Comparison of Two Algorithms to Reduce Muscular Movement Artifacts in EEG Data

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Abstract—Muscular movement artifacts constitute a major problem in studies involving electroencephalography (EEG) measurements. EEG measurements are used in a variety of different fields like diagnosing epilepsy and other brain related diseases or in biofeedback for athletes. A major drawback is that EEG is susceptible to artifacts of neck muscles due to the low signal amplitude of the electrical activity of the brain. Hence, recording an artifact-free EEG signal during movement or physical exercise is not feasible at the moment.

These additional artifacts can be recorded using electromyography (EMG). Various computational methods for the reduction of muscle artifacts in EEG data exist like the ICA algorithm and the AMICA algorithm. However, there exists no objective measure to compare different algorithms concerning their performance on EEG data.

We defined a test protocol with specific neck and body movements and measured EEG and EMG simultaneously to compare the ICA algorithm InfoMax and the AMICA algorithm. A novel objective measure enabled to compare both algorithms according to their performance. Results showed that the AMICA algorithm outperformed the ICA algorithm. In further research, we will continue using our novel objective measure to test the performance of other artifact removal algorithms.

I. INTRODUCTION

Human brain activity can be recorded by non-invasive techniques. Normally, brain activity is measured in immobile settings. The accurate, non-invasive recording of human brain activity during overall movement or physical exercise could bring several benefits [15], e.g. mental processes and body interactions could be monitored and evaluated. There exists a connection between brain activity and locomotion [8], [9]. Another aspect is the usage of biofeedback in training [20], [22]. This means that the athlete instantly receives feedback on his performance in his training process and hence can directly adapt his movements to achieve better results.

Brain activity can be measured with functional magnetic resonance imaging, positron emission tomography or EEG. EEG is the only non-invasive method that allows brain activity to be recorded during movement, as its sensors are lightweight enough and easy to carry [8], [9]. Further, the temporal resolution of EEG is sufficiently high to record brain activity during movement [8], [20]. EEG recordings consist of surface electrodes that are placed on the scalp. These electrodes measure the electrical manifestation of the electrical activity of the brain [18].

Unfortunately, EEG is susceptible to various artifacts like eye movements or eye blinks, power line interference, high-frequency noise and muscular artifacts [6], [9], [12], [19], [20]. Various solutions exist for the removal of eye artifacts, like the regression model proposed by Gratton and coworkers [7]. Power line interference and high-frequency noise can be reduced with band-pass or notch filtering.

Muscular artifacts can be recorded using EMG as a reference. EMG produces an amplitude of about 100 µV to 1000 µV, considerably higher than that of EEG data (near 10 µV to 100 µV) [20]. Muscular artifacts that interfere EEG recordings are for example head movements. These artifacts are more difficult to remove as the frequency bands of the EEG and EMG recordings overlap. The frequency band of normal brain activity lies between 0 Hz and 30 Hz [18]. EMG recordings have a frequency distribution from 0 Hz to 200 Hz [6].

Various computational methods for the reduction of EMG artifacts exists. These include methods like the General Linear Model [19], linear or non-linear low-pass filtering [6], Independent Component Analysis (ICA) [12], [14], [19], parallel factor analysis (PARAFAC) [2], [3], Adaptive Mixture of Independent Component Analyzers (AMICA) [5] or blind source separation - canonical correlation analysis (BSS-CCA) [21].

Although different methods exist to remove EMG artifacts from EEG, it is unknown which method performs best. In this work, we performed a study with specialized exercises like isometric forward and backward contractions or isometric right and left contractions of neck muscles. We also measured sports activities such as running on a treadmill, cycling on an ergometer or lifting weights. Besides the EEG data, we acquired EMG data of the sternocleidomastoid and the trapezius muscle. The simultaneously measured EMG and EEG recordings should allow to remove muscular artifacts using computational methods. This study aims at testing and comparing the two algorithms ICA and AMICA in regard to their ability to reduce the effect of EMG on the EEG data. We further provide a novel objective measure on the basis of the SNR to calculate how good each algorithm performs.

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II. METHODS

A. Data acquisition

The used hardware consisted of the QuickAmp-72 amplifier (Brain Products GmbH, Gilching, Germany), the electrode positioning system ELPOS (zebris Medical GmbH, Isny i. Allgäu, Germany), the h/p/cosmos quasar treadmill (h/p/cosmos sports & medical gmbh, Nussdorf-Traunstein, Germany), and the ergometer sanabike 250F (MESA Medizintechnik GmbH, Benediktbeuern, Germany). The 72 channels of the QuickAmp amplifier were divided into 64 unipolar EEG channels, four bipolar channels and four auxiliary inputs. The four bipolar channels were employed as the EMG electrodes. The four auxiliary inputs were not used in this study. The electrode positions were registered with ELPOS in combination with the Electrode Guide ElGuide software (zebris Medical GmbH, Isny i. Allgäu, Germany). The actiCAP 64 Channel (Brain Products GmbH, Gilching, Germany) was used as EEG cap. The EMG was measured on the left and right sternocleidomastoid muscle and on the left and right sagittal plane of the trapezius muscle (Fig. 1).

Five healthy male subjects (age 25 ± 2 years, mean ± standard deviation (SD)) were recruited for the study. All subjects were in good physical state and gave written informed consent. The study was approved by the ethics committee of the University Erlangen-Nuremberg.

The subjects performed eight exercises with a break in between. The experiments started with a baseline measurement to obtain clean datasets that was followed by seven different specialized exercises. In all, 35 datasets with specialized exercises of five different subjects were measured. In the following, the whole procedure will be explained.

The baseline measurement consisted of two minutes in supine position without any movement. The eyes were closed to minimize ocular artifacts. Subsequently, each of the four isometric contraction exercises, isometric forward contraction (Isoforw), isometric backwards contraction (Isoback), isometric right contraction (Isoright) and isometric left contraction (Isoleft), was executed eight times for 15 s each. 30 s pauses occurred between two contractions. During the exercises, the subjects pressed their head against an immovable object. The first four exercises were performed in randomized order. The next exercise consisted of running on a treadmill at the constant speed of 2.316 m s\(^{-1}\). This is 20% above the average speed where people, with normal fitness, switch from walking to running [10]. The inclination was set to 1% to simulate the air resistance existent during outdoor running [11]. Then, cycling on an ergometer (Cycle) with the cycling frequency of half the step frequency and the resistance level of 50 W was performed. The treadmill and the ergometer exercises lasted for two minutes each. In the last exercise, the subjects performed a strength exercise on a chest press. The weight of the chest press was above 70% of the maximum weight the subject was capable of lifting. The subjects rested for two minutes between two executions.

B. Preprocessing

The BrainVision Analyzer 2 software (Brain Products GmbH, Gilching, Germany) was used for data preprocessing. First the data were band-pass filtered in the frequency range of 0.5 Hz to 70 Hz. Then a notch filter of 50 Hz was applied to remove power line interference, followed by an ocular artifact correction to remove blinks and eye artifacts. Afterwards, the data was imported into EEGLAB [4], an open source toolbox for Matlab (MathWorks Inc., USA), and EMG-artifact free epochs, the pauses between subsequent exercises, were manually removed.

C. Algorithms

In this work, we compared the ICA algorithm InfoMax [1], [13], [14] to the AMICA algorithm [17]. Both algorithms are mathematical transforms with the goal of finding the statistically independent sources inside a mixture of these sources.

In 1996, Makeig et al. [14] applied the ICA algorithm of Bell and Sejnowski [1] to EEG data for the first time. This algorithm is available in the EEGLAB Toolbox [4]. We employed this algorithm to the data. Further, we applied the AMICA algorithm [16] implemented by Palmer [17]. The AMICA algorithm is an asymptotic Newton algorithm to calculate the maximum likelihood estimate for a mixture model of independent components. In general, every algorithm was applied to the data twice. Each time five components were removed according to the localization of the main activity and the power spectral density. A high power in frequencies higher than 30 Hz indicated EMG artifacts.

The AMICA algorithm has many parameters, which need to be set prior to the decomposition: the number of ICA models to be trained, the number of mixture components to be assumed in the input data, the initial learning rate for the newton method and the initial learning rate for the natural gradient. We optimized these four parameters in a grid search regarding the improvement in artifact reduction (Sec. II-D) over one dataset with consistent muscle contribution.
D. Evaluation methodology

For the evaluation of the different algorithms, an objective measure was necessary. Hence, we suggested a new objective measure on the basis of the signal-to-noise ratio (SNR). The improvement could be calculated as:

\[ m_{SNR} = 1 - \frac{SNR_{before}}{SNR_{after}} \]  

(1)

As SNR values were unknown for real-world data, an approximation for evaluating the performances was necessary.

The clean data, as reference obtained from the baseline measurement, data before artifact reduction and data after artifact reduction were used in our procedure. We divided this procedure into five steps (Fig. 2):

1) Feature extraction
2) Determining the reference value
3) Calculation of Euclidean distances to reference value
4) Averaging the Euclidean distances
5) Calculation of the improvement factor

In the first step, we extracted three features on an empirically defined window size of 2000 samples of all three datasets. The features were: Normalized power between 13 Hz and 100 Hz, normalized power between 30 Hz and 100 Hz, and the mean value of the squared derivative. In the second step, we determined the reference value by averaging all feature vectors from clean data. In the third step, Euclidean distances between the reference value and each feature vector were calculated. This was done separately for the data before artifact reduction and the data after artifact reduction. In the fourth step, the Euclidean distances of the third step were averaged over both datasets (before and after artifact reduction). This results in two distances, \( d_{before} \) and \( d_{after} \). In the last step, the improvement factor was calculated. Our improvement factor was defined as following:

\[ m = 1 - \frac{d_{after}}{d_{before}} \]  

(2)

III. RESULTS

The optimized AMICA parameters for muscle artifact reduction were: one ICA model was trained and three mixture components were assumed in the input data. 1.0 was chosen as initial learning rate for the newton method and 0.1 for the natural gradient. Further settings were the rejection of time points based on log likelihood and the dimensionality reduction by the number of rejected components of the first run for the second AMICA run.

Apart from the baseline measurement, five subjects performed seven specialized exercises. This resulted in a total of 35 datasets. Of these datasets, four datasets had to be excluded as these datasets included too much non-muscle related artifacts like

- very high amplitude noise in multiple channels or
- severe electrode movement artifacts.

Further, two more exercises, the isometric left and right exercises from one subject, were also not suitable. Summing up, both algorithms were applied to 29 instead of 35 datasets.

AMICA converged in all of the remaining datasets. ICA only converged in 23 cases. Fig. 3 illustrates the number of measurements that converged for both algorithms for each exercise. For the calculation of the averaged improvement rates (Fig. 4), four datasets of the chest press exercise and the isometric right contraction and three datasets of the remaining five exercises were used. The algorithms were performed on each exercise separately for every subject. After averaging over all subjects, the averaged improvement rate for each exercise was obtained. In two exercises, both algorithms performed the same. The AMICA algorithm outperformed the ICA algorithm in the remaining five exercises.

IV. DISCUSSION

The AMICA optimization was performed on one of the datasets and therefore did not necessarily fit all EEG recordings best. Further, the AMICA algorithm was only performed with one ICA model. Therefore, unexploited potential lay in this algorithm, especially as soon as more irregular artifacts are considered.

Six datasets had to be excluded due to the existence of too much non-muscle related artifacts. The ICA algorithm did not converge for all remaining datasets. Only 23 datasets were used for the evaluation of the algorithms. In future research, we have to increase the number of datasets, especially with the problem of non-convergence of the ICA algorithm.

We applied each algorithm twice on the data and after the performance of one algorithm, we rejected five components after each application. The number of components was chosen heuristically. The decision on how many components to reject from the data should lie in the hand of a human or in a human trained classification system, as this greatly impacts the result [4]. We decided to reject five components to maintain comparability between the used algorithms. The results are therefore not purely dependent on the effectiveness of the algorithm, but also on the competence of the
We suggested an objective improvement parameter for the evaluation of different artifact reduction algorithm on EEG data. We further applied the ICA algorithm InfoMax and the AMICA algorithm and calculated for each exercise an improvement measure. In summary, the AMICA algorithm outperformed the ICA algorithm. In further research, we will continue using our novel objective measure to test the performance of other artifact removal algorithms.

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