Brain Computer Interfaces as Stroke Rehabilitation Tools: Optimization of current strategies

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Brain-Computer-Interface (BCI)

“A system for controlling a device e.g. computer, wheelchair or a neuroprothesis by human intention which does not depend on the brain’s normal output pathways of peripheral nerves and muscles” [Wolpaw et al., 2002].

HCI – Human Computer Interface
DBI – Direct Brain Interface (University of Michigan)
TTD – Thought Translation Device (University of Tübingen)
Activate a device that assists movement to train patients to produce more normal brain activity.

Daly, J. J. & Wolpaw, J. R. *Brain-computer interfaces in neurological rehabilitation; The Lancet Neurology, 2008, 7, 1032-1043*
Stroke Rehabilitation

Motor imagery (MI) based rehabilitation was proven to be an effective therapy.

Andrea Zimmermann-Schlatter, Corina Schuster, Milo A Puhan, Ewa Siekierka and Johann Steurer. *Efficacy of motor imagery in post-stroke rehabilitation: a systematic review*; Journal of NeuroEngineering and Rehabilitation
Neurological rehabilitation via robotic devices shows promising results in clinical trials.
Stroke Rehabilitation

The **logical next step combines** the two approaches into an integrative rehabilitation strategy.
How to induce brain plasticity?

Close the feedback loop and induce “Hebbian plasticity”

“Cells that fire together, wire together.”
Imagination of hand movement causes an ERD which is used to classify the side of movement. The desynchronization occurs in motor and related areas of the brain. Therefore, for analyzing and classifying ERD-patterns the electrodes must be placed close to sensorimotor areas.
Paradigm for motor imagery BCI experiment

TRAINING

Recording of 40 trials minimum

Offline data classification
Paradigm for motor imagery BCI experiment

- Fixation cross: 0-2 seconds
- CUE: 3-4 seconds
- Feedback (FB): 5-8 seconds
- Classifier: Arrowheads on the monitor indicate the direction of movement.
Right/Left hand motor imagery with Common Spatial Patterns - principle

- Common Spatial Patterns weight each electrode according to the importance to the discrimination task.

\[
\vec{w}^* = \arg\max_{\vec{w} \in \mathbb{R}^N} \left\{ \frac{\vec{w}^T R_{\vec{x}|c_1} \vec{w}}{\vec{w}^T R_{\vec{x}|c_2} \vec{w}} \right\}
\]

- The difference between left and right population is maximized.

- CSPs reflect the EEG source distribution.

- Setup of 4 CSPs: influence of electrode montage, sensitive to artifacts.

- The spatial filter suppresses artifacts.

- Variance calculation of 1 second segments -> fast feedback.
Right/Left hand motor imagery with Common Spatial Patterns: live experiment
Classification expected
Comparison bar-FB and VR-FB

Error rate from the two feedback runs for S1. The vertical bar indicates the cue onset.
Study

Test of a generic set of Common Spatial Patterns (CSP) and Linear Discriminant Analysis (LDA), for Motor Imagery (MI) - Brain-Computer Interfaces with stroke patients.
Eleven healthy subjects did EEG recordings with 64 EEG channels.

Users were instructed to imagine right or left hand movement according to the arrow presented.

All healthy test users performed one session, consisting of 80 trials.

A general classifier and CSP feature vector was calculated using data of this 11 subjects.

The test was done over 11 healthy and 11 stroke patients.

For check long term effect 5 stroke patients perform 4th more sessions.
Mean accuracy rates of the two groups participating in the VR paradigm

<table>
<thead>
<tr>
<th></th>
<th>Healthy</th>
<th>Stroke</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Session #</strong></td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td><strong>Participants</strong></td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td><strong>Mean Acc.</strong></td>
<td>63.77</td>
<td>60.67</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>16.52</td>
<td>13.05</td>
</tr>
</tbody>
</table>

Results from 80 trials. The first number shows the mean error rate beginning from 3.5 seconds until 8 seconds. The number in parenthesis shows the minimum error rate within this time.
Conclusions

- Generic CSP and LDA classifier can be used for healthy persons and also for stroke patients for MI training.
  - Time is reduced -> keep motivation and ability of control

- Five stroke patients that participated to more training sessions, increased their accuracy from 59.70% up to 72.48%.

- Difference accuracy between healthy users and stroke patients is only about 3% on average.
Krzeszowice Rehabilitation Center, Poland

- Testing motor imagery in stroke patients.

- Study changes of ERD curves in stroke.

- Prove if stroke patients can control MI – BCI.
If enough runs performed to divide data into test runs (for calculating classifier and spatial filters) and test data, some patients able to achieve very high accuracies.

Results, classifier same session

Min. Error = 2.5%
Mean Error = 14.5% (from second 5 to 8)
Number of trials = 80
Confidence level = 38.6%
Calculating ERD over time

? ERD in stroke survivors is significantly lower

Right trials – good performer
Calculating ERD over time

Left trials – good performer

Event Related Desynchronization / Synchronization

Parameter:
- Montagename: ...
- Nr. trials: 34
- Calc. from file: ...
- Average opt.: [mean 16 samples]
- Type: BP
- F.-borders: [8 12]
- Realization: butter
- Order: 4
- Used signal: Induced components
- Ref. int.: [128 640] samples
- With envelope: no

Legend:
- relative power change
- significance
- reference

Calculating ERD over time
Next Steps

g.REHAbci with robotic feedback
g.tec introduces lectures for biosignal recording and analysis. They are divided into a first part which contains the theoretical background, hands-on examples and several tasks to solve and a second part which contains only the solutions for the tasks. The lectures allow researchers to get a quick start in the specific field and to perform already state of the art experiments after just a few hours. The lectures are also perfectly suited for teaching because of the separation of tasks and solution manuals.

<table>
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<tr>
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<tbody>
<tr>
<td>Average time to perform the lecture: 450 min</td>
<td>Average time to perform the lecture: 465 min</td>
<td>Average time to perform the lecture: 700 min</td>
<td>Average time to perform the lecture: 330 min</td>
</tr>
<tr>
<td>Pages of lecture: 47</td>
<td>Pages of lecture: 89</td>
<td>Pages of lecture: 58</td>
<td>Pages of lecture: 65</td>
</tr>
</tbody>
</table>

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