Neuronale Informationsverarbeitung für Gehirn-Computer Schnittstellen

Neural Information Processing for Brain-Computer Interfaces

Outline of the lecture

1. A history of research on brain-computer interfaces (BCIs)
   - Non-invasive BCIs
   - Invasive BCIs
   - BCIs in stroke rehabilitation
   - Passive BCIs
2. Cognitive neuroscience
3. Recording neural activity
4. Signal Processing
5. Machine Learning
6. Spatial filtering of EEG/MEG signals
7. Paradigms for non/semi-invasive brain-computer interfacing
8. Practical day: Building a first BCI

Outline of the current lecture

1. A history of research on brain-computer interfaces (BCIs)
   - Non-invasive BCIs
     - The very first study
     - P300 speller systems
     - Motor-imagery systems
     - Slow cortical potentials: The first study with a severely paralyzed patient
     - The introduction of machine learning in BCIs
     - 2D control by SMR modulation
     - Control of complex systems by BCIs
     - BCIs in completely locked-in state
     - BCIs based on high-level cognitive processes
   - Invasive BCIs
     - BrainGate
     - BrainGate2
   - BCIs in stroke rehabilitation
   - Passive BCIs

A history of research on brain-computer interfaces

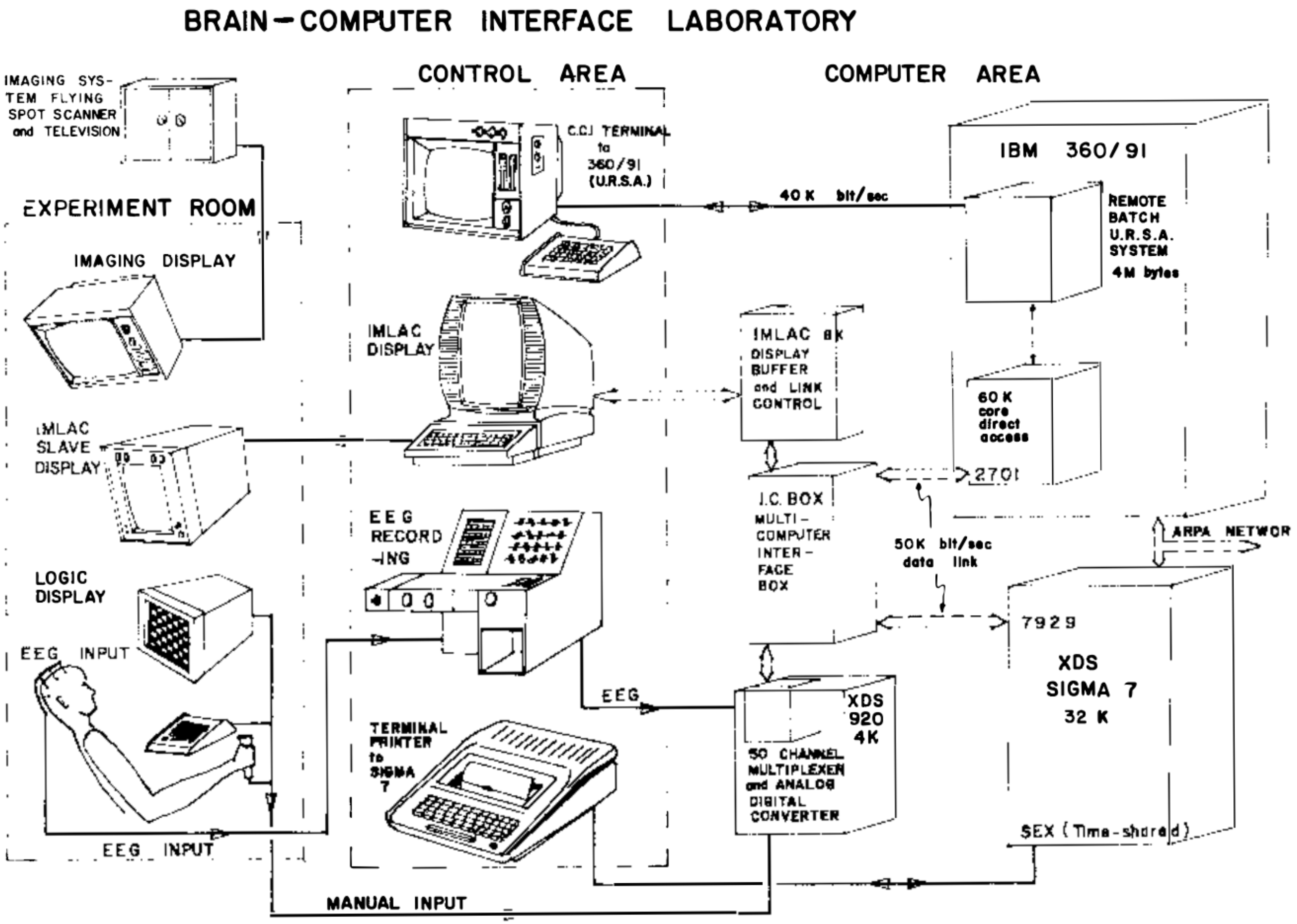
NON-INVASIVE BRAIN COMPUTER INTERFACES

The very first study (Vidal, 1973)

- Very first motivation for the use of brain-computer interfaces for direct man-machine communication

> "Can these observable electrical brain signals be put to work as carriers of information in man-computer communication for the purpose of controlling such external apparatus as prosthetic devices or spaceships?"

The very first study (Vidal, 1973)



P300 speller systems (Donchin, 1988)

- Brain wave signal P300 is a component of the event-related brain potential (ERP)
  - Enhanced positive-going component with a latency of about 300ms
  - The event-related brain potential is assumed to be the product of a rare event in a classification series
  - Event-related brain potential were recorded using EEG

- Performance depends on the subjects ability to discriminate and classify the events correctly
  - Target group were "locked-in" patients (without sufficiently working motor system)

- 6×6 matrix forms the basis of the P300 speller system
  - Rows and columns were intensified ("flashed")

CRT Display Used in the Mental Prosthesis

MESSAGE

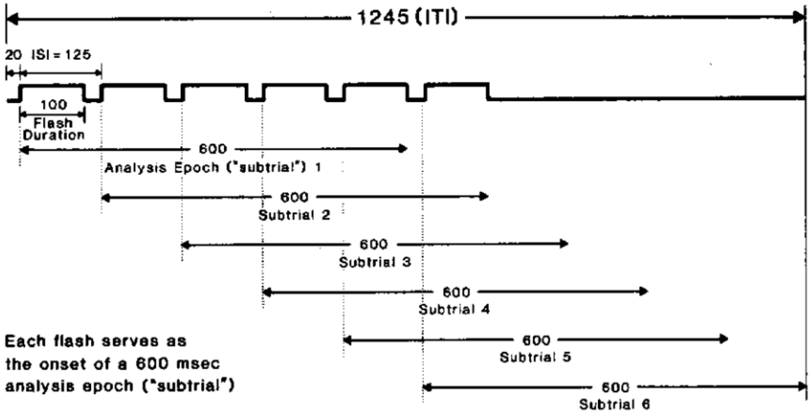
BRAIN

Choose one letter or command

A	G	M	S	Y	*
B	H	N	T	Z	*
C	I	O	U	*	TALK
D	J	P	V	FLN	SPAC
E	K	Q	W	*	BKSP
F	L	R	X	SPL	QUIT

P300 speller systems (Donchin, 1988)

- 6×6 matrix forms the basis of the P300 speller system
  - Rows and columns were intensified ("flashed")
  - Compute score of the P300 appearance for each sub trial to select rows and columns on the device



- Output of 12 bits per minute (i.e. 2,3 characters per minute)

Motor-imagery systems (Wolpaw, 1991)

- Patients were trained to use the Mu waves to move a pointer on a video screen up or down
  - Experimental setup:
    - Large amplitudes will move a mouse pointer up and small amplitudes will move it down

  - Mu waves (from approximately 8 to 12 Hz) were recorded using EEG
  - Training of the patients lasted several weeks

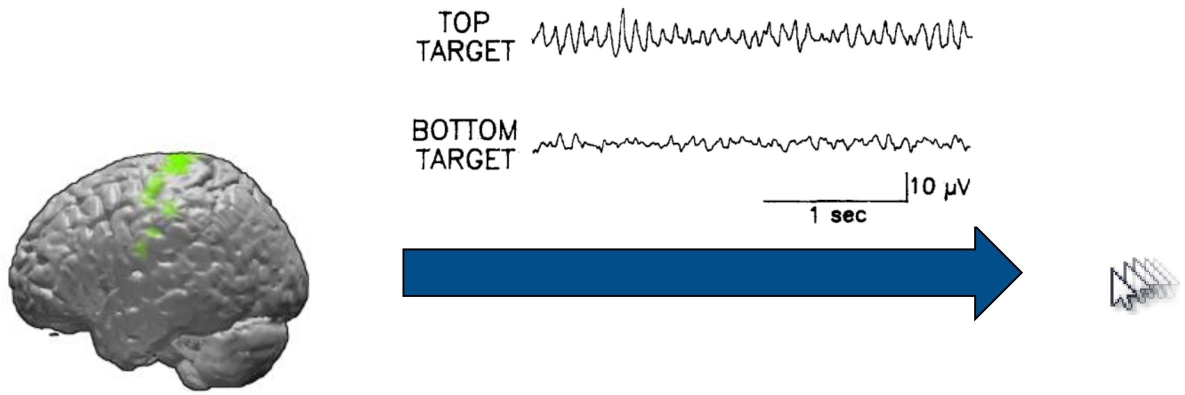
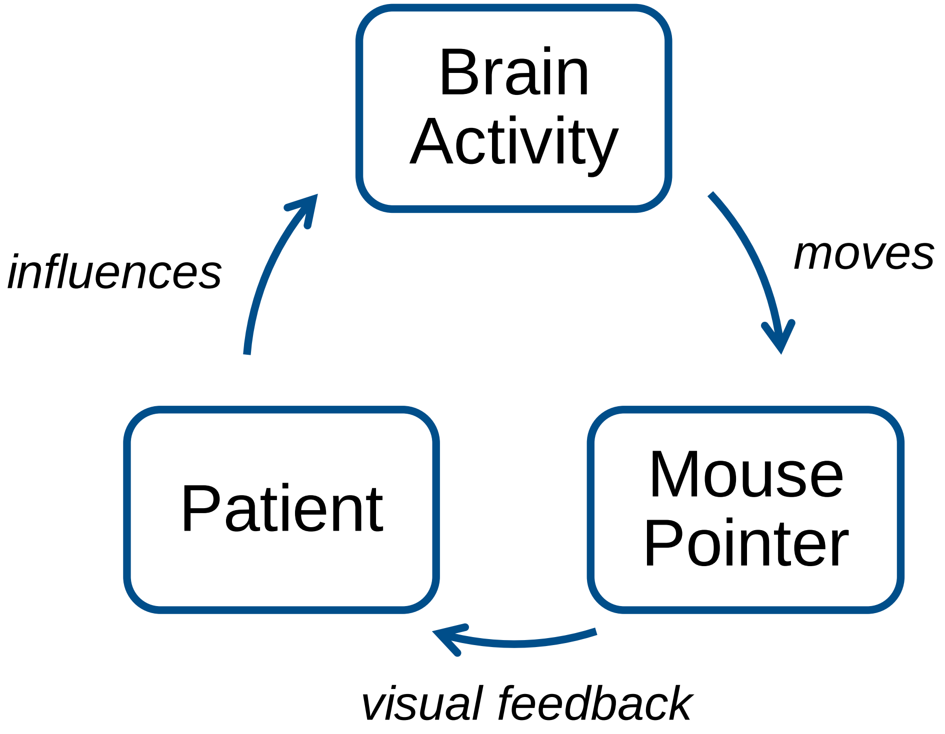


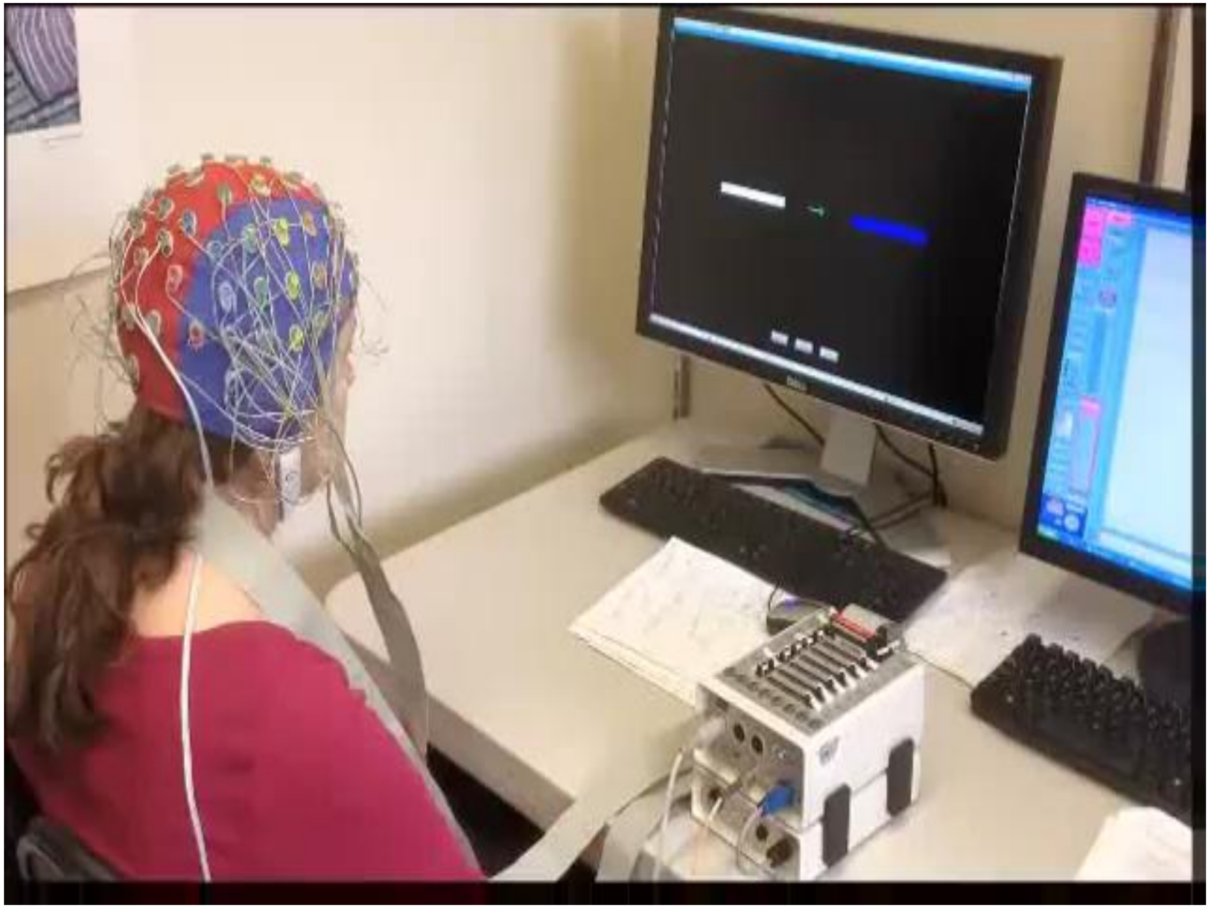
Image source: http://en.wikipedia.org/wiki/Mu_wave

Motor-imagery systems (Wolpaw, 1991)

- Translation of the mu rhythm to a cursor movement through evaluation of the amplitude distribution over top and bottom targets
  - Key concept that lead to success



Motor-imagery systems



Video source: http://youtu.be/aOaeAYD1qBI

Slow cortical potentials (Birbaumer, 1999): The first study with a severely paralyzed patient

- Very first study with solely advanced amyotrophic lateral sclerosis (ALS) patients
  - Target group were locked-in patients

- Locked-in patients were trained to produce high slow cortical potentials (SCP) over 2 to 4 seconds
  - Complete trial lasted 4 to 6 seconds
    (depending on the mental state of the patient)
  - Patients were able to control the slow cortical potentials

- Slow cortical potentials were recorded using EEG
  - Slow cortical potentials were extracted from the regular EEG using a time constant of 8 seconds and a low-pass filter of 40 Hz
  - Slow cortical potentials contain a wide range of brain signals (e.g. ERP, P300, etc.)

The introduction of machine learning in BCIs (Ramoser, 2000)

- Poor discriminative results led to a very low character output per minute
  - Need for sufficiently fast and reliable Brain-Computer Interfaces (BCI) for discrimination of EEG patterns

- How to get better results?

  Depends on the hardware we have…

1-2 EEG channel(s)	Multiple EEG channels
▪ Extract discriminative-relevant features ▪ Use of better classifiers	▪ "directly" obtain the state of the brain
+ No need for costly hardware	+ Produces good results
- No good performance	- Expensive hardware is sufficient - Produces a lot of data

The introduction of machine learning in BCIs (Ramoser, 2000)

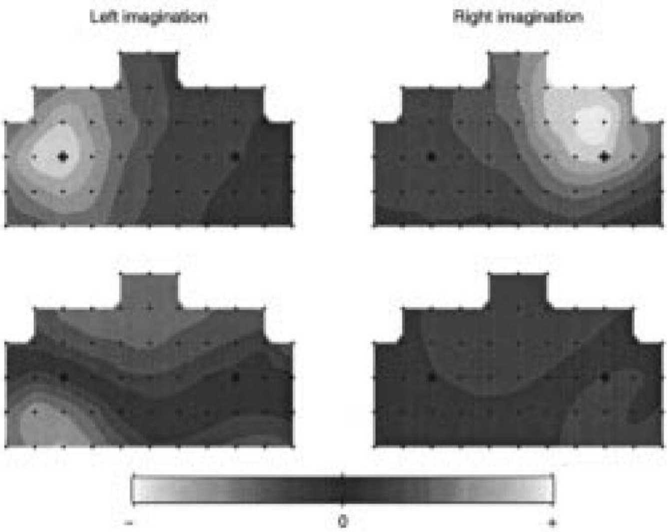
- Multiple EEG channel produce a lot of data – how to tackle this issue?
  - Method of common spatial patterns (CSP) to construct new time series (contain most of the discriminative information)

- Method of common spatial patterns was applied to two single trial populations (raw EEG data)
  - The resulting patterns maximize the variance between the populations

- Spectral decomposition of the covariance matrix of two single trial populations give rise to the spatial patterns
  - Spatial patterns can be seen as time-invariant EEG source distribution vectors

The introduction of machine learning in BCIs (Ramoser, 2000)

- What are the spatial patterns all about and where is the connection to machine learning?
  - The connection to machine learning is given by the spatial patterns
  - Example:
    Cubic interpolated spatial pattern
    grayscale contour plot of imagined
    left and right hand movements



  - We can build features from the spatial patterns
  - These features can be used to train a classifier for the specific patient

2D control by SMR modulation (Wolpaw, 2004)

- Previous research on non-invasive BCIs focused on one-dimensional control
  - Back then, it was believed that only invasive BCIs could handle higher dimensional control

- Sensorimotor-rhythm modulation (SMR) is the identification of differences in the activation pattern of the EEG (e.g. imagination of hand movement may move a cursor up and imagination of a foot movement may move a cursor down)

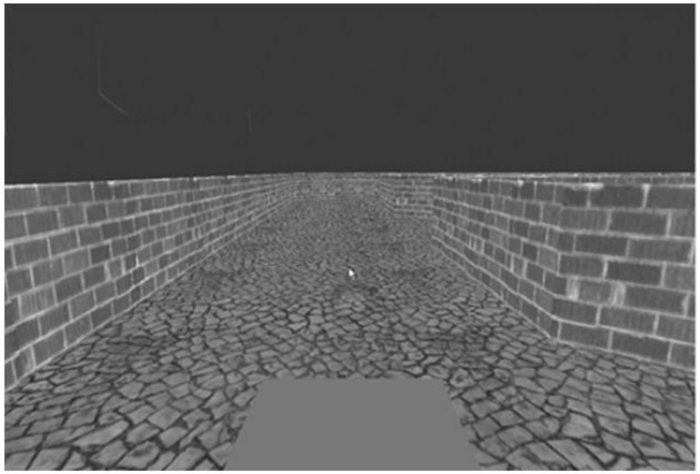
- How was control in 2D (of a mouse cursor) possible?
  - Vertical movement was established by beta waves and horizontal movement was established by mu waves
  - Control in vertical and horizontal direction was formulated as a respectively weighted left and right movement
  - Weights were adapted by an adaptive algorithm

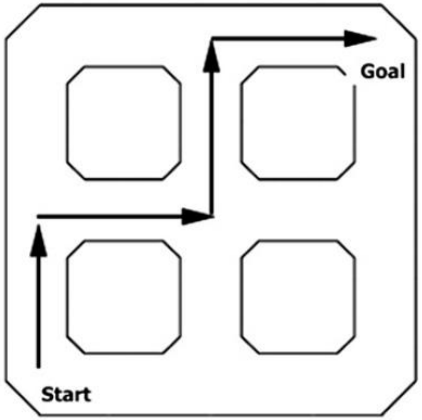
Control of complex systems by BCIs (Gallan, 2008)

- Move an wheelchair based on a shared control system
  - Shared control system consists of a controller that regulates the wheelchair motor commands and a combination of distributions which provide the input for the controller
  - The combining distribution complex is made of a BCI System and an intelligent simulated wheelchair
    - The BCI System supplies the patients intents
    - The intelligent simulated wheelchair simply avoids obstacles given a Context-Based Filter (and is only in use when the BCI System accuracy is poor)
  - The BCI System comprises a feature extractor and a classifier

Control of complex systems by BCIs (Gallan, 2008)

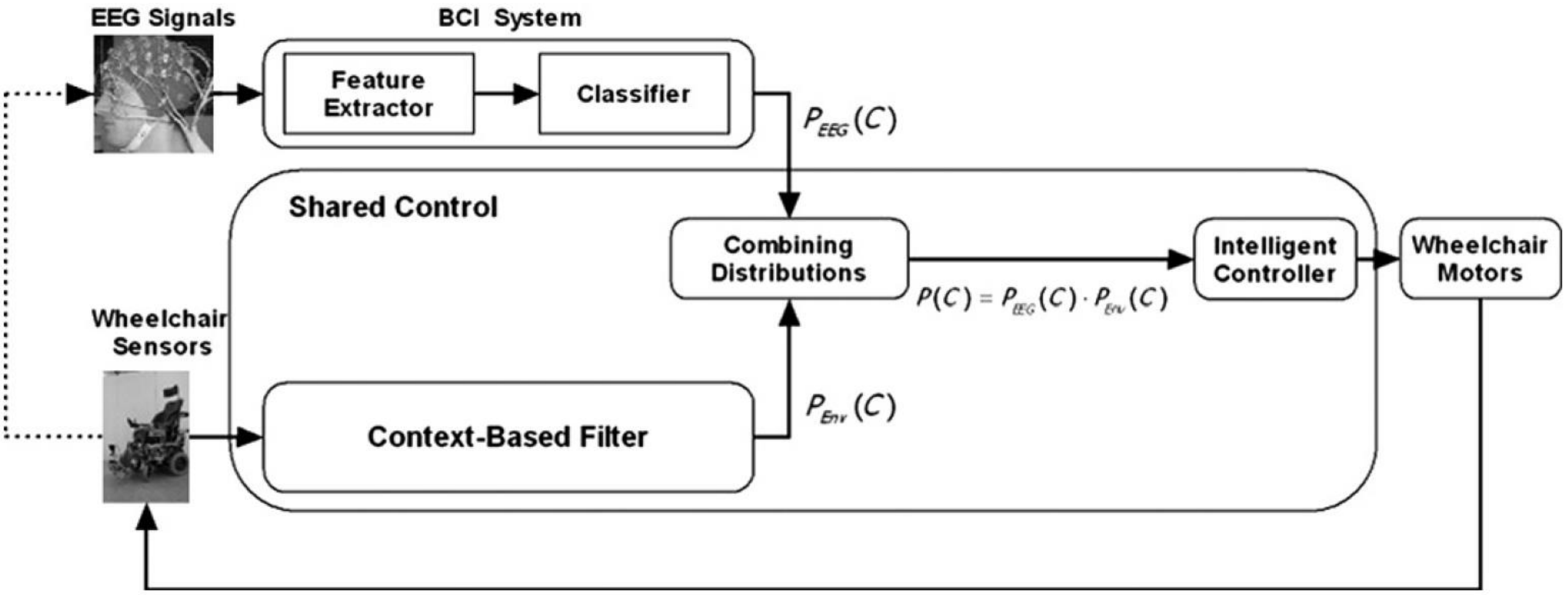
- The subjects were asked to mentally drive the simulated wheelchair from a starting point to a goal following a pre-specified path by executing three different mental tasks
  - Left hand imagination movement to turn left
  - Rest to go forward
  - Words association to turn right





Control of complex systems by BCIs (Gallan, 2008)

- System of the control of a complex system (such as driving a wheel chair) by BCIs



BCIs in completely locked-in state (Kuebler, 2008)

- The complete locked-in state (CLIS) is described as a state…
  - …in which the patient is not able to communicate anymore…
  - …as a consequence of complete motor paralysis due to a neurological disease
- Patients in CLIS have the biggest need for a precise BCIs
  - It was found that BCI performance and the stage of the physical impairment correlate
- Unable to restore basic communication in CLIS patients
  - It is largely unknown why this is the case (up until today)

> "Will CLIS patients ever be able to transfer learned brain control (e.g. in late stage of amyotrophic lateral sclerosis)?"

BCIs based on high-level cognitive processes (Grosse-Wentrup, 2014)

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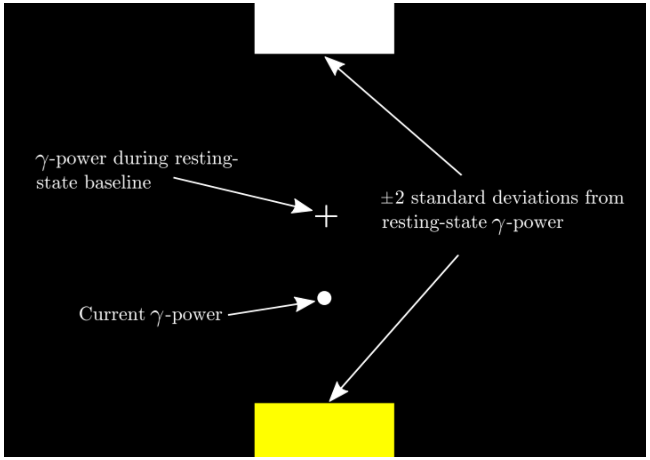
- Motor neurons of completely locked-in (CLI) patients typically degenerate (at late stage)
  - Impairment of motor and / or sensory processes

- Novel approach of using high-level cognitive processes
  - Empirical evidence states that gamma oscillations originating from the superior parietal cortex (SPC) are useable for BCIs

- Patients were trained to regulate their gamma oscillations for vertical mouse pointer movement

- Five out of eleven (healthy) patients received an accuracy above 70% after 20 minutes of training and one CLI patient reached a score of 55.8% (H_0: chance-level was refused)



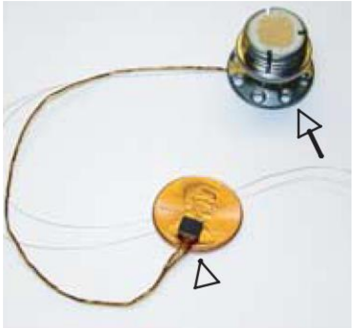
A history of research on brain-computer interfaces

INVASIVE BRAIN COMPUTER INTERFACES

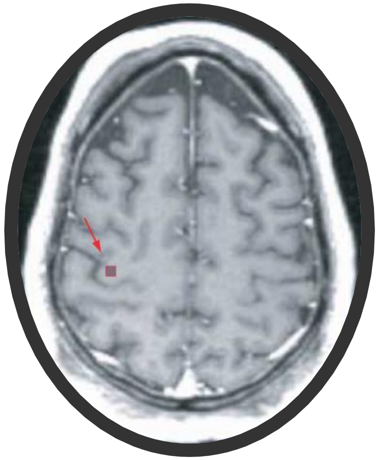
BrainGate (Hochberg, 2006)

- Neuromotor prosthesis aim to restore lost motor functions in completely locked-in patients

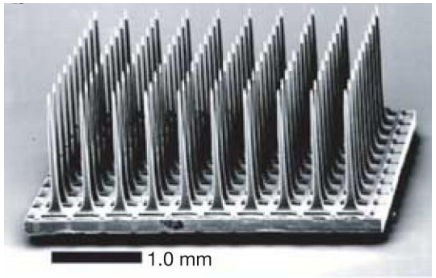
- BrainGate is such a neuromotor prosthesis that consists of
  - Chronically implemented sensor and
  - External signal processor



- A 96-microelectrode array is implanted in the primary motor cortex



- Movement signals must persist in cortex after spinal cord injury

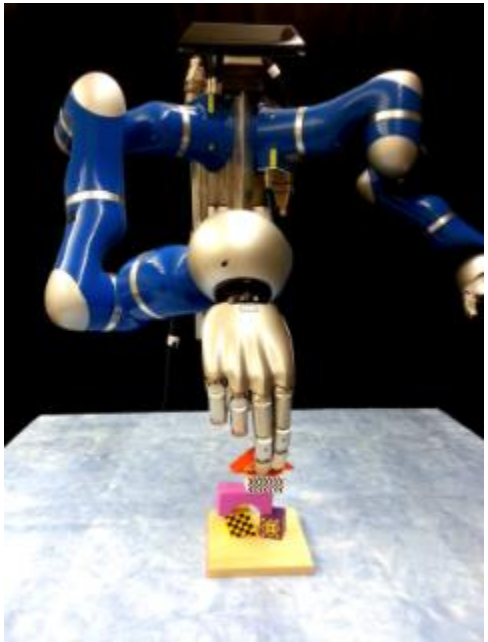


BrainGate (Hochberg, 2006)

- Neuromotor prosthesis aim to restore lost motor functions in completely locked-in patients

- BrainGate is such a neuromotor prosthesis that consists of
  - Chronically implemented sensor and
  - External signal processor

- Tasks that were tackled ranged from the control of a virtual mouse cursor to control of a prosthetic hand and robotic arm

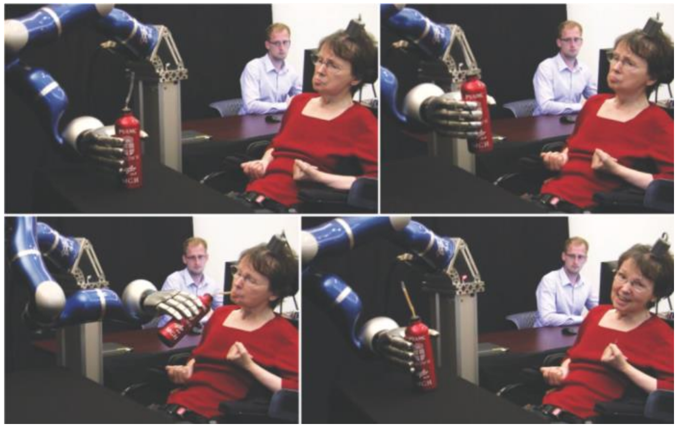


BrainGate2 (Hochberg, 2012)

- Filtering of electrical potentials revealed extracellular action potentials to decoded intended movements
  - Extracellular action potentials were measured in “units”
  - Measured units were used to calibrate the decoders of velocity and hand state actions

- Both robots were operated under continuous user-driven neuronal ensemble control of end effector velocity in 3D space

- One patient maneuvered a bottle in 2D space to her mouth, drank through a straw, and replaced the bottle on the table



BrainGate2 (Hochberg, 2012)

Video source: http://youtu.be/QRt8QCx3BCo

A history of research on brain-computer interfaces

BRAIN COMPUTER INTERFACES IN STROKE REHABILITATION

BCIs in stroke rehabilitation (Gomez-Rodriguez, 2011; Ramos, 2013)

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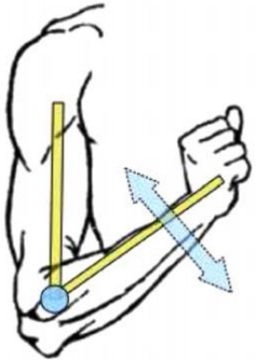
- Neurorehabilitation of stroke patients using brain-computer interfaces with robot-assisted physical therapy
  - Possible due to the neuroplasticity effect of the human brain
  - Increase in performance of cortical plasticity through the integrated system likely possible

- Key aspect: How to reestablish the disrupted sensorimotor feedback loop artificially?
  - How does closing the loop influences the BCI decoding performance?

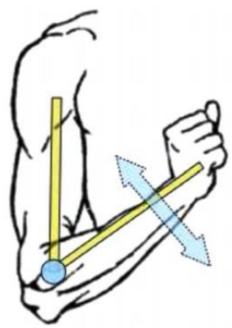
- Major future rehabilitation key concept is to provide haptic feedback with the patients intention to move the arm and not after the motor imagery
  - This strategy follows Hebbian-type learning rules (likely to result in increase of cortical plasticity)



BCIs in stroke rehabilitation (Gomez-Rodriguez, 2011; Ramos, 2013)

- Major future rehabilitation key concept is to provide haptic feedback with the patients intention to move the arm and not after the motor imagery
  - The strategy follows Hebbian-type learning rules because this is likely to result in an increase of cortical plasticity

- The presence of proprioception in the patient is important because the effect of increased cortical plasticity is likely dependent

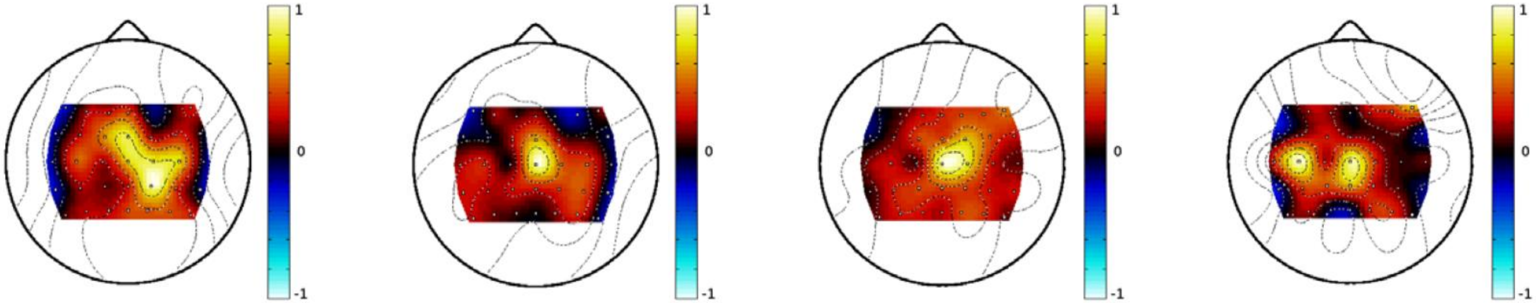


Motor imagery

Haptic feedback

BCIs in stroke rehabilitation (Gomez-Rodriguez, 2011; Ramos, 2013)

- Brain-controlled movement support decreases involvement of contralesional areas



(a) 8–16 Hz, robot (group average)

(b) 8–16 Hz, no robot (group average)

(c) 18–28 Hz, robot (group average)

(d) 18–28 Hz, no robot (group average)

A history of research on brain-computer interfaces

PASSIVE BRAIN COMPUTER INTERFACES

Passive BCIs (Zander, 2011)

- Passive BCIs are an extension of BCIs by additional cognitive monitoring
  - Basically, BCIs provided with user intentions, situational interpretations and emotional states
  - Target group solely includes healthy persons only up to now

> “ derives its outputs from arbitrary brain activity arising
> without the purpose of voluntary control,
> for enriching a human–machine interaction with
> implicit information on the actual user state ”

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