algorithm optimization Plan

**Automated artifact correction in resting state EEG using machine learning techniques**

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| Short Title: | Automated artefact correction in resting state EEG |
| Version: | 1 |
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| CHDR number: | CHDR9999 |

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| CHDR | Centre for Human Drug Research |
| CNS | Central Nervous System |
| EEG | Electro-encephalography |
| ML | Machine Learning |
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# Background and rationale

One of the methods used at the Centre for Human Drug Research (CHDR) to assess the effects of drugs on the central nervous system (CNS) is the quantification of resting state electro-encephalography (EEG). For the duration of a few minutes, the cortical activity is measured in subjects during periods with eyes closed and periods with eyes opened. These recordings are transformed to the frequency domain, and split into frequency bands. The total power per frequency band is then calculated and can be used as a measure to describe the current state of the CNS.

One of the issues while recording EEG is that the amplitude of EEG signals is relatively low in comparison to, for example, background noise and other artefacts. Common artefacts in EEG recordings are caused by the propagation of ocular and muscular activity through the skull. Without correction of these artefacts, the calculated power spectrum is contaminated by them. For example, ocular activity in EEG recordings generally results in an overestimation of the low-frequency components, while muscular activity is generally found in the high-frequency components.

Currently at CHDR, the Grubbs’ test for outliers is used to detect artefacts in EEG recordings, and the contaminated parts are rejected for further analyses. As a result, there may be a loss of relevant information since the final endpoints are then based on fewer data-samples. An alternative strategy could be not removing the contaminated recording, but use Machine Learning (ML) techniques for correcting it such that only the artefact is removed. Here, we propose a project in which an EEG cleaning techniques are studied. At the end of the project, one technique is implemented, validated, and operationalized within CHDR.

## Project goal

### Primary goals

The primary goals of this project are:

1. Obtain a good understanding of existing methodology to automatically detect and correct non-cortical activity in EEG recordings.
2. Implement, validate, and operationalize an automated artefact correction method

### Secondary goals

The secondary goals of this project are:

1. Obtain theoretical and practical knowledge on Machine Learning techniques.
2. ?

### Boundary conditions

The focus of this project will be mainly on, but not limited to, the detection and correction of ocular artefacts. Furthermore, the test-case scenarios will be based on resting-state EEG recordings, with both eyes closed and eyes opened conditions. A challenge for determining the efficiency and performance of artefact correction techniques is that in ‘real’ acquired data, the uncorrupted desired signal is unknown. Therefore, we propose to start with a simulated dataset and then continue to ‘real’ datasets as follows: the simulated dataset will be divided into 70% for training and 30 % for validation. The training dataset will be used to train and optimize the model, while the validation dataset will be used to evaluate it. Finally, the optimal model will also be evaluated on a ‘real’ acquired dataset.

# Work packages

## WP1: Literature research

CHDR is interested in applying Machine Learning techniques to automatically detect and correct artefacts in EEG recordings. First, an overview of existing methods to analyze data from EEG in the presence of (ocular) artifacts, using Machine Learning, filtering, and pattern recognition is required. This overview provides methods to (1) detect, and (2) correct EEG data contaminated with ocular artefacts.

The literature research will provide recommendations on the performance evaluation of considered techniques. Also, based on the report, a decision will be made on what technique to continue working on.

## WP2: Implementation and optimization of an algorithm

### Task 2.1: Develop and test preliminary scripts

### Task 2.2: Optimize scripts

The goal is to have an implementation of the model that requires as few computational resources as possible. Therefore, fast algorithms to perform model’s calculations will be researched and implemented. Benchmarks of the different model’s implementations on the (simulated) training dataset will be compared.

### Task 2.3: Optimization of algorithm parameters

The goal is to optimize the parameters required by the model such that there is a good trade-off between output-quality and calculation speed. Cross-validation on the (simulated) training dataset will be used together with parameter grid searches.

Cross-validation: use training set (simulated data).

## WP3: Validation of the algorithm

### Task 3.1: Simulated data-set

The goal is to asses how the model will generalize to an independent dataset. For this reason, the optimal model will be first evaluated on the (simulated) validation dataset.

### Task 3.2: Healthy human subjects

The goal is to asses whether the model for artefact correction will improve the statistical power of relevant EEG endpoints. For the CHDR studies below, we propose to do the statistical analysis of the EEG endpoints derived from data with and without the artefact correction technique. Finally, the statistical power from both cases is compared.

CHDR1721.will enroll 178 healthy participants between 18 and 55 years of age.

CHDR1633 will enroll 200 elderly subjects. Each subject will have 5-minute EEG recordings with eyes closed and with eyes opened. WP4: Operationalization

### Task 4.1: Implement algorithm in existing resting-state EEG method

### Task 4.2: Technical validation of combined methodology

# Planning

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|  | jul-17 | aug-17 | sep-17 | oct-17 | nov-17 | dec-17 | jan-18 | feb-18 | mar-18 | apr-18 | may-18 |
| **WP1** |  |  |  |  |  |  |  |  |  |  |  |
| **WP2** |  |  |  |  |  |  |  |  |  |  |  |
| Task 2.1. |  |  |  |  |  |  |  |  |  |  |  |
| Task 2.2. |  |  |  |  |  |  |  |  |  |  |  |
| Task 2.3. |  |  |  |  |  |  |  |  |  |  |  |
| **WP3** |  |  |  |  |  |  |  |  |  |  |  |
| Taks 3.1. |  |  |  |  |  |  |  |  |  |  |  |
| Task 3.2. |  |  |  |  |  |  |  |  |  |  |  |
| Taks 3.3. |  |  |  |  |  |  |  |  |  |  |  |
| **WP4** |  |  |  |  |  |  |  |  |  |  |  |
| Task 4.1. |  |  |  |  |  |  |  |  |  |  |  |
| Task 4.2. |  |  |  |  |  |  |  |  |  |  |  |
|  | Done |  |  |  |  |  |  |  |  |  |  |
|  | To start | |  |  |  |  |  |  |  |  |  |
|  | Started | |  |  |  |  |  |  |  |  |  |

# Budget

For WP1 and WP2, and Task 3.1., a student can be temporarily hired to perform these tasks. WP3 can be performed