31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Functional Reorganization of Upper-Body Movements for Wheelchair Control

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Abstract—**In general, survivors of neuromotor disorders and injuries need to reorganize their body movements in order to achieve goals that used to be easy and natural. Often, disabled people are offered the option to control assistive devices that will facilitate the recovery of independence and capability in their daily lives. The knowledge acquired during the last few years in the motor control field can be used to study and enhance this learning process. Furthermore, this knowledge may aid in finding methods for optimizing the use of residual voluntary muscular control in disabled users and searching for an easily learnable map between body motor space and devices control space.**

To investigate movement reorganization we asked healthy subjects to control a cursor performing a reaching task using shoulders and upper arm movements. These movements were mapped to a lower dimensional space by principal components analysis and were used to control the cursor. We found that all subjects were able to learn to control the cursor with ease and precision while reducing the proportion of ineffective body movement components in favor of the components that mapped directly into the control space. Moreover, with practice the movements of the controlled device – the cursor - became faster, smother, more precise and with a nearly symmetric speed profile.

I. Introduction

A broad spectrum of injuries and disorders lead to severe loss of mobility. Subjects' residual motor functions provide the disabled with the means for controlling assistive devices, such as wheelchairs, tools, or computers. However, optimal use of these devices requires radical reorganization of movements. The overall goal of this study is to explore an innovative approach to the reorganization of movements for the control of powered wheelchairs. It is expected that the findings will be of broad relevance to different types of assistive technology. Our approach is based on the idea of providing disabled users with an overabundant number of signals for control, and on facilitating the process of motor learning by which they can reorganize their actions in a natural way, depending on their residual motor skills. We assume that, having a large number of control signals at their disposal, the users will eventually be able to identify a reduced number of natural movements that are optimal, or at least adequate, to operate the assistive device. We wish to investigate the development of these movements and how they may form a basis for designing efficient wheelchair controllers. We report here a preliminary step toward this goal where subjects were asked to control a cursor in a virtual environment. The cursor was driven by signals derived from the motions of the shoulders and upper arms of unimpaired subjects. Subjects were asked to move the cursor from some initial point to an end target in a fixed amount of time. The protocol was analogous to a typical experiment on arm reaching movements[1-2]. We investigated the learning process in which subjects reorganized the motions of their shoulders and upper arms so as to control efficiently the motions of the cursor over the computer monitor. Stated differently, instead of learning to control a joystick - the input device of some powered wheelchair systems - we investigated how one can reorganize coordination so as to transform one's whole upper body into a joystick.

Manuscript received 04/07/2009. This work was supported by NIH grant 1R21HD053608 and by the Craig H. Neilsen and the Brinson Foundations.

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II. Materials and Methods

A. Experimental Set-up

A total of seven subjects (mean age 30±6 yrs, 6 male 1 female) participated in this experiment, after signing the informed consent form approved by Northwestern's Institutional Review Board. Subjects sat comfortably and faced a 19" LCD computer display positioned roughly 1 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) was used to track active infrared light sources, which were attached to the subject's right and left shoulders and two upper arms (see Fig. 1). Shoulder and arm positions were captured at 75 samples per second using proprietary software (Modification of a C++ SDK supplied by Naturalpoint). These data were also presented online to the subjects (see section C).

B. Dimensionality Reduction.

The entire set of signals captured by the cameras was first mapped into a 2-dimensional signal controlling the cursor location on the monitor. Eventually, the same set of low-dimensional output signals will control the actuation of the physical wheel chair, which also requires a 2-dimensional command. In the current configuration the conversion is from 8 dimensions (4 cameras, each with a planar sensor of dimension 2) to 2 dimensions.

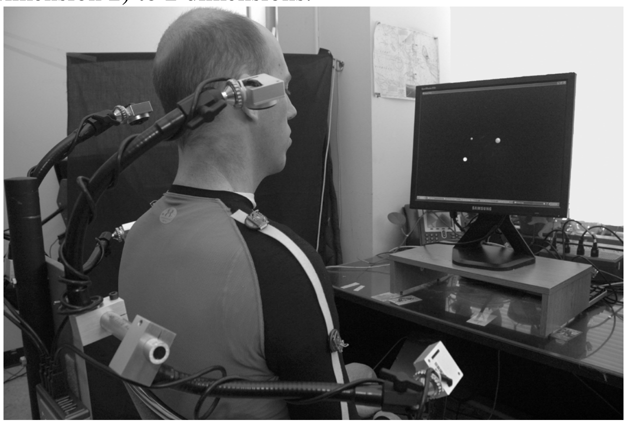

Fig. 1: Subject performing the experiment.

The map from body signals to cursor was constructed in the following three steps:

1. "Dance" – Subjects were asked to explore their entire range of motion capability by moving in all possible directions with their shoulders and upper arms for some time. This was instructed as a free "dance"-motions of the body that the subjects would generate naturally and effortlessly. The instruction was to move in various directions and combinations so the majority of the workspace would be visited. However, the purpose of this approach is to explore a range of body motions that each individual is easily capable of executing. We expect that the type and degree of impairment in individual disabled users will constrain and shape the movements generated in this phase. We verified that at least two principal components with significant variance can be extracted from this high dimensional signal.

2. PCA – The eight principal components of the data were estimated using standard techniques. The eigenvectors corresponding to the two largest components were chosen as the basis for the low dimensional signal (the cursor) and their values were projected on the monitor. Once these two components were chosen, the high dimensional signal was projected on the low dimensional monitor where the subject controlled the location of the cursor using his upper body motions.

3. Adjustments – Inherently, the choice of the two largest principal components might include biases and scaling that are not well-suited for controlling the cursor by the subjects. Three corrections were manually introduced on-line to facilitate a more natural control scheme: scaling, shifting and rotation. These three were adjusted until each subject was able to comfortably reach the various locations of the workspace.

C. Experimental Protocol and Task

The task consisted of controlling a cursor using small shoulder/trunk movements in six different equally-spaced directions (see Fig 2), starting from the same initial position in the center of the workspace. Targets were presented on the screen as round white circles 1 cm in diameter against a blue background. The instructions were to arrive at the target within 0.4 seconds after leaving the initial position. To inform the subject of this time constraint, the target changed its color to red once the time limit had elapsed. The importance of the time constraint was stressed to the subjects.

The cursor "location," or current value of the projection to the lower dimension (see Section B), was displayed as an orange circle (0.4 cm diameter). The amplitude of the required movements (distance of the targets from the center) was 5 cm. The sequence of target presentations alternated between the central target and one of six peripheral targets in random order.

The experimental protocol was organized into three phases: learning, blind test and generalization. The learning phase was organized into 6 target sets, each consisting of a sequence of target presentations in which each peripheral target occurred 9 times, for a total 54 center–out movements plus the corresponding 54 return movements.

Starting at the second target set, we introduced randomly interspersed "No vision" trials; in these trials the cursor disappeared when the movement started and reappeared 0.4 seconds later. "No vision" trials were about 1/3 of all trials in each trial set, corresponding to three catch trials per direction per trial set. The blind test phase was equivalent to the learning phase 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 we tested the ability of the subject to reach a target in three new directions which were not experienced previously (Fig. 2, right panel). All trials were "no vision" and each target was randomly presented 5 times.

D. Data Analysis

The x and y components of cursor position were smoothed with the a 4th order Savitzky-Golay filter (equivalent cut-off frequency about 10 Hz) [3], 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.

We focus the analysis on the center-out movements. The following set of indicators (under the "vision" condition) was assessed in order to evaluate performance:

– Movement duration: time elapsing between movement onset and termination. Movement onset was computed as the first time instant in which the cursor velocity exceeded a threshold equal to 10% of the peak velocity for at least 200 ms. Movement termination was computed as the first time after onset in which movement speed went below the threshold, and remained there for at least 200 ms.

– Symmetry: ratio between the durations of acceleration and deceleration phases within the motion.

– Aiming Error: difference between the target direction and the actual movement direction in the early phase of the movement (until 100 ms after movement onset). The

100-ms aiming error is indicative of the performance of the feed-forward component of control.

- Linearity: percent increment of the length of the trajectory traced by the cursor, between onset and termination times, with respect to the straight line distance between the initial and final points of the trajectory.
- Jerk index: The square root of the jerk (norm of the third time derivative of the trajectory), averaged over the entire movement duration and normalized with respect to duration and path length [4]. This measure is sensitive to smoothness – large jerk indexes correspond to less smoothness. The square root is used to compress the large range of variation of the jerk integral
- Jerk ratio: ratio of the jerk indexes calculated during the deceleration (after the peak in the speed profile) and acceleration phase of the movement. It indicates a difficulty in compensating for self-generated errors and therefore a problem using sensory information[5].
- PCA values were evaluated for each one of the target sets within the learning phase. The data used was the first 0.4 seconds after the subject left the starting position.

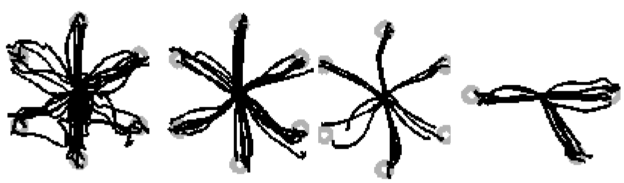

Fig 2. Trajectories in the different phases of the experiments, for a typical subject.

Finally, in all target sets both vision end no vision conditions we analyzed:

- The end-point error as the distance between the target and the cursor position when the target becomes red (0.4 seconds after the subject left the starting position).

Statistical analyses are based on repeated measures ANOVA method and were performed using the Statistica 7.1 software (*Stat Italia* srl, Italy).

III. Results

All subjects were able to complete the task without difficulties. Fig. 2 shows an example of the movements recorded during the various experimental phases and Fig.3 display typical speed profiles in the early and late phases of learning.

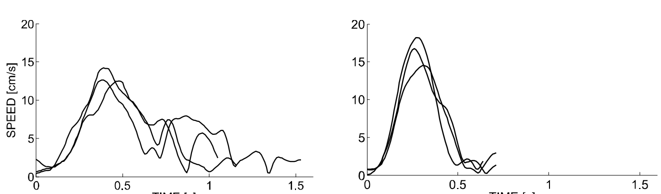

Fig 3. Speed profiles in early (left) and late (right) phases of learning, for a typical subject.

The figures suggest that subjects improved their performances and were able to perform the task correctly, even without visual feedback and in new directions.

A. Subjects Performance Improved with Practice

In order to test the learning process during this novel task (under the vision condition) we run, for all the indicators mentioned above, a repeated-measures ANOVA. Two factors were included: time (first and last learning sets) and directions (1-6).

As shown in Fig. 4, the movement duration (Fig. 4A) decreased significantly with time (time effect: $F(1,6)=38.98$, $p=0.0007$) due, not to changes in the initial acceleration phase that remained nearly invariant ($p>0.05$), but instead to a more rapid deceleration phase ($F(1,6)=34.41$, $p=0.001$). Thus, at the end of adaptation phase the speed profile became bell shaped and more symmetrical (Fig. 3 and 4B) than in the early phase of adaptation ($F(1,6)=8.08$, $p=0.029$). Additionally, the aiming error (Fig. 4C) and the linearity index (Fig. 4D) decreased significantly ($F(1,6)=9.56$ $p=0.02$ and $F(1,6)=9.94$ $p=0.020$, respectively). The trajectories became smoother (-Fig. 4E): $F(1,6)=6.34$ $p=0.045$)) and the jerk ratio (Fig. 4F) decreased ($F(1,6)=8.86$ $p=0.025$), tending to one in the last learning phase. Target direction had no significant effect on any of the indicators.

B. Performance is not determined by visual feedback.

We ran repeated measures ANOVA with 2 factors: vision and time (for the second and sixth target sets) on *end point error* (Fig. 4G) indicator. We found no vision effect as well as no interaction between vision and time.

C. Generalization

We compared the performance in the two last target sets. On the second to last, subjects were asked to arrive to the same target set they practiced during the training phase, but without visual feedback (blind). On the last target set they were asked to reach three new (not experienced) targets (generalization). The performances regarding *the end point error* indicator (Fig. 4G) was slightly worse in the generalization phase compared to the blind phase, but the statistical analysis did not show any significant difference. We noticed informally that for some subjects it was more challenging to move in an un-experienced direction. Nevertheless, the learning of the mapping allowed them to arrive to those un-explored targets.

D. Subjects reduce the dimensionality of body motions.

During the "dance task" the main movement variance was explained, almost completely, by the first 4 principal components (Fig 5-A). As subjects started the experiment and worked in the plane of the two main principal components, immediately the fourth component was reduced (figure 5-C). Moreover, throughout learning (Fig. 5-B) the variance accounted for by the two principal components (VAF) increased significantly with time ($F(5, 30) = 3.47$, $p=0.01$). The increase in VAF by the two top PCs suggests that subjects through training learned to shift the control of body motions toward the two components that were used as axes for the target space (Fig. 5-C and 5-D). We see this as a form of geometrical adaptation, which implies that as subjects learn the task they are implementing a measure of dimensionality reduction in the control space. During the initial phase some subjects organize this control along the first component while others vary control along the third. In general there is a bigger inter-subject diversity in the chosen approach, on this initial phase. This diversity decreases during learning and most subjects converge to a relatively similar strategy. Most of them balance the contributions of the first and second components and make almost no use of higher components (Fig 5-D).

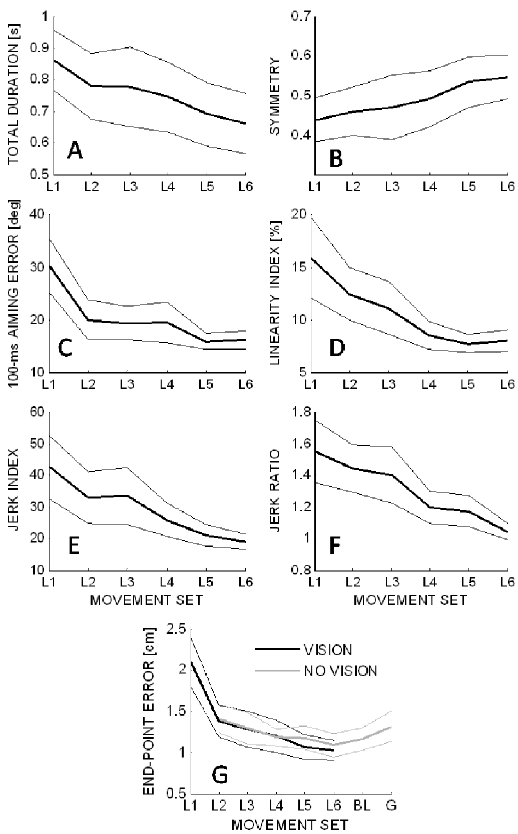

Fig 4. Time course of movement performance indicators during the different phases of the experiment (L: learning phase, B: Blind test G: generalization). Bold line: mean over all subjects; Thin line: standard error.

IV. DISCUSSION

Our findings suggest that healthy subjects readily learn to operate a low dimensional control signal which is controlled via a higher dimensional signal derived from shoulders and upper arm movements. Subjects successfully operated a visual cursor, guiding it to virtual targets by moving their upper body, which was effectively operating as a joystick. Motor learning was evidenced by the ability of subjects to generalize the reaching skill to portion of the workspace not explored during training.

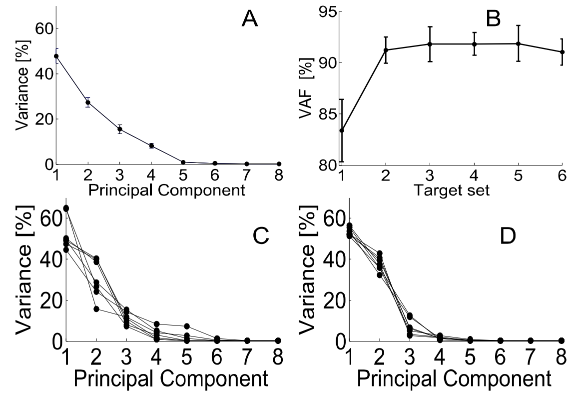

Fig 5, A: The averaged amount of variance which is explained by each one of the principal components during the "dance" task (error bar show the standard error). B: Amount of variance which is accounted for by the two largest principal components on each target set. C: Variance accounted for by each of the principal components during the first target set. D: Variance accounted for by each of the principal components during the last target set.

Furthermore, we observed a change in strategy as seen in the number of principal components of body motions participating to the task. As they became more skilled, subjects also learned to reduce the relative amount of body motion that did not translate into motions of the controlled cursor. This is in contrast with the view that the motor system shifts variance to an "uncontrolled manifold" [6-8]. The findings here are encouraging because they demonstrate the ability of the nervous system to reorganize coordination of upper body movements to operate an external device. Therefore, this technique could potentially be used for controlling powered wheelchairs and other assistive devices by subjects suffering from injuries that reduce but do not totally suppress mobility, such as high level spinal cord injury.

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