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RESEARCH ARTICLE

Functional reorganization of upper-body movement after spinal cord injury

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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

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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 (Kaye 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.

Table 1 Anagraphic and clinical data of the SCI subjects

Subject	Gender	Age (years)	Level of injury	ASIA	Time after injury (months)
SCI 1	*M*	22	*C4*	*A*	34
SCI 2	*F*	*27*	*C5*	*C*	*84*
SCI 3	*M*	20	C4R, C5L	*A*	7
SCI 4	*M*	*25*	C2R, C3L	*A*	5

Gender: male/female. Age: years. Time between the injury onset and the experimental session (months)

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, NaturalpointInc., 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).

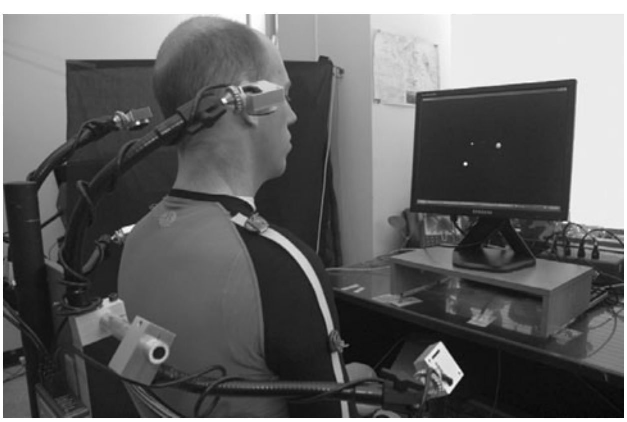

Fig. 1 Experimental set-up

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 $66\ \mathrm{s} - 75$ 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 $(\underline{a}_1, \underline{a}_2, \ldots, \underline{a}_N)$. By applying PCA to the calibration data set, we created a new basis that was a linear combination of the original basis:

$$P' = \begin{bmatrix} \underline{a_1} \\ \underline{a_2} \\ \cdots \\ \underline{a_N} \end{bmatrix} \cdot P = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{N,1} & a_{2,2} & \cdots & a_{N,N} \end{bmatrix} \cdot P = AP. \quad (1)$$

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:

$$\underline{u} = \begin{bmatrix} x \\ y \end{bmatrix} \quad (2)$$

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 $\underline{u}$ by the following linear transformation:

$$\underline{u} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \end{bmatrix} \cdot \begin{bmatrix} h_1 \\ h_2 \\ \cdots \\ h_N \end{bmatrix} = A_{\mathrm{Task}}\ \underline{h} \quad (3)$$

where A_{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"

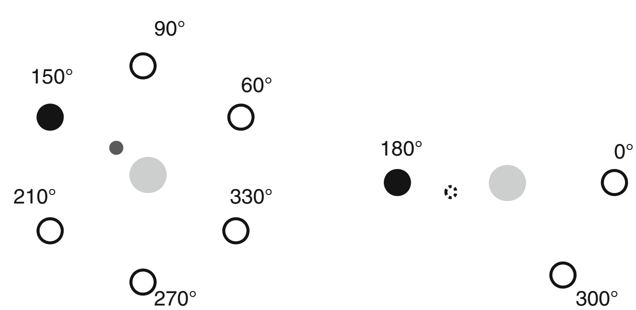

Fig. 2 *Left panel circles* on the periphery are the six possible target locations for both T1–T6 and BL movement sets (1 cm in diameter). Only the target (*black filled circle*) and the starting position (*gray filled circle*) for the current trial were displayed. The initial position was slightly bigger 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).

$$\text{Jerk index} = \frac{1}{2}\sqrt{\frac{\left(\int \|j(t)\|^2 \mathrm{d}t\right)T^5}{L^2}} \tag{4}$$

  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 re-appeared (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 coordinates, determined two at a time by each of the four 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:

$$\underline{h}' = \begin{bmatrix} h'_1 \\ h'_2 \\ \cdots \\ h'_N \end{bmatrix} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,N} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{N,1} & a_{N,2} & \cdots & a_{N,N} \end{bmatrix} \cdot \begin{bmatrix} h_1 \\ h_2 \\ \cdots \\ h_N \end{bmatrix} = A\underline{h} \tag{5}$$

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_{Task}, as described in Eq. 3, and the projection of the signals on the space defined by these two vectors determine 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_{Task}. Therefore, these vectors form the $(N-2) \times N$ matrix A_{Null} that is the basis of the "null space" associated with task space A_{Task}, i.e. a space where signal variation does not affect the command vector $\underline{u}$.

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

$$\begin{aligned}\underline{n} = \begin{bmatrix} n_1 \\ n_2 \\ \cdots \\ n_{N-2} \end{bmatrix} &= \begin{bmatrix} a_{3,1} & a_{3,2} & \cdots & a_{3,N} \\ a_{4,1} & a_{4,2} & \cdots & a_{4,N} \\ \cdots & \cdots & \cdots & \cdots \\ a_{N,1} & a_{N,2} & \cdots & a_{N,N} \end{bmatrix} \cdot \begin{bmatrix} h_1 \\ h_2 \\ \cdots \\ h_N \end{bmatrix} \\ &= A_{\text{Null}}\,\underline{h}\end{aligned} \tag{6}$$

where each elements n_i is the scalar product between the ith eigenvectors orthogonal to the task space and the instantaneous signal vector. Thus, by definition, $\underline{n}$ 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):

$$\begin{aligned}V &= \frac{\sum_{i=1}^{2} \sigma^2\left(h'_i\right)}{\sum_{i=1}^{N} \sigma^2\left(h'_i\right)} \cdot 100 \\ &= \frac{\sum_{i=1}^{2} \sigma^2(u_i)}{\sum_{i=1}^{2} \sigma^2(u_i) + \sum_{i=1}^{N-2} \sigma^2(n_i)} \cdot 100\end{aligned} \tag{7}$$

where $\sigma^2\left(h'_i\right)$ is the variance of the signals associated with the ith eigenvector, $\sigma^2(u_i)$ is the variance of the signals associated with the ith eigenvector of the task space U, and $\sigma^2(n_i)$ is the variance of the signals associated with the ith 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 ($P > 0.6$).

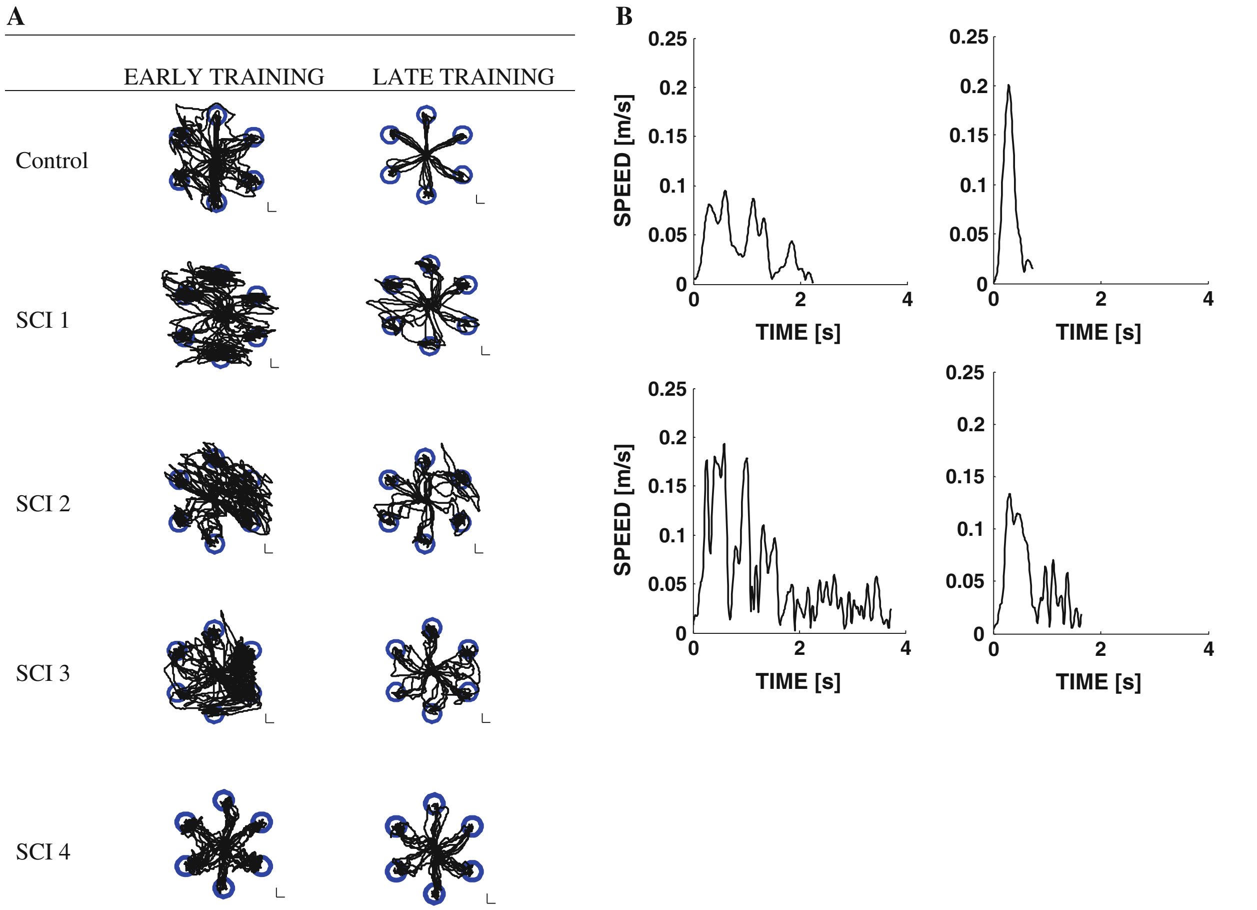

Fig. 3 **a** Movement trajectories in early (*left*) and late (*right*) phases of learning, for a control subject and 4 SCI subjects. Calibration lines on bottom right corner of each panel: 1 cm on the computer screen. **b** Example of speed profiles in early (*left*) and late (*right*) phases of learning for a control (*upper*) and a SCI subject—SCI 3—(*bottom*)

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

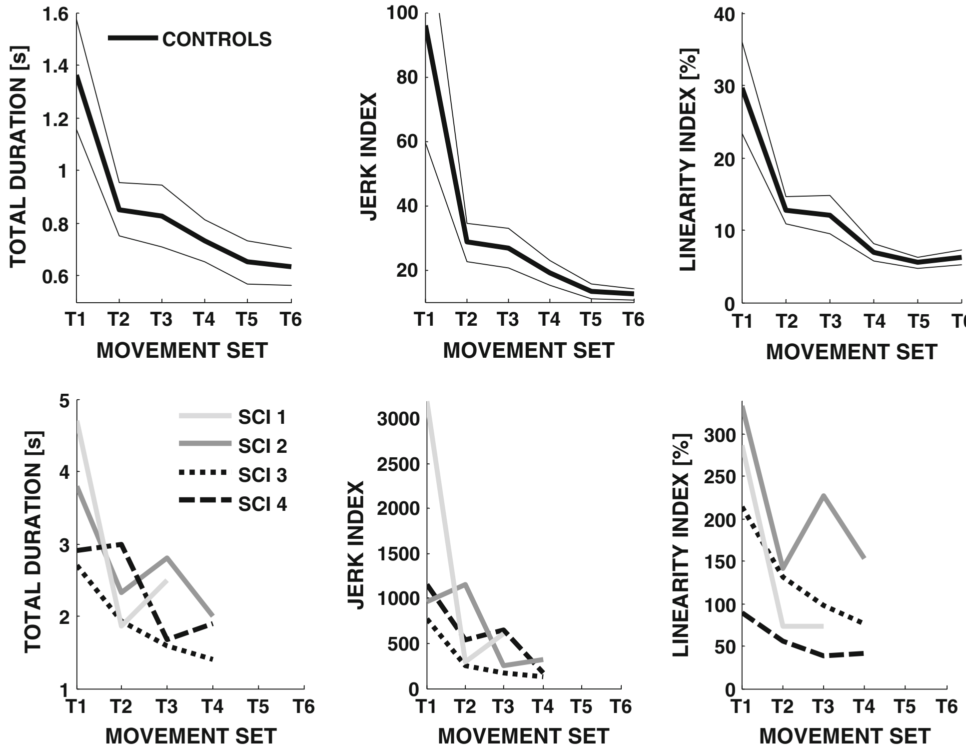

Fig. 4 Time course of duration, jerk, and linearity index of controls (*top*—mean + SE) and SCI subjects (*bottom*)

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

Movement set	Duration (s)		Jerk index		Linearity index	
	First	Last	First	Last	First	Last
SCI 1	*4.7 ± 0.7*	2.5 ± 0.3*	*3287.6 ± 1164.4*	604.0 ± 128.4*	*286.6 ± 60.5*	73.5 ± 11.2*
SCI 2	*3.8 ± 0.5*	2.0 ± 0.3*	*1156.2 ± 251.0*	173.9 ± 40.2*	*333.2 ± 79.2*	153.5 ± 39.6*
SCI 3	*2.7 ± 0.2*	1.4 ± 0.2*	*768.0 ± 132.5*	125.4 ± 31.6*	*214.4 ± 35.6*	77.0 ± 10.8*
SCI 4	*2.9 ± 0.4*	1.9 ± 0.2*	*962.9 ± 183.9*	319.1 ± 55.4*	*89.1 ± 17.1*	41.2 ± 6.0*

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

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 associate 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.

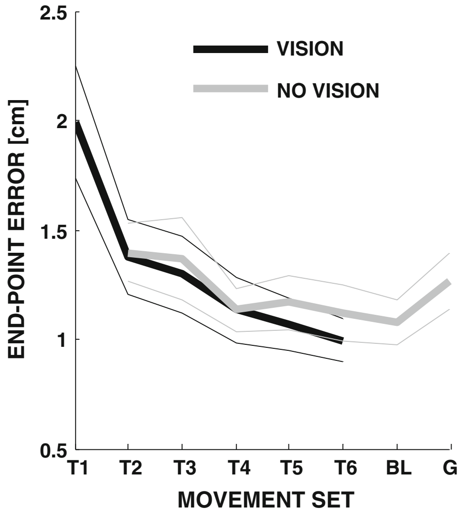

Fig. 5 Time course of end-point error (mean + SE) in vision (*black line*) and blind trials (*gray line*) of controls

Table 3 End-point error for all spinal cord injury subjects in the last movement set (mean ± SE) under "vision" and "no vision" condition

Movement set	End-point error (cm)	
	Last—vision	Last—no vision
SCI 1	2.9 ± 0.2	3.3 ± 0.3
SCI 2	2.9 ± 0.2	2.5 ± 0.3
SCI 3	2.0 ± 0.3	1.7 ± 0.3
SCI 4	2.9 ± 0.2	3.0 ± 0.3

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 $\underline{a}_1$, $\underline{a}_2$ and the variance associated with the other six dimensions that span the null space, $\underline{a}_3, \ldots, \underline{a}_8$.

Table 6 shows that initially there was considerable variance in the null space associated with the third eigenvector, $\underline{a}_3$ 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 $\underline{a}_3$, $\underline{a}_4$ decreased in favor of the variance associated with $\underline{a}_1$, $\underline{a}_2$ 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 $\underline{a}_1$, $\underline{a}_2$, $\underline{a}_3$ 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 $\underline{a}_3$ (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 $\underline{a}_1$, $\underline{a}_2$.

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 ± 18 to 74 ± 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)

	% Variance accounted for							
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Controls (mean ± SD)	48.1 ± 7.4	27.8 ± 5	14.9 ± 4.9	7.5 ± 3.1	0.9 ± 0.7	0.3 ± 0.2	0.1 ± 0.1	0.1 ± 0.1
SCI 1	*64.7*	*29.4*	*3.8*	*1.7*	*0.2*	*0.1*	*0.1*	*0*
SCI 2	*62.5*	*17.4*	*13.5*	*4.2*	*1.2*	*0.7*	*0.5*	*0.1*
SCI 3	*79.8*	*9.5*	*8.2*	*2*	*0.3*	*0.1*	*0.1*	*0*
SCI 4	*68.3*	*18.5*	*6.3*	*6*	*0.5*	*0.2*	*0.1*	*0*

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

	% Variance accounted for							
	First movement set				Last movement set			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
Controls (mean ± SD)	52.4 ± 10	33.8 ± 9	9.0 ± 2	3.0 ± 1.8	50.8 ± 5.8	39.0 ± 5.0	7.1 ± 3.9	2.0 ± 1.2
SCI 1	*51*	*36.6*	*6.4*	*5.1*	*51.4*	*36.8*	*7.6*	*3.1*
SCI 2	*55.2*	*25.1*	*12.3*	*5.1*	*61.4*	*29*	*6*	*2*
SCI 3	*66.4*	*24.4*	*3.8*	*3.0*	*67.8*	*25.7*	*3.9*	*1.8*
SCI 4	*45.1*	*35.9*	*10.6*	*3.4*	*58*	*30.4*	*7.5*	*3.1*

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

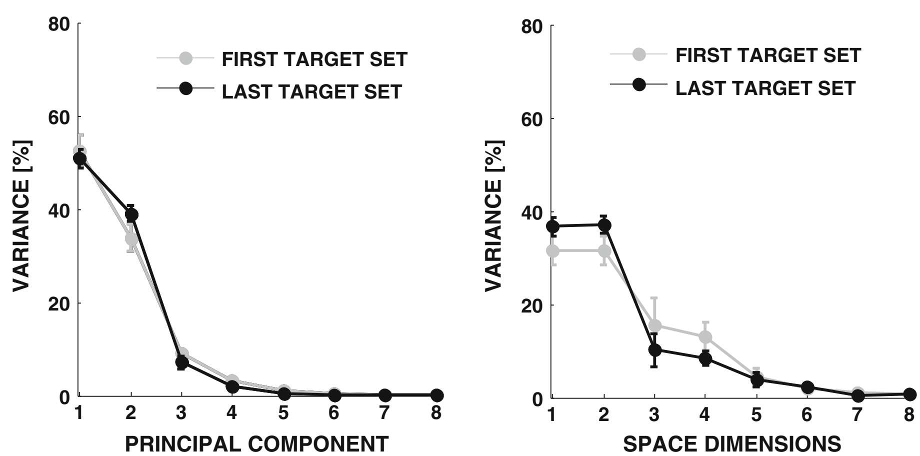

Fig. 6 *Left panel* results of principal component analysis on the first (*gray*) and last movement set (*black*) for control subjects (mean + SE). In the first movement set (*gray*), more than 95% of variance was explained by four principal components. At the end of the training session (*black*), unimpaired 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 $\underline{a}_3$, $\underline{a}_4$ decreased with training in favor of the variance associated with $\underline{a}_1$, $\underline{a}_2$, the two "task relevant" components

Table 6 Movement variance associated with the two eigenvectors that define the task space $\underline{a}_1$, $\underline{a}_2$ and variance associated with the other two eigenvectors that define the null space, $\underline{a}_3$, $\underline{a}_4$during the first (left) and last (right) movement set

	% Variance accounted for							
	First movement set				Last movement set			
	$\underline{a}_1$	$\underline{a}_2$	$\underline{a}_3$	$\underline{a}_4$	$\underline{a}_1$	$\underline{a}_2$	$\underline{a}_3$	$\underline{a}_4$
Con 1	23.5	24.5	9.2	31.8*	34.6	36.8	8.9	13.3
Con 2	29.2	29.7	11.6	4.2	31.4	34	10.3	2.1
Con 3	21.1	20.6	29.9*	13.9	37.4	36.8	10.5	3.9
Con 4	17.7	17.6	57.7*	2.2	25.1	25.6	35.4	6
Con 5	35.8	33.8	8.8	10.3	43.3	41.4	4.8	3.7
Con 6	34	36.2	5.2	22.8	41.1	40	4	9.6
Con 7	43	43.9	3.1	8	43.2	45	1.6	8.5
Con 8	42.7	41.3	1.6	11.1	39.4	38.8	1.9	15.4
Con 9	37.5	36.1	12	13.4	34.5	35.2	14.5	13.3
SCI 1	*34.8*	*38.7*	*6.9*	*17.3*	*35.9*	*40.2*	*4.9*	*16.4*
SCI 2	*12.2*	*12.4*	*43.5**	*20.7**	*28.6*	*28.5*	*29.7*	*5.4*
SCI 3	*57.7*	*3.9*	*31**	*3.5*	*56.5*	*9.9*	*30.6*	*1.9*
SCI 4	*40.8*	*38.5*	*13*	*4.6*	*29.9*	*31*	*31.1*	*3.7*

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 $\underline{a}_3$, $\underline{a}_4$. * 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

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.

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

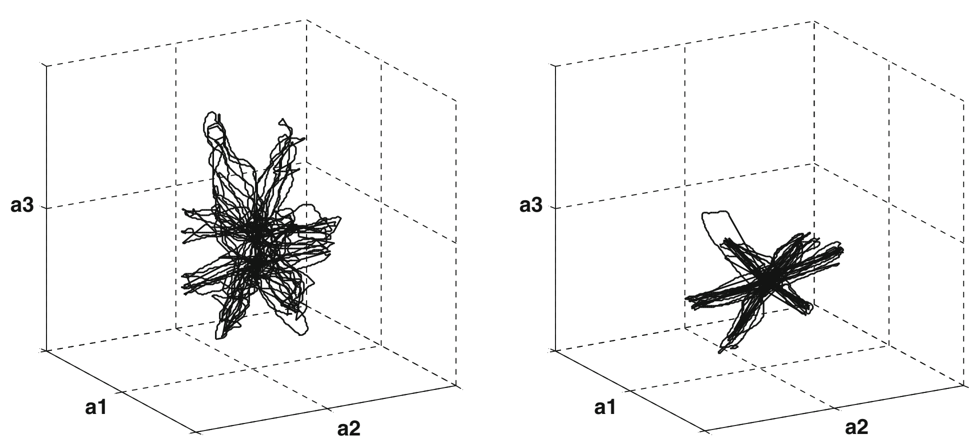

Fig. 7 Movement of subject no 3 projected on the space defined by $\underline{a}_1$, $\underline{a}_2$, $\underline{a}_3$ in the early (*left panel*) and late (*right panel*) phases of learning. In the first movement set, there was a relevant movement variance in the third dimension of the space $\underline{a}_3$ (null space). That 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 $\underline{a}_1$, $\underline{a}_2$

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.

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