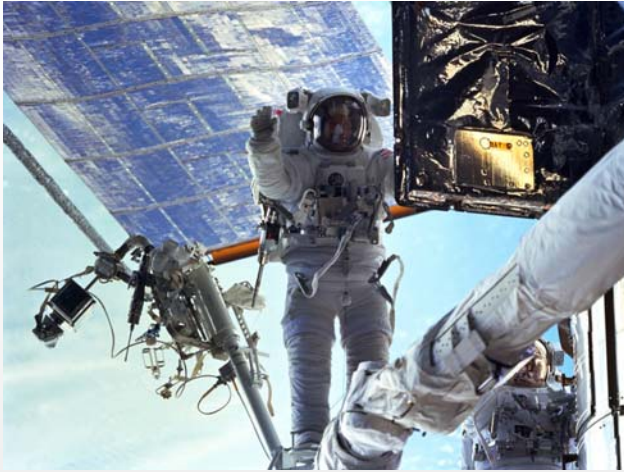


Brain-Computer Interfaces for 1-D and 2-D Cursor Control: Designs using Volitional Control of the EEG Spectrum or Steady-State Evoked Potentials



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Context and Relevance to NASA Missions



Problem

- Increasing mental and physical demands in long-duration human exploration
- Adverse and restricted environments, risk of fatigue, exhaustion, overload

Goals

- New interfaces for mobile or restricted environments
- Augmented interaction in normal environments
- Increased bandwidth / multi-tasking
- Quickening the interface
- Enhanced situational awareness
- Increased mission safety and reliability by early detection of adverse states and adaptive automation

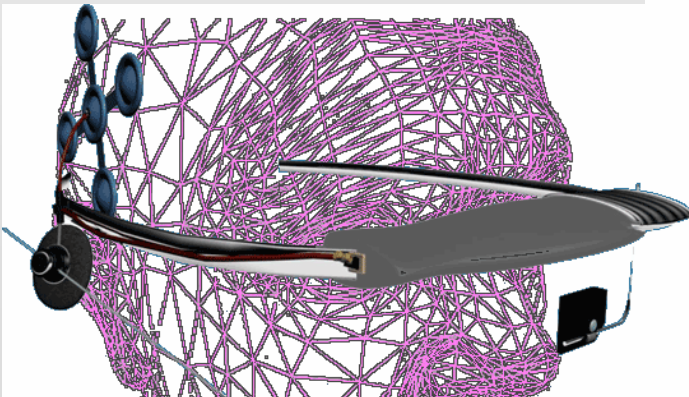
Context and Relevance to NASA Missions

Projects

- Voluntary control of EEG (mu-rhythm) for cursor control
- SSVEP-based BCI for hands-free control of displays (moving maps)
- Mental state estimation

Recent Advances

- Feature selection
- Classification algorithms
- On-line adaptation

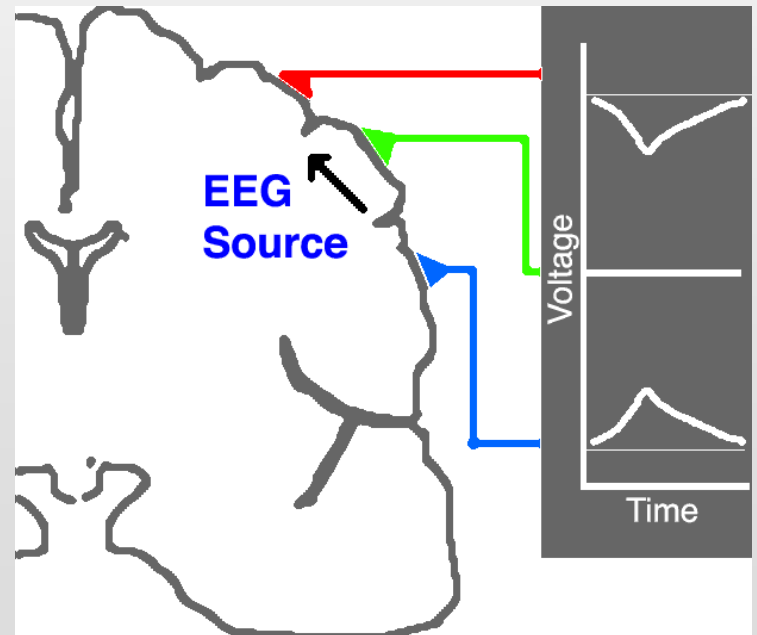
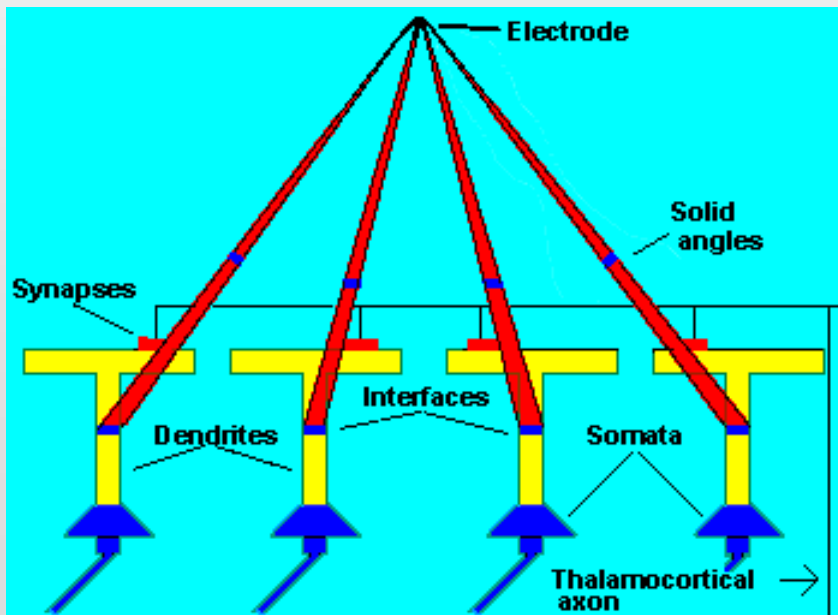
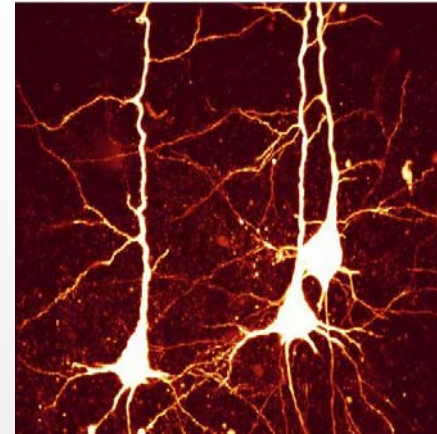
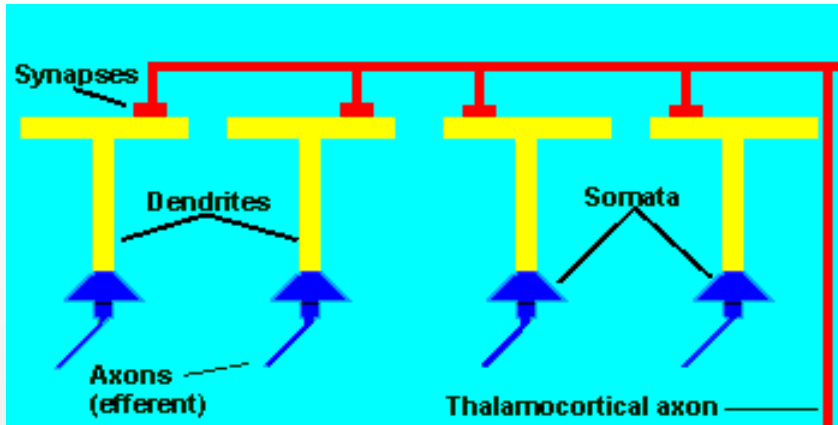


Challenges

- Artifact removal
- Training methods
- Contactless sensors

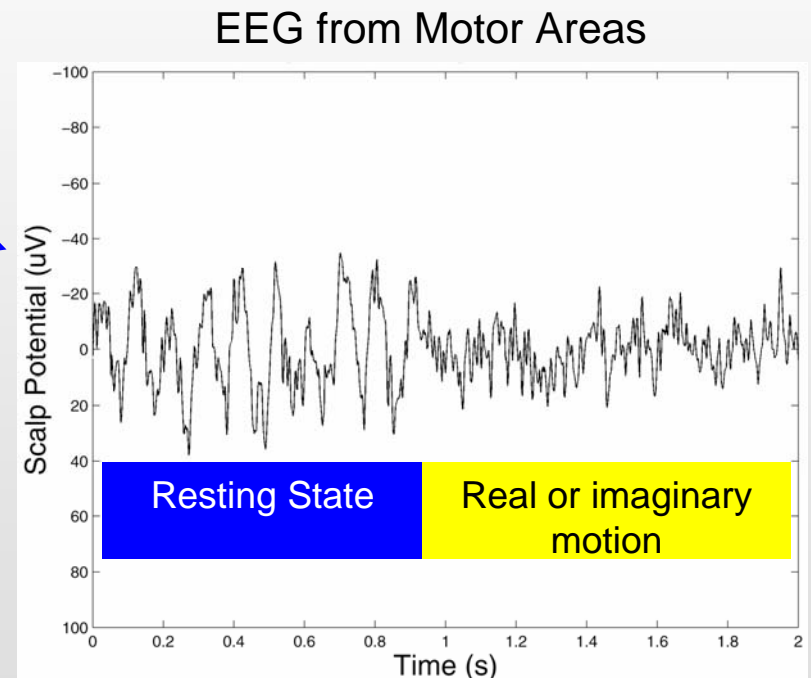
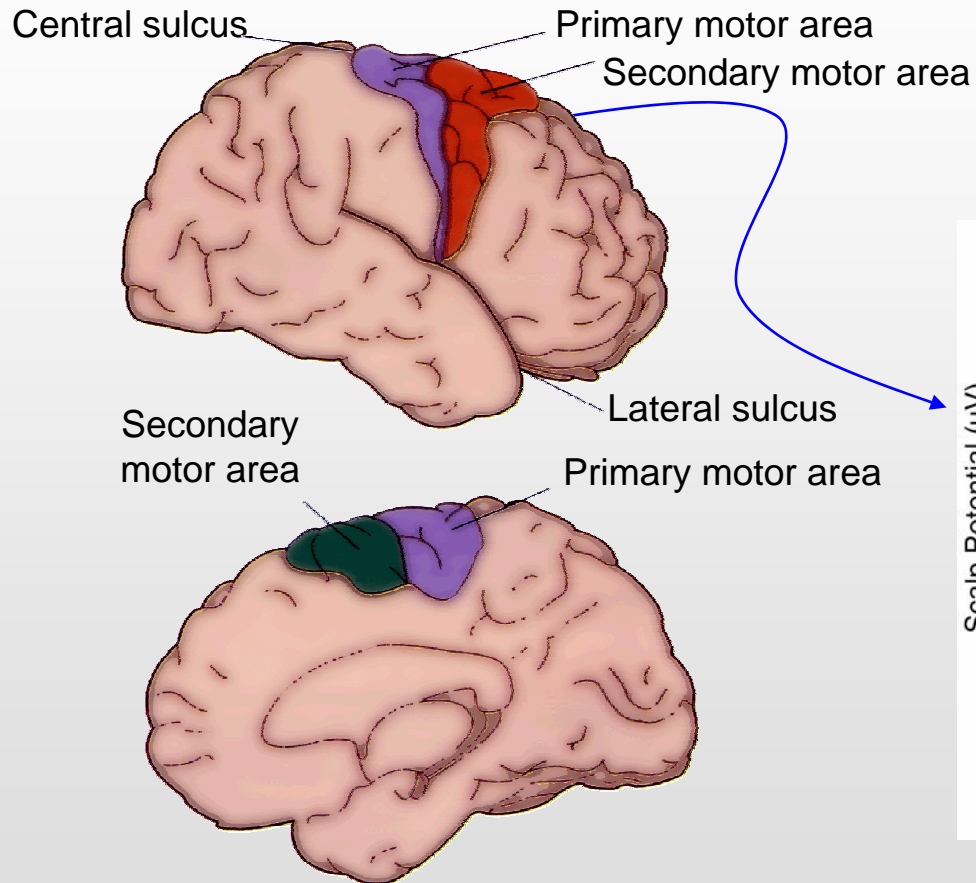
Electroencephalography 101

Basis of EEG



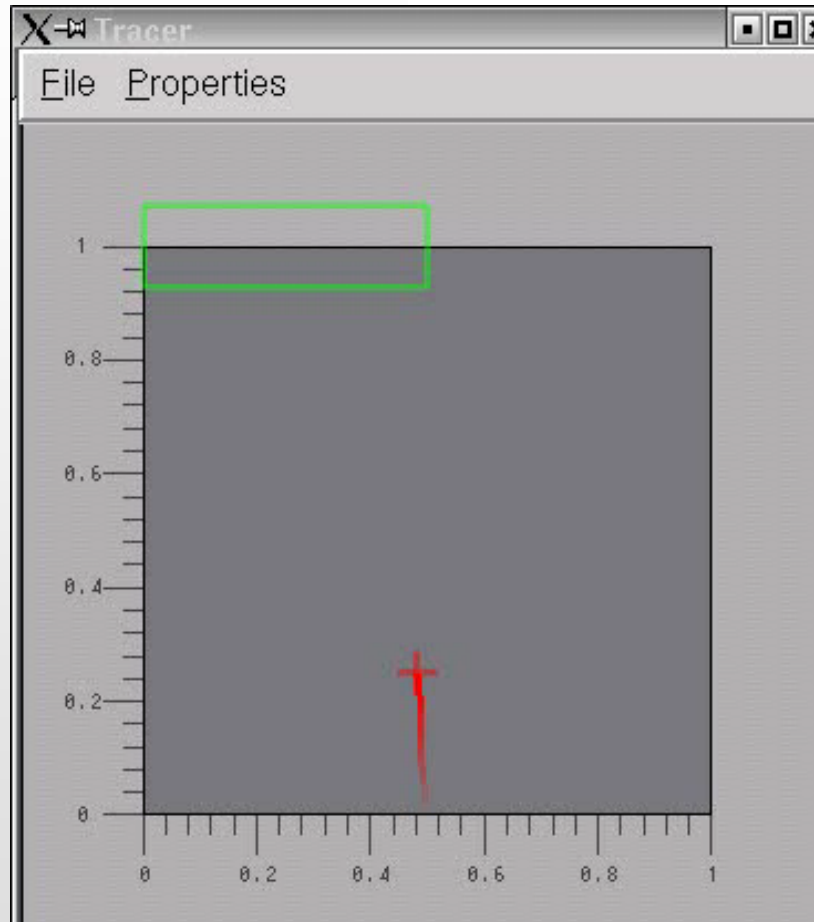
Biophysical Basis of Voluntary EEG Control

(Desynchronization of μ -rhythm)



(Adapted from Beatty, 1995)

Target Practice



PLS-based EEG Processing

- We regard the power spectral density of single EEG epochs of C channels and F spectral lines as a vector \mathbf{x} (M), with $M = C \times F$ dimensions.
- Each \mathbf{x}_i ($i = 1, 2, \dots, n$) is a row vector of a matrix of explanatory variables, \mathbf{X} ($n \times M$), with M variables and n observations.
- The n observations are the power spectral densities or PSDs of single EEG epochs from two classes, (e.g., experimental conditions, alert/fatigued, etc.).

PLS-based EEG Processing

- We regard the class membership of each EEG epoch as a matrix \mathbf{Y} ($n \times 1$) in which Class 1 is assigned the value 1 and Class 2 is assigned the value -1.
- PLS models the relationship between the explanatory variables and class membership by decomposing \mathbf{X} and \mathbf{Y} into the form

$$\begin{aligned}\mathbf{X} &= \mathbf{TP}^T + \mathbf{F} \\ \mathbf{Y} &= \mathbf{UQ}^T + \mathbf{G}\end{aligned}$$

- \mathbf{T} and \mathbf{U} are matrices of p extracted score vectors (components),
- \mathbf{P} and \mathbf{Q} are matrices of loadings
- \mathbf{F} and the $(n \times M)$ matrix \mathbf{G} are matrices of residuals.

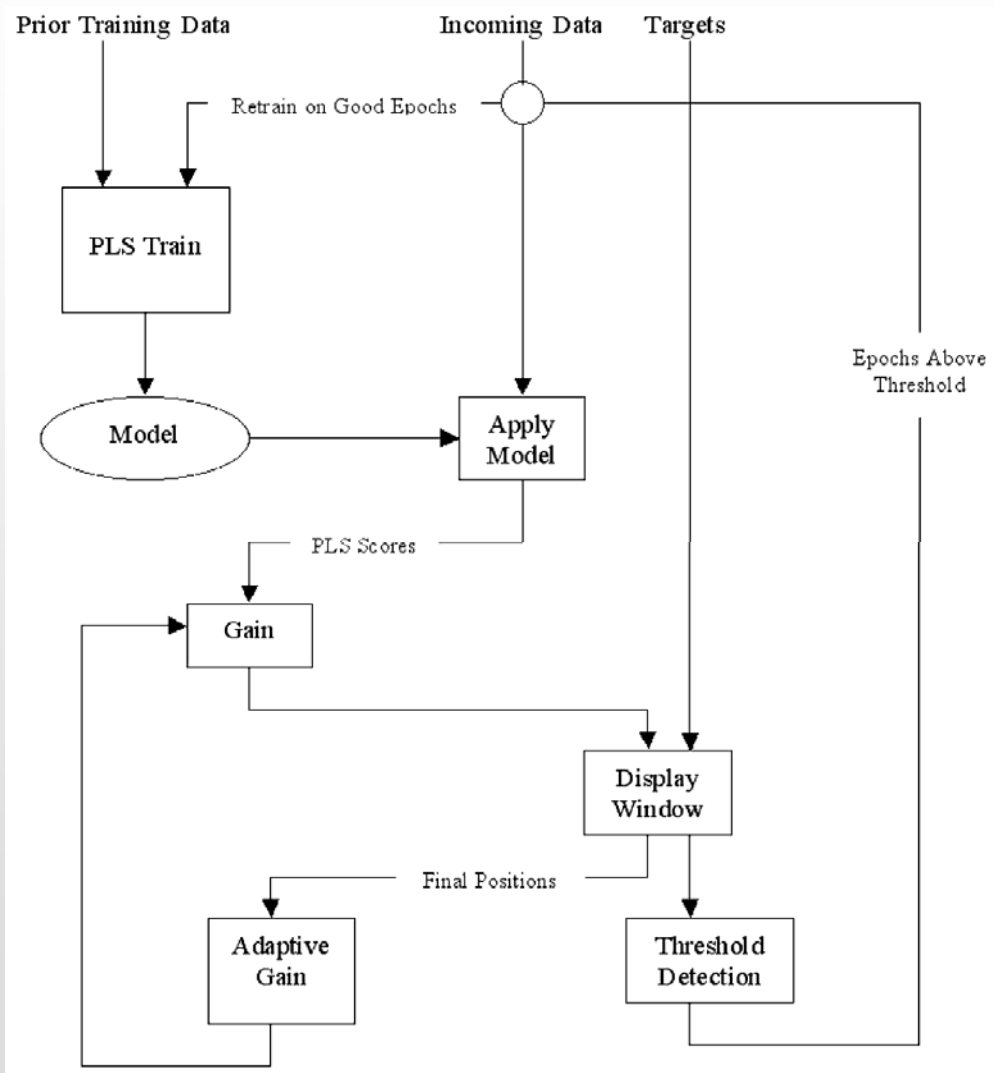
PLS-based EEG Processing

- PLS maximizes the covariance between the components of the explanatory variables and class membership.
- We use the nonlinear iterative partial least squares algorithm (NIPALS), which finds weight vectors \mathbf{w} , \mathbf{c} such that

$$\max_{|\mathbf{r}|=|\mathbf{s}|=1} [\text{cov}(\mathbf{X}\mathbf{r}, \mathbf{Y}\mathbf{s})]^2 = [\text{cov}(\mathbf{X}\mathbf{w}, \mathbf{Y}\mathbf{c})]^2 = [\text{cov}(\mathbf{t}, \mathbf{u})]^2$$

- $\text{cov}(\mathbf{t}, \mathbf{u}) = \mathbf{t}^T \mathbf{u} / n$ denotes the sample covariance between the score vectors \mathbf{t} and \mathbf{u} .
- Application of the weight vectors to normalized data produces component scores that serve as inputs to a classifier.
- We have tested both discretized linear regression (DLR) and support vector classifiers (SVC).

On-line PLS EEG Processor

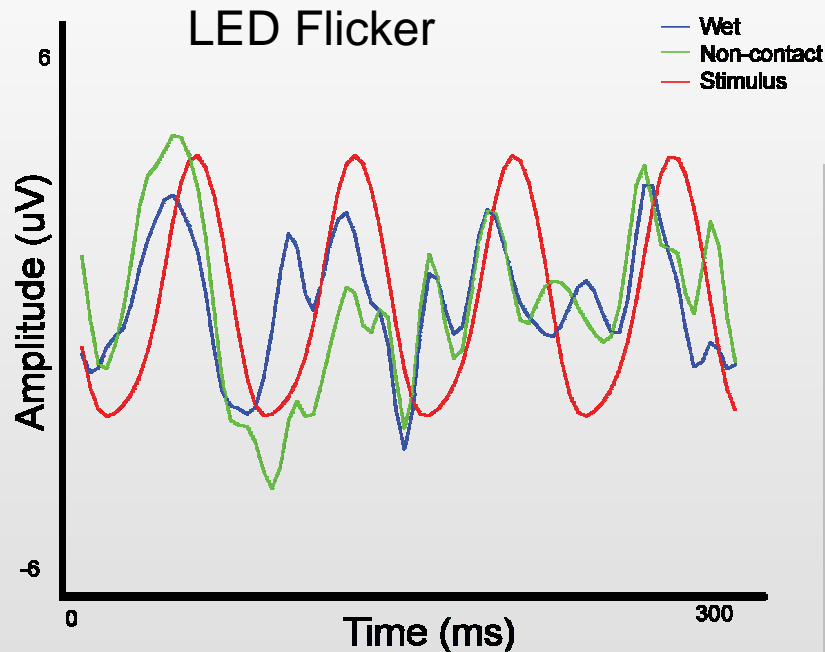


Control System for Target Practice

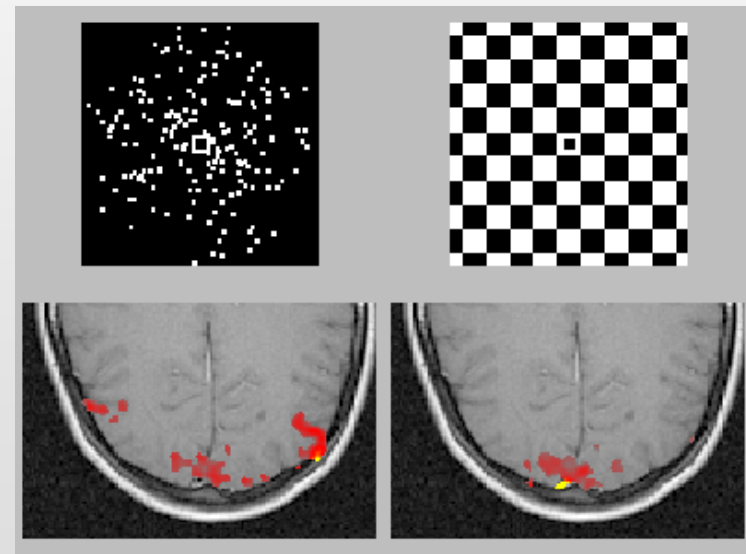
- Trial-by-trial classification (left, right)
 - 250 ms display update
- Dual adaptive controller design
 - Adaptive PLS pattern recognition
 - Adaptive gain control for motion

Biophysical Basis of Steady-State VEP

Repetitive patterned visual stimulation produces a frequency-following (or doubling) response in primary visual cortex, which is easily recorded by occipital EEG electrodes.



Checkerboard Flicker



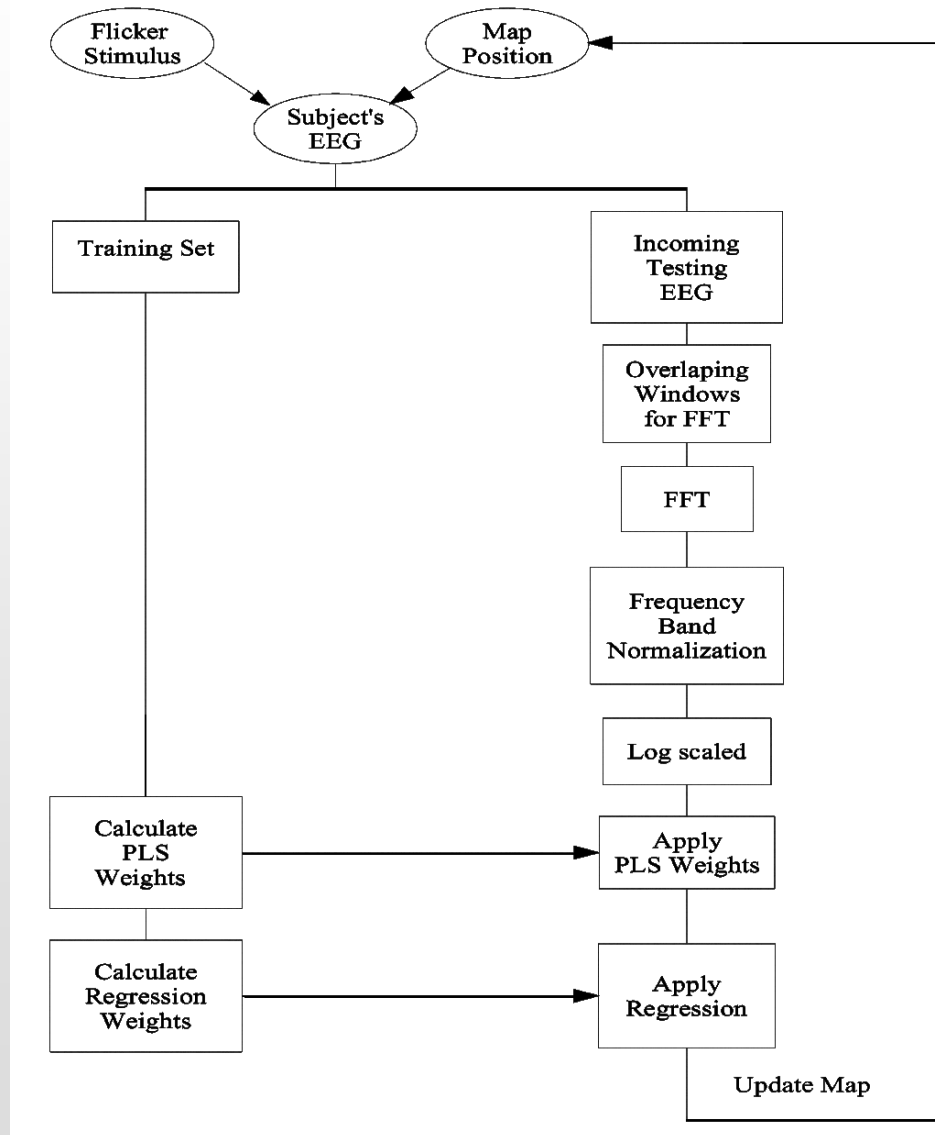
Demo from David Heeger's lab at NYU

<http://www.cns.nyu.edu/~david/fmri-demos/V1MTmovie.mpg>

SSVEP-based BCI



On-line PLS EEG Processor



Summary and Conclusion

Successful demonstrations of 1-D and 2-D control

- Voluntary control of EEG
- SSVEP based BCI
- On-line adaptive feature extraction/classification

Future applications

- Telerobotics
- Virtual or restricted environments
- Restricted environments
- Disabled personnel