Brain – Computer Interfaces

Physiologic basis for feature selection, and decoding techniques

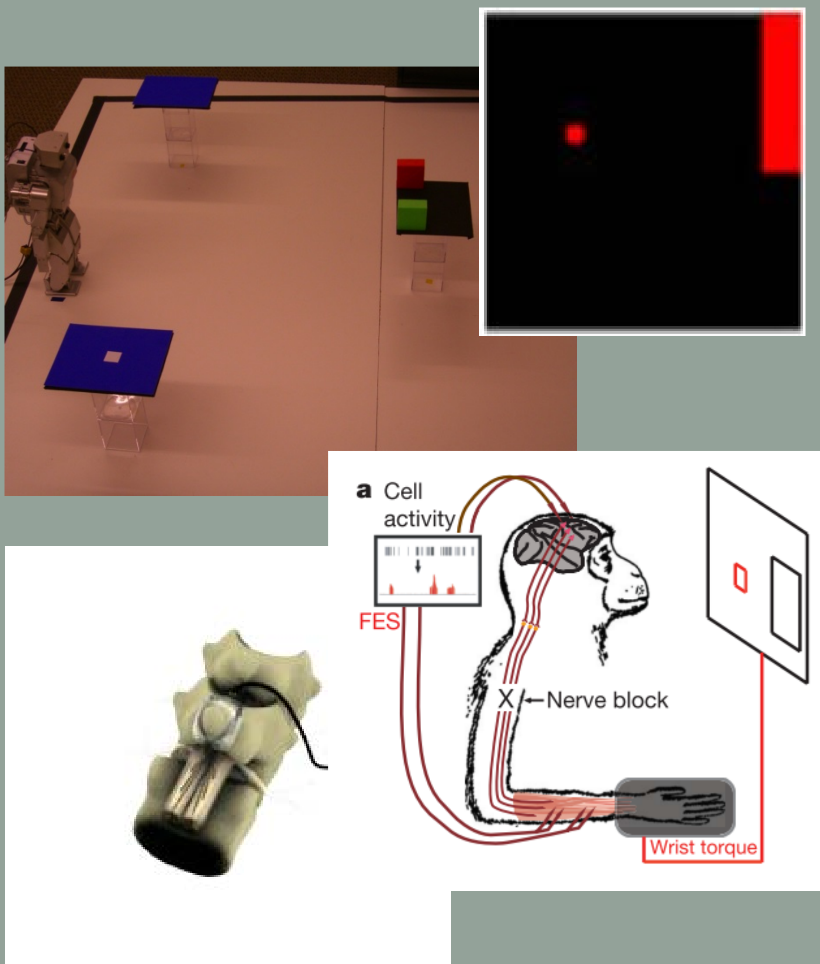
Brain – Computer Interfaces

For dexterous motor control

Hochberg 2012

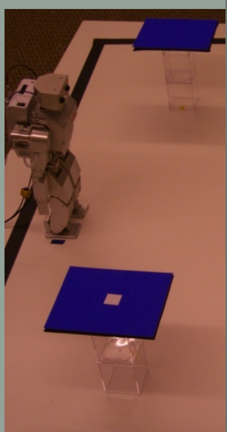
Brain – Computer Interfaces

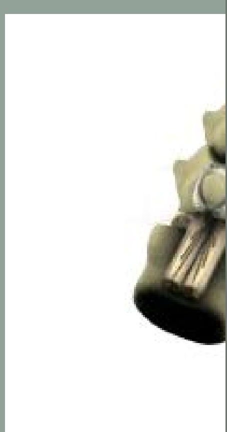
Control of end effectors



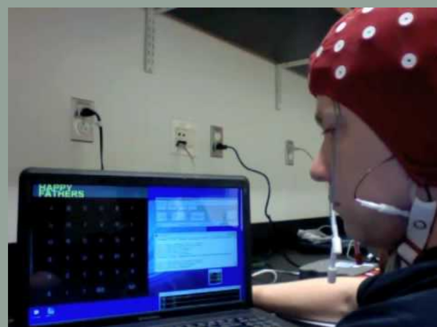
Brain – Computer Interfaces

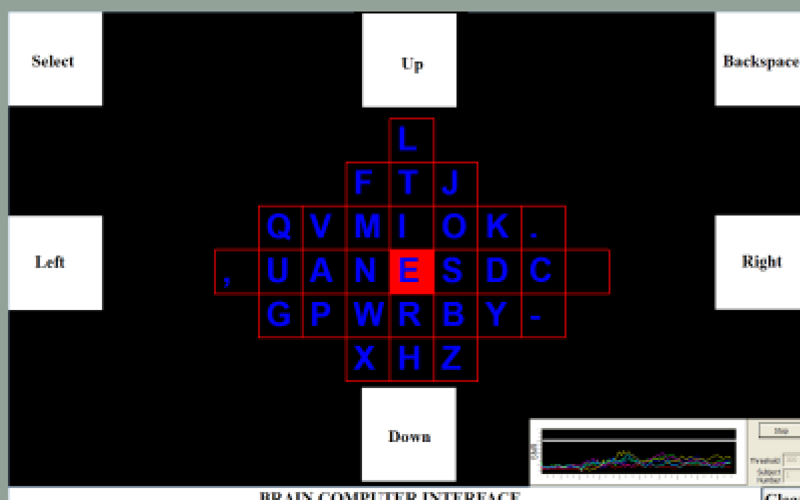
Co





Communication





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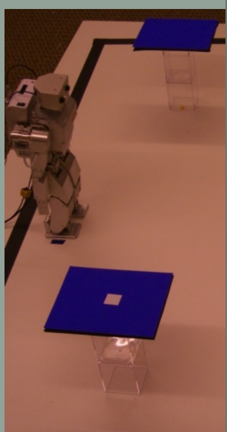

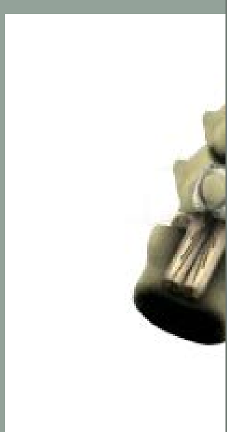

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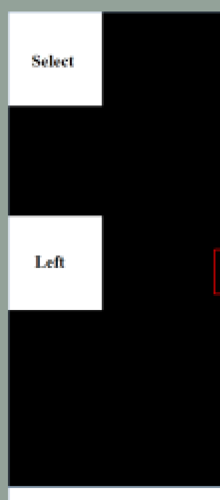
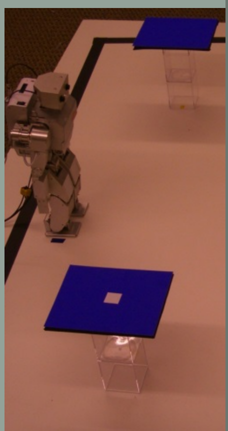
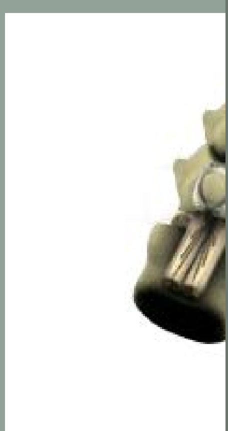


Neuromodulation to replace lost senses

Brain – Computer Interfaces

Co





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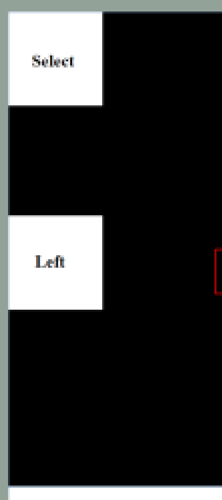
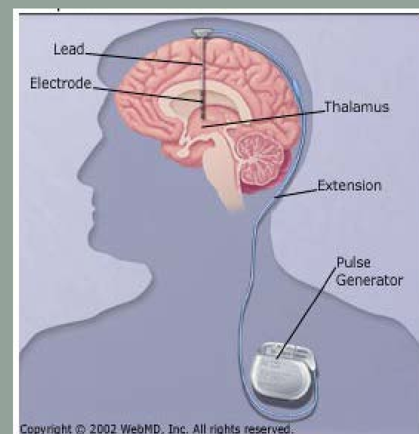
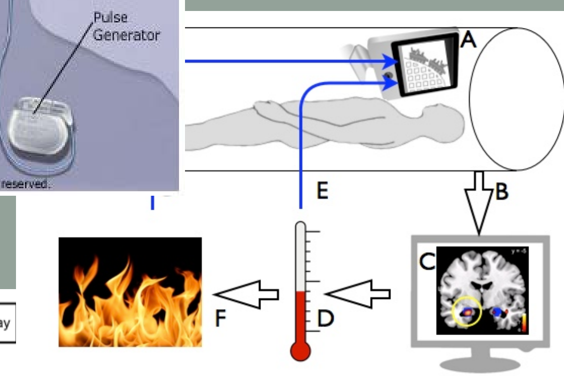
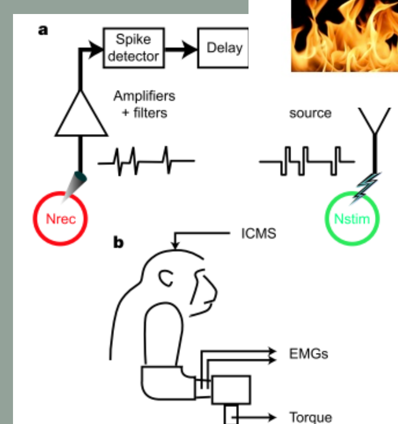


Neu
rep

Other Neuromodulation / Biofeedback







Brain – Computer Interfaces

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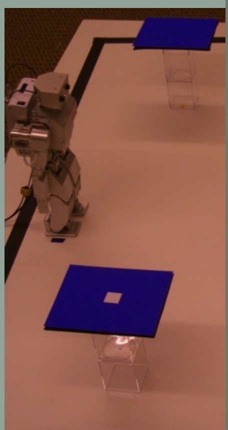

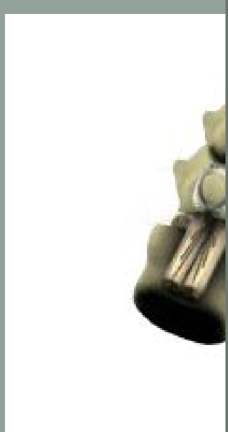

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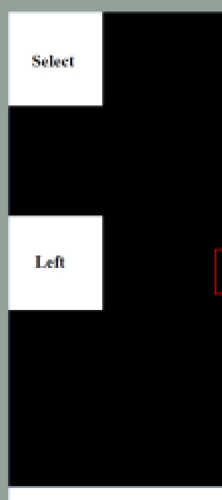
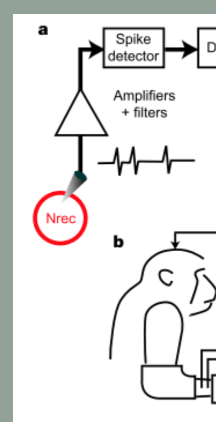
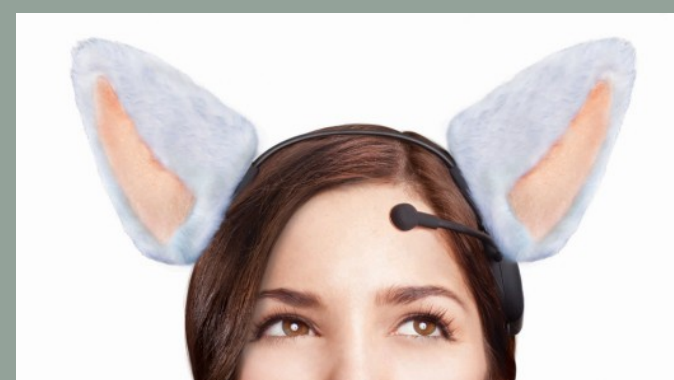


Ne
rep

Other Neu



Consumer BCI



Brain – Computer Interfaces

Many Applications ->
  Many Engineering Requirements ->
    Many Architecture Considerations

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But in general: need to **isolate**, **translate**, and **utilize** a neural signal

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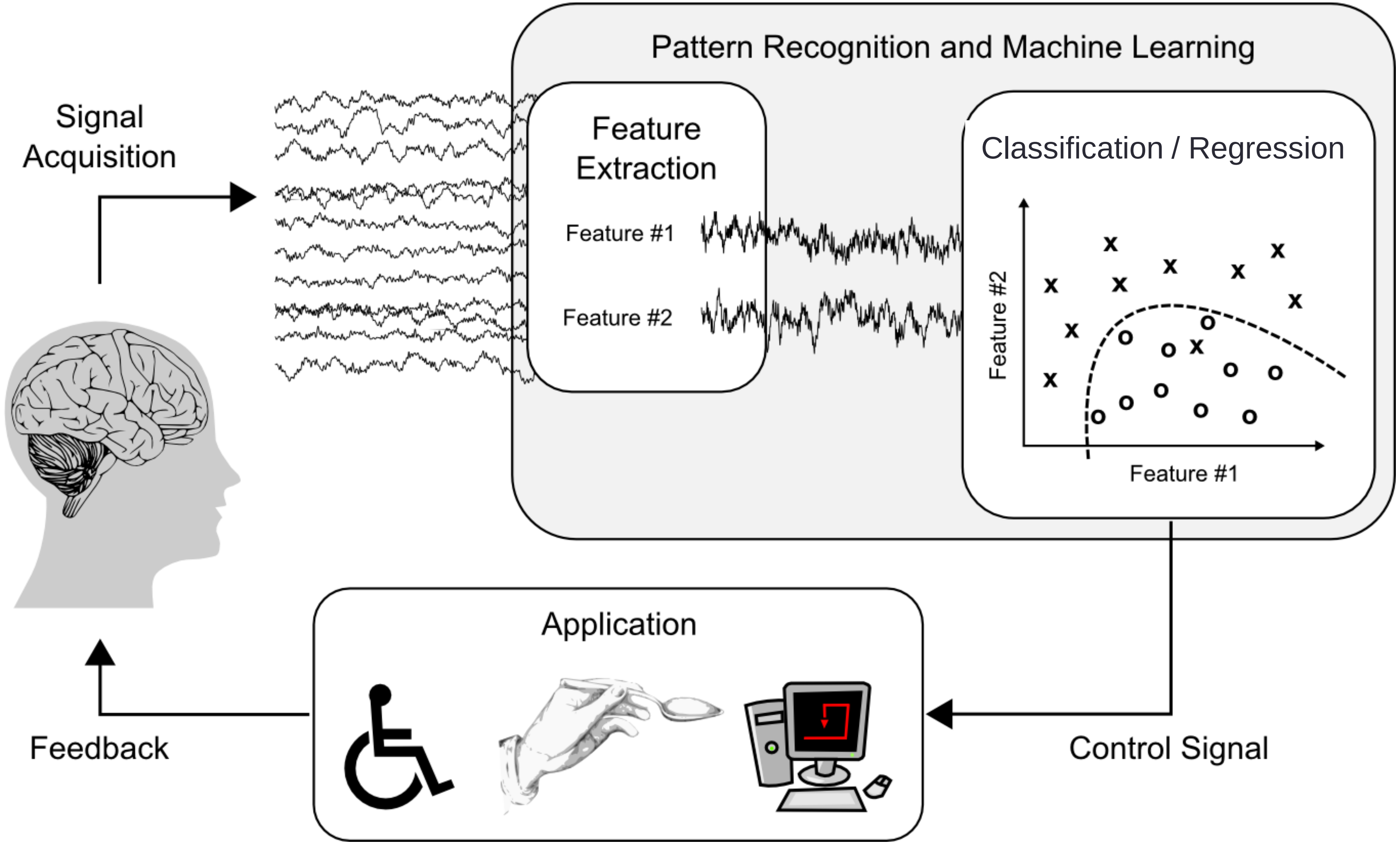
Architecture of a BCI



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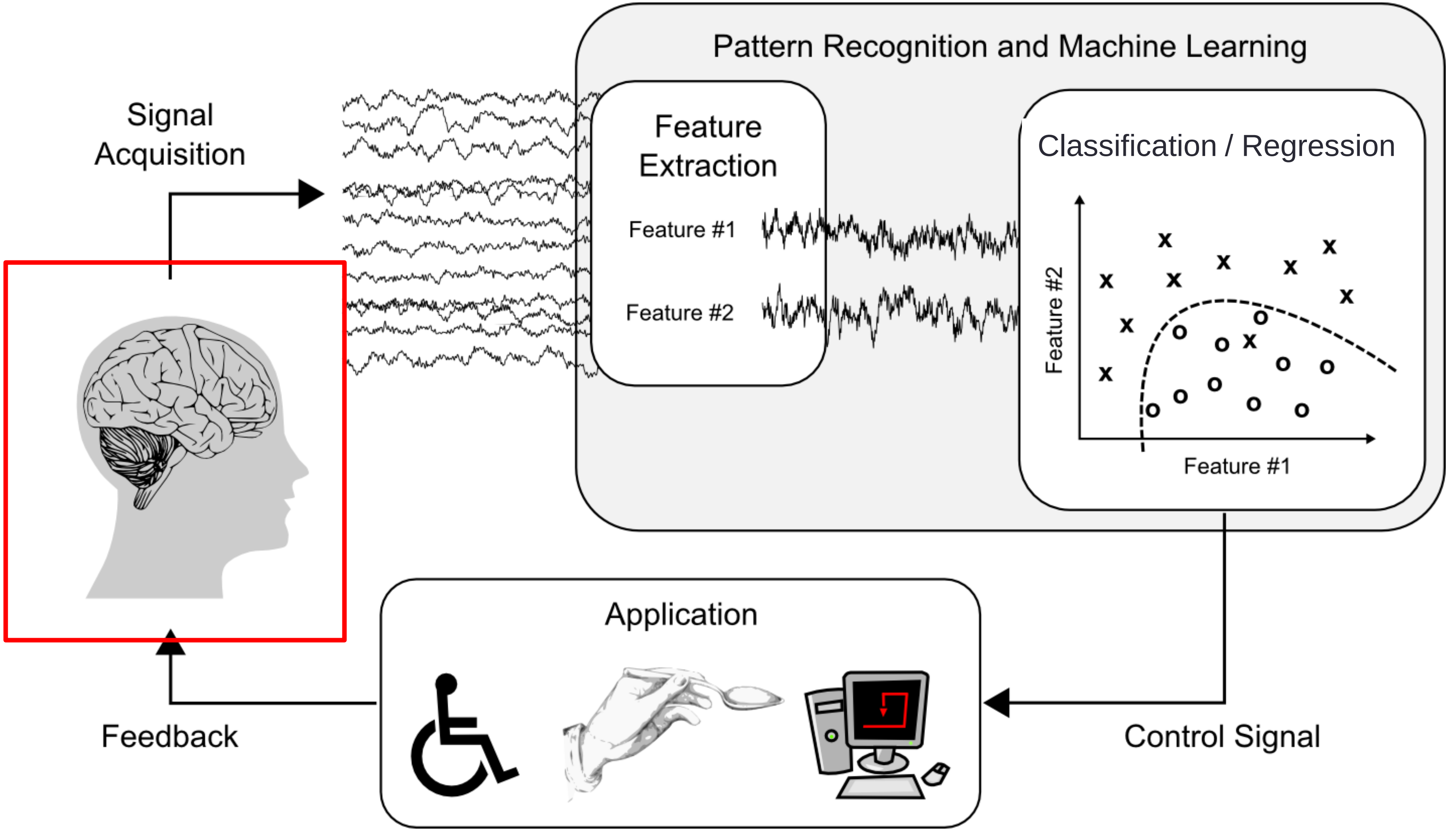
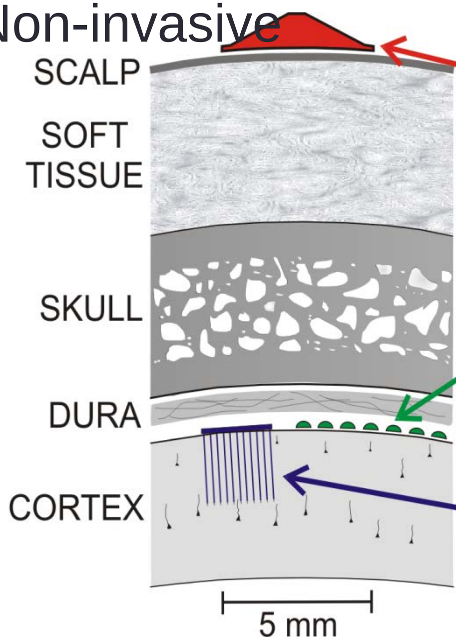


BCI Signal Types

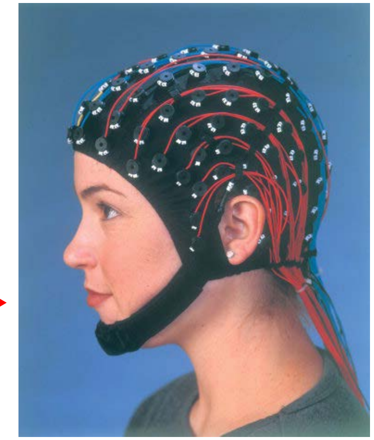
Non-invasive



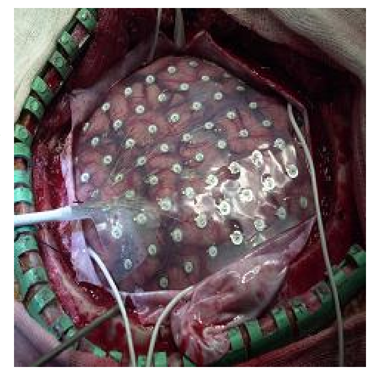
(Picture credit: Wadsworth Center)

Invasive

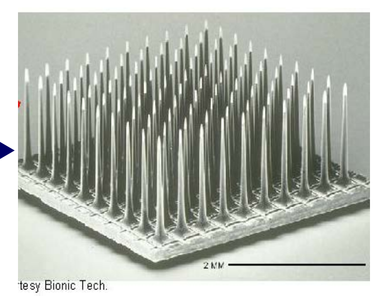
EEG (scalp)



ECoG (brain surface)



Intracortical Electrodes

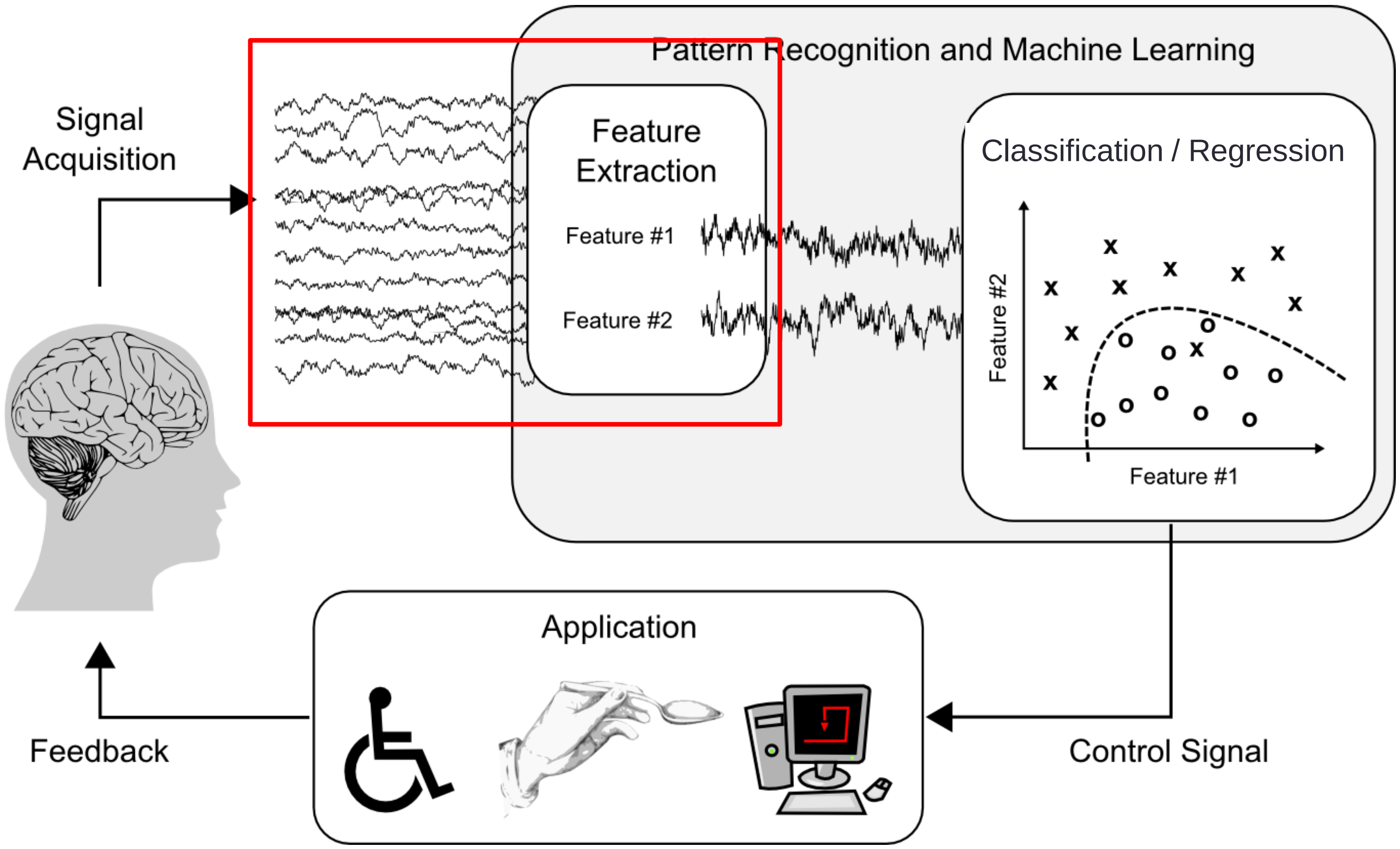


BCI Signal Types

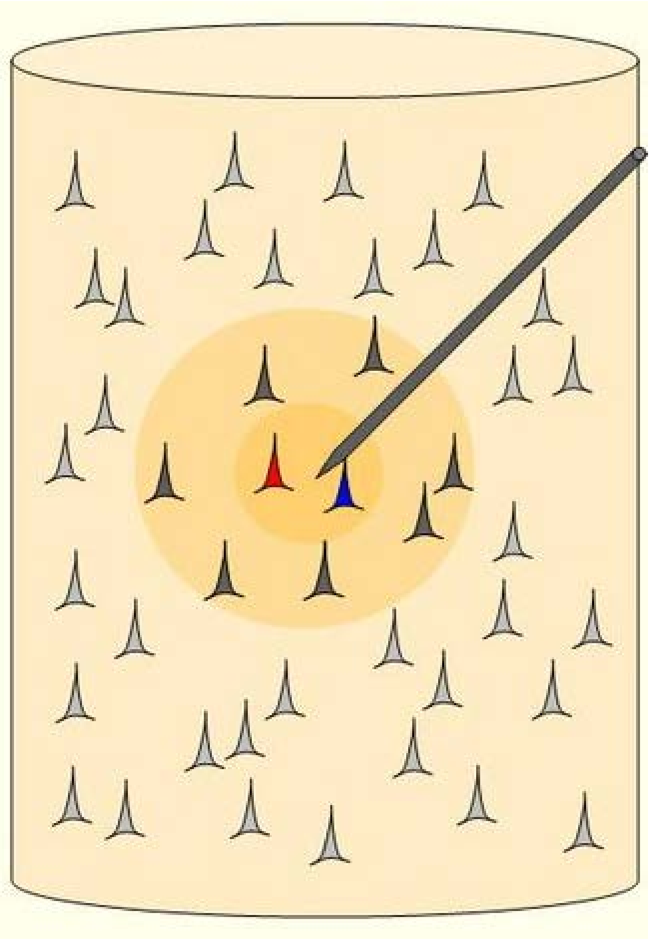
Signal	Cell count	Raw Magnitude	Feature Z (depends)	Spatial Specificity	Signal Stability
EEG (non-invasive)	> 1M	~50 uV	3-5	1-5 cm	Long-term?
ECoG (semi-invasive?)	500K	~500 uV	10-20	3-10 mm	Months
Intracortical (invasive)	1-???	10s of mV	Very high	< 300 um	Days

Appropriate modality choice depends on application.
Consider subject population. Research/Clinical goals.
Stimulation requirements.

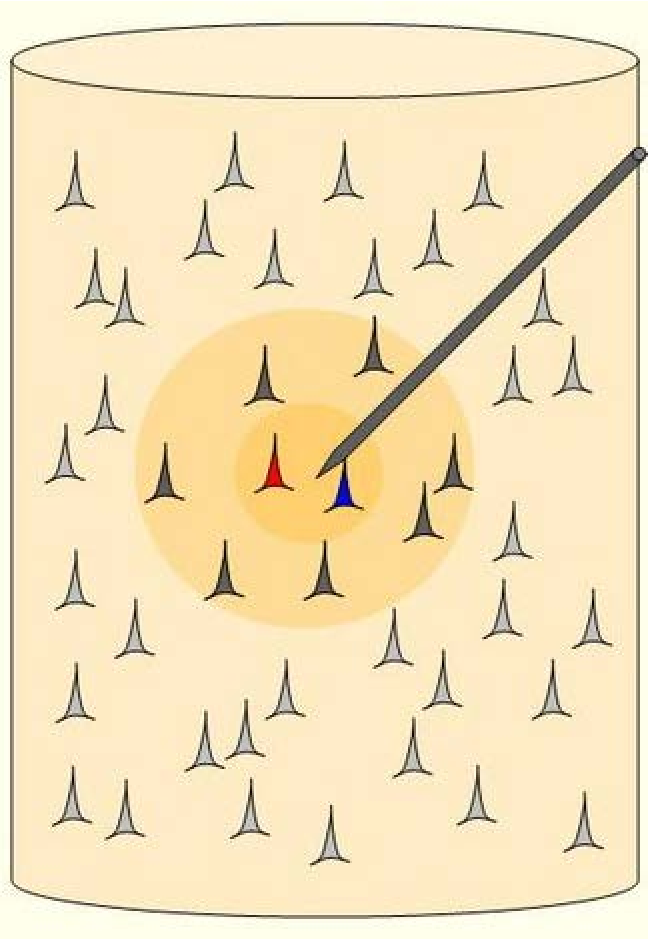
Architecture of a BCI



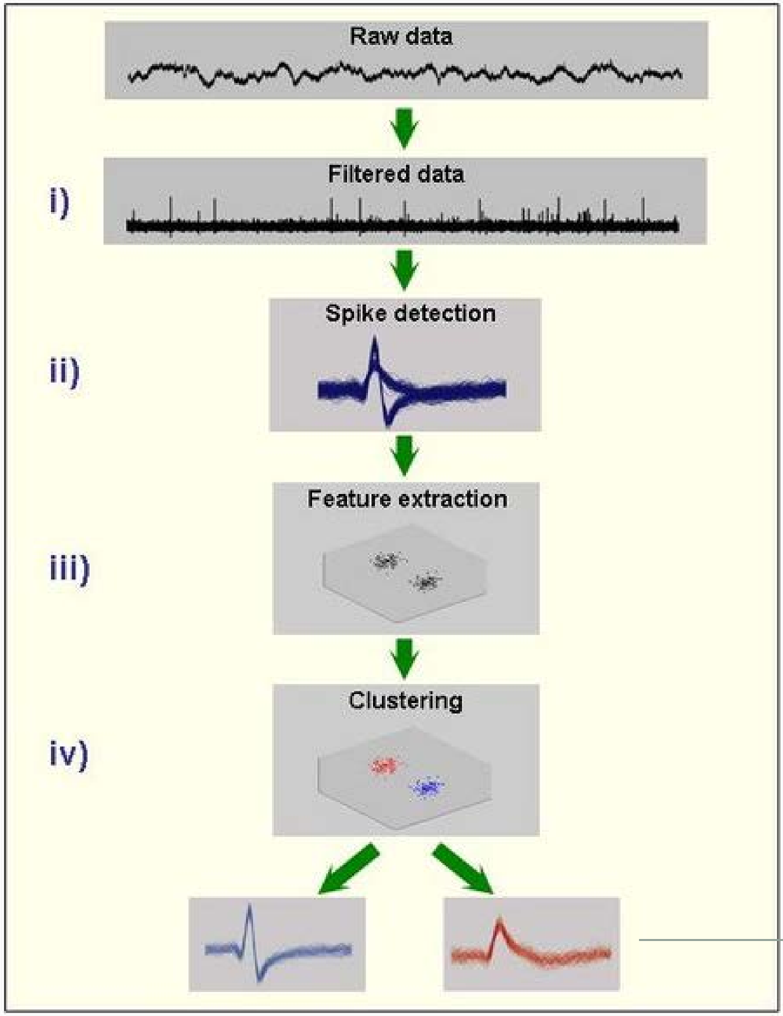
Feature extraction, intracortical recordings



Feature extraction, intracortical recordings

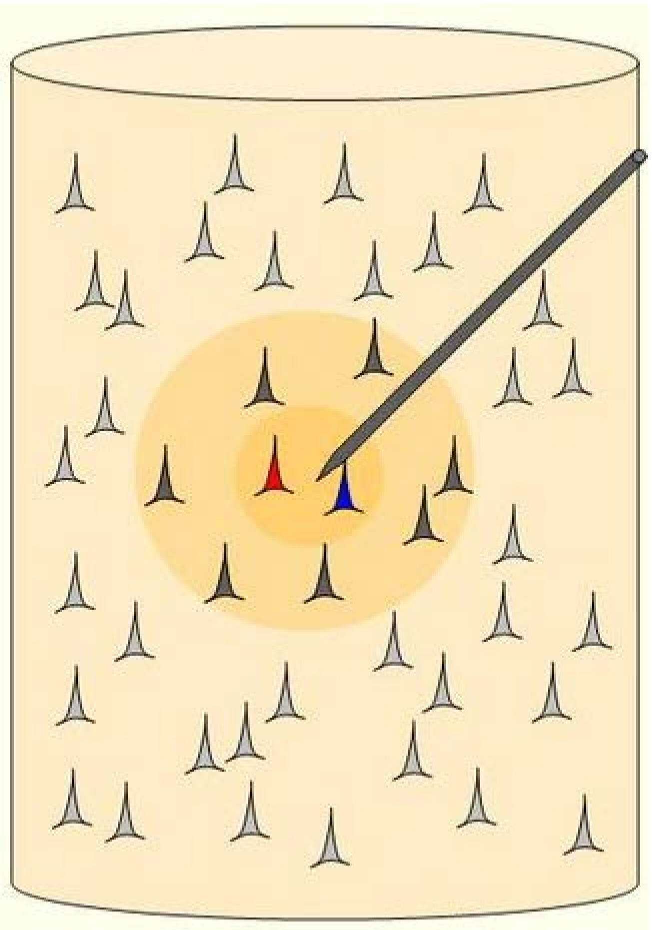


The quest for single units

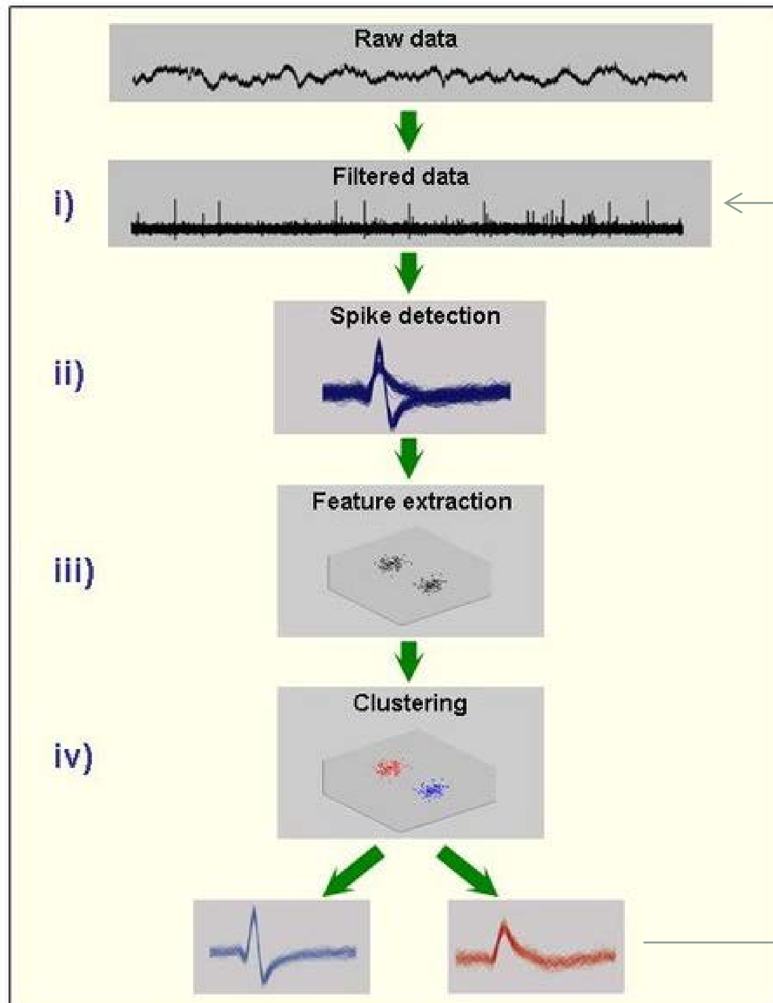


mean firing rates

Feature extraction, intracortical recordings



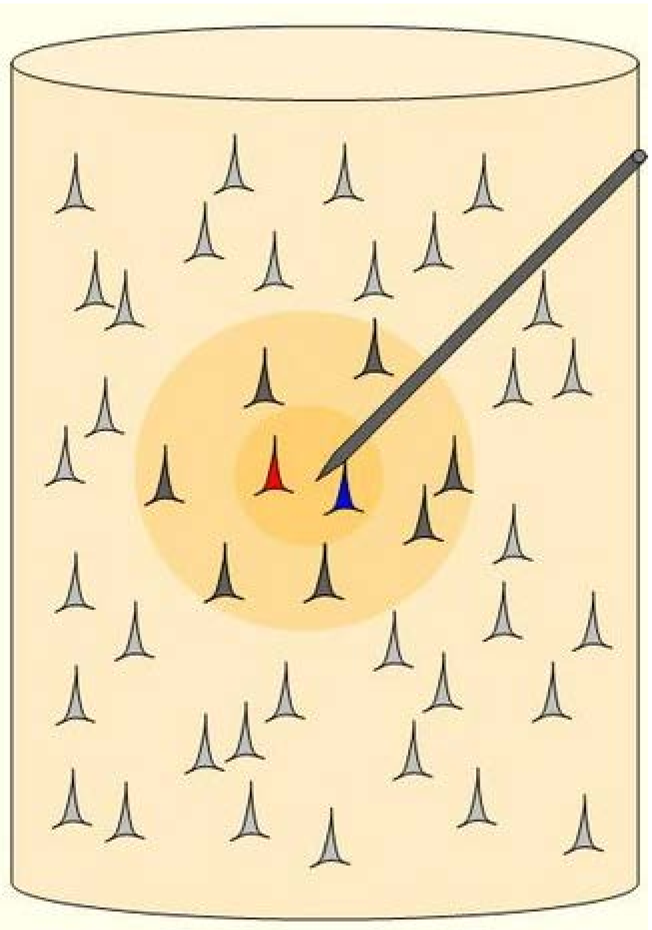
The quest for single units



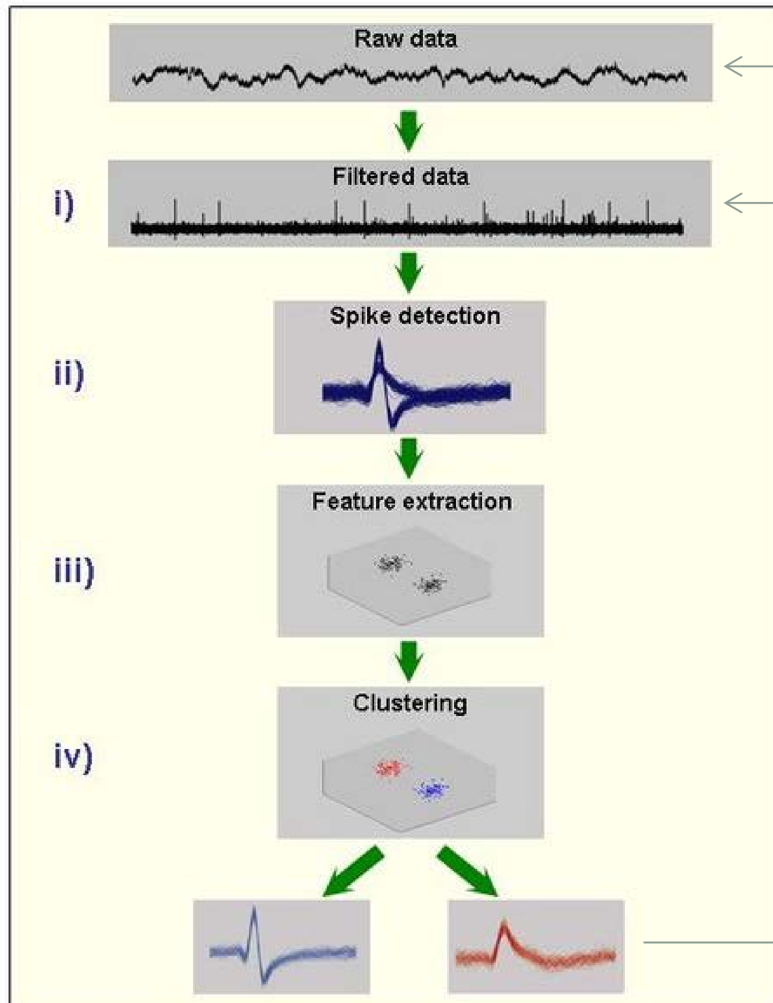
Ensemble spiking

mean firing rates

Feature extraction, intracortical recordings



The quest for single units

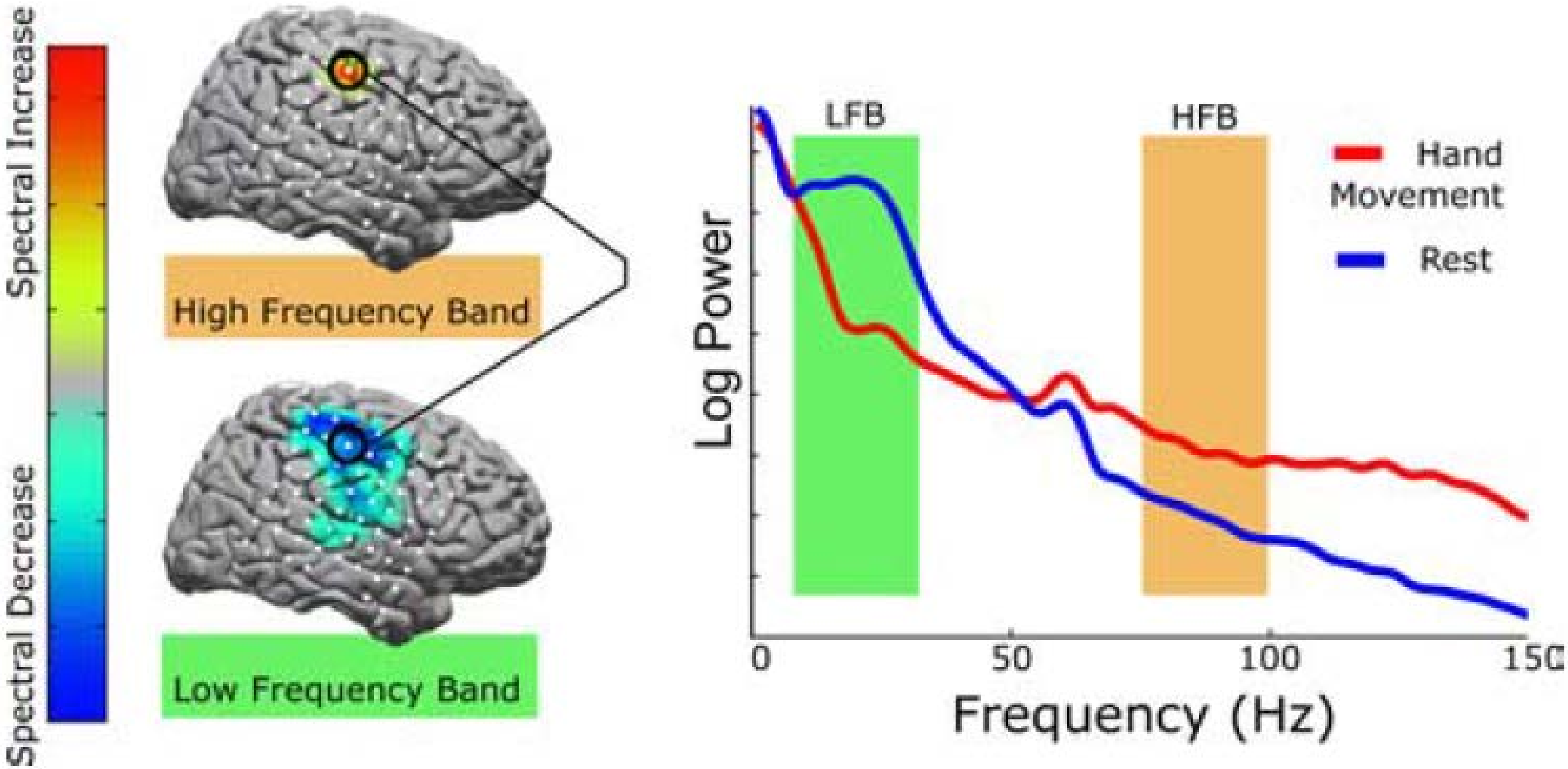


Local Field Potentials (LFPs)

Ensemble spiking

mean firing rates

Feature extraction, ECoG and LFPs



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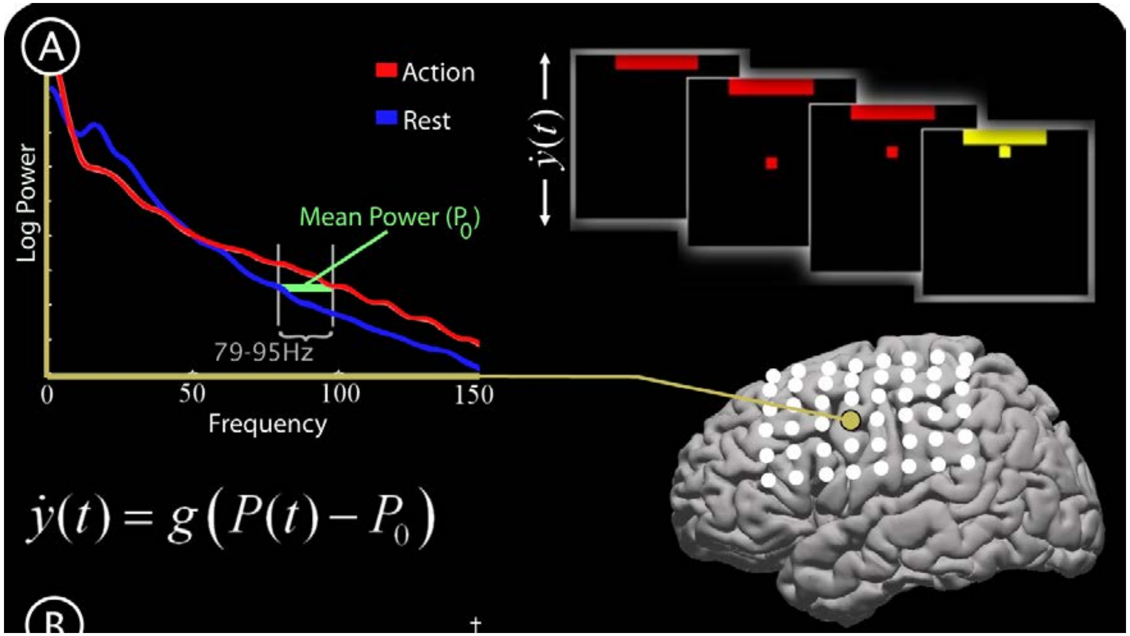
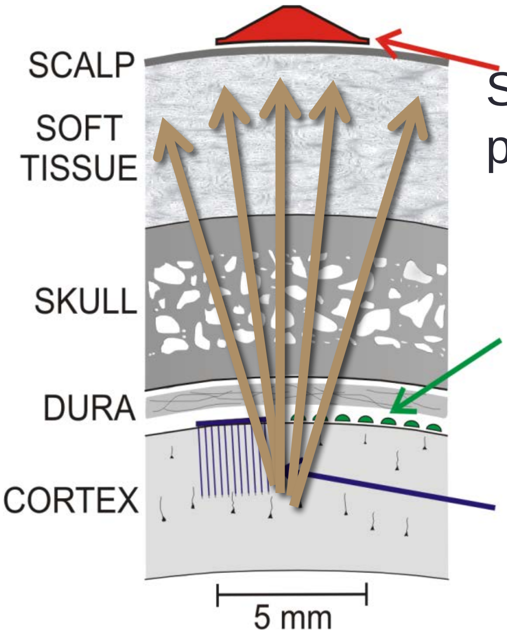


Spectral Estimation:

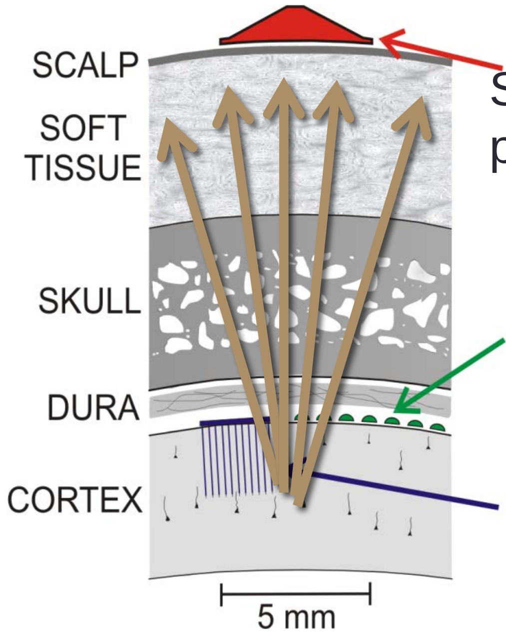
- STFFT
- Wavelets
- Band filtering and envelope detection
- Auto-regressive model

Feature extraction, EEG



Signal spreads as it passes through meat

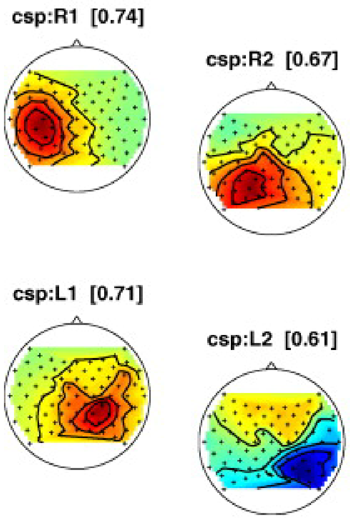
Feature extraction, EEG



Signal spreads as it passes through meat

1) Correct for spatial spreading

Common Spatial Patterns – Linear combination of electrodes maximizing two class discriminability



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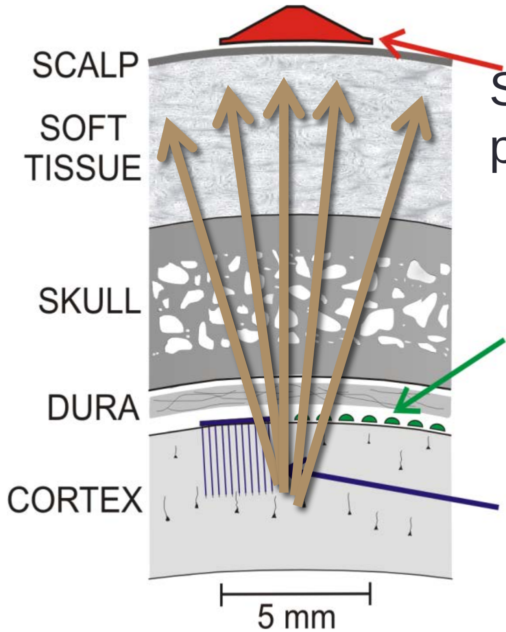

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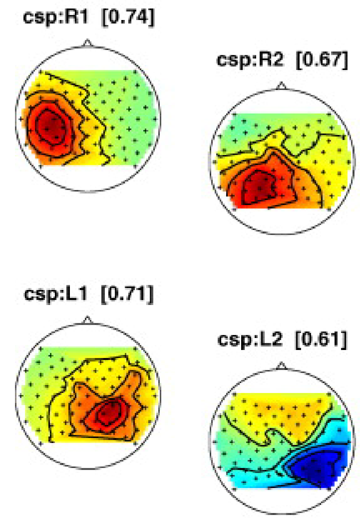
Use of spherical head model as solution to forward model



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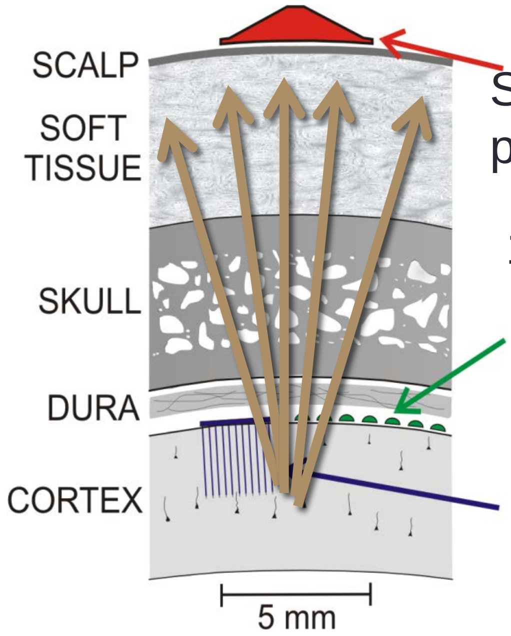

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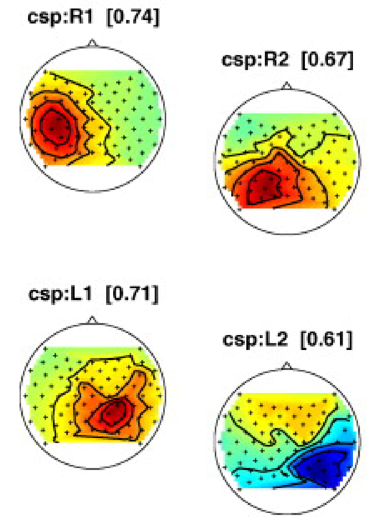

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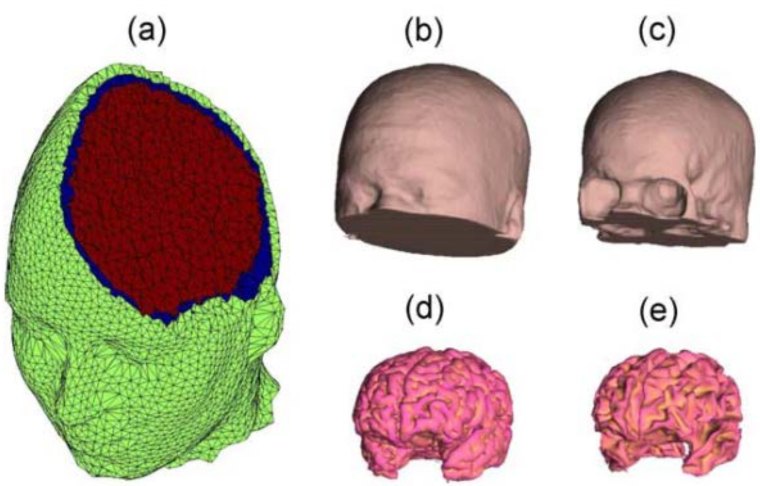
Subject specific MRI as solution to forward model



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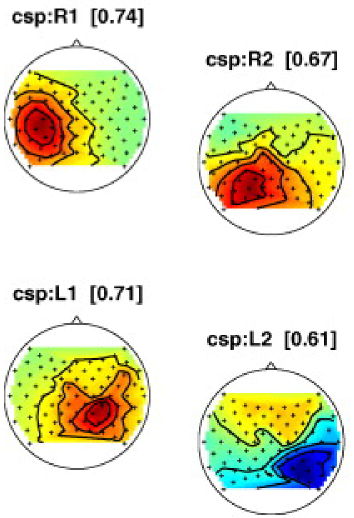

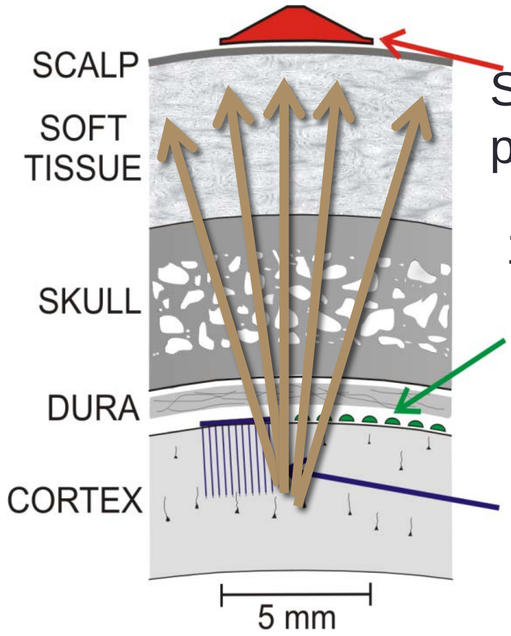

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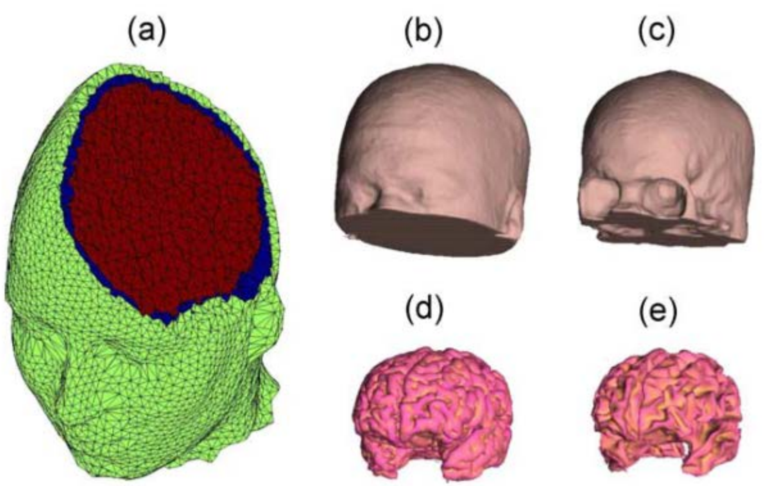
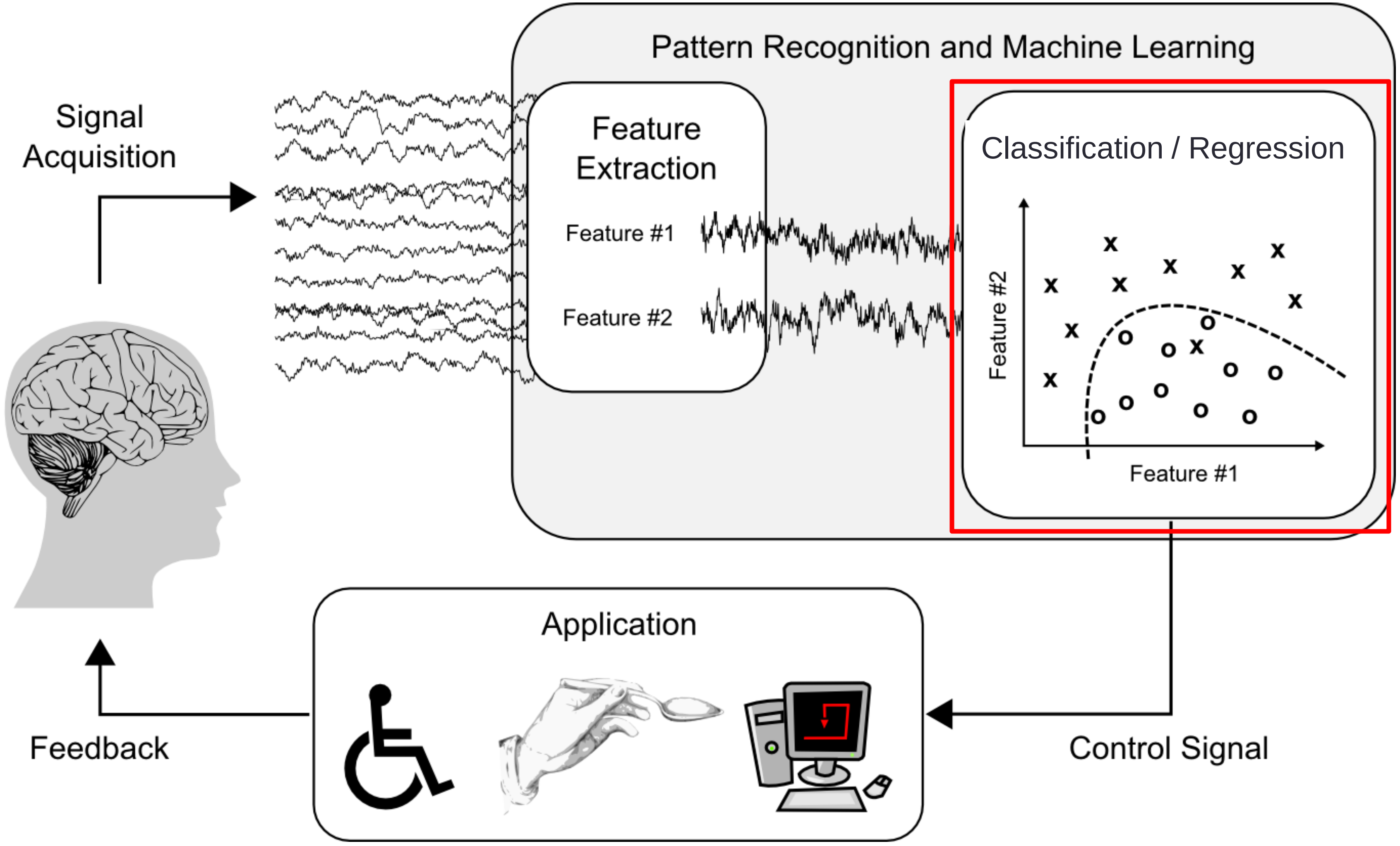


2) Apply same spectral estimation techniques used in ECoG (50 Hz and below) for SMR and SSVEP

Or

Simple LPF for EPs

Architecture of a BCI



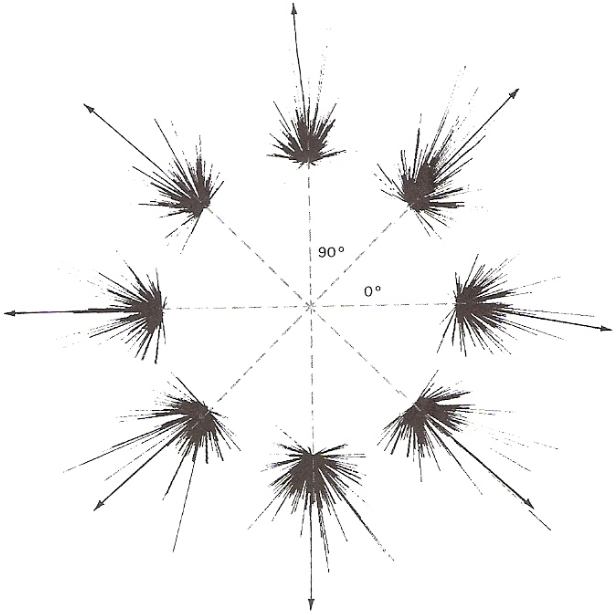
Decoding, intracortical recordings

Translation of neural signal to one or more continuous variables

Decoding, intracortical recordings

Translation of neural signal to one or more continuous variables

Population Vector



$$\hat{\mathbf{d}} = \sum_i \mathbf{p}_i \left(\frac{r - r_0}{r_{\max}} \right)_i$$

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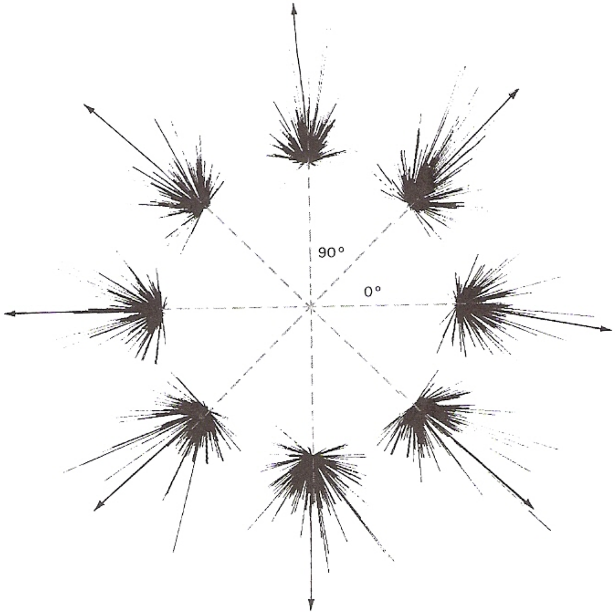

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Kalman Filter

$$\begin{aligned} x_{t+1} &= Ax_t + w_t \\ y_t &= Cx_t + q_t \end{aligned}$$

Estimate

$$\begin{aligned} \hat{x}_{t|t-1} &= A\hat{x}_{t-1} \\ P_{t|t-1} &= AP_{t-1}A^T \end{aligned}$$

Update

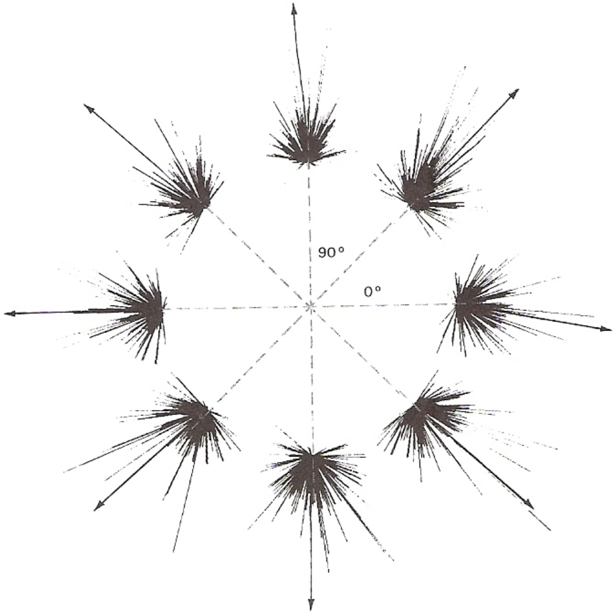
$$\begin{aligned} K_t &= P_{t|t-1}C^T \left(CP_{t|t-1}C^T + Q\right)^{-1} \\ \hat{x}_t &= \hat{x}_{t|t-1} + K_t \left(y_t - C\hat{x}_{t|t-1}\right) \\ P_t &= (I - K_t C)\, P_{t|t-1} \end{aligned}$$

Bonus: Incorporates effector kinematics

Decoding, intracortical recordings

Translation of neural signal to one or more continuous variables

Population Vector



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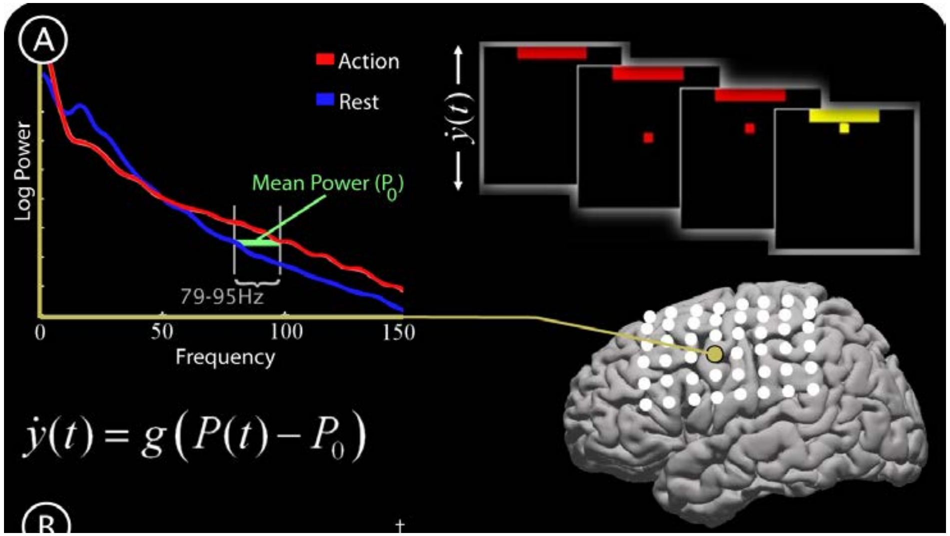
Bonus: Incorporates effector kinematics

Many Others: Neural Networks, ARMA Models, etc

Decoding, ECoG

Translation of neural signal to one or more continuous variables,
High SNR allows (causes ☹) us to be lazy.



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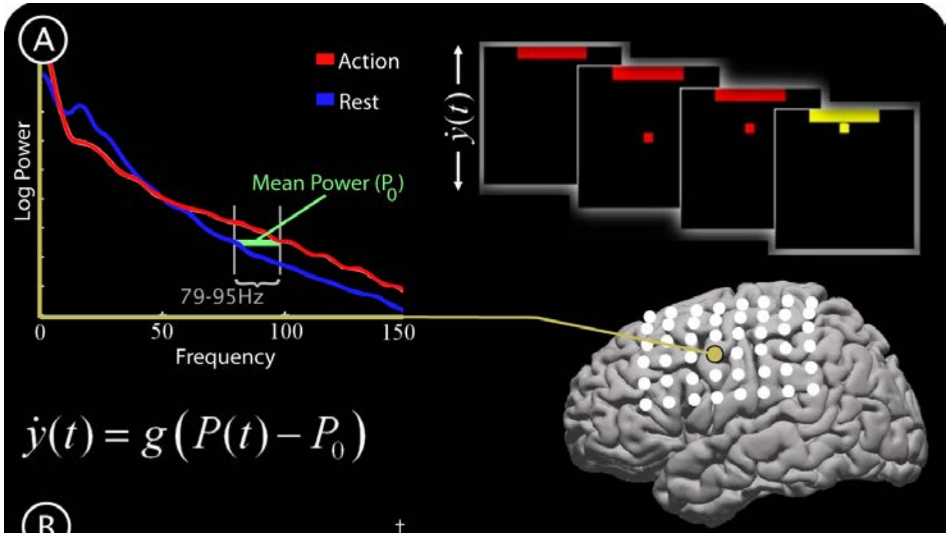
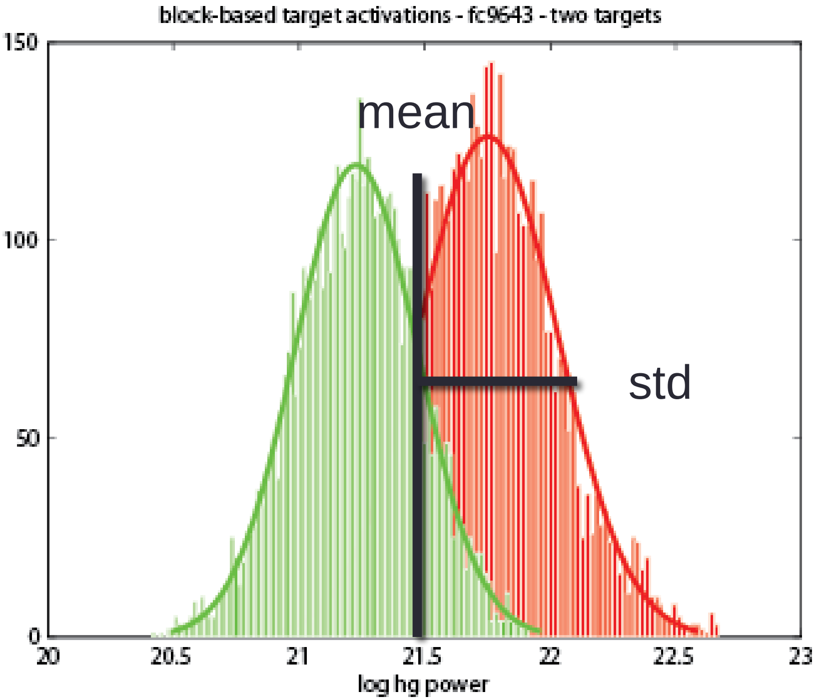
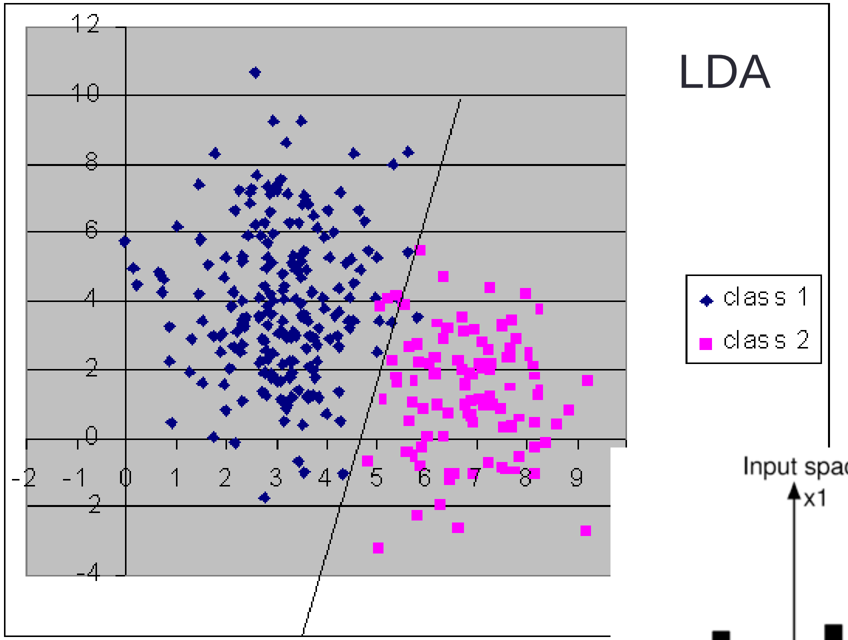




dy/dt = (x-mu) / std

Decoding, EEG

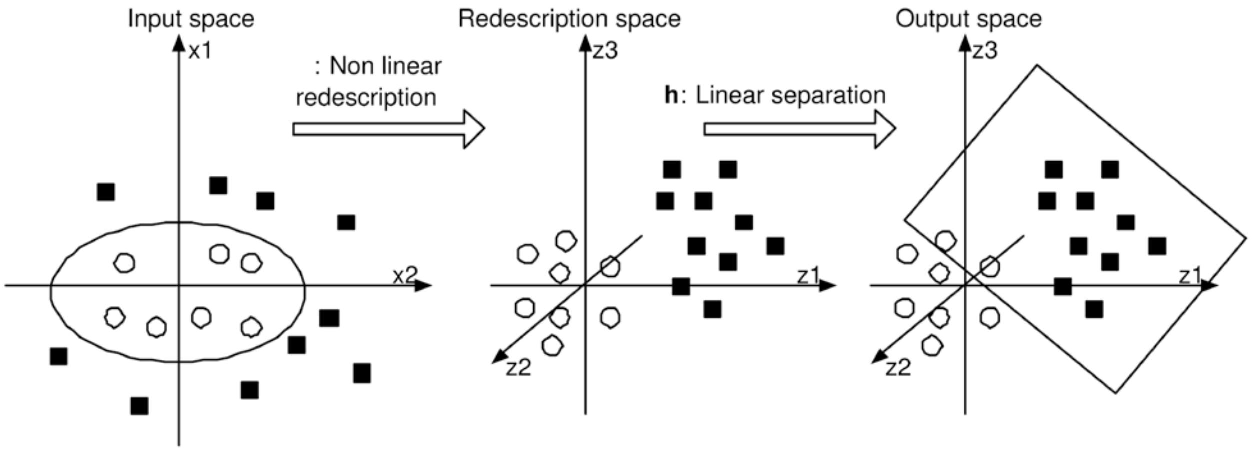
Much harder computational problem, because of low SNR Neural signal typically translated to discrete variable with pre-defined (and pre-trained) number of states



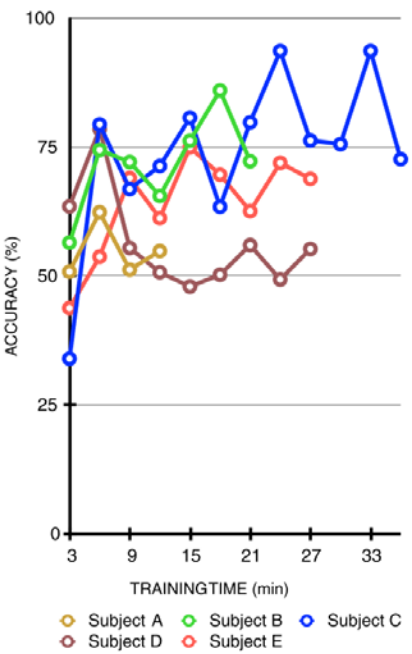
SVM, Naïve Bayes, Decision Trees, Random Forest, Neural Network, on and on…

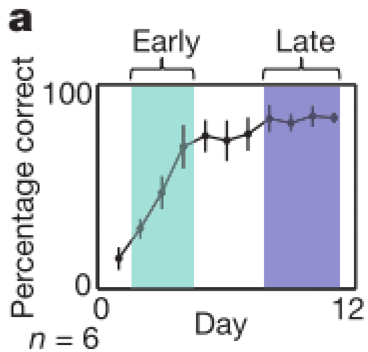
BCI competition

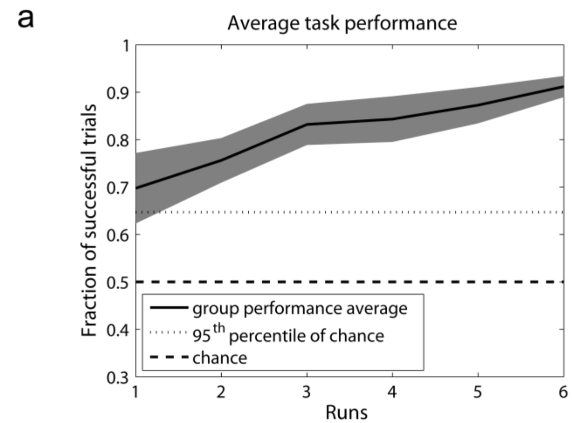
Non-linear transform + LDA

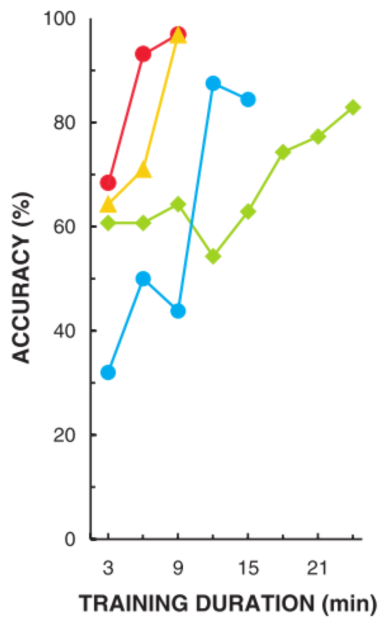


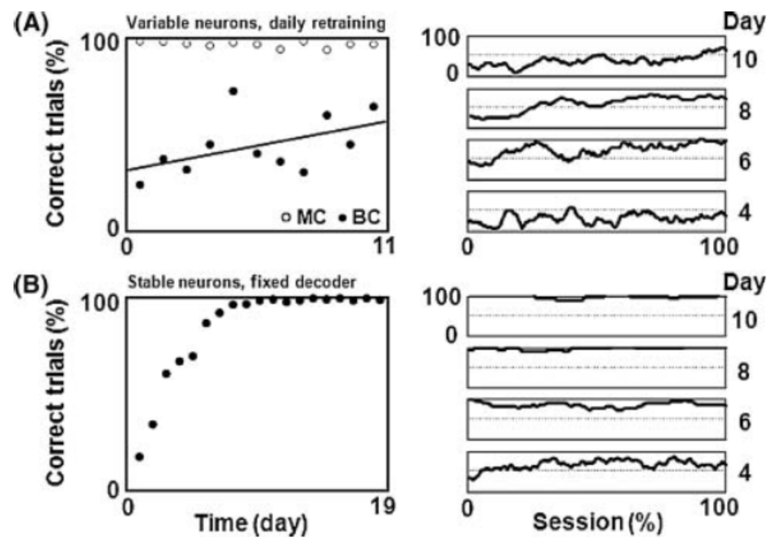
An Inherent Problem



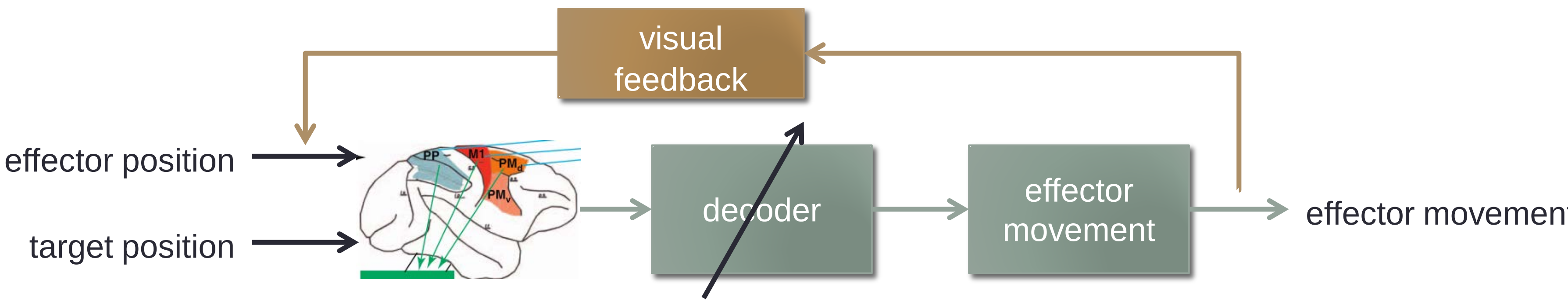


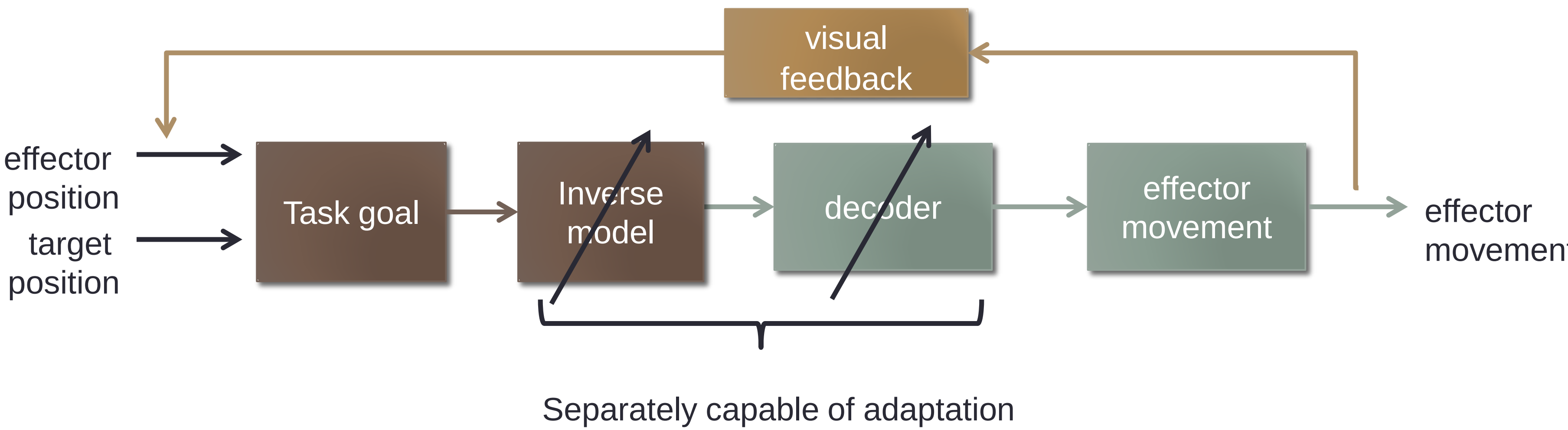






The Underlying Model





Closed-loop decoder adaptation