Navigating Adaptive Design: Advancing the Body-Machine Interface for 6D Control in Assistive Applications

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ABSTRACT

Designing wearable technology presents a unique set of challenges in order to facilitate widespread adoption. Devices need to generalize and be intuitive in order for users to integrate these devices into their daily lives in a meaningful way. When designing assistive technology for individuals with neuromotor impairments, rather than focusing on generalizing to a diverse target population, one approach is to customize the device for each user. Customization in the target population thereby enhances the device performance to its particular use case. The purpose of this work is to highlight the evolution of a Body-Machine Interface (BoMI) to control a 7 degree-of-freedom (DoF) robotic arm and to discuss the experimental protocol for individuals with cervical spinal cord injuries (cSCI). The vetting study, a subset of the work documented in this submission, assesses learning with an interface without the need for mode switching. The transition from a pilot study with control subjects to the first stages of studies with cSCI participants and the corresponding design adaptations are discussed. Preliminary results from the vetting study (acquired from an uninjured test subject) suggest learning of the interface. Results and feedback prompted further changes which are currently being vetted on end-users.

CCS CONCEPTS

• **Human-centered computing** → *Accessibility design and evaluation methods*; **User interface design**; **Interface design prototyping**; **Accessibility technologies**.

KEYWORDS

Body-Machine Interface, Rehabilitation Robotics, Spinal-Cord Injury, Interface Design, Accessibility, Assistive Devices

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1 INTRODUCTION

Design for mass adoption does not impose the same limitations as designing systems for those with neuromotor impairments. The shift from designing for uninjured subjects to designing for the injured population underscores the complexities and unique scenarios encountered with a research project's system. These special design considerations are important in the field of assistive technology to combat device abandonment rates. Prior research shows, 29.3% of assistive devices were abandoned by people experiencing a variety of impairments, with device performance falling within the top three predictors [7]. For those with cSCI–in this work targeting an injury range of complete (ASIA A) lesion at C3-6 or an incomplete injury (ASIA B, C, or D) lesion in the cervical cord or upper thoracic region (T1-T4)–the difficulty in design stems from the same classifications of injuries manifesting themselves differently from person to person [6].

For individuals with a cSCI, assistive devices are their main means of gaining independence, but the effects of having the appropriate assistive device goes beyond self-sufficiency. By providing adequate assistive technologies, people are more likely to participate in society and are less likely to develop certain noncommunicable diseases [9]. One of the most common devices employed is the wheelchair. For others experiencing tetraplegia, the use of a robotic arm is the main solution to compensate for limited hand and arm function. The corresponding interfaces with these devices–joysticks, head arrays, sip-n-puffs–employ low dimensional methods of control, with joysticks offering the highest mode of control in 3 dimensions. When these systems are used to interface with devices with high dimensional control spaces, such as the robotic arm, the main design flaw arises in the necessity for frequent mode switching to access all control dimensions. Without mode switching, the user will never have access to all 6 control dimensions–defined in this paper as Cartesian end-effector control: x, y, z, ϕ_p, ϕ_y, ϕ_r. This results in frustration and mental fatigue as additional planning becomes necessary with each mode switch. These interfaces do not conform to accommodate the specific physiological constraints of the user, rather the user must conform to the constraints of the interface. These are all scenarios in which the performance of the device is compromised.

These pain points underscore the much needed customized design of an interface capable of controlling in high dimensions without mode switching. The BoMI [2, 5, 11] is an interface capable of addressing these challenges and is customizable to the physiological constraints of the user. At a high level, the BoMI captures the upper body motions of an individual using inertial measurement units (IMUs) and transforms those signals to the velocity control space via a mapping scheme. In the current iteration of the BoMI, the user first calibrates the system by collecting the following body motions: (1&2) right/left shoulder forward/backward; (3&4) right/left shoulder up/down; (5&6) right/left arm abduction/adduction. These recordings are used to generate a map using a supervised learning approach. During runtime, a k-nearest neighbors (KNN) classifier is used to initially predict the probability of a given motion. The magnitude of the motion is determined from the 6 principal component analysis (PCA) maps derived from the calibration data. The first principal axis of each is used to determine the amplitude of the control signal.

With the end goal to target the cSCI population, prior studies were conducted with uninjured participants in a pilot study to assess the viability of mapping upper body motions to high dimensional control [4]. Building upon the findings of this experiment, the next phase transitions the pilot design to fit within the cSCI user requirements. This paper extends the work demonstrated in [10] and presents the evolution of the design process of the BoMI system, study design, and learning paradigm. The end goal is to have end-users control a 7 DoF robotic arm using residual upper body motions. Preliminary results from a vetting study which implemented these changes are presented.

2 DESIGN FOR THE END-USER

From equipment to protocol, transitioning from control subjects to cSCI participants impacts design in all aspects. These adaptations necessitate further exploration to validate their effectiveness within the target population. The discussed adaptations to the BoMI and body-motion prompt designs were evaluated in a scoping study with end-users.

2.1 Body-Machine Interface

The pilot BoMI comprised 5 IMUs: One on each shoulder, one on each upper arm, and one in the center of the chest. These IMUs were adhered to a compression shirt using Velcro. For the IMUs to accurately capture the upper body motions, the shirt needs to be close fitting. Upon introduction, control subjects reported the shirt was difficult to don and doff due to the compressive nature. With the pilot design, neither the end-user nor the caregiver would be able to assist in situating the BoMI without great difficulty.

The transition to the use case on cSCI participants requires modifications to streamline the donning and doffing process. The BoMI now resembles a vest with Velcro fasteners on the sides. This allows the vest to easily slip over the head of the user without the need to significantly raise their arms. The arm sensors are secured to removable bands above and below the elbow allowing further flexibility in customization and fully leverage the user's input space to capture greater amounts of variance in their movements.

2.2 Prompt Design

The basis for the mapping scheme lies in the calibration data collected for computation. With the shoulder joint being classified as a compound joint [12], this poses the challenge of designing 6 distinct prompts in a highly coupled region of the body befitting for those with cSCI. The initial body motion prompts consist of (1&2) right/left shoulder forward/backward, (3&4) right/left shoulder up/down, and (5&6) right/left arm shoulder curl in/out. The shoulder curl motion requires the user to bring the shoulder across the front of their body instead of straight forward as in prompts 1 and 2. When these prompts were presented to lab members not affiliated with the project, the reported initial impressions include (1) not "feeling" the difference between the curl prompts and shoulder forward/backward and (2) significant discomfort performing the motion.

Following this feedback, two additional prompts were developed–right/left shoulder abduction/adduction (referred to as elbow prompts). The elbow prompts were added as a means to replace curl with motions that were further removed from the coupled motions of the shoulder joint. Furthermore, the elbow prompts introduce more variance into the signals. Participants are instructed to place their hands in a stationary position on the armrests of a wheelchair or resting on their lap and then push the elbow out and pull it in towards their body.

3 SCOPING STUDY

The culmination of these changes led to a *scoping study* to assess the viability within the cSCIs population. The scoping study serves as means to (1) validate that the motion prompts provided enough variance in those with limited RoM compared with the control population, (2) compare the curl and elbow prompts, and (3) to gain feedback on the vest design from end users.

Participants For this study, 3 participants were recruited with varying levels of RoM and cSCI: C3 Complete, C4 Incomplete, and C5 Incomplete (3M, age 63 ± 20.4) with the goal of evaluating these changes on a variety of upper body RoM levels.

Hardware & Software For this study, 4 IMUs (3 Space Sensors, Yost Labs, Portsmouth, OH, USA) were used to capture upper body motions using quaternions. These signals were streamed via Bluetooth to a computer running the Ubuntu 18.04 operating system and recorded using the Robotic Operating System (ROS) Noetic.

ProtocolThe data collection protocol requires participants to repeatedly execute the same prompt for 2 minutes while wearing the BoMI; this was repeated for each of the 8 prompts. Participants were then asked to undergo a free-exploration recording in which they were instructed to move their shoulders "randomly" for 3 minutes. For each participant, two maps were computed one using prompts 1-4 plus the curl prompts and second one using prompts 1-4 plus the elbow prompts.

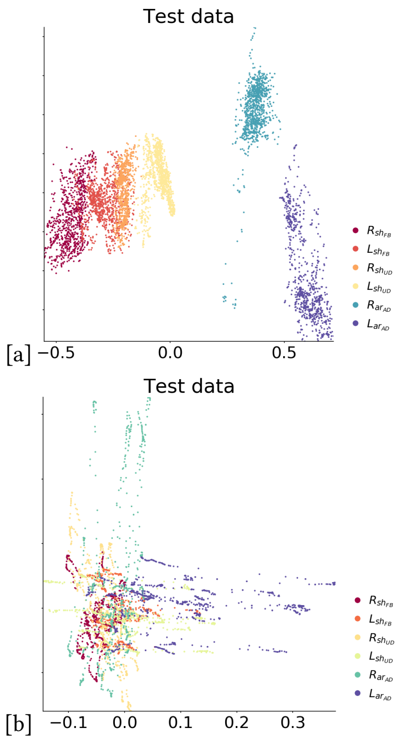

Figure 1: (a) PCA embedding of IMU signals of C5 Incomplete (scoping study) (b) PCA embedding of IMU signals of C7 Incomplete (vetting study)

Results With the elbow prompts, the cSCI participants were able to account for 73.8 ± 1.3% of the net amount of motion exhibited in the unimpaired data [10]. When comparing the curl and elbow prompts, the feedback from the injured population aligned with reports from the control subjects. The most frequent complaint was the lack of understanding of what the curl prompt is and how it differs from shoulder forward/backward. The main priority was addressing discomfort participants also reported feeling when performing the curl prompts, an opinion also shared by several of our control subjects. With end-user adoption as the main goal, the opinion of the end-users was heavily weighted when making a decision about the final two prompts. Ultimately, the elbow prompts were selected. At the conclusion of the scoping study, these changes were implemented.

4 HIGH DIMENSIONAL CONTROL

With the altered prompt and BoMI designs, the next phase is integration of the interface with a simulated 6D control environment. The BoMI visualizer feedback GUI has 6 channels representing one of the 6 dimensions of BoMI control. Color-coded arcs within these channels are controllable by the BoMI. The *deadzone* is denoted by a grey band in each channel. This is an adjustable region in the control space that does not actuate to account for small unintended motions. When tested on lab members, control with this interface was inconsistent and unreliable. These results prompted investigation into the raw IMU signals the model was trained on which revealed significant drift. Drift in IMUs is a known problem that often worsens with time [3, 13], meaning prompts recorded later in the sequence are most affected by drift. During real-time control, motions of the later prompts in the recording sequence are unrecognizable to the model. The following changes were made to combat drift and unreliable signals (1) implement new IMUs, (2) modify calibration protocol and (3) add more arm sensors.

Instead of clustering the prompts into 2 minute intervals, the new protocol requires participants to perform a full cycle of the 6 prompts successively, 6 times. The new protocol was designed with the intent of feeding the model data for all prompts affected by varying levels of drift. Additionally, recording signals in a *staccato* fashion is hypothesized to more closely resemble real-time input data. Sensors were added below the elbows to capture more variance in the arm motions.

Validation of these changes is on going, with preliminary comparisons being made from participants in the scoping study and the current cSCI participant in our vetting study (Sec. 6). Figure 1 shows a plot of the 2D PCA embedding of a scoping study participants under the original calibration protocol compared with our current cSCI vetting study participant under the updated protocol. Figure 1a lacks several of the characteristics displayed in Figure 1b that we hypothesize suggest a *viable map*–defined as actuatable in all 6 dimensions. These features include (1) perpendicular axes with respect to the two side of the body [8] and (2) portions of all these axes overlapping. The perpendicular axes suggest a reflection of the expected symmetry across the two sides of the body. All axes overlapping would suggest the presence of the *deadzone* in which the participant is able to reach their rest position for every prompt. Finally, the spread of clusters along the x-axis, as shown in 1a, suggests the presence of IMU drift accumulating over the recording. Using the updated protocol, from observational analysis, GUI control appears more consistent and reliable.

5 VETTING STUDY

The feedback and the results from the scoping study inspired changes to the system design and study protocol. These main changes are (1) switching to elbow prompts, (2) additional arm sensors, (3) new IMU hardware, and (4) updated calibration protocol. These changes led to vetting the full experiential protocol and training paradigm on an uninjured participant (M 45).

Experimental Protocol In the vetting study, we aim to gain insights into how a participant learns to interact with the robotic arm using a *supervised map* based on classifying the 6 body prompts explored in the scoping study. The study furthermore follows a sliding dimensionality *training paradigm* to aid in human learning.

Training Paradigm The phased learning protocol iteratively unlocks control dimensions to the user, and additionally engages adaptive robot autonomy to assist with learning. In particular, the user begins with operating only 3 dimensions of the BoMI, which map to position control of the robot end-effector. Sessions evolve in groups of 3, where each new block of 3 sessions unlocks an additional control dimension, and the progression of control dimension unlocking occurs as 3⟶4⟶5⟶6.

Robot autonomy is employed to assist with learning for a sequential reaching (SR) task. Throughout and across a 3-session block,

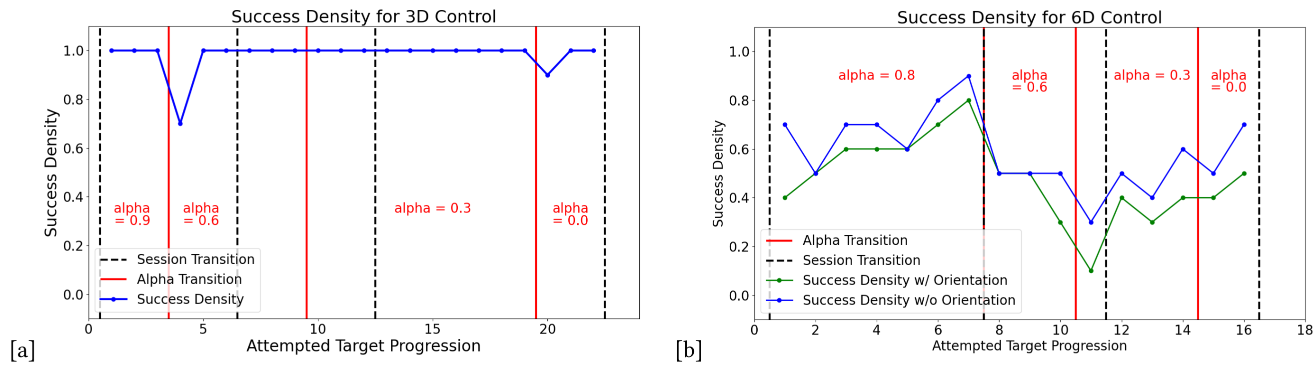

Figure 2: Average success throughout and across sessions. Red vertical lines denote an α transition. Black vertical dashed lines denote a session transition. (a) Plot the success density for 3D control–x, y, and z unlocked– and the corresponding α values. A target is considered reached when the end-effector frame is within 10cm in each translation direction. (b) Plot of the success density for 6D control–all control dimensions unlocked–with the corresponding α values. The blue line considers a target reached when the user reaches the target within a translation threshold of 10cm. The green line considered a target reached when the user is within the translation threshold and an orientation threshold of 0.4 radians in ϕ_r, ϕ_p, ϕ_y.

we iteratively reduce the autonomy contribution to in turn reduce participant dependence on autonomy assistance. At the start of a new block, a high level of assistance is engaged, which recedes over the three sessions until the human is in full control by the end of the third session [1]. The autonomy signal is generated via a potential fields controller that knows of obstacles (table, cage) and the target location. The autonomy signal is linearly blended with the user command via:

$$\mathbf{u} = (1 - \alpha) \cdot \mathbf{u}_{human} + \alpha \cdot \mathbf{u}_{autonomy}$$

and progressively decreasing the value of α accomplishes the phased reduction in autonomy assistance. The α adaptation schedule within a given block proceeds as $\alpha = 0.8 \longrightarrow 0.6 \longrightarrow 0.3 \longrightarrow 0$.

Hardware In this study, a participant interfaces with a 7DoF JACO v2.0 robotic arm (Kinova Robotics, Quebec, Canada). Participants do not have control over the gripper state, and Kinova's inverse kinematics maps the 6D robot (end-effector) control command to the 7 robot joints. The BoMI-mounted IMUs (MbientLab, San Jose, CA) collect orientation data from the end-user at 40 Hz, formatted as quaternions. These quaternions are transformed via our mapping scheme to the 6D end-effector control. The Kinova onboard controller maps these control signals to joint torques which will move the end-effector along the actuated control dimension.

Targets for reaching tasks are presented as wooden blocks affixed to the inside boundaries of an icosahedral cage.

5.1 Preliminary Results

Preliminary results from this vetting study are found in Figure 2. These plots summarize how the target success density for the SR task of the user is impacted by changes in the α level and as more dimensions are unlocked. There is a moving window of 10 targets with an overlap of 5 applied to the data; this moving window counts successful reaches as 1 and counts unsuccessful reaches as 0 and resets the metric at every α and session transition.

From these results, we see in Figure 2a how low dimensional translation control poses little challenge to the participant as they are able to consistently reach targets. This holds even when there is no autonomy assistance. However, during 6D control, they are less consistent in achieving the targets as they might unintentionally activate other control dimensions. When looking at Figure 2b, the blue line denotes a target reached when the user is within the translation threshold dimension and the green line denotes a target reached when the user is within the translation and orientation thresholds. Comparing these lines we see a monotonically increasing trend where the user is able to reach a success density higher than at which they started for both session 10 and session 12. This trend is not seen in session 11, which is hypothesized to be because the user has majority influence over the control space in the new unlocked dimension for the first time. These results also indicate that there are instances in which the user is able to reach the target in the translation dimensions but could not in the orientation dimensions; supported by participant feedback citing orientation being more difficult to reach than translation.

The results from this vetting study suggest that with this protocol and learning paradigm the participant is able to achieve a final success density without autonomy comparable to their starting rate with majority autonomy control across a dimension block.

6 CONCLUSION

The evolution of transitioning to designing and evaluating assistive systems for those with cSCIs is iterative. End-user involvement through fact-finding missions to influence downstream system changes early on is valuable. For this project, the evolution to evaluating a full pipeline on an end-users from an initial pilot study involved a scoping study with end-users to better understand the degree of limitations a person might experience and gain feedback on the system design. From these results, adaptations surrounding calibration methods, vest, design, and study protocol were implemented. The changes reported as a result of the vetting study are currently being vetting by an cSCI participant. Early results and feedback are prompting further design changes.

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