Assistive Robotic Manipulation through Shared Autonomy and a Body-Machine Interface

Siddarth Jain*, Ali Farshchiansadegh‡, Alexander Broad*, Farnaz Abdollahi§,
Ferdinando Mussa-Ivaldi‡§¶, Brenna Argall*¶
Sensory Motor and Performance Program, Rehabilitation Institute of Chicago, Chicago, IL, USA
*Department of Electrical Engineering and Computer Science, Northwestern University, Evanston, IL, USA
‡Department of Biomedical Engineering, Northwestern University, Evanston, IL, USA
§Department of Physiology, Northwestern University, Chicago, IL, USA
¶Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, USA
Email: sidd@u.northwestern.edu

***Abstract*—Assistive robotic manipulators have the potential to improve the lives of people with motor impairments. They can enable individuals to perform activities such as pick-and-place tasks, opening doors, pushing buttons, and can even provide assistance in personal hygiene and feeding. However, robotic arms often have more degrees of freedom (DoF) than the dimensionality of their control interface, making them challenging to use—especially for those with impaired motor abilities. Our research focuses on enabling the control of high-DoF manipulators to motor-impaired individuals for performing daily tasks. We make use of an individual's residual motion capabilities, captured through a Body-Machine Interface (BMI), to generate control signals for the robotic arm. These low-dimensional controls are then utilized in a shared-control framework that shares control between the human user and robot autonomy. We evaluated the system by conducting a user study in which 6 participants performed 144 trials of a manipulation task using the BMI interface and the proposed shared-control framework. The 100% success rate on task performance demonstrates the effectiveness of the proposed system for individuals with motor impairments to control assistive robotic manipulators.**

I. Introduction

People with motor impairments often have difficulty performing activities of daily living. According to the Americans with Disabilities report [1] over 12 million people need assistance in their daily lives. This number grows to about 20 million people when asked specifically about dealing with difficulties that stem from lifting and grasping tasks. Assistive technologies like powered wheelchairs, walkers, canes and prosthetic devices have greatly enhanced the quality of life for individuals with disabilities. For those with motor impairments that limit the functionality of their arms or hands, robotic assistive manipulators have the potential to enhance their independence. With assistive manipulators, people with impairments can regain the ability to perform daily living tasks which would otherwise be difficult without the aid of a caregiver.

Pre-development surveys with potential users of robotic manipulators indicate that reaching, grasping, and picking up objects from the shelf and floor are tasks that are highly prioritized [2]. Assistive manipulators can allow users to independently perform activities such as pick-and-place tasks, object manipulation, opening doors, pushing buttons and/or light switches, and even personal hygiene and feeding. However, robotic manipulators often have more degrees of freedom (DoF) than the dimensionality of their control interfaces, making them challenging to use—especially for those with impaired motor abilities. Using a limited control interface such as the sip-and-puff—whose control output dimensionality is even lower (e.g. 1-D) than that of standard joysticks—means manipulation tasks are often tedious, if not impossible, to perform.

Some works offer the solution of making the control of robotic manipulation fully or partially autonomous [3], [4]. Studies have shown that users prefer to retain as much control as possible when working with assistive devices [5]. Therefore, an attractive solution is to develop a shared-control system where robotic autonomy is used to enhance and aid the user's input for manipulation tasks. A shared-control paradigm has been shown to be effective in a number of different areas such as obstacle avoidance and navigation of powered wheelchairs [6]. Within the context of robotic arms, explicit planning and control within a high dimensional space is a formidable challenge that can become feasible and learnable by allowing for a variable sharing of control between the user and the robot.

Another challenge for people with motor impairments is the rehabilitation process, which aims to allow patients to keep their remaining motor function and possibly even recover some lost function. To encourage the continued use of muscular activity, a participant's residual body movements can be captured to provide control signals for an assistive device. The question then becomes how to use these limited signals to enable the control of a high-Dof robotic arm.

We propose a shared-control framework for assistive manipulation that is built on the concept of autonomous piecewise trajectory segments and the use of a body-machine control interface, to address the aforementioned problems. Our novel approach enables assistive manipulation for people with motor-impairments with beneficial rehabilitation effects. We demonstrate the feasibility of the proposed control framework by conducting a user study. The experiments were performed with the MICO robotic arm (Kinova Robotics, Canada)—the research edition of the commercially available JACO arm, which is designed specifically for use

978-1-4799-1808-9/15/$31.00

Fig. 1. *Left*: MICO manipulator from Kinova Robotics. *Right*: Our Body-Machine Interface

within assistive domains (Figure 1, left). In the next section, we review related work. Section III details the proposed system and Section IV describes the evaluation approach followed with experimental results. In the final section we conclude with directions for future work.

II. Related Work

Human-machine interfaces are rapidly developing technologies to restore function in people with motor impairments. These interfaces are built upon the reorganization of motor coordination patterns to control different devices such as a prosthetic arm moving with EMG signals [7], driving a wheelchair using tongue motions [8], compensatory strategies in stroke survivors [9], and many more.

Researchers have employed brain-machine interfaces to investigate how the brain controls redundant limb kinematics. Since the turn of the new millennium, a growing number of researchers have begun to consider how brain activities recorded both by implanted electrode arrays [10] and by non-invasive electroencephalographic (EEG) systems [11] can be used to control external devices. These earlier works stemmed from a long history of neurophysiological studies aimed at investigating what motor information is encoded in brain activities, and particularly in the primary motor area of the cortex [12]. In the early 1970's Fetz and Finocchio [13] provided the first demonstration of the possibility for a monkey to control by operant conditioning the activity of individual brain neurons. However, a few decades elapsed before the technologies of electrode arrays and the methods for decoding population activities made possible the development of the first brain machine interfaces based on multi-unit recordings.

Brain-machine and body-machine interfaces share not only the same acronym (BMI) but also a large number of equivalent computational problems, most notably (i) the challenge to decode the user's movement intention from multiple signals containing related information and (ii) techniques for connecting the decoded signals to external devices. Several examples exist of interfaces that exploit overt motor activities, such as gaze control [14], head motions (as in the Headmouse, Origin Instruments, USA), EMG signals [15], EEG signals [16] and even tongue motions [17]. A recent extensive review and classification of non-invasive human-machine interfaces can be found in Lobo-Prat *et al.* [18]. Unlike brain-machine interfaces, body-machine interfaces engage their users in sustained physical activities that by maintaining mobility can prevent muscle atrophy, promote cardiovascular health and support partial recovery of movement skills. The BMI utilized in this study has the distinctive feature of being based on upper-body motions captured by multiple inertial sensors with the combined purpose of operating external devices and of promoting, preserving and remapping residual mobility that remains available to persons with severe paralysis. Our previous work involved using the BMI to address 2-D control problems [19], [20]—control the speed and heading of a powered wheelchair, a cursor position on a screen, typing on a virtual keyboard and playing games including pong. In this paper, we use our BMI within a framework to facilitate the control of high-dimensional assistive robotic arms.

It is challenging to scale up the lower-dimensional signals from limited interfaces to control high-DoF robotic arms. When using a 2- or 3-axis joystick interface, it is not possible simultaneously to control both position and orientation of the end-effector (a 6-D control problem). Commercial solutions involve toggling modes to operate a subset of robot's DoF, such as in the 6-DoF MANUS arm (Exact Dynamics B.V., Netherlands) and the 6-DoF JACO arm (Kinova Robotics, Canada), which can however add cognitive and physical burden on the user. Some works have targeted to simplify the operation of assistive robotic arms via full autonomy where the human specifies the target object or task [3], [4]. Users however typically prefer to retain some control of the system and, moreover, autonomy may fail to achieve task success [21].

In this work we incorporate shared-control autonomy to reduce the control burden on the user while still keeping them engaged in the task execution. Shared-control frameworks have proven useful for robotic powered wheelchairs [22], however, shared control becomes much more difficult to achieve in case of high-DoF assistive robotic arms. For example, in the VICTORIA system, shared control is provided for wheelchair control, but not for the assistive robotic arm mounted to it [23].

III. System Description

In this section, we present the system description for the body-machine interface and the proposed shared-control framework for assistive manipulation.

A. Body Machine Interface and Control Signals

In a body-machine interface, body motions generate control signals to operate external devices. The BMI provides an effective pathway for control because even in people with severe impairments, some residual movements remain available. These movements are captured by multiple sensors, whose combined outputs define a signal space for controlling the external device.

In the proposed BMI system, a high dimensional control signal captured from the participant's residual movements is mapped to a lower dimensional control vector. Importantly, these surviving degrees of freedom captured from the body are higher dimensional than the required control signal. This kinematic redundancy provides the BMI user with a unique opportunity to identify and coordinate a convenient subset of movements to achieve task objectives with a flexible and adaptable motor behavior [24]. This enables the user to effectively issue control signals for the robotic arm via a reorganization of their own high-dimensional upper body motions.

In the current BMI setup the user wears a vest that is equipped with four MTx (Xsens Technologies B.V., Netherlands) motion trackers in order to capture shoulder movements. An IMU is placed on the front and back of each shoulder as can be seen in Figure 1 (right). The orientation of each sensor is computed by a sensor fusion algorithm through the combination of the output of 3-DoF embedded accelerometers, gyroscopes and magnetometers. For the purpose of this study we only use roll and pitch as input signals for the interface because the yaw signals, derived from the magnetometer, have a tendency to drift in the presence of electric motors and large metallic objects. The IMU signals are captured at the rate of 50Hz. With four IMUs the body space is defined by an eight dimensional vector of coordinates captured from the four sensors.

The available residual movements depend on the injury and therefore the interface is user-specific. To this end, we use a calibration phase to map the user's movements to control signals. During the calibration phase, the participants are asked to engage in free-style motions of the upper body for twenty seconds. The purpose of this activity is to characterize the space of IMU signals that each subject could comfortably span. The mapping matrix A is obtained by Principal Component Analysis (PCA). A linear transformation, $C = A \cdot h$, is defined to map the body movements onto the 2-D vector C, that controls the motion of the robot.[1] PCA lends itself quite naturally to this task, since the principal eigenvectors represent the dimensions with largest variability in the data—and thus also the dimensions with the largest capacity for movement from the user. The first two principal eigenvectors of the calibration data are extracted to form a 2-D control space. For further details of the interface and calibration, see [20].

B. Control Framework for Assistive Manipulation

We are interested in a system that keeps the user in control and at the same time provides assistance in manipulation tasks. Using low-dimensional control signals from the BMI, our aim is to enable the simultaneous operation of all degrees of freedom of a high-DoF robotic arm. To address this challenge, we introduce robot autonomy to reduce the user's control burden. By contrast, under direct teleoperation the user would be responsible for individually controlling each joint of the robotic arm at each time step, or equivalently the position and orientation of the end-effector. (For our experimental platform, both are 6-D control problems.)

Our intended system will create a sequence of functionally relevant piecewise segments based on the semantics of actions performed during a typical execution of a given manipulation task—such as reaching, grasping, and pouring. As a first step, in this work the autonomous system plans piecewise trajectory segments for predefined manipulation task using autonomously perceived goals (Section IV-B).

[1]We begin with a mapping to 2-D, as this has been shown in our previous work to be both feasible and effective [20]. Future work will scale up C to higher dimensions.

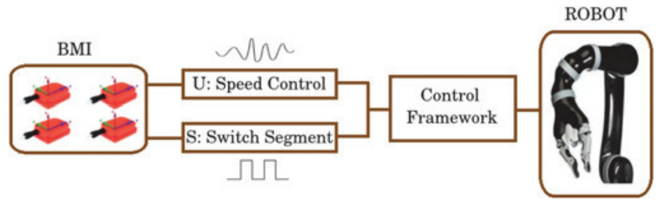

Fig. 2. Schematic of the system pipeline.

Next, the motor-impaired user influences the execution of these trajectories through (i) control of the speed (U) of the manipulator along each segment of the task, and (ii) dynamically switching (S) between trajectory segments in order to complete the desired task. The 1-D continuous valued signal U, controls the speed of the manipulator along the current trajectory. The 1-D binary signal S triggers a switch between motion segments. The threshold to generate the binary signal is set as twice the standard deviation of the second principal component, and is obtained during the calibration stage of the BMI interface. This approach allows for operation of a high-DoF arm with the limited control signals $\langle U, S \rangle$ available from the BMI interface. Users thus are able to inject their preference and situational awareness into the otherwise autonomous task execution.

The first step in the technical implementation of this framework is to autonomously generate trajectories from the robot's current configuration Q to the desired goal configuration. Any suitable motion planner can be used for this purpose. We used task-constrained motion planning [25] and the Constrained Bi-directional Rapidly exploring Random Tree (CBiRRT) [26] in our implementation. To achieve speed control along the trajectory, we calculate joint velocities

$$v = \frac{\delta}{\tau} \cdot U$$

based on (i) the user's input signal, $U \in [0,1]$, and (ii) the autonomy command, computed as the Euclidean distance δ between the current configuration Q of the robot and the next configuration waypoint along the path, divided by timestep τ. Here the command velocity $v \in \mathbb{R}$ is the set of joint velocities sent for execution on the robot manipulator. In order to progress along the trajectory, we update which waypoint is the current subgoal based on distance to current configuration Q, and continue to do this until we have achieved the final goal configuration.

IV. System Implementation and Evaluation

To evaluate our proposed system, a user study was performed by subjects with and without high-level Spinal Cord Injury (SCI).

A. Task

The manipulation task of the user study consisted of using the robotic arm to pour the contents of a cup into a bowl. The task was a sequence of the following four motion segments: (i) reach for the cup, (ii) grasp it, (iii) carry it to the bowl and (iv) pour the contents of the cup into the bowl.

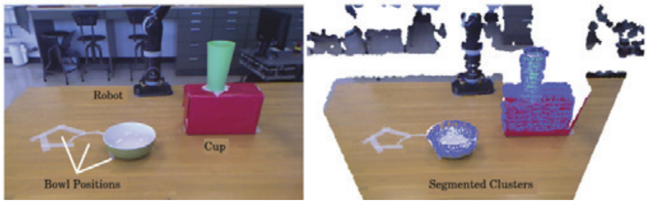

Fig. 3. *Left*: Experimental set-up. *Right*: Segmented point cloud clusters (shown in blue).

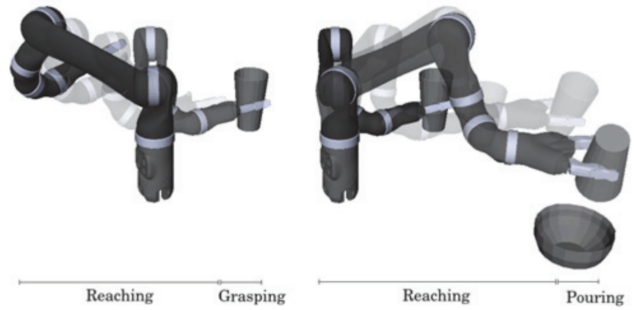

Fig. 4. Illustration of the piecewise segments associated with the experimental task.

To assess more extensively the effect of the user's input, variability was introduced into the task by modulating the position of the bowl (three positions). Task success thus depended on the user appropriately triggering the transition between segments (iii) and (iv). If they did not switch in time, the assistive manipulator would continue along its trajectory, overshooting the bowl. The pouring task was explained to each participant, along with the effect of the control signals $\langle$U, S$\rangle$.

B. Autonomy

For the first and third segments we used the CBiRRT planner to generate a set of waypoints that define a path from the robot's current configuration to each subgoal position, where the final goal was defined to be past the furthest of the three bowl positions (so that the final trajectory segment passed over all possible bowl locations). For the second and fourth segments, no planning was needed: segment (ii) involved simply closing the gripper, while segment (iv) involved rotating the wrist.

To compute the position of the cup, we implemented a tabletop segmentation and Euclidean clustering approach using the point cloud data obtained from the Kinect RGB-D sensor. This results in segmented clusters of the objects present in the scene (Figure 3).

C. User Input

The user provided 2-D input to the system using the BMI, as described in Section III-B. The first signal allowed the user to control the speed of the arm along the various trajectories, and the second signal allowed the user to transition between segments (iii) and (iv). The transitions between other piecewise trajectories was performed autonomously, to simplify the task design, since these transitions were not modulated within the study design.

D. Execution

For each trial one of three bowl positions was randomly selected. The user began the execution by controlling the speed U during trajectory segment (i). As the robotic arm reached the cup, the autonomous system transitioned to segment (ii) and the user controlled the speed U at which the gripper was closed in order to grasp the cup. During segment (iii), the user again controlled the speed of the robotic arm along the path, until signal S was issued by the user to switch to segment (iv). During segment (iv), the user speed U mapped to control the wrist rotation, and thereby poured the contents of the cup. Figure 4 represents an illustration of the experimental procedure.

Fig. 5. An SCI user controlling the robot with the BMI during the experimental task.

E. Subjects

One SCI survivor (31 year old male, 13 years post-injury at the C5 level) and five uninjured control individuals (mean age: 28 $\pm$3) participated in the user study. All participants gave their informed, signed consent to participate in this experiment, which was approved by Northwestern University's Institutional Review Board. The SCI participant and one of the control participants were not naive to the BMI due to their previous participation in another study [20]. The remaining participants did not have any prior experience with the interface. After the calibration of the BMI each participant performed 24 reaching and pouring trials (8 trials per bowl position) in a randomized sequence. Note that continuous visual feedback of the control signals together with the switching threshold was provided on a computer screen that was positioned in front of the participants. Figure 5 shows the experimental setup and a user performing the task using the proposed system.

V. Experimental Results

All subjects were able to perform the task by reorganizing their shoulder movements. They learned to perform the task effectively after the very first trial and the performance level stayed the same for the rest of the experiment. We furthermore observed similar performance between the SCI

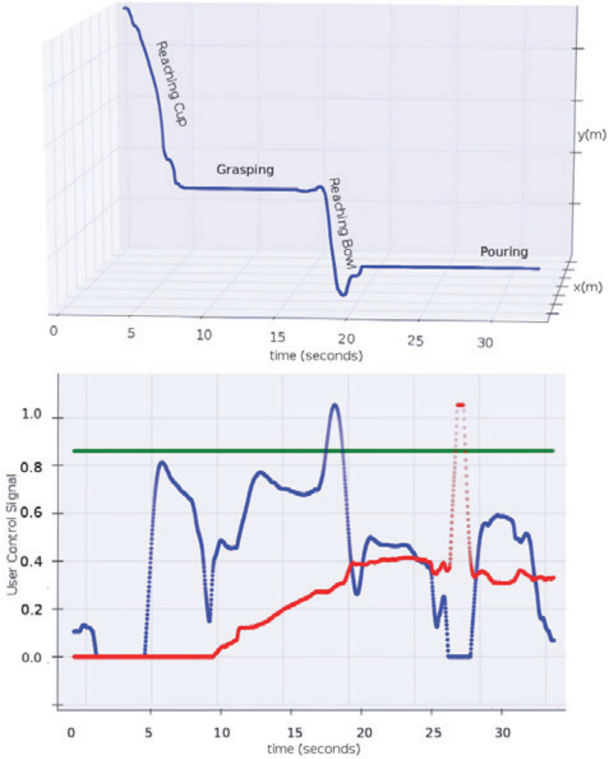

Fig. 6. *Top*: Robot's end-effector in (x,y) space. *Bottom*: User's control signals U (blue) and S (red), and the threshold used to switch between segments (green).

and non-injured subjects, across all measures. The end-effector position and task completion time were recorded for each of the trails.

Figure 6 shows the user control signals $\langle \mathrm{U}, \mathrm{S} \rangle$ and the end-effector position for a representative task trial. Note the use of signal U for the reaching, grasping and pouring segments, and the use of signal S to switch (around second 28) to pouring after reaching the bowl position.

Figure 7 shows the position of the robot end-effector at the end of each trial for the SCI participant and a representative control subject. It can be seen that the subjects were able to successfully switch the trajectory segment in order to perform the pouring task for each of the three bowl positions. More importantly, the performance of the SCI participant was comparable to other uninjured control individuals.

Figure 8 (top) represents the average time to completion for all participants. The time taken by the SCI participant for task completion was comparable that of the able-bodied individuals (C1-C5).

Furthermore, to quantify movement smoothness we calculated jerk as

$$J = \left| \sum_{k=1}^{n} \dddot{x}(k) \right|$$

where $x(k)$ corresponds to discrete samples of the Euclidean norm of the robot end-effector position. Jerk is the third derivative of position, and a standard measure to quantify movement smoothness [27]. A second-order Butterworth filter with a cutoff frequency of 5Hz was used to smooth

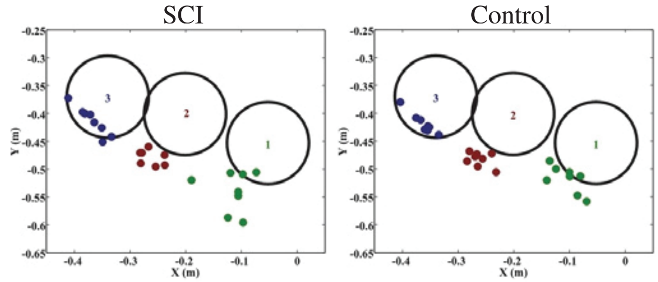

Fig. 7. Position of the robot end-effector at the end of each trial for the SCI participant (left) and a representative control subject (right). Each color corresponds to one of the three positions of the bowl. Note that a successful pouring motion aligns the top of the cup over the bowl, which results in the robot end-effector position being offset (since the cup has non-negligible length).

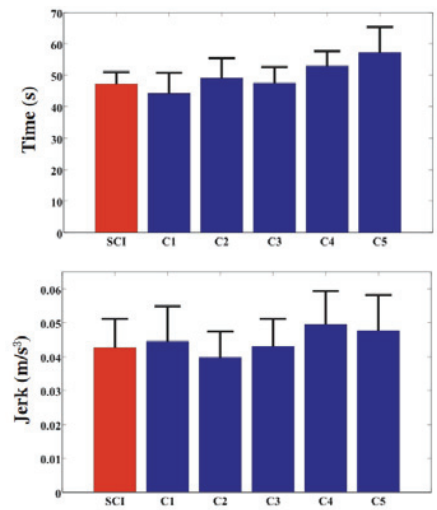

Fig. 8. *Top*: Average time to completion for all participants. *Bottom*: Average movement smoothness for all participants. For both plots, error bars represent standard deviation.

and attain the end-effector trajectory for each trial. Figure 8 (bottom) shows the average jerk index for all participants. Note that the SCI participant was as smooth as the uninjured subjects in controlling the arm movements.

The above results demonstrate the effectiveness of the proposed shared-control and BMI interface system as the performance of the SCI participant was comparable to the control individuals for the manipulation task. Our next steps will generalize the system to achieve assistive control on a range of daily manipulation tasks. Our future work also will explore mapping the BMI signal to alternate subsets of the control space, as well as the generation of higher dimensional BMI signals.

VI. Conclusions

We have introduced a novel system for the control of assistive robotic manipulators, that makes use of both robot autonomy and a body-machine interface. We conducted a user study with six participants (one SCI and five uninjured control individuals) and all participants were able to use the system to successfully perform a manipulation task. The results of the user study indicate that individuals with severe motor impairments can effectively operate assistive robotic manipulators using the proposed system. Furthermore, the BMI engages the users in physical activity while they operate the manipulator, which may have potential rehabilitation benefits. While the focus of this paper has been on the integration of the BMI for a shared-autonomy control of robot arm, the presented control framework does generalize to any number of other control interfaces (e.g. 2-axis joystick, sip-and-puff). The system was evaluated on a well-defined manipulation task (picking and pouring motion), as the aim of this work was a first evaluation of the proposed control framework. Future work will expand this framework to a larger set of manipulation tasks and alternate interpretations of the BMI signal.

Acknowledgment

This research was supported by NIBIB grant R01-EB019335, NICHHD grant 1R01HD072080 and NIDRR grant H133E120010.

References

[1] M. W. Brault and United States Bureau of the Census, *Americans with disabilities: 2010*, 2012.

[2] C. A. Stanger, C. Anglin, W. S. Harwin, and D. P. Romilly, "Devices for assisting manipulation: a summary of user task priorities," *IEEE Transactions on Rehabilitation Engineering*, vol. 2, no. 4, pp. 256–265, 1994.

[3] A. Jain and C. C. Kemp, "EL-E: an assistive mobile manipulator that autonomously fetches objects from flat surfaces," *Autonomous Robots*, vol. 28, no. 1, pp. 45–64, 2010.

[4] K. M. Tsui, D.-J. Kim, A. Behal, D. Kontak, and H. A. Yanco, "I want that: Human-in-the-loop control of a wheelchair-mounted robotic arm," *Applied Bionics and Biomechanics*, vol. 8, no. 1, pp. 127–147, 2011.

[5] D.-J. Kim, R. Hazlett-Knudsen, H. Culver-Godfrey, G. Rucks, T. Cunningham, D. Portee, J. Bricout, Z. Wang, and A. Behal, "How autonomy impacts performance and satisfaction: Results from a study with spinal cord injured subjects using an assistive robot," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 42, no. 1, pp. 2–14, 2012.

[6] J. G. Storms and D. M. Tilbury, "Blending of human and obstacle avoidance control for a high speed mobile robot," in *Proceedings of the American Control Conference*, 2014.

[7] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *Jama*, vol. 301, no. 6, pp. 619–628, 2009.

[8] X. Huo and M. Ghovanloo, "Using unconstrained tongue motion as an alternative control mechanism for wheeled mobility," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 6, pp. 1719–1726, 2009.

[9] M. Cirstea and M. F. Levin, "Compensatory strategies for reaching in stroke," *Brain*, vol. 123, no. 5, pp. 940–953, 2000.

[10] C. A. Buneo and R. A. Andersen, "The posterior parietal cortex: sensorimotor interface for the planning and online control of visually guided movements," *Neuropsychologia*, vol. 44, no. 13, pp. 2594–2606, 2006.

[11] J. R. Wolpaw, "Brain-computer interfaces (BCIs) for communication and control: a mini-review," *Supplements to Clinical neurophysiology*, vol. 57, pp. 607–613, 2004.

[12] J. F. Kalaska, D. Cohen, M. L. Hyde, and M. Prud'Homme, "A comparison of movement direction-related versus load direction-related activity in primate motor cortex, using a two-dimensional reaching task," *Journal of Neuroscience*, vol. 9, no. 6, pp. 2080–2102, 1989.

[13] E. E. Fetz and D. V. Finocchio, "Operant conditioning of isolated activity in specific muscles and precentral cells," *Brain Research*, vol. 40, no. 1, pp. 19–23, 1972.

[14] R. J. Jacob, "The use of eye movements in human-computer interaction techniques: what you look at is what you get," *ACM Transactions on Information Systems (TOIS)*, vol. 9, no. 2, pp. 152–169, 1991.

[15] A. B. Barreto, S. D. Scargle, M. Adjouadi *et al.*, "A practical EMG-based human-computer interface for users with motor disabilities," *Journal of Rehabilitation Research and Development*, vol. 37, no. 1, pp. 53–64, 2000.

[16] A. Ferreira, W. C. Celeste, F. A. Cheein, T. F. Bastos-Filho, M. Sarcinelli-Filho, and R. Carelli, "Human-machine interfaces based on EMG and EEG applied to robotic systems," *Journal of NeuroEngineering and Rehabilitation*, vol. 5, p. 10, 2008.

[17] C. Salem and S. Zhai, "An isometric tongue pointing device," in *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*, 1997.

[18] J. Lobo-Prat, P. N. Kooren, A. H. Stienen, J. L. Herder, B. F. Koopman, and P. H. Veltink, "Non-invasive control interfaces for intention detection in active movement-assistive devices," *Journal of Neuroengineering and Rehabilitation*, vol. 11, no. 1, p. 168, 2014.

[19] M. Casadio, A. Pressman, S. Acosta, Z. Danzinger, A. Fishbach, F. Mussa-Ivaldi, K. Muir, H. Tseng *et al.*, "Body machine interface: remapping motor skills after spinal cord injury," in *Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2011.

[20] A. Farshchiansadegh, F. Abdollahi, D. Chen, M.-H. Lee, J. Pedersen, C. Pierella, E. J. Roth, I. S. Gonzalez, E. B. Thorp, and F. A. Mussa-Ivaldi, "A body machine interface based on inertial sensors," in *Proceedings 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2014.

[21] I. Volosyak, O. Ivlev, and A. Graser, "Rehabilitation robot FRIEND ii-the general concept and current implementation," in *Proceedings of 9th International Conference on the Rehabilitation Robotics*, 2005.

[22] Q. Zeng, C. L. Teo, B. Rebsamen, and E. Burdet, "A collaborative wheelchair system," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 2, pp. 161–170, 2008.

[23] F. Bley, M. Rous, U. Canzler, and K.-F. Kraiss, "Supervised navigation and manipulation for impaired wheelchair users," in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, 2004.

[24] N. A. Bernstein, "The co-ordination and regulation of movements," 1967.

[25] D. Berenson, S. S. Srinivasa, and J. Kuffner, "Task space regions: A framework for pose-constrained manipulation planning," *International Journal of Robotics Research*, vol. 30, no. 12, pp. 1435–1460, 2011.

[26] D. Berenson, S. S. Srinivasa, D. Ferguson, and J. J. Kuffner, "Manipulation planning on constraint manifolds," in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2009.

[27] T. Flash and N. Hogan, "The coordination of arm movements: an experimentally confirmed mathematical model," *Journal of Neuroscience*, vol. 5, no. 7, pp. 1688–1703, 1985.