User Preference in Shared-Control of a Robotic Wheelchair: a Longitudinal Study

Mahdieh Nejati Javaremi*
Northwestern University
Chicago, Illinois
m.nejati@u.northwestern.edu

Michael S. Young*
Northwestern University
Chicago, Illinois
mikesyoung@u.northwestern.edu

Deepak Gopinath*
Northwestern University
Chicago, Illinois
deepakgopinath@u.northwestern.edu

Brenna D. Argall†
Northwestern University
Chicago, Illinois
brenna.argall@u.northwestern.edu

ABSTRACT

Assistive robotic machines, such as powered wheelchairs and robotic arms can provide improved levels of mobility, independence for longer periods of time, and assistance to people with severe motor impairments that are otherwise unable to use assistive devices. However, motor-impaired users of these machines prefer to retain as much control authority as possible and tend not to prefer fully autonomous assistive systems [6]. However, there are many ways in which control can be shared and there is no one-size-fits-all solution [5]. In this preliminary study we analyze what features of control sharing algorithms influence user preference. Our results show that the most important features which affect user preference change over two sessions. Further, the trends differ between uninjured and spinal-cord injured groups. These results will be used for the design of shared-control paradigms which are useful over long-term use.

ACM Reference format:

Mahdieh Nejati Javaremi, Michael S. Young[1], Deepak Gopinath[1], and Brenna D. Argall. 2018. User Preference in Shared-Control of a Robotic Wheelchair: a Longitudinal Study. In *Proceedings of Human Robot Interaction Workshop on Longitudinal Human-Robot Teaming, Chicago, Illinois USA, March 2018 (HRI),* 4 pages.

DOI: 10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Assistive and rehabilitation machines such as powered wheelchairs can help to reduce a motor-impaired person's dependence on caretakers, increase the person's ability to perform activities of daily living, and positively impact the way they interact with society [11]. To operate an assistive machine, the human directly controls the motion via a control interface; commonly a joystick or switch-based headarray. These control interfaces are limited in bandwidth and dimensionality, and depending on the task can require significant cognitive effort and steering precision on the user's part.

The introduction of shared-control turn these assistive machines into a "smart" robot. The system takes partial responsibility of task execution, alleviating the cognitive and physical burden on the user. Shared-control paradigms come in different flavors, depending on the specification of the arbitration between the user and the robot control command [1, 10].

One approach is a hierarchical shared-control scheme, where the higher-level aspects of a task, such as goal selection, are performed by the user through a communication modality—such as a laser pointer or speech interfaces [8]—and the low-level aspects such as path-planning and obstacle avoidance are delegated to the robot. A second method is to have the human and the robot operate in the same control space. For example, the user control command and the robot autonomy might be mapped to the heading and forward velocity of a smart wheelchair and the final control command that gets executed will be a blended version of the human and the robot control command. The blending parameter determines the level of assistance. A third approach to sharing control is to have a set of predefined assistance behaviors for different kinds of scenarios. Some examples for smart wheelchairs include doorway-navigation [3], obstacle avoidance and safe stopping [9]. These predefined behaviors can possibly differ from each other in the way user signal is incorporated or in the way the autonomy decides to assist the user (either by blending or by switching) thereby resulting in different user experiences.

The success of assistive technologies relies heavily on how well the user's needs are met, the level of user satisfaction, and how adaptable these solutions are to the changing needs of the users over time. Given the variety of ways in which control can be shared between the human and autonomy, it is clear that the end-user preference should play a significant role in the design aspect of assistive technologies.

Modeling user preference is commonly employed in research outside robotics and many tools have been developed for this purpose. Although these tools can be applied in the domain of assistive robotics, previous research has generally relied on standard statistical techniques [12] or machine learning methods [5, 7].

*Mechanical Engineering, Northwestern University, and the Shirley Ryan AbilityLab, Chicago, IL - USA

†Physical Medicine and Rehabilitation, Electrical and Computer Engineering, and Mechanical Engineering, Northwestern University, and the Shirley Ryan AbilityLab, Chicago, IL - USA

HRI, Chicago, Illinois USA

DOI: 10.1145/nnnnnnn.nnnnnnn

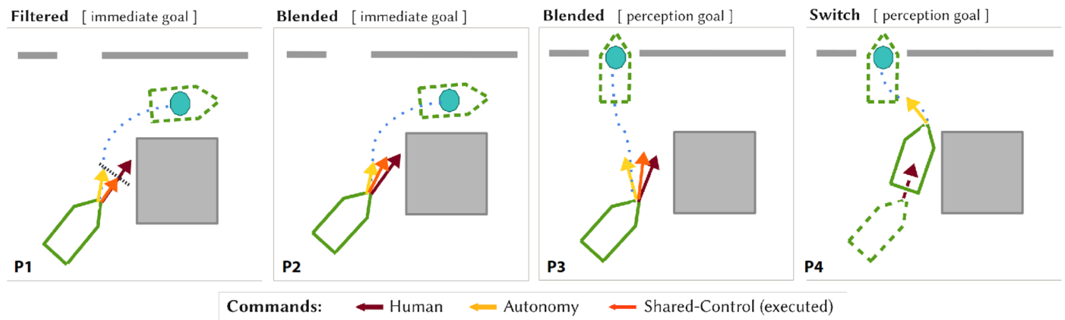

Figure 1: The four different control sharing paradigms. P1: Immediate goal detection with filtered command arbitration. P2: Immediate goal detection with blended command arbitration. P3: Perception goal detection with blended command arbitration. P4: Perception goal detection with switching command arbitration. P0: No autonomy (not shown). The green pentagon is the wheelchair footprint, the blue circle is the goal generated by the autonomy, and the gray shapes are the obstacles/walls.

We apply conjoint analysis to extract attributes of importance to user preference over a set of autonomy paradigms developed for doorway navigation on our smart wheelchair system. In the subsequent sections, we present results from the preliminary study and the insights we gained from them.

2 EXPERIMENTAL DESIGN

In this study we evaluate data collected from a previously conducted two-session experiment which looked at the effect of control paradigms and interfaces on user-preference, effort, and performance [4, 5].

Figure 2: Robotic wheelchair platform with added sensors and computational units.

Hardware, Participants and Tasks: We conducted the study using our powered wheelchair platform retrofitted with an on-board computer and sensors, as seen in Figure 2. The subjects used a proportional two-axis joystick, and a one-dimensional discrete head-array switch to control the powered wheelchair. Our user population included 7 uninjured and 7 Spinal Cord-Injured (SCI) subjects. The task, as illustrated in Figure 3, required subjects to navigate through a doorway from room 1 to a larger room 2, navigate around a large table, and traverse a 2nd door into a 3rd room. The user would then turn around and repeat, totaling four doorway traversals. We refer our readers to [4, 5] for further details of the experimental setup.

Shared-Control Paradigms: For this study, each subject completed the doorway-traversal task for the four different control-sharing paradigms (P1, P2, P3, P4) as illustrated in Figure 1, plus a full teleoperation paradigm (P0). The subjects were unaware of the active paradigm and the order was randomly balanced among subjects. Each control paradigm is generated by a combination of levels from two attributes: (1) **goal detection** and (2) **command blending**. Two different goal detection levels were used: *a) Immediate* - in which the goal is briefly projected in the direction of user's input command, and *b) Perception* - in which an RGBD camera is used for doorway detection. Three different command arbitration levels were used: *a) Filtered* - in which the user's command is limited conditioned on the autonomy, *b) Blended* - in which the autonomy command is linearly blended with the user command, and *c) Switch* - in which the robot takes over control when the user cedes manual control completely.

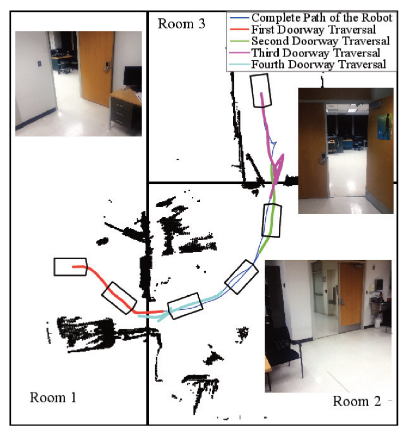

Figure 3: Experimental setup.

Protocol: A week after the first session, subjects were asked to come back and repeat the task for all profiles again (in a different random order) to test for longitudinal effects on user preference.

At the conclusion of each session, the users filled out a survey which required them to choose their least and most preferred paradigm. They also rated the robot on three qualities of **utility**, **contribution** and **trust** on a 7 point Likert scale (1-7).

3 RESULTS

The results of the survey are shown in Tables 1, 2. Qualitative analysis of the data presented in the tables provides insight into how the user preferences changed depending on the day as well as the interface used. The following are some of the salient observations from the data:

Table 1: Most preferred paradigm by user population and trial day.

Interface	Profile	SCI		Uninjured	
		Day 1	Day 2	Day 1	Day 2
Joystick	P0	14.29%	**42.86%**	0.0%	0.0%
	P1	0.0%	14.29%	0.0%	0.0%
	P2	14.29%	14.29%	0.0%	14.29%
	P3	14.29%	0.0%	28.57%	**42.86%**
	P4	**57.14%**	28.57%	**71.43%**	**42.86%**
Headarray	P0	0.0%	0.0%	0.0%	0.0%
	P1	0.0%	0.0%	0.0%	0.0%
	P2	14.29%	0.0%	28.57%	0.0%
	P3	14.29%	28.57%	28.57%	28.57%
	P4	**71.43%**	**71.43%**	**42.86%**	**71.43%**

Table 2: Least preferred paradigm by user population and trial day.

Interface	Profile	SCI		Uninjured	
		Day 1	Day 2	Day 1	Day 2
Joystick	P0	14.29%	14.29%	28.57%	**42.86%**
	P1	**57.14%**	**42.86%**	**57.14%**	**42.86%**
	P2	14.28%	0.0%	14.29%	14.29%
	P3	14.28%	28.57%	0.0%	0.0%
	P4	0.0%	14.29%	0.0%	0.0%
Headarray	P0	14.29%	42.86%	14.29%	42.86%
	P1	**28.57%**	**57.14%**	**57.14%**	**57.14%**
	P2	**28.57%**	0.0%	14.29%	0.0%
	P3	**28.57%**	0.0%	0.0%	0.0%
	P4	0.0%	0.0%	14.29%	0.0%

(1) SCI subjects using the joystick interface predominantly chose P4 as the most-preferred paradigm on day one. However, their preference changed to P1 on day two likely because the subjects became more comfortable with the operation of the wheelchair using joystick and preferred to be in control.

(2) With the exception of SCI subjects on day two, none of the subject groups chose P1 as the most-preferred paradigm. This is probably because unlike other paradigms, P1 is a 'restrictive' form of shared-control and does not actively lead the user towards the goal.

(3) When using the headarray, no subject group chose P0 or P1 as the most-preferred paradigm. The inherent limitations of the control interface (low-dimensional/discrete) can result in frustrating user experience and as a result P0 is not favored at all. Although P1 guarantees safety via obstacle avoidance, it can exacerbate user frustration due to additional filtering of control signals that are already low-dimensional and discrete.

(4) Overall, both subjects groups using both interfaces predominantly chose P4 as the most-preferred paradigm; however, the fact that on day two P0 and P3 were also preferred may be indicative of the users becoming more familiar with the teleoperation using the control interfaces.

(5) P1 was chosen as the least-preferred autonomy paradigm for the most part by both subject groups regardless of the interface used. This is because P1 can possibly lead to very low user satisfaction as a result of not letting the users execute the control commands at all times. Therefore, the users might have perceived the autonomy to be more restrictive than helpful.

(6) All subject groups (except Uninjured-headarray-day one, SCI-joystick-day two) chose P4 as the least-preferred paradigm. This indicates that the presence of autonomy was welcome in all scenarios.

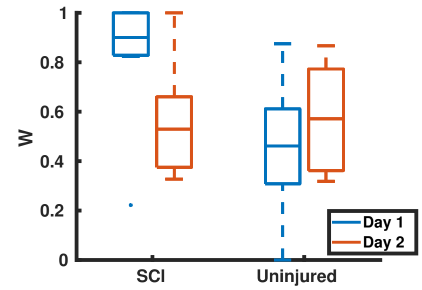

Figure 4: Normalized importance of the command blending attribute for each subject group and across both sessions.

The presence of these trends is a strong argument for an in-depth evaluation of how preferences evolve in time and therefore the need for longitudinal user preference modeling.

3.1 Conjoint Analysis

To extract which attribute and/or levels of attributes contributed most to a user's preference, we leveraged a technique called *conjoint analysis*. Conjoint analysis assigns a part-worth α to each attribute level by building a model, Equation 1, via regression with dummy variables. A higher part-worth indicates that the specific attribute level is important to the surveyed population. In the model, $U(x)$ is the sum of the user's Likert scores, k_i is the number of levels of attribute i, M is the total number of attributes, α_{ij} is the part-worth of the specific attribute level, and x_{ij} is the attribute i at level j.

$$U(x) = \sum_{i=1}^{M} \sum_{j=1}^{N_i} \alpha_{ij} x_{ij} \tag{1}$$

To provide further insight, we look at the variation between levels within an attribute to ascertain the effect of switching between levels on the overall utility of a profile. This is called importance I_i and we are interested in normalized importance W_i to compare across subjects, Equations 2 and 3.

$$I_i = \max([\alpha_{i1}, ..., \alpha_{ik_i}]) - \min([\alpha_{i1}, ..., \alpha_{ik_i}]) \tag{2}$$

$$W_i = \frac{I_i}{\sum_{j=1}^{M} I_j} \tag{3}$$

W_i is interpreted as the percent effect that an attribute with all of its levels has on the overall utility of a specific profile. If an attribute has a <5% effect and 2 attributes exist for a specific product, it is likely that the users cannot tell the difference between the levels of that attribute. Conversely, a higher percent importance will indicate that users may base their decision solely on that attribute and its levels. Due to length restrictions, we highlight some results of the normalized importance for operation via joystick, shown in Figure 4.[1] From these results, we find two primary insights:

(1) The SCI results do not correlate with the uninjured subject so we cannot design shared-control systems using information from the uninjured population.
(2) Variations exist across days for the SCI subject group that need to be considered when designing for this population.

4 DISCUSSION

One of the primary issues with the results was the sample space of attributes and levels. Each profile (**P1-P4**) is a function of the attribute levels, $X = [x_{11}, x_{12}, x_{13}, x_{21}, x_{22}]$, where x_{ij} corresponds to the i^{th} attribute and j^{th} level. The levels 'filtered' and 'switch' were only tested once which resulted in a rank-deficient matrix for sampling (Eqn. 4). The profiles are defined as:

$$P_1(X) = [1, 0, 0, 1, 0] \qquad P_2(X) = [0, 1, 0, 1, 0]$$
$$P_3(X) = [0, 1, 0, 0, 1] \qquad P_4(X) = [0, 0, 0, 0, 1]$$

$$P = [P1, P2, P3, P4]^T \tag{4}$$

For the conjoint analysis, we can only consider the sample space of user ranked profiles—**P1-P4**. For a fully ranked sample space we need to add two more paradigms to our experiment: (1): Filtered with Perception Goal, and (2): Switch with Immediate Goal. We may need to consider correlation effects as well.

An important consideration in experimental design is having enough data such that the results are statistically significant. If statistical power is high, the probability of making errors in conclusions or deductions goes down. In order to perform a balanced one-way analysis of variance (ANOVA) test comparing the 6 groups with a medium effect size of 0.2 and statistical power of 0.8, we need a within group sample size of 36 people—about 2.5× more samples than we currently have.

The age, gender, and injury-level demographics of the subjects in this exploratory study are not balanced. All but one subject use a joystick as their main control interface. The one subject that uses the sip and puff interface may throw off the results comparing joystick tasks. Balancing the demographics is important to ensure we can make correct inferences from our data.

The current survey only asked the user to score the control-sharing paradigms immediately after completing the task, but not the full-teleoperation (no autonomy) level. Further, the scores do not measure the relative ranked preference of the user. With the current experimental setup, it is not possible to ask the users to rank their preferences, because they perform each task and control sharing scheme in series; i.e. they cannot rank the schemes comparatively before they have tested all 5 (4 control sharing + 1 sans autonomy) modes, and once they have tested all five (at the end of the session), they may have forgotten about the earlier tasks. Another way to model this experiment better would be to use a Preference-based Policy Learning (PPL) approach [2]. The user performs the same task with two randomly chosen control paradigms out of the 7 (6 control sharing + 1 sans autonomy) back-to-back. The user preference is collected and a ranking of the policies computed. This is done for all binary combinations in a random fashion and a vector is made for each user, where each element of the vector is an aggregate score for each policy. For more details we refer the readers to [2]. This ensures that the highest ranking policy has a score of 1 and the lowest ranking policy has a score of 0. Using these vectors as inputs, we can use different techniques to model user preference. The problem with this method is the requirement for a sufficiently large sample size.

[1]Because importance is normalized, we know that W for goal selection is equal to one minus W for command blending and do not include in the plot for ease of reading.

5 CONCLUSIONS

We performed an exploratory study which gave us insight into how user's preferences of control-sharing methods can change over multiple sessions of use. We analyzed the attributes and levels that affected the change in preference in both SCI and uninjured groups. The differences in the highlighted trends indicate that future work should focus on data collected specifically from SCI end-users, even though this may be more time-consuming and costly. With the current exploratory study we cannot make generalizations for the larger population, but we found that ranked user preference data can inform shared-control paradigms that are useful over periods of long-term use. This information will inform the next iteration for a more extensive study.

REFERENCES

[1] Jenay M Beer, Arthur D Fisk, and Wendy A Rogers. 2014. Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of Human-Robot Interaction* 3, 2 (2014), 74.
[2] Josh C Bongard and Gregory S Hornby. 2013. Combining fitness-based search and user modeling in evolutionary robotics. In *Proceedings of the 15th annual conference on genetic and evolutionary computation*. ACM, 159–166.
[3] Matthew Derry and Brenna D. Argall. 2013. Automated doorway detection for assistive shared-control wheelchairs. In *2013 IEEE International Conference on Robotics and Automation (ICRA),*. IEEE, 1254–1259.
[4] Ahmetcan Erdogan and Brenna D. Argall. 2017. The effect of robotic wheelchair control paradigm and interface on user performance, effort and preference: an experimental assessment. *Robotics and Autonomous Systems* (2017), 282–297.
[5] Ahmetcan Erdogan and Brenna D. Argall. 2017. Prediction of user preference over shared-control paradigms for a robotic wheelchair. In *2017 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 1106–1111.
[6] Deepak Gopinath, Siddarth Jain, and Brenna D. Argall. 2017. Human-in-the-Loop Optimization of Shared Autonomy in Assistive Robotics. *IEEE Robotics and Automation Letters* 2, 1 (2017), 247–254.
[7] T. Inamura, M. Inabe, and H. Inoue. 2000. User adaptation of human-robot interaction model based on Bayesian network and introspection of interaction experience. In *Proceedings. of IROS*. 2139–2144.
[8] Charles C Kemp, Cressel D Anderson, Hai Nguyen, Alexander J Trevor, and Zhe Xu. 2008. A point-and-click interface for the real world: laser designation of objects for mobile manipulation. In *2008 3rd ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 241–248.
[9] Axel Lankenau and Thomas Rofer. 2001. A versatile and safe mobility assistant. *IEEE Robotics & Automation Magazine* 8, 1 (2001), 29–37.
[10] Selma Musifj and Sandra Hirche. 2017. Control sharing in human-robot team interaction. *Annual Reviews in Control* 44 (2017), 342 – 354.
[11] Anna-Liisa Salminen, Åse Brandt, Kersti Samuelsson, Outi Töytäri, and Antti Malmivaara. 2009. Mobility devices to promote activity and participation: a Systematic review. *Journal of Rehabilitation Medicine* 41, 9 (2009), 697–706.
[12] Cory-Ann Smarr, Akanksha Prakash, Jenay M Beer, Tracy L Mitzner, Charles C Kemp, and Wendy A Rogers. 2012. Older adultsfi preferences for and acceptance of robot assistance for everyday living tasks. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 56. SAGE Publications Sage CA: Los Angeles, CA, 153–157.