A 4-dimensional virtual hand BMI using active dimension selection

Adam G. Rouse and Marc H. Schieber
Neurobiology and Anatomy
University of Rochester Medical Center, Rochester, NY

Objective

Brain-machine interface (BMI) research has dramatically increased and improved over recent years. To date, almost all BMIs have relied on a fixed, linear transformation from neural to control signals. A BMI is typically classified by the number of independent degrees of freedom (DOF) that it can control. In this study, we explored and challenged the assumption that a brain-machine interface must control a fixed, orthogonal basis set. Instead, we used a hybrid controller that combined active dimension selection (ADS) with velocity control along the selected dimension.

Methods

Experimental Setup

One monkey was trained to control a virtual hand presented on an LCD monitor. A target hand image showed one of eight possible postures that the virtual hand was to match for the subject to obtain a reward (Fig. 1). The movement of the virtual hand was controlled by a velocity signal decoded from 16 units recorded from floating microelectrode arrays (MicroProbes, Inc.) implanted in premotor and primary motor cortex. The novel innovation here involved the way the neural signals were transformed to the velocity along the different dimensions being controlled. Rather than fixed control of all four dimensions simultaneously, the neural signals were used in a hybrid fashion, both i) selecting an active dimension for control while the other dimensions were stabilized toward a centered, neutral position, and ii) generating velocity along the selected dimension.

Figure 1. The BMI controlled virtual hand with 4 DOF. The non-orthogonal dimensions of control were flexion/extension of four different grasps—precision pinch (green), three-finger tripod (cyan), power grasp (light blue), and thumb/little finger opposition (dark blue)—here illustrated in two dimensions.

- Firing rate was estimated for 16 units, using spikes in 10 ms bins convolved with a 500 ms Gaussian window (σ = 125ms).
- A running average of the smoothed firing rates was calculated from the previous trials.
- The neural signal for each unit (n) used for control was normalized by taking the square root and subtracting the running average from the current smoothed firing rate.

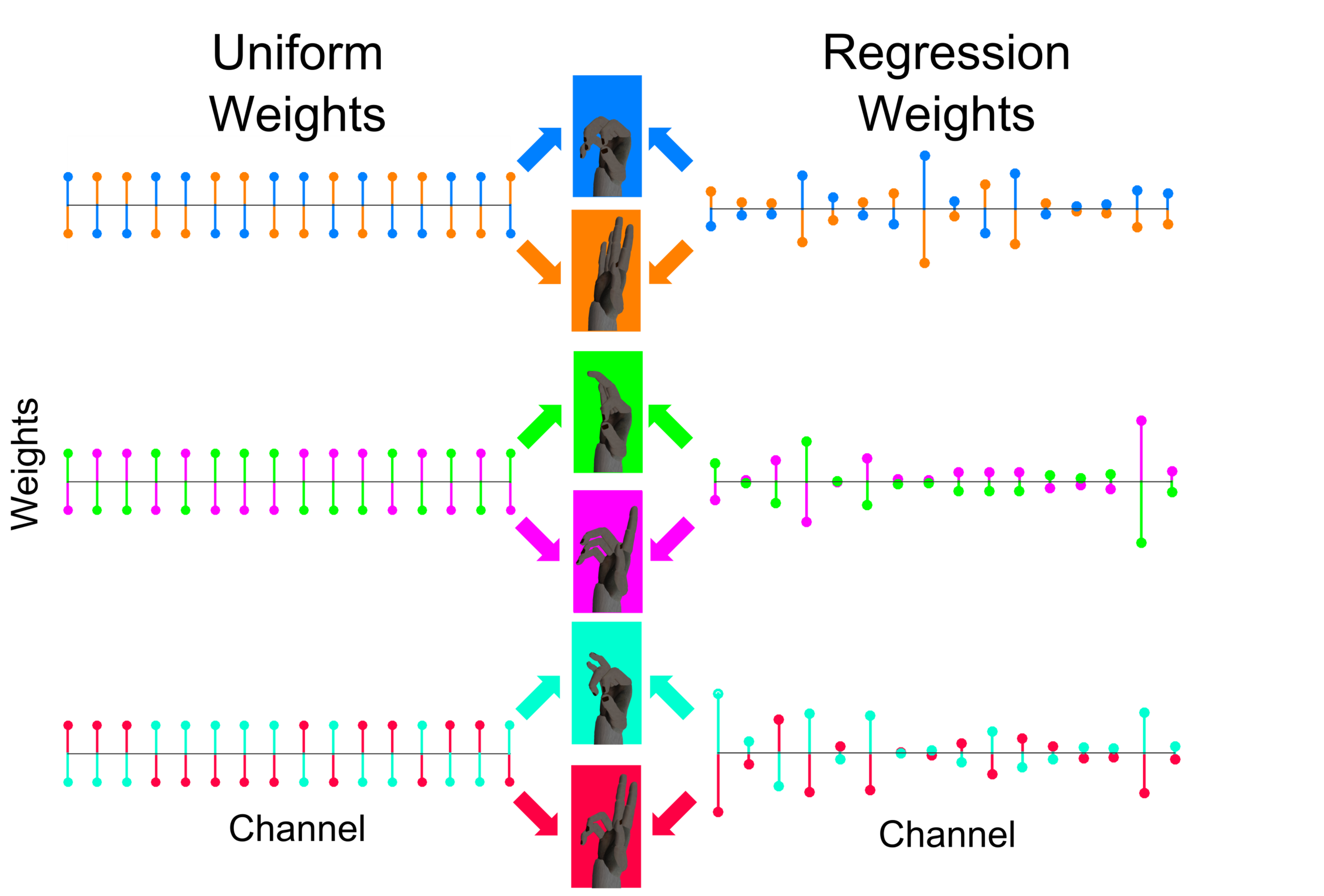

Figure 2. During the experiment, two different types of weights were used for translating the 16 neurons' firing rates into the velocity of the digits of the hand avatar. First, uniform weights were used where each dimension had 8 positively and 8 negatively weighted channels. The weights were constructed so that the weights in each dimension were orthogonal. After using uniform weights in the two and three dimensional case, linear regression was performed to generate weights. These weights were also constrained to be orthogonal. Weights were always generated from the previous day's data.

Eqn. 1 $$\dot{\mathbf{x}} = W_{4\times16} N_{16\times1}$$

16 neural signals combined ***(N)*** to control the virtual hand velocity ($\dot{\mathbf{x}}$) based on weights ***(W)***.

Eqn. 2 $$x_{t,i} = x_{t-1,i} + W_{i\times16} N_t \qquad i \in \max\{\dot{\mathbf{x}}\}$$

Eqn. 3 $$x_{t,j} = \alpha x_{t-1,j} \qquad , for\ all\ j \neq i$$
$$\alpha = 0.926$$

Active Dimension Selection (ADS): hand position ($\mathbf{x}$) along the active dimension (i) is actively controlled (*Eqn. 2*), while velocity along other dimensions (j) decays to zero (*Eqn. 3*).

Results

Trial Timing

- Avatar hand automatically returned to center
- Target hand was presented at Cue
- Avatar hand allowed to move after 300ms
- Trial ended when one of the targets was contacted or 5 s had elapsed
- Performance metrics:
  - -Percentage Correct
  - -Average movement time
  - -Bit Rate

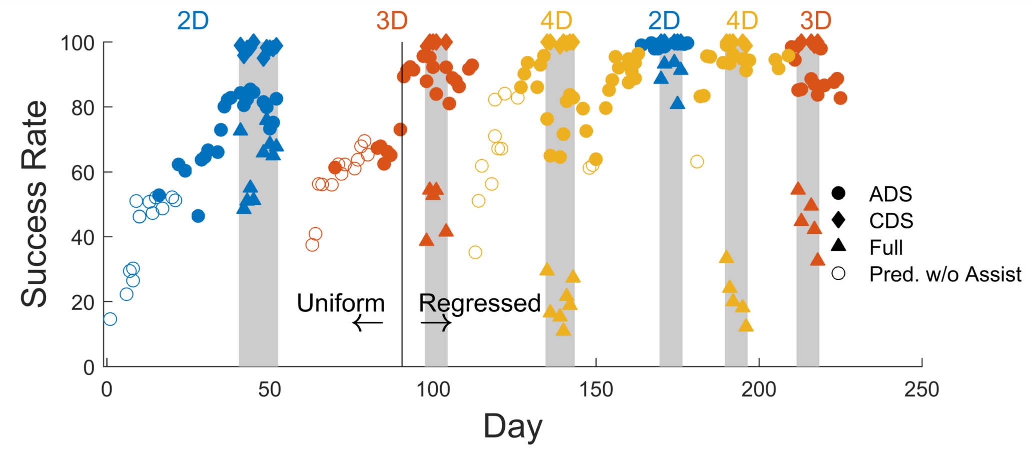

Figure 3. Performance improvement. Daily training sessions were performed in 2, 3, and 4 dimensional workspaces with 4, 6, and 8 targets, respectively. To limit the monkey's frustration, initial training i) used computer assistance and/or ii) did not abort trials if the avatar hand entered the wrong target. For such sessions, the percent correct that would have been achieved without these two forms of assistance was estimated using the recorded neural signals (open circles). Most sessions were performed entirely with the ADS hybrid controller. During other sessions (vertical grey bars) catch trials either with 1D control (diamonds) or with full dimensional control (triangles, no dimension selection) were interleaved with ADS control.

Active Dimension Selection

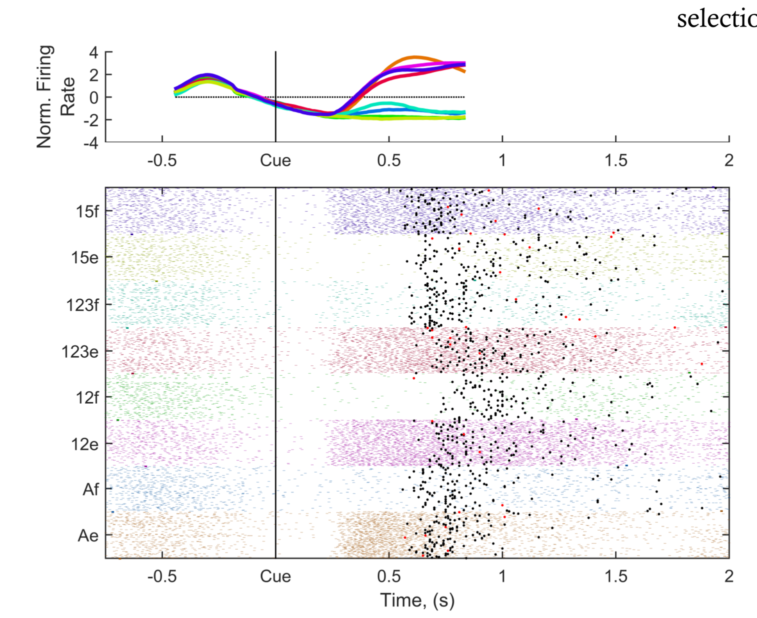

Figure 4. Example neuron (C15a) during a 4D session. A) Mean normalized firing rate for each of the eight trial types (Fig. 1). B) Spike raster plot for all trials grouped by target type. Trials are aligned on cue appearance (vertical line) and larger black (correct target) and red (incorrect target) ticks represent entry into the target.

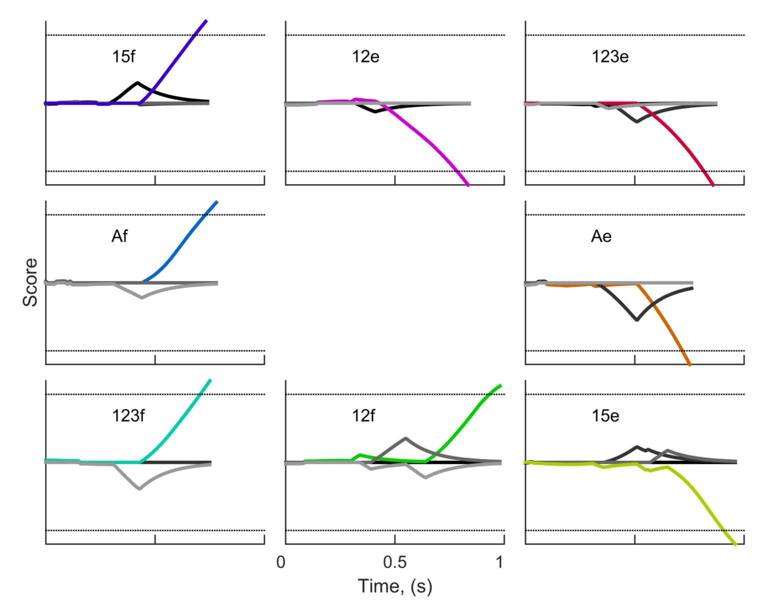

Figure 5. State variables as a function of time from an example trial of each target type. The state variable for the desired target is color-coded as in Fig. 1. When that variable exceeded the horizontal lines, the avatar hand was in the target. Other dimensions are shown in grayscale.

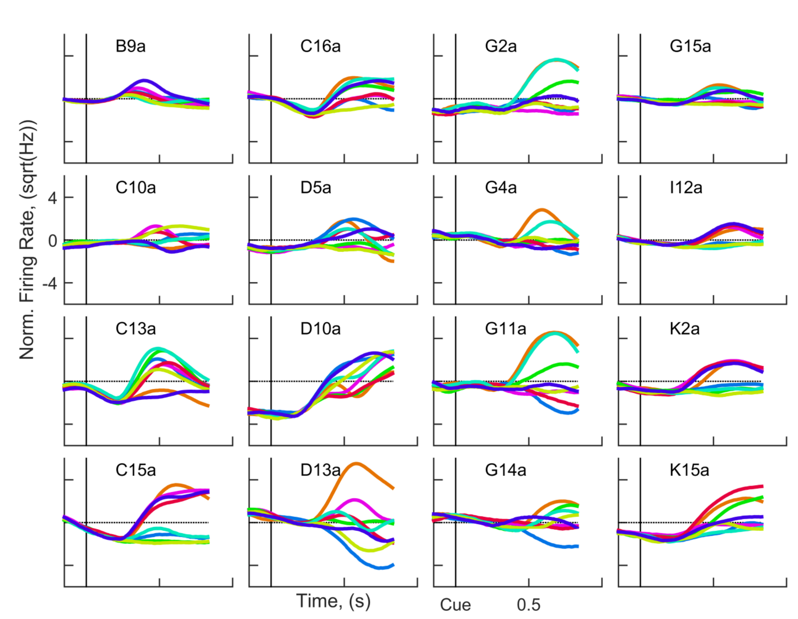

Figure 6. Mean normalized firing rate for each target posture (Fig. 1) for all 16 units used for control of the avatar hand in one session. Vertical lines indicate the time at which the target hand posture was displayed.

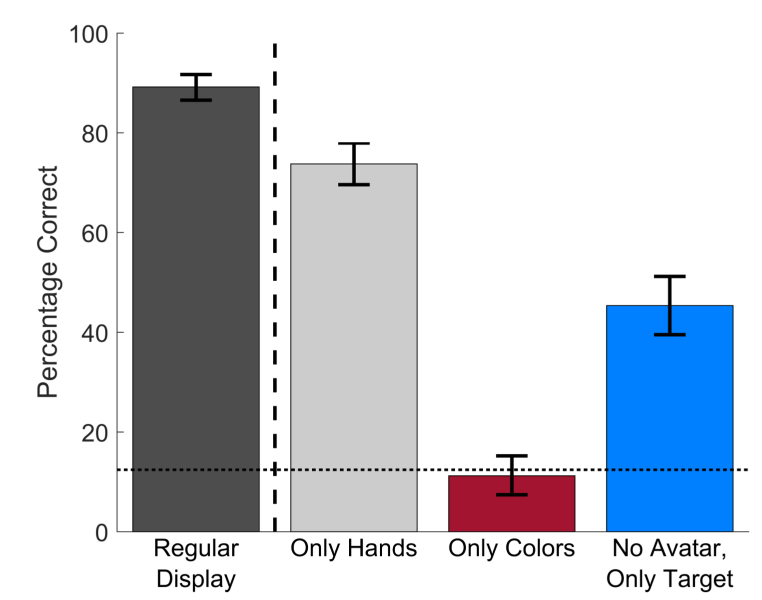

Figure 7. Sessions of 4D ADS were conducted with the visual display altered in one of three ways: i) the avatar and target hands were displayed with no background colors (Only Hands), ii) the background colors were displayed without the avatar or target hand (Only Colors), or the target hand and color were displayed with no feedback of the avatar hand or color (Only Target Hand+Color). Error bars represent 95% C.I.

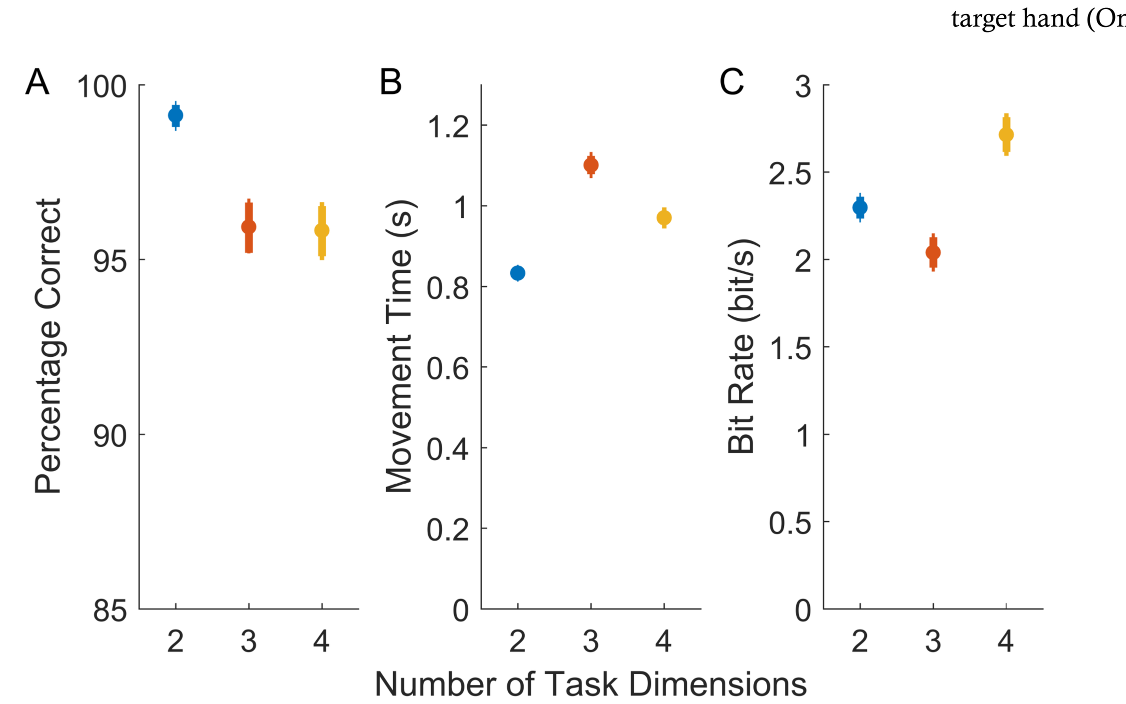

Figure 8. 2 vs. 3 vs. 4 dimension comparison. The percentage correct, mean firing rate, and calculated bit rate for five high-performing recording sessions for each number of dimensions. Error bars represent 95% confidence intervals.

Comparing ADS with other types of control

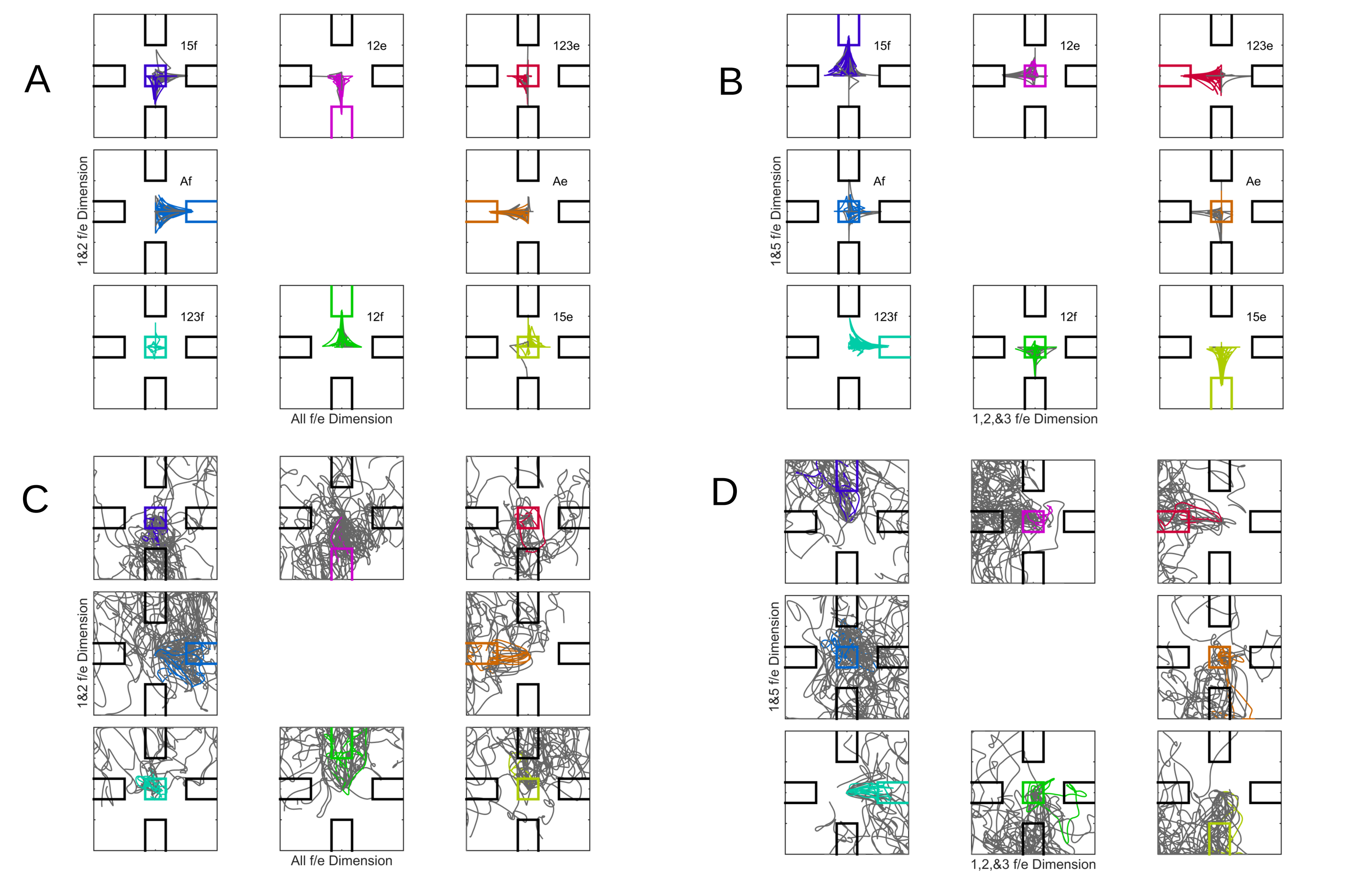

Figure 10. Trajectories for all trials from a single 4D session for hybrid (A & B) and full control (C & D). The 4D trajectories are projected in two of the dimensions on the left (A & C), and in the other two dimensions on the right (B & D). Correct trials are colored according to the target posture (Fig. 1) while incorrect and timed-out trials are in gray. The hybrid trial trajectories (A & B) demonstrate how the restricted movements in the non-active dimensions allow more consistent movements with a higher percentage correct as compared to full control (C & D).

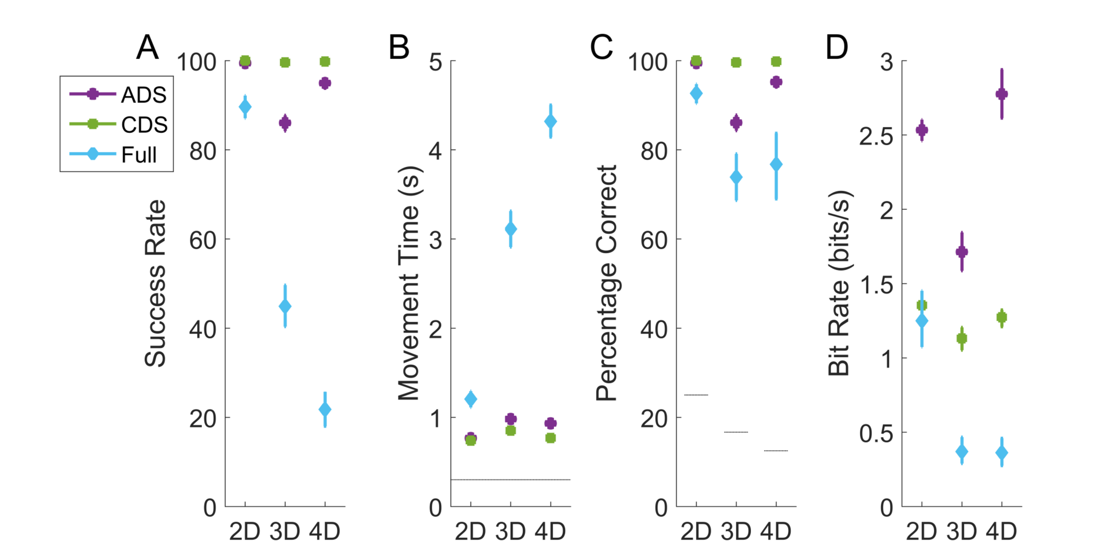

Figure 11. Performance metrics for ADS compared with catch trials of either automatically selected 1D control, or full, linear control of all dimensions. As the number of dimensions increases, ADS shows considerably less deterioration in percent correct and movement time than full control, remaining closer to performance with only 1D control. Additionally, because the subject only chose between two targets during 1D control, ADS resulted in the highest bit rate.

Conclusion

- Active Dimension Selection successfully controlled a 4 DOF virtual hand to match 8 different hand postures (95% correct, 2.7 bits/s)
- ADS bit rates were higher than either 1D or full dimensional control
- Active Dimension Selection allows the activity of more neurons to span the full dynamic range for a given movement.
- Further work is needed to examine increasing number of units, increasing DOFs, improving precision, and online updating.

Significance

Most commonly used BMI models have relied on linear state variables to describe neural encoding. Incorporating neural dynamics that go beyond these fixed, static descriptions will be crucial for advancing the dexterity of BMI control. The work presented here shows that a novel, dynamic, hybrid model of neural activity can be harnessed to provide simpler control for the practical goal of restoring lost hand function with motor BMIs. Additionally, further exploration of dynamic encoding of different grasps beyond simple linear encoding could provide insights into the natural neural control of movement.

Acknowledgments

This work was supported by NINDS R01-NS065902.