

Towards a Bayesian Decoder for ECoG

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Phenomenon

Tracking an object in space requires constant planning and correction throughout the trajectory. Therefore, a spatio-temporal-freq encodes the movements of a hand.

Gamma-band (γ > 90Hz) activity has been implicated in feedforward and (β [15-20]Hz) in feedback activity. (Pascal Fries et al.,)

Question

Can we build a decoding model that uses information in the different frequency bands to infer hand movements? And, do that in a manner neuroscientifically interpretable.

Background

- •People have successfully built predictors of hand-movement from ECOG data before. (Chao et. al. 2010)
- •They mainly use an entire filter bank of activities to decode the signal
- •Interpreting those decoding models is tricky and it is difficult to provide error bars or confidence intervals around the estimate of the decoded signal.

Hypotheses

Assume that we can extract features from ECoG data that has a linear mapping between motion and feature.

 γ and β band are more informative on prediction of monkey hand velocity.

- ☐ Frequency-channel interactions will be the key contributor to decoding ECog signals.
- ☐ Given the intuition that:
- □ γ -- feed-forward signal
- \Boxoldsymbol{eta} -- feed-back signal (Michalareas et. al. 2016)

Parameters and variables

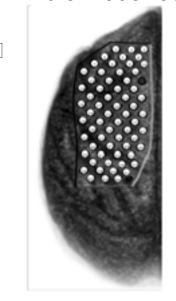
- □1. How do we construct the feature vectors?
- 2. Selection of power bands with different frequency(alpha, beta, gamma)
- \square 3. Time periods before motion for prediction.
- □ 4. Selection of channels for decoding.
- □ 5. Velocity threshold.
- □ 6. number of "eigen vector" in singular value decomposition to extract from input space(Motion).

Selected toolkit

- •Pursued a decoding model based on an encoder.
 - A encoder will provide a description of ECOG power spectrum as a function of hand motion.
- •It is straightforward to derive a decoding model from an encoding model than vise versa.
- NOT an exercise in pure BCI techniques and/or data mining!

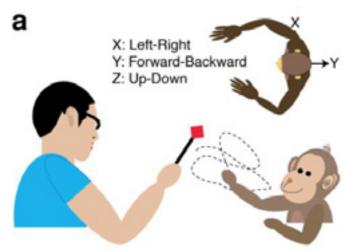
Experimental Data

- 1. Two monkeys, fed at random positions for 15 minutes recording session, using fork length of 20 cm, n = 3.8 +/- 1.0 times per minute.
- 2. Link of task video: http://neurotycho.org/food-tracking-task
- In each recording session, 6 position points from the monkey is measured at a rate of 120 Hz in location of left shoulder, left elbow, left wrist, right shoulder, right elbow, right wrist.
- 4. ECoG signals are obtained from 64 channels on either side of the monkey brain at a rate of 1000 Hz.





http://www.zooportraits.com/japane se-macaque/



Chao ZC, Nagasaka Y, Fujii N (2010)

Outline of Progress

- Inspect experimental settings and data acquisition by the experiment.
- Data Preprocessing (lessons learnt)
- Encoding. (Got to a "decent encoder")
- Decoding (built likelihood functions & priors)

Data Preprocessing

Motion Data:

- Wrist position and velocity is obtained relative to body centered coordinate(point between two shoulders)
- 2. obtain α , β , and γ band from original data set.
- 3. Filter out time points where monkey's wrist velocity is below a designed threshold for a time interval.
- Frequency correction for 1/f and Cycles from electric supply (the Japanese case)

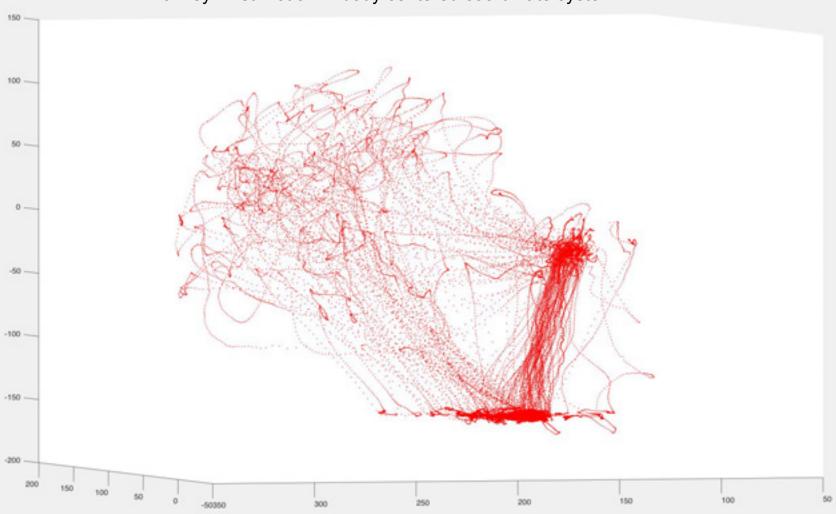
ECoG Data:

1. Frequency is preprocessed and resampled to calculate power time courses. Then it is grouped into separate ranges for 3 frequency bands:

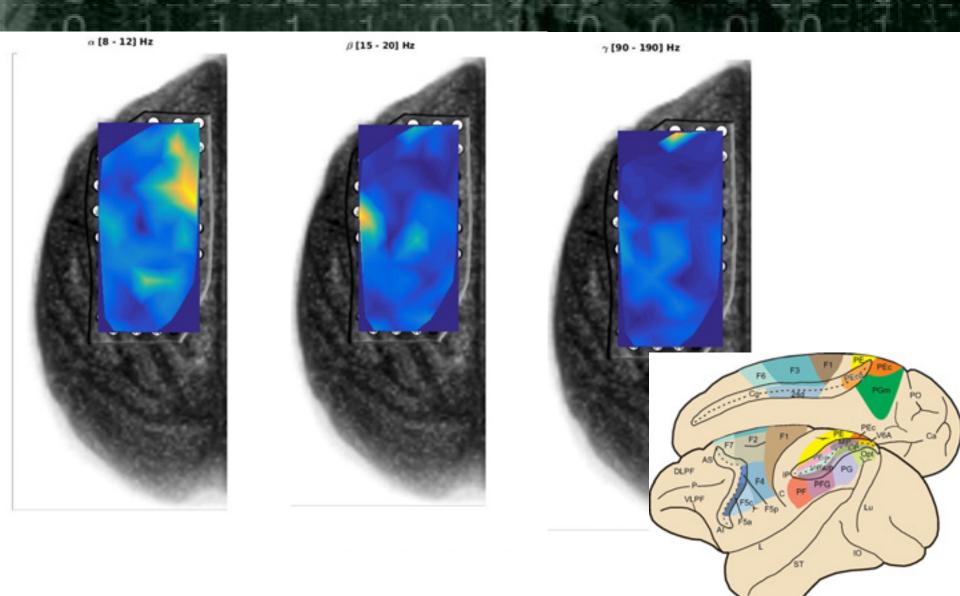
α	8 ~ 12 Hz
β	15 ~ 20 Hz
γ	90 ~ 190 Hz

Data Preprocessing: Visualization

Monkey wrist motion in body centered coordinate system.



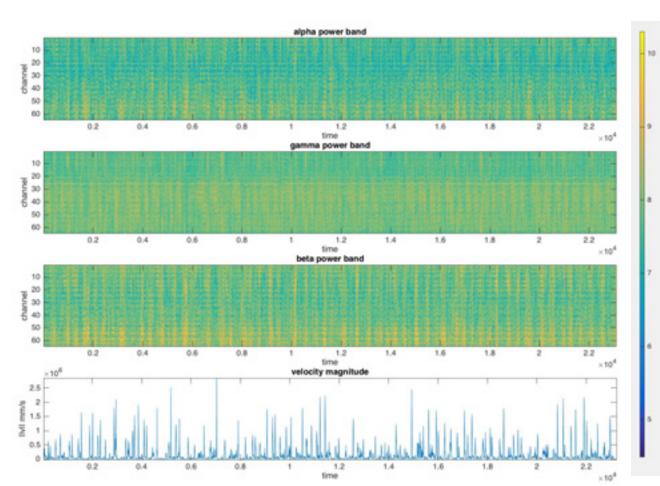
Data Preprocessing: Visualization



Data Preprocessing: Visualization

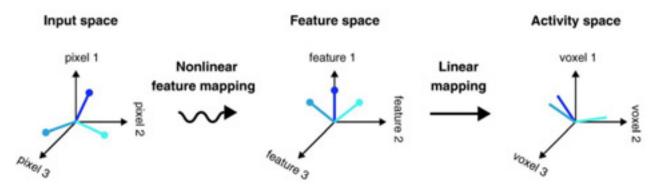
Activity for α , β , and γ bands in 64 channels across time. Color represents log(power).. β most active in channels 1 to 10, and 40 to 60. γ activity is complementary, showing continuous activity in 1~20 and 45~64.

Power activity and motion seem to be qualitatively similar, Velocity magnitude of wrist motion is plotted. Visually it seems like monkey motion is causing some activity in β , and γ bands, but it is not significant enough to draw any conclusion.

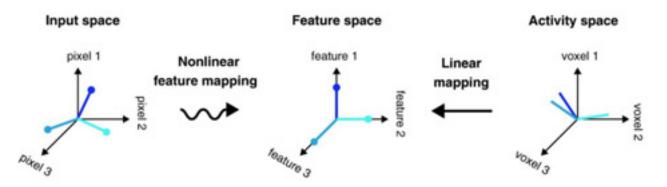


Encoding: scheme

Linearizing encoding model



Linear classifier



Naselaris et. al. 2011

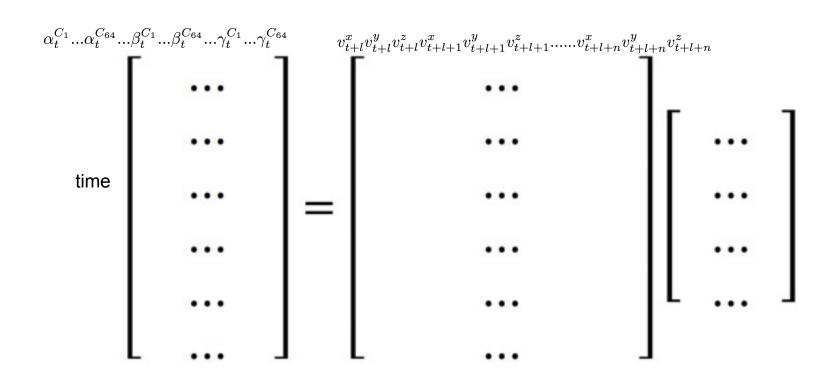
Encoding---equation

$$\mathbf{E} = \mathbf{V} \mathbf{W} + \epsilon$$

ECoG
Data

Motion Weight
Data Matrix

Error



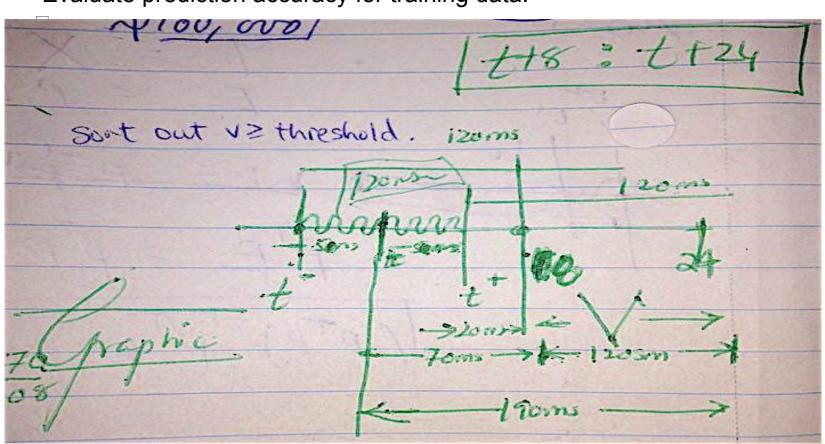
Encoding

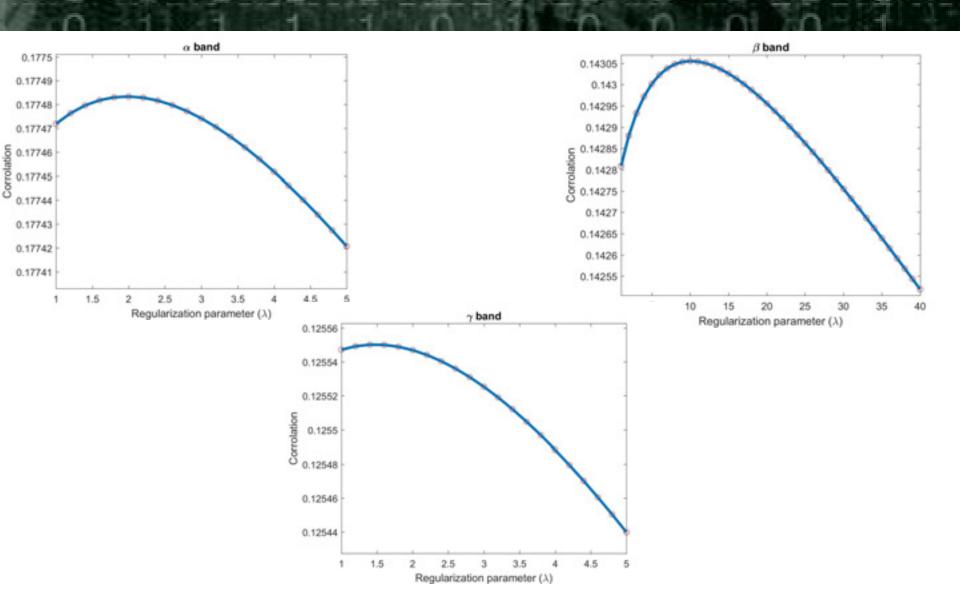
□Encoding:

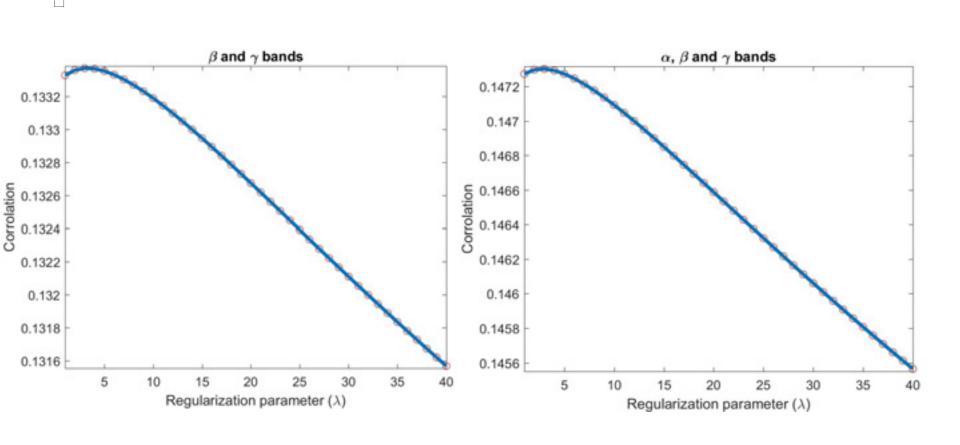
An optimized set of future event is considered.

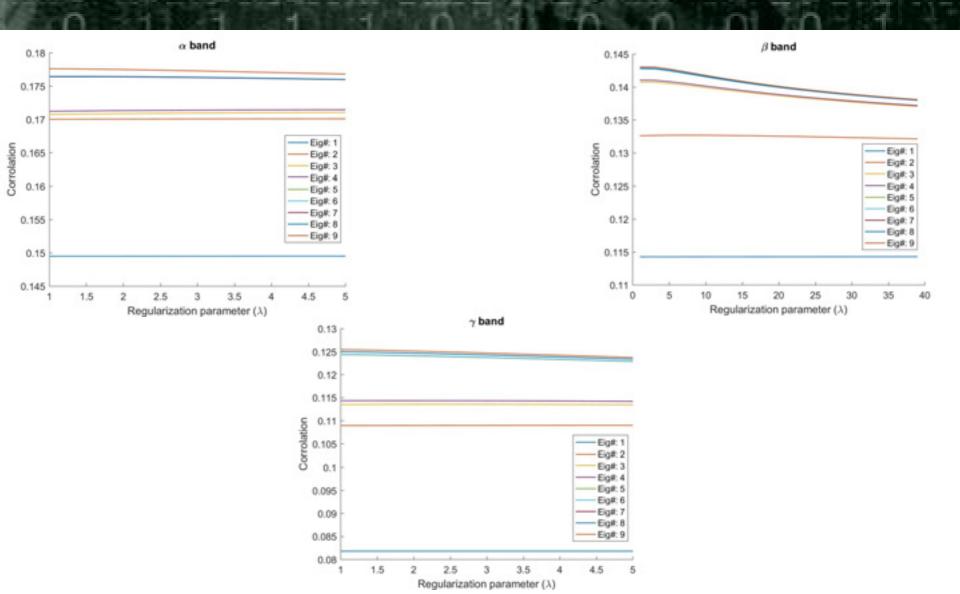
Data is trained and validated using k-fold cross validation.

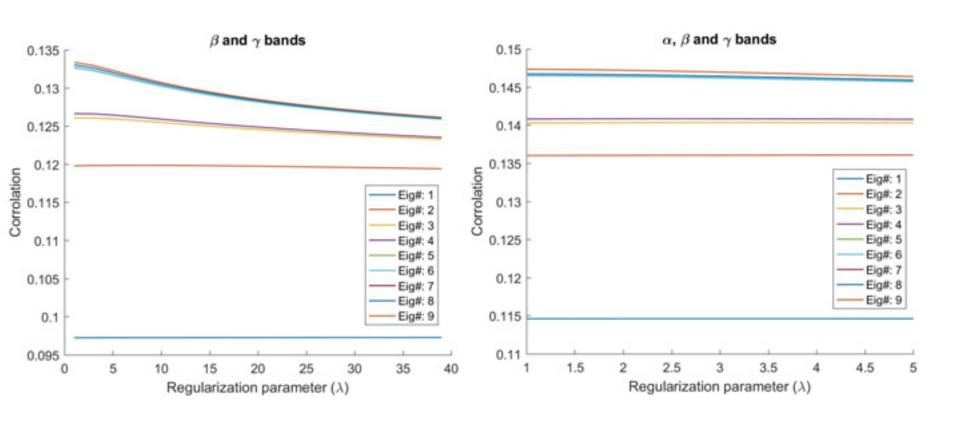
Evaluate prediction accuracy for training data.











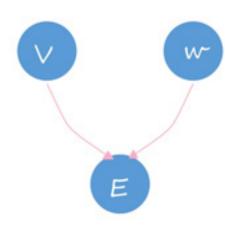
Thoughts/Evaluation

- More work needs to be done fine tuning the feature vectors.
- •Understand the dataset better to eliminate more artifacts. (chewing in Epi vs Sub electrode implantation)
- Huge potential from ECoG dataset.

Summary

- • γ and β bands are important, but why is α so great?
- •Predictions have a temporal window 100ms ~ 180 ms
- Velocity better than velocity amplitude in our case
- Build your feature vectors carefully.
- •Be careful using data from someone else:) Trials?.

Future Steps:



- 1. Complete the Bayesian decoder
- 2. Explore other data sets (Features, Features, Features!!)
- 3. Bayesian decoders for ECoG -> EEG transform

$$p(v|E) \propto p(E|v)p(v)$$

Likelihood

$$p(E|v) = \mathcal{N}(vw, \sigma^2)$$

$$p(v) = \mathcal{N}(\left[ar{\overline{v}_x}{\overline{v}_y}\right], \sigma_v^2)$$



