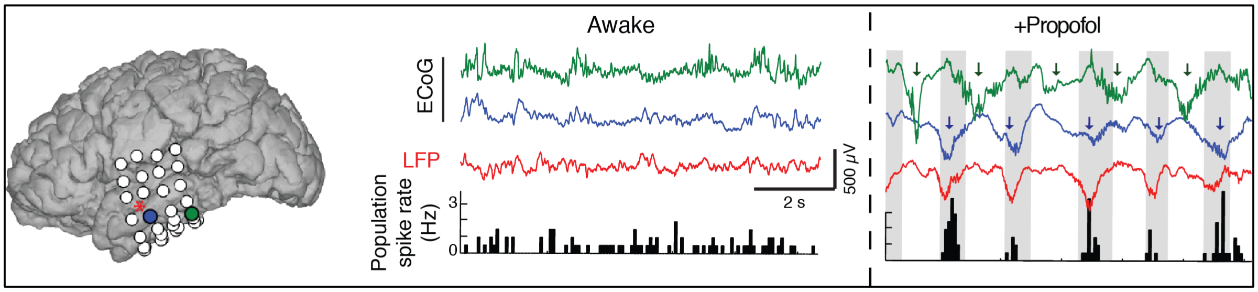
Cogs 118C, Spring 2017: Neural Signal Processing

Description

This course will cover theoretical foundations and practical applications of signal processing to neural data. Topics include EEG/field potential methods (filtering, Fourier (spectral) analysis, coherence) and spike train analysis (reverse correlation, spike sorting, multi-electrode recordings). Some applications to neural imaging (optical microscopy, fMRI) data will also be discussed.



Prerequisites: Math 18 or 20f or equivalent preparation in linear algebra; CogSci 14B or Psych 60; CogSci 109; or equivalent preparation

Important dates: Midterm exam TBD in class; Final exam – take home, distributed on the last day of the quarter.

Time and location: MWF 9-9:50 am, Peterson 103

Instructor: Prof. Eran Mukamel (emukamel@ucsd.edu)

Office hours: F 10-11 am, SSRB 255 (or by appointment)

TA: TBD; office hours TBD

Lectures and discussion: Each week we will introduce fundamental technical concepts during lecture on Monday and Wednesday. On most Fridays, we will explore neuroscience applications by discussing a related research paper.

Student responsibilities:

1. <u>Problem sets:</u> We will have weekly problem sets to practice signal analysis techniques, including a mix of conceptual questions, calculations, as well as computer-based coding exercises. Students are encouraged to work together on problem sets, but you must write up your final solutions on your own. If you share any code with other students, all students should list the names of their partners on their problem set.
2. <u>Reading:</u> *All* students are responsible for reading the research paper prior to the discussion on Friday.
3. <u>Class discussions:</u> Students are required to participate in the class discussions each Friday. One absence will be automatically excused; if you must miss more than one discussion, you may request to complete an alternative written assignment.
4. <u>Reading responses:</u> Each student must post a brief (5-10 sentences) substantive response to any 3 of the research papers on the TeD site before the in-class discussion. To receive credit, responses must be posted under the TeD discussion topic for that paper by midnight of the Thursday before the class discussion on Friday. Responses should (1) identify a key scientific goal or hypothesis of the paper; (2) describe a signal processing or other method that was used to address the goal; (3) raise at least one follow-up question, criticism, or caveat related to the study.

Evaluation

Grades will be assigned based on the following scheme:

1. Response papers and class discussion participation -- 20%
2. Problem sets -- 40%
3. Midterm -- 20%

4. Final exam -- 20%
5. SONA research participation -- 1 point extra credit per hour, up to 2 points
6. Extra credit points may also be earned by answering some of the homework questions marked with an asterisk.

Guidelines for in-class discussion of research papers

As scientists, scholars and students, it is critical that we strive for rigor and objectivity in our evaluation of scientific work. This means we should avoid being overly optimistic and credulous about papers (the "gee-whiz" approach). At the same time, we should avoid being narrowly critical. If we focus on technical flaws or assumptions with which we disagree, we may miss an opportunity to grasp a new insight. To keep us on the right path, we will divide our discussions into two phases: First, we will assess the paper from the point of view of the authors. This means that we will strive to understand, as fully as possible, the authors' own interpretation of their data, analysis and conclusions. Second, we will move on to a critical phase of discussion when we talk about potential limitations, flaws, or caveats of the study. Unless we first understand a paper sympathetically, we risk attacking a "straw man" version of the paper's arguments.

Course Materials

Main text: *Signal Processing for Neuroscientists: An Introduction to the Analysis of Physiological Signals,* Wim van Drongelen

Available in an electronic version from UCSD library at roger.ucsd.edu . Set up a UCSD VPN to access the resource from an off-campus IP address. The Ebrary version is limited to 1 user from UCSD at a time, but the Knovel version is not limited and can be downloaded and/or printed. Note that the electronic version is in color.

Software: Computational exercises will be an integral part of the course. We will frequently use scientific programming software to explore signal processing procedures in class, and homework will include computational exercises. I will use MATLAB in my lectures and examples. Students may use either MATLAB or Python. MATLAB is available for UCSD students in the ACMS computer labs, or through the virtual computer: http://acms.ucsd.edu/services/software/.

Supplementary texts:

1. *Signal processing for neuroscientists: a companion volume : advanced topics, nonlinear techniques and multi-channel analysis /* Drongelen, Wim van

2. *Observed Brain Dynamics* / Partha Mitra and Hemant Bokil

Supplementary code

1. MATLAB scripts to illustrate concepts from the van Drongelen book

2. Chronux toolbox for multi-taper spectral analysis of continous time series and point processes (http://chronux.org/)

Data

Although public sharing of neurophysiology data is not yet a broadly accepted norm, there are increasingly sources of data which may be useful for exploring applications of techniques from this class. A good collection of various types of neurophysiological recordings is available from CRCNS - Collaborative Research in Computational Neuroscience (http://crcns.org) (you will need to create an account).

Weekly schedule (preliminary; subject to change)

Except where noted, book chapters below refer to *Signal Processing for Neuroscientists* by Wim van Drongelen.

Week 1, 4/3 Signal and Noise in the Time Domain

Reading: WvD Ch. 1-3

- 4/3 Introduction: Neurophysiology and Signal Processing
- 4/5 Digital and analog signals; statistics for neural signals
- 4/7 Paper:

Boly, M., Garrido, M. I., Gosseries, O., Bruno, M.-A., Boveroux, P., Schnakers, C., et al. (2011). Preserved feedforward but impaired top-down processes in the vegetative state. Science (New York, NY), 332(6031), 858-862. http://doi.org/10.1126/science.1202043

Week 2, 4/10 Signals in the Frequency domain

Reading: WvD Ch. 5-7

- 4/10 Fourier series
- 4/12 Continuous and discrete Fourier transform
- 4/14 Paper:

Gervasoni, D., Lin, S.-C., Ribeiro, S., Soares, E. S., Pantoja, J., & Nicolelis, M. A. L. (2004). Global forebrain dynamics predict rat behavioral states and their transitions. The Journal of Neuroscience, 24(49), 11137–11147. http://doi.org/10.1523/JNEUROSCI.3524-04.2004

Week 3, 4/17 Linear Signal Transformations

Reading: WvD Ch. 8.1–8.4, Ch. 10 (skip Ch. 9)

- 4/17 LTI systems; Convolution, Correlation
- 4/19 Linear filters: RC circuit; Continuous & Discrete
- 4/21 Paper:

Cardin, J. A., Carlén, M., Meletis, K., Knoblich, U., Zhang, F., Deisseroth, K., et al. (2009). Driving fast-spiking cells induces gamma rhythm and controls sensory responses. Nature, 459(7247), 663–667. http://doi.org/10.1038/nature08002

Week 4, 4/24 Filtering

Reading: WvD Ch. 12-13; Cohen Ch. 14

- 4/24 Designing and analyzing filters
- 4/26 Uncertainty principle; Short-time FFT; Morlet Wavelets
- 4/28 Paper:

Bitterman, Y., Mukamel, R., Malach, R., Fried, I., & Nelken, I. (2008). Ultra-fine frequency tuning revealed in single neurons of human auditory cortex. Nature, 451(7175), 197–201. http://doi.org/10.1038/nature06476

Week 5, 5/1 Time-Frequency and Phase-based Analysis

Reading: Cohen Ch. 12, 13, 15

- 5/1 Hilbert transform, Phase-amplitude coupling
- **5/3 Midterm**
- 5/8 Paper:

Tort, A. B. L., Kramer, M. A., & Kopell, N. J. (2008). Dynamic cross-frequency couplings of local field potential oscillations in rat striatum and hippocampus during performance of a T-maze task. PNAS, 105(51), 20517–20522. http://doi.org/10.1073/pnas.0810524105

Week 6, 5/8 Spatial Analysis of Multi-Channel Data

Reading: WvD Ch. 8.5, Cohen ch.19-20

- 5/8 Spatial coherence and the cross-spectrum
- 5/10 Stimulus-triggered spectrogram and cross-spectrum; phase coherence
- 5/12 Paper:

Hipp, J. F., Engel, A. K., & Siegel, M. (2011). Oscillatory Synchronization in Large-Scale Cortical Networks Predicts Perception. Neuron, 69(2), 387–396. http://doi.org/10.1016/j.neuron.2010.12.027

Week 7, 5/15   Spike Trains from Single Neurons

Reading: WvD ch. 14

- 5/15 Recording techniques and spike sorting; LNP model
- 5/17 Modeling spike trains, reverse-correlation analysis
- 5/19 Paper (** Note this week we will discuss research papers on BOTH Monday and Friday**)

Pillow, J. W., Paninski, L., Uzzell, V. J., Simoncelli, E. P., & Chichilnisky, E. J. (2005). Prediction and decoding of retinal ganglion cell responses with a probabilistic spiking model. The Journal of Neuroscience, 25(47), 11003–11013. http://doi.org/10.1523/JNEUROSCI.3305-05.2005

Week 8, 5/22   Spike Trains From Neural Populations

Reading: WvD ch. 14

- 5/22 Spike-field correlation; modeling spike trains
- 5/24 Maximum entropy models of population spiking
- 5/26 Paper:

Schneidman, E., Berry, M. J., Segev, R., & Bialek, W. (2006). Weak pairwise correlations imply strongly correlated network states in a neural population. Nature, 440(7087), 1007–1012. http://doi.org/10.1038/nature04701

Week 9, 5/29   High-Dimensional Data and Imaging

Drongelen companion, ch. 6

- 5/29 *Memorial Day, no class*
- 5/31 PCA and SVD
- 6/2 ICA and applications to EEG, fMRI and optical imaging

Week 10, 6/5   Model-Based Analyses

- 6/5 Paper:

Mukamel, E. A., Nimmerjahn, A., & Schnitzer, M. J. (2009). Automated analysis of cellular signals from large-scale calcium imaging data. Neuron, 63(6), 747–760. http://doi.org/10.1016/j.neuron.2009.08.009

- 6/7 Dynamic causal modeling
- 6/9 Course review and Outlook

Week		Main paper
1	Signal and Noise in the Time Domain	Boly, M., Garrido, M. I., Gosseries, O., Bruno, M.-A., Boveroux, P., Schnakers, C., et al. (2011). Preserved feedforward but impaired top-down processes in the vegetative state. Science (New York, NY), 332(6031), 858-862. http://doi.org/10.1126/science.1202043 Read only through Figs. 1 & 2.
2	Signals in the Frequency domain	Gervasoni, D., Lin, S.-C., Ribeiro, S., Soares, E. S., Pantoja, J., & Nicolelis, M. A. L. (2004). Global forebrain dynamics predict rat behavioral states and their transitions. The Journal of Neuroscience, 24(49), 11137–11147. http://doi.org/10.1523/JNEUROSCI.3524-04.2004
3	Linear Signal Transformations	Cardin, J. A., Carlén, M., Meletis, K., Knoblich, U., Zhang, F., Deisseroth, K., et al. (2009). Driving fast-spiking cells induces gamma rhythm and controls sensory responses. Nature, 459(7247), 663–667. http://doi.org/10.1038/nature08002
4	Filters	Bitterman, Y., Mukamel, R., Malach, R., Fried, I., & Nelken, I. (2008). Ultra-fine frequency tuning revealed in single neurons of human auditory cortex. Nature, 451(7175), 197–201. http://doi.org/10.1038/nature06476
5	Time-Frequency analysis, Phase	Tort, A. B. L., Kramer, M. A., & Kopell, N. J. (2008). Dynamic cross-frequency couplings of local field potential oscillations in rat striatum and hippocampus during performance of a T-maze task. Proceedings of the National Academy of Sciences of the United States of America, 105(51), 20517–20522. http://doi.org/10.1073/pnas.0810524105
6	Spatial analysis of multi-channel data	Hipp, J. F., Engel, A. K., & Siegel, M. (2011). Oscillatory Synchronization in Large-Scale Cortical Networks Predicts Perception. *Neuron*, *69*(2), 387–396. http://doi.org/10.1016/j.neuron.2010.12.027
7	Spike trains from single neurons (Note this paper will be discussed on the Monday of week 8, 5/16)	Pillow, J. W., Paninski, L., Uzzell, V. J., Simoncelli, E. P., & Chichilnisky, E. J. (2005). Prediction and decoding of retinal ganglion cell responses with a probabilistic spiking model. The Journal of Neuroscience, 25(47), 11003–11013. http://doi.org/10.1523/JNEUROSCI.3305-05.2005

8	Spike trains from neural populations	Schneidman, E., Berry, M. J., Segev, R., & Bialek, W. (2006). Weak pairwise correlations imply strongly correlated network states in a neural population. Nature, 440(7087), 1007–1012. http://doi.org/10.1038/nature04701
9	High-Dimensional Data and Imaging	Mukamel, E. A., Nimmerjahn, A., & Schnitzer, M. J. (2009). Automated analysis of cellular signals from large-scale calcium imaging data. Neuron, 63(6), 747–760. http://doi.org/10.1016/j.neuron.2009.08.009
10	Model-based analyses	Boly, M., Garrido, M. I., Gosseries, O., Bruno, M.-A., Boveroux, P., Schnakers, C., et al. (2011). Preserved feedforward but impaired top-down processes in the vegetative state. Science (New York, NY), 332(6031), 858-862. http://doi.org/10.1126/science.1202043 (Continued) Read only through Figs. 3 & 4.