Comparing Artifact Removal Techniques for Daily-Life Electroencephalography with Few Channels

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Comparing artifact removal techniques for daily-life electroencephalography with few channels

Pasquale Arpaia[1,2,3], Egidio De Bendetto[1,2], Antonio Esposito[2,4], Angela Natalizio[2,4], Marco Parvis[4], and Marisa Pesola[2]

***Abstract*—This paper proposes a comparison between artifact removal techniques applied to real electroencephalographic data. The aim was to investigate the most suitable technique for artifact removal with a focus on wearability, portability, and low cost of the final system. A particular focus was thus put on the usage of few channels as a key feature to develop wearable and portable low-cost devices. Recent techniques relying on artifact subspace reconstruction or its Riemannian modification were considered along with more classical ones based on independent component analysis and principal component analysis. Different cut-off parameters were investigated in order to compare aggressive artifact removal to less aggressive one. The considered artifacts were divided into four categories: eye blinking, eye closing, eye moving, and muscle artifacts. Moreover, uncontaminated signal epochs were taken into account during the analysis for checking out if the artifact removal technique was affecting them too. The root means square error was exploited as the metric for assessing artifact removal. Results from three subjects suggest that artifacts subspace reconstruction is the most effective one, even when down to four channels are taken into account. Moreover, the results pave the way to the design of an hybrid technique to be applied when less than four channels are available for the analysis. Finally, optimization of the cut-off parameters should also be furtherly investigated.**

***Index Terms*—electroencephalography, artifact removal, brain-computer interface, wearable, portable, low cost.**

I. Introduction

Electroencephalography (EEG) is a widely spread and consolidated neuroimaging technique for acquiring the human brain activity. The reason behind that is the EEG non-invasiveness, ease of use, and possibly wearability, portability, and low cost. Due to its flexibility, EEG has shown great potential in both clinical and research contexts [1]. In clinical practice, EEG is a powerful diagnostic and monitoring tool. On the other hand, the development of new smart technology based on direct communication between the human brain and a machine is a popular idea in various fields of research.

A specific research area of interest is thus the *brain-computer interface* (BCI) field [2]. A BCI is a measurement system relying on brain signals acquisition and processing, usually providing a functional connection between the user and a device. Recently, the interest in wearable and portable EEG-based BCI systems has grown in targeting daily-life applications. Different EEG acquisition systems exist for that purpose, and each system presents peculiar measurement accuracy as well as number of channels. The most recent EEG-BCI systems rely on wireless headsets available on the market [3]. The non-invasive EEG records the electrical activity from a region of cortical neurons by placing surface electrodes on the scalp [4]. Small size, efficient power handling, and simple montage are further requirements for portable devices.

In this framework, daily-life applications are still limited because of the need to enhance EEG measurement. Indeed, in out-of-the-lab environments, EEG signals are greatly contaminated by interference and noises from both endogenous and exogenous sources [3]. In particular, physiological artifacts consist of undesired interference from other body processes [4], [5]. Literature mostly considers eye-related, cardiac, and muscular artifacts, while less relevant ones are sympathetic skin responses, skin perspiration, and respiration. Non-physiological artifacts, instead, include both environmental and experimental noises [6]–[8]. A typical environmental artifact is the line interference at 50 Hz or 60 Hz. Meanwhile, electromagnetic and radio frequency interference can arise from nearby instrumentation. In addition, incorrect procedural setup and inappropriate actions of untrained users can also lead to experimental artifacts [4], [5].

As a whole, EEG data represent a non-stationary mixture of desired brain signals and artifacts. Therefore, *EEG artifact removal* is crucial in properly measuring the neurophysiological phenomena of interest associated with brain activity. Currently, artifact removal techniques can be classified into four main groups [4], [9]:

- *regression methods* rely on the superposition principle, and the regression is used to remove artifacts by means of available reference signals (e.g. electrooculograms), with the goal to subtract those artifacts from the actual signals [10];
- *filtering methods* aim to filter out artifact-related bands that do not overlap with the signal band, where classical filters need a-priori knowledge for the artifacts spectral content, while adaptive filters have adjustable parameters to optimize [9]. This last filtering methods include the "artifact subspace reconstruction" (ASR), a novel and promising adaptive technique [11], as well as its Riemannian modification (rASR) [12]. Overall, filtering methods are largely exploited in EEG pre-processing;

[1] Department of Electrical Engineering and Information Technology (DIETI), Università degli Studi di Napoli Federico II, Naples, Italy
[2] Università degli Studi di Napoli Federico II - Augmented Reality for Health Monitoring Laboratory (ARHeMLab), Naples, Italy
[3] Centro Interdipartimentale di Ricerca in Management Sanitario e Innovazione in Sanità (CIRMIS), Università degli Studi di Napoli Federico II, Naples, Italy
[4] Department of Electronics and Telecommunications (DET), Politecnico di Torino, Turin, Italy

- *blind source separation* (BSS) methods estimate signal sources from the acquired data by assuming a linear mixing model $\mathbf{X} = \mathbf{AS}$ [9]. Several BSS algorithms exist, including the well-known independent component analysis (ICA) [13], principal component analysis (PCA) [14], and canonical correlation analysis (CCA). BSS methods process all the EEG channels simultaneously and, therefore, they are mostly employed in multi-channel EEG applications;
- *source decomposition* methods aim to identify and reject artifact components by decomposing each individual channel into basic waveforms [9]. Two common examples are the wavelet transform (WT) [15] and the empirical mode decomposition (EMD) [16]. In particular, EMD methods have recently evolved to ensemble empirical mode decomposition (EEMD) based on additional white-noise data [17].

Moreover, the interest in hybrid methods, where the mentioned techniques are combined, is growing more and more and a recent trend also consists of using neural network [3], [4].

Despite that, current literature has rarely taken into account artifact removal techniques for a limited number of channels. Most studies propose artifact removal by relying on many channels, and this limits the usage of such techniques in wearable and portable EEG, which is indeed a hot topic [3]. Furthermore, there is no method to be preferred in general for artifact removal and their limitations are not clearly identified, especially with respect to the minimum number of needed channels.

On these premises, this paper provides a comparative analysis between different artifact removal techniques with a particular focus on decreasing the number of EEG channels. This analysis appears essential in understanding if already the available techniques can be used with a limited number of EEG channels or if there is the need to develop novel techniques. Therefore, Section II presents the data and the methods adopted for the current analysis, while Section III reports and discusses the inherent results. Conclusions will follow and some future steps will be addressed.

II. Material and Methods

The main aim of the present study was to compare the effectiveness of consolidated artifact removal techniques and more recent ones in pre-processing EEG data from few channels. Hence, the focus was on assessing this effectiveness with a decreasing number of channels. However, as a side effect, these analyses could verify the result reported in literature for a multi-channel scenario. Despite the possibility to employ simulated data, real EEG data were actually exploited to get closer to daily-life applications. Therefore, in the following, the employed data are first introduced and then the proposed analysis is presented.

A. Dataset

EEG data were selected from a public dataset intended for testing artifact removal techniques [18]. This dataset provides data from 13 participants with one recording session each. Brain signals were recorded with an helmet by Brain Products [21] with 27 EEG electrodes and 3 EOG electrodes, at a sampling rate of $200\,\mathrm{Sa/s}$. The subjects sat in front of a screen to follow instructions for the experimental protocol. Two files were finally made available for each subject: a file with EEG records, and a file containing meta-information related to the record.

Each experimental session consisted of two parts. First a baseline acquisition was carried out, where the subjects were asked to focus on a fixed cross on the screen while reciting the reversed alphabet in their minds. Two 30-second-long traces were recorded from each subject at the beginning of the experiment. This baseline block is supposed to contain a small amount of artifacts and it can be considered pure EEG data. Secondly, 10 repetitions for nine different artifact conditions were carried out in random order. Each artifact condition lasted from $10\,\mathrm{s}$ to $30\,\mathrm{s}$. These record thus includes artifacts from both eye and muscle sources. The triggered eye artifacts were (i) eye blinking, (ii) eye closing, (iii-iv) fast eye movements to left and right, and (v-vi) smooth eye movements to left and right. The triggered muscle artifacts were (vii) talking, (viii) jaw clenching, and (ix) head flexing. Further details on artifact conditions can be found in the dataset documentation [18].

Regarding the present study, a simpler categorization of artifacts is proposed. *Eye blinking* and *eye closing* were treated separately. Instead, fast and smooth eye movements were grouped as *eye moving artifacts* due to their similarity, independently of the movement direction. Likewise, all the muscular artifacts were grouped together in the *muscle artifacts* category. Therefore, four different artifact types were ultimately considered.

B. Analysis

Data from three subjects were analysed in the present work, namely S01, S02, and S04. The rationale was to carry out this comparison with the first three subjects of the dataset. However, S03 was discarded after visual inspection due to some artifacts identified within the baseline period. Data were processed in MATLAB© by means of EEGLAB, an open-source toolbox for EEG analysis developed by Delorme and Makeig in 2004 [19]. In addition, the plug-in *clean_rawdata()* plug-in [20] was used to implement artifact removal techniques reported below.

For each subject, data were pre-processed as follows. First, the EEG record was imported by the *pop_loadset.m* function. Then, data were base-normalized and band-pass filtered in the $1\,\mathrm{Hz}$ to $40\,\mathrm{Hz}$ frequency range with the *pop_eegfiltnew.m* and the *pop_rmbase.m* functions. Next, an EEG trace of about $120\,\mathrm{s}$ length was obtained from the filtered data. In details, the pure data condition was entirely preserved as the first part of the trace ($60\,\mathrm{s}$ length). For the second part, $60\,\mathrm{s}$ of signal with a type of artifact (eye blinking, eye closing, eye moving, or muscle artifacts) was randomly selected from the 10 repetitions and by considering a random set of channels.

Therefore, a few-minute-long trace was extracted and saved as new file.

At this point, four artifact removal techniques were applied to the epoched data. In some cases, the same technique was tested with different values of the main parameters. These values were chosen by relying on literature's suggestions. On the contrary, the default values of hyperparameters have been left unchanged. The three EOG channels were excluded from the analysis. All the 27 EEG channels were instead used by randomly removing a channel at each iteration until reaching two channels. This randomization was done to investigate the effectiveness of the artifact removal technique independently of the actually selected channels.

The implemented artifact removal techniques were:

- ASR with an aggressive cut-off parameter $k = 15$;
- ASR with a non-aggressive cut-off parameter $k = 25$;
- rASR with an aggressive cut-off parameter $k = 2$;
- rASR with a non-aggressive cut-off parameter $k = 5$;
- ICA with 75% rejection threshold for eye and muscle artifacts;
- ICA with 90% rejection threshold for eye and muscle artifacts;
- PCA with rejection of the highest variance component.

ASR and rASR were implemented with the *clean_asr.m* function, ICA was implemented with the *runica.m* function, and PCA was implemented with the *pca.m* function.

Finally, root mean square error (RMSE) was chosen to assess artifact removal on each segment:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[EEG_{corr}(i) - EEG_{cont}(i)\right]^2}, \quad (1)$$

where EEG_{cont} is the contaminated signal and EEG_{corr} is the signal after one of the artifact removal techniques was applied. It must be noted that RMSE is a suggested metrics for analysis of simulated EEG data, while there is no consensus on one evaluation criterion on real EEG data [1]. However, RMSE has been used in this study to highlight the difference between the original contaminated signal and the corrected signal after the artifact removal. Ideally, an RMSE equal to zero would be desirable for the baseline condition analysis, because pure EEG epochs should be left unchanged in the artifact removal process. On the contrary, higher values of RMSE would be expected for along epochs with artifact because of the difference between contaminated EEG data and corrected EEG data.

In addition to the RMSE quantitative assessment, results were also visually inspected. For that purpose, the *vis_artifacts.m* function (included in the *clean_rawdata()* plug-in) was used to display the difference between the contaminated signal and the corrected signal.

For each subject, the analysis was repeated 10 times with random selection of channels. After these 10 runs, the mean and the standard deviation of the resulted values of RMSE were computed.

III. Results and Discussion

The results obtained with EEG data from the subject S01 are shown in Fig. 1-4. Each figure corresponds to a different artifact removal technique. On the x-axis, the number of exploited channels is reported, while the y-axis reports the RMSE in µV. Each curve represents a different condition. The black curve refers to the baseline segment, which should be left unchanged. Hence, the desired trend for the black line would be a constant value close to zero. Then, the yellow curve refers to the eye closing artifacts, the green one to the eye moving, the magenta one to the eye blinking, and the red one to the muscular artifacts. The RMSE value correlates positively with the artifact amplitude. Higher values of RMSE would be expected in these cases.

A. Artifact removal results

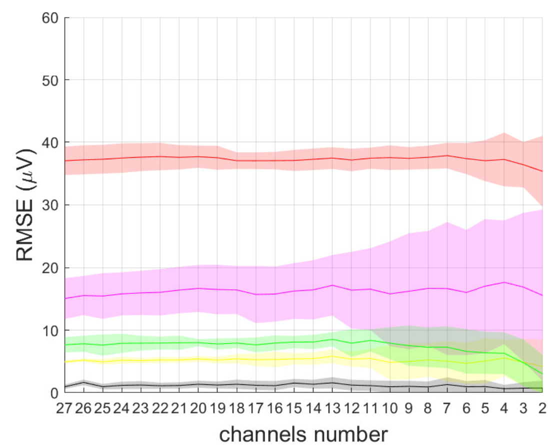

Fig. 1. ASR with $k = 25$ applied to S01 data. Black: baseline, yellow: eye closing, green: eye moving, magenta: eye blinking, red: muscle artifacts.

Fig. 1 shows the performances of ASR when the cut-off parameter is $k = 25$, but compatible results were obtained with $k = 15$. The RMSE for baseline condition appears close to the ideal trend, namely it remains constantly below $5\,\mu V$. Interestingly, the ASR implementations are able to remove all four artifacts type even when decreasing the number of exploited channels. However, there in an increase of the standard deviation highlighting a greater performance oscillation when less channels are considered. Results also suggest that, when the number of channels reaches 3, the ASR becomes less effective. In particular, ASR is not able to correctly remove eye movements (green line) and eye closing (yellow line).

Regarding the rASR, the fluctuations shown in Fig. 2 indicate that it less stable than the ASR. Moreover, though the baseline remains almost unchanged down to 10 channels, then the inherent RMSE significantly arises. Then, the artifact removal appears less effective than ASR for eye closing (yellow line) and eye movements (green line) even in the multi-channel case. This is especially true for the less-aggressive cut-off parameter associated with Fig. 2, while the more-aggressive resulted more effective in removing these artifacts. Overall,

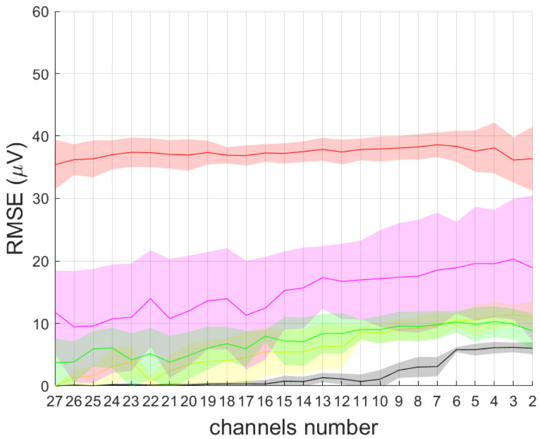

Fig. 2. rASR with $k = 5$ applied to S01 data. Black: baseline, yellow: eye closing, green: eye moving, magenta: eye blinking, red: muscle artifacts.

the ASR should be preferred in a few channels setup because it does not significantly affect the baseline signal. Nonetheless, it must be noted that the exploited rASR algorithm is still in a beta development version.

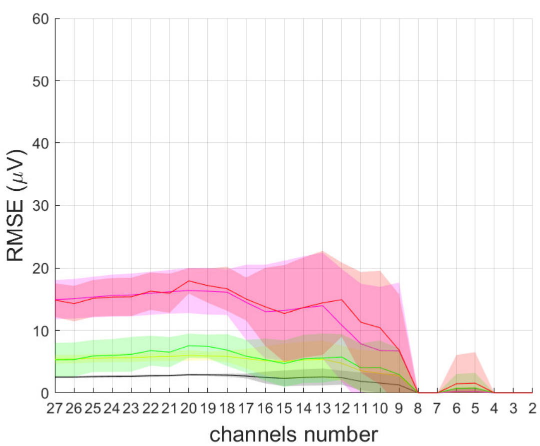

Fig. 3. ICA with $th = 90\,\%$ applied to S01 data. Black: baseline, yellow: eye closing, green: eye moving, magenta: eye blinking, red: muscle artifacts.

Fig. 3 represent the performance of artifacts removal with ICA with the less aggressive different threshold. RMSE values are generally lower than before for all the artifact types, thus indicating a less effective removal. In particular, the effectiveness of the less aggressive threshold drops below 8 channels, while it could be seen that the one of the more aggressive threshold drops at 5 channels. Therefore, as it was expected from literature, ICA cannot be exploited for few-channels EEG processing.

Finally, Fig. 4 shows artifact removal with PCA as the number of EEG channels decreases. Although all the curves show a constant trend, the RMSE for the baseline segment is higher than the other techniques (above $5\,\mu$V). Therefore, although effective in artifact removal, the PCA also affects

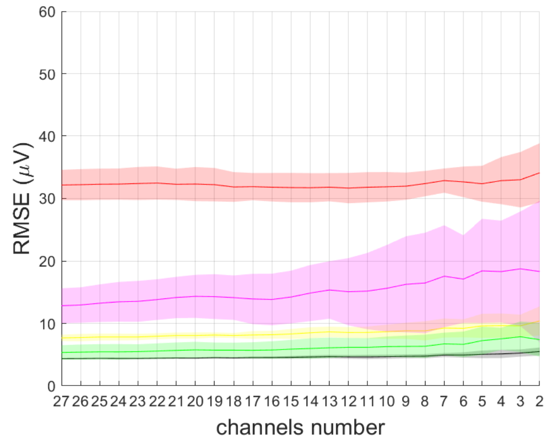

Fig. 4. PCA applied to S01 data. Black: baseline, yellow: eye closing, green: eye moving, magenta: eye blinking, red: muscle artifacts.

clean EEG signals. A visual inspection of the signal after artifact removal with PCA confirmed such an observation.

B. Discussion

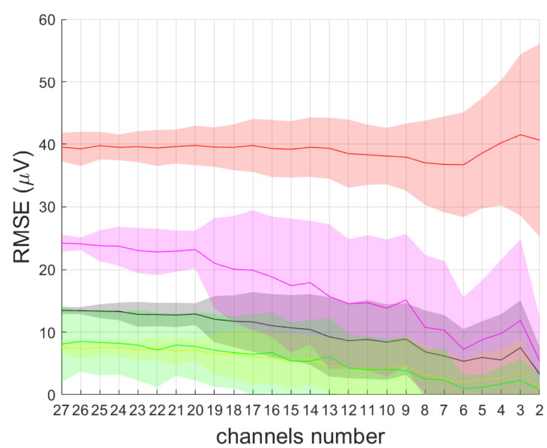

Fig. 5. ASR with $k = 25$ for S02 data. Black: baseline, yellow: eye closing, green: eye moving, magenta: eye blinking, red: muscle artifacts.

The main aspect taken into account in the present work is the effectiveness of the artifact removal techniques with respect to the number of exploited channels. As the number of channels decreases, ASR proves to be the best artifact removal choice due to its stability and its capacity to preserve the clean EEG signal (baseline). The major drawback of rASR and PCA, instead, is that they also affect the clean signal. Finally, the ICA is not able to perform in a few-channel setting.

Results were confirmed by analysing the EEG data from the subject S04, while slight differences are remarkable for the subject S02, which has a less clean EEG signal in the baseline period. As a consequence, when the ASR technique is applied on EEG signals of S02, the RMSE values are higher than those of S01. This is reported in Fig. 5. Moreover, the standard deviation associated with the few-channels case is even greater than the S01 one, and the effectiveness of artifacts removal appear unclear in such a case. Despite that, visual inspection of the signals suggests a still effective artifact removal. As an example, Fig. 6 shows EEG signals before (red) and after (blue) artifacts removal for S02. In there, the ASR with $k = 25$ applied to a random channel is considered, its application to the baseline period (a) is compared to the removal of the muscle artifact segment (b). It can be seen that the baseline segment contains some artifacts corrected by ASR technique. In accordance with literature, the muscle artifact removal results appears less effective, because a main requirement for the ASR is a clean baseline.

Some general considerations can be finally derived from these results. First, it can be noted that the RMSE associated with the muscle artifact segment is systematically higher for all the techniques except ICA. This can be explained by the larger noise amplitude of muscle artifacts if compared to other artifact types, which eases the removal by ASR, rASR, or PCA. Eye-related artifacts have also been successfully removed from all techniques in multi-channel EEG, while the few-channel case is less neat. Standard deviation generally increases when the number of channels is diminished, hence performance is less stable. The obtained standard deviation values can be also explained by the location of the selected electrodes in the few-channels setting. Indeed, if the randomly selected electrodes are on the frontal lobe, eye-related artifacts removal will be more effective, while the RMSE will be lower when the considered electrodes are not largely affected by those artifacts. This observation was also confirmed by visual inspection of different channels.

In conclusion, it is worth mentioning that the four considered techniques require different execution times. The execution of each technique during the analysis on subject S01 was timed at each iteration as the number of exploited channels decreased. The chosen value of the main parameter of a technique did not affect the execution time. On the contrary, it was observed that a higher number of channels implies longer execution times. In detail, PCA is the fastest technique and has a minimal dependence on the number of channels, with an average execution time of 0.46 ± 0.01 s. In general, ASR and rASR have comparable execution times, slightly longer than PCA. The average execution time of ASR is of (1.04 ± 0.34)s, while rASR has an average execution time of (0.93 ± 0.23)s. Finally, ICA has an average execution time of (9.88 ± 4.86)s. In conclusion, ICA performs 10 times slower than the other considered techniques. On the other hand, ASR is suitable for online processing due to its low execution time.

IV. Conclusion

In this paper, a comparative analysis between artifact removal techniques has been carried out on real EEG data. The goal was to investigate the most suitable technique for artifact removal with a special focus on a few-channel setting, which would pave the way to develop low-cost wearable devices. This study is considered a preliminary analysis of these techniques, which allows both to confirm the literature knowledge regarding the multi-channel case and then test the techniques effectiveness in the less-treated few-channel case.

Four artifacts removal techniques were taken into account. In particular, ICA and PCA are well-known in literature, while ASR and its Riemannian modification (rASR) are more recent ones. Two different cut-off parameters were used for ASR, rASR, and ICA, in order to also test different levels of aggressiveness for the artifacts removal. To assess the effectiveness of each technique, the RMSE between the contaminated EEG signal and the corrected one was exploited. Results from three subjects suggest that ASR generally outperforms the other technique, independently of its aggressiveness. Interestingly, ASR remains effective with fewer channels, down to about four employed channels. Such results were also confirmed by visual inspection. In addition, ASR would also be more suitable for online processing if compared to the widely used ICA.

By relying on these results, further aspects can be studied in the future. First, optimizing the cut-off parameter and other hyperparameters of the algorithm would be desirable. Then, the design of an ASR-based hybrid technique could enhance the performance in order to expand its applicability to 2 or 3 EEG channels. Finally, another important open question concerns the reliability of RMSE as a performance indicator for real EEG data, which has been currently used along with visual inspection.

In conclusion, this study identifies ASR as a very promising artifact removal technique, whose potential in few-channel daily-life applications needs to be further explored.

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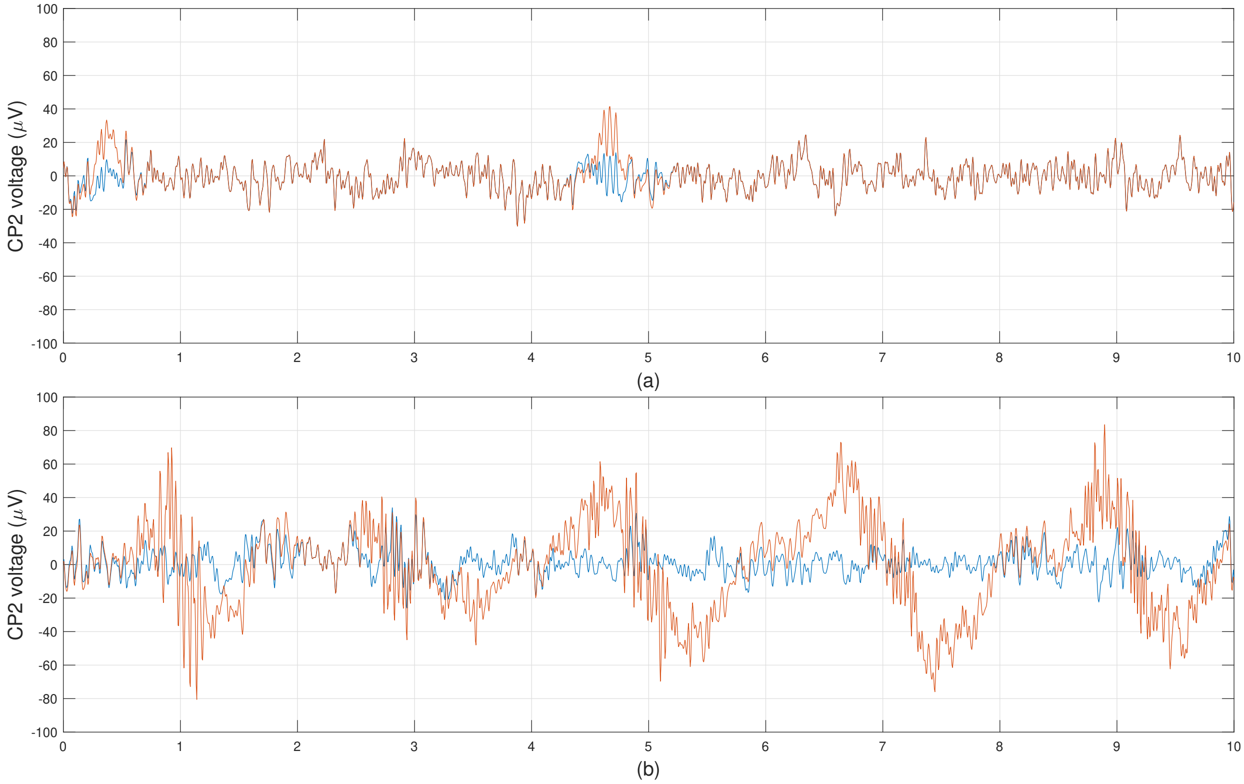

Fig. 6. Visual inspection of EEG signals from S02 before (red line) and after (blue line) artifact removal with ASR: (a) baseline period, (b) muscle artifact. The channel CP2 was randomly selected for this inspection.

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