Comparison of the AMICA and the InfoMax Algorithm for the Reduction of Electromyogenic Artifacts in EEG Data

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***Abstract*— Electromyogenic or muscle artifacts constitute a major problem in studies involving electroencephalography (EEG) measurements. This is because the rather low signal activity of the brain is overlaid by comparably high signal activity of muscles, especially neck muscles. Hence, recording an artifact-free EEG signal during movement or physical exercise is not, to the best knowledge of the authors, feasible at the moment. Nevertheless, EEG measurements are used in a variety of different fields like diagnosing epilepsy and other brain related diseases or in biofeedback for athletes.**

Muscle artifacts can be recorded using electromyography (EMG). Various computational methods for the reduction of muscle artifacts in EEG data exist like the ICA algorithm InfoMax 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 InfoMax algorithm 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 InfoMax algorithm. In further research, we will continue using the established objective measure to test the performance of other algorithms for the reduction of artifacts.

I. INTRODUCTION

Electromyogenic or muscle artifacts overlay human brain activity. 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 [1], e.g. mental processes and body interactions could be monitored and evaluated. There exists a connection between brain activity and locomotion [2], [3]. Another aspect is the usage of biofeedback in training [4], [5]. 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 non-invasive techniques like functional magnetic resonance imaging, positron emission tomography or EEG. 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 [6]. 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 [2], [3]. Further, the temporal resolution of EEG is sufficiently high to record brain activity during movement [3], [4].

Unfortunately, EEG is susceptible to various artifacts like eye movements or eye blinks, power line interference, high-frequency noise, and muscle artifacts [2], [4], [7]–[9]. Various solutions exist for the removal of eye artifacts, like the regression model in the time domain proposed by Gratton and coworkers [10] or in the frequency domain proposed by Woestenburg et al. [11]. Power line interference and high-frequency noise can be reduced with band-pass or notch filtering.

Muscle artifacts can be recorded using EMG as a reference. EMG produces an amplitude of about $100\,\mu V$ to $1000\,\mu V$, considerably higher than that of EEG data (near $10\,\mu V$ to $100\,\mu V$) [4]. Muscle artifacts that interfere with EEG recordings are for example head movements. Muscle artifacts are problematic in EEG data, as the frequency bands of the EEG and EMG recording overlap. The frequency band of normal brain activity lies between $0\,Hz$ and $30\,Hz$ [6]. EMG recordings have a frequency distribution from $0\,Hz$ to $200\,Hz$ [9]. This overlapping is also the reason that muscle artifacts are difficult to remove.

Various computational methods for the reduction of EMG artifacts exists. These include methods like the General Linear Model [8], linear or non-linear low-pass filtering [9], Independent Component Analysis (ICA) [7], [8], [12], parallel factor analysis (PARAFAC) [13], [14], Adaptive Mixture of Independent Component Analyzers (AMICA) [15] or blind source separation - canonical correlation analysis (BSS-CCA) [16].

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 treadmill running, ergometer cycling 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 muscle artifacts using computational methods. This study aims at testing and comparing the two algorithms InfoMax and AMICA with 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 $\pm$ 2 years, mean $\pm$ standard deviation (SD)) were recruited for the study. All subjects were in good physical condition 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 pause between consecutive exercises. The experiments started with a baseline measurement to obtain clean datasets. This baseline measurement was followed by seven different specialized exercises. The complete experimental procedure is explained. In all, 35 datasets with specialized exercises of five different subjects were measured.

The baseline measurement consisted of two minutes in supine position without any movement. The eyes were closed to minimize ocular artifacts. Next, four isometric contraction exercises (performed in randomized order) were executed eight times for $15\,\mathrm{s}$ each. A pause of $30\,\mathrm{s}$ occurred between two contractions. During the exercises, the subjects pressed their head against an immovable object. The four contraction exercises were: isometric forward contraction (Isoforw), isometric backwards contraction (Isoback), isometric right contraction (Isoright), and isometric left contraction (Isoleft). The next exercise consisted of running on a treadmill at the constant speed of $2.316\,\mathrm{m\,s^{-1}}$. This is 20% above the average speed where people, with normal fitness, switch from walking to running [17]. This speed guaranteed that the treadmill exercise was physically demanding. The inclination was set to 1% to simulate the air resistance existent during outdoor running [18]. Next, cycling on an ergometer (Cycle) with a cycling frequency of half the step frequency and a resistance level of $50\,\mathrm{W}$ 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.

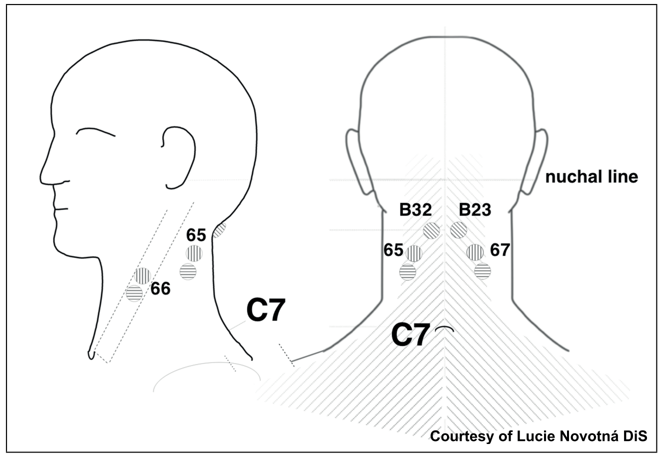

Fig. 1. Positioning of the EMG electrodes. EMG electrode labels: 65, 66, and 67; EEG electrode labels: B32 and B23; C7: seventh cervical vertebra; The electrodes 65 and 67 recorded the activity of the trapezius muscle, the electrodes 66 and 68 (not visible) recorded the sternocleidomastoid muscle.

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 $0.5\,\mathrm{Hz}$ to $70\,\mathrm{Hz}$. Then a notch filter of $50\,\mathrm{Hz}$ was applied to remove power line interference, followed by an ICA based ocular artifact correction to remove blinks and eye artifacts [10]. Afterwards, the data was imported into EEGLAB [19], an open source toolbox for Matlab (MathWorks Inc., Natick, 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 [12], [20], [21] to the AMICA algorithm [22]. 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. [12] applied the InfoMax algorithm of Bell and Sejnowski [21] to EEG data for the first time. This algorithm is available in the EEGLAB toolbox [19]. We employed this algorithm to the data. Further, we applied the AMICA algorithm [23] implemented by Palmer [22]. The AMICA algorithm is an asymptotic Newton algorithm to calculate the maximum likelihood estimate for a mixture model of independent components. 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 $30\,\mathrm{Hz}$ indicated EMG artifacts [6].

The AMICA algorithm has four 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 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 factor for the SNR was calculated as:

$$m_{\text{SNR}} = 1 - \frac{\text{SNR}_{before}}{\text{SNR}_{after}} \tag{1}$$

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 resulted in two distances, d_{before} and d_{after}. In the last step, the novel objective improvement factor was calculated. We defined the objective improvement factor as following:

$$m = 1 - \frac{d_{after}}{d_{before}} \tag{2}$$

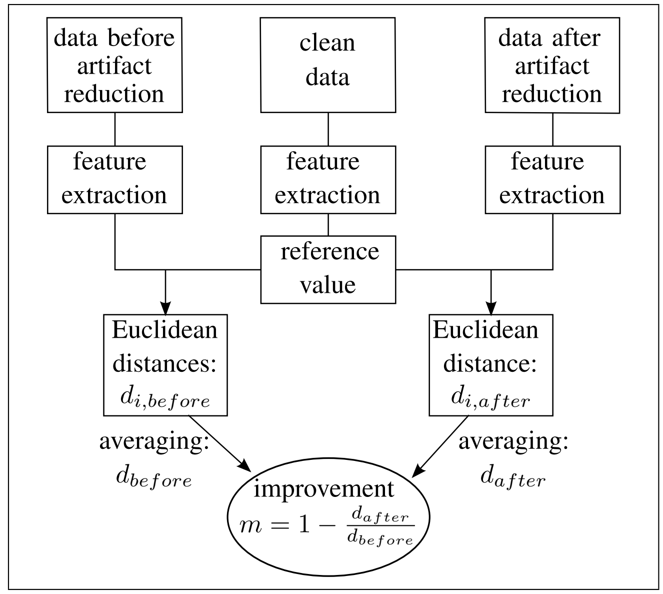

Fig. 2. Flow chart of the evaluation methodology procedure.

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.

Of our 35 datasets, four datasets had to be excluded due to too much non muscle related artifacts like 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. In total, both algorithms were applied to 29 of 35 datasets.

AMICA converged in all of the remaining datasets. InfoMax only converged in 23 cases. Fig. 3 illustrates the number of measurements that converged for both algorithms for each exercise. The remaining datasets were used for the calculation of the averaged improvement rates (Fig. 4). These were four datasets of the chest press exercise and the isometric right contraction and three datasets of the remaining five exercises (compare Fig. 3). 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 InfoMax 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 InfoMax 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 InfoMax 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 [19]. 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 researcher.

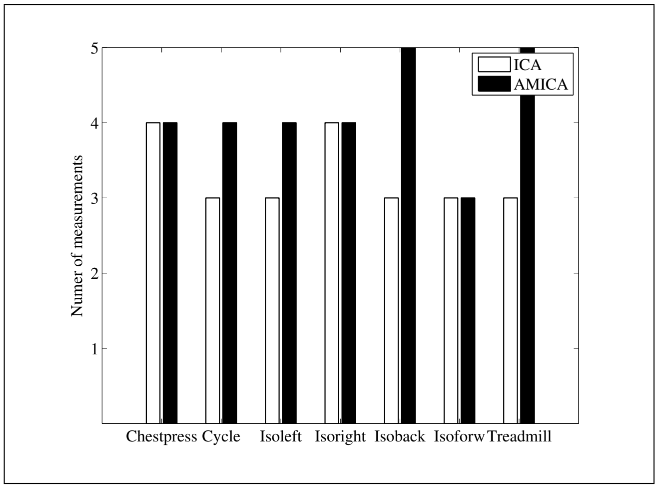

Fig. 3. Number of convergent measurements of the InfoMax and the AMICA algorithm. AMICA converged in all datasets.

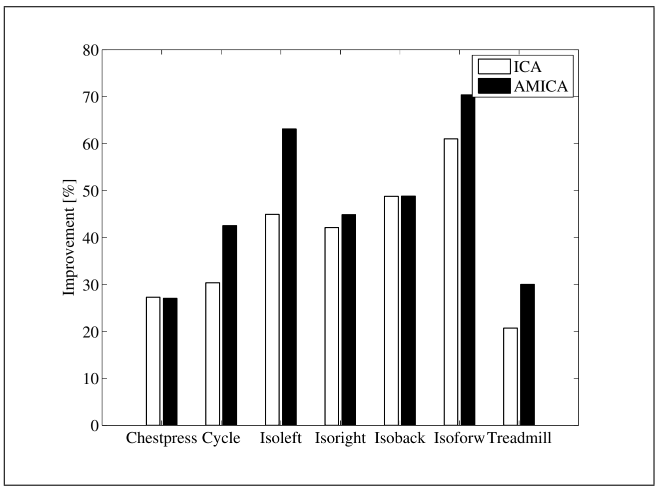

Fig. 4. Averaged improvement rates for both algorithms. Only datasets were both algorithms converged are considered.

The datasets consisted of data from young, male, and physically fit adults. Our results do therefore not account for any differences between males and females or different age groups. In further studies, subjects of either sex and a variety of ages should be considered.

We suggested an objective improvement parameter for the evaluation of different artifact reduction algorithm on EEG data. We further applied the InfoMax algorithm InfoMax and the AMICA algorithm and calculated for each exercise an improvement measure. In summary, the AMICA algorithm outperformed the InfoMax algorithm. Based on our study, we therefore recommend to use AMICA for the reduction of muscle artifacts in EEG data instead of InfoMax. In further research, we will continue using our novel objective measure to test the performance of other artifact removal algorithms.

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