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**Tutorial: Signal Processing in Brain-Computer Interfaces**

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Abstract: Research in Electroencephalogram (EEG) based Brain-Computer Interfaces (BCIs) has been considerably expanding during the last few years. Such an expansion owes to a large extent to the multidisciplinary and challenging nature of BCI research. Signal processing undoubtedly constitutes an essential component of a BCI system since from the EEG acquisition to the translation of brain activity into meaningful commands, multivariate signal processing algorithms are intensively applied.

In this tutorial, the basic BCI concepts, EEG monitoring, BCI operation, the electrophysiological sources of BCI control, future directions, and ambitions are introduced. The main BCI types, namely motor imagery (ERD/ERS), steady state visual evoked potentials (SSVEP), and P300 based BCIs are presented along with practical application examples. The EEG processing for BCI applications is then described in depth. The multivariate nature of the EEG combined with the neuroscience knowledge on hemispheric brain specialization are advantageously taken into account to derive spatial filters (i.e. across the EEG electrodes) to analyze the patterns resulting from motor imagery, visual evoked potentials, and the P300 paradigm.

Conclusions:

- BCIs can presently offer a viable communication alternative not only for physically challenged users but also for healthy users.
- Most of the present BCIs rely on the following neural-mechanisms: motor imagery, visual evoked potentials, and the P300 potentials.
• EEG patterns characterizing the neural-mechanisms can be automatically identified from the EEG.
• Given the multivariate nature of EEG, methods that can extract relevant information from several electrodes are needed. Spatial filtering techniques fulfill this need.
• Personalization is critical in EEG. This advocates for BCI customization which needs to be fast for practical use.
Management Summary

Brain-computer interfaces (BCIs) are communication systems that enable communication and control by simply thinking. A BCI detects the presence of specific patterns in the user's ongoing brain-activity that relates to the user's intention to initiate control. The BCI translates these patterns into meaningful commands.

Research on BCI considerably expanded during the last decade. In addition to the primary application of BCIs on restoring communication for the physically challenged, further applications are proposed for healthy users on enhanced human-computer interaction, enriched gaming experience, safety, and security.

BCIs are composed of three essential modules: 1) brain signal acquisition, 2) translation into commands, and 3) the application. Signal processing is essential in all the modules. This tutorial document primarily focuses on the role of signal processing in BCI. It provides a comprehensive introduction to the BCI field, discusses the most common types of BCI, and describes the signal processing algorithms that are used to distinguish particular patterns of brain activity.

This document is composed of the slides that were presented during the tutorial lecture held in the International Conference on Information Science, Signal Processing and their Applications (ISSPA) 2010 (Kuala Lumpur, Malaysia).
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1. Introduction

The interaction between humans and computers has been an expanding field of research and development in recent years. Thus, innovative human-computer interfaces that use voice, vision, haptics, and a combination of these (multimodality) as communication support have emerged.

During the last two decades, effective attempts to achieve communication based on the analysis of electrical brain signals have begun. They were mainly fostered by the will to help people suffering from severe neuromuscular disorders and to provide them with new communication channels. Recent advances in neuroscience, psychology, signal processing, machine learning, and hardware made it possible to develop direct brain-computer interfaces (BCI). A BCI is a communication system in which the messages or commands that the subject sends to the external world do not pass through the brain normal output pathways of peripheral nerves and muscles.

Akin to any communication system a BCI has inputs (electrophysiological signals resulting from brain activity monitoring) outputs (actions executed on an application), elements that transform inputs into outputs, and a protocol that determines its operation.

Subjects control the application by performing certain mental activities (MAs) which are associated with commands. Typical applications include cursor positioning, spelling programs, and wheelchair control. The association between MAs and actions requires the selection of a set of MAs to operate the BCI and the identification of signatures in the brain activity that univocally characterize each MA.

Objective

The objective of this document is to provide a comprehensive introduction to the BCI field with a particular emphasis on the signal processing methods.

Intended audience

The subjects in this tutorial are comprehensibly presented and are suitable for a wide range of signal processing professionals. The approaches, methods, and algorithms in this tutorial can be readily applied to domains where multivariate signals are handled.
2. **Brain computer interface (BCI): basic concepts**

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**Brain-Computer Interface (BCI)**

A BCI detects the presence of specific patterns in a person’s ongoing brain-activity that relates to the person's intention to initiate control. The BCI translates these patterns into meaningful commands.

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BCI Operation can be synchronous or asynchronous
Synchronous BCI operation

- Active intervals are pre-defined by the system.
- The user receives notification on the beginning of an active interval.
- The system reacts to user commands during the active intervals only.

Asynchronous BCI operation

Challenge:
To automatically recognize the EEG patterns that are relevant for the BCI application
3. Brain activity monitoring for BCIs

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Brain activity monitoring techniques for BCI

- Functional Magnetic Resonance Imaging (fMRI)
- Positron Emission Tomography (PET)
- Near-infrared brain monitoring (NIR)
- Magnetoencephalography (MEG)
- Electroencephalography (EEG)
- Electrocorticography (EcoG)

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Brain-activity monitoring for BCI

- fMRI and MEG systems are large, expensive, and require a magnetically shielded environment
- fMRI and PET depend on blood flow and consequently have long time constants. They are less amenable to rapid communication
- The scatter component of NIR brain monitoring can be useful for BCI, but the technology is currently very expensive
- Electrical potential measurements (action potentials, field potentials) are a good alternative for BCI. A noninvasive field potential measurement such as EEG is currently the preferred technology for BCI
4. The electroencephalogram (EEG)

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Electroencephalogram (EEG) recording

- The appearance of EEG rhythmic activity results from the coordinated activation of neuron groups, whose summed synaptic events become sufficiently large.
- Neuronal oscillators are composed of neurons that can coordinate their activity through excitatory and inhibitory connections in such a manner that they constitute a network with pacemaker properties.
5. Translation of EEG patterns into BCI commands

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Translation into commands. Two approaches exist:
the user learns vs. the machine learns

- **The user learns**
  - If appropriate feedback is provided, the user must learn to asynchronously control a BCI
  - The brain can learn faster and more effectively than any machine learning algorithm

- **The machine learns**
  - The burden of learning must be offloaded to the machine
  - Machine learning is at an advanced state and should make BCI operation easy for the user

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BCI: Translation into commands

![Diagram](image-url)
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**Artifact processing**

In the BCI context, the signal of interest is the **endogenous brain activity measured as voltage changes at the scalp** while an artifact is any voltage change generated by other sources.

**External electromagnetic interferences**
- powerline noise
- electrical equipment

**User generated artifacts:**
- Ocular artifacts, e.g. eye blinks, eye movements
- Muscular activity (mainly from head and facial muscles)

➤ Artifacts are strong interfering phenomenon which can cause many false activations.

➤ Most BCIs do not perform any operation when an artifact is detected.

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**Artifact types: facial muscular movement**

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Artifact types: eye blinks

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Artifact types: horizontal eye movement
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Artifact types: vertical eye movement

![Graphs showing vertical eye movement artifacts](image)

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Artifact topography: Signal to artifact ratio (SAR)

\[ SAR = 10 \log \frac{E_{baseline EEG}}{E_{artifact EEG}} \]

- **Eye blink**
- **Horizontal movement**
- **Upward movement**
- **Downward movement**

Low values of SAR (blue regions) indicate the places where the artifact is more prominent.
BCI: Translation into commands

Brain signals → Translation into commands → Commands

Artifact processor → Post processing → Feature classification

Feature extraction

Dependent on the MAs to operate the BCI
6. Electrophysiological sources of control in BCIs

**Mental activities to control BCIs**

<table>
<thead>
<tr>
<th>Type of mental activity</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensorimotor activity</td>
<td>Changes in brain rhythms (μ, β) [ERD/ERS]</td>
</tr>
<tr>
<td></td>
<td>Mu and beta rhythms (8-12 Hz &amp; 13-30 Hz) originating in the sensorimotor cortex, are more prominent when a person is not engaged in processing sensorimotor inputs or in producing motor outputs. A voluntary movement results in a circumscribed desynchronization in the mu and lower beta bands. This event related desynchronization (ERD) begins in the contralateral Rolandic region ~2 s prior to the onset of a movement and becomes bilateral before execution of movement. After the movement, the power in the brain rhythm increases (event related synchronization, ERS). Motor imagery elicits similar patterns of activity.</td>
</tr>
<tr>
<td>Movement related potentials (MRPs)</td>
<td>MRPs are low-frequency potentials starting ~1-1.5 s before a movement. They have bilateral distribution and present maximum amplitude at the vertex. Close to the movement they become contralaterally preponderant.</td>
</tr>
<tr>
<td>Visual evoked potentials (VEPs)</td>
<td>VEPs are small changes in the ongoing EEG (more prominent in the occipital cortex) generated in response to visual stimuli (e.g., flashing lights). If a visual stimulus is presented repetitively at a rate &gt; 5 Hz, a continuous oscillatory response is elicited in the visual pathways. This response is termed steady-state visual evoked potential (SSVEP).</td>
</tr>
<tr>
<td>P300</td>
<td>Infrquent or particularly significant auditory, visual, or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke in the EEG over the parietal cortex a positive peak at about 300 milliseconds after the stimulus presentation. This peak is called P300.</td>
</tr>
</tbody>
</table>

**Mental activities to control BCIs (continued)**

<table>
<thead>
<tr>
<th>Neuromechanism</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow Cortical potentials (SCPs)</td>
<td>SCPs are slow, non-movement potential changes generated by the subject. They reflect changes in cortical polarization of the EEG lasting from 300 ms up to several seconds.</td>
</tr>
<tr>
<td>Response to mental tasks</td>
<td>BCI systems based on non-movement mental tasks assume that different mental tasks (e.g., solving a multiplication problem, imagining a 3D object, and mental counting) lead to distinct, task-specific distributions of EEG frequency patterns over the scalp.</td>
</tr>
</tbody>
</table>
Most of current BCIs utilize:

- **Sensorimotor activity (mainly motor imagery)**
- **Visual Evoked Potentials**

**P300**

<table>
<thead>
<tr>
<th>Mental activities used in BCI</th>
<th>Sensorimotor activity</th>
<th>VEP</th>
<th>P300</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td></td>
<td></td>
<td>24%</td>
<td></td>
</tr>
<tr>
<td>Red</td>
<td></td>
<td>15%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orange</td>
<td></td>
<td>15%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td>46%</td>
<td></td>
</tr>
</tbody>
</table>
7. BCI based on motor imagery

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BCI based on motor imagery

Motor imagery may be seen as mental rehearsal of a motor act without any overt motor output.

The topics that are discussed in this section are:

- Event Related (de)synchronization (ERD/ERS)
- Voluntary movement
- Motor imagery and the EEG
- Synchronous/Asynchronous BCI operation
- Common spatial patterns

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Event related synchronization/desynchronization (ERS/ERD)

(Term coined by Pfurtscheller and Aranibar 1977 "Event-related cortical desynchronization detected by power measurements of scalp EEG")

![Diagram of Event Related Synchronization/Desynchronization](image)

- % of change (usually power in a certain freq. band)
- Hypothetical curve: Prior ERD & Posterior ERS
- Zero level
- Reference interval
- Time
- t=0 (relevant event)
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**VOLUNTARY right index finger lifting**

- 10-12 Hz
- 14-18 Hz
- 36-40 Hz

From: G. Pfurtscheller and F. H. L. da Silva, “Functional meaning of event-related desynchronization (ERD) and synchronization (ERS),”

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**Motor imagery**

Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement.

<table>
<thead>
<tr>
<th>Actual movement</th>
<th>Motor imagery</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Mu ERD ~2.5 s prior to movement</td>
<td>• The execution is locked at certain cortico-spinal level</td>
</tr>
<tr>
<td>• Maximum of gamma ERS immediately prior to movement</td>
<td>• The ERD seems to be concentrated on the contralateral side only</td>
</tr>
<tr>
<td>• Maximum of the beta ERS within the first second after movement</td>
<td></td>
</tr>
<tr>
<td>• Mu ERS during movement</td>
<td>• The observation of movement elicits a bilateral ERD</td>
</tr>
<tr>
<td>• The initially contralateral ERD develops a bilateral distribution</td>
<td>• Mirror-nervous-system (MNS) The functional significance of mu rhythms translating “seeing” and “hearing” into “doing”, J. Pineda</td>
</tr>
</tbody>
</table>

*Motor Imagery and Direct Brain–Computer Communication: G. Pfurtscheller and C. Neuper*
Motor imagery: results (ideal text-book subject)

The visual cue instructs the subject to perform the motor imagery.

Imagined movement of the left index finger
Imagined movement of the right index finger

BCI based on motor imagery: Operation modes

Synchronous operation

Lifting hand movement

EEG monitoring

Active interval (the BCI reacts to user’s intent)

Inactive interval

Active interval (the BCI reacts to user’s intent)

Decide L or R

Application commands

Cursor movement

Asynchronous operation

Lifting hand movement or nothing else

EEG monitoring

e.g. contralateral Mu-ERS

Beta ERS

Decide L, R, or other

Application commands

Wheelchair movement

The BCI is continuously active, whenever it detects the relevant mental activities it executes the associated action.
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BCI based on motor imagery: in practice

- The EEG patterns associated with motor imagery are subject dependent
- The focus of activity is not precisely located on C3 and C4. Spatial (across electrodes) filters can be constructed to identify the electrode locations that are best suited for discriminating between two EEG populations
- A method termed “Common Spatial Patterns” permits to construct such filters
- A training set enables the filter construction

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Common spatial patterns (CSP): Training trials

The CSP method allows us to determine spatial filters to optimally discriminate between two EEG populations (classes)

\[ X_i, Y_j \in \mathbb{R}^{M \times T} \]

- \( M \): Number of electrodes
- \( T \): Number of samples per trial
- \( N \): Number of trials
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Common spatial patterns: Covariance matrices: classes 1 & 2

\[
C_x = \frac{1}{N} \sum_{i=1}^{N} \frac{X_i X_i^T}{\text{trace}\{X_i X_i^T\}}
\]

\[
C_r = \frac{1}{N} \sum_{i=1}^{N} \frac{Y_i Y_i^T}{\text{trace}\{Y_i Y_i^T\}}
\]

\[
X_i, Y_j \in \mathbb{R}^{H \times T}\\
C_x, C_r \in \mathbb{R}^{M \times M}
\]

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Common spatial patterns: Joint diagonalization of the covariance matrices

\[
C_x, C_r \text{ are by definition symmetric positive semi-definite}
\]

\[
C_x + C_r = U D \frac{1}{2} U^T C_x U D \frac{1}{2} + D \frac{1}{2} U^T C_r U D \frac{1}{2} = I
\]

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Common spatial patterns: Joint diagonalization of the covariance matrices

\[ \frac{1}{2} D^{-\frac{1}{2}} U^T C_\chi U D^{-\frac{1}{2}} + \frac{1}{2} D^{-\frac{1}{2}} U^T C_\gamma U D^{-\frac{1}{2}} = I \]

\( S_x = V \Delta V^T \quad S_\gamma = D^{-\frac{1}{2}} U^T C_\gamma U D^{-\frac{1}{2}} = V (I - \Delta) V^T \)

\( S_x, S_\gamma \) are positive semi-definite \( \Rightarrow \Delta \) and \( I - \Delta \) have elements in \([0,1]\)

\[ V^T D^{-\frac{1}{2}} U^T C_\chi U D^{-\frac{1}{2}} V = W C_\chi W^T = \langle WX, X' W' \rangle_i = \Delta \]
\[ V^T D^{-\frac{1}{2}} U^T C_\gamma U D^{-\frac{1}{2}} V = W C_\gamma W^T = \langle WY, Y' W' \rangle_j = I - \Delta \]

This can be visualized as shown in next slide

Common spatial patterns: Spatial filters

\( w_m C_\chi w_m^T = 1 - w_m C_\gamma w_m^T = \delta_m \) (\( m^{th} \) diagonal element in \( \Delta \))

\( \langle w_m X, X' w_m^T \rangle_i = \langle \| w_m X \|_i^2 \rangle_i = 1 - \langle \| w_m Y \|_j^2 \rangle_j = \delta_m \)

\( w_m X, w_m Y \) are spatially (across electrodes) filtered signals

if \( \delta_m \)
  - is close to 1 \( \Rightarrow \| w_m X \| \) is Maximum (Minimum)
  - is close to 1 \( \Rightarrow \| w_m Y \| \) is Maximum (Minimum)
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Common spatial patterns: Spatial filters

To facilitate the interpretation of \( \mathbf{w}_m \), its coefficients can be portrayed on a topographic map.

\[
\begin{bmatrix}
\mathbf{w}_m(1) \\
\vdots \\
\mathbf{w}_m(k) \\
\vdots \\
\mathbf{w}_m(M')
\end{bmatrix}
\]

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Common spatial patterns: Frequency content

CSP has permitted to build a spatial filter \( \mathbf{w}_m \) (or set of spatial filters) to discriminate between \( \|\mathbf{w}_m \mathbf{X}_i\|^2 \) and \( \|\mathbf{w}_m \mathbf{Y}_j\|^2 \). So far the frequency content of \( \mathbf{X}_i \) and \( \mathbf{Y}_j \) has not been considered.

Consider the toy example:

\[
\mathbf{X}_i = \begin{bmatrix}
n_i(t) \\
\sin(2\pi f_i t + \phi_i)
\end{bmatrix} \quad \mathbf{Y}_j = \begin{bmatrix}
n_j(t) \\
\sin(2\pi f_j t + \phi_j)
\end{bmatrix}
\]

\( n_i(t), n_j(t) \) are zero-mean, unit variance white noise processes

\( f_i \neq f_j \)

\( \phi, \phi' \) are random phases \( \in [0, 2\pi] \)

However:

\[
\mathbf{C}_x - \mathbf{C}_y = \begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix} \Rightarrow \mathbf{\Delta} = \begin{bmatrix}
\frac{1}{2} & 0 \\
0 & \frac{1}{2}
\end{bmatrix} \Rightarrow \langle \|\mathbf{w}_m \mathbf{X}_i\|^2 \rangle - \langle \|\mathbf{w}_m \mathbf{Y}_j\|^2 \rangle
\]

No distinction between \( \mathbf{w}_m \mathbf{X}_i \) and \( \mathbf{w}_m \mathbf{Y}_j \)!

CSP is sensitive to variance changes. To take into account frequency content, the trials are band-pass filtered.
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**Common spatial patterns: Frequency band selection**

The band-pass filters can be selected according to the classical frequency-band classification:

- **Lower mu (δ-10 Hz)**
- **Mu (10-12 Hz)**
- **Lower beta (12-15 Hz)**
- **Beta (15-30 Hz)**

The filters can also be selected to cover the interesting frequency range (5-30 Hz) in narrow bands (e.g., 2Hz wide).

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**Common spatial patterns: Frequency band selection**

Given a set of $B$ frequency bands, $B \{w_1, \ldots, w_b, \ldots, w_B\}$ spatial filters can be found:

- $w_b$ is such that $\left(\|w_b X(b)\|_F^2\right)_b = 1 - \left(\|w_b Y(b)\|_F^2\right)_b = \delta_b = \max \text{ (diag } \Delta(b)\text{ )}$

- $X(b)$ and $Y(b)$ are the trials filtered in the $b^{th}$ frequency band
- $\Delta(b)$ results from jointly diagonalizing $\left(\langle X(b)X(b)\rangle_b\right)$ and $\left(\langle Y(b)Y(b)\rangle_b\right)$

The set $\{w_b\}$ needs to be constructed for each user (customization)!
8. **BCIs based on visual evoked potentials**

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**BCI based on visual evoked potentials**

The topics that are discussed in this section are:

- Visual evoked potentials: transient and steady state
- Stimulation properties
- BCI operation
- Signal processing to determine optimal spatial filters

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**Sensory Stimuli Evoke Specific Brain Potentials**

- **Gustatory Evoked Potential**
  - Murayama et al., *Gustatory Evoked Magnetic Fields in Humans*, *Neuroscience Letters*

- **Olfactory Evoked Potential**
  - C. Murphy et al., *Olfactory event-related potentials and aging: normative data*, *International Journal of Psychophysiology*

- **Somatosensory Evoked Potential**
  - S. Ishihara et al., *Effect of Theta Burst Stimulation over the Human Somatosensory Motor Cortex on Motor and Somatosensory Evoked Potentials*, *Clinical Neurophysiology*

- **Auditory Evoked Potential**

- **Visual Evoked Potential (VEP)**
  - Garcia et al., *Automatic determination of the optimum stimulation frequencies in an SSVEP based BCI*
Repetitive Sensory Stimuli evoke Steady State Brain Potentials

Repetitive Auditory Stimuli (Binaural beats)

Repetitive Haptic Stimuli (vibration)

Steady State Auditory Evoked Potential

Steady State Somatosensory Evoked Potential

Repetitive Visual Stimuli (RVS)

Steady State Visual Evoked Potential (SSVEP)

---

Steady State Visual Evoked Potential (SSVEP)

- The SSVEP is the oscillatory component in the EEG that appears in response to a repetitive visual stimulus (RVS)
- The frequency of the SSVEP matches that of the RVS and/or its harmonics

Repetitive visual stimulus

SSVEPs recorded at electrode O2

5 Hz
11 Hz
23 Hz
31 Hz
41 Hz
Steady State Visual Evoked Potential (SSVEP)

The strength of the SSVEP depends on the stimulation frequency.

RVS frequency: 15 Hz

RVS frequency: 35 Hz

Spectral peaks
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The strength of the SSVEP depends on the stimulation frequency

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SSVEP based Brain-Computer Interface

The SSVEP corresponding to the RVS on which the user focuses her/his attention is the most prominent

M. Pastor et al., Human Cerebral Activation during Steady-State Visual-Evoked Responses, The Journal of Neuroscience
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**SSVEP detection model**

(G. Garcia et al., Spatial Filters for Detecting SSVEPs: BCI Application)

The signal at each electrode can be represented as a vector

\[ x_i(t) = \sum_{h=1}^{H} \left[ a_{i,h} \sin(2\pi h f t) + b_{i,h} \cos(2\pi h f t) \right] + y_i(t) \]

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The sinusoidal SSVEP components generate a vector space (\(\Pi\))

\[ \Pi = \{\sin 2\pi h f t, \cos 2\pi h f t \mid h = 1, \ldots, H\} \]

\[ P = S(S' S)^{-1} S' \]

Projection matrix

\[ S = [\Pi] \]

The elements of \(\Pi\) are the columns of \(S\)
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**SSVEP strength maximization**

\[
X = S A + Y \\
X = [x_1 \cdots x_N] \\
Y = [y_1 \cdots y_N]
\]

Goal: Determine a linear combination of \(\{x_i\}\) that maximizes the SSVEP strength at frequency \(f\):

\[
x_\omega = \sum_{i=1}^N \omega_i x_i = X \omega
\]

\[
\omega = \arg \max \frac{\text{Power in } X \tilde{\omega} \text{ due to SSVEP}}{\text{Power in } X \tilde{\omega} \text{ due to something else}}
\]

\[
\omega = \arg \max \frac{\tilde{\omega}' X X \tilde{\omega}}{\tilde{\omega}' (X - PX)' (X - PX) \tilde{\omega}}
\]

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**SSVEP strength maximization**

![SSVEP strength maximization diagram](image)
9. P300 based BCIs

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BCI based on P300 potential

The topics that are discussed in this section are:

- P300 Event Related Potential
- P300 based BCI systems
- Signal processing in P300 based BCIs

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P300 Event Related Potential

Exogenous ERPs: result from early, automatic processing of stimuli and have a latency, amplitude and topographic distribution that depends mainly on the stimulus characteristics.

Endogenous ERPs: result from later, more conscious processing of stimuli and have characteristics that depend mainly on the stimulus context.

*The basic explanations in this section comes from "Bayesian Machine Learning Applied in a Brain-Computer Interface for Disabled Users", EPFL Thesis by Ulrich Hoffmann*
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Paradigms for evoking the P300: Oddball paradigm (P3b)

A sequence of target (T) and nontarget (N) stimuli is presented in random order

- Subjects are instructed to react to the targets, either by a button press or by silently counting the targets
- Each target stimulus evokes a P3b
- The P3b has a latency of about 300-500 ms and can be observed mostly over parietal brain regions.

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Paradigms for evoking the P300: Three-stimulus paradigm (P3a,b)

- A P3a is evoked by surprising distracter stimuli
- The P3a has a latency of about 200-400 ms and can be observed mostly over fronto-central brain regions.

<table>
<thead>
<tr>
<th>P3b</th>
<th>P3a</th>
</tr>
</thead>
<tbody>
<tr>
<td>The P3b appears only if subjects pay attention to stimuli and disappears if subjects do not pay attention to stimuli</td>
<td>When subjects do not pay attention to stimuli, the target stimuli in the oddball paradigm evoke a P3a</td>
</tr>
</tbody>
</table>
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Important factors influencing the P300

<table>
<thead>
<tr>
<th>Factor</th>
<th>Influence</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARGET PROBABILITY</td>
<td>The P3b peak amplitude is inversely related to the probability of the evoking stimulus. Low target probability → High amplitude of the P3b wave</td>
</tr>
<tr>
<td>INTERSTIMULUS INTERVAL (ISI)</td>
<td>Long ISI → High amplitude of the P3b wave</td>
</tr>
<tr>
<td></td>
<td>Short ISI → Low amplitude of the P3b wave</td>
</tr>
<tr>
<td>HABITUATION</td>
<td>After many presentations of the distracter, the P3a amplitude decreases</td>
</tr>
<tr>
<td></td>
<td>The P3b is mostly unaffected by the stimuli repetition</td>
</tr>
<tr>
<td>ATTENTION</td>
<td>The P3b completely disappears if subjects are not completely engaged in the oddball task</td>
</tr>
<tr>
<td></td>
<td>The P3a is unaffected by attention changes</td>
</tr>
<tr>
<td>TASK DIFFICULTY</td>
<td>Increased task difficulty → the latency of the P3b increases and the amplitude decreases</td>
</tr>
</tbody>
</table>

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P300 based BCI systems

The user decides on the command s/he wants to execute with the BCI’s help

Stimuli are presented and the user concentrates on the stimulus associated to the desired command

After stimulus presentation, the recorded EEG is analyzed to determine which stimulus was chosen by the user

Example P300 speller

- Flashes of rows or columns are used as stimuli
- The sequence of stimuli is randomized

If the user concentrates on the letter “O”, a P3b will be evoked for stimuli 3 and 7

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Algorithms for P300 based BCI systems

A (single) trial in the context of P300 based BCI is defined as a short EEG segment (lasting for about 500ms) that is time-locked to a single stimulus presentation. P300 detection on a single trial is challenging. Averaging across several stimuli sequences is commonly used to increase the detection accuracy. Yet, this increases the system's reaction time and slows down the communication.

Let's go for single trial classification.

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Single trial P300 detection

$X = \sigma_s a \cdot s^t + \sum_i \sigma_i b \cdot n^t$

*From: Single-trial P300 estimation with a spatiotemporal filtering method, R. Li, A. Keil, and J.C. Principe*
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Single trial P300 detection

Hypothesis:
- The morphology of the P300 can be considered as (relatively) fixed, but may vary in both peak latency and amplitude from trial to trial.

- The P300 can be modeled by a fixed temporal template $g_i$, where:
  - $t$ is the unknown peak latency
  - $\sigma$ is the variable amplitude across trials

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P300 (peak) detection: temporal template $g_{\tau}$

Gamma function

$g_{\tau}(t) = c t^{-1} \exp\left(\frac{-t}{\tau}\right)$

Scale parameter

Normalization constant

Shape parameter

The mode of $g_{\tau}(t)$ occurs at $t = (r - \theta) \tau$

$r = 10 \quad \theta = 26$
$r = 10 \quad \theta = 28$
$r = 10 \quad \theta = 30$
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P300 detection: Determining the peak latency $l$

$$w = \arg \min_{\hat{w}} \left\| \hat{w}^T X - g_x \right\|^2$$

Template with time-lag $r$ as parameter

Spatial filter to detect P300

$$\frac{\partial \left( \left\| \hat{w}^T X - g_x \right\|^2 \right)}{\partial \hat{w}} = 0 \Rightarrow w(\tau) = \left( XX^T \right)^{-1} X g_x$$

Optimal solution for $w(\tau)$

Cost as a function of the time-lag $r$ only!

$$J(\tau) = \left\| g_x \left[ X^T \left( XX^T \right)^{-1} X - I \right] \right\|^2$$

$$l = \arg \min_{\tau \in \Theta} J(\tau)$$

Peak latency $l$

Set of possible latencies (100-500 ms for P3)

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P300 detection: Determining the P300 amplitude

$$\hat{S} = \frac{X^T w(l)}{\left\| X^T w(l) \right\|}$$

Estimate of $s$ in: $X = \sigma_2 a \cdot s^i + \sum_i \sigma_i b \cdot n^i$

$$X \cdot \hat{S} = \sigma_2 a \cdot s^i \cdot \hat{S} + \sum_i \sigma_i b \cdot n^i \cdot \hat{S} \approx 0$$

Orthogonality Assumption

$$\sigma_2 a \approx X \cdot \hat{S}$$

Estimate of $a$

$$\hat{a} = \frac{(1/K)\sum_{i=1}^K \hat{a}_i}{\left\| (1/K)\sum_{i=1}^K \hat{a}_i \right\|}$$

$$X \arg \min_{\hat{\sigma}_2} \left( \left\| \hat{S} - \hat{\sigma}_2 \hat{a} \right\| \right) \Rightarrow \sigma_2$$

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10. Summary of Spatial Filters for BCI

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<table>
<thead>
<tr>
<th>Type of BCI</th>
<th>Spatial filtering method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor imagery based BCI</td>
<td>Joint diagonalization of two covariance matrices; corresponding to trials of imagined movements of the left hand (X) and the right hand (Y)</td>
</tr>
<tr>
<td></td>
<td>$C_X = XX^T, C_Y = YY^T, D^{1/2} U C_X U D^{1/2} = V \Lambda V^T$</td>
</tr>
<tr>
<td></td>
<td>$C_X + C_Y = U D U^T$</td>
</tr>
<tr>
<td></td>
<td>$\begin{bmatrix} WXX'W' = \Lambda \ WYY'W' = I - \Lambda \end{bmatrix}$</td>
</tr>
<tr>
<td></td>
<td>The rows of W are the spatial filters</td>
</tr>
</tbody>
</table>

Steady state visual evoked potential based BCI

Maximization of the SSVEP strength

$\mathbf{x}_0 = \sum \omega_i \mathbf{x}_i = X \omega$

$\omega = \arg \max \frac{\text{Power in } X \omega \text{ due to SSVEP}}{\text{Power in } X \tilde{\omega} \text{ due to something else}}$

$\delta(x \chi \tilde{\omega}) = \delta(x - E(x)(x - E(x))) \tilde{\omega}$

$P$: projection matrix on the space generated by the stimulus harmonics

P300 based BCI

$X = \sigma X (I - \sum_{i} \sigma_{z} a \cdot s^{i} + \sum_{i} \sigma_{b} b \cdot n^{i})$

$w = \arg \min_{\tilde{\omega}} \|\tilde{\omega} X - g_z\|^2$

$g_z(t) = ct^{-1} \exp\left(-\frac{t}{\tau}\right)$

P300 peak template

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BCI types comparison:
information transfer rate vs. training time

- Motor imagery based BCIs operate more “naturally” because they do not require stimulus presentation
- SSVEP and P300 based BCIs are more amenable to be deployed for consumer applications
11. Conclusions

- BCIs can presently offer a viable communication alternative not only for physically challenged users but also for healthy users.
- Most of the present BCIs rely on the following neural-mechanisms: motor imagery, visual evoked potentials, and the P300 potentials.
- EEG patterns characterizing the neural-mechanisms can be automatically identified from the EEG.
- Given the multivariate nature of EEG, methods that can extract relevant information from several electrodes are needed. Spatial filtering techniques fulfill this need.
- Personalization is critical in EEG. This advocates for BCI customization which needs to be fast for practical use.

12. Acknowledgements

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