the magnitudes are discrete for the head array and sip/puff interfaces and $\hat{\mathbf{u}}$ is a unit vector.

*2) Trajectory Following:* The trajectory following task was designed to evaluate how well users were able to follow a predefined path (Fig. 2a). Trajectory following can be thought of as the inherent ability to generate commands to follow way points while using visual feedback correction. The ability to follow a trajectory where there was a single known goal—without interference from the wheelchair dynamics and external sources of noise—aimed to uncover how a person's intended goal may differ from the signal they output through the interface. The task consisted of controlling the motion of a 2-D simulated wheelchair (the yellow pentagon shape in Figure 2b) along a predefined path. The trajectory began with a square path, followed by a curved path. Only the path in the immediate vicinity of the wheelchair was visible at any given moment (as in Fig. 2b). The participants were instructed to stay within the bounds of the clearly marked path and to avoid going into the out-of-bounds grey area. The square and curved paths were designed such that they contained the basic commands covered by all three interfaces. The square path consisted of two forward, two backward, two 90° left turn and two 90° right turn trajectories. The curved path consisted of two long arcs and two small arcs.

### *D. Protocol*

Each of the two tasks were performed with a single interface per study session. The order of the interfaces was randomly balanced across participants. Each uninjured subject participated in all three sessions. Not every SCI subject was able to control all three interfaces. Four SCI participants were not able to use the joystick, due to no upper-limb control, and one participant did not have neck support and was not able to use the head array switch. In each session, the subject first performed a standardized training phase (using a clinical standard, the Wheelchair Skills Test[†]) to become accustomed to the use of that session's interface. Then they performed the trajectory and command following tasks during the experiment phase.

### *E. Experimental Design*

We used a 2x3 mixed design, where the interface was a *within-group* factor and whether or not the participant was uninjured or had a spinal-cord injury was a *between-groups* factor. Novelty and expertise was also a factor for the SCI group since they were experts with one interface—the

[†]https://wheelchairskillsprogram.ca/en/

interface they use when controlling their personal powered wheelchair. Therefore, we did an additional analysis between expert interfaces (that the person used daily and was accustomed to) and novice interfaces (that they did not use and were unaccustomed to). We did this extra analysis only for the SCI group, as all of the interfaces were novel for the uninjured group.

## IV. Performance Measures

Each task is designed to extract specific information about how people interact with different interfaces. Thus, we use different metrics to evaluate the performance for each task.

### A. *Command Following*

For the command following measures, $M$ is the total number of prompted commands, $\hat{\mathbf{u}}^m$ is the $m^{th}$ prompted command which occurs at time $t^m$ and has duration $T^m$, $\mathbf{u}_h^t$ is the human command at time t, and $\epsilon$ is the tolerance which is set to $\pm 10°$ of the target command.

Average response time (**tR**): The average of all the time differences between when a command prompt is given to the first instance when the subject is able to issue the correct command (Fig. 3, blue line).

$$tR = \frac{1}{M}\sum_{m=1}^{M}[t_{\mathbf{u}_h,\epsilon} - t^m]$$

$$\text{where} \quad t_{\mathbf{u}_h,\epsilon} = min\{t \in [t^m, T^m] \;\big|\; |\mathbf{u}_h^t - \hat{\mathbf{u}}^m|^{\S} < \epsilon\}$$

Here $t_{\mathbf{u}_h,\epsilon}$ is the time of the first within-tolerance human command.

Successful response percent (**%R**): The percentage of command prompts to which the user is able to successfully respond.

$$\%R = \frac{1}{M}\sum_{m=1}^{M} I^m$$

$$I^m = \begin{cases} 1, & \text{if } \exists \; t \in [t^m, T^m] \;\; s.t. |\mathbf{u}_h^t - \hat{\mathbf{u}}^m|^{\S} < \epsilon \\ 0, & \text{otherwise.} \end{cases}$$

Here, $I^m$ is a tracking index.

Average settling time (**tS**): The time from when a command prompt is given to when the subject is able to steadily issue within $\epsilon$ of the prompted command (Fig. 3, green line).

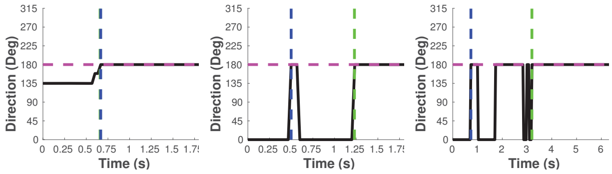
$$tS = \frac{1}{M}\sum_{m=1}^{M}[t_{\mathbf{u}_h,\epsilon_s} - t^m]$$

where

$$t_{\mathbf{u}_h,\epsilon_s} = min\{t \in [t^m, T^m] \;\big|\; |\mathbf{u}_h^k - \hat{\mathbf{u}}^m|^{\S} < \epsilon \,\forall k \in [t, T^m]\}$$

Here $t_{\mathbf{u}_h,\epsilon_s}$ is the time at which the human command settled to within-tolerance.

[§]When the dimensionality of $\hat{\mathbf{u}}$ is greater than 1, the $arctan(\mathbf{u}_h^t, \hat{\mathbf{u}}^m)$ operator is used to compute this difference.




(a) (b) (c)

Fig. 3: Example user responses (black line) to a target command with heading $\theta = 180°$ (magenta dashed line). tR (blue line) and tS (green line) are annotated for the (a) joystick (here, tR and tS are superimposed), (b) head array and (c) sip/puff interfaces.

Settling percent (**%S**): The percentage of trials for which the user is able to settle to within $\epsilon$ of the prompted command.

$$\%S = \frac{1}{M}\sum_{m=1}^{M} I^m$$

$$I^m = \begin{cases} 1, & \text{if } \exists \; t_{\mathbf{u}_h,\epsilon_s} \;\; s.t.(|\mathbf{u}_h^t - \hat{\mathbf{u}}^m|^{\S} < \epsilon \;\forall\; t \geq t_{\mathbf{u}_h,\epsilon_s}) \\ 0, & \text{otherwise.} \end{cases}$$

Here $I^m$ is a tracking index.

m2

Average difference between settling and response times (**dSR**): The time difference between the initial correct response to the time the response settled to within $\epsilon$.

$$dSR = tS - tR$$

A larger dSR means that there is a discrepancy between when a person can issue a correct response and when they can continue to issue a steady response, which is indicative of a noisy transient period of user input.

### B. *Trajectory Following*

For the trajectory following measures, $N$ is the number of samples in the trajectory and $\epsilon$ is the allowable tolerance which we set to 5% of the 2-D wheelchair surface area.

Number of times breaking barrier (**nBB**): The number of times the 2-D wheelchair breaks the path barrier during task execution and enters the out-of-bounds gray area.

$$nBB = \sum_{n=1}^{N} I^n$$

$$\text{where} \quad I^n = \begin{cases} 1, & \text{if } A_{t^{n-1}}^{ob} \leq \epsilon \text{ and } A_{t^n}^{ob} > \epsilon. \\ 0, & \text{otherwise.} \end{cases}$$

Here $A_{t^n}^{ob}$ is the area of the 2-D wheelchair footprint out of bounds at time sample $t^n$ and $I^n$ is a tracking index.

Percent time out of bounds (**tOB**): The percentage of total task execution time when the 2-D wheelchair is more than the allowable tolerance outside of the path barriers.

$$tOB = \frac{\sum_{n=1}^{N} t_i^n - t_o^n}{t^N - t^0}$$

Here $t_o^n$ and $t_i^n$ are the $n^{th}$ time the 2-D wheelchair went outside and came back into the barrier, respectively.

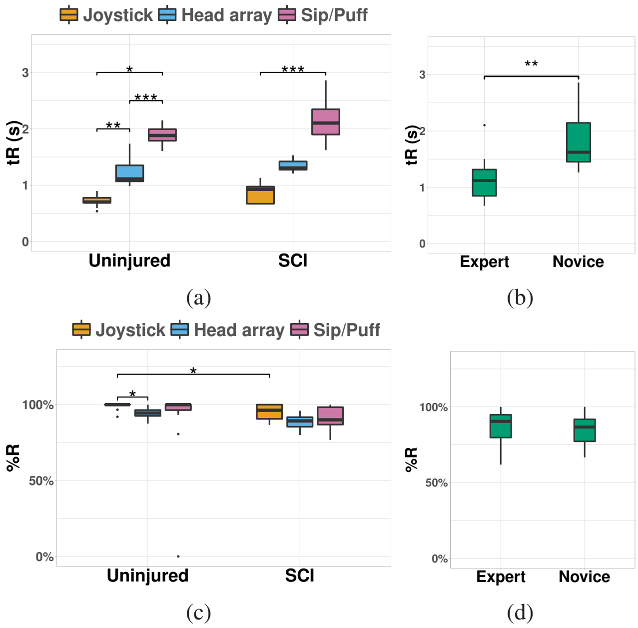



Fig. 4: Response times (tR) per (a) interface for the uninjured and SCI groups and (b) expertise for the SCI group. Percent of command prompts that were correctly followed (%R) per (c) interface for the uninjured and SCI groups and (d) expertise for the SCI group.

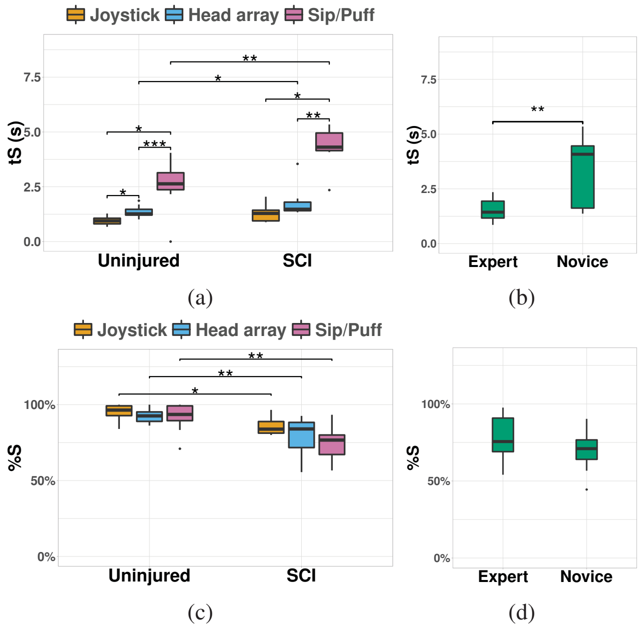



Fig. 5: Settling times (tS) per (a) interface for the uninjured and SCI groups and (b) expertise for the SCI groups. Percent of times the user settled within $\pm 10°$ of the prompted command (%S) per (c) interface for the uninjured and SCI groups and (d) expertise for the SCI group.

## V. Results

First we present the statistical analyses for each of the performance measures described in Sections IV-B and IV-A, and follow with prediction analysis as it pertains to shared-control. We analyze group performances for each of the tasks based on interface type. We use the non-parametric Kruskal-Wallis test to establish significance. We perform multiple post-hoc pairwise comparisons with Bonferroni correction ($\alpha = 0.05$) to find the strength of significance. For all figures, the notation $*$ implies a p-value of $p < 0.05$, $**$ implies $p < 0.01$, and $***$ implies $p < 0.001$.

### A. *Command Following Performance*

To analyze the performance during the command following task, we first look at the initial correct response to the command prompt (tR, %R), and then we look at the time for the user command to reach and stay within $\pm 10°$ of the prompted command direction (tS, %S).

Figure 4 shows the tR and %R statistics. When we look at tR, we see significant differences across all three interfaces within the uninjured group, and between the joystick and sip/puff interface within the SCI group (Fig. 4a). Furthermore, there is significant difference in tR when comparing novice and expert interface performance within the SCI group (Fig. 4b). However, we see that the SCI group performed similarly across interfaces in terms of %R (Fig. 4c-4d), meaning that the ability to (eventually) reach the target command is not significantly different across interfaces, but the time to reach the target command is. When comparing the head array device, the ability to reach the target command

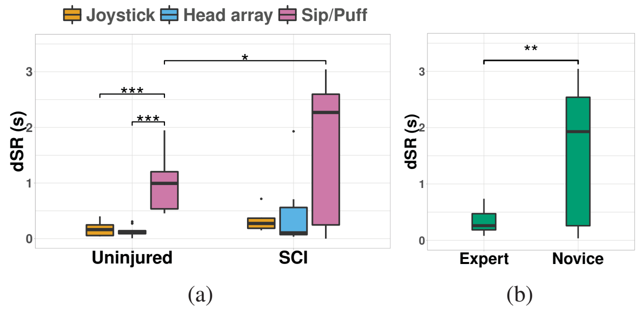
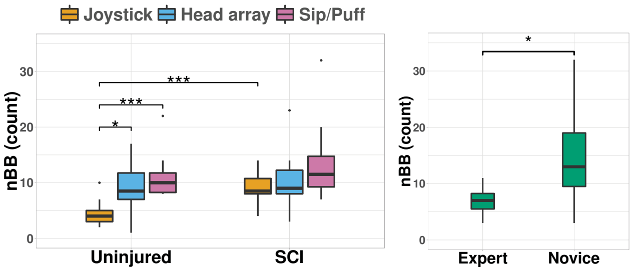



Fig. 6: Difference between settling and response time per (a) interface for both groups and (b) expertise for the SCI group.

is significantly lower for the SCI group than the uninjured group, but when they do reach the target command, response times are similar.

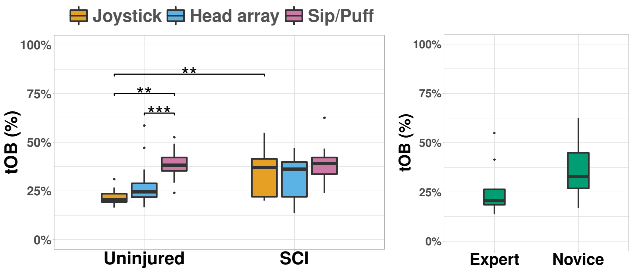
Figure 5 shows the tS and %S statistics. There are significant differences in both tS and %S between the uninjured and SCI group when comparing the head array and sip/puff device. With those two interfaces, the SCI group responds fewer percent of the time, and when they do settle to a steady and accurate command, the settling times are longer. When comparing tS, there are also significant differences seen across all three interfaces within both the uninjured group and the SCI group (Fig. 5a). Additionally, there is also significant differences in tS when comparing novice and expert interfaces within the SCI group.

Figure 6 shows the dSR statistics. We observe significant differences between sip/puff and the other two interfaces. There is also significant difference when comparing novice




(a) (b)

Fig. 7: Number of times participants broke the path barrier (nBB) per (a) interface for the uninjured and SCI groups and (b) expertise for the SCI group.




(a) (b)

Fig. 8: Percent of task time when participants were not fully within the marked path (tOB) per (a) interface for the uninjured and SCI groups and (b) expertise for the SCI group.

and expert interfaces within the SCI group.

### B. Trajectory Following Performance

We analyze the trajectory following group performances by looking at (1) the total number of times that participants broke the path barrier nBB (Fig. 7) and (2) the percent of total task time where the participants were not fully within the path bounds tOB (Fig. 8).

Comparing within the SCI group, we see significance when looking at the nBB measure across novice and expert interface usage (Fig. 7b). It is worthwhile to note that all SCI joystick data is coming from expert users, because every SCI person who is able to use the joystick also uses a joystick interface for their personal wheelchair. Despite their expertise, we see significantly poorer performance in both trajectory following metrics in comparison to the uninjured group when using the joystick interface. We also see significant difference in both nBB and tOB performance measures across all three interfaces within the uninjured group, with the best performance being achieved with the joystick and the worst performance with the sip/puff interface in both cases.

### C. Interface and Intent Prediction Results

We perform two additional analyses to demonstrate (1) that it is possible to use our proposed measures for interface-awareness and (2) the importance of interface-awareness in shared-control.

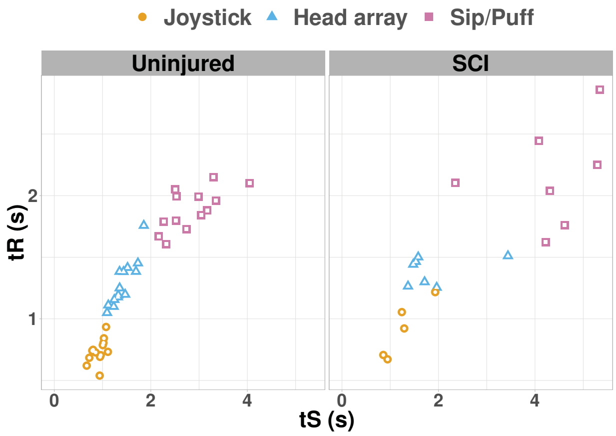



Fig. 9: Response times (tR) versus settling times (tS) for (right) uninjured and (left) SCI groups.

Given the results from the %R, tR, %S, and tS statistics, we expect that the interfaces can be grouped using these measures. In Figure 9 we plot tR against tS. We see that the interfaces fall into distinct clusters with different distributions. With a combination of both uninjured and SCI group data, we are able to fit a second order polynomial regression model to the data, with $R^2 = 0.96$ and $RMSE = 0.34$. We are also able to classify the interfaces with %96 accuracy using a k-nearest neighbors model (k=10) with 5-fold cross validation. These results demonstrate not only the ability to accurately classify the interfaces with tS and tR, but also the capability to predict the tS response given tR.

Furthermore, we use the intent inference method implemented on our smart wheelchair platform to predict the goal given each sampled user input [14], which is possible because we designed the trajectory following task such that there is no ambiguity regarding the intended goal at any given time. There is a significant difference in the percent of wrong predictions between interfaces within the uninjured group (Fig. 10) and the same trend appears for the SCI group, which demonstrates that using the same intent inference strategy results in significantly different prediction errors depending on the interface—evidence for the importance of interface-awareness in shared-control.

## VI. Implications for Shared-Control

We now discuss how the results of Section V can inform decisions that should be made when formulating control sharing for assistive devices for people with SCI. Particularly, we are interested in (a) how we interpret the user input command, (b) with the intention of inferring a local goal, and (c) deciding when and if autonomy steps in based on the user input command.

### A. User Signal Interpretation

Putting together the results from Figures 4 and 5, we see that the SCI group is able to give an initial response to the prompted command similar to the uninjured group, but they take longer to respond and they are not able to hold the response as steadily as the uninjured group. This is similar

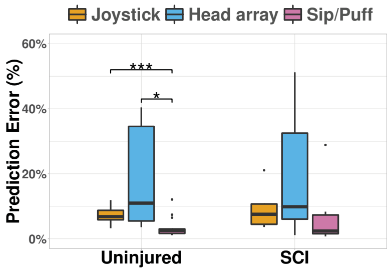



Fig. 10: Percent prediction error for forward projected goal.

to a noisy signal with lag which suggests that instead of using the raw user command signal, we need to filter the SCI command in order to receive a clearer user input. This may seem counter intuitive at first because, with limited interfaces such as the sip/puff, the teleoperation signal is already filtered through the control interface. From Figure 9 we also see that the interfaces fall into distinct clusters when looking at the correlation between settling and response time, which indicates that the filtering parameters will differ based on the characteristics of the interfaces.

When considering tR and tS, the head array and sip/puff both have longer values than the joystick, which means there is a delay in the signal issued from the user and what prompted them to issue that signal. Furthermore, with the sip/puff device, dSR is large in comparison to either the joystick or head array interfaces. This implies that not only is there a delay in the signal, but the signal contains more noise and vacillations.

Differences in performance measures between novice and expert interfaces within the SCI group indicate that user skill and expertise need to be accounted for in addition to the interface characteristics. Furthermore, the differences between the uninjured and SCI group in %R, nBB, and tOB for the joystick interface, tS for the head array and sip/puff interfaces, and %S for all three interfaces provides evidence for why we need to treat the SCI signals differently and we cannot rely on algorithms designed solely on uninjured data.

### B. Intent Inference

In shared-control, typically a fully autonomous robot command $\mathbf{u}_r(t)$ is generated and then arbitrated between with the human command $\mathbf{u}_h(t)$. In order to generate $\mathbf{u}_r(t)$ in a way that assists the human, we need a notion of the human's intentions. In some cases, there is a global desired goal $\mathbf{g}_d$ (e.g. navigating through a doorway, picking up a cup), but often there is not, and the robot must make a best estimate of the local position or low-level velocity goal $\mathbf{g}_p$ that the human is trying to achieve. Different estimation methods have been proposed in literature, and one common practical method for finding $\mathbf{g}_p$ in mobile robotics is to forward project the pose $\mathbf{X}_t$ into the future for some time $\Delta t$ given the human command $\mathbf{u}_h(t)$ (either the current command or a filtered window of previous commands [22]). That is, $\mathbf{g}_p = \mathbf{X}_t + \mathbf{u}_h(t)\Delta t$.

However, as we have seen from our results in Section V, the current $\mathbf{u}_h(t)$ may be delayed and/or noisy. As a result, forward projecting the current $\mathbf{u}_h(t)$ may result in inferring a wrong or invalid $\mathbf{g}_p$, which in turn can lead to the autonomy providing incorrect assistance. Unwanted or incorrect assistance can lead to the human user's frustration. The results of our experiments thus imply that the autonomy should wait for the user signal to settle before reasoning about what the goal should be. This may make autonomy less responsive but at the benefit of hopefully being more correct and reduced conflict between the human and autonomy.

Our results also show that the amount of delay in the human command can differ between interfaces. As such, when designing shared-control paradigms that explicitly reason about this delay, the paradigm should adapt the delay window based on the interface, either deterministically or probabilistically from the distributions we have found experimentally. Furthermore, combining $\mathbf{u}_h(t)$ with sensor data $\mathbf{z}(t)$—such as distance to obstacles or identifiable landmarks—can yield more information about a human's intent. However, if there is a delay in $\mathbf{u}_h(t)$, the robot autonomy should reason carefully about the time-synchronization between user signal and sensor signal.

The results of Figure 10 demonstrate that when the autonomy does not take into account the interface—more specifically, the operation characteristics of the interface—it can make erroneous predictions. These errors vary significantly based on the individual usage characteristics of the interface.

### C. Autonomy Cue

There are various ways to formulate the shared-control strategy in how it arbitrates between $\mathbf{u}_h(t)$ and $\mathbf{u}_r(t)$, given $\mathbf{g}_d$ and/or other environmental features such as obstacles. One common approach in the literature is linear blending, where a blending factor $\alpha$ is used to weight how much each command contributes to the final output $\beta(\mathbf{u}_h^t, \mathbf{u}_r^t) = (1-\alpha)\cdot\mathbf{u}_h^t + \alpha\mathbf{u}_r^t$ [16]. Again, here we see a potential issue with time synchronization, if the human command $\mathbf{u}_h(t)$ is received with a delay and is in response to an earlier world state, while the autonomy command $\mathbf{u}_r(t)$ is formulated in response to the current world state time $t$.

There is a recent trend toward automatically adjusting or scaling the level of autonomy using implicit cues [5]. One implicit cue that has been used in several implementations as a trigger for when autonomy should step in is when a human is giving an incorrect or dangerous signal. As our results show, however, this may be a transient or temporary settling signal. If the autonomy does not account for the settling time, it may unnecessarily take control away from the user. For an SCI person who is adept at driving a powered wheelchair and can issue a correct signal eventually, the autonomy and intent inference would make more frequent mistakes, increasing the disagreement between human and autonomy which can lead to the dissatisfaction of the human and an unwillingness to adopt the autonomy.

### D. Guidelines

Using the above insights, we provide guidelines for formulating control sharing in the domain of assistive devices for people with SCI who use varying interfaces.

*1) How do we interpret the user input command?*

- Based on the interface and injury, anticipate signal delay or transient noise (or both).
- If filtering out transient noise, the filter properties should be interface-aware.

*2) What is the user's intended goal?*

- Intent inference should be aware of and anticipate the delays or noise in human signal that is filtered through an interface.
- Tools that rely on a comparison of human and autonomy commands should consider a prior human command when comparing it to the current autonomy command, or wait until the user signal settles.

*2) When should autonomy step in?*

- Shared-control should reason about which human signals to act on or respond to (trigger).
- Uncertainty and error can be mitigated by interface-awareness, which in turn can improve agreement between the human and autonomy.

## VII. Conclusions and Future Work

In this work, we highlighted the importance of interface awareness for adaptive shared-autonomy in the domain of assistive devices for people with motor impairments who often use limited interfaces. Our experimental data suggested it is important to consider the usage characteristics of an interface when reasoning about user input for the purposes of intent inference, goal projection, and control sharing. Based on the statistical analyses of our results, we provided guidelines to consider when formulating shared-control that is interface aware. Our future work will implement these findings into a shared-control framework and evaluate our approach against standard techniques.

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