Introduction to Computational Neuroscience

Lecture 4: Data analysis I
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Analysis is what lies between data and results
Learning objectives

- Understand the basic analyses for continuous and spiking electrophysiology data
Continuous signals

Spikes
Continuous signals

Event Related Potentials (ERPs)

Analysis of rhythmic data (power spectrum)

Association measures (networks)
In many experiments we are interested in the activity generated by some event... (ex., sensory stimulus or behavior)
Event Related Potential

Individual responses are highly variable...

To reveal the activity temporally locked to some event:
align and average many repetitions (signal-to-noise ratio \( \uparrow \))

= ERP
ERP (nomenclature)

P or N depending on the polarity (traditionally, negative is plotted up)

Numbers after the letter indicate the approximate peak latency (1, 2, 3 are short for 100 ms, 200 ms, 300 ms...)

viernes, 28 de febrero de 14
ERP (examples)

MMN

P300
Analysis of rhythmic data

...one can distinguish larger first order waves with an average duration of 90 milliseconds and smaller second waves with an average duration of 35 milliseconds.
Why?

Quantifying brain waves is a great tool for the clinics:

* epilepsy
* coma/anesthesia
* sleep
* encephalopathies
* brain death
* BCI
Why?

* More prominent and regular oscillations during sleep
Why?

* More prominent and regular oscillations during sleep

* 3 orders of magnitude
Why?

* More prominent and regular oscillations during sleep
* 3 orders of magnitude
* Phylogenetically conserved
Why?

* More prominent and regular oscillations during sleep
* 3 orders of magnitude
* Phylogenetically conserved
* Change with stimulus, behavior, or disease
Visual inspection

EEG

Visual inspection: looks rhythmic but very complicated

How can we simplify?
Power spectrum

Power spectrum (EEG)

Axes: Power (dB) vs Frequency (Hz)

Simpler representation in frequency domain. Four peaks at \{7, 10, 23, 35\} Hz
Idea

Separate the signal into oscillations at different frequencies

Represent $V$ as a sum of sinusoids (e.g., part 7 Hz, part 10 Hz,...)
Idea

We want to decompose data $V(t)$ into sinusoids

We need to find the coefficients:

- **Fourier transform**
- **Power (complex coefficients squared)**

Sinusoids with better match to $V(t)$ will have larger power
In practice

$$V[f] = \int_0^1 v[t] e^{-2\pi i ft} dt$$

$$P[f] \sim |V[f]|^2$$

To compute the power spectrum in MATLAB use command

```matlab
fft
```

```matlab
>> pow = abs(fft(v)).^2*2/length(v);
```
Example

EEG

\[ V = \]

\[ T = 1 \text{ s} \]
\[ dt = 1 \text{ ms} \]
\[ \text{length}(V) = 1000 \]
Example

MATLAB code

>> pow = abs(fft(v)).^2*2/length(v);
>> pow = 10*log10(pow);
>> plot(pow)

Incomplete: Must label x-axis?

1000 data pts

Matches
length of v
Power spectrum x-axis

Indices and frequencies are related in a funny way...

Examine vector $\text{pow}$:

<table>
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<tr>
<th>Freq Index</th>
<th>Frequency resolution (df)</th>
<th>$f &gt; 0$</th>
<th>Nyquist frequency ($f_{NQ}$)</th>
<th>$f &lt; 0$</th>
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<tr>
<td>0</td>
<td>df</td>
<td></td>
<td>$f_{NQ}$ - df</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2df</td>
<td></td>
<td>500</td>
<td>501</td>
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What remains?
Find $df$ and $f_{NQ}$
What is $df$?

$$df = \frac{1}{T}$$

where $T$ = Total time of recording

$V = \begin{array}{c}
\end{array}$

$T = 1 \text{ s}$

$df = 1 \text{ Hz}$

**Q:** How do we improve frequency resolution?

**A:** Increase $T$ (record for longer time)
What is $f_{NQ}$?

$$f_{NQ} = \frac{f_0}{2}$$

where $f_0$ = sampling frequency

The Nyquist frequency $f_{NQ}$ is the highest frequency we can observe in the data.

$$dt = 1\, \text{ms}$$

$V =$

$f_0 = 1/dt$

$f_0 = 1000\, \text{Hz}$

$f_{NQ} = 500\, \text{Hz}$

Q: How do we increase the Nyquist frequency?

A: Increase the sampling rate $f_0$ (hardware).
Example (MATLAB code)

```matlab
>> pow = abs(fft(v)).^2*2/length(v);
>> pow = 10*log10(pow);
>> pow = pow(1:length(v)/2+1);  % First half of pow
>> df = 1/max(t);  fNQ = 1/dt/2;  % Define df & f_NQ
>> faxis = (0:df:fNQ);  % Frequency axis
>> plot(faxis,pow);  xlim([0 50]);
```

% Frequency [Hz]

![Frequency plot](image_url)
Summary

\[ pow = \text{abs}(\text{fft}(v)).^2*2/\text{length}(v); \]

For finer frequency resolution: use more data

To observe higher frequencies: increase sampling rate

Built-in routines: \[ \text{periodogram}(...) \]

Many subtleties....
Spectrogram

What if signal characteristics change in time?

Different spectra at beginning and end of signal

Idea: split up data into windows & compute spectrum in each
Example (MATLAB code)

\[ [S, F, T] = \text{spectrogram}(v, 1, 0.5, 1, 1000); \]
\[ S = \text{abs}(S); \]
\[ \text{imagesc}(T, F, 10 * \log10(S / \text{max}(S(:)))); \]

Window overlap padding
Overlap \( f_0 \)

Plot of power (color) vs frequency and time
A better representation of data
Association measures

In many experiments we collect tens or hundreds of channels

How are the activities of different channels related?
Association measures

Association measures quantify some degree of interdependence between two or more time series:

**Correlation** (cross-correlation)
Synchronization
Granger causality
Mutual information

...
Correlation

Given two time series: \( X = \{x_1, x_2, x_3, \ldots, x_n\} \) & \( Y = \{y_1, y_2, y_3, \ldots, y_n\} \)

the correlation coefficient \( r \) measures the linear “similarity” between them

\[
Y(t) = a*X(t) + w(t)
\]

\[
 r = \frac{\sum_{i=1}^{n} ((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}
\]

\[
>> r = \text{corr}(X,Y);
\]
Cross-correlation

Cross-correlation measure the degree of linear similarity of two signals as a function of a time shift (lag).
Cross-correlation

The value and position (lag) of the maximum of the cross-correlation function can give information about the strength and timing of interactions

\[ Y(t) = a \times X(t-d) + w(t) \]

\[
r = \frac{\sum_i [(x_i - \bar{x})(y_{i-d} - \bar{y})]}{\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_{i-d} - \bar{y})^2}}
\]

\[
\text{>> } r = \text{xcorr}(X,Y,\text{maxlag}); \quad \% \text{ returns a vector } r \text{ of length } 2^*\text{maxlag} + 1
\]
Networks

Set of nodes and edges

It allows to study a set of channels as a whole

In structural networks the edges represent physical connections between nodes (synapses or white matter tracts)

**Functional networks** rely on the co-activation or coupling of the dynamics of separate brain areas
Networks

1. Compute a measure of “coupling” between two channels (e.g. cross-correlation)

2. Draw an edge if the “coupling” > threshold

3. Repeat for all pairs of channels

Network → characterize its structure (degree, length, hubs, clusters,...)
Networks

The easy way to estimate connectivity: HERMES toolbox

http://hermes.ctb.upm.es
Default Mode Network (DMN)

fMRI (BOLD) → Spontaneous modulations during resting → Correlations (functional connectivity)
Continuous signals

Spikes
Spikes

Raster plot

Post-stimulus time histogram

Receptive field

Spike triggered average
A spike train is a series of discrete action potentials from a neuron taken as a time series.

A **raster plot** represents spike train along time in the x-axis and cell number (or trial number) in the y-axis.
Spike trains (rate)

Each neuron can be characterized by its firing rate $r$

$r = \text{average number of events per unit of time}$

If properties change over time a more refined measure is the instantaneous rate $r(t)$:

$r(t) \times dt = \text{average number of events between } t \text{ and } t+dt$
Spike trains (rate)

IT neuron from monkey while watching video

Binning
dt = 100 ms

Rectangular window

Gaussian window
Post-Stimulus Time Histogram

PSTH is an histogram of the times at which neurons fire

\[ \text{rate} = \text{average over several runs} \]

(single neuron, repeated runs)

PSTH is used to visualize the rate and timing of spikes in relation to an external stimulus. \( \text{PSTH}/\#\text{trials} \sim r(t) \)
Receptive field

The **receptive field** of a neuron is a region of space in which the presence of a stimulus will alter the firing of that neuron.

The space can be a region on an animal’s body (somatosensory), a range of frequencies (auditory), a part of the visual field (visual system), or even a fixed location in the space surrounding an animal (place cells).

http://www.youtube.com/watch?v=8VdFf3egwfg
The Spike Triggered Average (STA) is the average stimulus preceding a spike.
Spike Triggered Average (Ex.)

Weakly electric fish (Eigenmannia)

STA from neuron in the electrosensory antennal lobe
Event related potentials (ERPs) and post-tim stimulus histograms (PSTH) average the neural responses near some event of interest

Power spectrum can reveal the presence of rhythms or oscillations in recordings

Functional networks are defined by the co-activation of separate brain areas

Receptive fields describes what a neuron is sensitive to
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- **Basics**
- **Analyses**
- **Models**
- **Cognitive Applications**