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**BCI Seminar – Written report**

Based on the paper : Leamy, D.J., Kocijan, J., Domijan, K. *et al.* **An exploration of EEG features during recovery following stroke – implications for BCI-mediated neurorehabilitation therapy**. *J NeuroEngineering Rehabil* (2014). https://doi.org/10.1186/1743-0003-11-9

**ABSTRACT**

*Background*

Neuro-rehabilitation following stroke may be enhanced by BCI, the study focuses on EEG-based BCI in particular. Many stroke survivors suffer paralysis of a limb and this measurement method provides a mean to help in recovering motor control.

*Methods*

The method is a 32-channel electroencephalogram (EEG) recording while proceeding to the Kapandji finger opposition test. 10 healthy subjects realized one session and 5 stroke affected subjects realized 2 session 6 months apart. To compare the efficiency of training a rehabilitative BCI with stroke affected and healthy EEG data, a BCI design based on Filter Bank Common Spatial Patterns (FBCSP) was implemented.

*Results*

The classification accuracy of the late session stroke EEG is lower when using a BCI trained with healthy EEG rather than when training the BCI with the early session of stroke affected patient's datasets.

*Conclusion*

Knowing that healthy EEG may help but doesn't have the best results for an effective BCI rehabilitation system after stroke, the inter-subject's changes must be taken into account as part of the a neurofeedback therapy and must be adapted individually.

## INTRODUCTION :

A stroke, sometimes called a brain attack, occurs when something blocks blood supply to a part of the brain or when a blood vessel in the brain bursts. This causes brain tissue to become damaged or die. Most of BCI studies being conducted on subjects with no damage to the brain, relatively little is known about requirements for the design of a rehabilitative BCI system.

Neurorehabilitation techniques involves the recording and decoding of local brain signals generated by the patient during the execution of a task. There are two different ways to proceed : either the subject tries to physically perform a particular task (even if imperfect), either performs a Motor imagery (MI) task. MI can be defined as a dynamic state during which a subject mentally simulates a physical action, without any motor output. By coupling this tasks experiments to BCI, a feedback can be observed and help both motor learning and therapy engagement alongside.

In this study, the goal is not to control an external device (using motor imagery) but to actually regain motor control of the affected limb, therefore we are not interested in MI but actual physical attempted movement of a subject. The study focuses on reinforcing engagement of the subject's motor networks while performing a targeted task.

Finally, as a stroke is an injury to the brain, the cortical reorganization (plasticity) differs for each individual. After a stroke, recovery that continues beyond 3 or 4 weeks has been attributed to plasticity, a reorganization of the brain in which functions previously performed by the ischemic (damaged) area are assumed by other brain areas. BCI translate the patterns of local brain activation into a desired action, when our motor system is lacking the capacity to perform. In consequence, the usual BCI responses from healthy brain are expected to be different. The goal here is to determine if such features are sufficiently universal that machine learning parameters trained using healthy subjects can be used for stroke-affected patients.

If it is relevant to use BCI trained with healthy subjects to help stroke subjects during recovery, then the deployment would be far more practical. On the other hand, if the stroke affected EEG presents too many differences and/or changes over time then a more sophisticated design will be needed.

The study attempts to shed some light on this latter aspect.

## MATERIAL AND METHODS:

### *The subjects*

Stroke patients were recruited from the Adelaide & Meath Hospital, Dublin while control subjects were recruited from the National University of Ireland Maynooth. Ten healthy subject (8 men and 2 women, mean of age: 57.2±17.6 years) participated in one recording session while five stroke patients (3 men and 2 women, mean of age : 59.0±9.4 years) participated in 2 sessions. A first "early" recording session was taking place 22.2(±12.9) days after the stroke occurred. The second session was 190.6(±26.1) days later, roughly 6 months after the early session.

The location of brain tissue damage due to stroke were varied, including both cortical and subcortical bilateral tissues but all chosen subject had one hand affected by the stroke.

*The task*

To determine their motor ability, the subjects performed the Kapandji finger opposition test. The subject is required to touch 10 points on their stroke affected hand with their thumb as shown in Figure 1. Healthy subjects used their dominant hand and the stroke subjects were instructed to use their stroke-affected hand.

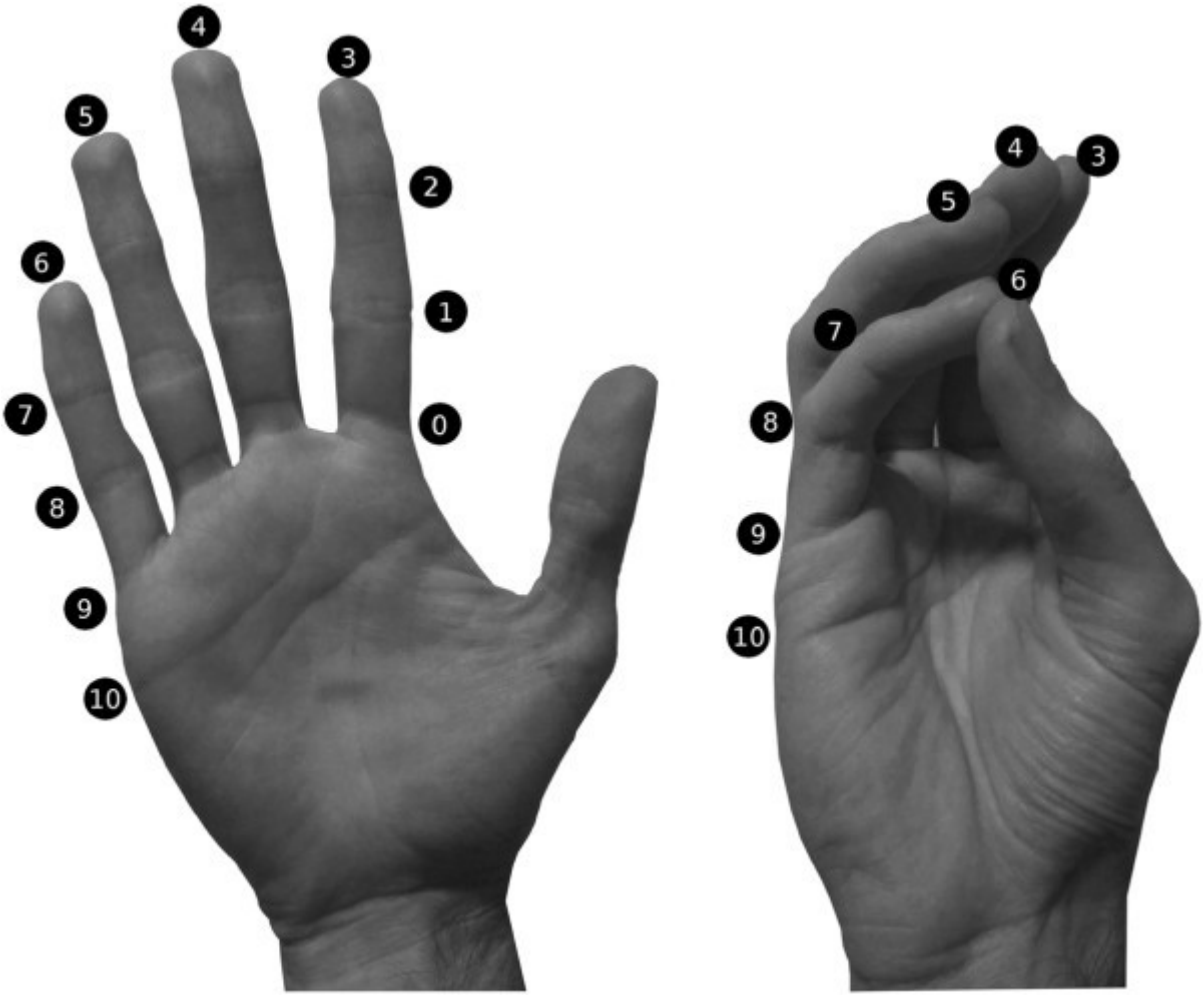



Figure 1

*Experimental setup*

The recording session took place as followed: the subject was seated in front of a screen displaying the instructions : “The experiment will begin shortly” ,“Move your fingers” , “Relax” , “Experiment now over. Please stay still”. A session consisted of 20 activation trials and 20 rest trials, each trial lasted 10 seconds.

Subject number 3 (S3) completed only 32 trials during his first session because of fatigue. He was unable to touch any of the points with his thumb but still had some movement.

Early session results (table 1)

| ID | Sex | Dominant hand | Tested hand | Age | Time from stroke | Kapandji score | MMSE score |
|---|---|---|---|---|---|---|---|
| S1 | M | Right | Right | 58.8 | 6w 0d | 6/10 | 28/30 |
| S2 | M | Right | Right | 56.3 | 3w 2d | 6/10 | 28/30 |
| S3 | M | Right | Left | 75.0 | 2w 5d | 0/10 | 29/30 |
| S4 | F | Right | Right | 51.9 | 0w 6d | 6/10 | 27/30 |
| S5 | F | Right | Right | 53.0 | 3w 0d | 9/10 | N/A |

Late session results (table 2)

| ID | Sex | Dominant hand | Tested hand | Age | Time from early | Kapandji score | MMSE score |
|---|---|---|---|---|---|---|---|
| S1 | M | Right | Right | 58.8 | 25w 6d | 6/10 | 28/30 |
| S2 | M | Right | Right | 56.3 | 25w 2d | 10/10 | 28/30 |
| S3 | M | Right | Left | 75.0 | 25w 1d | 3/10 | 30/30 |
| S4 | F | Right | Right | 51.9 | 26w 0d | 8/10 | 27/30 |
| S5 | F | Right | Right | 53.0 | 33w 6d | 9/10 | 28/30 |

### *EEG Data acquisition & analysis*

- 32-channel electroencephalogram (EEG)
- BioSemi ActiveTwo system (BioSemi B.V., Amsterdam, Netherlands) providing 32 Ag/AgCl electrodes positioned according to the 10/20 system.
- Sample rate of 1024 per second.

Recorded EEG data was processed in Matlab 7 using a combination of scripts from EEGLAB, Ramussen and Williams' GPML code, and custom code. The implemented BCI is based on Filter Bank Common Spatial Patterns (FBCSP) which is an adaptation of the Common Spatial Patterns (CSP) algorithm.

The steps followed by this algorithm are (recap on figure 2):

1. Filter the EEG into a number of frequency ranges.

2. Apply the CSP algorithm separately to each frequency range, decompose the EEG and perform feature extraction.

3. Rank and select features.

4. Train or test the classifier.

Marginal relevance was used to rank the features and Gaussian Process Classification (GPC) to classify the selected features. (More information about these methods in further sections).

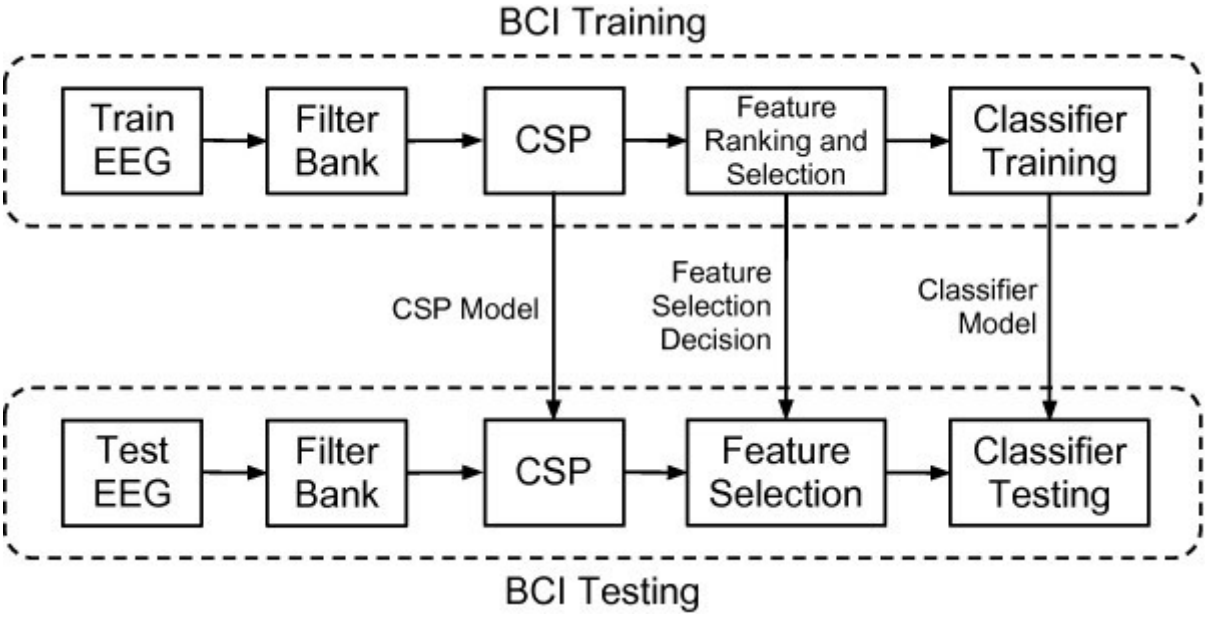



Figure 2

### *Pre-processing*

Raw EEG data was first filtered using a zero-phase 4th-order Butterworth filter into the following frequency ranges: 4-8, 8-12, 12-16, 16-20, 20-24, 24-28, 28-32, 32-36 and 36-40 Hz.

Once filtered, the EEG was then separated into time segments: CSP window ( between 2 points : 2 seconds following the trial onset and lasted 6 seconds as shown in Figure 3).




Figure 3

### *Common spatial patterns*

For each segment of EEG data from all frequency range the CSP algorithm was applied and produces a set of spatial filters. These spatial filters are used to generates signals with variances that allow us to optimally discriminate two classes.

$Z_{b,i}=W_{Tb}E_{b,i}$ where $E_{b,i}\in R^{c_t\times t}$ is the $i$ th trial EEG measurement from the $b^{th}$ frequency range, $W_b\in R^{c_t\times c_t}$ is the CSP projection matrix for the $b^{th}$ frequency range, $Z_{b,i}\in R^{c_t\times t}$ is the $i^{th}$ trial spatially filtered EEG signals for the $b^{th}$ frequency range, $c_t$ is the total number of channels, $t$ is the number of time samples per trial and $T$ denotes the transpose operator.

### *Marginal relevance & Gaussian process classification*

A selection of CSP is made for training and testing classification. In this study, Marginal Relevance was chosen as ranking method. The marginal relevance score for each feature in a feature set is the ratio of their between-group to within-group sum of squares. The four highest ranked features were selected.

Various applications fields (e.g. in medicine and bioengineering fields) exploited properties of Gaussian Process (GP) models for regression problems. A GP is a generalization of the Gaussian probability distribution. But beside regression, GP models can also be used for probabilistic classification. This means that the output of GP model represents the probability of a data point belonging to one of two types (close to 0 indicates belongs to one class, close to 1 belongs to the other class). In practice, most events take intermediate values. A threshold of 0.5 was set to determine which class an event had been classified as belonging to by GPC.

### *Analyses*

Two types of BCI training were explored: individual and grouped. For Individual BCI training, one EEG dataset was used to train the BCI and another EEG dataset was used to test the BCI. For grouped BCI training, all event data from a subset of datasets was used to train the BCI and obtain a general CSP model.

Useful comparison cases:

Individual classification accuracies when training the BCI on each healthy dataset independently and then testing on all other datasets. → trained a BCI for each healthy dataset

Grouped BCI training is carried out using all the healthy subject datasets and train the BCI on this grouped dataset → trained a single BCI on all healthy datasets grouped together.

Individual BCI training was also carried out for each stroke subject, this time to test the differences between the early and the late session results. The trained BCI is using the early session subject's dataset to train the BCI and then confronted it with the late session dataset (of the same subject).

## RESULTS

Datasets are identified primarily by Subject ID (table 1). Stroke subjects took part in an "early" (E) and a "late" (L) session and the datasets from these sessions are labelled accordingly. Therefore, healthy subject datasets are labelled H1–H10, early stroke datasets are labelled S1E–S5E and late stroke datasets are labelled S1L–S5L.

### *Individual healthy dataset models applied to all data*

In this section we verify the classification accuracies when training the BCI on each healthy dataset.

There Significant statistical differences in classification results between the following groups:

- Healthy (Median = 82.5) and All Stroke (Median = 70.0) ($Z=5.55, p<0.05, r=0.40$),
- Healthy (Median = 82.5) and Early Stroke (Median = 71.25) ($Z=-3.97, p<0.05, r=0.34$)
- Healthy (Median = 82.5) and Late Stroke (Median = 61.25) ($Z=-5.18, p<0.05, r=0.44$)

### *Grouped healthy dataset model applied to stroke data*

In this section we compare the classification accuracies of each stroke dataset when the BCI is trained on the grouped healthy EEG datasets and when the BCI is trained on the individual healthy EEG datasets.

No significant change in classification accuracy for datasets S1E, S1L, S2L, S3E and S4E.

Significant increases in classification accuracy for datasets S3L, S4L, S5E and S5L and a significant decrease ($p<0.05$) for dataset S2E.

### *Early Stroke datasets used to classify corresponding Late Stroke datasets*

In this section we verify the classification accuracy of the Late Stroke datasets when training with the corresponding Early Stroke dataset. The accuracy rate ranged from 62.5% to 95% with a median of 75.0%.

We can compare these results to those obtained when training the BCI on individual healthy datasets. A significant ($p<0.05$) increase was seen for S1L, S2L and S3L. There was no significant change ($p<0.05$) found for S4L and S5L.

Finally, we can compare classification accuracies to those obtained when training the BCI on grouped healthy datasets, we see that S1L improved from 62.5% to 82.5%, S2L improved from 55% to 72.5%, S3L improved from 87.5% to 95%, S4L reduced from 65% to 62.5% and S5L reduced from 90% to 75%.

## DISCUSSION

Three options for training a BCI were analysed. In the first case, a different BCI was trained for each healthy dataset and in the second, a single BCI was trained on all healthy datasets grouped together.

### *Two first methods: Individual & grouped healthy dataset models*

Training numerous BCIs on each healthy EEG dataset may be useful for exploring further aspects of stroke-affect EEG for BCI, but do not represent a real-world implementation of BCI training. For example, that dataset S1E was classified with an accuracy of 97.5% with the healthy dataset H3 but only 47.5% with the healthy dataset H6. A full investigation into these potential reasons is beyond the scope of this study and the goal here is to find a more typical general BCI method.

This is the purpose of the single general BCI trained on grouped healthy EEG datasets. We can observe that 4/5 classification rates displayed an improvement compared to the BCI trained individual heathy dataset.

The first two methods, training on each BCI healthy individual and healthy grouped datasets possess a substantial advantage: no need to train the BCI on the stroke subject (zero-training method). This is an important consideration for stroke rehabilitation BCI because subjecting a stroke patient to an EEG recording session may have negative effects including anxiety (as many stroke patients are elderly and may have apprehension about participating in an EEG recording session), loss of therapy time (as time spent training) and fatigue (leaving little energy for the therapeutic interaction).

For the patients for which the enumerated negative factors are prevalent, the BCI may have to be trained using healthy data. The decision to record a session of EEG activity to train a BCI for each subject relies on a trade-off between classification accuracy and possible negative effects of subjecting a stroke patient to an EEG recording session.

### *Third method : Early Stroke datasets used to classify corresponding Late Stroke datasets*

About the third method, training the BCI on individual EEG dataset of the stroke subject's early session and then apply it to the late session results. Table 3 presents the classification results of the three methods and shows us that for 4/5 late stroke datasets, training the BCI on the early stroke dataset provides the best classification accuracy.

| Dataset | Individual healthy | | Grouped healthy | Early stroke |
|---|---|---|---|---|
| | Avg | StDev | | |
| S1E | 77.8 | 14.9 | 87.5 | |
| S1L | 69.8 | 11.9 | 62.5 | 82.5 |
| S2E | 65.5 | 11.5 | 52.5 | |
| S2L | 54.5 | 6.2 | 55.0 | 72.5 |
| S3E | 74.4 | 9.5 | 75.0 | |
| S3L | 76.8 | 13.1 | 87.5 | 95.0 |
| S4E | 61.3 | 9.5 | 65.0 | |
| S4L | 55.8 | 9.4 | 65.0 | 62.5 |
| S5E | 72.0 | 12.5 | 82.5 | |
| S5L | 71.0 | 15.4 | 90.0 | 75.0 |
| All average | 67.9±8.3 | | 72.3±14.1 | |
| Early average | 70.2±6.7 | | 72.5±14.0 | |
| Late average | 65.6±9.9 | | 72.0±15.8 | 77.5±12.1 |

Table 3

### *Discussion points*

Some interesting points regarding whether to train a rehabilitation BCI on healthy EEG or on the subject's early EEG recording:

1. Using the healthy EEG datasets, classification results are lower.

Consequence: may lead to frustration for the stroke patient, resulting in non-compliance with rehabilitation BCI therapy.

2. Training on the early stroke EEG patterns, classification results are higher.

Consequence: potentially less frustrating experience and better engagement from the patient, improving their rehabilitation outcomes.

3. Unfortunately, the early stroke EEG patterns are not characteristic of EEG from a healthy brain but will probably look like the network pathophysiology resulting from the stroke.

It is of the utmost importance to determine what is better between using machine learning to adapt the interface to the EEG patterns and forcing the patient to adapt to a classifier which is targeting the appropriate cortical networks for healthy movement.

### *Why not fully adapting to the patient?*

Natural recovery in stroke is often suboptimal (spasticity, abnormal muscle synergies, etc.), these neurological symptoms are due to compensatory networks that comes from the reorganization process. Therefore, if a machine learning algorithm adapts to the patient all along to optimize communication with the feedback interface, the therapy will end up reinforcing these maladaptive changes. Instead, it should lead the patient to adapt to a classifier which is set up to expect EEG features associated with healthy movement. However, this may be far too frustrating and difficult to reach for the patient.

To summarize, for an effective BCI instrument there is a trade-off to make between encouraging and directing recovery. The advantages and disadvantages of training a rehabilitative BCI on either general healthy EEG or a subject's own earlier recorded EEG will have to be considered.

## CONCLUSION

To optimize aid in recovery, the rehabilitative BCI should take into account the differences between heathy and stroke affected EEG patterns. On one hand it is possible to use only healthy EEG and this would be ideal knowing that the training has many negative effects on the stroke affected patient. However, the classification accuracy is lower in that case and that can be excessively frustrating for patients. On the other hand, when using subject-specific dataset of early training sessions, the classification accuracy improved significantly. This comes at the cost of loss of rehabilitation time and may end up over-adapting to the patient which may be detrimental. Consequently, it is clear that theses differences must be considered when developing a rehabilitative BCI and use the right machine learning scheme depending on the use case. To conclude, motor retraining BCI should initially be tailored to individual patients.