

Using Variational Bayesian Least Squares for EMG Data Prediction from M1 and Premotor Cortex Firing



Jo-Anne Ting¹, Aaron D'Souza², Kenji Yamamoto³, Toshinori Yoshioka⁴, Donna Hoffman⁵, Shinji Kakei⁶, Lauren Sergio⁷, John Kalaska⁸, Mitsuo Kawato⁴, Peter Strick⁵ & Stefan Schaal^{1,4}

¹University of Southern California, Los Angeles, USA; ²Google, Inc., Mountain View, USA; ³National Institute of Radiological Sciences, Chiba, Japan; ⁴ATR Comp. Neuroscience Labs, Kyoto, Japan;

⁵University of Pittsburgh, Pittsburgh, USA; ⁶Tokyo Metropolitan Institute for Neuroscience, Tokyo, Japan; ⁷York University, Toronto, Canada; ⁸University of Montreal, Montreal, Canada

Motivation:

- Can EMG data collected from arm movement of monkeys be faithfully reconstructed from neural activity in motor cortices?

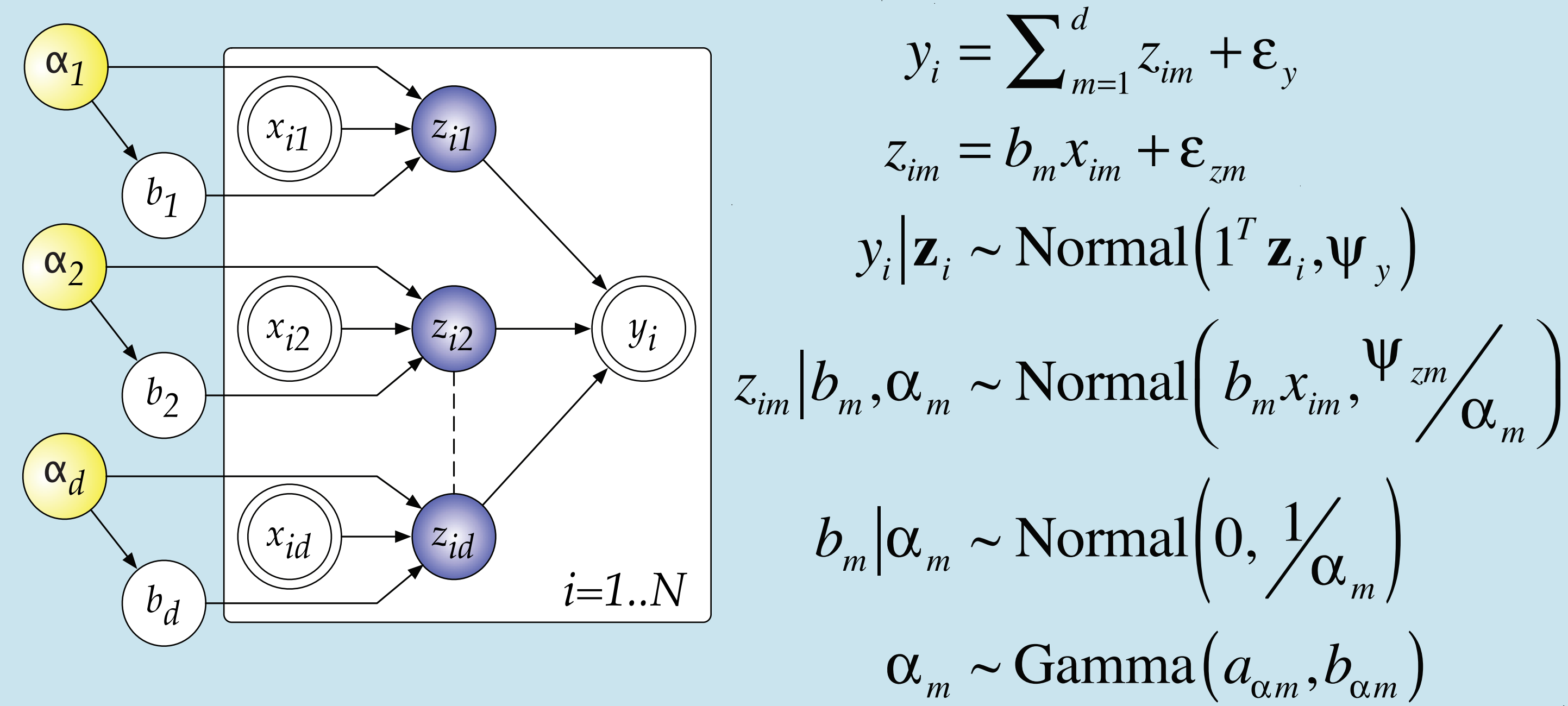
Classical linear analysis tools:

- Are numerically fragile in high dimensions due to irrelevant, redundant & noisy information
- Require careful human supervision or intensive cross-validation for optimal performance

Variational Bayesian Least Squares:

- Automatically detects relevant features
- Regularizes against overfitting
- Is computationally efficient and easy to use

- Given observed data $D = \{\mathbf{x}_i, y_i\}_{i=1}^N$, our model is:



- We use the EM algorithm (Dempster & Laird, 1977) for inference:

$$\max E[\log p(\mathbf{y}, \mathbf{Z}, \mathbf{b}, \alpha | \mathbf{X})]$$

and a variational factorial approximation to overcome analytical intractability (e.g., Ghahramani & Beal, 2000):

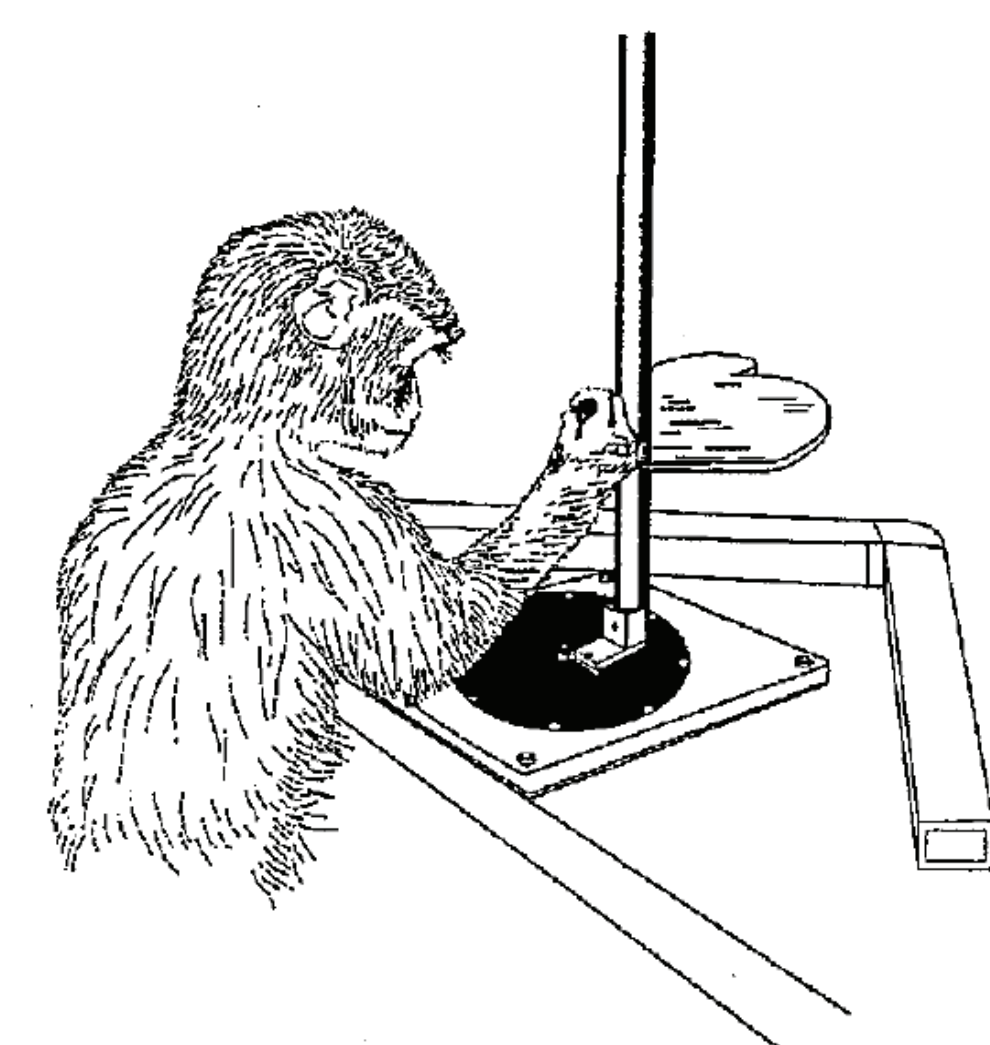
$$Q(\alpha, \mathbf{b}, \mathbf{Z}) = Q(\alpha, \mathbf{b}) Q(\mathbf{Z})$$

Quality of (x,y) velocity fits appears to be reduced compared to EMG data.

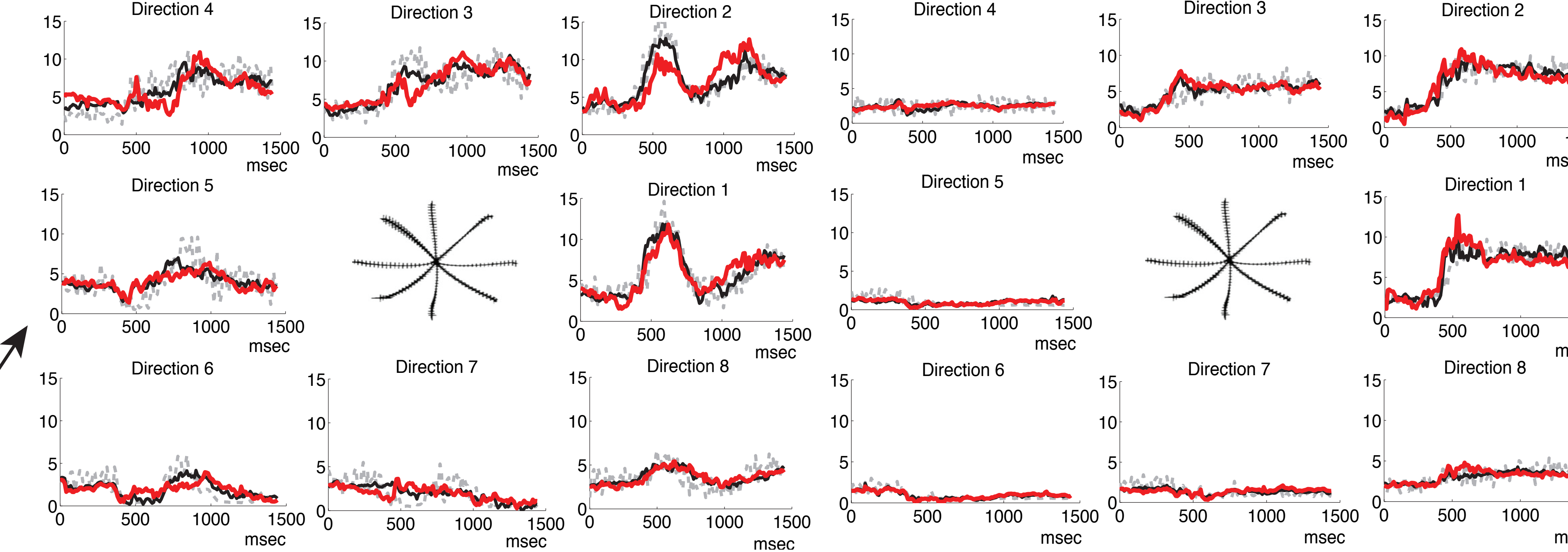
Experiments:

- In Sergio & Kalaska (1998), a monkey moved a manipulandum in a center-out task in 8 different directions, equally spaced in a horizontal planar circle. A variation of the experiment held the manipulandum rigidly in place while the monkey applied isometric forces in the same 8 directions. The data consisted of the average neural firing of 71 M1 neurons and the EMG outputs of 11 muscles (2320 samples/neuron).
- In Kakei et al. (1999, 2001), a monkey performed 8 combinations of wrist flexion-extension and radial-ulnar movements while in 3 different arm postures (pronated, supinated and midway between the two). These experiments led to 2 datasets. The first consisted of the recorded EMG outputs of 7 muscles, along with neural data of 92 M1 neurons at all wrist postures (2616 samples/neuron). The second data set had EMG outputs of the same 7 muscles but contained the spiking data of 72 PM neurons at the 3 wrist postures (2592 samples/neuron).

Results:



Predicted EMG for infraspinatus muscle, given M1 neural firing (Sergio & Kalaska)

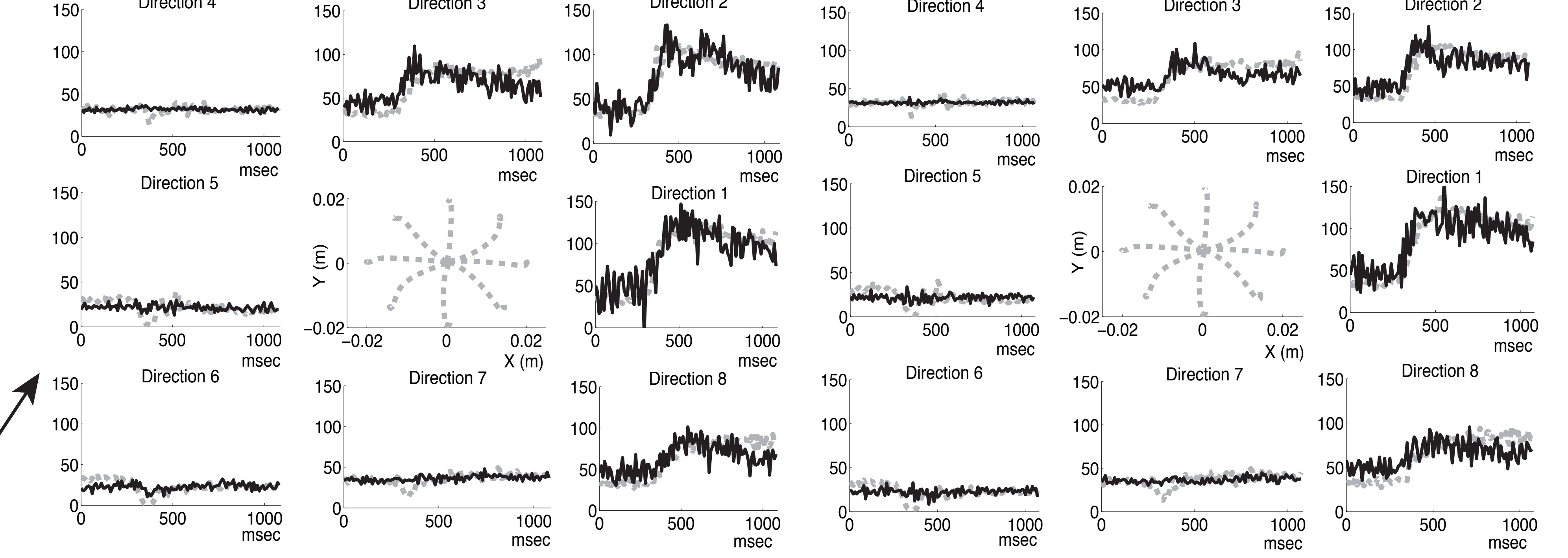


EMG traces under movement force conditions

EMG traces under isometric force conditions

M1 neural firing predicts EMG traces very well. Good cross-validation fits confirm Sergio & Kalaska's conclusion that recorded M1 neurons behave like units that code directly motor commands.

Predicted EMG for ECRB muscle in supinated wrist position (Kakei et al.)



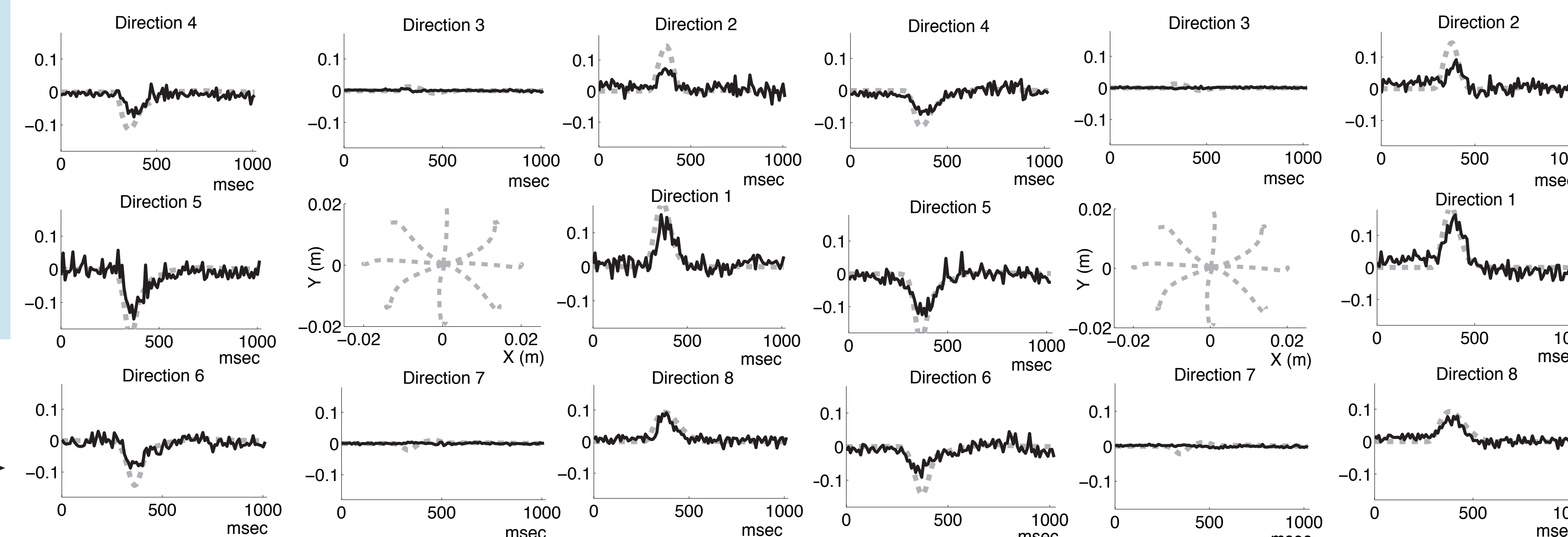
EMG traces from M1 neural firing

EMG traces from PM neural firing

Both M1 and PM neurons achieve good reconstruction of EMG traces

VBLS produces a generalization error comparable to the combinatorial-like model search technique (that took weeks) in ~8 hours.

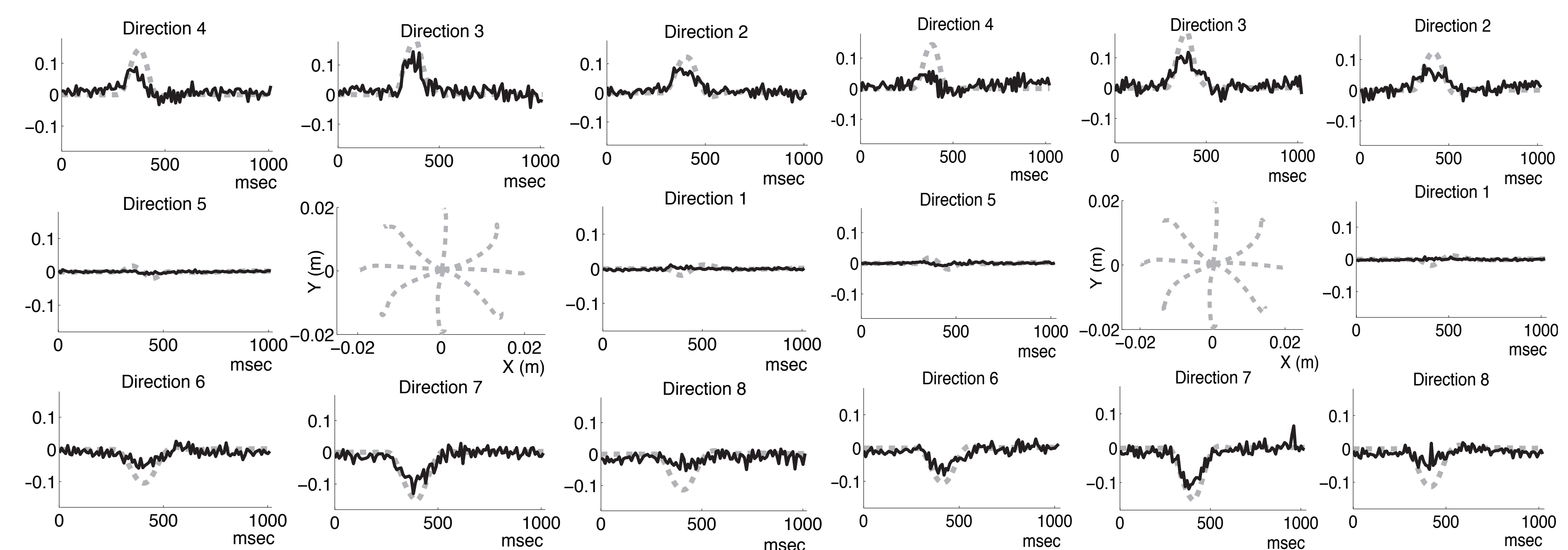
Predicted x velocities in supinated wrist position (Kakei et al.)



Predicted x velocities given M1 neural firing

Predicted x velocities given PM neural firing

Predicted y velocities in supinated wrist position (Kakei et al.)



Predicted y velocities given M1 neural firing

Predicted y velocities given PM neural firing

