EEG artifact correction

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July 2017

1 Problem description

One of the methods used in the CHDR to asses the effect of a drug is resting state EEG. For the duration of a few minutes, cortical activity is measured in subjects who close and open their eyes. From the power spectrum some indications about the state of the central nervous system can be extracted. However, these measurements are often influenced by artifacts (e.g. eye and muscle movements). Parts of the EEG recording are rejected when an artifact has been (sometimes manually) detected.

Within CHDR there is a growing interest in acquiring Machine Learning techniques to analyze data. One possibly interesting application of such techniques is the automatic detection and correction of artifacts in EEG recordings.

The aim of this report is to provide an overview of methods to analyze data from functional brain imaging (EEG) in the presence of (ocular) artifacts, using Machine Learning, filtering and pattern recognition. The purpose of these methods is to detect the presence and correct the effects of such artifacts. Besides providing an overview of methods, this report will recommend performance measurements and a modelling/experimental set up, and establish the amount of data needed to asses and implement such methods.

2 Electroencephalography

Electroencephalography (EEG) is a monitoring method to record electrical activity of the brain. The recording is non-invasive with electrodes placed on the scalp [17]. In measuring EEG, the interest typically lies in underlying neural potentials. The various wave forms of the EEG contain clinically valuable information, which make the methods for detection and quantification of characteristics to facilitate interpretation important [18].

The joint activity of millions of cortical neurons produce and electrical field that is sufficiently strong to be detected along the scalp. The amplitude of the EEG signal is related to whether the excitation of the generating neurons is synchronized or not. The measured activity reveals oscillatory behaviour in specific frequency bands which are considered to be well-known EEG rhythms [23].

Artifacts

Signals detected by the EEG recording that did not originate from the cortex are considered artifacts. The EEG signal is often contaminated with various physiological factors other than cerebral activity [24]. Ocular movements and eye blinks are some of the most common types of biological artifacts. The correction or rejection of artifacts is an important issue in EEG signal processing and an necessary component of most signal analysis.

Ocular artifacts

The eye forms a electric dipole, where the cornea is positive and the retina is negative. Eye movements change the electrical field around the eye producing an electrical signal known as the electro-oculogram (EOG). The electrical activity produced by eye movement is usually strong enough to be recorded along with the EEG [7]. As a result, EEG recordings are often significantly distorted. The eye-movement related voltages propagate to sites along the scalp with an inverse relation to the squared distance from the eyes. About 0.20 of the vertical eye-moment voltage reaches F_z, and this amount decreases posteriorly to about 0.05 at occipital sites.

Blinking is another cause for contamination of the EEG, in a more abrupt manner than eye movement and with a higher amplitude.

When the effect of ocular activity can be estimated, this signal can be removed from the EEG (EOG correction).

3 Performance Evaluation

The greatest challenge for determining the relative efficiency and performance is that the uncorrupted desired signal is not known a priori. The majority of techniques are evaluated with simulated data and thus the validity of conclusions depends on the fidelity of the used model [12]. Methods can first be assessed and compared to other methods by using simulations, but recorded EEG should be used as a final testbed for evaluating the true performance, reliability and reproducibility [24].

3.1 Validation of correction with simulated data

One advantage of using simulated data is that the quality of the a priori signal $X^s(t) = B^s(t) + O^s(t)$, with $B^s(t)$ being the simulated clean signal and $O^s(t)$ being the simulated ocular artifact, and the signal after artifact removal $C^s(t)$ can be assessed through performance measures.

3.1.1 Percent correlation increase

The Pearson product-moment correlation coefficient ρ of two timeseries $x(t), y(t)$ is defined as

$$\rho = \frac{\frac{1}{T}\sum_{t=1}^{T-1}(x(t)-\bar{x}(t))(y(t)-\bar{y}(t))}{\sigma_x\sigma_y}$$

with σ_x and σ_y being the standard deviations, and $\bar{x}(t)$ and $\bar{y}(t)$ the mean values of those timeseries.

The percentage increase in correlation after correction is calculated as

$$\frac{\rho_a-\rho_c}{\rho_b-\rho_c} * 100\%$$

where ρ_a is the correlation between $B^s(t)$ and $C^s(t)$ in the parts of the signal where artifacts occur, ρ_c is the correlation between $B^s(t)$ and $X^s(t)$ in the same parts, and ρ_b is the correlation of $B^s(t)$ and $X^s(t)$ in the parts of the signal with known clean data.

3.1.2 Signal to noise ratio

The signal to noise ratio (SNR) is calculated for both $X^s(t)$ and $C^s(t)$ with regards to the simulated artifact free signal $B^s(t)$ [13]. For the a priori signal, the SNR is defined as

$$SNR_X = \frac{\frac{1}{T}\sum_{t=1}^{T} B^s(t)^2}{\frac{1}{T}\sum_{t=1}^{T}(X^s(t)-B^s(t))^2}$$

Similarly, the SNR of the corrected signal is defined as

$$SNR_C = \frac{\frac{1}{T}\sum_{t=1}^{T} B^s(t)^2}{\frac{1}{T}\sum_{t=1}^{T}(C^s(t)-B^s(t))^2}$$

The gain in SNR after correction can be calculated per electrode as

$$\gamma = \frac{SNR_C}{SNR_X}$$

The overall score is obtained by averaging the γ-values of all M electrodes and converting to a decibel scale

$$G = 20 * \log_{10} \left[\frac{1}{M} \sum_{m=1}^{M} \gamma_m \right]$$

3.1.3 Normalized mean squared error

The normalized mean squared error (NMSE) measures the deviation between the corrected signal $C^s(t)$ and the simulated clean signal $B^s(t)$ [1]. The NMSE is calculated for each channel as

$$NMSE = \left(\frac{\sum_{t=1}^{T} (C^s(t) - B^s(t))^2}{\sum_{t=1}^{T} B^s(t)^2} \right)$$

3.2 Validation of correction with acquired data

The validation of methods on acquired data depends on a number of factor, of which the most important is the availability of reference EOG channels.

3.2.1 Regression validation (with EOG channels)

Regression validation is based on the assumption that the EOG and EEG channels are relatively uncorrelated [8]. The correlation between the corrected data and the reference EOG channels is determined by employing least-squares linear regressions where corrected EEG is the criterion variable and the EOG channels the predictor variables.

3.2.2 Intentionally corrupted and ground-truth channels (without EOG channels)

When there is full control of the EEG recording, two highly correlated signals can be produced: one that is a reference artifact free 'ground-truth' signal, and one signal intentionally corrupted [13]. With these signals it is possible to apply artifact removal methods to the noisy EEG recording and compare the corrected signal to the ground-truth with methods proposed in section 3.1.

4 Methods

4.1 EOG correction [7] [6] [5]

EOG correction generally refers to methods that assume the measured EEG is a linear combination of the true signal and ocular artifacts. The proportion of ocular activity present in each channel is calculated by regression. The correction is done by estimating and subtracting the regressed portion of the EOG reference wave forms from each EEG channel. The use of two EOG channels in the correction procedure provides a better correction than one, and so multiple regression is often used.

Advantage: robust

Disadvantage: need for H and V-EOG reference signals, problem of bidirectional contamination is not solved, propagation factors need to be constant, assumption of linearity

4.2 Filtering

Filtering techniques try to adapt the filter in order to minimize the mean squared error between the corrected EEG signal $C(t)$ from the measured EEG $X(t)$, and the desired artifact free signal $B(t)$.

Advantages of filtering: no need for labeled training data, can be automated

Disadvantages of filtering: need a reliable model or measurement of ocular artifacts

4.2.1 Adaptive filtering [2] [10] [20]

An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. The adaption of filter parameters is based on minimizing the mean squared error between the filter output and the desired signal. The most common adaptation algorithms are Recursive Least Square (RLS) and Least Mean Square (LMS). RLS offers a higher convergence speed but LMS offers computational simplicity. The filter is controlled by a set of coefficients or weights $w(n)$. LMS is based on gradient search according to the equation

$$w(n+1) = w(n) + \mu e(n)x(n)$$

where $w(n)$ is the weights vector at sample n, $x(n)$ is the input signal simple vector, $e(n)$ is the filters error and μ is the filters convergence factor.

To remove ocular artifacts with adaptive filtering, separately recorded vertical EOG and horizontal EOG signals are used as reference inputs.

Advantage: adaptive, minimal training

Disadvantage: need for EOG reference signal, assumes uncorrelated sources

Data needed for training: none

4.2.2 Wiener filtering [14] [9] [20]

Wiener filtering produces a filter that minimizes the mean square error between the desired signal and its estimate. The filter is calculated from the spectra of both the signal $\phi_{signal}(\omega)$ and the noise $\phi_{noise}(\omega)$, which are in turn estimated from the averages of spectra of the measured signals or by obtaining pure eye blinking components with Independent Component Analysis. Therefore, Wiener filtering does not need a reference signal. The signal and the artifacts are assumed to be stationary linear stochastic processes with known spectral characteristics or known auto- and cross-correlations. The signal and the artifact are assumed to be uncorrelated.

Advantage: no need for EOG reference

Disadvantage: need a reliable model of artifact and true signals, needs calibration

Data needed for training: representative true signal and artifact recordings

4.2.3 Bayesian filtering [21] [24] [20]

Bayesian filtering refers to formulating the problem of estimating the state of a time-varying system that is indirectly observed in terms of Baying probability theory. Like the Kalman filter, the Bayesian filter produces an estimate of current state variables from a probability distribution using all the available information contained in the observations. However, the states are assumed to be independent given the current state and the estimate requires formulating a joint probability distribution over all previous measurements. Therefore, Bayesian filtering is limited by its computational complexity. For every observation O_t and true state S_t the sensor model is defined by $P(O_t|S_t)$. Using the Bayes rule, the distribution of probabilities for the current state $P(S_t|O_0, .., O_t)$ based on the observation history is computed. This computation step is exponentially complex with the number of observations, and therefore impossible to implement. Bayesian filtering assumes the process is Markov, meaning that knowledge of the current state contains all relevant information about the true process. The Kalman and particle filters approximate the Bayesian filter.

Advantage: no need for EOG reference, only need a sensor model

Disadvantage: computationally intractable, need a prior distribution, need reliable sensor model

Data needed for training: a lot of representative data to calculate prior distributions

4.2.4 Kalman filtering [25] [9] [16] [20]

The Kalman filter is a set of equations that provide a means to estimate the state of a process from a series of measurements in a way that minimizes the mean squared error. The algorithm for establishing the true state works in a two-step manner: in the prediction step, the filter produces an estimate of the current state variables and their uncertainties. In the update step, the measurement is used to update the estimates using a weighted average (the lower the uncertainty, the higher the weight). The Kalman filter needs a model for measurement noise and process noise variances to produce reliable predictions, but is only dependent on the current measurement and those models. If EOG is available, it can be used as an aid in the modeling of the signals.

Advantage: no need for EOG reference (if measurement noise model is available)

Disadvantage: need reliable measurement and process noise models (if EOG reference is not available)

Data needed for training: data on measurement and process noise

4.2.5 Particle filtering [20]

Particle filtering uses Monte Carlo sampling to calculate a state transition model of the process. N samples are selected from a probability density function, and are weighted according to the amplitude of the probability density function at their sample point. The weights of new particles are determined using an update equation that uses the sensor model, and the estimates state is the mean of the probability density function. Particle filtering depends less on the accuracy of process and sensor models than the Kalman filter, but may converge to the dominance of only a few particles.

Advantage: no need for EOG reference, no need for process and measurement noise model

Disadvantage: sampling doesn't necessarily lead to a good state transition model, may not converge correctly

Data needed for training: representative data to calculate prior probability density distributions

4.3 Blind Source Separation

Blind source separation uses the observations $X(t)$ to generate an unmixing matrix W that determines an estimation of the original sources, including the artifact. Once the original sources of $X(t)$ are known, they can be selected and removed, and the signal is reconstructed without the artifacts to produce $C(t)$.

Advantages: unsupervised learning

Disadvantages: a lot of assumptions needed, hard to automate

4.3.1 Independent component analysis with Bayesian classification [24] [15]

Independent component analysis separates a multivariate signal into additive sub-components using only recorded information, by imposing statistical independence of the signal sources. This independence implies no spatial, temporal or time-frequency correlation between source signals. The ICA algorithms that exploit higher-order statistics (HOS-ICA) start by applying a orthogonal transformation (PCA), and then finding the linear transformation that results in the most independent estimated sources. ICA algorithms that apply second-order statistics are based on decorrelating the data in the time domain. Even when the assumption of independent sources does not exactly hold, ICA has been reported to be successful at removing artifacts.

A drawback of ICA is the required intervention of a trained professional to manually identify the components related to artifacts. ICA can be combined with Bayesian classification to be automated, by computing the probability that an epoch represents EEG activity. Again, calculating the necessary probabilities for Bayesian learning is computationally intractable, but they can be estimated by using tree-augmented naive Bayesian networks that construct a maximum spanning tree based on feature dependencies.

When a reference signal is introduced, ICA (then ICA-R) can be automated as well.

Advantages: combines the best of ICA and Bayesian learning, automating a reliable and tested method

Disadvantage: violates the notion of unsupervised learning by introducing Bayesian learning

Data needed for training: around 200 recordings, according to [15]

4.3.2 Second order blind inference [3], [11] [26]

Second order blind inference (SOBI) uses decorrelation across several time points as its basic computational step. SOBI considers the relationship between components at different time lags and insists that these are decorrelated as much as possible. SOBI can be automated by identifying components that correlate with components from EOG channel recordings.

Advantage: requires less assumptions than PCA or ICA, can separate correlating sources

Disadvantage: need for EOG reference channel

Data needed for training: none

4.3.3 Principal component analysis [24] [22]

Principal component analysis (PCA) is a statistical method that can be used to capture the variability of data in less attributes. PCA uses orthogonal transformation to represent the data in statistical uncorrelated variables called principal components. Reconstructing the data from a number of principal components that is smaller than the number of original variables causes the loss of a certain amount of variation in the data. PCA tends to identify the strongest patterns in the data. Since patterns caused by unlikely measurements are probably weaker than patterns caused by unlikely measurements, reduction of dimensionality can eliminate some of the measurement noise. The biggest problem with PCA for EEG applications is that the assumption of orthogonality between neural activity and typical physiological artifacts does not hold.

Advantages: effective

Disadvantage: requires assumptions of linearity and independence, cant be automated

4.3.4 Canonical Correlation Analysis [24] [20] [4]

Canonical Correlation Analysis (CCA) measures the linear relation between two multidimensional random variables. CCA takes the source vector as the first multidimensional random variable and a temporally delayed version of the source vector as the second multi-dimensional random variable. By looking for uncorrelated components, CCA accounts for temporal correlations. Artifact removal can be introduced by setting the columns of the unmixing matrix that represent artifacts to zero during the reconstruction. CCA does not require independence of the sources.

Advantages: computationally efficient, deterministic

Disadvantage: hard to automate?

4.4 Source decomposition methods

Decompose each individual channel into basic wave forms that represent either the signal or the artifact.

Advantages: no need for reference channel, no need for training data

Disadvantages: sources should be represented by a single decomposition unit

4.4.1 Wavelets [24] [20]

The wavelet transform has been widely uses in the context of EEG denoising. The WT is unable to remove artifacts which overlap in the spectral domain. Good separation of the signal and noise depends on the wavelet basis and its similarity to the source signals, and requires manual selection. WT can be combined with ICA to overcome shortcomings.

Advantages: versatile

Disadvantage: needs manual artifact selection

4.4.2 Empirical mode decomposition [24] [20] [19]

Empirical Mode Decomposition (EMD) is a technique for non-linear signal processing that aims at decomposing a signal into its basis functions called intrinsic mode functions (IMFs). These IMFs can then be used as inputs to an ICA algorithm. The technique is intended for non-linear signal processing but it known for its low robustness against noise. Manual selection of artifacts is required.

Advantage: signals and artifacts can be represented by one or more IMFs

Disadvantage: low robustness against noise, cannot be automated

5 Recommendations

5.1 Methods

5.2 Validation

5.2.1 Simulated data

5.2.2 Acquired data

In a controlled setting, two electrodes are secured to the scalp of the subject using an electrode cap. The cap is manufactured using material that allows the movement of one electrode without disturbing the other. The two electrodes are placed in close proximity (20 mm) and two accelerometers are attached to ensure that the orientation of each accelerometer is kept consistent with respect to each other. Subjects are instructed to keep their eyes closed and to maintain a stationary head position throughout the experiment, limiting the number of artifacts. Each trial consists of 9 minutes with motion induced artifacts to Channel 2's electrode at 2 minute intervals. This artifact is induced by mechanically disturbing the electrode by pulling on the connecting lead [13].

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