Body machine interface: remapping motor skills after spinal cord injury

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Abstract- The goal of a body-machine interface (BMI) is to map the residual motor skills of the users into efficient patterns of control. The interface is subject to two processes of learning: while users practice controlling the assistive device, the interface modifies itself based on the user’s residual abilities and preferences. In this study, we combined virtual reality and movement capture technologies to investigate the reorganization of movements that occurs when individuals with spinal cord injury (SCI) are allowed to use a broad spectrum of body motions to perform different tasks. Subjects, over multiple sessions, used their upper body movements to engage in exercises that required different operational functions such as controlling a keyboard for playing a videogame, driving a simulated wheelchair in a virtual reality (VR) environment, and piloting a cursor on a screen for reaching targets. In particular, we investigated the possibility of reducing the dimensionality of the control signals by finding repeatable and stable correlations of movement signals, established both by the presence of biomechanical constraints and by learned patterns of coordination. The outcomes of these investigations will provide guidance for further studies of efficient remapping of motor coordination for the control of assistive devices and are a basis for a new training paradigm in which the burden of learning is significantly removed from the impaired subjects and shifted to the devices.

Keywords-Spinal cord Injury, Movement reorganization, body machine interface, Learning, Wheelchair

I. INTRODUCTION

Injury to the cervical spinal cord causes a loss of motor and sensory functions, leading to limb weakness, uncoordinated movements and altered reflexes. However, even in individuals with injuries at a high level of the spinal cord, some residual motor and sensory capacity remains available. These residual functions are potentially very important, as they provide the means to control assistive devices such as wheelchairs, tools, or computers. To make optimal use of these residual movement capabilities, the injured person needs to learn how to redirect limb function to achieve alternative, potentially useful applications. In this framework one of the major problems stems from the limits of the interfaces for assistive devices. These interfaces are typically built with a “one-size fits all” approach, delegating the burden of learning to the impaired subjects. Powered wheelchairs are one important example. In the United States there are more than 150,000 [1-2] users of powered wheelchairs. However, the commercially available devices and their controls are operated by joystick or sip and puff switches [3] and only partially match the different degrees of impairments of subjects’ mobility. The lack of customizability is highlighted by a clinical survey [4]. The possibility of incurring difficulties and accidents is not uniformly distributed across types of disability [5] and subjects with poor control of the upper body are at the greatest risk. Therefore, it is important to understand and facilitate the reorganization of residual motions for the control of powered wheelchairs and other assistive devices after spinal cord injury, through a user specific approach. Hence, we have developed a novel body-machine interface[6] based on two key concepts:

1. remapping the residual motion ability into a low dimensional control space, and

2. matching this control space to the evolving skills of the user.

The proposed interface establishes a form of continuous mobility that is analogous to the mobility of the natural limbs. This paradigm differs sharply from others previous approaches based upon the recognition of discrete control patterns. Our goal is to evaluate the feasibility of using this method as a new controller for training and for enhancing upper body motor skills in high level spinal cord injury (SCI) subjects. Our hypothesis was that by engaging subjects through practicing different actions, such as operating a virtual joystick and a keyboard for playing videogames or piloting a wheelchair in a virtual environment, they concurrently would learn how to improve the control of their residual movements and how to proficiently use the interface that links them to the external world. In this preliminary study, control and SCI subjects were able to improve their performance over different tasks and multiple sessions while the interface was adaptively recalibrated every day. Moreover, subjects modified the relationship between their movements and the control space over which they operated.
II. METHODS

This multisession study investigated the reorganization of upper-body coordination when performing tasks that required different motor skills. We developed a body-machine interface that provides impaired individuals with a continuous signal space operated directly by the combination of residual motions that the users are most capable of controlling [6]. Here, we used this interface for engaging subjects in virtual reality games that trained specific control actions. The evaluation of motor learning was based on a “reaching” task performed as a test at the beginning and at the end of each session.

A. Experimental setup and protocol.

We used an array of four infrared video cameras (V100, Naturalpoint Inc., OR, USA) to track four active light markers, which were attached to the subject’s upper-body garments (Fig.1). Shoulder and arm positions were captured at 75 samples per second using proprietary software (Modification of a C++ SDK supplied by Naturalpoint).

![Figure 1](image.png)

Figure 1. Experimental set up. Subjects sit on a chair reclined at about 40 deg. Such position is easy to maintain for SCI subjects. The four markers were placed on the subject's shoulders and upper arms, two for each side of the body.

The 8-dimensional body-signal vector (two dimensions for each camera) of sensor signals \( h = [h_1, h_2, \ldots, h_8]^T \) was mapped onto the 2-dimensional command vector, \( u = [u_1, u_2]^T \) via a linear transformation:

\[
\begin{bmatrix}
    u_1 \\
    u_2
\end{bmatrix} =
\begin{bmatrix}
    a_{1,1} & a_{1,2} & \cdots & a_{1,8} \\
    a_{2,1} & a_{2,2} & \cdots & a_{2,8}
\end{bmatrix}
\begin{bmatrix}
    h_1 \\
    h_2 \\
    \cdots \\
    h_8
\end{bmatrix} = Ah
\]

where \( A \) is the matrix of mapping coefficients, \( [A]_{i,j} = a_{i,j} \).

The control space \( u \) had reduced dimension with respect to the body signal space \( h \), thus we can decompose the body signals into their “null-space” components that do not change the control vector, and the orthogonal “task space” components that determine the value of the command vector [6-7]. At the same time this mapping offers a large variety of specifications. By setting the map coefficients, we were able to assign higher or lower relevance to different parts of the body. For example, the motions of a body part can be excluded by setting to zero the coefficients that multiply the sensor signals affected by that part. Conversely, the motions of a body part could be enhanced by large values of the related coefficients.

**Calibration.** The \( A \) matrix was set at the beginning of each session by a calibration procedure. Subjects wore the sensing elements and executed random motions with the upper arm, shoulder and trunk. No specific requirement was imposed except that of moving the upper body continuously in a natural and comfortable way. One minute of continuous recordings were taken. After this initial session, the data were analyzed and the body/cursor map, \( A \), was derived using principal component analysis (PCA), as explained in [6]. PCA was a means to identify an abstract low-dimensional subspace where subjects tend to move with more ease. We used PCA as a way to implement a good learnable map. This method also allowed us to detect changes in the subjects’ residual abilities or preferences and to modify the map accordingly. If during training subjects would improve and gain more mobility or if they had pain in one shoulder and couldn’t use it the space over where they move more easily may change. This change would be captured by PCA in the calibration phase and the BMI would generate a new and different control space.

**Training sessions.** After calibration, the subjects’ arm and shoulders movements controlled a cursor or a simulated wheelchair on a computer screen, using the two dimensional command vector described in Eq.1. Subjects engaged in the following tasks:

1. **Reaching test I (30 center out movements).** Subjects controlled the position of a cursor on the monitor. Starting from the same initial position in the center of the workspace, subjects moved to six equi-spaced peripheral targets that were presented in random order. The distance of the targets from the center on the monitor was 5 cm. For 0.4 seconds after the cursor left the initial position, there was no visual feedback in two randomly selected trials per direction, corresponding to 2/5 of “blind” trials. The purpose of this part of the experiment was to understand if subjects were guided by visual feedback or if instead they learned a predictive, “feedforward”, map between their body and the cursor space.

2. **Training:** Playing videogames (Tetris, up to 35 minutes). Subjects operated a virtual keyboard with four keys. Different shapes appeared at the top of the game board and dropped down. Subjects had to move and place shapes to complete rows. The completed rows disappeared, allowing the pile of shapes to fall. As subjects improved their performance, the speed of the shapes dropping increased, making the game more challenging. To manipulate the falling shape, subjects moved to the top, bottom, right and left keys starting from a key positioned in the center of the workspace; this performed the following actions on the shape: spin, drop, move right, move left.
We performed an evaluation of the SCI subjects’ shoulders before and after the training sessions to characterize residual mobility and to test if, from the clinical point of view, the training had a beneficial influence or, at least, no negative interference with the reorganization of the subjects’ upper body function. Therefore, SCI subjects were evaluated with a modified Manual Muscle Test (MMT)[8]. This modified test is used routinely at the Rehabilitation Institute of Chicago with the tetraplegic population who experience injury at the cervical level. All tests were performed while subjects were sitting in their wheelchair. We followed the procedure described in the Guide for Muscle Testing of the Upper Extremity, Department of Occupational Therapy, Ranchos Los Amigos Hospital. We omitted the tests in prone position i.e. scapular depression/adduction, because the majority of the SCI subjects in this study cannot lie prone (acute patients) due to spinal restrictions. Instead, we tested protraction/retraction, which is not in the Ranchos Los Amigos guide. The subjects might use these movements to play the games (Table II).

### TABLE II. MOVEMENTS EVALUATED WITH THE MMT

<table>
<thead>
<tr>
<th>Movement</th>
<th>MMT Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Scapular elevation</td>
<td></td>
</tr>
<tr>
<td>2. Shoulder protraction</td>
<td></td>
</tr>
<tr>
<td>3. Shoulder retraction</td>
<td></td>
</tr>
<tr>
<td>4. Shoulder flexion</td>
<td></td>
</tr>
<tr>
<td>5. Shoulder abduction</td>
<td></td>
</tr>
<tr>
<td>6. Shoulder horizontal abduction</td>
<td></td>
</tr>
<tr>
<td>7. Shoulder horizontal adduction</td>
<td></td>
</tr>
<tr>
<td>8. Shoulder external rotation</td>
<td></td>
</tr>
<tr>
<td>9. Shoulder internal rotation</td>
<td></td>
</tr>
<tr>
<td>10. Elbow flexion with palm up</td>
<td></td>
</tr>
<tr>
<td>11. Elbow flexion with forearm in mid position</td>
<td></td>
</tr>
<tr>
<td>12. Elbow extension</td>
<td></td>
</tr>
</tbody>
</table>

Each movement was evaluated according to an ordinary scale ranging from 1 to 5 (0=zero, 1=trace; 2=poor movement without gravity, 3=fair—movement against gravity, 4=good, 5=normal). In our modified test, the maximum score was 60 (control subject). We finally compared the MMT results with the measures of isometric forces applied by the shoulder in the backward, forward, and upward directions to a force transducer (Gamma SI-130-10, ATI Industrial Automation Inc).

### III. RESULTS

#### A. SCI subjects’ evaluation

All SCI subjects had a MMT score (fig 2 left panel) far below the controls’. The MMT score improved significantly for all subjects after training (F(1,5)=10; p=0.02). The Manual Muscle test is not a direct measure of strength,
however the correlation between the MMT total score and the total force measured with the force sensor (sum of the forces in the three tested directions) was high $R=0.81 p<0.0001$ (fig 2, right panel). We found also significant correlations by comparing the force exerted by shoulder muscles in the upper, forward and backward directions with respect to the score obtained for the scapular elevation, shoulder protration and retraction (respectively $R=0.55 p=0.0073$, $R=0.72 p=0.0012$, $R=0.75 p<0.0001$). Moreover, the total isometric force exerted by the subjects’ shoulders also improved after training for 5 out of 6 subjects.

### B. Movement reorganization in the task space

**Reaching tests.** At the beginning of the first session, performing Reaching Test I (Figure 3, column I and II, top panel) was really difficult for both controls and SCI subjects. Next, they used the same interface for operating a computer game keyboard and for piloting the speed of a virtual wheelchair in a VR environment. After less than one hour, when we tested the subjects again in the reaching task (figure 3, test II), their performance were quite improved. They not only reorganized their movements; but they also transferred and generalized the learned skills across different tasks.

**Figure 3.** Reaching Test performance during the first and last session for a control subject (left panels) and a SCI subject (right panel). Top panels are referred to the Reaching test I performed at the beginning of the session, bottom panels are referred to reaching test II performed at the end of the session. Scale bar =1 cm.

In the following sessions subjects kept improving. Most interestingly, the improvement was also evident during test I at the beginning of each session and before practicing any task, in spite of the initial recalibration. This result showed not only a retention of the learned skills through different sessions, but also demonstrated that the everyday recalibration had a positive or, at least, non negative, influence on the learning process. At the end of the training the performance at the beginning of the session (test I) converged toward the performance obtained at the end of the session (test II). SCI subjects had poor initial performance with respect to control subjects, but they improved significantly with practice both within the same session and across multiple sessions. These observations were confirmed by the analysis of an error measure, that is the distance between the target and the cursor position after 0.4 seconds that the subject left the starting position (figure 4 and table III). This measure [9] is particularly suitable for a global performance evaluation because it takes into account the effects of movements accuracy (aiming) and velocity. Comparisons were based on repeated measured

![Graph showing error vs. session](image)

**Figure 4.** Control subjects: endpoint error with (VISION) and without (NoVision) visual feedback (mean ± SE). The results of test I are represented with red and black lines, while magenta and blue lines are referred to the reaching test II. Notice that the sessions 10 and 11 were referred only to 6 of 8 subjects.

ANOVA with three factors: session (first/last), test (I,II), and vision (trials with/without visual feedback).

As expected, between the first and the last session, the errors decreased (Controls: $F (1,7) = 21 p=0.002$; SCI subjects: $F(1,5)=9.35 p=0.028$). Within the same session, the errors between the initial and final tests were different (Controls: $F (1,7) = 18 p=0.003$; SCI $F(1,5) =42 p=0.001$), but this difference decreased with practice (Controls: $F(1,7) =7.47 p=0.03$, SCI subjects: not significant $p=0.07$). All controls reached a similar and stable level of performance at the end of the training. Moreover, when 6 out of 8 control subjects were recalled after more than three weeks for testing retention, they didn’t show significant differences with respect to the last training sessions. Furthermore, the absence of visual feedback had no influence (Controls and SCI subjects $p>0.1$) on the endpoint error. Therefore, this multisession study proved that, both the control and SCI subjects improved their performance without visual feedback (table III) i.e. they were able to define a predictive map between their body and the cursor space.

**TABLE III.** SCI SUBJECTS: END POINT ERROR

<table>
<thead>
<tr>
<th>Reaching</th>
<th>Test I</th>
<th>Test II</th>
<th>Test I</th>
<th>Test II</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCI1</td>
<td>3.94</td>
<td>4.51</td>
<td>2.39</td>
<td>2.90</td>
</tr>
<tr>
<td>SCI2</td>
<td>4.50</td>
<td>5.22</td>
<td>3.83</td>
<td>4.10</td>
</tr>
<tr>
<td>SCI3</td>
<td>4.78</td>
<td>4.58</td>
<td>3.98</td>
<td>3.85</td>
</tr>
<tr>
<td>SCI4</td>
<td>3.75</td>
<td>4.42</td>
<td>4.21</td>
<td>3.68</td>
</tr>
<tr>
<td>SCI5</td>
<td>2.19</td>
<td>2.33</td>
<td>1.85</td>
<td>1.65</td>
</tr>
<tr>
<td>SCI6</td>
<td>3.88</td>
<td>3.60</td>
<td>2.38</td>
<td>2.52</td>
</tr>
</tbody>
</table>

End point error [cm] during reaching tests with (white columns) and without (gray columns) visual feedback.

**Training performance: play videogames (Tetris)**

During the first session, while all the controls were immediately able to play Tetris, half of the SCI subjects were not (Fig 5).
However, both control and SCI subjects improved significantly (Controls: F(1,7) =92.69 p<0.0001 SCI subjects: F(1,5)=18.5 p=0.007). At the end of the training, after a few hours of practice, every subject, even with different speed and performance, was able to play and – perhaps most importantly – enjoy the game. Moreover 6 out of 8 control subjects were recalled after more than three weeks from testing the retention of the learned skills. Retention was evident, even if some of the control subjects showed a slight decrease in performance with respect to the last training session.

Navigation in a VR environment.

After playing Tetris, all subjects drove a wheelchair in a VR environment. Surprisingly, the SCI subjects who exhibited a poor videogame performance at the beginning of the training (e.g. SCI 4) were immediately able to navigate in the virtual environment. All subjects easily learned to remap the two control variables they learned to use for operating the videogame keyboard into the two speeds of the simulated wheelchair. Also, when the VR environment became more complex and they were forced to follow well defined paths, they were able to pilot the wheelchair without difficulties. All the spinal cord injury as well as all the control subjects succeeded to explore almost the entire virtual world as shown in fig.6.

Reorganization in the body movement space.

The signals derived from the upper body movements were mapped, by Eq.1 into two control variables. These were used, as described above, in different tasks with different operational functions.

However, the transformation (A) between high dimensional body space and low dimensional control space was always defined by the calibration map. This allowed us to investigate if subjects modified the relationship between their movements and the two dimensional structure over which they operated. Therefore, we looked at the percentage of the variance accounted for by the task space components of the movement signals with respect to the overall variance [6-7] and we investigated if it changed:

- Within the same session by comparing the reaching test at the beginning (test I) and at the end (test II) of the first session.
- Over multiple sessions by comparing the performance of the reaching tests I in the first and in the last session.

We focused on the data collected during the reaching tests when the subjects were on target because We did not want to “contaminate” the null-space variability with the natural variability of the cursor trajectories between the same start and end targets[6]. The statistical analysis was based on repeated measure ANOVA. Even if the percentage of the task space variance for the control subjects was on average slightly higher with respect to SCI group, we found no statistically significant differences between the behavior of the two groups. We found that the majority of the subjects -both control and SCI- had a marked tendency to align their movement subspace with the two dimensional space established by the cursor map not only within the same session, (F(1,12)=7.9 p=0.016), but also over multiple sessions (F(1,12)= 6.9 p=0.022). Subjects did not shift their variance from the low-dimensional task to the null-space. Instead, as learning progressed, variance in the null-space decreased, consistent with the hypothesis that the motor system built a map that matches the structure of the novel geometrical space over which they operated.

IV. DISCUSSION

After a severe injury, people have to “remake their body” and “reconstruct the self identity in relation to their new bodily state” [10]. Assistive devices are a part of this “re-embodiment”, because they will be no longer external object appended to the body, but they will become part of the “body schema”. Wheelchairs are a clear example. Since wheelchairs are the only way to regain mobility, SCI survivors don’t use a wheelchair as we use a bicycle, they become “en-wheeled” [11]. Consequently, learning how to use an assistive device is a different and wider process than learning a motor skill and the body machine interfaces play a key role in this process.

This work validated a new approach for operating assistive devices that can be beneficial for individuals who suffered substantial injuries limiting, but not totally suppressing, their...
mobility. This is the case, for example, of high level spinal cord injury.

Here, we tested the feasibility of a new interface design based on three important concepts:
- Tapping into a broad spectrum of residual subject movements
- Providing the impaired users with a continuous signals space operated directly by the combination of residual motions that the users are most capable of controlling.
- Adaptively changing the body-device map based on the user’s residual abilities and preferences

We engaged subjects in practicing virtual reality games aimed at training specific control actions. These actions include: a) interacting with a virtual keyboard; b) practicing wheelchair maneuvers, and c) reaching targets. We found that control and SCI subjects were both able to improve their performance over different tasks and multiple sessions while the interface was adaptively recalibrated every day. We discovered that subjects easily remapped the two control variables that they were using for activating the videogame keyboard into the two speeds of the simulated wheelchair. To drive the wheelchair was easy also when playing the game was hard. This initial study supports the feasibility of using a same controller for solving tasks with different operational functions. Training based on different tasks has a beneficial effect on the learning process[12], because it induces a wider knowledge of the possibilities offered by the controller and requires a more versatile reorganization of the body movements.

**Implication for rehabilitation**

Our preliminary observations indicate that the proposed training has no negative interference with the subject’s clinical recovery and may lead to enhanced mobility of the shoulder and upper arms. The proposed body-machine interface is suited to exercise all of the available upper body degrees of freedom through targeted practice of control actions in VR environments. It is also possible to create a transformation from body motions to a “command” space that emphasizes degrees of freedom that are more difficult to control (as determined by principal components during the calibration). This would likely facilitate strengthening a subject’s weaker muscle combination. The reduced or absent mobility of upper arms and/or hands limits shoulder use in daily living activities. This contributes to shoulder weakness, poor posture and, with time, produces pain and attenuates voluntary control of shoulder motion [13-14].

Our interface can map any targeted residual movement capacity into a specific operational function, which makes this system capable of finding a natural balance between ease of device control and exercise underutilized muscle to prevent atrophy and enhance the recovery process. The rehabilitative potential of the BMI may be beneficial for different types of disabling conditions (e.g. SCI and stroke), where the secondary shoulder complication is frequently a focus of the rehabilitative programs[15].

**ACKNOWLEDGMENT**

This research was supported by NNINDS grant 1R21HD053608-01A1 and 1R01NS053581-01A2, the Colman, Neilsen, Brinson and Davee Foundation

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Functional reorganization of upper-body movement after spinal cord injury

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Received: 27 April 2010 / Accepted: 12 September 2010 / Published online: 24 October 2010 © Springer-Verlag 2010

Abstract Survivors of spinal cord injury need to reorganize their residual body movements for interacting with assistive devices and performing activities that used to be easy and natural. To investigate movement reorganization, we asked subjects with high-level spinal cord injury (SCI) and unimpaired subjects to control a cursor on a screen by performing upper-body motions. While this task would be normally accomplished by operating a computer mouse, here shoulder motions were mapped into the cursor position. Both the control and the SCI subjects were rapidly able to reorganize their movements and to successfully control the cursor. The majority of the subjects in both groups were successful in reducing the movements that were not effective at producing cursor motions. This is inconsistent with the hypothesis that the control system is merely concerned with the accurate acquisition of the targets and is unconcerned with motions that are not relevant to this goal. In contrast, our findings suggest that subjects can learn to reorganize coordination so as to increase the correspondence between the subspace of their upper-body motions with the plane in which the controlled cursor moves. This is effectively equivalent to constructing an inverse internal model of the map from body motions to cursor motions, established by the experiment. These results are relevant to the development of interfaces for assistive devices that optimize the use of residual voluntary control and enhance the learning process in disabled users, searching for an easily learnable map between their body motor space and control space of the device.

Keywords Spinal cord injury · Reorganization of movement · Motor learning · Human–machine interface

Introduction

A broad spectrum of injuries and disorders lead to severe loss of mobility. Residual motor functions provide impaired people with the means for controlling devices, such as power wheelchairs, computers, prostheses, and environmental control devices. However, optimal use of these devices requires radical reorganization of residual movements. The goal of this study is to understand and facilitate the reorganization of movements for the control of such devices. Our approach is to harness the over-abundant number of signals from the cache of body movements that paralyzed users are still capable to execute, and then to facilitate the process of motor learning by which they reorganize these motions to control a device. This idea stems from the concept of “motor redundancy”,
whereby the human motor system contains an imbalance between the large number of degrees of freedom available to control a particular movement and the smaller number of variables that are needed to specify and plan that movement (Bernstein 1967). While redundancy poses some computational challenges (Klein and Huang 1983; Baillieul 1985; Baker and Wampler 1988; Mussa-Ivaldi and Hogan 1991), the motor control system exploits redundancy to reorganize movements in ordinary circumstances, such as dealing with obstacles (Latash, Scholz et al. 2002), loss of limbs, general disability (St-Onge et al. 2004; Cote et al. 2005), and for redirecting motor commands over different parts of the motor apparatus (Chen et al. 1998; et al. 2002; Grea et al. 2000). By mapping redundant degrees of freedom into control variables we provide subjects with the opportunity to identify a comfortable and natural subset of their entire range of motion that is optimal, or at least adequate, to operate the device. Some assistive devices are often operated by only two control signals. For example, powered wheelchairs are controlled by setting two variables: forward/backward linear speed and rightward/leftward turning speed (Cooper 1999). The identification of a disabled user’s residual motions would allow us to design interfaces that translate the user’s most controllable degrees of freedom into the two command variables of the powered wheelchair. This is a conjunction of a physiological and geometrical problem. The geometrical problem is the identification of a natural “residual subspace” that the user can control reliably. This subspace may be spanned by a combination of anatomical degrees of freedom, such as individual joints. The physiological problem arises from the fact that such a subspace is likely to vary in time, either from the progression of the underlying pathology or, conversely, from the mobility improvements and motor learning induced by repeated practice of control actions.

In this study, we asked subjects to control a cursor (another two-dimensional device) in a virtual environment. The cursor was driven by signals derived from the motions of the shoulders and upper arms of unimpaired and spinal cord injured (SCI) subjects. Subjects were asked to move the cursor from a central point to an end target. This “center-out” protocol is common to many studies of arm reaching movements (Georgopoulos et al. 1986). Several studies used synergic models to allow hemi- and tetraplegic subjects to control their arms or prostheses during reaching and grasping movements (Miller et al. 1989; Crago et al. 1998; Grill and Peckham 1998; Bryden et al. 2000; Popovic and Popovic 2001; Popovic 2003; Mijovic et al. 2008). Upper extremity neural prostheses, such as the implantable device of the Freehand System (Kilgore et al. 1989, 1997, 2008; Kilgore and Peckham 1993a, b; Peckham et al. 2002) and the arm prosthesis based on targeted muscle reinnervation (Kuiken et al. 2004, 2007, 2009; Kuiken 2006; O’Shaughnessy et al. 2008) were shown to operate well. In this study, we investigated with a noninvasive protocol the learning process, through which subjects reorganized the motions of their shoulders and upper arms to control efficiently the motions of the cursor on the computer monitor. Stated differently, instead of learning to control a joystick—a common input device for powered wheelchair systems—we investigated whether one can reorganize coordination so as to use one’s whole upper body as a joystick—i.e. as a simple two-dimensional control device.

We found that subjects—both SCI and control—were able to reorganize their upper-body motions, so as to match the geometry of the planar monitor where the task was presented. In particular, they reduced the effective amount of kinematic redundancy to generate a unique inverse of the transformation from body configuration to cursor position.

This study is a first proof of concept of a new alternative control framework that could be particularly useful for people with severely limited arm and hand functions such as SCI survivors. Our framework, instead of proposing a “one-size fits all approach”, allows subjects to reorganize their actions in a natural way, depending on their residual motor skills.

This approach is independent of any specific motion-capture technology and can be easily implemented with any available system, which may be more convenient than the one used here for a specific level of disability. The motion-capture device is not intended as a means to measure the kinematics of the body, but merely as an “output pathway”, which gives the user an amount of controllable signals, the more the better. Therefore, we expected that our findings will be of broad relevance to different types of assistive technology and will benefit a large population of patients with a variety of motor impairments (Kay et al. 2000).

**Methods**

**Subjects**

Nine control subjects with no known history of motor impairment (mean age 30 ± 6 years, 6 male 3 female) and 4 SCI subjects (see Table 1) participated in this experiment, after signing the informed consent form approved by Northwestern University Institutional Review Board. For SCI subjects, the inclusion criteria were (1) being medically stable, (2) level of injury at C5 or above, (3) being able to perform shoulder protraction, retraction, or elevation, (4) being able to see in adequate light, (5) being able to follow simple instructions, and (6) being able to maintain sitting position up to an hour. The SCI subjects were recruited from the Rehabilitation Institute of Chicago.
Experimental set-up

Subjects sat comfortably and faced a 19" LCD computer display positioned about one meter in front of them, at eye level. The display provided subjects with continuous feedback of their performance. An array of four video cameras (V100, Naturalpoint Inc., OR, USA) tracked active infrared light sources, which were attached to the subject’s right and left shoulders and two upper arms (see Fig. 1).

The position of these markers was captured at 75 samples per second using proprietary software (Modification of a C++ SDK supplied by Naturalpoint). The entire set of signals captured by the cameras was first mapped into a two-dimensional signal, controlling the cursor location on the monitor.

Dimensionality reduction

The key concept in our approach is to transform the signal space associated with body motions, from a space of relatively high dimension to an adequate low-dimensional projection subspace, sufficient for control purposes. In the current configuration, the conversion from higher to lower dimensional space is from eight dimensions (4 cameras, each with a planar sensor of two dimensions) to two dimensions (the cursor coordinates). To perform this dimensionality reduction, we use a simple and well-established method, Principal Component Analysis (PCA).

While there are many alternatives—such as Independent Component Analysis, as well as nonlinear methods, such as Isomap—PCA is the simplest approach, both from a mathematical and from an algorithmic point of view (Jolliffe 2002). It is based on the decorrelation of the raw signals by diagonalization of their covariance matrix. Dimensionality is reduced by ranking the eigenvalues and keeping only the two eigenvectors corresponding to the largest eigenvalues. Therefore, PCA provides a computationally straightforward and easy to interpret method for assessing where in the sensor signal space subjects tend to distribute the largest extent (i.e. the largest variance) of body motions.

We constructed the map from body signals to cursor position in the following three steps:

1. Calibration: We asked subjects to freely explore their range of motion for about 60 s, by moving in all possible directions with their shoulders and upper arms. We described this as a free “body dance”. Subjects moved their shoulders various self-paced directions and combinations of degrees of freedom, so as to visit a vast portion of the range of motion for the upper body. The free movements produced during this phase were continuous in time and space. There was no interruption, and the “dance motions” took place along continuous curvilinear trajectories in the body configuration space. We expected that the type and degree of impairment shaped the movements generated in this phase. We verified that at least two principal components with significant variance could be extracted from this eight-dimensional signal. The “calibration” data set, $P$ (the mean value was subtracted from each signal), is organized as an $N \times M$ matrix, where $M$ is the number of samples ($M = 5,000$ collected over 66 s – 75 samples $\times$ s) and $N$ is the number of measurement signals ($N = 8$).

2. PCA: We estimated the N principal components of the data set, $P$, using principal component analysis. Specifically, we estimated the covariance matrix $C^{N \times N}$ of $P$ and calculated its $N$ eigenvalues, ranked in a decreasing order, $(\lambda_1, \lambda_2, \ldots, \lambda_N)$, and the corresponding $N$ eigenvectors $(\omega_1, \omega_2, \ldots, \omega_N)$. By applying PCA to the calibration data set, we created a new basis that was a linear combination of the original basis:

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Age (years)</th>
<th>Level of injury</th>
<th>ASIA</th>
<th>Time after injury (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCI 1</td>
<td>M</td>
<td>22</td>
<td>C4</td>
<td>A</td>
<td>34</td>
</tr>
<tr>
<td>SCI 2</td>
<td>F</td>
<td>27</td>
<td>C5</td>
<td>C</td>
<td>84</td>
</tr>
<tr>
<td>SCI 3</td>
<td>M</td>
<td>20</td>
<td>C4R, C5L</td>
<td>A</td>
<td>7</td>
</tr>
<tr>
<td>SCI 4</td>
<td>M</td>
<td>25</td>
<td>C2R, C3L</td>
<td>A</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 1: Anagraphic and clinical data of the SCI subjects

Fig. 1 Experimental set-up
Here, $A$ is the $N \times N$ matrix of eigenvectors and $P'$ is a new $N \times M$ matrix that, by linear transformation, expresses $P$ in the coordinates of the new orthonormal basis, $A$. The eigenvectors of $A$ are ordered according to the size of their corresponding eigenvalues, from largest to smallest. Therefore, movement combinations with high signal excursion are associated with larger eigenvalues, and as such, with the leading vectors in $A$. We assume that these high-variance movements are the subject’s “best controlled” dynamics, and that the low-variance movements can be regarded as “motor noise”.

The shoulder movements determined the “command vector,” $u$:

$$u = \begin{bmatrix} x \\ y \end{bmatrix}$$

(2)

which specified the horizontal ‘$x$’ and vertical positions ‘$y$’ of the cursor. The $N$-dimensional vector of sensor signals $h = [h_1, h_2, \ldots, h_N]^T$ (after subtracting for each entry the mean of the corresponding signal of the calibration data set) was mapped onto this two-dimensional command vector $u$ by the following linear transformation:

$$u = \begin{bmatrix} a_{1,1} & a_{1,2} & \ldots & a_{1,N} \\ a_{2,1} & a_{2,2} & \ldots & a_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N,1} & a_{N,2} & \ldots & a_{N,N} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_N \end{bmatrix} = A_{\text{Task}} h$$

(3)

where $A_{\text{Task}}$ is the $2 \times N$ matrix of mapping coefficients.

3. Adjustments: While the two main principal components define the two-dimensional subspace that represents the most important body motions, it does not specify how these two dimensions should be optimally mapped into the (Cartesian) cursor geometry. For example, the two top principal components could correspond to (i) a combined forward motion of the shoulders and (ii) the independent lowering or rising of each shoulder. In such case, a subject may prefer to associate the $y$ (forward) axis to the first PC and the $x$ (lateral) axis to the second PC. Since the second PC generally has a smaller amount of variance than the first, a gain adjustment may be required to obtain the same amount of cursor motion on each axis. Therefore, we allowed the subjects to set the origin, orientation, and scaling of the axes, upon which each PC was mapped, based on their preference. Accordingly, three corrections were manually introduced prior the beginning of the experiment to facilitate a more natural control scheme: scaling, shifting, and rotation. These three values were adjusted until each subject was able to comfortably reach the various locations of the workspace.

Experimental protocol and task

The task consisted of moving the shoulder-controlled cursor on a computer screen using minimal upper-body motions. Starting from the same initial position in the center of the workspace (see Fig. 2, left panel), subjects moved to six equi-spaced peripheral targets that were presented in random order.

Targets were presented on a blue background as round white circles, 1 cm in diameter. The cursor (Eq. 2) was an orange circle (0.4 cm diameter). The distance on the monitor of the targets from the center was 5 cm. The instruction was to reach the target within 0.4 s after leaving the initial position. To inform the subject of this time constraint, the target changed color to red, once the time limit had elapsed.

The training session was organized into six movement sets (T1–T6). Each set consisted of a sequence of target presentations in which each peripheral target occurred nine times, for a total 54 center-out movements, plus the corresponding 54 return movements. During the training session, we introduced randomly interspersed “No vision” trials starting with the second movement set. In these trials, the cursor disappeared after leaving the starting position and reappeared 0.4 s later. There were three “No vision”

Fig. 2 Left panel circles on the periphery are the six possible target locations for both T1–T6 and BL movement sets (1 cm in diameter). Only the target (black filled circle) and the starting position (gray filled circle) for the current trial were displayed. The initial position was slightly bigger than the target and was represented by a different color. The cursor was 0.4 cm in diameter (small dark gray circle). The right panel shows the three directions of reaching generalization (these directions do not correspond to those of the left panel), and here the cursor was not visible during movement (small dotted circle). In every movement set, the amplitude of the required movements (distance of the targets from the center) was 5 cm
trials per direction and per movement set, corresponding to 1/3 of all trials in each movement set. The purpose of this part of the experiment was to understand whether subjects were guided by visual feedback or whether they learned a predictive, “feedforward,” map between their body and the cursor space.

At the end of the training sessions, we asked control subjects to perform two additional movement sets: the blind test (BL) and the generalization (G) movement set.

The blind test set was similar to the training set, except that all trials were “no vision” and the number of targets was smaller: 18 center-out random movements, three for each direction.

In the generalization phase (G), we tested the ability of the subject to reach three targets which were not presented previously (Fig. 2, panel B). All trials were “no vision,” and each target was randomly presented five times.

Subjects were allowed to rest at any time. The duration of the experimental session was always limited to 1 h, whether or not the protocol was completed.

Control subjects always completed the training session (T1–T6) in less than 1 h. This allowed us to test them with the blind and generalization movement sets (BL-G) in the same day, immediately after the training session. SCI subjects were more prone to become tired and were not involved in this additional testing, nor were they given any time constraint about movement duration.

We expected that that the ability to generalize and build internal models is the same in control and SCI subjects, since the SCI survivors involved in this study have no significant cognitive impairment. However, this particular issue deserves to be fully tested in a separate investigation.

Data analysis

We analyzed the functional reorganization of the upper-limb motion both in the two-dimensional and in the eight-dimensional space.

The x and y components of cursor position, as well as the signals from the camera, were smoothed with a 4th order Savitzky-Golay filter (equivalent cut-off frequency about 10 Hz) (Savitzky and Golay 1964), which also allowed us to estimate the first three time derivatives \((\dot{x}, \ddot{x}, \dddot{x}, \dot{y}, \ddot{y}, \dddot{y})\) of the cursor position.

Analysis 2D task space

We investigated whether subjects were able to learn to control the cursor in the task space easily and with precision. In particular, we verified whether, with training, movements became faster, smoother, and more precise. The analysis focused on the center-out movements in the “vision” condition. We used the following set of indicators to evaluate performance:

- Movement duration: time elapsed between movement onset and termination. Movement onset was computed as the first sampling time in which the cursor velocity exceeded a threshold equal to 15% of the maximal peak velocity. Movement termination was computed as the time in which movement speed went back and remained below that threshold.
- Jerk index: The square root of the jerk (norm of the third time derivative of the cursor position), averaged over the entire movement duration and normalized with respect to duration \((T)\) and path length \((L)\) (see Teulings et al. 1997).

\[
\text{Jerk index} = \frac{1}{2} \sqrt{\int_{T}^{T+T} \left(\left\| \dot{j}(t) \right\|^2 \right) dt} \frac{T^5}{L^2}
\]

This measure is sensitive to smoothness—larger jerk indexes correspond to less smoothness.
- Linearity: percent increment of the length of the path traced by the cursor, between onset and termination times, with respect to the distance between start and end points. This parameter indicated if the cursor movements became straighter.

Finally, for analyzing the performance without visual feedback and in new directions we computed the end-point error. This is the distance between the target and the cursor position when the target changed color (vision trials) or reappeared (blind trials) i.e. 0.4 s after the subject left the starting position.

We analyzed the end-point error for all movement sets in both vision and no vision condition, and compared it across the different conditions.

Analysis in the high-dimensional space of the body motions

The analysis in the high-dimensional space of the body motions was based on PCA. We performed two PCAs on two separate data sets. First, we computed PCA of spontaneous “dance” movements to generate a two-dimensional target space where subjects would be naturally capable to produce motions of the controlled cursor. This was the initial calibration for each subject. The “dance motions” took place along continuous curvilinear trajectories in the body configuration space, where movement direction was a continuously changing variable. Therefore, these free movements were different from the reaching movements of the following experimental
phases, where targets were presented in different locations.

Second, we performed PCAs on data collected during the movement sets of the training phase (T1–T6). Only cursor data at rest in the target regions were used in this analysis. The reaching task involves redundancy that allows subjects to achieve the same two-dimensional cursor position with different upper-body configurations. The shoulder motions were captured indirectly by the eight markers recorded by the four cameras. We carried out these PCAs to evaluate how the dimensionality of the data changed through time. We further tested how many principal components accounted for at least a minimum amount (2%) of variance.

In addition, we also projected the same data set from the first and last target set over the eigenvectors of the initial PCA. This allowed us to evaluate how the subjects learned not only to reduce dimensionality of motions, but also to match their motion with the coordinates of the cursor. The linearity of PCA, associated with the orthonormality of the principal components, facilitates the analysis and in particular the decomposition of movement signals into “task space” and “null space” (Mosier et al. 2005). The former represents the signal’s components which affect the control vector (i.e. the cursor motion), the latter represents the components which do not affect the control vector.

The PCA computed during the calibration phase (see “Dimensionality reduction” section) provided an N-dimensional orthonormal basis. The matrix A, consisting of N eigenvectors of the covariance matrix, represents this basis and defines completely the signal space.

The data of each movement set can, therefore, be projected back onto the operational space defined by these N eigenvectors as follows:

\[ A' = \begin{bmatrix} h_1' \\ h_2' \\ \vdots \\ h_N' \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_N \end{bmatrix} = A h \]  

(5)

In the same way that \( P' \) is the calibration data expressed in the basis A (Eq. 1), here \( h' \) is the instantaneous signal vector \( h \) expressed in \( A \).

The two eigenvectors associated with the two main principal components define the task space with basis \( A_{\text{Task}} \), as described in Eq. 3, and the projection of the signals on the space defined by these two vectors determines the two-dimensional control signal, \( u \).

As a direct consequence of orthonormality of the eigenvectors provided by PCA, the remaining N-2 eigenvectors of the matrix A are orthogonal to the task space \( A_{\text{Task}} \). Therefore, these vectors form the \((N - 2) \times N\) matrix \( A_{\text{Null}} \) that is the basis of the “null space” associated with task space \( A_{\text{Task}} \), i.e. a space where signal variation does not affect the command vector \( u \).

By projecting the data of each movement set on the null space, we obtain a N-2 dimensional vector \( \mathbf{n} \):

\[ \mathbf{n} = \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_{N-2} \end{bmatrix} = A_{\text{Null}} h \]  

(6)

where each elements \( n_i \) is the scalar product between the \( i \)th eigenvector of the null space, \( U \), and the instantaneous signal vector. Thus, by definition, \( \mathbf{n} \) has no image in the task space.

Using this technique with the data of each movement set, we can compute the movement variance associated with each eigenvector. By definition, the variance associated with the first two eigenvectors was the variance in the cursor space, while the variance associated with the other eigenvectors represented the variance in the null space.

We looked at the variance accounted for by the task space components with respect to the overall variance (\( V \)):

\[ V = \frac{\sum_{i=1}^{2} \sigma^2(h'_i)}{\sum_{i=1}^{N} \sigma^2(h'_i)} \cdot 100 \]

\[ = \frac{\sum_{i=1}^{2} \sigma^2(u_i)}{\sum_{i=1}^{N} \sigma^2(u_i) + \sum_{i=1}^{N-2} \sigma^2(n_i)} \cdot 100 \]  

(7)

where \( \sigma^2(h'_i) \) is the variance of the signals associated with the \( i \)th eigenvector, \( \sigma^2(u_i) \) is the variance of the signals associated with the \( i \)th eigenvector of the task space \( U \), and \( \sigma^2(n_i) \) is the variance of the signals associated with the \( i \)th eigenvector of the null space. We focused on the data collected when the subjects were on target for separating the analysis of variance over the null space from the global variance of movement that takes place over the task space. We did not want to “contaminate” the null space variability with the natural variability of the cursor trajectories between the same start and end targets. In this case, if the map between body and task space does not change during the training, the variance of the task space \( \sum_{i=1}^{2} \sigma^2(u_i) \) is fixed (it is determined by the target size and position), and the only variable is the null space variance.

Thus, the variance \( V \) accounted for by the task space, with respect to the overall variance, would increase only if the variance associated with null space \( \sum_{i=1}^{N-2} \sigma^2(n_i) \) would decrease. The variance in this data set did not contain contributions from the movement to each target. The variance did include contribution from the different movement directions, as the cursor moved toward and away from each target, because the data were collected over all the targets.
However, this factor was a constant through the experiment. In the end, the variability of body postures as the same positions were achieved was the only relevant source of variance. In other words, we were looking at what other authors called the “uncontrolled manifold” (Scholz and Schoner 1999; Latash et al. 2001, 2002; Todorov 2004), although in a simplified case because we used a linear map whose the null space could be determined by standard algebra.

Statistical analysis

We tested the performances of control subjects, which we assumed to be a homogenous population, using a repeated measures ANOVA method (Statistica 7.1 software, Stat Italia srl, Italy). Additionally, we tested the performance of each SCI subject separately by comparing the indicator values between the first and last target sets using a paired t test. Threshold for significance was set at $P < 0.05$.

Results

2D “task” space

Training session

Control and spinal cord injured (SCI) subjects learned to control efficiently the motions of the cursor on the computer monitor using signals derived from the motions of the shoulders and upper arms. We asked subjects to move the cursor in six different equally spaced directions (see Fig. 3), starting from the same initial position at the center of the workspace. All control subjects completed the entire protocol without difficulty. All SCI subjects were able to use their shoulder movements for piloting the cursor for about 1 h. They performed four target sets, except subject SCI-1 who performed only three target sets.

Subjects performance improved with practice

All subjects improved their performance with practice. An example of the movements recorded from control and SCI subjects during the first and last experimental phases is displayed in Fig. 3a (trajectories) and Fig. 3b (speed profiles).

The analysis based on various different indicators supported the same conclusion (Fig. 4).

The top panel of Fig. 4 displays the time course of duration, jerk, and linearity index for the nine unimpaired subjects. We ran a repeated measure ANOVA for all these indicators. Two factors were included: practice (first and last training sets) and directions (1–6). The movement duration decreased significantly with practice ($F(1,8) = 16.99$, $P = 0.0033$). Also, trajectory linearity increased significantly ($F(1,8) = 13.51$, $P = 0.006$), and the trajectories became smoother (jerk index $F(1,8) = 5.58$, $P = 0.045$). Target direction had no significant effect on any of the indicators.

The bottom panel (Fig. 4) shows the time course of movement duration, jerk, and linearity of each SCI subject. The scales used for representing these data for SCI and Control subjects are different because there was a systematic difference in performance between the two populations: as expected, SCI subjects had worse initial performance compared to controls. However, at the end of the first hours of training, SCI subjects approached the initial performance level of control subjects. Furthermore, as seen also in the control group, each spinal cord injured subject achieved a statistically significant improvement with practice, for all indicators. The results are reported on Table 2.

Blind and generalization test

During the first movement set (T1), subjects received complete visual feedback of the cursor motion. Starting with the second movement set (T2), we introduced randomly (1/3) interspersed “no vision” trials, where the cursor disappeared as the movement started and reappeared 0.4 s later. Control Subjects were tested also in the Blind (BL) and Generalization (G) movement sets. These sets had only “no vision” trials. In the blind test phase, the target movement directions were the same as in the learning phase, while in the generalization phase we tested three previously untrained movement directions (Fig. 2, left panel). Figure 5 shows, for all control subjects, the time course of the end-point error in vision (black) and blind trials (gray) for each movement set. The difference between vision and “no vision” trials was surprisingly small. This figure suggests that control subjects improved their performances and were able to execute the task without visual feedback and in new directions.

Performance is not determined by visual feedback

To determine whether control subjects performance was affected by visual feedback, we ran repeated measures ANOVA with two factors of vision and practice (the second and sixth movement sets) on the end-point error indicator. While we found a significant effect of practice ($F(1,8) = 17.69$, $P = 0.00297$), there was no vision effect ($P > 0.33$) and no interaction between vision and practice ($P > 0.6$).
Blind trials: SCI subjects

As for the analysis of the others indicators, SCI subjects had worse performance than controls in terms of the end-point errors.

We did not enforce any time constraint for the SCI subjects. Nevertheless, the data reported on Table 3 demonstrate that in the last target set the performances in vision and no vision trials were comparable. Moreover, though statistical significance was not achieved for all SCI subjects, the average performance for all these subjects in the last movement set, both in “vision” and in “no vision” condition, shows a trend of improvement with respect to the first movement set.

Generalization

To verify whether control subjects were able to generalize the reaching skill to untrained targets, we compared the performances during the two last no vision movement sets: blind test set—where targets are the same as in the training phase—and generalization set—where subjects were asked to reach three new (not trained) targets. The end-point error indicator (Fig. 5, right) appeared to be slightly worse in the generalization set compared to the blind test set, but the statistical analysis did not show any significant difference ($P > 0.1$). We noticed informally that for some subjects it was more challenging to move in an untrained direction. Nevertheless, the learning of the mapping allowed them to reach those untrained targets as well.

Higher dimensional space

*Evaluation of principal components during free movements*

For all subjects, the variance of the free movements was explained almost completely (more than 95%) by the first four principal components (Table 4). Therefore, the effective dimension of the subjects’ movement was four instead of the maximum possible (eight). For the SCI subjects, it was possible to extract at least two principal components...
components with significant variance from the eight-dimensional signals.

On average, PCA succeeded in capturing the main characteristics of the movements of SCI subjects. Indeed, their impairment constrained and shaped the movements; compared to controls, they had on average a bigger variance associated with the first component and smaller variances corresponding to the second through fourth components.

Evaluation of principal components during task execution

When subjects began driving the cursor and reaching targets presented in different locations, their variance was still almost completely explained (more than 95%) by four principal components (Table 5).

At the end of the training session, for both controls and SCI subjects, more than 95% of the overall variance was explained by three principal components (Table 5). Additionally, through practice, the variance accounted for (VAF) by the two first principal components slightly increased. However, there was a difference between controls and SCI subjects. Controls mainly changed the movements associated with their degrees of freedom in order to use two balanced principal movements: they tended to increase the variance associated with the second principal component (as summarized in Fig. 6, left panel), thus achieving a better balance between the variance explained by the first two components. This behavior was consistent with the consideration that they practiced a two-dimensional task, with a balanced on-screen excursion in both dimensions. In contrast, at the end of the training, SCI subjects maintained the predominance of the variance explained by the first component: they all increased the variance explained by the first component and decreased the fourth. This confirms the finding of the calibration phase that their impairment constrained or shaped their movements during the execution of the reaching task as well as during the free exploration of the space.

Table 2 Duration (s), jerk, and linearity index for all spinal cord injury subjects in the first and last movement set (mean ± SE)

* Indicates that the difference between first and last movement set is statistically significant (P < 0.05)

<table>
<thead>
<tr>
<th>Movement set</th>
<th>Duration (s)</th>
<th>Jerk index</th>
<th>Linearity index</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCI 1</td>
<td>4.7 ± 0.7</td>
<td>2.5 ± 0.3*</td>
<td>3287.6 ± 1164.4</td>
</tr>
<tr>
<td>SCI 2</td>
<td>3.8 ± 0.5</td>
<td>2.0 ± 0.3*</td>
<td>1156.2 ± 251.0</td>
</tr>
<tr>
<td>SCI 3</td>
<td>2.7 ± 0.2</td>
<td>1.4 ± 0.2*</td>
<td>768.0 ± 132.5</td>
</tr>
<tr>
<td>SCI 4</td>
<td>2.9 ± 0.4</td>
<td>1.9 ± 0.2*</td>
<td>962.9 ± 183.9</td>
</tr>
</tbody>
</table>

Fig. 4 Time course of duration, jerk, and linearity index of controls (top—mean + SE) and SCI subjects (bottom)
Evaluation of variance in the task space and its changes with training

The principal component analysis on calibration and task sets shows that control and SCI subjects reorganize their body motions, consistent with the low dimensionality of the controlled cursors. Did they also match the subspace of their movements with the two-dimensional space established by the body-cursor map? Note that this does not necessarily have to be the case. One could confine one’s movements to a 2D subspace that differs from the 2D subspace defined by the calibration. In that case, the motions of the body would simply have a significant null space component. To answer this question, as explained in the methods section, we projected the data collected when the subjects were on target of each training movement set (T1–T6) onto the space defined by the eight eigenvectors derived by the PCA of the calibration data set. We computed the variance over the training targets associated with each dimension of this space. Then, we looked at variance associated with the two eigenvectors that define the task space \( a_1 \), \( a_2 \) and the variance associated with the other six dimensions that span the null space, \( a_3, \ldots, a_8 \).

Table 6 shows that initially there was considerable variance in the null space associated with the third eigenvector, \( a_3 \) and for three of nine control subjects the variance associated with the third or fourth eigenvector was higher than the one associated with the first/second one. This trend was also present in two SCI subjects (Table 6, bottom). However, the variance accounted for by the task space components changed with training.

For most of the control subjects in the last movement set, the variance associated with \( a_3 \), \( a_4 \) decreased in favor of the variance associated with \( a_1 \), \( a_2 \) the two “task relevant” components (as summarized in Fig. 6, right panel). This trend was particularly evident (Table 6) in subjects that initially had a dominant third/fourth component. The limited number of dimensions involved in the task allowed us to have, as a qualitative example, a three-dimensional representation of the “subspace-matching” process. Figure 7 shows the movement of subject 3 projected in the space defined by \( a_1 \), \( a_2 \), \( a_3 \) in the early (left panel) and late (right panel) phases of learning. In the first movement set, there was a relevant movement variance in the third dimension of the space \( a_3 \) (null space). That component of the variance was strongly reduced in the last movement set, and the movement’s space seemed to become more planar, with the majority of variance accounted for by the task space defined by the sum of the eigenvectors \( a_1, a_2 \).

For control subjects, the variance accounted for by the task space with respect to the overall variance (Eq. 7, method section) significantly increased with practice (from \( 63 \pm 18 \) to \( 74 \pm 11, F(1,8) = 6.4, P = 0.035 \)). In spite of the reduced number of training movements, the same trend was present in three SCI subjects (Table 6 right). Only the trend shown by one SCI subject—SCI3—can be attributed not only to a change in the null space, but to a change in the map between the body and the task space because the subject slightly changed the initial scale factor (adjustment) of the map during training.

Taken together, these results indicate that both control and SCI subjects with practice aligned their movement with the structure of the task space (Table 6). Control subjects also demonstrated a trend toward a more balanced distribution of variance among the two top PCs (Table 5). This trend, however, was not observed in the SCI subjects, who maintained a strong predominance of the first PC over the second through the course of training.

Discussion

This work is a first step toward the development of a new family of adaptive “body–machine interfaces”, a different kind of BMI, mapping the residual motor skills of disabled people into efficient patterns of control. Our long-term goal
Table 4 Results of the principal components analysis on the calibration (free movements)

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>PC6</th>
<th>PC7</th>
<th>PC8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td>48.1 ± 7.4</td>
<td>27.8 ± 5</td>
<td>14.9 ± 4.9</td>
<td>7.5 ± 3.1</td>
<td>0.9 ± 0.7</td>
<td>0.3 ± 0.2</td>
<td>0.1 ± 0.1</td>
<td>0.1 ± 0.1</td>
</tr>
<tr>
<td>SCI 1</td>
<td>64.7</td>
<td>29.4</td>
<td>3.8</td>
<td>1.7</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
<td>0</td>
</tr>
<tr>
<td>SCI 2</td>
<td>62.5</td>
<td>17.4</td>
<td>13.5</td>
<td>4.2</td>
<td>1.2</td>
<td>0.7</td>
<td>0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>SCI 3</td>
<td>79.8</td>
<td>9.5</td>
<td>8.2</td>
<td>2</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
<td>0</td>
</tr>
<tr>
<td>SCI 4</td>
<td>68.3</td>
<td>18.5</td>
<td>6.3</td>
<td>6</td>
<td>0.5</td>
<td>0.2</td>
<td>0.1</td>
<td>0</td>
</tr>
</tbody>
</table>

The table shows the variance accounted for by each principal component in controls subjects (mean ± SD) and in the four SCI subjects (italicized cells). For all subjects, the variance of the free movements was explained almost completely (more than 95%) by the first four principal components: the effective dimensionality of the subjects’ movement was four. SCI subjects have at least two principal components with significant variance.

Table 5 Results of the principal component analysis on the first (left) and last (right) movement set

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td>52.4 ± 10</td>
<td>33.8 ± 9</td>
<td>9.0 ± 2</td>
<td>3.0 ± 1.8</td>
<td>50.8 ± 5.8</td>
<td>39.0 ± 5.0</td>
<td>7.1 ± 3.9</td>
<td>2.0 ± 1.2</td>
</tr>
<tr>
<td>SCI 1</td>
<td>51</td>
<td>36.6</td>
<td>6.4</td>
<td>5.1</td>
<td>51.4</td>
<td>36.8</td>
<td>7.6</td>
<td>3.1</td>
</tr>
<tr>
<td>SCI 2</td>
<td>55.2</td>
<td>25.1</td>
<td>12.3</td>
<td>5.1</td>
<td>61.4</td>
<td>29</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>SCI 3</td>
<td>66.4</td>
<td>24.4</td>
<td>3.8</td>
<td>3.0</td>
<td>67.8</td>
<td>25.7</td>
<td>3.9</td>
<td>1.8</td>
</tr>
<tr>
<td>SCI 4</td>
<td>45.1</td>
<td>35.9</td>
<td>10.6</td>
<td>3.4</td>
<td>58</td>
<td>30.4</td>
<td>7.5</td>
<td>3.1</td>
</tr>
</tbody>
</table>

The table shows the variance accounted for by each principal component for control subjects (mean ± SD) and for the four SCI subjects (italicized cells).

Fig. 6 Left panel results of principal component analysis on the first (gray) and last movement set (black) for control subjects (mean + SE). In the first movement set (gray), more than 95% of variance was explained by four principal components. At the end of the training session (black), unimpaired controls mainly tended to increase the variance associated with the second principal component. Right panel control subjects (mean + SE). Results of the projection of the data of the first (gray) and last movement set (black) over the space defined by the transformation i.e. the space defined by the eight eigenvectors provided by the PCA computed on the calibration data set. For most of the control subjects, the movement variance associated with the dimension μ1, μ2 decreased with training in favor of the variance associated with μ1, μ2, the two “task relevant” components.
is to develop an interface for assistive or prosthetic devices that could “understand” the residual motor ability of the user and then adapt the device control system to this ability. Specifically, our study was focused on

1. The identification—using PCA—of control signals for the operation of a two-dimensional device by unrestricted/residual upper-body motions. Examples of such devices are powered wheelchairs, controlled by speed, and rotation signals, or computer monitors, where the position of a cursor is defined by two coordinates.

2. The study of the reorganization of upper-body movements for controlling two-dimensional devices by unimpaired and spinal cord injured subjects (SCI).

Both SCI and unimpaired control subjects demonstrated fast body movement reorganization to operate the upper body–cursor interface with smoother, faster and more precise trajectories.

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Principal component analysis as a tool to build controllable maps

The identification of motor primitives through observed correlations between movement components is an intensely debated topic (Lee 1984; Mussa-Ivaldi and Bizzi 2000; Slotine and Lohmiller 2001; Todorov and Jordan 2002; Capaday 2004). Principal components of observed motions can hardly be considered as physiological motor primitives, or synergies, as they do not correspond to particular patterns of muscle activations. Principal components are orthonormal vectors that together constitute a coordinate system to describe the distribution of movement variance. Instead of attempting to identify physiological motor primitives, we used PCA as a means to identify a low-dimensional movement subspace where subjects tend to move with more ease. Understanding how their movements are generated by muscle synergies or other neuromotor primitives is beyond the scope of this study. In our

<table>
<thead>
<tr>
<th>% Variance accounted for</th>
<th>First movement set</th>
<th>Last movement set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$g_1$</td>
<td>$g_2$</td>
</tr>
<tr>
<td>Con 1</td>
<td>23.5</td>
<td>24.5</td>
</tr>
<tr>
<td>Con 2</td>
<td>29.2</td>
<td>29.7</td>
</tr>
<tr>
<td>Con 3</td>
<td>21.1</td>
<td>20.6</td>
</tr>
<tr>
<td>Con 4</td>
<td>17.7</td>
<td>17.6</td>
</tr>
<tr>
<td>Con 5</td>
<td>35.8</td>
<td>33.8</td>
</tr>
<tr>
<td>Con 6</td>
<td>34</td>
<td>36.2</td>
</tr>
<tr>
<td>Con 7</td>
<td>43</td>
<td>43.9</td>
</tr>
<tr>
<td>Con 8</td>
<td>42.7</td>
<td>41.3</td>
</tr>
<tr>
<td>Con 9</td>
<td>37.5</td>
<td>36.1</td>
</tr>
<tr>
<td>SCI 1</td>
<td>34.8</td>
<td>38.7</td>
</tr>
<tr>
<td>SCI 2</td>
<td>12.2</td>
<td>12.4</td>
</tr>
<tr>
<td>SCI 3</td>
<td>57.7</td>
<td>3.9</td>
</tr>
<tr>
<td>SCI 4</td>
<td>40.8</td>
<td>38.5</td>
</tr>
</tbody>
</table>

Control subjects and the four SCI subjects (italicized cells). During the first movement set (left panel), there was a considerable variance in the null space associated with eigenvectors $g_3$, $g_4$. * Indicates subjects with the third/fourth eigenvector variance higher than the variance associated with the first/second eigenvector. In the last movement set, for the majority of the subjects in both groups, the variance accounted for in the null space decreases in favor of the variance accounted for by the task space components.

The component of the variance was strongly reduced in the last target set, and the movement’s space seemed to become more planar, with the majority of the movement variance accounted by the task space defined by the eigenvectors $g_1$, $g_2$. 

![Fig. 7](image-url) Movement of subject no 3 projected on the space defined by $g_1$, $g_2$, $g_3$ in the early (left panel) and late (right panel) phases of learning. In the first movement set, there was a relevant movement variance in the third dimension of the space $g_3$ (null space). That
approach, we first provided subjects with an interface to acquire a larger number of input signals encoding their upper-body motion. Then, we extracted lower dimensional subspaces embedded in these signals and restricted the map of the controlled device commands to these subspaces. Finally, we tested the hypothesis that by limiting the domain of training to a dimensionally reduced signal space associated with the top principal components of natural movements we can induce motor learning and facilitate a good final performance.

The map between the sensors that captured the body motions and the two-dimensional device—a simple cursor on a computer monitor—was based on PCA because this is a well-understood statistical technique, with simple and unambiguous implementation and interpretation. Unlike more sophisticated methods, like independent component analysis, there is no arbitrary step to follow. PCA has been widely used for identifying components of movements and electrophysiological data (Flanders 1991; Santello et al. 1998; Holdefer and Miller 2002). The linearity of the method associated with the orthonormality of the principal components is often, and correctly, understood to limit the biological significance of the PCs. However, here we were only seeking a decomposition of the movement signals that can be effectively used for control. We found that PCA provided a good and easy way to implement a learnable map.

Subjects learn to control the two-dimensional cursor

Our findings suggest that unimpaired and SCI subjects readily reorganized their upper-body motions for controlling a two-dimensional variable. All subjects successfully learned to guide a cursor and to reach virtual targets by moving their upper body. Thus, they learned to operate their upper body as if it were a standard joystick. Motor learning was also demonstrated by the ability of unimpaired subjects to generalize the reaching skill to targets that were not presented during training. These results support the efficacy of an approach based on two closely related factors: (a) the large number of degrees of freedom of the human body, and (b) the ability of the motor system to reorganize the control of movements so as to match the geometry of the space where movements take place. Our findings confirmed the ability of the motor control system—both in control and in SCI subjects—to exploit motor redundancy for reorganizing motor coordination (Chen et al. 1998, 2002; Grea et al. 2000).

Movement economy

Both SCI and control subjects training in a high-dimensional space of upper-body movements reorganized their control authority into two dominant principal components in order to manipulate the two-dimensional cursor projection. This suggests that the motor system reduces the effective dimensionality of body motions by utilizing a small number of simple and coordinated shoulders movements. The result is a reduction in complexity of the coordination of movements, consistent with the simple geometrical properties of the cursor movements that are being controlled. Furthermore, we observed a change in strategy with practice. As subjects became more skilled, they also learned to reduce the relative amount of body motion that did not translate into motions of the controlled cursor. This result confirmed those obtained in the more complex case of finger motion (Mosier et al. 2005; Danziger et al. 2009). However, it may be incongruent with the view that the motor system shifts its variance to an “uncontrolled manifold” (Scholz and Schoner 1999; Latash et al. 2001, 2002; Todorov 2004). Moreover, in our simple case (from 4 to 2 effective dimensions), the reorganization of movement was very fast.

Relevance to human–machine interfaces

The ability to reorganize motor commands when facing a new task or a change in the properties of the limbs and muscles is a prominent feature of the healthy motor system. A growing body of evidence indicates that this movement reorganization takes place thorough plastic changes at different sites of the central nervous system (Cohen et al. 1999; Sanes and Donoghue 2000; Cooke and Bliss 2006; Fouad et al. 2010). This functional plasticity is also critical for motor rehabilitation (Nudo et al. 1996; Bregman et al. 1997; Nudo and Friel 1999; Blesch and Tuszynski 2002; Frost et al. 2003; Nudo 2003a, b, 2006; Ward 2004; Jurkiewicz et al. 2007; Curt et al. 2008; Dunlop 2008; Blesch and Tuszynski 2009; Darian-Smith 2009; Fawcett 2009) and for the interaction with assistive devices, prosthetic devices, and brain-machine interfaces. This work provided a deeper understanding of the mechanisms underlying the reorganization of motor functions that can have important implications for a large user population. Reorganization of motor function takes place, for example, when an amputee must learn to control a prosthetic hand by activities generated by shoulder muscles (Kuiken et al. 2009) and when a paralyzed subject learns to control a cursor by recorded brain signals (Birbaumer et al. 2009; Sepulveda 2009). Moreover, when faced with the task of operating a powered wheelchair, a spinal cord injured subject must form new motor programs within neural and mechanical structures that are naïve to the control of this device (Fehr, Langbein et al. 2000; Hunt et al. 2004).

At present, if impaired subjects must learn to control an assistive or a prosthetic device, they must carry the entire
burden of learning. In general, the lack of customizability of those devices creates different problems across types and levels of disability (Hunt et al. 2004) and subjects with poor control of the upper body are at a greater risk of incurring difficulties and accidents.

Our findings suggest that a user-specific calibration and interface paradigm may reduce difficulties and learning times associated with becoming proficient with new devices and prostheses. The proposed method is relatively independent of the technology that we used and can be easily applied to different hardware, such as, for example, smart materials (Gandhi and Thompson 1992), wearable sensors (Winters and Wang 2003), and instrumented gloves (Kessler et al. 1995) that allow capturing natural body motions with more degrees of freedom.

This is a first step toward the development of a new family of body machine interfaces that can facilitate and expand the access to assistive devices by “understanding” the residual motor ability of the users and extracting low-dimensional control signals from the motor space that survived the injury and that may evolve through time.

Acknowledgments This work was supported by NINDS grants 1R21HD053608 and 1R01NS053581-01A2, by the Neilsen Foundation and by the Brinson Foundation.

References


New perspectives on the dialogue between brains and machines

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Brain-machine interfaces (BMIs) are mostly investigated as a means to provide paralyzed people with new communication channels with the external world. However, the communication between brain and artificial devices also offers a unique opportunity to study the dynamical properties of neural systems. This review focuses on bidirectional interfaces, which operate in two ways by translating neural signals into input commands for the device and the output of the device into neural stimuli. We discuss how bidirectional BMIs help investigating neural information processing and how neural dynamics may participate in the control of external devices. In this respect, a bidirectional BMI can be regarded as a fancy combination of neural recording and stimulation apparatus, connected via an artificial body. The artificial body can be designed in virtually infinite ways in order to observe different aspects of neural dynamics and to approximate desired control policies.

Keywords: brain-machine interface, dynamical system, dynamical dimension, neural plasticity, lamprey

INTRODUCTION

The possibility of controlling the motion of a robotic arm “by mere thought,” as suggested by popular media since the advent of brain-machine interfaces (BMIs), has captured the imagination of fiction writers and science journalists. The image of a magician displacing objects by mental powers can be entertaining. But is mind control a reasonable or even a desirable practical goal for the future of neuroprosthetics? If the ultimate clinical objective is to endow amputees and paralyzed people with the ability to act naturally through the interaction of their brain with an artificial limb, then “controlling by thought” is not quite an appropriate objective. The fact is that, as we carry out the simplest actions, such as opening the handle of a door, we do not occupy our minds with what we are doing. We do not think about opening up the grasp, closing it on the handle, twisting the wrist and so on. This is because motor acts are stored in the brain in hierarchically organized goal-directed actions. The addressing of a given action representation is the only thing the brain must do in order to cause the cascade of events leading to execution. In other words, our nervous systems do all that is needed without loading our thought processes, apart from the explicit activation of a very
Brain-machine interface
Hardware and software systems that enable the communication between the brain and an external device. BMI research received a strong boost from advances in micro-electrode technologies and in the decoding of neural signals. A bidirectional BMI involves translating neural signals into commands to the external device and translating signals from the device into neural stimulation. It is only in the early stages of learning that one must be aware of the details of one’s detailed movements. Once a skill is practiced it becomes automatic and requires minimal thinking. The goal of this review is to provide a perspective that emerged from work by our group and others on how BMIs, based on the bidirectional flow of information between a neural population and a controlled device, may lead to the creation of automatic behavior. But there is more. These interactions are also a fundamental tool for investigating how information is processed by the brain.

In the early 90s, Sharp, Abbott and Marder, introduced a new method to bridge the gap between experimental and computational analysis of neural behavior (Sharp et al., 1992, 1993). They established a direct dialogue between a computer simulation and a group of neurons in a dish. The technique is called “dynamic clamp” and is based on an exquisitely simple idea: to simulate on a computer the input/output properties of a membrane conductance by obtaining the input membrane potential from an actual neuron and injecting the output – a current – into another neuron. To derive the current from the potential, one must integrate a system of ordinary differential equations; a task that can be done in real-time if the size of the system is within the available computational power. The difference between this and a more standard computer simulation is that the variables in question are exchanged between simulation and real neurons. The dynamic clamp establishes a symbiosis between the artificial computation and the biological element, or, to quote Sharp and colleagues (Sharp et al., 1993): “the dynamic clamp behaves as if the channels described by the programmed equations were located at the tip of the microelectrode.”

The concepts that led to the dynamic clamp can be extended from the cellular to the system’s level of analysis. A number of recent studies provided a similar closed-loop feedback to neural systems involved in motor task learning. In this focused review, we discuss how the physical connection between biological neural systems and artificial computational processes established by BMIs may lead to new paths for understanding neural information processing and be harnessed to benefit people suffering from paralysis. We begin by describing a simple neuro-robotic system, in which a small mobile robot provides an artificial body to a brain preparation maintained in a Ringer’s solution. We discuss how the analysis of the coupled behavior may provide insight on the connectivity of the neural system that transforms input stimuli into output control signals. Then, we review more recent work aimed at characterizing the dynamical behavior of a neural system engaged in a two-way interaction with an external device. This knowledge is likely to be critical, also for pursuing the goal of “programming” the operation of BMIs by gaining control on the plastic properties of neurons. We conclude with a new perspective on tuning the maps implemented by bidirectional interfaces so as to approximate the desired behavior of a control system expressed as a force field.

A NEURALLY CONTROLLED VEHICLE
Almost three decades ago, Valentino Braitenberg wrote a small manifesto in semi-fictional form (Braitenberg, 1984). He considered a family of hypothetical vehicles, endowed with various sensors and motor-driven wheels, in the form of mobile robots. The book narrates in entertaining but also thoughtful terms, how the electrical connections between sensors and wheels determine a repertoire of different responses to the stimuli in the environment. It presents two distinct viewpoints: one is the viewpoint of an electrical engineer who puts together the wiring scheme starting from a desired behavior of the vehicle; the other is the analytical viewpoint of a scientist who observes the behavior and attempts to find out how it derives from some possible “neural wiring”. The insight that we obtained from Braitenberg’s vehicles is that neural structures and properties can be established by artificially constraining the relation between neural system and behavior. This guided our group to develop an experimental approach, in which the behavior of a simple artificial device is generated by an isolated neural preparation (Reger et al., 2000; Karniel et al., 2005).

Figure 1 presents the scheme of our initial setup. The brains of sea lamprey larvae were extracted and placed in a recording chamber where they were maintained at constant physiologically relevant temperature in a Ringer’s solution. We placed two stimulation microelectrodes, one on the right and one on the left side of the midline, among the axons of the rhombencephalic vestibular pathways. We also placed two recording glass-electrodes, one on each side of the brainstem’s midline, among visually identified reticulospinal neurons of the reticular formation, which represent the final command neurons to activate and maintain locomotion in vertebrates (Grillner et al., 2008). A simple interface decoder converted the spiking activities detected by the recording electrodes into driving signals for the corresponding wheels of a small robot (a Khepera, by K-Team). A set of optical sensors on the robot measured the light coming from the right and left side, implementing two very
phototaxis – a tendency to move away from the light source – was observed as well (Karniel et al., 2005) and reflected the action of ipsilateral connections between vestibular and reticular neurons. As the robot was exposed to a single source of light, it moved along rather complex and curvilinear pathways. It was immediately evident that the neural circuitry responsible for the observed movements had properties that go beyond the structure of a simple linear feedforward network. A notable feature of this neuro-robotic interaction is that it allowed us to make a direct comparison between behaviors generated by the neural preparation and behaviors generated by a computational model. This was possible (a) because the robotic system was a simple artificial body whose dynamics were simpler and much better known than those of any biological body, and (b) because the interactions between the robot and the neural preparation were confined to a set of well defined signals. The dynamics of the robot were captured by two first-order ordinary differential equations. The light intensities were then mapped by the interface encoder into the frequencies of two impulse generators connected to the two stimulating electrodes. This was effectively the first implementation of a bidirectional interface, which closed the loop from recorded neural activities to electrical stimulation via a robotic device. It was quite impressive to see the small robot responding to a shining light by movements that were most often directed toward it. This response is called “positive phototaxis” and reflects the predominance of excitatory pathways crossing the brainstem’s midline (Figure 2). This was indeed one of the first models discussed in Braitenberg’s book: if the right sensor is connected to the left wheel and vice-versa, then a light shining on one side will cause the wheel on the opposite side to spin faster. As a result, the vehicle will tend to orient itself toward the light and to proceed in the forward direction. However, positive phototaxis was not the only observed behavior of the neuro-robotic system exposed to a light source. Negative phototaxis – a tendency to move away from the light source – was observed as well (Karniel et al., 2005) and reflected the action of ipsilateral connections between vestibular and reticular neurons.

As the robot was exposed to a single source of light, it moved along rather complex and curvilinear pathways. It was immediately evident that the neural circuitry responsible for the observed movements had properties that go beyond the structure of a simple linear feedforward network. A notable feature of this neuro-robotic interaction is that it allowed us to make a direct comparison between behaviors generated by the neural preparation and behaviors generated by a computational model. This was possible (a) because the robotic system was a simple artificial body whose dynamics were simpler and much better known than those of any biological body, and (b) because the interactions between the robot and the neural preparation were confined to a set of well defined signals. The dynamics of the robot were captured by two first-order ordinary differ-
More complex, yet particular, non-linear relations can also be considered. For example polynomials of higher degree, as by analyzing the responses of the neural preparation to stimuli of different frequencies applied to both stimulation electrodes, it was possible to estimate the parameters in polynomial models (Karniel et al., 2005). Then, the models were used to predict the motor behavior of the robot in the presence of a fixed light stimulus. Figure 2 shows a comparison between actual trajectories, and trajectories simulated using models from linear to 4th degree. The data for the fit were generated in a separate session, in which stimulation patterns with different frequencies were applied to the two electrodes placed among vestibular axons. The responses were collected from the two recording electrodes in the posterior rhombencephalic reticular nuclei (PRRN) on the right and left side of the midline. Thus, the data were a collection of points \( \{x_i, y_i\} \) for \( i = 1, \ldots, N \) (\( x \): stimulus, \( y \): response) from the right and left side. These were used to derive, by least squares, the parameters \( W \) in Eq. 3.

\[
y = Wx
\]  

(2)

More complex, yet particular, non-linear relations can also be considered. For example polynomials of higher degree, as

\[
\begin{align*}
y_L &= W_{1.0} + W_{1.1}x_L + W_{1.2}x_R + W_{1.3}x_L^2 + W_{1.4}x_R^2 \\
y_R &= W_{2.0} + W_{2.1}x_L + W_{2.2}x_R + W_{2.3}x_Lx_R + W_{2.4}x_L^2 + W_{2.5}x_R^2
\end{align*}
\]  

(3)

By analyzing the responses of the neural preparation to stimuli of different frequencies applied to both stimulation electrodes, it was possible to estimate the \( W \) parameters in polynomial models (Karniel et al., 2005). Then, the models were used to predict the motor behavior of the robot in the presence of a fixed light stimulus. Figure 2 shows a comparison between actual trajectories, and trajectories simulated using models from linear to 4th degree. As the polynomial degree increases from linear to cubic, there is a visible increase of the model's ability to reproduce the data. However, with the 4th degree polynomial there is a clear col-

Figure 2 | Actual and simulated robot trajectories.
Leftmost panel: Trajectories generated by the neuro-robotic system. The five light bulbs placed on the circular boundary of the workspace were turned on in sequence. Movements toward the lateral lights were curved, with an initial part in the forward direction, followed by a turn toward the light. The four panels on the right show the simulation results obtained after fitting the neural responses of the neural preparation with polynomial surfaces of various degrees, from linear to 4th degree.
Dynamical system
A system that evolves in time under the influence of its environment. The state of a dynamical system is any minimal set of variables that is sufficient to determine the future evolution of the system under the action of a known external input.

The state equation is an ordinary differential equation that relates the rate of change of the state to the state and to the external input.

\[ y_i(n) = W_{i1}x_i(n-1) + W_{i2}x_2(n-1) + V_{i1}y_i(n-1) + V_{i2}y_2(n-1) \\
\]

They found that, with this correction the performance of the model was much better than higher order polynomial models, despite a reduced number in free approximation parameters.

THE DIMENSION OF CLOSED-LOOP DYNAMICS

The interaction between a neural system and an external device provides a framework for further investigating the dynamical properties of a neural system (Kositsky et al., 2003, 2009). The diagram of Figure 3 describes this framework schematically. The interaction between device and neural tissue is entirely self-contained. To simplify our discussion, we assume that the nervous system and the artificial device are governed by some deterministic dynamics. Of course, while the dynamics of the external device are generally well known, the neural dynamics are unknown and are the object of study.

The external device does not need to be a physical one. It can be a computer simulation, for example, of a spring-mass system. The use of simulated devices is particularly useful for investigating specific properties of the neural system. Moving along the diagram of Figure 3 in a clockwise direction, the device sends an output vector variable to the input interface, which encodes this variable into a stimulus pattern, e.g., a frequency of a pulse train. The neural preparation receives the stimulus and responds to it with a pattern of activities. These are recorded either extracellularly or intracellularly with one or more electrodes, depending on the experimental setup. Here, again, we need to make the critical assumption that the recorded activities depend in a deterministic way upon the stimulus. Of course, such assumption is likely to be violated in reality – and in various ways. In fact, an important but difficult task facing the experimenter is to ensure that the preparation is isolated as much as possible from external influences, which tend to create time-dependent fluctuations in the observed neural activity. And, of course, such fluctuations need to be analyzed as a form of “experimental noise.” Finally, the loop is closed by an output interface, which converts the recorded activity into an input vector to the external device.

A fundamental parameter of any dynamical system is the minimum number of independent state variables that are needed to predict the response to an external input. More concisely, this is the dimension of the state space, also known as dynamical dimension. A point mass in free space has dimension 6, as its state is determined by 3 position and 3 velocity coordinates. A spring-mass system constrained to move along a line has dimension 2. The dynamical dimension of

![Figure 3](https://www.frontiersin.org)

Figure 3 | Computational maps associated with an ideal closed-loop interaction between a device and a neural preparation. The external device and the neural tissue dynamics are described by a state equation, yielding the next state as a function of the current state and the input. The output of the device is mapped into a stimulation pattern by the input interface. The recorded neural activities are mapped into a control signal for the external device. By combining these dynamical equations, one obtains an autonomous system \([q_i(n) = m(q_i)]\) whose behavior is entirely determined by its initial conditions (from Kositsky et al., 2009).
Autonomous system

A system governed by a differential equation that contains no explicit dependence upon time. This corresponds to the system being isolated from external influences. Determinism implies that the state trajectories of an autonomous system do not intersect each other, each trajectory being completely determined by the initial state.

Neural systems is unknown. However, the closed-loop system described in Figure 3 can be used to estimate it by exploiting the simple fact that the dimension of the neural (s) and artificial (x) component combine by addition to yield the dimension of the closed-loop hybrid system (q)

\[ \text{dim}(q) = \text{dim}(x) + \text{dim}(s) \]  

(5)

The unknown dimension of the neural system – dim(s) – is derived by subtracting the known dimension of the external device from the measured dimension of the combined system. Therefore, the problem is reduced to measuring the dimension of the combined system. Fortunately, this can be done with rather standard techniques – see (Abarbanel, 1996) for a review. The combined system is autonomous by construction, as it does not receive any external input and we make the assumption that its parameters are time-independent (at least within sufficiently long time intervals.) A well known theorem (Arnold, 1973) establishes that, under broad conditions of smoothness, the solutions of an ordinary differential equation are unique. This implies that the state-space trajectories of an autonomous system, corresponding to different initial conditions, do not overlap. This fact is exploited by a technique (Kaplan and Glass, 1992; Kaplan, 1994) which seeks to find the dimension of a dynamical system by embedding observed trajectories into candidate state-spaces of increasing dimension, until all intersections are removed (Figure 4, bottom left panel). Applying this technique, Kositsky et al. (2009) were able to estimate the dynamical dimension of several preparations from the lamprey’s brainstem. Importantly, as t is shown in Figure 4, the estimated dimension of the neural tissue remained unchanged as the dimension of the simulated external system varied from two to four.

BI-DIRECTIONAL INTERFACES
FOR UNDERSTANDING AND CONTROLLING NEURAL PLASTICITY

Bidirectional BMIs may lead to a new level of understanding of neural plasticity and its role in shaping new behaviors. While different forms of neural plasticity, such as long term potentiation (LTP) (Bliss and Lomo, 1973) and long-
tested the possibility of inducing plastic changes in the Lamprey’s vestibulo-reticular pathways by performing an “artificial lesion” in the robotic system of Figure 1. This is another peculiar opportunity offered by such hybrid systems: they allow us to produce reversible changes in the communications between external device and neural preparation. Then, to assess the occurrence of a plastic change in the neural preparation, one can observe the difference between the behavior that takes place after the lesion is reversed and the behavior before the lesion was applied. The investigators performed this experiment by temporarily “blinding” the left electronic eye of the mobile robot. For this, it was sufficient to reduce the gain of the left optical sensor by a factor of 0.1. Then, they exposed the system to random light stimulation for about 20 min. At the end of this period, they restored the initial optical gain and tested the system on a set of standard light sources. Exposure to the unilateral reduction of the optical gain was sufficient to induce a sustained tendency of the robot to veer toward the right after the balance between the sensors was reestablished. This effect could be explained in two ways: either by a reduction of the spinning rate in the right wheel or by an acceleration of the left wheel (or both). The comparison of this behavioral observation with the prediction of a simple computational model driven by the recorded stimulus/activity patterns revealed that the main change was likely caused by a reduction of the recurrent dynamical gain which relates the activity of the right population of reticular neurons to their own state of firing (the term $V_{\text{sd}}$ in eq. 4). This indicates a general reduction of excitability in the output population contralateral to the lesion and can be attributed to the fact that this population received a reduced input from the lesioned site for an extended period of time.

Is it possible to modify the connectivity in a biological neural network to achieve a desired behavior? The theory of artificial neural networks (Bishop, 1996) has grown and advanced precisely on this premise. But can we exploit the actual mechanisms of neural plasticity to create a desired behavior of the external device? This question has not yet been answered; however, there are signs of progress. Different groups around the world (DeMarse et al., 2001; Martinoia et al., 2004; Bakkum et al., 2008; Marom et al., 2009) are working on systems conceptually similar to that described in Figure 3, but using a different biological model. The neural preparation in these studies is a culture of dissociated neurons from rat cortices grown onto micro-electrode arrays (MEAs). Each electrode of the MEA is able to both record and stimulate the extracellular activity of the cultured network. The external device is a simulated or a real vehicle that navigates over an arena. Even with different methods and approaches, these groups succeeded to “program” the unstructured neuron culture in order to make the vehicle able to solve specific behavioral tasks, such as obstacle avoidance. In one example, the network was programmed by the delivery of tetanic stimulation (Chiappalone et al., 2008) to “punish” the wrong behavior of the robot in case of a collision with an obstacle. After repeated stimulation, an improvement in the robot’s performances (i.e., a lower number of collisions) was observed (Novellino et al., 2007). While this is still a very preliminary result, it demonstrates that – at least in principle – it may be possible to reach the goal of programming the behavior of a bidirectional BMI by inducing controlled changes in neural excitability. A critical milestone, still unreached, is the controlled induction of plastic changes in both directions (potentiation and depression) with brief exposure to targeted conditioning signals.

**FUTURE DIRECTIONS**

Most work on BMIs, so far, has developed decoding paradigms to translate the neural activities captured by surface electrodes or by MEAs into commands for an external device. This requires the users to keep a constant focus of attention on the execution of detailed motor commands. In these setups, feedback is limited to vision, which involves long delays and requires gaze to be constantly on the moving device. Furthermore, non-kinematic information, such as the weight, rigidity and temperature of a manipulated object, are not directly sensed. These limits have propelled investigations toward the development of goal-decoding
related to earlier evidence that spinal interneurons organize muscles into synergy groups whose mechanical outputs are force fields acting upon the limbs (Bizzi et al., 1991; Giszter et al., 1993; Tresch and Bizzi, 1999). These studies demonstrated a simple mechanism of vector summation capable of generating a repertoire of control policies out of a small set of non-linear force fields (Mussa-Ivaldi et al., 1994; Mussa-Ivaldi and Bizzi, 2000). As a future direction, we propose to program bidirectional BMIs for generating control policies in the form of force fields acting on the controlled external devices. We call “dynamic shaping” the interface algorithm that implements this neuro-mechanical translation (Figure 5).

A bidirectional interface can, in principle, be programmed to implement a pattern of neural stimuli and responses capable of approximating a desired behavior of the controlled system (Chao et al., 2008). Mathematically, this process corresponds to translating the behavior of the neural system into a control policy that maps the current observed state of the controlled system into a corresponding action. This concept is closely related to earlier evidence that spinal interneurons organize muscles into symmetry groups whose mechanical outputs act as force fields upon the limbs (Bizzi et al., 1991; Giszter et al., 1993; Tresch and Bizzi, 1999). These studies demonstrated a simple mechanism of vector summation capable of generating a repertoire of control policies out of a small set of non-linear force fields (Mussa-Ivaldi et al., 1994; Mussa-Ivaldi and Bizzi, 2000). As a future direction, we propose to program bidirectional BMIs for generating control policies in the form of force fields acting on the controlled external devices. We call “dynamic shaping” the interface algorithm that implements this neuro-mechanical translation (Figure 5).

Dynamic shaping has two components: (1) a decoder that maps the recorded output activity interfaces (Mussallam et al., 2004) and of bidirectional BMI’s (Mussa-Ivaldi and Miller, 2003; Fagg et al., 2007). Bidirectional BMI’s are devices that can not only decode neural activity but also encode external information in the form of brain stimuli. If successful, BMI prosthetic control systems are to be developed which will surely require the use of a trainable bidirectional interface.

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**Figure 5 | Dynamic shaping simulation.** A simple artificial feedforward neural network is connected to a pattern of stimuli, delivered to 6 binary input units (C; white: on, black: off) and generates responses over a set of 16 output neurons. In this model, there are no hidden units between input and output units but there is a set of four hidden “noise” units that generate random inputs to the output units. Input and output units are connected by a “synaptic matrix” (B) with positive and negative weights. The output units respond to the weighted sum of their input via a sigmoid transfer function. A set of 21 calibration stimuli (C) are presented in sequence to the input units and 21 responses (A) are recorded from the output units. The calibration stimuli and responses are used to approximate a desired force field (E), acting on a mass-damping system. To perform the calibration, the two top principal components of the 21 neural responses are mapped over the ranges of the force vector components in the desired field. This mapping is performed by the linear decoder. Then, for each force vector, the corresponding point of application is determined and is associated to the stimulus pattern that generated the force vector (D). A simple form of the stimulus encoder maps the current location of the mass-damping system into the nearest point determined in the calibration. The resulting field generated by the encoder/decoder system (F) is a fragmented approximation of the desired field. (G): Simulated trajectories of the spring-damper system under the field generated by the interface.
into a force vector, and (2) an encoder that maps the state of the device into a pattern of stimuli. If the dimension of the vector field is smaller than the number of recorded units, the transformation from recorded activities to force vector involves a dimensionality reduction (e.g., by principal component analysis.) In a dynamically shaped interface, the external neural input sets an initial condition and the dynamic field – in the absence of other influences– determines the ensuing trajectory. This approach would free the user from the need to guide the connected device instant by instant. At the same time, however, the user would be able to perform a continuous control, thus guiding the device through arbitrary paths. So far, we have implemented and tested dynamic shaping with a simulated neural system, a simple feedforward neural network model of the biological component (Figure 5).

As dynamic clamps provide us with the means for isolating particular elements of cellular physiology, such as individual channels, the bidirectional interactions between brain and machines – either physical or simulated – provide the nervous system with artificial bodies that are endowed with well known properties and that communicate through well defined channels. This marriage of the nervous system with artificial devices offers an unparalleled opportunity to acquire knowledge about neural computation and plasticity while opening a path for restoring functions lost to accident or disease.

ACKNOWLEDGMENTS
This research was supported by ONR grant N000149910881, NINDS grants NS048845 and 1R21HD053608 to FAM-I and EU grants Neurobotics, RobotCub and Poeticon to Luciano Fadiga. We are grateful to Dr. Citlali Lopez-Ortiz for comments on the manuscript.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Received: 30 September 2009; paper pending publication: 14 October 2009; accepted: 24 November 2009; published: 15 April 2010.
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