UCSD

Principles and Applications of Brain-Computer Interfaces

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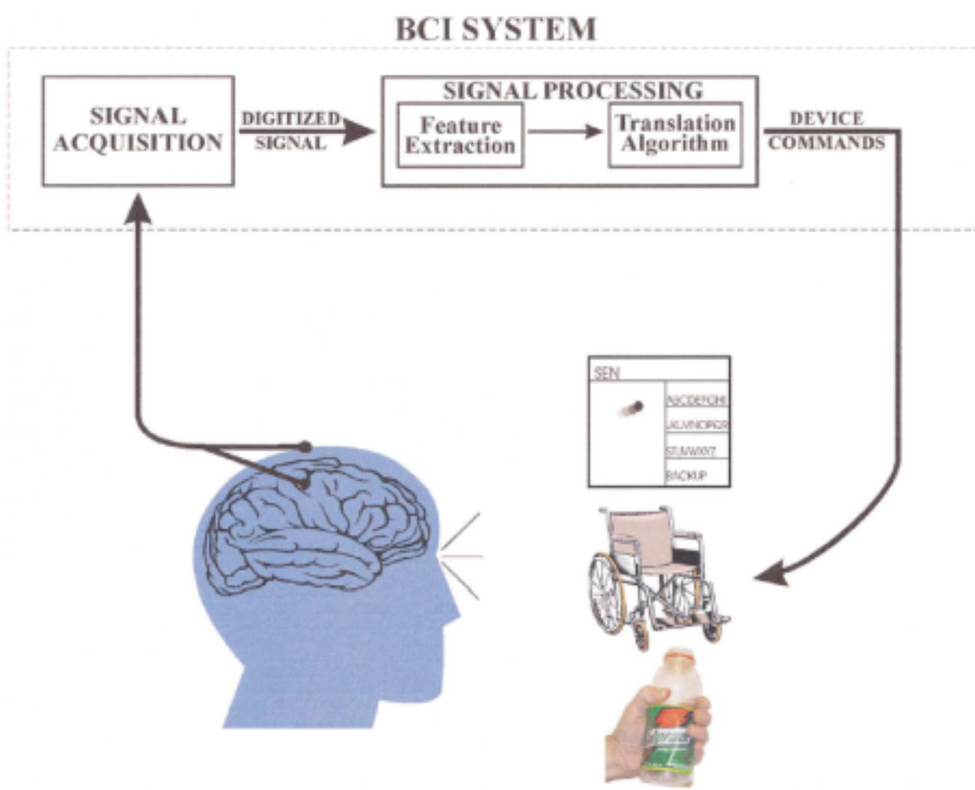
Outline

- Working definitions of BCIs
- Types of BCIs
- Bio-signals for BCIs
- Typical EEG features used in BCIs
- Available tools
- Major components in BCIs
- Evaluations of BCI performance
- Application areas and examples
- Challenges in BCIs

A Traditional Definition of a BCI

A **brain–computer interface** (**BCI**), sometimes called a **direct neural interface** or a **brain–machine interface**, is a direct communication pathway between a brain and an external device. BCIs are often aimed at assisting, augmenting or repairing human cognitive or sensory-motor functions.



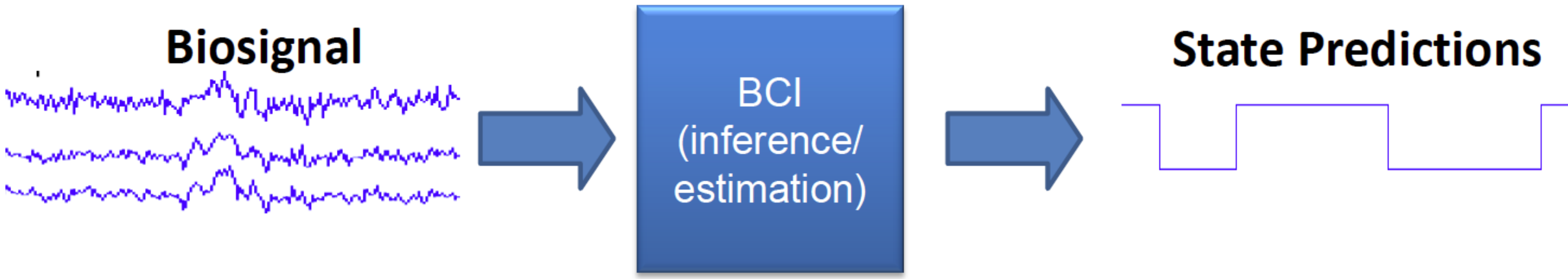
Wolpaw *et al.* 2002.

Criteria for BCIs

- **Direct:** The system must rely on direct measures of brain activity.
- **Real-time:** real-time refers to a maximum of a one minute delay between the user's formation of a relevant message or command and resulting feedback.
- **Feedback:** BCIs must present real-time feedback to the user. That is, the system must act on the user's intent so that the user can know whether s/he successfully conveyed the desired message or command.
- **Intentional:** The user must perform some voluntary, intentional, goal-directed mental activity each time s/he wishes to convey information. This criterion excludes all passive BCIs.

Our Working Definition of a BCI

A system which takes a biosignal measured from a person and predicts (in real time / on a single-trial basis) some abstract aspect of the person's neurological state, cognitive state, attention, or intention.



Types of BCIs

- **Active BCI (BMI):** a BCI derives its outputs from brain activity which is directly consciously controlled by the user, independently from external events, for controlling an application.
- **Reactive BCI:** a BCI derives its outputs fron brain activity arising in reaction to external stimulation, which is indirectly modulated by the users for controlling an application.
- ***Passive or Affective BCI (BMI)*** derives its outputs from spontaneous brain activity without the purpose of voluntary control.

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Bio-signals for BCIs

- EEG or MEG

BioSemi B.V.

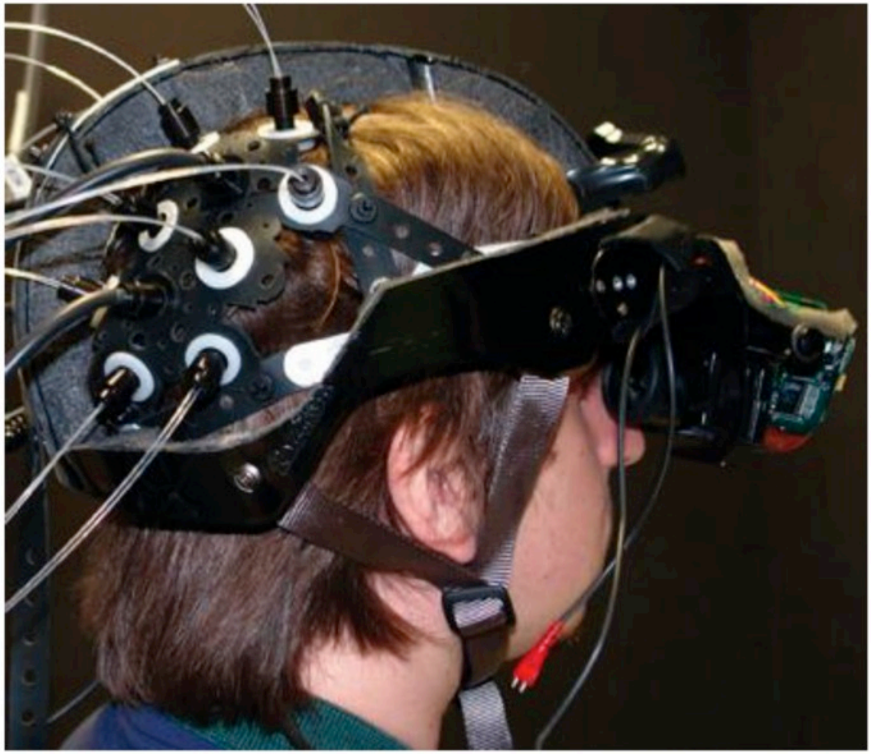
MINDO

Cognionics, Inc

NIMH

Bio-signals for BCIs

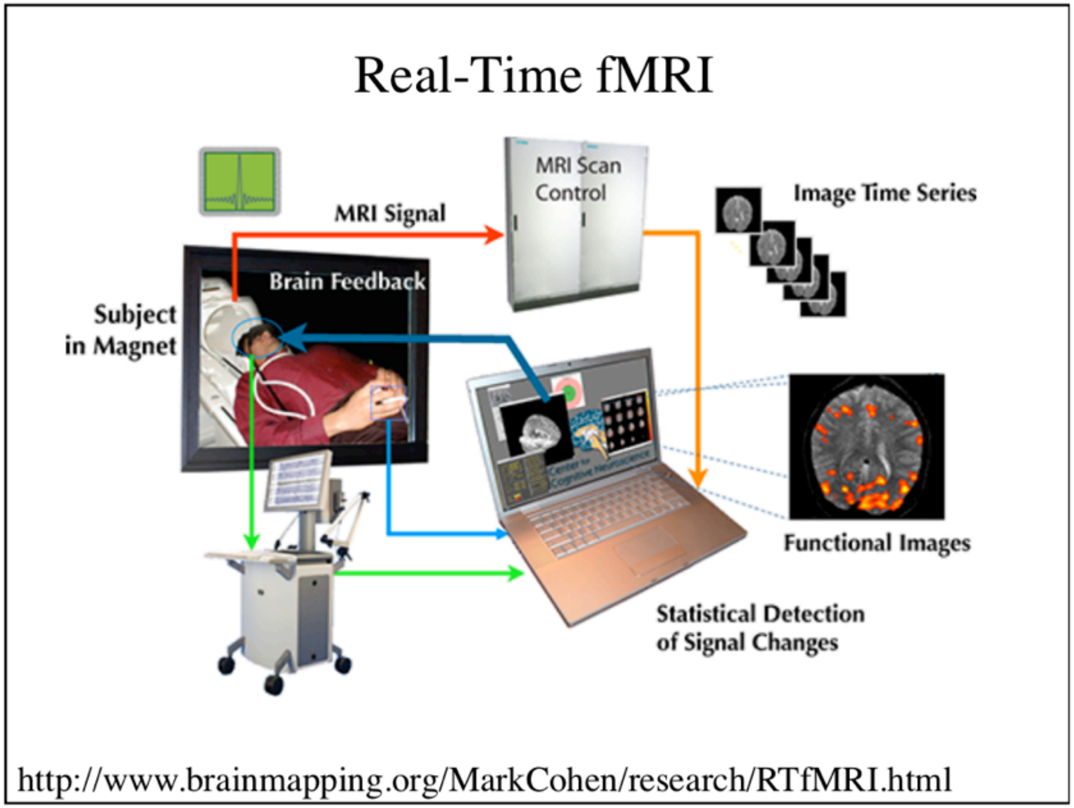
- Functional Near-Infrared Spectroscopy (fNIRS)



Seraglia et al., 2011

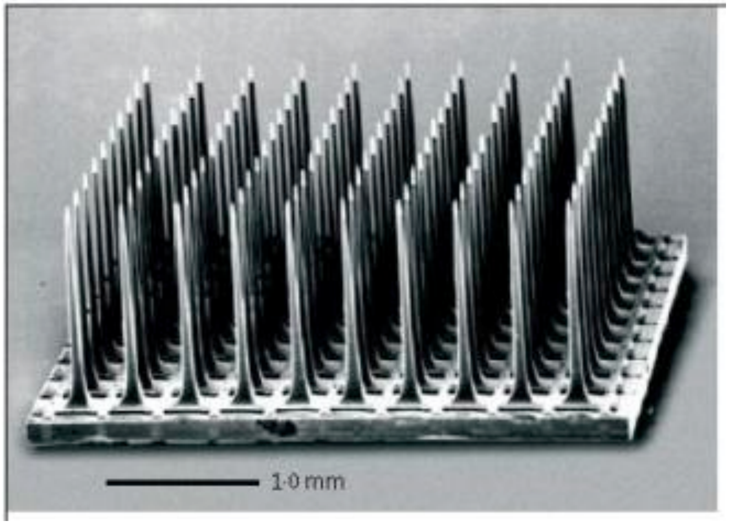
Bio-signals for BCIs

- fMRI

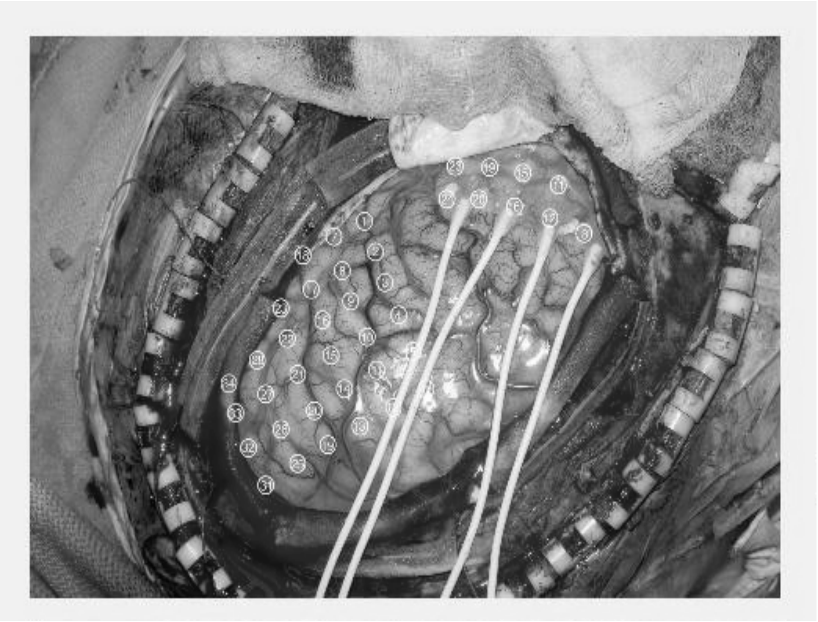


Invasive Bio-Signals for BCIs

- Microarrays, ECoG, Neurochips, etc.



Utah Electrode



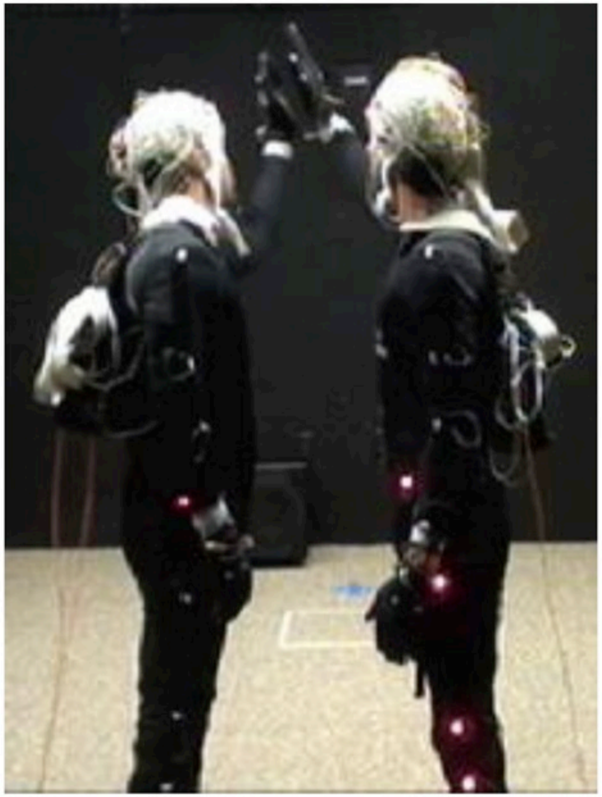
Non-Brain Signals for BCIs

- Electromyography (EMG), Electrocardiography (ECG), Electrooculography (EOG)

Microsoft, Inc

Non-Brain Signals for BCIs

- Motion capture, eye-tracking



SCCN MoBI Lab

SensoMotoric Instruments
(EEG: Emotiv)

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Typical EEG Features Used in BCIs

- P300 event-related potential BCI. (e.g. Donchin et al, *IEEE Trans Rehabil Eng* 2000.)
- Sensorimotor rhythm BCI.
- Steady-state Visual Evoked Potential.
- Time-frequency EEG features

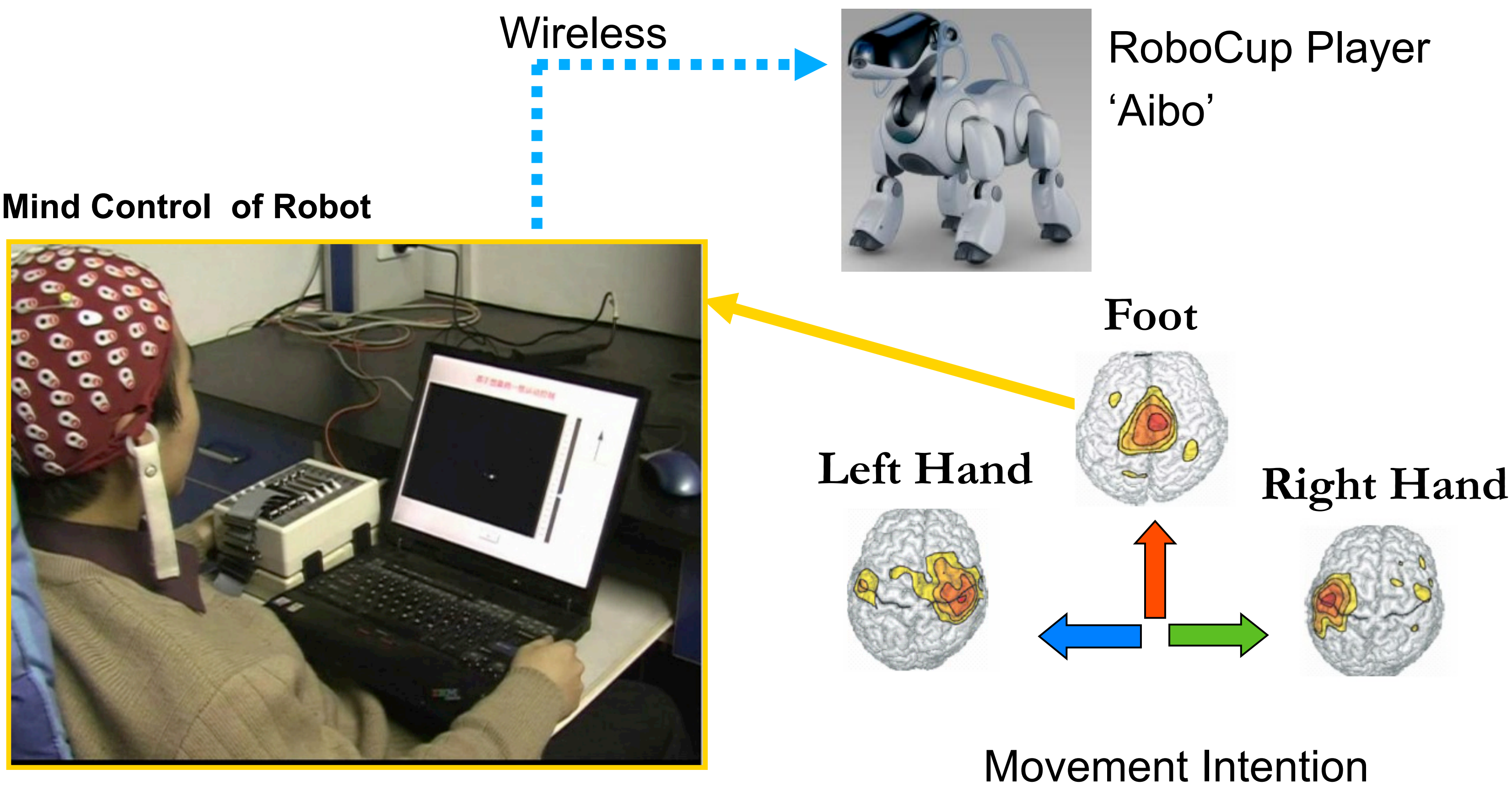
P300 BCIs

- Farwell and Donchin 1988
- P300 Speller

Figure 1. Example of display used in Donchin's P300-based speller paradigm.

Sensorimotor Rhythm BCI

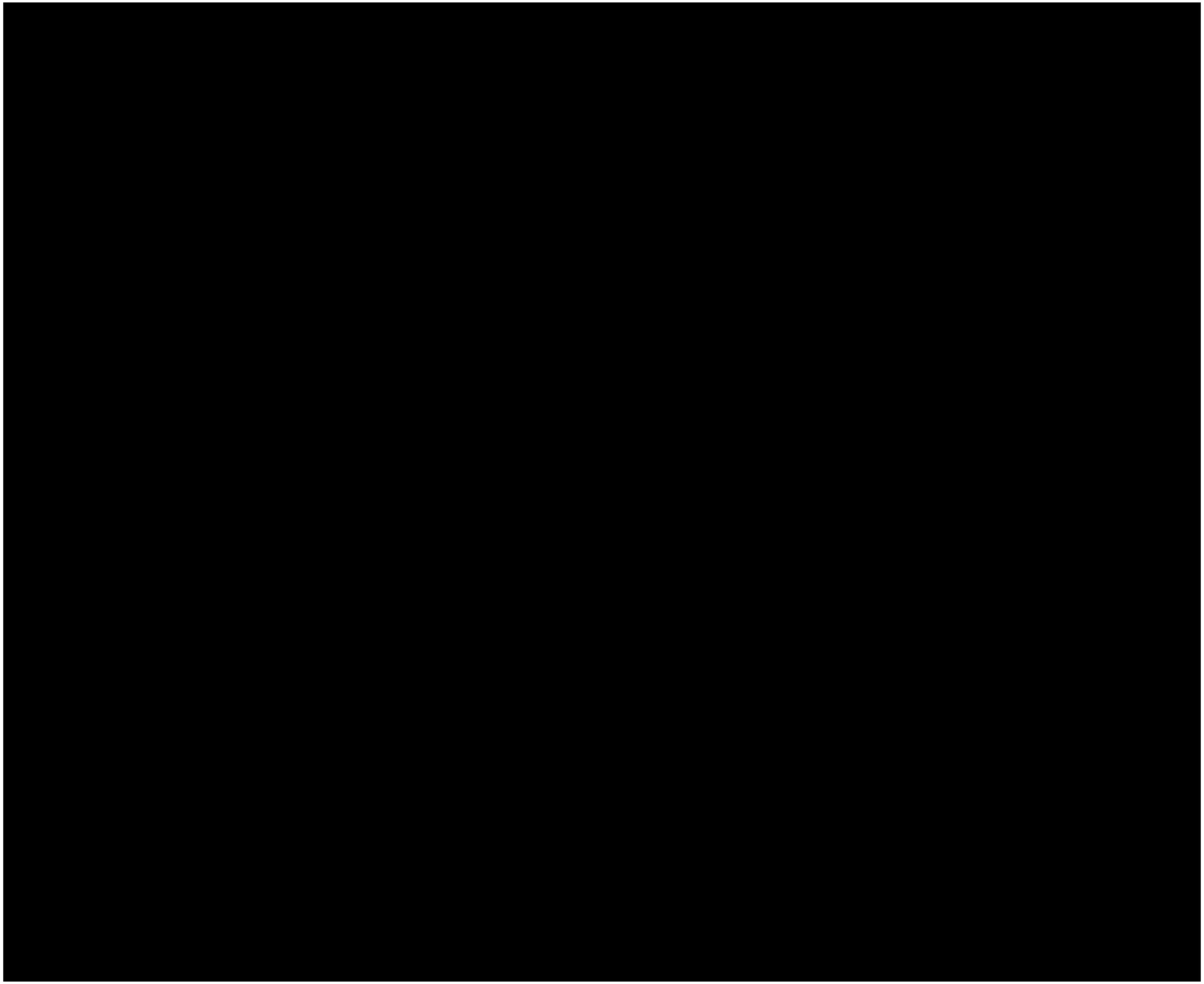
- Motor imagery BCI



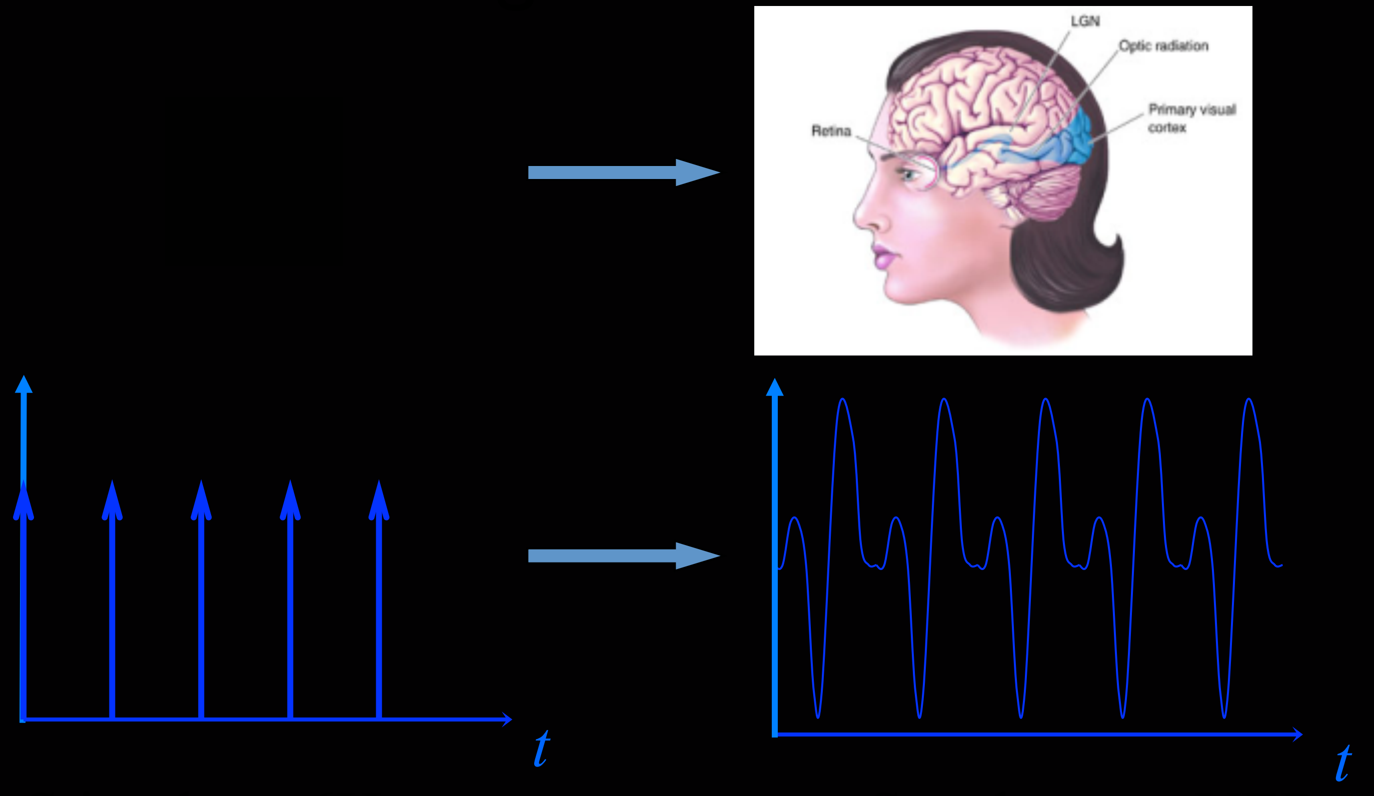
Wang et al., NE Workshop 11, Hsinchu, Taiwan

Mu BCIs

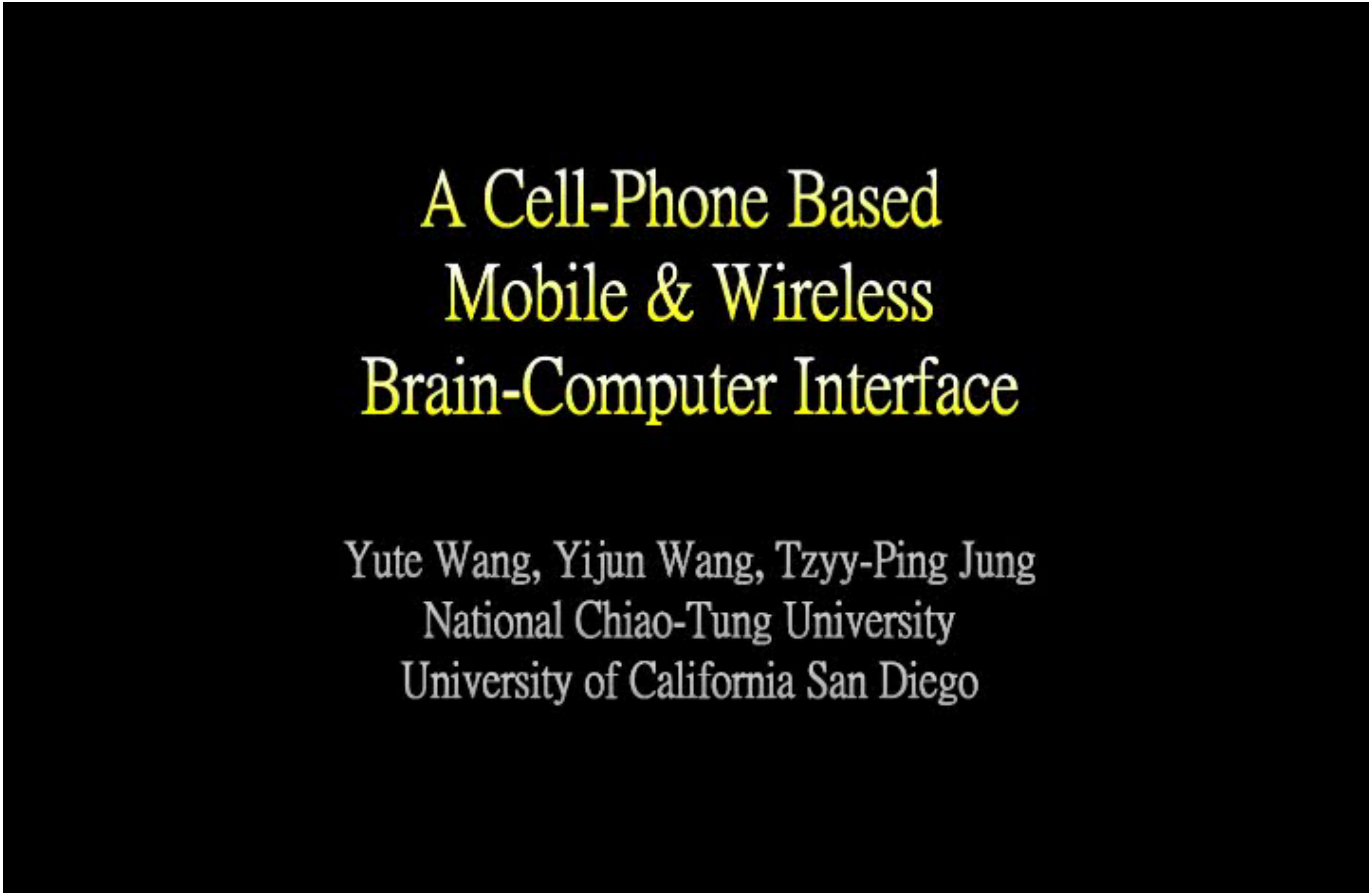
Mu BCIs



Reactive (SSVEP) BCIs



SSVEP BCIs


A Cell-Phone Based
Mobile & Wireless
Brain-Computer Interface
Yute Wang, Yijun Wang, Tzyy-Ping Jung
National Chiao-Tung University
University of California San Diego

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BioSig

- Developed at TU Graz since at least 2002
- One of the oldest open-source BCI toolboxes, for MATLAB/Octave (cross-platform)
- *Large amount of functionality* from statistics and time-series analysis: Adaptive Autoregression (AAR), Blind Source Separation (BSS), Common Spatial Patterns (CSP), Classifiers (LDA, SVMs, …), Cross-Validation
- *Offline analysis only* -- no real-time hardware or computation support
- *Not easy to use* (no GUI, fairly complicated code, not very modular…)

From C. Kothe, BCILAB Workshop Tutorials

BCI2000

- Developed at Wadsworth Center since 2000
- *Large, modularized C++ system*, primarily aimed at real-time acquisition, signal processing, stimulus presentation, experiment control, deployment; robust, "enterprise-grade" implementation (though Windows only)
- Supports a *wide range of acquisition hardware* (currently 19 systems)
- Solid documentation, workshops, book, big community
- *Lack of advanced signal processing and machine learning* algorithms (tough extensions and in-house versions available)

From C. Kothe, BCILAB Workshop Tutorials

OpenViBE

- Developed at INRIA, relatively young project
- Implemented in modular C++, focusing on *visual programming and dataflow programming*
- *Very user-friendly design, interface and documentation*
- Focus on basic signal processing building blocks, weaker support for complex information flows (machine learning, adaptive signal processing, …)
- Relatively hard to extend due to complex framework
- Supports a broad range of acquisition hardware (15 systems), runs on Windows and Linux

From C. Kothe, BCILAB Workshop Tutorials

g.BSanalyze

- Commercial System developed by g.Tec
- MATLAB/Simulink-based framework
- Broad collection of turnkey algorithms, evaluation methods, etc.
- Extensive, high-quality graphical user interface
- Primarily supporting in-house amplifiers

From C. Kothe, BCILAB Workshop Tutorials

BCILAB

- Developed since 2010 at Swartz Center for Computational Neuroscience, UCSD (precursors dating back to 2006)
- MATLAB-based, cross-platform, offline and online analysis; stand-alone versions available
- *Largest collection of BCI algorithms* from signal processing, machine learning, etc.
- Relatively little native support for acquisition systems (5), but can tie into real-time experimentation frameworks (BCI2000, LSL)

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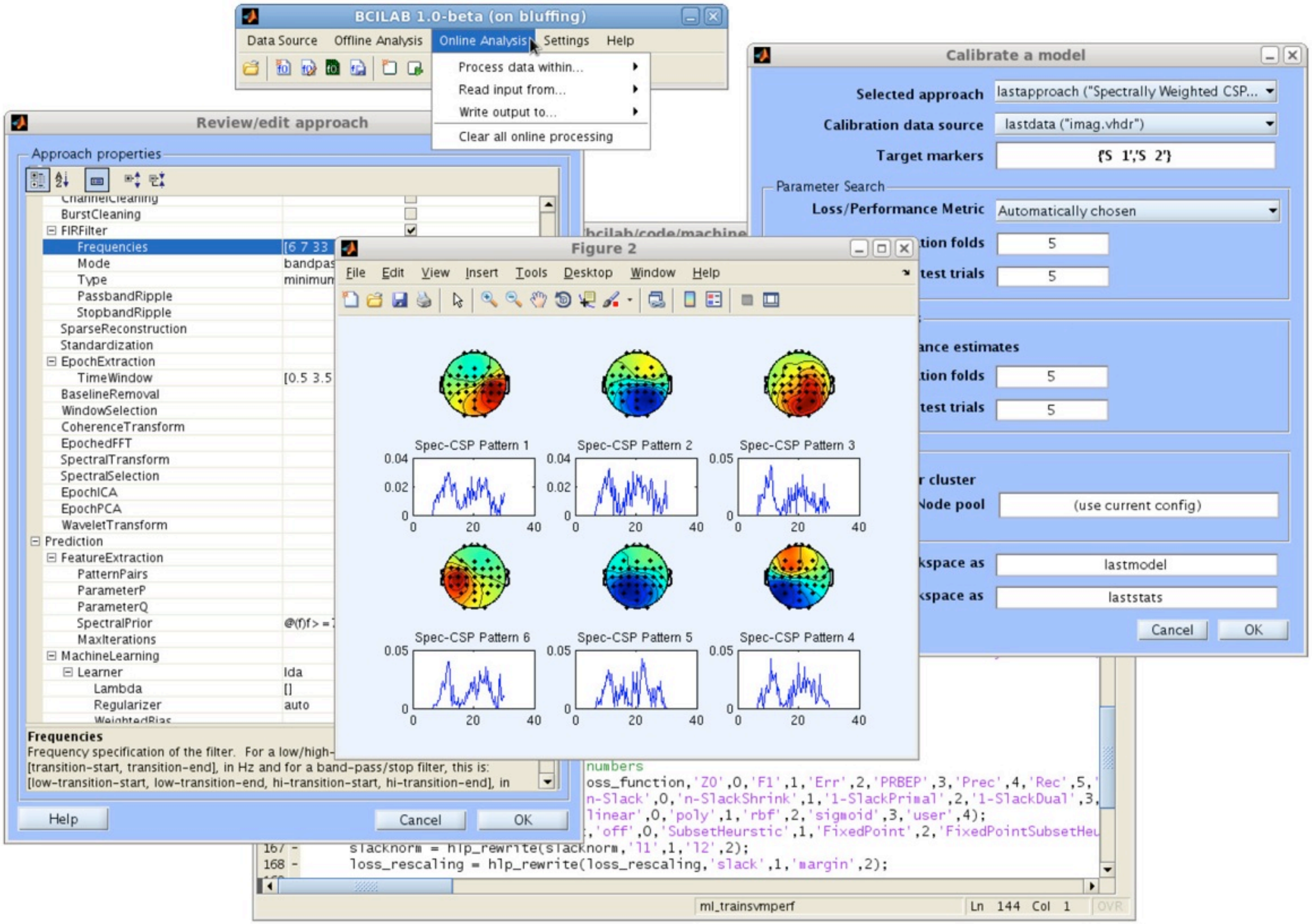
BCILAB Sample GUI



http://sccn.ucsd.edu/wiki/BCILAB

ftp://sccn.ucsd.edu/pub/bcilab

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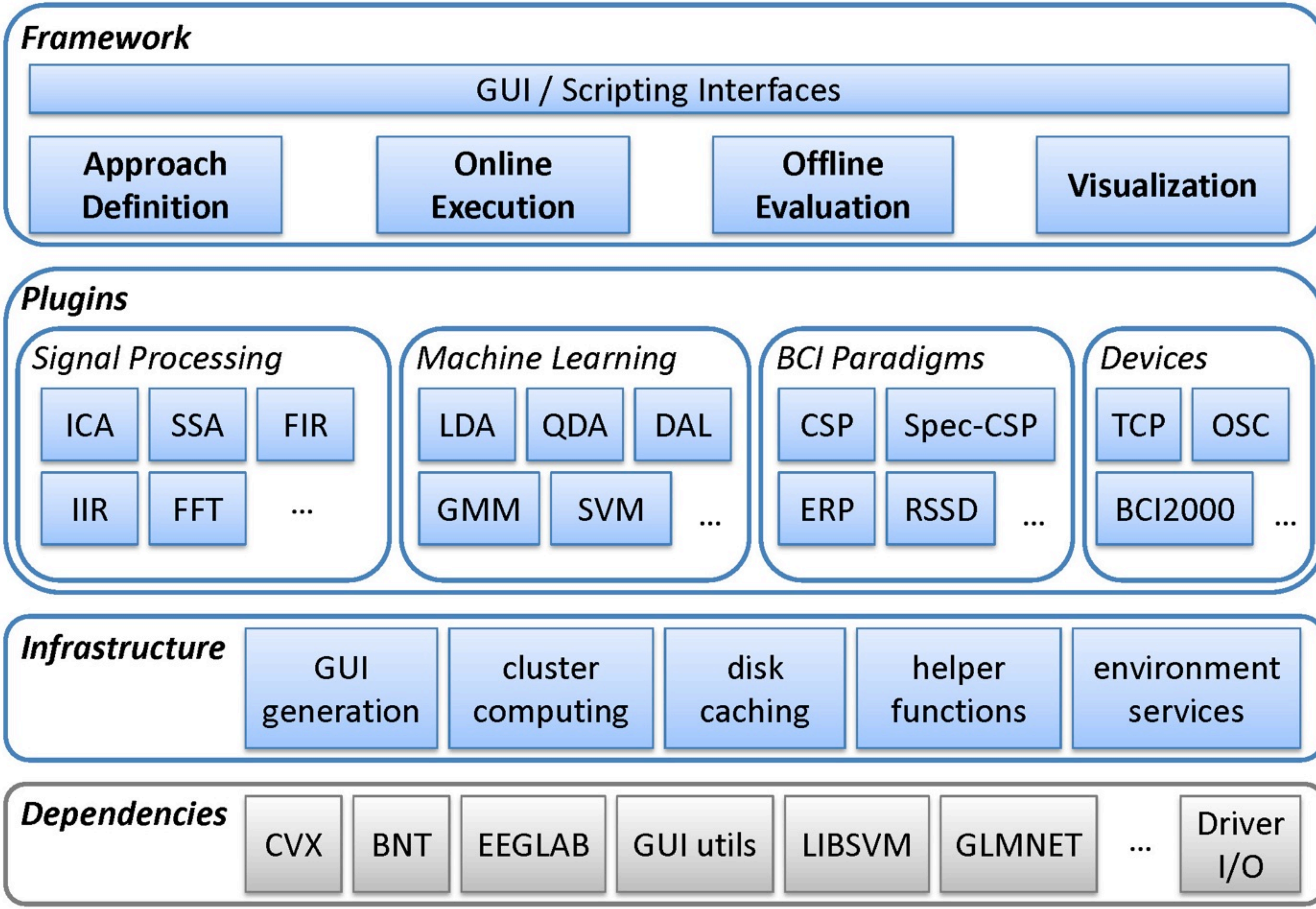
Toolbox Organization



Other Packages

- **xBCI:** New C++ framework focused on online operation, GUI-centric, cross-platform
- **BF++**: Mature BCI framework (developed since 2000), however not very well known – mostly for offline analysis & modeling with UML and XML
- **TOBI:** Protocol suite for BCI interoperability and data acquisition
- **PyFF:** Python-based BCI stimulus presentation system
- **BBCI:** In-house MATLAB-based system developed at TU Berlin; very comprehensive, potentially for licensing
- **BCI++:** Relatively new C++ system, focused on human-computer interaction and virtual reality (still growing)

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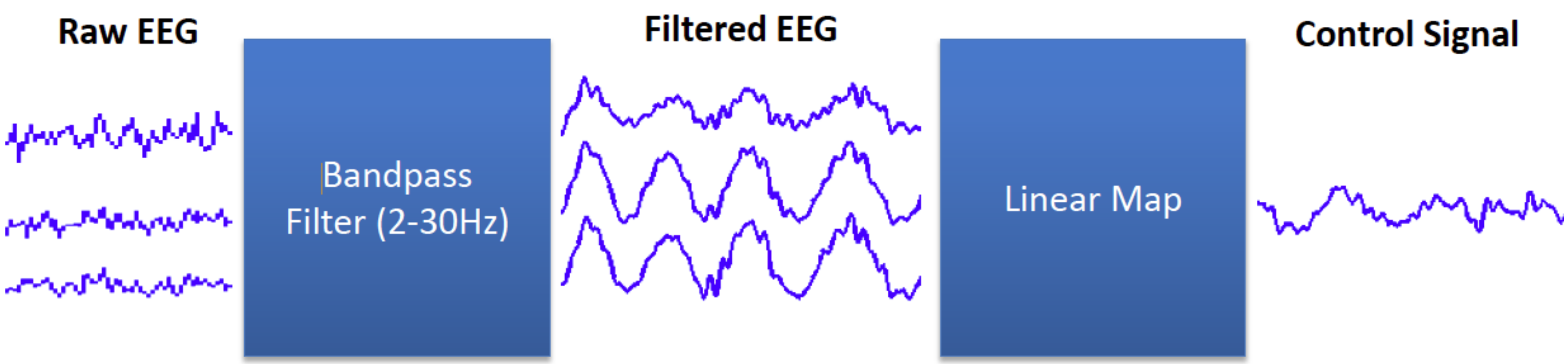
Major Components of a BCI

1. **Signal processing**: transforms one signal to another
   - From the point of view of Signal Processing, a BCI transduces the input signal $x(n)$ (for example EEG) into a control signal $y(n)$
   - BCI components can be conveniently described as filters.
   - Relevant filter classes: Spatial Filters, Temporal Filters, Spectral Filters, Spatio-Temporal Filters, etc.



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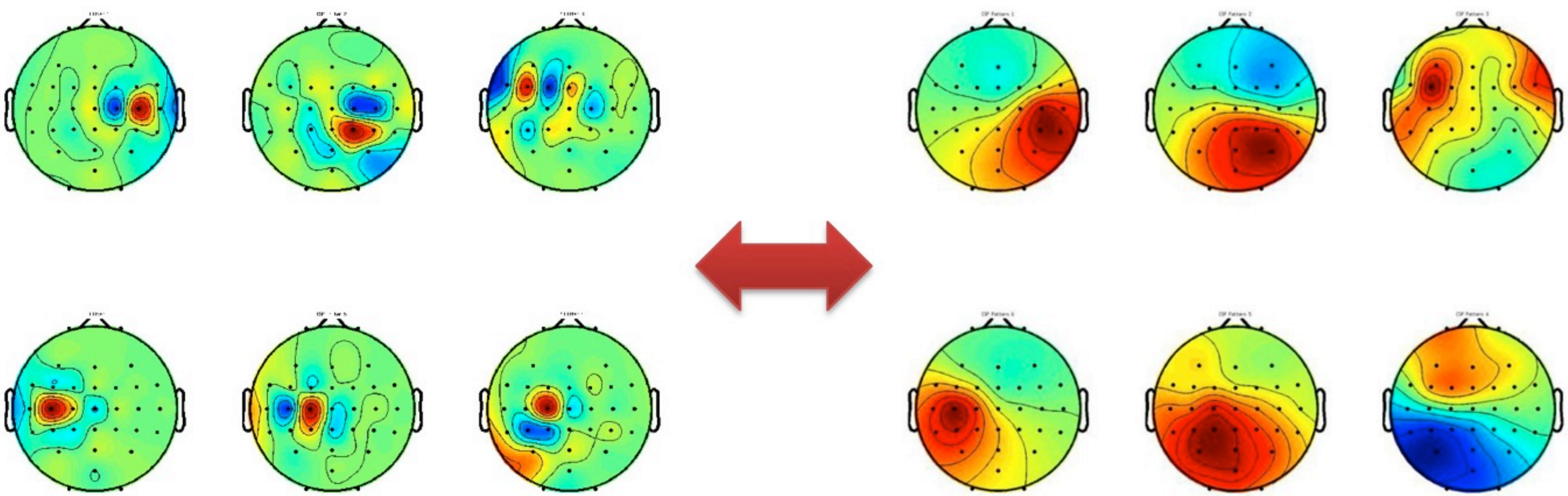
Swartz Center for Computational Neuroscience

Spatial Filters vs. Forward Projections

- Spatial filters are *not* the same as forward projection maps of some source signal – they are the inverse operation



$S(n) = \boldsymbol{W}X(n)$

$\mathrm{X}(n) = \boldsymbol{W}^{-1}S(n)$

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Temporal Filters

- Transform a multi-channel signal $X(n)$ such that each channel $y_i(n)$ in $Y(n)$ depends only on the channel $x_i(n)$
- They are conceptually orthogonal to spatial filters
- Examples include time windowing, wavelet transform, etc.
- Special case: Spectral filters

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Example Temporal Filters

- **Moving Average:**

$$\mathcal{T} \;:=\; y_i(n) \;=\; \frac{1}{m-1}\sum_{k=0}^{m} x_i\,(n-k)$$

  - Effectively a smoothing (low-pass) operator
  - In fact a simple example of a spectral filter

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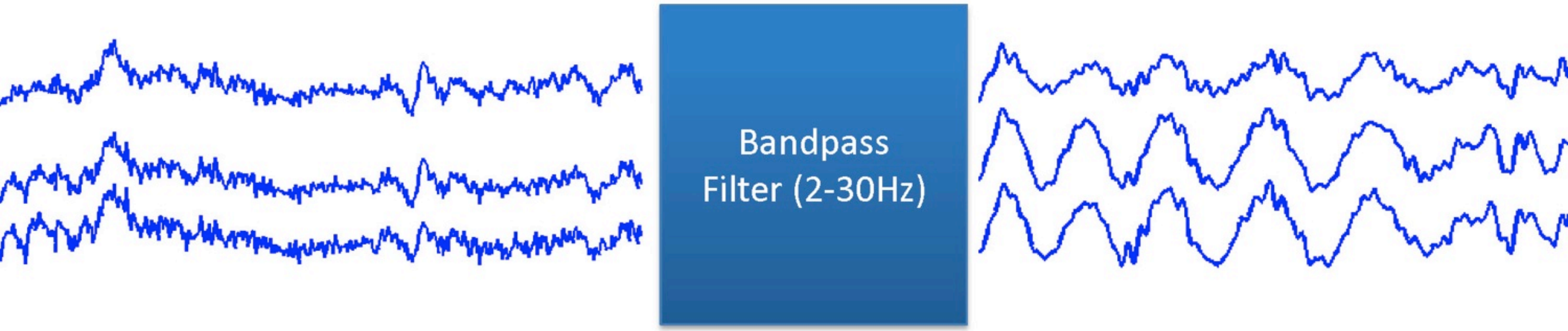
Spectral Filters

- Examples include: High-pass, Low-pass, Band-pass filters, Notch filters
- Their main utility in BCIs is to isolate oscillations or ERPs of interest



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Major Components of a BCI

2. **Feature Extraction**:

Off-the-shelf machine learning methods often do not work very well when applied to raw signal segments of the calibration recording

- too high-dimensional (too many parameters to fit)
- too complex structure to be captured (too much modeling freedom, requires domain-specific assumptions)

Typical Solution: Introduce additional mapping (called "feature extraction") from raw signal segments onto feature vectors which extracts the key features of a raw observations.

- output is usually of lower dimensionality
- hopefully statistically "better" distributed (easier to handle for machine learning).

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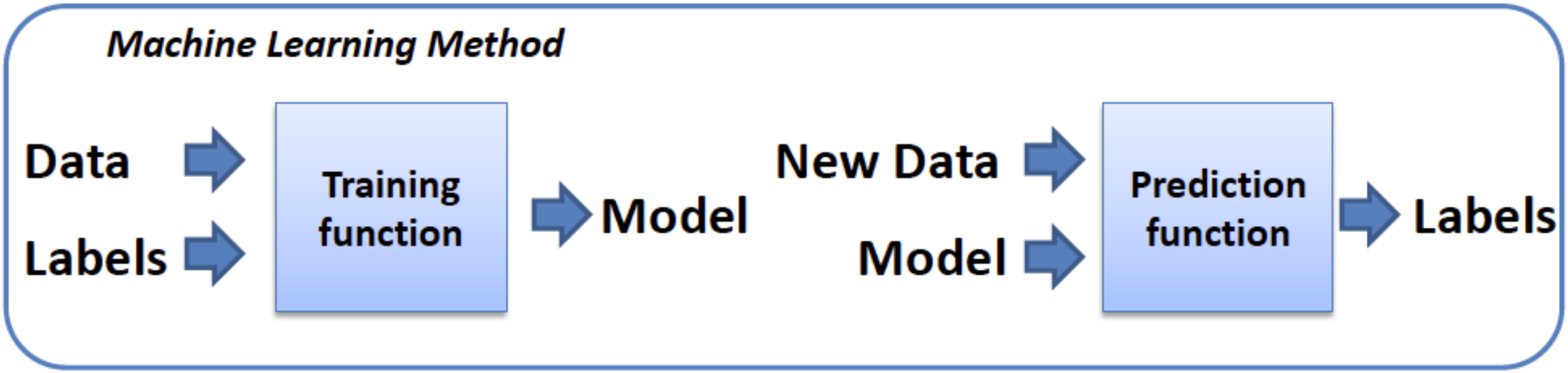
Major Components of a BCI

3. Machine Learning

Most methods conform to a common framework of a training function and a prediction function



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Types of Machine-learning Algorithms

- **Supervised Learning:** given a set of (input,output) pairs as training data, learn a parametric (or "non-parametric") model M that encodes the mapping from input to output
- **Unsupervised Learning:** given a set of training examples, learn the structure in the input space (e.g. clusters, manifolds, probability density)
- **Semi-Supervised Learning:** Some training examples have labels, others do not

Example Calibration Problem

- **Task:** A person is presented with a sequence of 300 images (one ever 2 seconds). Half of the images are exciting, the other half are not. One channel of EEG (at Cz location) is recorded.
- **Question:** How to design a BCI that can determine whether a person is shown an exciting or a non-exciting image?
- **Approach:** For each trial k, cut out an epoch $\mathbf{X}_k$ of 1s length, extract a short vector of features $\mathbf{f}_k$, and assign a label y_k in {E,NE}. Use machine learning to find an optimal statistical mapping from $\mathbf{f}_k$ onto y_k.

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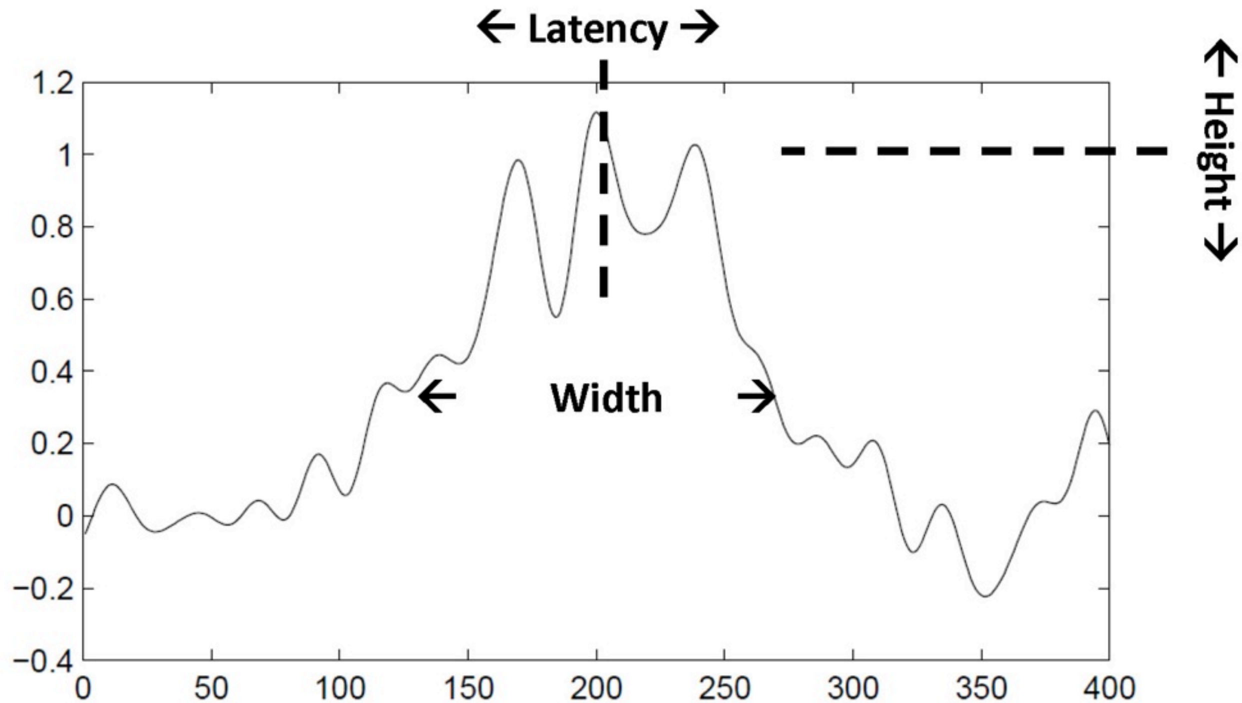
Extracting Features of a Peak

- A supposed characteristic peak in a time window (relative to an event) could be characterized by three parameters:



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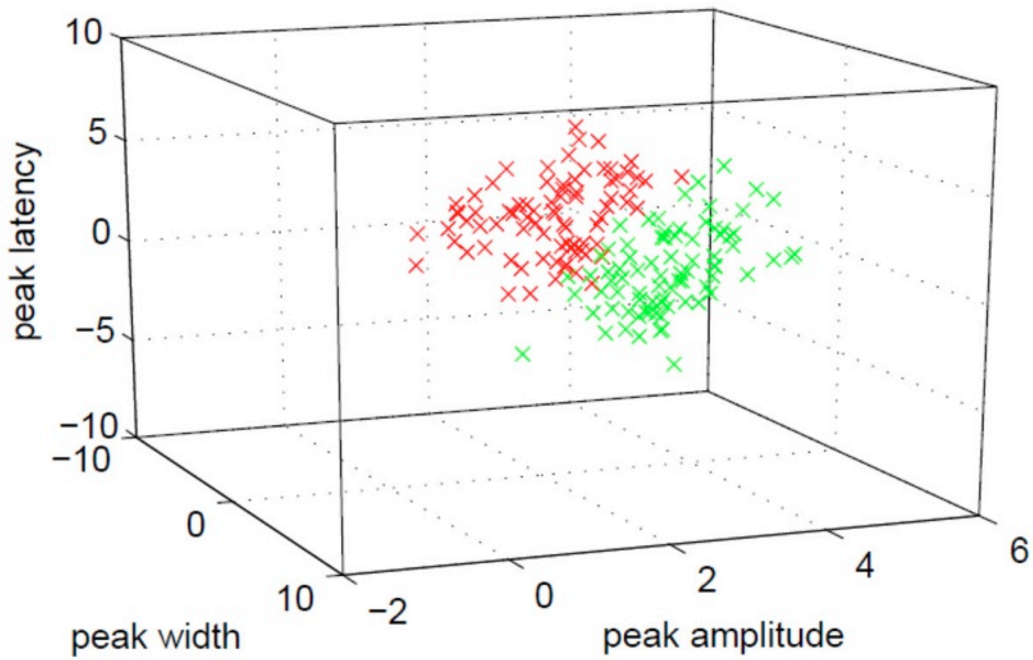
Resulting Feature Space

- Plotting the 3-element feature vectors for all exciting trials in red, and non-exciting trials in green, we obtain two distributions in a 3d space:



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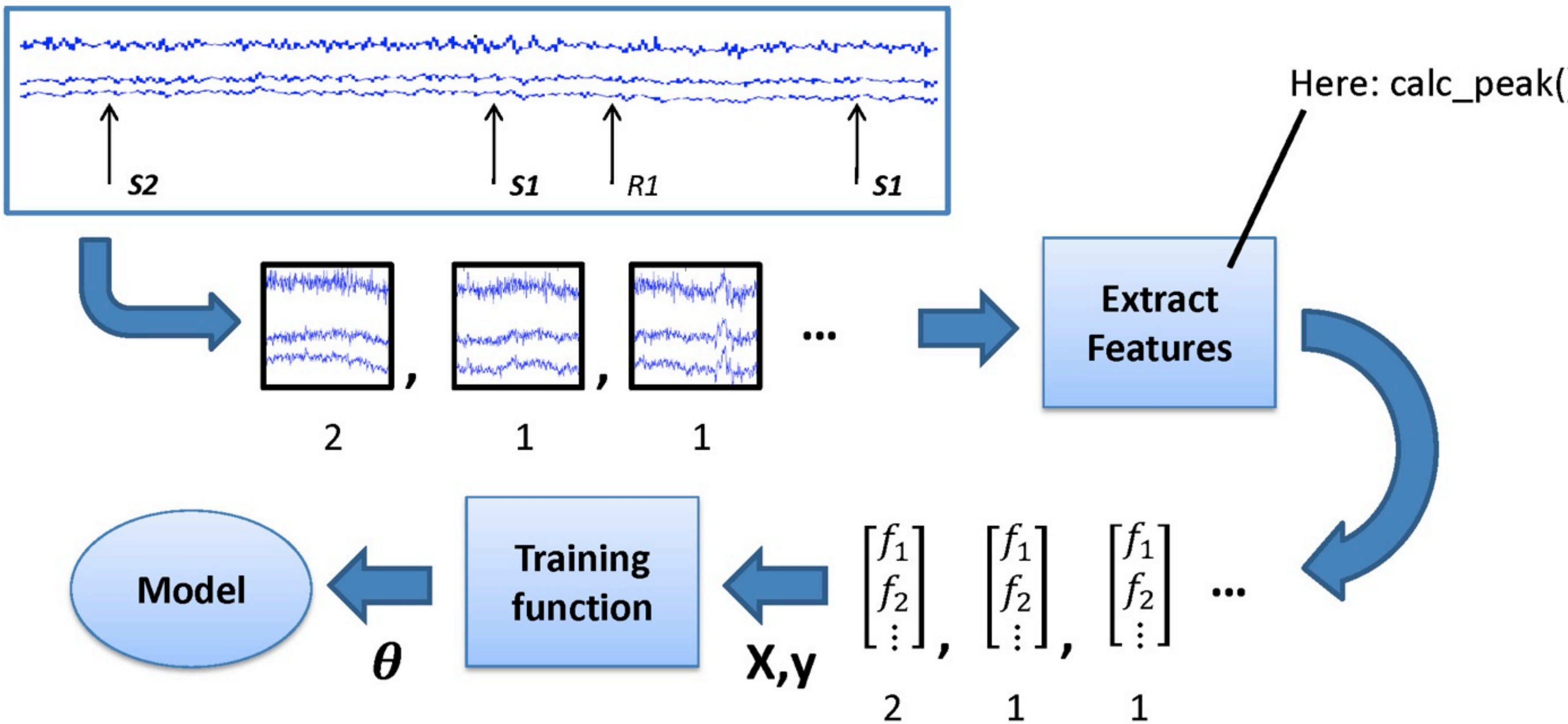
ML with Feature Extraction

- Including the feature extraction, the analysis process is as follows:



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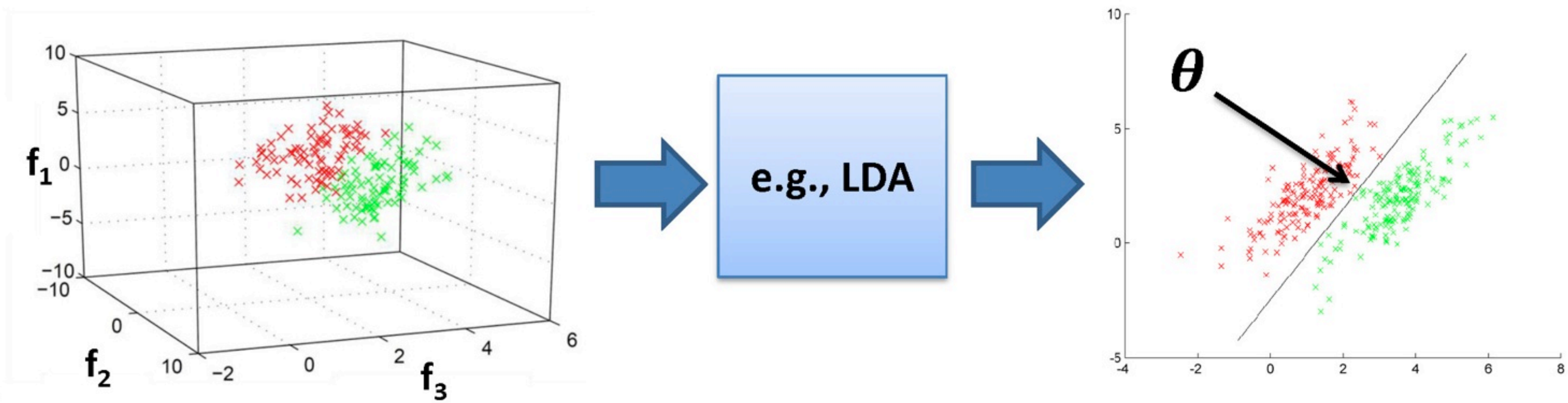
Using Machine Learning

- The feature vectors are passed on to a machine learning function (e.g., Linear Discriminant Analysis)
- … which determines a parametric predictive mapping



LDA generates parameters of a linear mapping: $y = \theta x - b$,
For classification, the mapping is non-linear: $y = sign(\theta x - b)$.

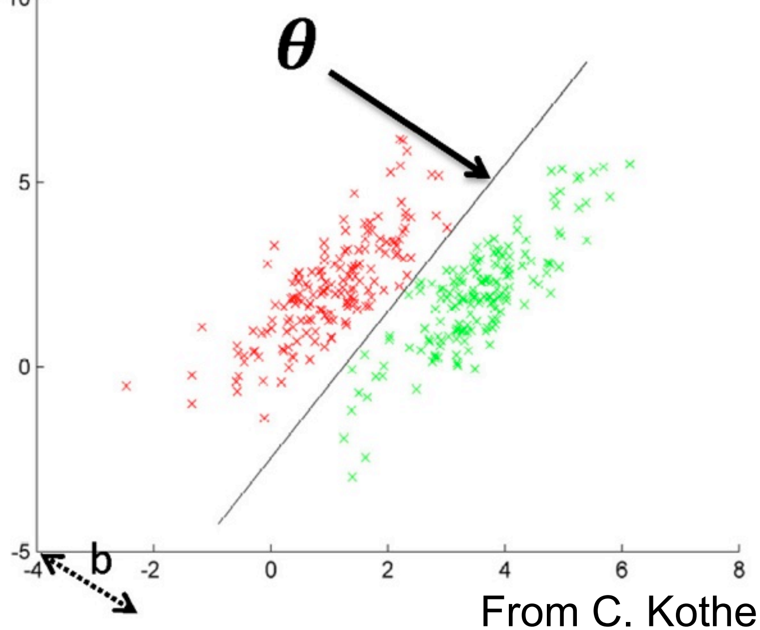
Adapted from C. Kothe, BCILAB Workshop Tutorials

LDA In a Nutshell

- Given trial segments $\boldsymbol{x}_k$ (in vector form) in $\mathcal{C}_1$ and $\mathcal{C}_2$,

$$\boldsymbol{\mu}_i = \frac{1}{|\mathcal{C}_i|}\sum_{k\in\mathcal{C}_i}\boldsymbol{x}_k\,, \qquad \Sigma_i = \sum_{k\in\mathcal{C}_i}(\boldsymbol{x}_k - \boldsymbol{\mu}_i)(\boldsymbol{x}_k - \boldsymbol{\mu}_i)^\intercal$$

$$\boldsymbol{\theta} = (\Sigma_1 + \Sigma_2)^{-1}(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1), \qquad \mathrm{b} = \boldsymbol{\theta}^\intercal(\boldsymbol{\mu}_1 + \boldsymbol{\mu}_2)/2$$



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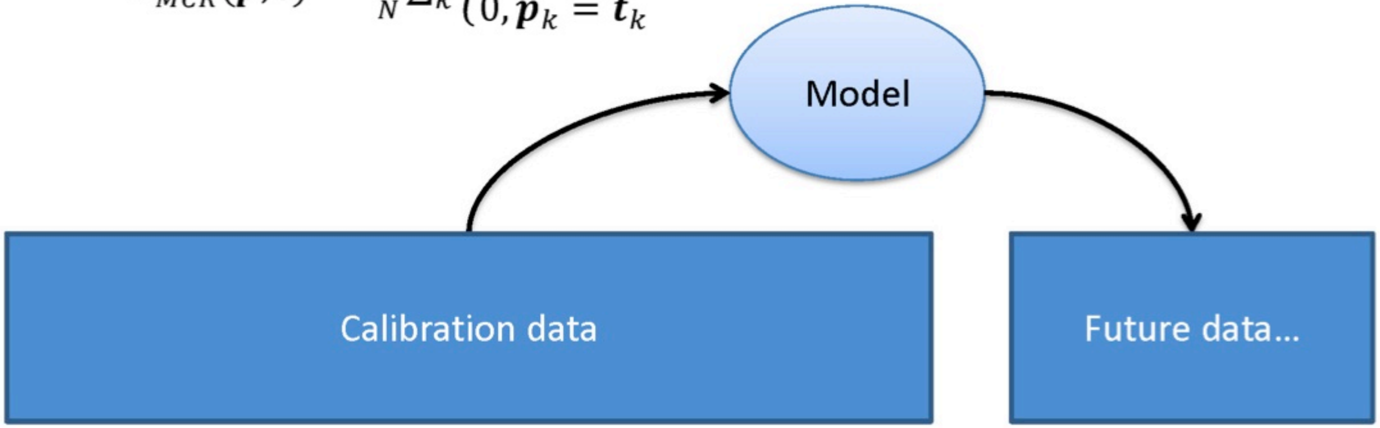
Evaluating the Efficacy of BCIs

1. Both calibration data and test data are available
   - Estimate model parameters (for filters, features, ML algorithm)
   - Apply the model to new data (online / single-trial)
   - Measure prediction performance or loss between a vector of predictions $\boldsymbol{p}$ and a vector of targets $\boldsymbol{t}$ using, for instance,
     - **Mean-Square Error:**

$$-L_{MSE}(\boldsymbol{p},\boldsymbol{t}) = \frac{1}{N}\sum_k (\boldsymbol{p}_k - \boldsymbol{t}_k)^2$$

     - **Mis-Classification Rate:**

$$-L_{MCR}(\boldsymbol{p},\boldsymbol{t}) = \frac{1}{N}\sum_k \begin{cases} 1, \boldsymbol{p}_k \neq \boldsymbol{t}_k \\ 0, \boldsymbol{p}_k = \boldsymbol{t}_k \end{cases}$$



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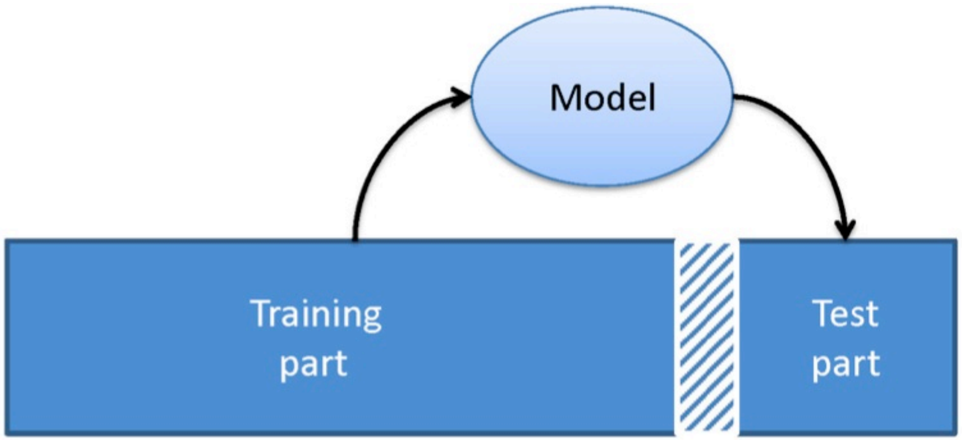
Evaluating the Efficacy of BCIs

2. Test (future) data are not available
   - Split one data set repeatedly into training/test blocks systematically, a.k.a. cross-validation
   - Time series data: Prefer block-wise cross-validation over randomized
   - Consideration: Since neighboring trials are more closely related than training and future online data, leave a margin of several trials/seconds between training and test
   - Standard splitting schemes: 5x, 10x



Adapted from C. Kothe, BCILAB Workshop Tutorials

Evaluating the Efficacy of BCIs

3. Time (speed) matters
   - Information Transfer rate (ITR)

$$B_t = \log_2 N + p \log_2 p + (1-p) \log_2 \left[\frac{1-p}{N-1}\right]$$

N is the number of different types of mental tasks and the *P* the accuracy of classification.

Wolpaw et al. "Brain–computer interface technology: A review of the first international meeting," *IEEE Trans. Rehab. Eng.*, 8: 164–73, 2000.

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Application Areas and Examples

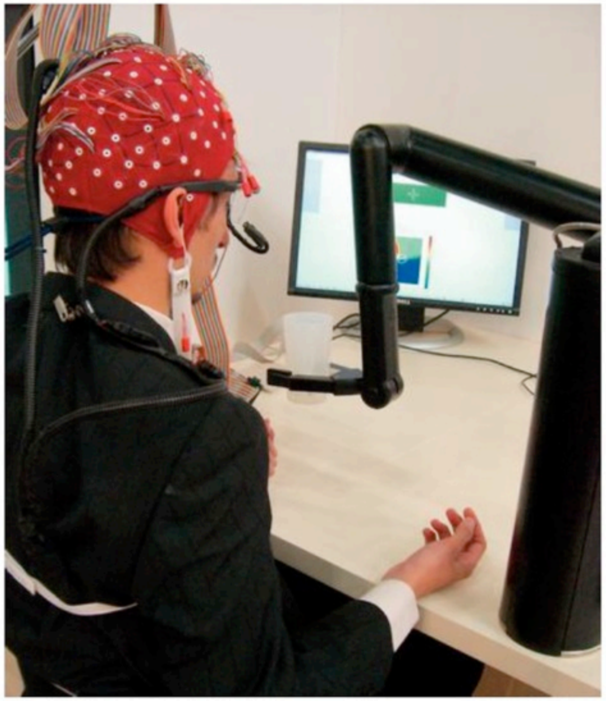
- Communication tool for severe disabilities such as tetraplegia, locked-in syndrome

P300 Speller

Application Areas and Examples

- Prosthetic control for severe disabilities such as tetraplegia, locked-in syndrome

KU Leuven



Brain2Robot (Fraunhofer FIRST)

Application Areas and Examples

- Neurorehabilitation after neurological diseases or injuries

Takata et al., 2011

Gao, Wang et al.

Application Areas and Examples

- Entertainment and gaming

Application Areas and Examples

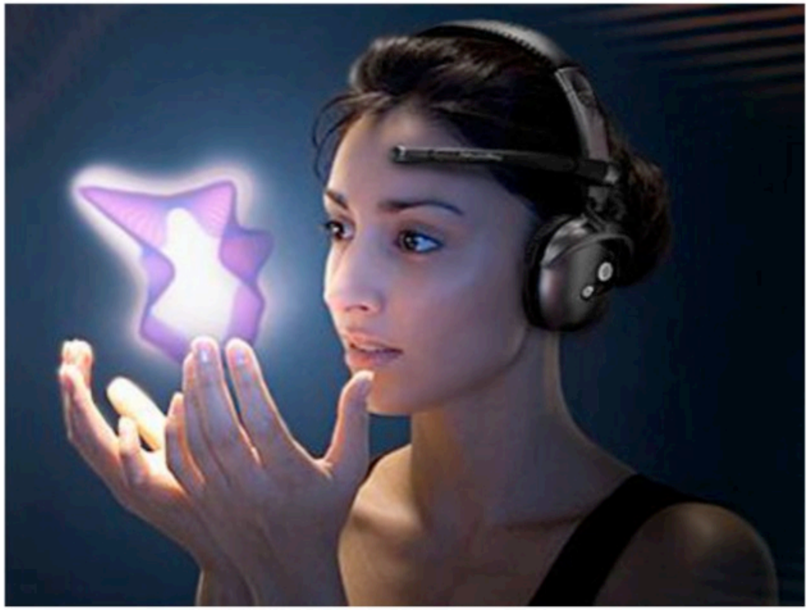
- Lie detection, Brain Fingerprinting, Trust assessment

Farwell et al. 2000

Application Areas and Examples

- Health such as sleep-stage or mood monitoring

iBrain



Neurosky Mindset

Application Areas and Examples

- Cognitive-state, such as workload/fatigue/alertness, monitoring in pilots, air traffic controllers, plant operators

Lin *et al*, 2008.

Haufe et al., 2011

Considerations in BCIs

- Ethical issues
- Acceptance by patient groups, etc.
- Difficult to prove their advantages over surrogate methods

Challenges in BCIs

- Signal-to-noise ratio of EEG is extremely low, especially in real-world environments,
- EEG signals are mathematically complicated to handle since all sensors record almost the same signal.
- Brain dynamics are very complex
  - Folding of cortex differs between any two persons
  - Relevant functional map differs across individuals
  - Sensor locations differ across recording sessions
  - Brain dynamics are non-stationary at all time scales
  - Brain dynamics are very variable across subjects, tasks, experimental conditions, etc.

Further Reading

- BCILAB tutorials and presentations: ftp://sccn.ucsd.edu/pub/bcilab/
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