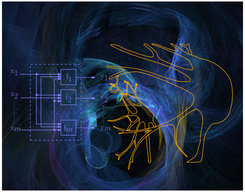
Brain Computer Interfaces

Marion Kurz   Wilhelm Almer   Florian Landolt

26. 01. 2006



Outline

Motivation and Milestones

- Locked - in - Syndrome: Severe motor disabilities.
- 17th - 19th Century:
  Jan Swammerdam (1664), Benjamin Franklin (1747), Luigi Galvani (1781), André Marie Ampere (1820), Michael Farraday (1831), James Clerk Maxwell (1864), Robert Bartholow (1881), Jaques Arsenne d'Arsonval (1896).
- Hans Berger (1929): Electroencephalogram (EEG), 2 major rhythms.
- Jacques Vidal (1970s): Brain Computer Interface Project. Government sponsored research in biocybernetics and human computer interaction.
- 2006: Contributions from different disciplines, standardization, clinical trial

Motivation and Milestones

- Locked - in - Syndrome: Severe motor disabilities.
- 17th - 19th Century:
  Jan Swammerdam (1664), Benjamin Franklin (1747), Luigi Galvani (1781), André Marie Ampere (1820), Michael Farraday (1831), James Clerk Maxwell (1864), Robert Bartholow (1881), Jaques Arsenne d'Arsonval (1896).
- Hans Berger (1929): Electroencephalogram (EEG), 2 major rhythms.
- Jacques Vidal (1970s): Brain Computer Interface Project. Government sponsored research in biocybernetics and human computer interaction.
- 2006: Contributions from different disciplines, standardization, clinical trial

Motivation and Milestones

- Locked - in - Syndrome: Severe motor disabilities.
- 17th - 19th Century:
  Jan Swammerdam (1664), Benjamin Franklin (1747), Luigi Galvani (1781), André Marie Ampere (1820), Michael Farraday (1831), James Clerk Maxwell (1864), Robert Bartholow (1881), Jaques Arsenne d'Arsonval (1896).
- Hans Berger (1929): Electroencephalogram (EEG), 2 major rhythms.
- Jacques Vidal (1970s): Brain Computer Interface Project. Government sponsored research in biocybernetics and human computer interaction.
- 2006: Contributions from different disciplines, standardization, clinical trial

Motivation and Milestones

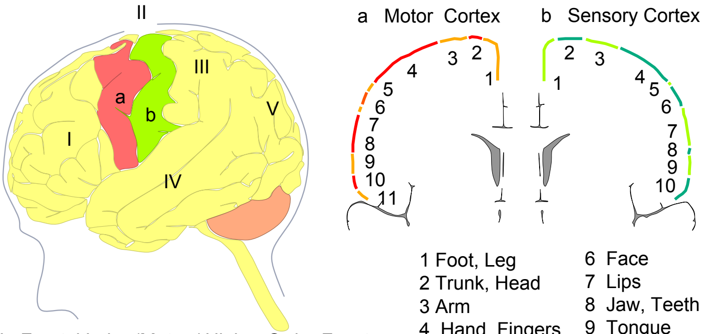
- Locked - in - Syndrome: Severe motor disabilities.
- 17th - 19th Century:
  Jan Swammerdam (1664), Benjamin Franklin (1747), Luigi Galvani (1781), André Marie Ampere (1820), Michael Farraday (1831), James Clerk Maxwell (1864), Robert Bartholow (1881), Jaques Arsenne d'Arsonval (1896).
- Hans Berger (1929): Electroencephalogram (EEG), 2 major rhythms.
- Jacques Vidal (1970s): Brain Computer Interface Project. Government sponsored research in biocybernetics and human computer interaction.
- 2006: Contributions from different disciplines, standardization, clinical trial

Motivation and Milestones

- Locked - in - Syndrome: Severe motor disabilities.
- 17th - 19th Century:
  Jan Swammerdam (1664), Benjamin Franklin (1747), Luigi Galvani (1781), André Marie Ampere (1820), Michael Farraday (1831), James Clerk Maxwell (1864), Robert Bartholow (1881), Jaques Arsenne d'Arsonval (1896).
- Hans Berger (1929): Electroencephalogram (EEG), 2 major rhythms.
- Jacques Vidal (1970s): Brain Computer Interface Project. Government sponsored research in biocybernetics and human computer interaction.
- 2006: Contributions from different disciplines, standardization, clinical trial

Outline

Brain



I Frontal Lobe (Motor / Higher Order Funct.
II Fissure of Rolando (Central Sulcus)
III Parietal Lobe (Sensation, Motor Control)
IV Temporal Lobe (Emotion, Hearing, Memory)
V Occipital Lobe (Vision, Color Recognition)

1 Foot, Leg
2 Trunk, Head
3 Arm
4 Hand, Fingers
5 Eye
6 Face
7 Lips
8 Jaw, Teeth
9 Tongue
10 Pharynx
11 Intra – abdominal

Brain cont'd

- Each of the brain hemispheres is segmented into four lobes with different functions.
- The lobes are separated by fissures (sulcus).
- Signal generation / processing initially occurs at the outer surface (2.5 - 4 mm) = Grey Cortex (Grey Matter).
- The Primary Somatic Sensory Cortex (Parietal Lobe) and the Primary Motor Cortex (Temporal Lobe) are the most important regions for BCI research.
- Cross - section: The amount of neural tissue associated with different regions of the body is in correlation with the complexity of the signals.

Brain cont'd

- Each of the brain hemispheres is segmented into four lobes with different functions.
- The lobes are separated by fissures (sulcus).
- Signal generation / processing initially occurs at the outer surface (2.5 - 4 mm) = Grey Cortex (Grey Matter).
- The Primary Somatic Sensory Cortex (Parietal Lobe) and the Primary Motor Cortex (Temporal Lobe) are the most important regions for BCI research.
- Cross - section: The amount of neural tissue associated with different regions of the body is in correlation with the complexity of the signals.

Brain cont'd

- Each of the brain hemispheres is segmented into four lobes with different functions.
- The lobes are separated by fissures (sulcus).
- Signal generation / processing initially occurs at the outer surface (2.5 - 4 mm) = Grey Cortex (Grey Matter).
- The Primary Somatic Sensory Cortex (Parietal Lobe) and the Primary Motor Cortex (Temporal Lobe) are the most important regions for BCI research.
- Cross - section: The amount of neural tissue associated with different regions of the body is in correlation with the complexity of the signals.

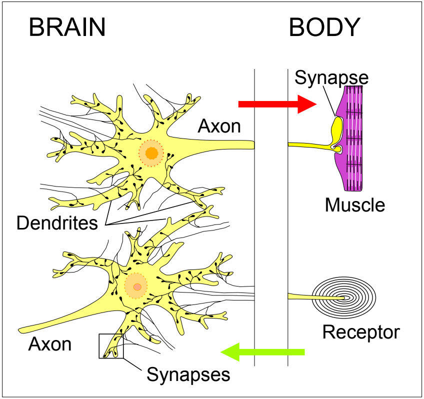
Brain cont'd

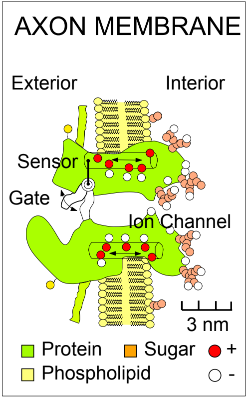
- Each of the brain hemispheres is segmented into four lobes with different functions.
- The lobes are separated by fissures (sulcus).
- Signal generation / processing initially occurs at the outer surface (2.5 - 4 mm) = Grey Cortex (Grey Matter).
- The Primary Somatic Sensory Cortex (Parietal Lobe) and the Primary Motor Cortex (Temporal Lobe) are the most important regions for BCI research.
- Cross - section: The amount of neural tissue associated with different regions of the body is in correlation with the complexity of the signals.

Brain cont'd

- Each of the brain hemispheres is segmented into four lobes with different functions.
- The lobes are separated by fissures (sulcus).
- Signal generation / processing initially occurs at the outer surface (2.5 - 4 mm) = Grey Cortex (Grey Matter).
- The Primary Somatic Sensory Cortex (Parietal Lobe) and the Primary Motor Cortex (Temporal Lobe) are the most important regions for BCI research.
- Cross - section: The amount of neural tissue associated with different regions of the body is in correlation with the complexity of the signals.

Nerve, Muscle, Receptor and Bioelectricity





Nerve, Muscle, Receptor and Bioelectricity cont'd

- Signal transduction pathway: Receptor → Nerve → Primary Sensory Cortex → Higher Order Sensory Region → Association → Pre Motor Region → Primary Motor Cortex → Nerve → Muscle.
- A nerve cell consists of the cell body (soma), a great number of short, highly branched cellular processes (dendrites), and one long projection (axon).
- The axon terminates into a number of buds. These form specialized cell - cell - contacts (synapses) with dendrites of other nerve cells or muscle cells.
- A cortical nerve cell may via its dendrites be contacted by several 100.000 axon ends.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Signal transduction pathway: Receptor → Nerve → Primary Sensory Cortex → Higher Order Sensory Region → Association → Pre Motor Region → Primary Motor Cortex → Nerve → Muscle.
- A nerve cell consists of the cell body (soma), a great number of short, highly branched cellular processes (dendrites), and one long projection (axon).
- The axon terminates into a number of buds. These form specialized cell - cell - contacts (synapses) with dendrites of other nerve cells or muscle cells.
- A cortical nerve cell may via its dendrites be contacted by several 100.000 axon ends.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Signal transduction pathway: Receptor → Nerve → Primary Sensory Cortex → Higher Order Sensory Region → Association → Pre Motor Region → Primary Motor Cortex → Nerve → Muscle.
- A nerve cell consists of the cell body (soma), a great number of short, highly branched cellular processes (dendrites), and one long projection (axon).
- The axon terminates into a number of buds. These form specialized cell - cell - contacts (synapses) with dendrites of other nerve cells or muscle cells.
- A cortical nerve cell may via its dendrites be contacted by several 100.000 axon ends.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Signal transduction pathway: Receptor → Nerve → Primary Sensory Cortex → Higher Order Sensory Region → Association → Pre Motor Region → Primary Motor Cortex → Nerve → Muscle.
- A nerve cell consists of the cell body (soma), a great number of short, highly branched cellular processes (dendrites), and one long projection (axon).
- The axon terminates into a number of buds. These form specialized cell - cell - contacts (synapses) with dendrites of other nerve cells or muscle cells.
- A cortical nerve cell may via its dendrites be contacted by several 100.000 axon ends.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Chemical signal transduction: Synapse (Axon end → Synaptic gap → Dendrite) → Soma → Axon origin.
- Electric signal transduction: Axon origin → Axon → Axon end.
- The mechanism guarantees unidirectional signal transmission.
- The electric signals are generated via ion - flux (sodium, Na^+, potassium, K^+, and chloride, Cl^-) across protein channels in the axon membrane.
- The direction of ion - flux is actively regulated in response to stimulation / inhibition. As a result, characteristic potentials are generated over the axon membrane.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Chemical signal transduction: Synapse (Axon end → Synaptic gap → Dendrite) → Soma → Axon origin.
- Electric signal transduction: Axon origin → Axon → Axon end.
- The mechanism guarantees unidirectional signal transmission.
- The electric signals are generated via ion - flux (sodium, Na^+, potassium, K^+, and chloride, Cl^-) across protein channels in the axon membrane.
- The direction of ion - flux is actively regulated in response to stimulation / inhibition. As a result, characteristic potentials are generated over the axon membrane.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Chemical signal transduction: Synapse (Axon end $\rightarrow$ Synaptic gap $\rightarrow$ Dendrite) $\rightarrow$ Soma $\rightarrow$ Axon origin.
- Electric signal transduction: Axon origin $\rightarrow$ Axon $\rightarrow$ Axon end.
- The mechanism guarantees unidirectional signal transmission.
- The electric signals are generated via ion - flux (sodium, Na^+, potassium, K^+, and chloride, Cl^-) across protein channels in the axon membrane.
- The direction of ion - flux is actively regulated in response to stimulation / inhibition. As a result, characteristic potentials are generated over the axon membrane.

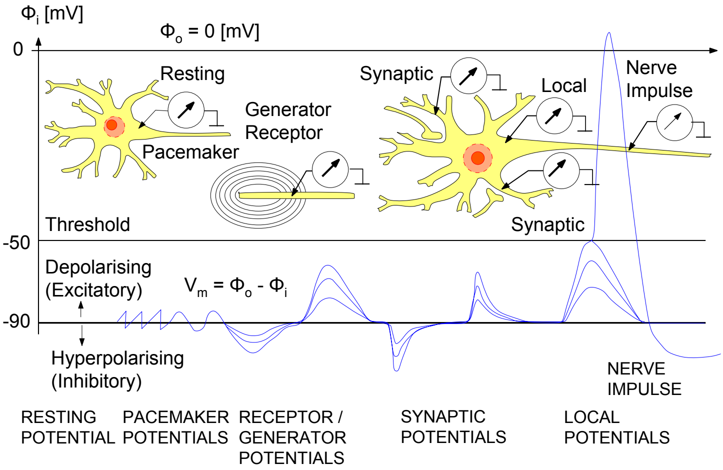
Nerve, Muscle, Receptor and Bioelectricity cont'd

- Chemical signal transduction: Synapse (Axon end $\rightarrow$ Synaptic gap $\rightarrow$ Dendrite) $\rightarrow$ Soma $\rightarrow$ Axon origin.
- Electric signal transduction: Axon origin $\rightarrow$ Axon $\rightarrow$ Axon end.
- The mechanism guarantees unidirectional signal transmission.
- The electric signals are generated via ion - flux (sodium, Na^+, potassium, K^+, and chloride, Cl^-) across protein channels in the axon membrane.
- The direction of ion - flux is actively regulated in response to stimulation / inhibition. As a result, characteristic potentials are generated over the axon membrane.

Nerve, Muscle, Receptor and Bioelectricity cont'd

- Chemical signal transduction: Synapse (Axon end $\rightarrow$ Synaptic gap $\rightarrow$ Dendrite) $\rightarrow$ Soma $\rightarrow$ Axon origin.
- Electric signal transduction: Axon origin $\rightarrow$ Axon $\rightarrow$ Axon end.
- The mechanism guarantees unidirectional signal transmission.
- The electric signals are generated via ion - flux (sodium, Na^+, potassium, K^+, and chloride, Cl^-) across protein channels in the axon membrane.
- The direction of ion - flux is actively regulated in response to stimulation / inhibition. As a result, characteristic potentials are generated over the axon membrane.

Signal Transduction and Potentials



Signal Transduction and Potentials cont'd

- Characteristic potentials result from different charge distribution across the axon membrane.
- The resting potential is at approximately -90 mV. It is lowered by inhibitory (hyperpolarisation) and raised by excitatory signals (depolarisation).
- A threshold level of ca. -50 mV has to be exceeded in order to generate a nerve impulse (action potential) that leads to further transmission across the synapse.
- After excitation, there is a latency period of decreased sensitivity (4 - 10 ms) during which the resting potential is re-established.
- EEG measures the electric activity of thousands of nerve cells. Therefore, the resulting signal contains considerable noise.

Signal Transduction and Potentials cont'd

- Characteristic potentials result from different charge distribution across the axon membrane.
- The resting potential is at approximately -90 mV. It is lowered by inhibitory (hyperpolarisation) and raised by excitatory signals (depolarisation).
- A threshold level of ca. -50 mV has to be exceeded in order to generate a nerve impulse (action potential) that leads to further transmission across the synapse.
- After excitation, there is a latency period of decreased sensitivity (4 - 10 ms) during which the resting potential is re-established.
- EEG measures the electric activity of thousands of nerve cells. Therefore, the resulting signal contains considerable noise.

Signal Transduction and Potentials cont'd

- Characteristic potentials result from different charge distribution across the axon membrane.
- The resting potential is at approximately -90 mV. It is lowered by inhibitory (hyperpolarisation) and raised by excitatory signals (depolarisation).
- A threshold level of ca. -50 mV has to be exceeded in order to generate a nerve impulse (action potential) that leads to further transmission across the synapse.
- After excitation, there is a latency period of decreased sensitivity (4 - 10 ms) during which the resting potential is re-established.
- EEG measures the electric activity of thousands of nerve cells. Therefore, the resulting signal contains considerable noise.

Signal Transduction and Potentials cont'd

- Characteristic potentials result from different charge distribution across the axon membrane.
- The resting potential is at approximately -90 mV. It is lowered by inhibitory (hyperpolarisation) and raised by excitatory signals (depolarisation).
- A threshold level of ca. -50 mV has to be exceeded in order to generate a nerve impulse (action potential) that leads to further transmission across the synapse.
- After excitation, there is a latency period of decreased sensitivity (4 - 10 ms) during which the resting potential is re-established.
- EEG measures the electric activity of thousands of nerve cells. Therefore, the resulting signal contains considerable noise.

Signal Transduction and Potentials cont'd

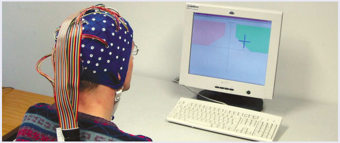
- Characteristic potentials result from different charge distribution across the axon membrane.
- The resting potential is at approximately -90 mV. It is lowered by inhibitory (hyperpolarisation) and raised by excitatory signals (depolarisation).
- A threshold level of ca. -50 mV has to be exceeded in order to generate a nerve impulse (action potential) that leads to further transmission across the synapse.
- After excitation, there is a latency period of decreased sensitivity (4 - 10 ms) during which the resting potential is re-established.
- EEG measures the electric activity of thousands of nerve cells. Therefore, the resulting signal contains considerable noise.

Outline

Categories

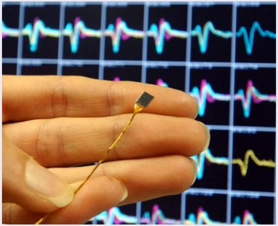
Detection of Mental States

- Non - invasive:
  Without penetrating the skalp, mostly EEG, rarely magnetoencephalogram (MEG)



Operant Conditioning

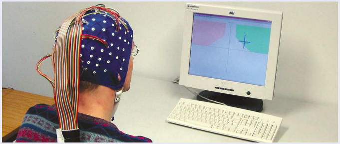
- Invasive:
  Implanted sensors (electrode array, needle electrodes, electrocorticogram (ECoG)



Categories

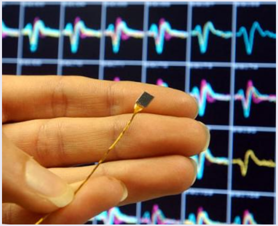
Detection of Mental States

- Independent
  from peripheral nerves and muscles, using only central nervous system (CNS) activity



Operant Conditioning

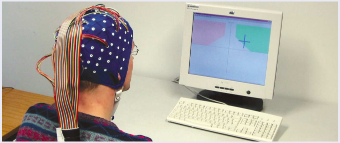
- Dependent
  on peripheral (non - CNS) - activity, e.g., controlled eye - movement



Categories

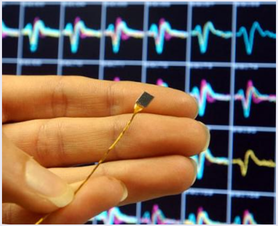
Detection of Mental States

- Unstimulated Brain Signals: Users can voluntarily produce the required signals



Operant Conditioning

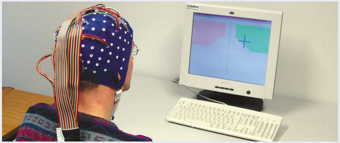
- Evoked Potentials: Users modulate brain responses to external stimuli (automatic or voluntarily)



Categories

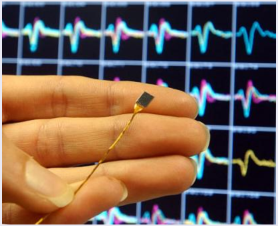
Detection of Mental States

- Asynchronous:
  The system detects when the user wants to emit a command

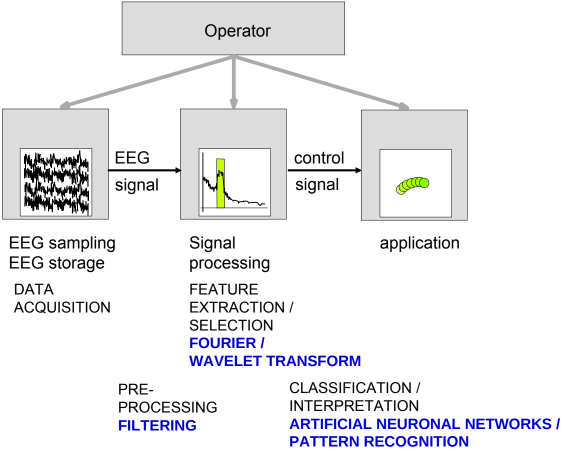


Operant Conditioning

- Synchronous:
  Commands can only be emitted synchronously with external pace.



BCI System


Operator
EEG
signal
control
signal
EEG sampling
EEG storage
DATA
ACQUISITION
Signal
processing
FEATURE
EXTRACTION /
SELECTION
FOURIER /
WAVELET TRANSFORM
application
PRE-
PROCESSING
FILTERING
CLASSIFICATION /
INTERPRETATION
ARTIFICIAL NEURONAL NETWORKS /
PATTERN RECOGNITION

BCI System cont'd

- In general, a BCI system comprises five units, all of which may be influenced by an external operator.
- The data acquisition unit is responsible for amplification, recording, and digitising of the brain signals.
- Preprocessing involves laplacian filtering to obtain reference - free signals, bandpass filtering between 4 and 40 Hz (the known frequency range of main brain activity), and wavelet denoising in order to remove white noise.
- Signal extraction / selection finally discriminates the relevant signals. While Fourier - analysis allows identification of sine and cosine functions only within fixed time windows, wavelet analysis may reveal signal discontinuity by means of varying time windows.

BCI System cont'd

- In general, a BCI system comprises five units, all of which may be influenced by an external operator.
- The data acquisition unit is responsible for amplification, recording, and digitising of the brain signals.
- Preprocessing involves laplacian filtering to obtain reference - free signals, bandpass filtering between 4 and 40 Hz (the known frequency range of main brain activity), and wavelet denoising in order to remove white noise.
- Signal extraction / selection finally discriminates the relevant signals. While Fourier - analysis allows identification of sine and cosine functions only within fixed time windows, wavelet analysis may reveal signal discontinuity by means of varying time windows.

BCI System cont'd

- In general, a BCI system comprises five units, all of which may be influenced by an external operator.
- The data acquisition unit is responsible for amplification, recording, and digitising of the brain signals.
- Preprocessing involves laplacian filtering to obtain reference - free signals, bandpass filtering between 4 and 40 Hz (the known frequency range of main brain activity), and wavelet denoising in order to remove white noise.
- Signal extraction / selection finally discriminates the relevant signals. While Fourier - analysis allows identification of sine and cosine functions only within fixed time windows, wavelet analysis may reveal signal discontinuity by means of varying time windows.

BCI System cont'd

- In general, a BCI system comprises five units, all of which may be influenced by an external operator.
- The data acquisition unit is responsible for amplification, recording, and digitising of the brain signals.
- Preprocessing involves laplacian filtering to obtain reference - free signals, bandpass filtering between 4 and 40 Hz (the known frequency range of main brain activity), and wavelet denoising in order to remove white noise.
- Signal extraction / selection finally discriminates the relevant signals. While Fourier - analysis allows identification of sine and cosine functions only within fixed time windows, wavelet analysis may reveal signal discontinuity by means of varying time windows.

BCI System cont'd

- Since the signals produced by individuals differ significantly from each other, the classification and interpretation unit must implement machine learning techniques.
- Bayesian classifiers take into account all available information from a given data set to identify the features of interest.
- Neural computing applications for pattern recognition usually make use of feed - forward network architectures, such as the multi - layer perceptron and the radial basis function network.
- Classifiers that modulate the machine output are trained by application of non - linear learning rules dependent on the proband's input.

BCI System cont'd

- Since the signals produced by individuals differ significantly from each other, the classification and interpretation unit must implement machine learning techniques.
- Bayesian classifiers take into account all available information from a given data set to identify the features of interest.
- Neural computing applications for pattern recognition usually make use of feed - forward network architectures, such as the multi - layer perceptron and the radial basis function network.
- Classifiers that modulate the machine output are trained by application of non - linear learning rules dependent on the proband's input.

BCI System cont'd

- Since the signals produced by individuals differ significantly from each other, the classification and interpretation unit must implement machine learning techniques.
- Bayesian classifiers take into account all available information from a given data set to identify the features of interest.
- Neural computing applications for pattern recognition usually make use of feed - forward network architectures, such as the multi - layer perceptron and the radial basis function network.
- Classifiers that modulate the machine output are trained by application of non - linear learning rules dependent on the proband's input.

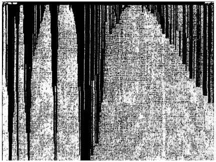
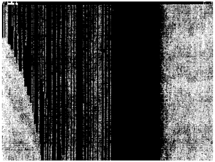
BCI System cont'd

- Since the signals produced by individuals differ significantly from each other, the classification and interpretation unit must implement machine learning techniques.
- Bayesian classifiers take into account all available information from a given data set to identify the features of interest.
- Neural computing applications for pattern recognition usually make use of feed - forward network architectures, such as the multi - layer perceptron and the radial basis function network.
- Classifiers that modulate the machine output are trained by application of non - linear learning rules dependent on the proband's input.

Outline

Frequency Thresholding

- Definition
- Nudge Shove

- Logical Navigation
- Implication of Frequency Thresholding using logical Navigation

Discrete Acceleration

- The Cyberlink-Technology
- Study 1: Discrete Acceleration

Figure 1: Tunnel-Interface

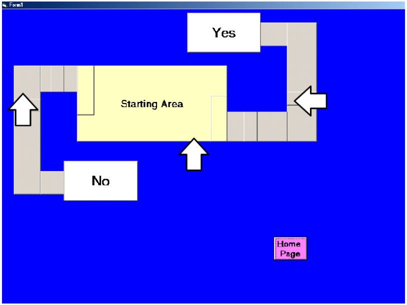


Figure 2: Discrete Acceleration

Personalized Tiling

- Study 2: Personalized Tiling

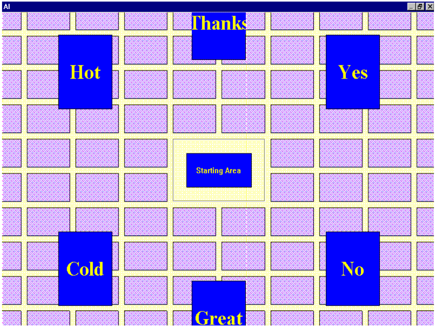


Figure 1: Tiling-Interface

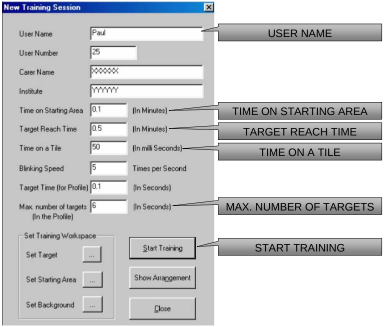
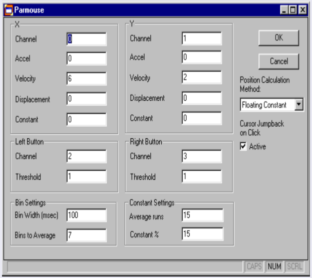


Figure 2: Properties-Dialogue

Outline

Device Control Driver

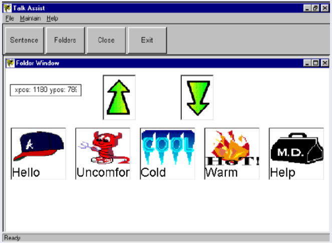


Parmouse Software

- A parallel mouse device driver allows neural signals to drive a cursor on a computer screen
- The pulses received from the signal processing computer are translated into cursor movements
- The graphical user interface allows configuring runtime parameters in order to tune the responsiveness of the interface

Outline

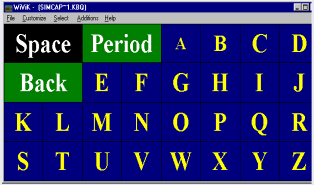
Communication



Talking to People

- Developed to assist nonverbal people in communicating
- Contains a customizable database of icons that are associated with phraces
- Can also be used as training aid storing also icons for navigation issues

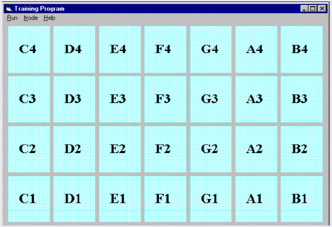
Communication



Virtual Keyboard

- Is used in conjunction with the WordPad and a speech synthesizer
- The synthesizer vocalizes words when the space or period keys are selected

Communication



Playing Piano

- The piano consists of 4 octaves for each one row
- A row consists of keys labeled with the note names
- Navigating the cursor horizontally plays the C scale
- Navigating the cursor vertically plays the note one octave lower or higher

Outline

Training - Synchronous acting BCI

- Synchronous acting BCIs base on fixed repetetive schemes, switching from one mental task to another
- A trial consists of two parts:
  1. A cue is telling the subject to get ready
  2. Next cue tells the subject to perform the desired mental task
- A trial lasts from 4 to 10 or more seconds
- This long time period is necessary because the phenomena of interest need time to recover

Training - Synchronous acting BCI

- Synchronous acting BCIs base on fixed repetetive schemes, switching from one mental task to another
- A trial consists of two parts:
  1. A cue is telling the subject to get ready
  2. Next cue tells the subject to perform the desired mental task
- A trial lasts from 4 to 10 or more seconds
- This long time period is necessary because the phenomena of interest need time to recover

Training - Synchronous acting BCI

- Synchronous acting BCIs base on fixed repetetive schemes, switching from one mental task to another
- A trial consists of two parts:
  1. A cue is telling the subject to get ready
  2. Next cue tells the subject to perform the desired mental task
- A trial lasts from 4 to 10 or more seconds
- This long time period is necessary because the phenomena of interest need time to recover

Training - Synchronous acting BCI

- Synchronous acting BCIs base on fixed repetetive schemes, switching from one mental task to another
- A trial consists of two parts:
  1. A cue is telling the subject to get ready
  2. Next cue tells the subject to perform the desired mental task
- A trial lasts from 4 to 10 or more seconds
- This long time period is necessary because the phenomena of interest need time to recover

Outline

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Training - Asynchronous Acting BCI

- Self-paced decisions when to begin and end are made
- Neural network classifier recognizes which mental task is concentrated on
- Analyzing continuous viariations of EEG rythms
- A mutual learning process is involved
- The neural network learns patient-specific EEG patterns
- The patient learns how to think to let the BCI better undestand
- The response toward an arriving EEG sample is the class with the greatest probability
- Responses to EEG patterns under a given confidence threshold are treated as **unknown**

Outline

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into "up" and "down" signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into “up” and “down” signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into "up" and "down" signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into "up" and "down" signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into "up" and "down" signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into “up” and “down” signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

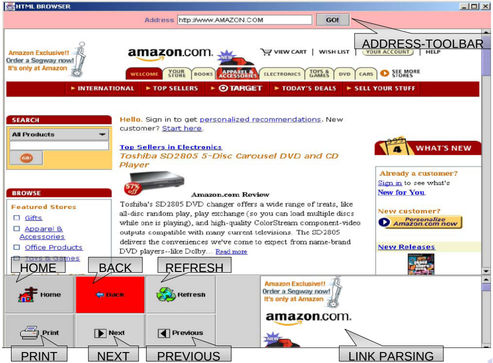
Alternative Data Processing - Invasive Method

- Analyses of brain signal data turned out that waveshapes produced from a single electrode are not unique
- Phase Releationships between the spikes changes when the direction of e. g. the cursor changed
- Recognizing these different patterns allows the patient to think of the direction of the cursor
- This enables the patient navigating in two dimensions with a single electrode
- The different signals will be clustered into "up" and "down" signals
- *Up* signals are than mapped to horizhontal cursor movement
- *Down* signals are mapped to vertical cursor movements

Outline

BrainBrowser

- Importance
- Problems with conventional Browsers in combination with BCIs
- Design and Layout



BrainBrowser (cont'd)

- Features
  - Link Parsing
  - Virtual Keyboard
- Serialization
- Alignment of components
- Grouping the Browsers controls

Outline

Summary

- Presently, BCI research is still in its infancy. Serious BCI use is restricted to completely paralised patients. Clinical Trial Phase.
- Standardisation: BCI2000
  General - purpose system for brain computer interface research. Incorporate currently used brain signals, implement objective measure of performance (bit rate), provide analysis tools, create common data pool.
  » foster BCI research
- Ethical considerations: Guilty Knowledge Test.

Summary

- Presently, BCI research is still in its infancy. Serious BCI use is restricted to completely paralised patients. Clinical Trial Phase.
- Standardisation: BCI2000
  General - purpose system for brain computer interface research. Incorporate currently used brain signals, implement objective measure of performance (bit rate), provide analysis tools, create common data pool.
  » foster BCI research
- Ethical considerations: Guilty Knowledge Test.

Summary

- Presently, BCI research is still in its infancy. Serious BCI use is restricted to completely paralised patients. Clinical Trial Phase.
- Standardisation: BCI2000
  General - purpose system for brain computer interface research. Incorporate currently used brain signals, implement objective measure of performance (bit rate), provide analysis tools, create common data pool.
  » foster BCI research
- Ethical considerations: Guilty Knowledge Test.

Contact

Wilhelm Almer
wilhelm.almer@inode.at

Florian Landolt
fl3@gmx.net

Marion E. Kurz
marion.kurz@gmx.at
www.nkis.info
www.kultart.at

For Further Reading: Books

B. Alberts, D. Bray, J. Lewis, M. Raff, K. Roberts, and J. D. Watson.
Molecular Biology of the Cell.
Garland Publishing, Inc., ISBN 0-8240-7283-9, 1st edition, 1983.

J. Dudel, R. Menzel, and R. F. Schmidt (Hrsg.).
Neurowissenschaft. Vom Molekül zur Kognition.
Springer-Verlag, ISBN 3-540-61328-5, 1st edition, 1996.

T. N. Lal.
Machine Learning Methods for Brain-Computer Interfaces, Reihe: MPI Series in Biological Cybernetics, Bd.12.
Logos Verlag, ISBN 3-8325-1048-6, 1st edition, 2005.

For Further Reading: Books cont'd

J. Malmivuo and R. Plonsey.
Bioelectromagnetism. Principles and Applications of Bioelectric and Biomagnetic Fields.
Oxford University Press, ISBN 0-19-505823-2, 1st edition, 1995.
http://butler.cc.tut.fi/~malmivuo/bem/bembook/index.htm

J. Orear.
Physik.
Carl Hanser Verlag, ISBN 3-446-12977-4, 1st edition, 1982.

For Further Reading: Articles

G. Blanchard and B. Blankertz.
BCI Competition 2003: Data Set IIa - Spatial Patterns of Self-Controlled Brain Rhythm Modulations.
IEEE Trans. Biomed. Eng. 51 (6), 1062-1066, 2004.
http://ida.first.fhg.de/publications/BlaBla04.pdf

B. Blankertz et al.
BCI Competition 2003: Progress and Perspectives in Detection and Discrimination of EEG Single Trials.
IEEE Trans. Biomed. Eng. 51 (6), 1044-1051, 2004.
http://ida.first.fhg.de/publications/BlaMueCurVauSchWolSchNeuPfuHinSchBir04.pdf

For Further Reading: Articles cont'd

G. Dornhege, B. Blankertz, C. Curio, and K.-R. Müller.
Boosting Bit Rates in Non-Invasive EEG Single-Trial Classififcations by Feature Combination and Multi-Class Paradigms.
IEEE Trans. Biomed. Eng. 51 (6), 993-1002, 2004.
http://ida.first.fhg.de/publications/DorBlaCurMue04.pdf

G. Dornhege, B. Blankertz, C. Curio, and K.-R. Müller.
Increase Information Transfer Rates in BCI by CSP Extension to Multi-Class.
Advances in Neural Inf. Proc. Systems (NIPS03) 16 (online), 2004.
http://books.nips.cc/nips16.html

For Further Reading: Articles cont'd

T. Hinterberger, S. Schmidt, N. Neumann, J. Mellinger, B. Blankertz, G. Curio, and N. Bierbaumer.
Brain Computer Communication with Slow Cortical Potentials: Methodology and Critical Aspects.
IEEE Trans. Biomed. Eng. 51 (6), 1011-1018, 2004.
http://ida.first.fhg.de/publications/HinSchNeuMelBlaCurBir04.pdf

J. Kohlmorgen and B. Blankertz.
Bayesian Classification of Single-Trial Event-Related Potentials in EEG.
Int. J. Bif. Chaos 14 (2), 719-726, 2004.
http://ida.first.fhg.de/publications/KohBla04.pdf

For Further Reading: Articles cont'd

S. Lemm, B. Blankertz, B. Curio, and K.-R. Müller.
Spatio-Spectral Filters for Improving the Classification of Single Trial EEG.
IEEE Trans. Biomed. Eng. 52 (9), 1541-1548, 2005.
http://ida.first.fhg.de/publications/LemBlaCurMue05.pdf

J. del R. Millàn.
Adaptive Brain Interfaces.
Comm. ACM 46 (3), 74-80, 2003.

For Further Reading: Articles cont'd

N. Neumann and N. Birbaumer.
Predictors of Successful Self Control During Brain-Computer Communication.
J. Neurol. Neuros. Psych. 74, 1117-1121, 2003.
http://jnnp.bmjjournals.com/cgi/content/full/74/8/1117

J. J. Vidal.
Toward Direct Brain-Computer Communication.
Ann. Rev. Biophys. Bioeng. 2, 157-180, 1973.
http://www.cs.ucla.edu/~vidal/BCI.pdf

For Further Reading: Articles cont'd

J. R. Wolpaw, D. J. McFarland, T. M. Vaughn, and G. Schalk.
The Wadsworth Center Brain-Computer Interface (BCI) Research and Development Program.
IEEE Trans. Neural Syst. Rehabil. Eng. 2, 204-207, 2003.
http://www.cs.cmu.edu/~tanja/BCI/Wadsworth2003.pdf

For Further Reading: Proceedings

P. Gnanayutham, C. Bloor, and G. Cockton.
Discrete Acceleration and Personalised Tiling as Brain-Body Interface Paradigms for Neurorehabilitation.
In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 261 - 270.
ACM Press, ISBN 1-58113-998-5, 2005.

For Further Reading: Proceedings cont'd

T. N. Lal et al.
A Brain Computer Interface with Online Feedback based on Magnetoencephalography.
In: Proceedings of the 22nd International Conference on Machine Learning ICML '05, 465 - 472.
ACM Press, ISBN 1-59593-180-5, 2005.
http://www.machinelearning.org/proceedings/icml2005/papers/059_BrainComputer_LalEtAl.pdf

For Further Reading: Proceedings cont'd

S. G. Mason, Z. Bozorgzadeh, and G. E. Birch.
The LFD-ASD Brain Computer Interface: On-Line Identification of Imagined Finger Flexions in Subjects with Spinal Cord Injuries.
In: Proceedings of the Fourth International ACM Conference on Assistive Technologies, 109 - 113.
ACM Press, ISBN 1-58113-314-8, 2000.

M. Moore and P. Kennedy.
Human Factors Issues in the Neural Signals Direct Brain-Computer Interfaces.
In: Proceedings of the Fourth International ACM Conference on Assistive Technologies, 114 - 120.
ACM Press, ISBN 1-58113-314-8, 2000.

For Further Reading: Proceedings cont'd

J. Mankoff, A. Dey, U. Batra, and M. Moore.
Web Accessibility for Low Bandwidth Input.
In: Proceedings of the Fifth International ACM Conference on Assistive Technologies, 17 - 24.
ACM Press, ISBN 1-58113-464-9, 2002.

J. R. Thorpe, P. C. van Oorschot, and A. Somayaji.
Pass-thoughts: Authenticating With Our Minds.
Cryptology ePrint Archive, Report 2005/121, 2005.
http://eprint.iacr.org/2005/121.pdf
Revised Version: Proceedings of the ACSA 2005 New Security Paradigms Workshop, September 2005 (in print).

For Further Reading: Abstracts

M. Moore, P. Kennedy, E. Mynatt, and J. Mankoff.
Nudge and Shove: Frequency Thresholding for Navigation in Direct Brain-Computer Interfaces. Conference on Human Factors in Computing Systems 2001.
In: CHI '01 Extended Abstracts on Human Factors in Computing Systems, 361 - 362.
ACM Press, ISBN 1-58113-340-5, 2001.

O. Tomori and M. Moore.
The Neurally Controllable Internet Browser (Brain Browser). Conference on Human Factors in Computing Systems 2003.
In: CHI '03 Extended Abstracts on Human Factors in Computing Systems, 796 - 797.
ACM Press, ISBN 1-58113-637-4, 2003.

For Further Reading: Theses

L. Laitinen.
Neuromagnetic Sensory Motor Signals in Brain Computer Interfaces (Thesis).
Department of Electrical and Communications Engineering, Helsinki University of Technology, 77 pp., 2003.
http://www.lce.hut.fi/research/cogntech/bci/Lauras_Thesis.pdf

J. Lehtonen.
EEG-based Brain Computer Interfaces (Thesis).
Department of Electrical and Communications Engineering, Helsinki University of Technology, 105 pp., 2002.
http://www.lce.hut.fi/research/cogntech/bci/jannes_thesis.pdf

For Further Reading: Theses cont'd

T. Nykopp.
Statistical Modelling Issues for the Adaptive Brain Interface (Thesis).
Department of Electrical and Communications Engineering, Helsinki University of Technology, 113 pp., 2001.
http://www.lce.hut.fi/research/cogntech/bci/tommis_thesis.pdf

For Further Reading: Links

- Berlin BCI.
  Cooperation between the Fraunhofer FIRST institute and the Charitè - University Medicine, Berlin. Development of EEG-driven systems for computer-aided working environments.
  http://ida.first.fhg.de/projects/bci/bbci_official/index_en.html

- Braingate Neural Interface System.
  System for pilot clinical trial.
  http://www.cyberkineticsinc.com/content/medicalproducts/braingate.jsp

For Further Reading: Links cont'd

- Cognitive Science and Technology.
  Research group at the Laboratory of Computational Engineering, Helsinki University of Technology.
  http://www.lce.hut.fi/research/cogntech/
- Laboatory of Brain Computer Interfaces at the Technical University of Graz.
  Several BCI - related research fields, platform for the BCI community.
  http://www.bci.tugraz.at/index.html

For Further Reading: Links cont'd

Oxford BCI.
Asynchronous BCI. Development of algorithms and dynamic models. Pattern Analysis and Machine Learning Research Group (PARG).
http://www.robots.ox.ac.uk/~parg/projects/bci/index.html

G. T. Toussaint.
School of Computer Science, McGill University, Quebec. Extensive list of links concerning pattern recognition and machine learning.
http://cgm.cs.mcgill.ca/~godfried/teaching/pr-web.html

For Further Reading: Links cont'd

Wadsworth BCI.
EEG-mediated cursor / robotic arm control. BCI2000, several videos.
http://www.bciresearch.org/