Learning and Exploration in a Novel Dimensionality Reduction Task

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Background

Many, if not all, motor tasks require control of a high-dimensional system in a lower-dimensional workspace. The typical example is moving the 7 joint-dofs of the arm to point to a position in 3D. In order to assess how humans learn such dimensionality reduction, Mussa-Ivaldi and colleagues (2005, 2008) developed an experimental paradigm in which subjects learned to move a cursor to targets on a screen (2D task space) with movements of the fingers. Finger movements were measured with a CyberGlove with 19 sensors. The sensors were mapped onto the 2D workspace via a linear mapping. This linear transformation eliminated the need for analysis of complex kinematics. Results showed that subjects learned to reliably control cursor movements in task space. Subjects performed straight cursor movements and reduced null space movement, without any explicit instruction. Importantly, subjects learned the task with either online feedback of their trajectory or only endpoint of their cursor, but they needed the online trajectory feedback to generalize the hand-to-screen mapping to other targets.

Previous research on natural finger movements by Ingram and colleagues (2008) measured with the same 19 sensors of the CyberGlove showed that finger movements are not controlled by 19 independent dimensions. Instead, using principal component analysis, this work showed that a relatively small number of PCs accounted for most of the variability in hand motion: 60% by the first 2 PCs and 93% within the first 10 PCs.

The present study extends this previous work using the same CyberGlove.

Questions of this Study

(1) Can subjects learn and generalize to reach to different targets in the same finger movement paradigm?

(2) How much does the type of feedback impact this learning and generalization?

(3) How many degrees of freedom are used in the hand in the task?

Glove and Mapping

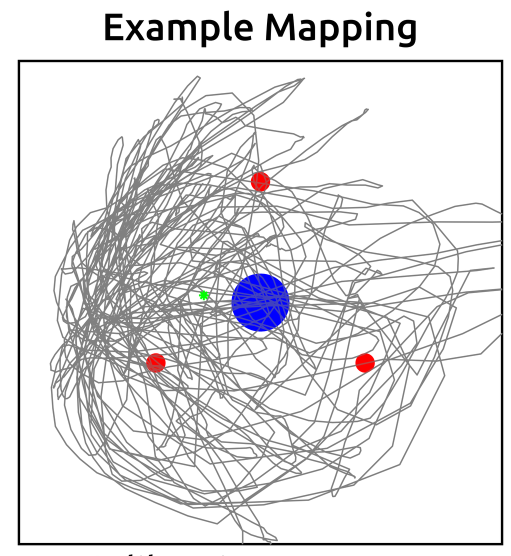
Glove and Calibration

Subjects wore an instrumented glove (CyberGlove 1, CyberGlove Systems) that measures the bending of 19 sensors on locations of the hand (not coincident with joint angles).

For calibration, subjects moved their fingers freely for 80 s. To encourage subjects to explore a variety of finger movements, a bar graph represented the signals from each sensor and subjects were asked to modulate the bar height as much as they could (Ranganathan et al., 2013). Principal component analysis (PCA) was performed on the data obtained from the sensors, and the first 2 PCs were used to define the matrix A that mapped hand position h (19D) to screen x,y (2D):

$$\begin{bmatrix}x\\y\end{bmatrix} = \begin{bmatrix}a_{x,1} & a_{x,1} & \cdots & a_{x,19}\\ a_{y,1} & a_{y,2} & \cdots & a_{y,19}\end{bmatrix}\cdot\begin{bmatrix}h_1\\h_2\\\dots\\h_{19}\end{bmatrix} = A\cdot h$$

Example Mapping

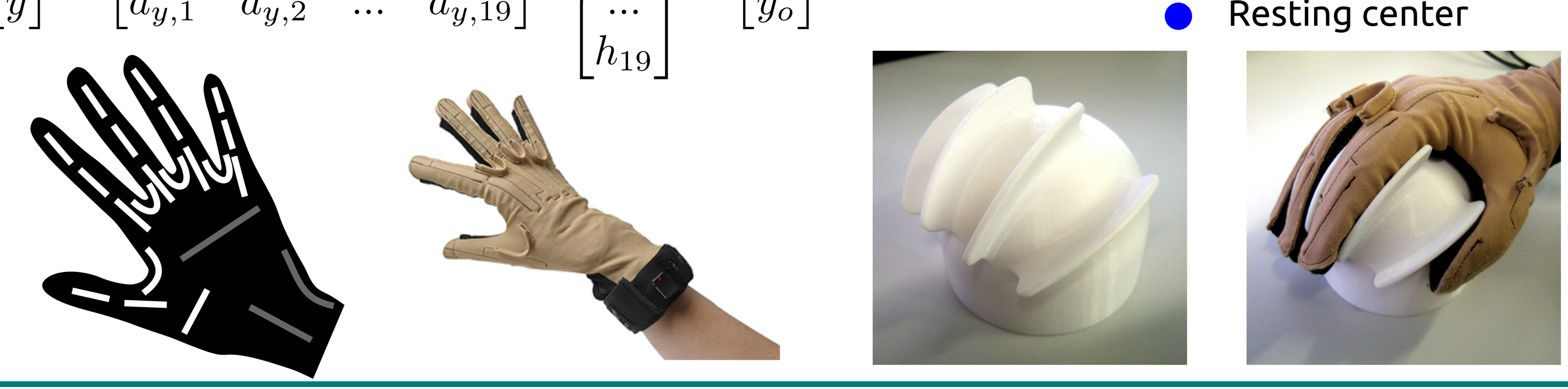


Offset Calculation

Subjects placed their hand on a custom-made mold. This finger position was mapped onto a location in 2D space that defined the center of the workspace.

$$o = \begin{bmatrix}x_o\\y_o\end{bmatrix} = \text{resting point} - \text{mapping mean}$$

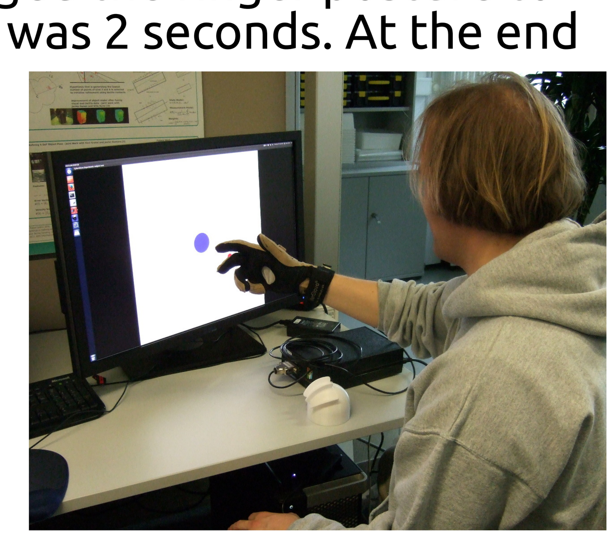
$$\begin{bmatrix}x\\y\end{bmatrix} = \begin{bmatrix}a_{x,1} & a_{x,1} & \cdots & a_{x,19}\\ a_{y,1} & a_{y,2} & \cdots & a_{y,19}\end{bmatrix}\cdot\begin{bmatrix}h_1\\h_2\\\dots\\h_{19}\end{bmatrix} - \begin{bmatrix}x_o\\y_o\end{bmatrix} = A\cdot h - o$$



Experiment

Reaching Task

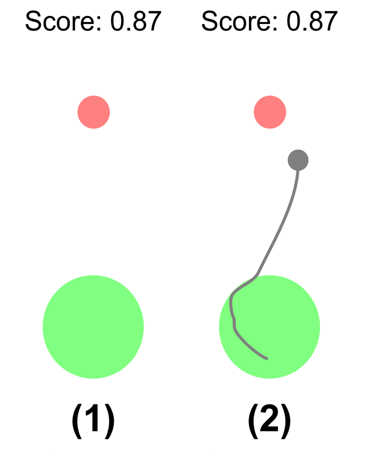
The task was to move a cursor on the 2D screen to one of 3 targets using finger movements. At the start of each trial subjects placed their hand on the mold to initialize hand position at the center of the workspace. To facilitate precise initialization, they saw a circle around the center indicating radial distance from the center. When the hand posture was centered, (indicated by green color), subjects removed their hand from the mold and changed the finger posture to reach the target. The maximum duration of each trial was 2 seconds. At the end of each trial, a feedback score was displayed for 3 seconds. This score was calculated from the distance to the target and normalized to be between 0 and 1.



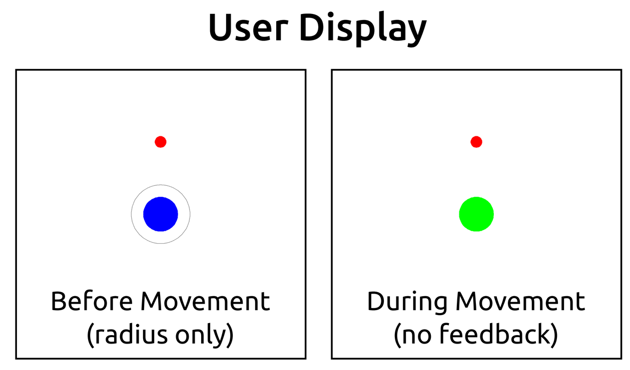
Feedback Conditions

(1) Score only (4 subjects)
(2) Score + trajectory (5 subjects)

Feedback Conditions



User Display



Experimental Design

Subjects performed 100 consecutive trials to each of three targets with feedback (learning phase). An additional 20 trials followed with no feedback (retention phase). This was repeated for 3 targets, presented in random order.

Results

Question 1: Learning and Generalization

Learning:
Subjects were able to increase the score for reaching movements to some but not all targets. There was no preference for any individual target across subjects.

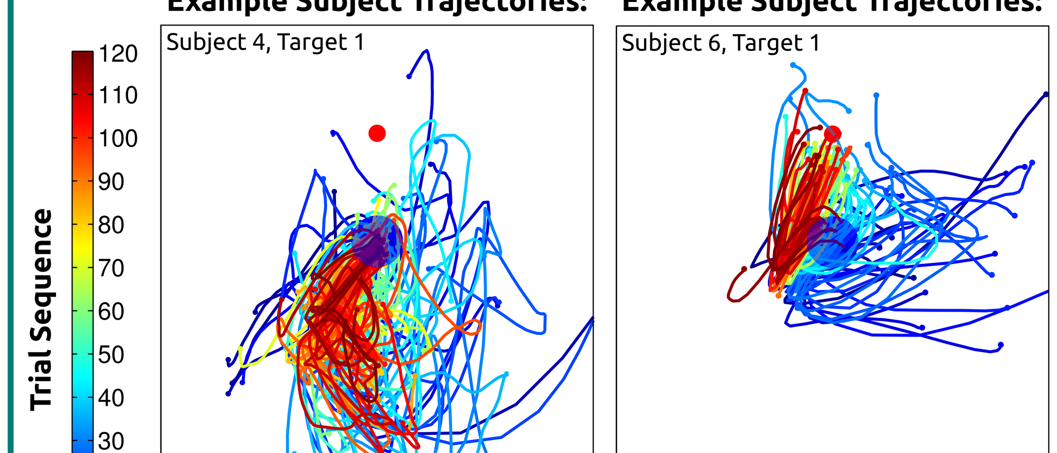
Generalization:
Performance in reaching to 2nd and 3rd targets was not always better. There was no uniform support for generalization.

Question 2: Effect of Feedback

Learning:
Subjects in the Score Only group could not consistently improve their performance for all targets. Subjects in the Score + Trajectory group were able to improve their scores for all three targets.

Generalization:
Neither of the two groups was able to generalize to new targets.

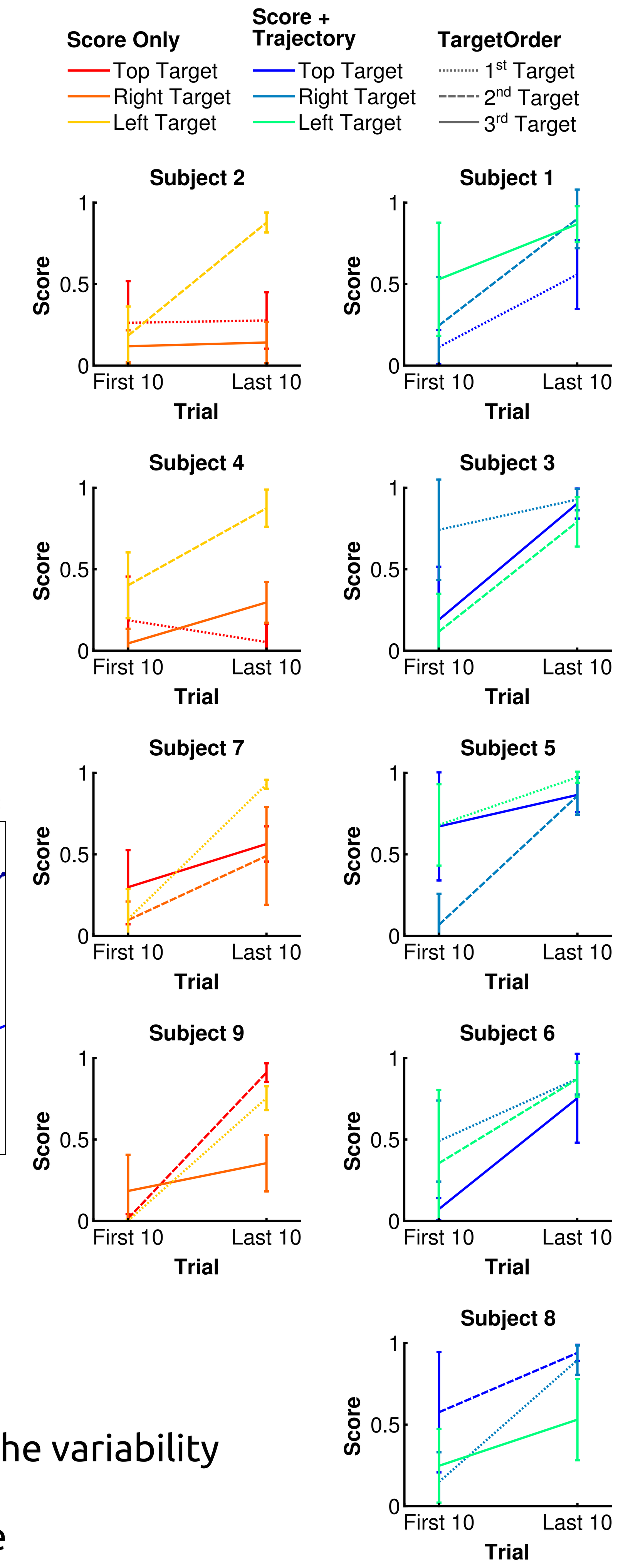
Score Only: Example Subject Trajectories: | Score + Trajectory: Example Subject Trajectories:



Unsuccessful Learning
Even if subjects obtained an occasional high score early in practice, this did not necessarily translate to long-term improved performance. This was only observed in subjects with Score Only feedback.

Successful Learning
High performance at the end of practice was possible even with poor early performance. This was observed consistently in Score + Trajectory feedback subjects and inconsistently in Score Only subjects.

Changes in Reward over Practice for Individual Subjects

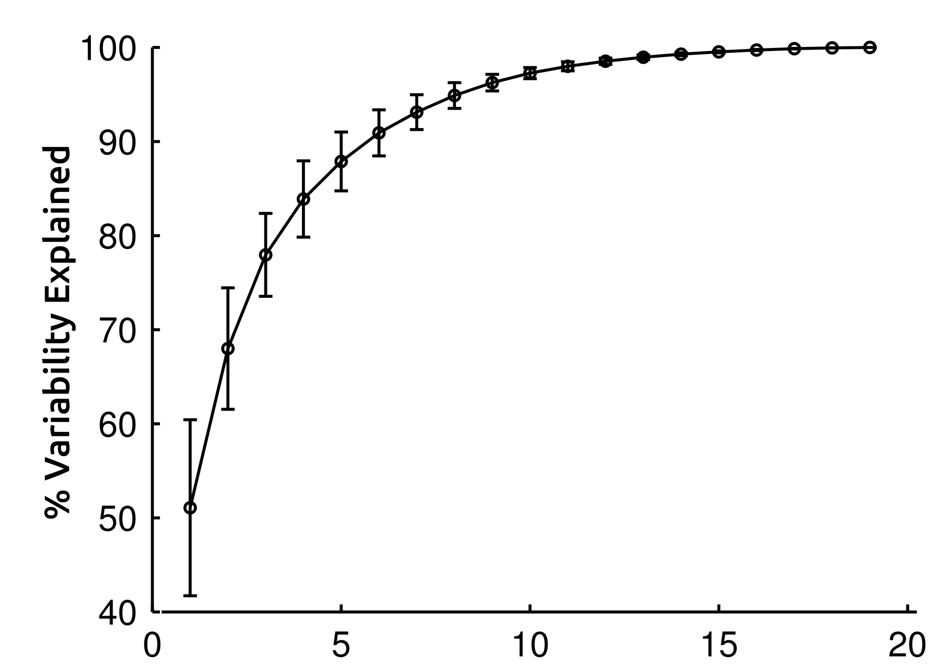


Question 3: Dimensionality of Control

PCA was performed on the calibration data. The variability accounted for by each PC was calculated.

PC1 accounted for 51.1 ± 9.4% of the variance
PC2 accounted for additional 16.9 ± 6.5%
10 PCs accounted for a total of 96.3 ± 0.9%

Cumulative Variability Explained by Principal Components in Calibration Data



Discussion and Conclusions

Learning:
Insufficient success in the Score Only condition indicates that the score feedback was not sufficient for learning. At least endpoint feedback is necessary for learning. Not all targets were as easily reachable for all subjects, and subjects may have found local maxima for score. Movements had low repeatability, even after a high score was obtained.

Generalization:
While subjects in the work of Liu and Scheidt (2008) could generalize to new targets with online feedback, subjects in this experiment were unable to generalize with offline feedback (Score + Trajectory). This indicates that offline feedback is less informative than online feedback and insufficient to learn the hand-to-screen mapping.

Dimensionality of Control:
The number of relevant PCs in this reaching task is relatively consistent with those reported for natural finger movements. While this demonstrates that the movement was controlled by significantly fewer than 19 degrees of freedom, it is unlikely that hand movement is physiologically controlled by PCs. This experiment used a non-physiological coordinate system (sensor values instead of joints). Future work will examine what variables (e.g. relative vs. absolute angles) may be physiologically more appropriate (Sternad et al., 2010).

References

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