An Evolution of Assistive Robot Control to Meet End-User Ability

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ABSTRACT

In this work, we present an evolution of system designs and studies that aim to facilitate the operation of high-DoF assistive robotic arms by persons with upper limb paralysis. We highlight the experimental pipeline and note developments in our efforts to design a suitable control map that can convert low variance residual body motions from neuromotor-impaired populations into 6-D velocity control signals for use in teleoperating a 7-DOF robotic arm. Notably, we provide results from variance analyses on raw IMU control signals from both neuromotor-impaired and unimpaired populations, and an analysis of the intrinsic dimensionality of map-building datasets gathered with and without movement guidance. We then present a preliminary 13-session study that vets the control map developed in light of these findings.

CCS CONCEPTS

• **Human-centered computing** → *Usability testing*; **Accessibility technologies**; *User interface programming*.

KEYWORDS

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

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1 INTRODUCTION

The variations in neuromotor impairment necessitate *customized* assistance solutions. Neuromotor impairments can present in a number of ways, even when they stem from a similar type of injury [9]. There are instances in which these end-users of assistive devices, such as wheelchairs or robotic arms, lack access to control interfaces able to account for their specific physiological constraints—and as a result, lack access to the assistive device itself.

A Body-Machine Interface (BoMI) [3, 7, 13] is an example of an interface able to customize to the residual movements of an individual, especially in their shoulders and arms, with demonstrated ability [6] to produce sufficiently high-dimensional control signals to operate a robotic arm without the need for switching between subsets of the control space. Critically, this high-dimensional control to date has been demonstrated only in persons without injury. In this work, we extend prior work on BoMI control of robotic arms to the use case of persons with cervical Spinal Cord Injury (cSCI).

A survey of spinal cord injury survivors with tetraplegia found their highest priority to be recovery of arm and hand function [2]. We consider in this work the recovery of that function via operation of an assistive robotic arm. Prior work [6] uses a statically-defined expert map derived via Principle Component Analysis (PCA) to convert 36-D upper body kinematics (captured via Inertial Measurement Units (IMUs)) into 6-D commands to operate a 6-DoF robotic arm, and then observational tuning to customize the expert map for each uninjured participant. Typically 6-DoF robot teleoperation by persons with motor impairments requires switching between control modes [5], that are subsets of the robot control space, with the result of added cognitive and physical burden. The reason is because the interfaces accessible to them (e.g. sip-and-puff, head array, perhaps joystick) span only a portion of a control space (1-D to 3-D). The demonstration [6] of robot teleoperation using a high-DoF BoMI control signal that obviates the need for mode switching, paired with the target of utility for populations with upper-body paralysis, prompts our current investigation into deriving customized BoMI maps that are suitable for use by, and derivation from, the movement capabilities of individuals with upper-body motor impairments.

Adapting high-DoF BoMI control to target populations with upper body paralysis poses new challenges, due to the reduced range of motion (RoM) at various levels of injury. Prior systems either control at most 2-DoF [3, 8], or have been operated by persons without mobility limitations [6]. To address these challenges, we first conduct a scoping study (Sec. 3) to gather RoM data from three individuals with cSCI performing a variety of body motion prompts, selected both to be accessible to the participant and to contain sufficient variance to generate a controllable 6-DoF map. Our exploratory analysis (Sec. 2) of the intrinsic dimensionality of

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unguided movements motivates the need for such guidance. We thus propose to use guided prompts to design a supervised BoMI mapping, which ties each prompt to a specific DoF of the robotic arm. We then vet this supervised BoMI map, along with an iterative training paradigm, in a 13-session study in which an uninjured participant operates an assistive robotic arm (Sec. 4).

2 MOTIVATION: DIMENSIONALITY ANALYSIS

We hypothesize that the traditional method of BoMI map generation, that extracts control signals from upper body movements in an unsupervised way [4, 11, 12], will not be suitable for control of devices with many DoFs even with the use of nonlinear mappings. To investigate this hypothesis, we first evaluate whether the Intrinsic Dimensionality (ID) of the free exploration data that is typically used to extract a BoMI control map matches the number of DoFs (6) required to position the end-effector of a robotic arm (3-D position + 3-D orientation). We can consider the ID of a given input dataset as reflecting of the ability of a participant to independently activate each DoF of the robot control.

In an exploratory analysis, we quantify the ID of free exploration data gathered from four uninjured lab members (2F/2M, age 24.5 ± 3.6) with no history of neurological disorders and who exhibit normal joint RoM. *Free exploration* data are recorded as they move their shoulders and upper arms for two minutes within the limits of their range of motion. We then estimate the ID by applying Parallel Analysis (PA) to the quaternion values recorded by the IMUs during free exploration. PA estimates the ID of those free upper body movements to be 2.7. This number is significantly lower than the number of DoF we aim for the BoMI users to control independently (6) and suggests that there is not enough information in the IMU signals to extract a high-dimensional map using purely unsupervised (free exploration) movements.

3 SCOPING STUDY

Our scoping study aims to determine whether guided movement prompts, with suitably high ID for 6-DoF robot control, are feasible persons with upper-body movement limitations to execute.

3.1 Experimental Design

The scoping study consists of a single experimental session in which participants are instructed to perform six distinct *body-motion prompts* (shoulder forward/backward, shoulder up/down, elbow in/out). We record the kinematic signals from the participants' shoulders and arms using 6 IMUs (3 Space Sensors, Yost Labs, Portsmouth, OH, USA) placed bilaterally on each shoulder (two per side on the anterior and posterior part of the shoulder) and arm (Fig. 1B). Each IMU derives orientation using an on-board sensor fusion algorithm in the quaternion format.

Participants are asked to perform each body-motion prompt, passing through the 'zero point' (the rest position of the body) between prompts, for two minutes. During data collection, a computer monitor is placed directly in front of the participant to display slides depicting the appropriate body motion prompts. We also collect *free exploration* data in which the participant is asked to span the range of possible upper body movements by freely moving their shoulders and arms for two minutes.

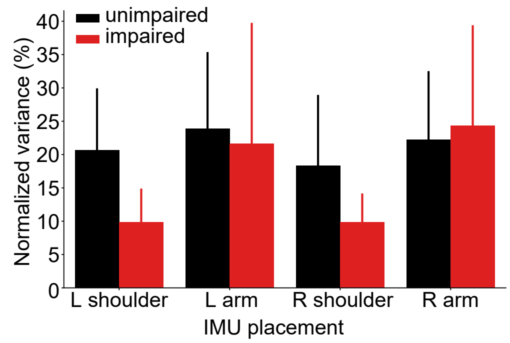

Figure 1: Comparison of net amount of motion between cSCI (red) and uninjured (black) volunteers. The percentage of variance measured by each of the four IMUs placed on participants' shoulders and arms, relative to the maximum value recorded within the uninjured population. Error bars show standard deviation. The shoulders of cSCI participants exhibited lower net motion in comparison to those without injury, whereas the net motion of the arms was relatively consistent across the two populations.

3.2 Participants

Three participants with cervical spinal cord injury (cSCI) were recruited. cSCI is defined in this study as either a 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). Potential cSCI participants were further screened for the presence of tremors, spasm, and/or other significant involuntary movements. All participants gave their informed, signed consent to participate in the experiment which was approved by the Northwestern University Institutional Review Board (IRB). Recruitment targeted spanning the range of injury level for which we expect a BoMI-controlled robotic arm to be of utility: for a complete injury at the cervical cord, shoulder movement no longer is possible to operate the BoMI interface, while for lower levels of SCI, without any upper limb paralysis, the need for assistance from a robotic arm is diminished. The levels of injury of the three SCI participants were: C3 Complete, C4 Incomplete, and C5 Incomplete (3M, age 63 ± 20.4).

3.3 Results

The amount of variance measured during each body motion prompt is related to the ID of this movement set. Having established the ID of the uninjured dataset to be 6 (Sec. 2), we now compare the variance represented within the uninjured and SCI datasets.

We compute the variance of the orientation (quaternion) values recorded by each IMU and for each body prompt to determine the net amount of motion on the participants' shoulders and arms. To better interpret variance expressed by quaternions, we normalize this metric for each IMU to the variance exhibited by the unimpaired participant with the largest value across the prompts (as in [10]).

We find the range of motion of the cSCI participants during the shoulder and arm prompts to be comparable to that of the uninjured population (Fig. 1). The cSCI participants retain 73.8 ± 1.3% of the

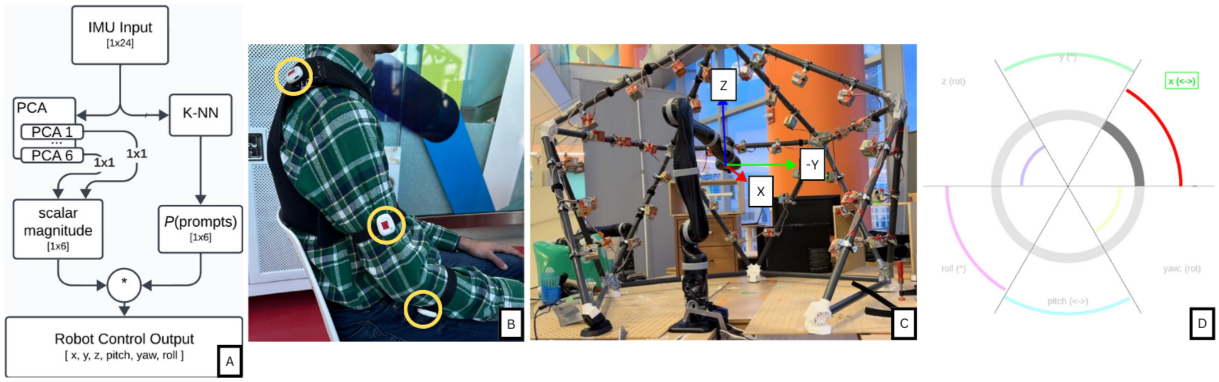

Figure 2: Experimental setup showing (A) the process chart of our BoMI system, (B) body placement of the BoMI IMUs to control an assistive robotic arm, (C) the icosahedral cage that presents reaching targets (LED-illuminated blocks), and (D) the BoMI visualizer feedback GUI, where each channel (wedge) represents one of the six dimensions of BoMI control. Color-coded arcs are controllable by the BoMI, in positive and negative directions radiating out from the deadzone (gray).

net amount of motion exhibited in the unimpaired data, when averaged across all prompts and sensor placements. Interestingly, the net amount of motion of the IMUs placed on the arms of the cSCI participants is notably larger than that of the sensors placed on their shoulders. We posit that this is due to the larger rotational variance present in sensors affixed to the end-user's elbow frame as opposed to the shoulder frame.

4 VETTING STUDY

From the results of our dimensionality analysis and scoping study, additional system changes were required in order to achieve viable online control with the robot; these changes include sensor placement, automated scaling of dimensional gains, and changes to our collection protocol. These changes have been implemented, and vetted in a preliminary study executed over 13 sessions during which a training paradigm is employed that pairs a phased scaling up of controllable dimensions with assistance from robotics autonomy.

4.1 Experimental Design

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 six 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 three, where each new block of three 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. Throughout and across a 3-session block, 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 is gradually pulled back 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 7-DoF JACO v2.0 robotic arm (Kinova Robotics, Quebec, Canada) using the BoMI. This is a non-anthropomorphic arm with 7 revolute joints defining its configuration and an additional DoF defining the state of the gripper. For this application, participants do not have control over the gripper state, and Kinova's inverse kinematics maps the 6-D 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 6-D end-effector (x, y, z, pitch, yaw, roll) 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, as shown in Figure 1C. The current target is indicated by an illuminated LED.

Supervised Map. The BoMI map (Fig. 1A) first predicts which motion prompt(s) the user currently is performing, and then converts the related upper body kinematics into a control signal to proportionally activate the robot DoF associated with the detected prompt(s).

Specifically, the supervised map first uses a k-nearest neighbors classifier to predict a probability distribution over the six motion prompts, taking the high-dimensional IMU signal as input. Each prompt label corresponds to a single robot DoF, and so the classifier output thus maps to activation of the robot end-effector control dimensions. The correspondence is chosen to loosely mirror end-effector translational movements with human shoulder movements:

right human [shoulder up/down, shoulder forward/back, arm abduction/adduction] → robot hand [up/down ($\dot{z}$), forward/back ($\dot{y}$), left/right ($\dot{x}$)], and left human [shoulder up/down, shoulder forward/back, arm abduction/adduction] → robot hand [pitch ($\dot{\phi}_{pitch}$), roll ($\dot{\phi}_{roll}$), yaw ($\dot{\phi}_{pitch}$)].

To determine the amplitude of the control command for each robot DoF, we derive six PCA maps from the collected user prompt data, one for each body-motion prompt. At runtime, we then use the value of each map's first principal component to proportionally move the corresponding robot DoF.

A screen-based 2-D task conveys visual feedback to the participant about their activation of each BoMI dimension. Created using the Pyglet wrapper for the OpenGL library, this environment consists of 6 wedge-like 'channels' arrayed radially to form a full circle (Fig. 2D). Each channel corresponds to a different control dimension and has two types of arcs: (1) a color-coded arc that the participant is able to control via the BoMI, and (2) a thin grey arc centered on the deadzone associated with each dimension.

This method of feedback is designed to be easier (than non-anthropomorphic robot arm motion) to visually parse when users first operate the BoMI. We also use this task to determine whether a map is *usable*, defined as the participant being able to activate each channel in both directions using their body motions.

Protocol. The first session is devoted to calibrating the BoMI map and does not involve interaction with the robot. Instead, two calibration datasets are collected using different protocols: the participant (1) performs a full cycle of the six prompts successively, six times, and (2) repeatedly performs each individual prompt for 45 seconds per prompt. Both datasets are used (together) in the computation of the BoMI map. Participants then perform the body-motion prompts while interfacing with the feedback GUI to determine usability.

The remaining 12 sessions execute *sequential reaching* tasks. The participant is asked to teleoperate the robotic arm to reach a sequence of targets (45 in total). A target is considered achieved if the position and orientation of the end-effector of the robot relative to the position and orientation of the target is within a threshold (15 cm for position, 0.1 rad for orientation). The participant has 45 seconds to accomplish a reach task. At the end of a set of three targets, the robot arm returns to its home position at the center of the cage before commencing another set of three targets.

4.2 Participants

One uninjured participant was recruited (1M, age 45). This participant was screened for past experience with assistive interfaces, ability to perform gross upper-arm and shoulder motions, and absence of chronic injuries of the back and spine. The participant gave their informed, signed consent to participate in the experiment which was approved by the Northwestern University IRB.

4.3 Results

Our analysis of this data is ongoing. Anecdotally, we confirm that the participant was able to successfully reach targets during each phase of the training paradigm (in each study session), even as the number of controllable dimensions increased and assistance from robotics autonomy was scaled back.

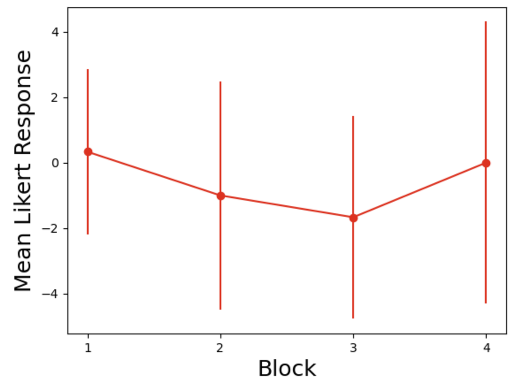

Figure 3: Likert responses. Mean across all (3) ease of use responses within a training block, for each of the 4 blocks.

We present here preliminary findings relating to perceived ease of use, assessed via Likert-scale questionnaire response to "It was easy to issue my intended command." In the session during which a new dimension was unlocked, the participant, on average, expressed that the system was more difficult to use, even with the highest level of autonomy assistance (highest α value).

Figure 3 presents the average (over 3 sessions) response within a given block. We observe ease of use progressively decline as dimensions are unlocked, with one exception: the final unlock, which in practice did not change the controllability of the system as none of the targets explicitly required motion in this final unlocked dimension (roll). Overall, these results speak to the difficulty of high dimensional control. One interpretation of the final unlock anomaly is the promise of continued practice: that having essentially hit the limit on robot operation complexity in the prior training block, the final block becomes essentially more practice at the plateaued complexity level, and ease of use increases during this practice.

5 CONCLUSION

In this work, we found that traditional methods of mapping body motion to control signals via a body-machine interface are not sufficient for populations with reduced range of motion (due to neuromotor impairment) and supported these claims by considering the intrinsic dimensionality of both impaired and unimpaired populations. We also vetted our experimental pipeline for generating user-specific BoMI maps (as well as training participants to use those maps) on an unimpaired participant. Our next step is to apply feedback from both studies to our experimental pipeline in preparation for a longitudinal with cSCI participants.

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