Design Principles for Neuroprosthetics

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BMI Architecture

Feature extraction → Classification / Regression → Action generation

Acquisition

Augmentation: voluntary learning new skills
BMI Modalities: Electrical Activity

Layers

- Scalp
- Skull
- Dura
- Arachnoid
- Pia
- Cortex
- White matter

Signal Source

- EEG
- ECoG (epidural or subdural)
- Intraparenchymal (single neuron or local field potential)

(Leuthardt et al., Neurosurg Focus 2009)
Requirement

A BCI has to be operational and reliable 24/24, 7/7
Requirement … or Pitfall?

A BCI has to be operational and reliable 24/24, 7/7

- Really ???
- No system on earth (animal or artificial) is!
- “Dependability”
Brain-controlled Robots

- Big challenge, fast & timing decision-making is critical
- How to bridge the cognitive gap?
BMI Architecture

Feature extraction

Classification / Regression

Action generation

Rhythms / Spontaneous

Acquisition

ERP

ERPs / Spontaneous
Interaction Principles

• Asynchronous approach
  - User can send commands anytime
  - Spontaneous activity, no external cues

• Machine Learning Way to BMI
  - Mutual learning process
  - Feature extraction & classification

• Blending of Intelligences
  - User’s mental capabilities
    + intelligent device
  - Shared Control, Context Aware

• Cognitive Interfaces
  - Recognition of human mental states
    (e.g., error awareness, anticipation)
Adaptive Shared Control

- User command
  - Planning
    - Adding *virtual* attractors
- Cameras
- Proximity sensors
  - Environment information
    - Adding attractors/repellors

Dynamical navigation system

- Obstacle
- Free path
Adaptive Shared Control
• Target Population
  ➢ Severely disabled people constrained to remain in bed
Manual control, mean:

<table>
<thead>
<tr>
<th></th>
<th>Path 1</th>
<th>Path 2</th>
<th>Path 3</th>
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<tbody>
<tr>
<td><strong>Time [s]</strong></td>
<td>285.6</td>
<td>253.8</td>
<td>298.9</td>
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<tr>
<td><strong>Commands</strong></td>
<td>29.3</td>
<td>27.5</td>
<td>27.0</td>
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<tr>
<td><strong>Distance [m]</strong></td>
<td>35.7</td>
<td>34.4</td>
<td>39.6</td>
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Telepresence Robot

Abdul Al-Khodairy. *Suva*

<table>
<thead>
<tr>
<th>Time</th>
<th>Mental / Manual</th>
<th>Time</th>
<th>Mental / Manual</th>
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<tbody>
<tr>
<td>s1-s4</td>
<td>1.15</td>
<td>d1-d6</td>
<td>1.16 (1.07)</td>
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<th>Mental / Manual</th>
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<tbody>
<tr>
<td>s1-s4</td>
<td>1.00</td>
</tr>
<tr>
<td>d1-d6</td>
<td>0.90 (0.75)</td>
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</table>
Brain-controlled Wheelchair
Brain-controlled Wheelchair

Drive along route
Dock and pause at 2 tables
Multitasking

Michele Tavella, Serafeim Perdikis

- Intentional non-control
Multitasking &
Intentional Non-Control
Multitasking & Intentional Non-Control

Michele Tavella, Robert Leeb

• Whole Hand Prehension
  ➢ Opening: m. extensor digitorum communis
  ➢ Closing: m. flexor digitorum superficialis

• Task
  ➢ Reach & Grasp pen
  ➢ Write a sentence
  ➢ Reach pen holder & Release
Self-Paced Reaching

Eileen Lew
S. Silvoni, P. Tonin. S Camillo, Venice

- Movement onset

Healthy, non-dominant arm

Stroke, paretic arm
Self-Paced Reaching

- **Center-out movements, 4 directions**

Healthy, dominant arm

[Diagram showing the phase plots at different time points (-1000ms, -500ms, -375ms, -250ms, -125ms, 0ms) with LDA accuracy ratio over time. The plots illustrate the instantaneous phase in the [0.1-1]Hz frequency band.]
Self-Paced Reaching

- Center-out movements, 4 directions

Stroke, paretic arm

[Graph showing neural activity over time]
Self-Paced Reaching

Eileen Lew
Margitta Seeck. Geneva Univ. Hospital

- **Center-out movements, 4 directions**

Epileptic, intracranial recordings, gamma oscillations [70-90] Hz

Left SMA
Cognitive States:
Human in the Loop

- Asynchronous
- Mental Commands

MONITORING

feedback

Cognitive States
Cognitive States: Error Recognition
ErrP: Online Implementation

- Two naïve subjects
- Two different days
- 150 ms window: 250 → 400 ms
- Above 200% increase in performance (Bits per Trial)
Human-in-the-Loop: Learning from ErrP

Ricardo Chavarriaga
I. Iturrate, J. Minguez. Univ. Zaragoza

- Reinforcement Learning approach:
  For each state $s$, estimate the value of performing action $a$ given the reward $ErrP$: $Q$-Value($s, a$)
Human-in-the-Loop: Learning from ErrP
Anticipation increases efficiency of a cognitive process by partial advanced activation of neural substrates involved.
Anticipation of Events, CNV
Anticipation of Events, CNV
Conclusions

- Fast & timing decision-making is critical
- How to bridge the cognitive gap?

- **Shared control** — Principled approaches to blend user’s mental capabilities and device’s intelligence

- **Natural interaction** — Support Multitasking and Intentional Non-Control

- **Brain signals carry cognitive information** — Cognitive States modulate interaction
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