Prediction of User Preference over Shared-Control Paradigms for a Robotic Wheelchair

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***Abstract*— The design of intelligent powered wheelchairs has traditionally focused heavily on providing effective and efficient navigation assistance. Significantly less attention has been given to the end-user's preference between different assistance paradigms. It is possible to include these subjective evaluations in the design process, for example by soliciting feedback in post-experiment questionnaires. However, constantly querying the user for feedback during real-world operation is not practical. In this paper, we present a model that correlates objective performance metrics and subjective evaluations of autonomous wheelchair control paradigms. Using off-the-shelf machine learning techniques, we show that it is possible to build a model that can predict the most preferred shared-control method from task execution metrics such as effort, safety, performance and utilization. We further characterize the relative contributions of each of these metrics to the individual choice of most preferred assistance paradigm. Our evaluation includes Spinal Cord Injured (SCI) and uninjured subject groups. The results show that our proposed correlation model enables the continuous tracking of user preference and offers the possibility of autonomy that is customized to each user.**

I. Introduction

Robotics autonomy has the potential to assist an estimated 1.4 to 2.1 million powered wheelchair users in the United States [1]. Recent years in particular have been marked by the development of different control paradigms that share the control with user in various ways. Deciding exactly *how much* and *how often* assistance should be provided is critical for end-user acceptance, and will be a key factor in the large-scale adoption of these systems.

Autonomy in wheelchairs can be tuned according to traditional robotics metrics that prioritize efficiency and success in task performance. However, an additional consideration is the fact that most end-users prefer to retain as much control as is possible [2]. Moreover, each user is unique in their needs, personal preferences and desired level of assistance. Maintaining a balance between performance and end-user preference, therefore, is essential in determining the proper sharing of control between the user and autonomy.

Within the smart (i.e robotics) wheelchair literature, subjective evaluations are most commonly utilized in order to gather opinions about no autonomy (only human input) versus full autonomy (no human input), or a single shared-control paradigm (a combination of human and autonomy input). There exist a limited number of studies that compare multiple control paradigms on hardware, and none of these studies investigate potential connections between objective execution metrics and subjective user preference metrics.

In order to bridge the gap between performance and preference, our work aims to experimentally model the correlations between subjective and objective metrics across multiple shared-control paradigms. We have previously compared multiple shared-control paradigms and control interfaces in a systematic experiment that spans multiple sessions [3]. The high variability observed in the most effective and accepted paradigms between subjects and over control interfaces supports the idea of offering end-users multiple control options to accommodate their individual needs and preferences.

It however may not be practical to continuously query the user for their preference. Therefore, we extend our previous work by modeling the correlation between task-related metrics and post-experiment subjective evaluations. Our model successfully captures the experimentally-observed changes between subject groups and sessions, while providing unique insight into the relative contribution of task metrics such as effort, safety, performance and utilization. Our overarching aim is to continuously estimate user preference over multiple assistance paradigms which can then be used to modify and/or switch the way in which control is shared.

The rest of the paper is organized as follows. Section II provides a review of related literature on smart wheelchair research. Section III details the control and hardware architectures of our NURIC Smart Wheelchair, including the four tested shared-control paradigms. The correlation model and experimental results are provided in Sections IV and V. Section VI concludes the paper.

II. Background

Exploratory qualitative studies that investigate the perspectives of caregivers, therapists and powered wheelchair users are common in the smart wheelchair domain. In these studies, open-ended questions are discussed to characterize the needs and desires of these populations—such as decreased risk of collisions and increased social behavior [4]. To address these desires, different shared-control approaches have been proposed that span a wide range of options between the two extremums of full autonomy and full teleoperation.

Studies that investigate the subjective evaluation of these systems highlight some key requirements from the users. End-users are shown to be *most frustrated* with full autonomy because they feel that they have the least control [5],

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and they demonstrate a high *desire to be in control* when they are asked to evaluate different controllers in simulation [6].

There are also shared-control methods that rely on user input for the entire trajectory in order to accommodate the desire to be in control. This approach necessitates a way to reason between two (possibly conflicting) signals generated by the user and autonomy. One possibility is to *continually blend* these two signals in a weighted sum, where the blending ratio may be constant or change with respect to metrics like comfort, transparency or safety [7]. A different approach is to *partition the control space* between the human and the autonomy. Here, the aim often is to find a safe heading that is as close to the user input as possible [8].

Some studies within the literature augment temporal and kinematic quantitative task execution metrics with subjective evaluations through questionnaires that solicit preference from the users with or without autonomy; for example, the NASA TLX questionnaire is used to observe workload from the user's perspective [9]. These approaches, however, may not generalize depending on the impairment of the subject, and continuously querying the user's satisfaction with the autonomy may undermine its acceptance.

One possible alternative is to observe continuous indications of the user's condition via additional physiological measurements (e.g skin conductivity gauges or heart rate monitors). These sensors provide a continuous metric that can be incorporated into the control paradigm; for example, by relating pulsioximeter readings to user anxiety [10]. However, such sensors introduce additional complexity and the results are susceptible to external disturbances.

The approach we present in this paper instead builds a correlation model between subjective evaluations (of user opinion and preference) and objective measures (effort, safety, performance and utilization) available from the sensors already onboard the robot platform (to enable the autonomy capabilities). With such a model, it becomes feasible to automatically adapt which shared-control paradigm is employed by the autonomy, which might help to facilitate the adoption of autonomy capabilities in powered wheelchairs.

III. Experimental Evaluation

In this work, we develop an experimentally-derived model to investigate the relationship between objective and subjective metrics of a shared-control task with an assistive robot. The model aims to estimate, from task execution metrics, a user's preference over multiple shared-control paradigms.

Utilizing our modular software structure, we have previously performed a multi-session experiment that evaluated user performance, effort and preference over assistive paradigms and control interfaces [3]. This section summarizes the experimental platform and protocol for that study.

A. Experimental Platform

We first present a brief summary of the control and hardware architecture of our NURIC Smart Wheelchair [3]. The software and hardware components are modular and customizable—allowing for various control formulations and sensors to be swapped in or out.

Fig. 1: NURIC Smart Wheelchair hardware configuration. The base system consists of an RGB-D sensor, a mini-PC, converter boards and wheel encoders. Additional hardware can be added based on a user's needs and preferences.

1) Control Architecture: The control framework consists of a modular software system which can be broadly characterized as high-level and low-level behaviors, and a set of reasoning modules for command and goal arbitration.

In particular, each high-level behaviors $f_{hi}(\cdot) \in \mathcal{F}_{hi}$ outputs a goal g

$$g \leftarrow f_{hi}(\mathbf{x}) \tag{1}$$

based on the current state $\mathbf{x}$ of the robot and the observable environment. These individual goals are generated from perception algorithms that identify locations of interest and inference algorithms that estimate intent from user commands. Examples of implemented high-level behaviors include traversing doorways, docking at tables and desks and driving up ramps—all commonly challenging scenarios for end-users. Once the goal set is populated $g \in \mathcal{G}$ (which also might be empty), the *goal arbitration* module computes a confidence c_g for each element based on conflicts, feasibility, perception confidence and agreement with human-generated commands. From this, the highest-confidence goal $g^\star \in \mathcal{G}$ that is above a predefined threshold is selected. Low-level behaviors $f_{lo}(\cdot) \in \mathcal{F}_{lo}$ then output a control command $\mathbf{u_r}$

$$\mathbf{u_r} \leftarrow f_{lo}(\mathbf{x}, g^\star) \tag{2}$$

based on the most confident goal $g^\star$ and state $\mathbf{x}$. The *command arbitration* module reasons between the autonomy-generated command $\mathbf{u_r}$ and the human-generated command $\mathbf{u_h}$. Specifically, arbitration function $\beta(\cdot)$

$$\mathbf{u} \leftarrow \beta(\mathbf{u_h}, \mathbf{u_r}) \tag{3}$$

generates a command $\mathbf{u}$—which consists of translational ν and rotational ω speed components—that drives the non-holonomic robot system.

2) Hardware: The mechanical design of the NURIC Smart Wheelchair intentionally utilizes commercial products to facilitate practical adoption by users. Specifically, our system is built on a commercially-available powered wheelchair, a Permobil C300 (Timra, Sweden), which we then outfit with additional components including a computer, electronics and sensors (Fig. 1).

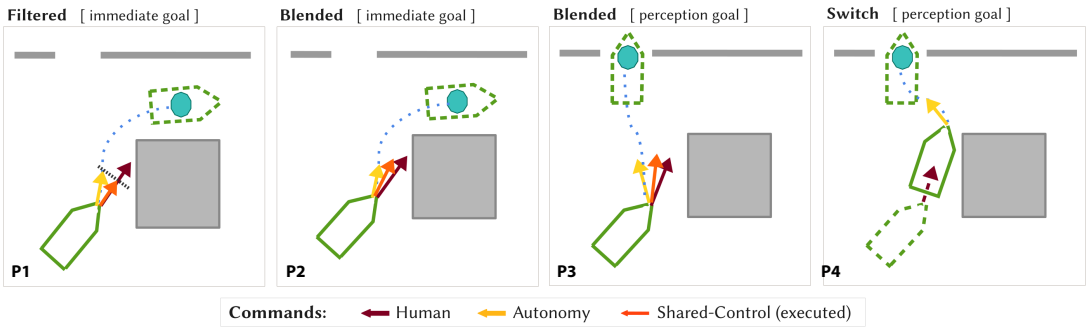

Fig. 2: The four shared-control paradigms of our study (P1-P4), which differ according to how the autonomy commands are generated (immediate or perception goals) and how the control is shared between the user and autonomy (blending, filtering or switching). In particular, navigation goals (blue circle) for the autonomy are inferred simply from a brief (0.5 sec) forward projection of the human's current control command (immediate goal, P1 and P2) or from a higher-level perception goal (doorway) detected from sensor data (perception goal, P3 and P4). In either case, the same planner is used to generate a path (dashed blue line) to the goal, and the same controller is used to drive that path. The human command might be linearly blended [7] with the autonomy command (Blended, P2 and P3) or be capped [11] to not exceed the autonomy command in safety-critical (e.g. collision with an obstacle) situations (Filtered, P1), or the autonomy might take over 100% control [12] when relinquished by the human (Switch, P4). Doorway shown as a gap in the top gray line, robot footprint as a green outline and obstacle as a gray box.

To interface with the proprietary wheelchair control loop, we use the expandable input OMNI interface from R-Net Electronics (Christchurch, UK)—originally designed to enable the use of third-party control interfaces. Our computer-generated control commands $\mathbf{u}$ can drive the wheelchair by mimicking a regular inductive joystick via a voltage regulator. Additional hardware add-ons include an onboard computer (mini-PC) that is powered by the wheelchair batteries, electronics boards, override buttons, wheel encoders and a top-mounted RGB-D sensor (Asus Xtion).

B. Shared-Control Paradigms

Our prior study evaluated four shared-control paradigms (Fig. 2), sampled from the literature on wheelchair navigation assistance. The paradigms differ in the way that (i) the control authority is allocated and (ii) autonomy goals are generated.

The overall purpose of each control paradigm is to compute a control input $\mathbf{u} = [v, \omega]$ that takes into consideration the user signal $\mathbf{u_h} = [v_h, \omega_h]$, autonomy signal $\mathbf{u_r} = [v_r, \omega_r]$ and environment information.

C. Experimental Protocol and Motivating Results

This section summarizes the experimental protocol of our previous study that investigated user performance, preference and effort under different shared-control paradigms and control interfaces. Readers are referred to [3] for a detailed analysis of this experiment.

Participants were asked to follow a predefined path in our laboratory that traversed four doorways (Fig. 3). Due to the challenging nature of the task and the prerequisite of dexterous control, doorway navigation has been evaluated in multiple smart wheelchair systems [13] and it is one of the tasks in the Powered Wheelchair Skills Test [14] that assess the ability of end-users to safely pilot a powered wheelchair.

Experiment participants included 7 SCI subjects (36-68 years old) and 7 uninjured subjects (23-37 years old). On average, it had been 23.6±11.0 years since injury and the SCI subjects had used a powered wheelchair for 21.0±11.4 years. The uninjured subjects had varying experience with robotic systems but were mostly naive to wheelchair driving.

The overall experiment was divided into four phases, each of which started two meters away from a door ($t = t_0$) and ended when the user safely traversed the doorway ($t = t_N$). All experimental data was collected via the ROS pipeline and the majority was sampled at 25 Hz (with the exception of computationally expensive topics such as the 2-D costmap, which was sampled at 7 Hz). MATLAB was used to segment the doorway traversal time intervals and for data processing.

In a session, each navigation assistance paradigm was evaluated twice and presented in a predefined randomized order. Subjects were asked to perform a secondary session at least one day and no more than 14 days after the first session to help identify learning artifacts.

Upon completing a session, subjects (i) indicate their most preferred control method and (ii) fill out the subjective evaluation questionnaires for each assistance paradigm—which queried for the user's trust in, and perceived utility and contribution of, the autonomy over a 7-point Likert scale.

Post-experiment analysis of the subjective evaluations showed that 7 of the 14 participants chose a different paradigm as most preferred in their second session. We also observed noticeable (and sometimes significant) differences in the performance, effort and preference of users under different shared-control paradigms [3]. In this paper, we extend our analysis to build a correlation model that maps objective execution metrics to subjective evaluations. Our aims are (i) to highlight the reasons for observed differences between subject groups, sessions and assistance paradigms, and (ii) to

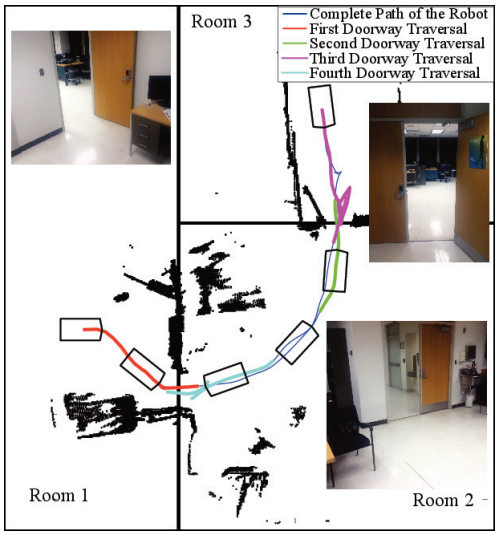

Fig. 3: Sample experimental run, originally presented in [3]. Doorway traversal phases shown as differently colored lines, and black dots are projected sensor data.

predict subjective evaluations online, which potentially could be used to switch or modify autonomy paradigms on the fly.

IV. Correlation Model between Objective and Subjective Metrics

Our approach models the correlation between user preference and execution metrics. This section formulates the objective task execution metrics that are the inputs to the correlation model, and then details the structure of the model.

A. Execution Metrics

For the execution metrics, four characteristics of robot operation upon which shared-control paradigms frequently are built [7] are chosen: effort, safety, performance and utilization. In particular, the chosen task-specific metrics are:

- *Task Completion Time*: $T = t_N - t_0$, provides a measure of task performance. Here t_0 and t_N represent the starting and ending time of each doorway traversal.
- *Minimum Distance to Obstacles*: $D = \frac{1}{N}\sum_{t_0}^{t_N} ||d_i||$, provides a measure for the user safety. Here $||d_i||$ is the minimum distance between the wheelchair footprint and obstacles and N is the number of samples.
- *Similarity of User and Executed Commands*: $S = 1 - \frac{1}{N}\sum_{t_0}^{t_N} ||\bar{\mathbf{u}}^{\mathbf{t}} - \bar{\mathbf{u}}^{\mathbf{t}}_{\mathbf{h}}||$, provides insight into utilization of autonomy by comparing the executed command $\mathbf{u}^{\mathbf{t}}$ with the user input $\mathbf{u}^{\mathbf{t}}_{\mathbf{h}}$.
- *Mean Frequency of User Commands*: $M = \frac{1}{N}\sum_{t_0}^{t_N}\sum_1^L f_i P_i / \sum_1^L P_i$, provides insight into user effort. (The mean frequency of surface EMG signals has been shown to indicate muscle fatigue [15].) Here f_i is the frequency value of the user signal's power spectrum P_i at frequency bin i, and L is the length of the frequency bin.

Note that command frequency and similarity are metrics specific to shared-control systems. By contrast, execution time and distance to obstacles are common performance-related metrics used to evaluate autonomous robotic systems.

B. Correlation Models

For the design of the correlation model, a cascaded model structure is chosen. Specifically, this model maps (A) objective task execution metrics to subjective evaluations (scored on a Likert scale) and (B) these estimated subjective evaluations to the most preferred assistance paradigm.

Eight pairs of A and B models are built, one for each combination of subject group (2) and shared-control paradigm (4). The end-to-end operation thus is to predict a distribution over shared-control paradigms from observed objective metrics, conditioned on the control paradigm (and subject affiliation) in use when the metrics are gathered. The dataset for each model contains only 14 samples (7 subjects in each of 2 sessions). Training and evaluation therefore is performed using 7-folds cross-validation, where each fold is a split of 70% training, 15% testing and 15% validation data (used during training to prevent over-fitting).

We evaluate a variety of off-the-shelf machine learning tools to build each model: including linear regression with Lasso regularization, decision and regression trees, support vector regression and neural networks (all implementations are performed in MATLAB using the Statistics and Machine Learning and Neural Network Toolboxes). For all models, the best regression performance is achieved with a multi-layer feed-forward neural network.

1) Model A: Prediction of Subjective Evaluations: The first model (A) of our cascade predicts the subjective scores. Its input vector $\mathbf{z} \in \mathbb{R}^4$ contains the 4 execution metrics (Sec. IV-A) computed over 2 trials. Its output vector $\mathbf{y} \in \mathbb{R}^3$ contains the 3 subjective evaluations (trust, contribution, utility) rated on a Likert score. Each prediction $y \in \mathbf{y}$ is continuous-valued and lies in $y \in [1, 7]$.

A grid search is performed to optimize the number of hidden layers and units that minimizes the total mean squared error. For all models, 2 hidden layers using radial basis activation functions with a single linear output layer are found to perform the best. The only difference between models is the number of neurons in each hidden layer. (SCI models: P1 and P2 5-5, P3 and P4 20-5, uninjured models: P1 5-5, P2 40-5, P3 5-5, P4 20-5.)

2) Model B: Prediction of Most Preferred Paradigm: The second model (B) of our cascade predicts a distribution of preference over shared-control paradigms. Its input vector $\mathbf{z} \in \mathbb{R}^3$ contains the 3 subjective evaluations (trust, contribution, utility) predicted by the first model (A). Its output vector $\mathbf{y} \in \mathbb{R}^5$ is a probability distribution of preference over the 4 shared-control paradigms plus a paradigm without any autonomy (direct teleoperation).

Models are trained using the same optimization and cross-validation routine described above. A neural network with 2 hidden layers again performs best, this time using hyperbolic

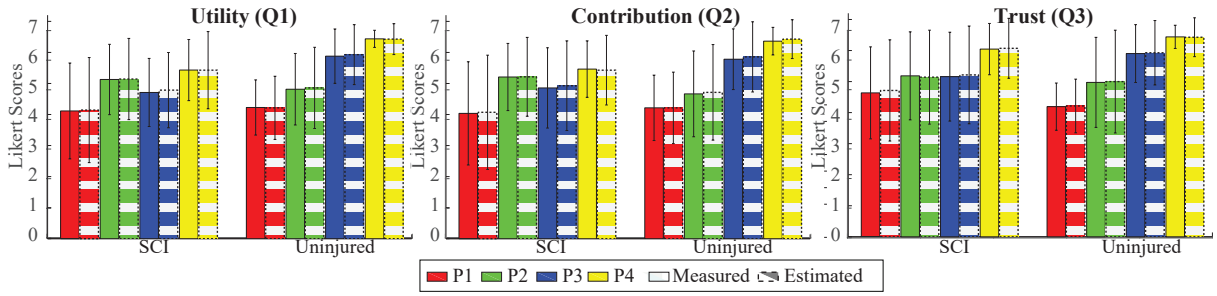

Fig. 4: Subjective evaluation scores, measured (solid bars) and predicted (dashed bars), averaged across subject groups and cross-validation folds.

tangent sigmoid activation functions and a soft max activation function in the final layer. Again, the only difference between models is the number of neurons in each hidden layer (all SCI models: 10-5, all uninjured models: 5-5).

V. Experimental Results

We evaluate the performance of the cascaded correlation model, and evaluate the relative contribution of each task metric. Results suggest that task execution metrics can infer user preference, even under different shared-control paradigms, subject groups and sessions. Furthermore, a relative contribution analysis is performed to examine the effect of different task execution metrics on user acceptance.

A. Prediction of Subjective Evaluations

The performance of the neural network regression is given in Figure 4. The normalized mean square error averaged over all control paradigms and cross-validation folds on the test dataset is 2.0±1.2% for the SCI models and 2.1±1.1% for the uninjured models. The proposed approach thus successfully estimates subjective evaluations based on the chosen objective execution metrics.

B. Relative Contribution of Each Objective Metric

We further analyze the contribution of each performance metric using sensitivity analysis. Input perturbation is shown to effectively capture the relative contribution of each input in comparison to other sensitivity analysis methods [16]. This method compares the rate of change in the mean squared error of the measured and estimated values when a perturbation is applied to each input as white noise with magnitude between 5% to 50%.

For this analysis, for each of the eight subject-paradigm datasets, we select from the 7-folds cross-validation the best performing model. The entire dataset then is run, with perturbations, through this model.

The corresponding mean squared error percentages are plotted as a function of perturbation amount in Figure 5. The sensitivity analysis results demonstrate that across shared-control paradigms, there is a high variability in the dependence of each model on the various metrics. That is, which metrics have the greatest impact on prediction performance changes depending on which shared-control paradigm is in use—which helps to explain why we see better performance when we partition the dataset and build paradigm-specific models. Moreover, we also observe differences between subject groups—meaning that subjects' evaluations of a control paradigm are influenced by different metrics.

C. Prediction of Most Preferred Paradigm

The predicted subjective evaluation scores provide a quantitative evaluation of each shared-control paradigm. From these values, estimating the most preferred paradigm could enable adaptive assistance based on the user's preference.

The prediction of most preferred paradigm is more complex than simply selecting the highest-scoring paradigm. In 9 out of 28 cases, the most preferred shared-control paradigm does not have the highest evaluation score. Moreover, in 3 of these 9 cases, no assistance was chosen as most preferred.

Our method computes a preference distribution over control paradigms. From this, we compute the *most* preferred paradigm by taking the maximum of this distribution.[1] A confusion matrix for the prediction of most preferred paradigm is given in Figure 6. The test data accuracy averaged over all models is 74.1% (while chance is 20%).

Unsurprisingly, performance declines with diminishing instances of a given class. Performance overall is promising, though still leaves room for improvement. The gap in prediction performance might be addressed with a more sophisticated model or a larger dataset, or simply might be a function of metrics unobservable to our current robotic system (e.g. user fatigue).

VI. Conclusion

For the large-scale adoption of smart wheelchairs, control sharing needs to accommodate each user's unique motor ability and personal preference. It is desirable to be able to predict this preference without needing to constantly query the user. In this work, we have shown that it is possible to estimate user preference based on objective execution metrics of the shared-control task chosen from the literature: effort, safety, performance and utilization. Results from our previous multi-session experiment revealed a subset of users that change their most preferred shared-control paradigm between sessions. Our proposed model successfully captures the relation between execution metrics and user opinion in this experimental data, including these preferences changes.

[1] For 5 of 28 datapoints, subjects indicated two paradigms equally as most preferred. For these datapoints, we consider the prediction of either as most preferred to be a true positive.

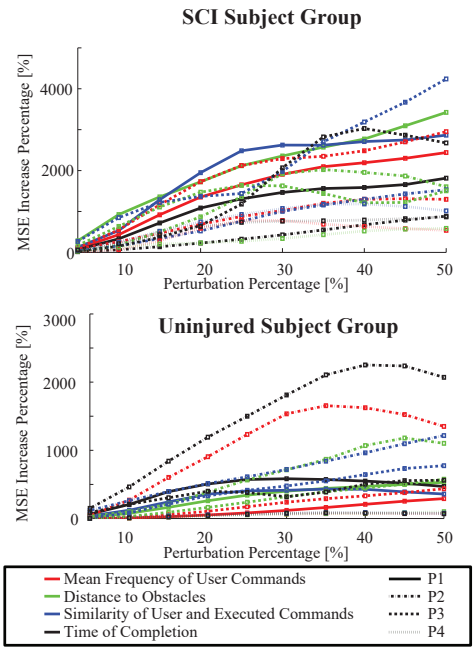

Fig. 5: Relative contribution to each execution metric on the prediction of subjective evaluations, for SCI (top) and uninjured (bottom) subject groups. Different metrics shown as colors, different control paradigms as line continuities.

The contribution of our work is to model the connection between task execution metrics and user preference in a human-robot system, while highlighting the relative contribution of each of these objective metrics in the prediction of most preferred paradigm.

Our future work includes a longitudinal study to investigate the adaptation of users to the autonomy and how this affects their preference. We expect that, with experience, dissimilarity between the user and executed signals will saturate to a steady state, and that the resulting change in driving characteristics would reshape the correlation model.

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References

[1] R. Simpson, E. LoPresti, and R. Cooper, "How many people would benefit from a smart wheelchair?" *Journal of Rehabilitation Research & Development*, vol. 45, no. 1, pp. 53–72, 2008.

[2] A. Lankenau and T. Röfer, "A versatile and safe mobility assistant," *IEEE Robotics Automation Magazine*, vol. 8, no. 1, pp. 29–37, 2001.

[3] A. Erdogan and B. D. Argall, "The effect of robotic wheelchair control paradigm and interface on user performance, effort and preference: An experimental assessment," *Robotics and Autonomous Systems*, vol. 94, pp. 282–297, 2017.

[4] P. W. Rushton, D. Kairy, P. Archambault, E. Pituch, C. Torkia, A. E. Fathi, P. Stone, F. Routhier, R. Forget, J. Pineau, R. Gourdeau, and L. Demers, "The potential impact of intelligent power wheelchair use on social participation: perspectives of users, caregivers and clinicians," *Disability and Rehabilitation: Assistive Technology*, vol. 10, no. 3, pp. 191–197, 2015.

Predicted Class \ Target Class	No Assistance	P1	P2	P3	P4
No Assistance	6/12 50.0%	1/109 0.9%	1/98 1.0%	0/89 0.0%	1/48 2.1%
P1	0/100 0.0%	0/3 0.0%	0/98 0.0%	0/89 0.0%	0/48 0.0%
P2	0/100 0.0%	0/109 0.0%	3/14 21.4%	1/89 1.1%	4/48 8.3%
P3	0/100 0.0%	0/109 0.0%	2/98 2.0%	18/23 78.2%	2/48 4.2%
P4	6/100 6.0%	2/109 1.8%	5/98 5.1%	4/89 4.5%	56/64 87.5%

Fig. 6: Confusion matrix of predicted preference (predicted class) versus ground truth (target class), summed over all 8 models and their datasets (112 samples). For each column, a cell counts the number of predictions of that target class as a fraction of (a) the number of instances of the class (diagonal elements, true positives) and (b) the number of instances of all other classes (off-diagonal elements, false positives).

[5] S. P. Parikh and V. Grassi, "Integrating human input with autonomous behaviors on an intelligent wheelchair platform," *IEEE Journal of Intelligent Systems*, vol. 22, no. 2, pp. 33–41, 2007.

[6] I. M. Mitchell, P. Viswanathan, B. Adhikari, E. Rothfels, and A. K. Mackworth, "Shared control policies for safe wheelchair navigation of elderly adults with cognitive and mobility impairments: Designing a wizard of oz study," in *Proceedings of the American Control Conference*, 2014.

[7] Q. Li, W. Chen, and J. Wang, "Dynamic shared control for human-wheelchair cooperation," in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2011.

[8] S. P. Levine, D. A. Bell, L. A. Jaros, R. C. Simpson, Y. Koren, and J. Borenstein, "The NavChair assistive wheelchair navigation system," *IEEE Transactions on Rehabilitation Engineering*, vol. 7, no. 4, pp. 443–451, 1999.

[9] P. Viswanathan, J. J. Little, A. K. Mackworth, and A. Mihailidis, "Navigation and Obstacle Avoidance Help (NOAH) for Older Adults with Cognitive Impairment: A Pilot Study," in *Proceedings of the International ACM Conference on Computers and Accessibility*, 2011.

[10] M. Fernandez-Carmona, B. Fernandez-Espejo, J. Peula, C. Urdiales, and F. Sandoval, "Efficiency based collaborative control modulated by biometrics for wheelchair assisted navigation," in *Proceedings of the IEEE International Conference on Rehabilitation Robotics*, 2009.

[11] T. Carlson and Y. Demiris, "Human-wheelchair collaboration through prediction of intention and adaptive assistance," in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2008.

[12] A. K. Makhtar, H. Yussof, H. Al-Assadi, L. C. Yee, M. R. M. Tomari, Y. Kobayashi, and Y. Kuno, "Development of smart wheelchair system for a user with severe motor impairment," in *Procedia Engineering International Symposium on Robotics and Intelligent Sensors*, 2012.

[13] P. TalebiFard, J. Sattar, and I. M. Mitchell, "A risk assessment infrastructure for powered wheelchair motion commands without full sensor coverage," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2014.

[14] R. L. Kirby, L. A. Worobey, R. Cowan, J. P. Pedersen, A. W. Heinemann, T. A. Dyson-Hudson, M. Shea, C. Smith, P. W. Rushton, and M. L. Boninger, "Wheelchair skills capacity and performance of manual wheelchair users with spinal cord injury," *Archives of Physical Medicine and Rehabilitation*, vol. 97, no. 10, pp. 1761–1769, 2016.

[15] A. Phinyomark, S. Thongpanja, H. Hu, P. Phukpattaranont, and C. Limsakul, "The usefulness of mean and median frequencies in electromyography analysis," in *Computational Intelligence in Electromyography Analysis - A Perspective on Current Applications and Future Challenges*, G. R. Naik, Ed. Intech, 2012.

[16] M. Gevrey, I. Dimopoulos, and S. Lek, "Review and comparison of methods to study the contribution of variables in artificial neural network models," *Ecological Modelling*, vol. 160, no. 3, pp. 249–264, 2003.