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ARTEFACT REMOVAL APPROACH FOR EPILEPTIC EEG DATA

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Clinical electroencephalographic (EEG) data are often contaminated by muscle and eye movement artefacts that can strongly influence the following analysis. Two existing methods (Independent Component Analysis and Robust Artefact Removal) used for the rejection of artefacts are applied to EEG data from epileptic patients. A comparison between the methods and a discussion on the results are made.

Keywords: EEG, epilepsy, ICA, RAR, artefact removal.

1. Introduction

In clinical neuroscience the EEG is used for diagnosis and monitoring of treatment efficacy in several diseases and dysfunctions of the brain. Data from long-term recordings of EEG become available in monitoring scenarios such as pre-surgical epilepsy and intensive care monitoring. In neuroscience and cognitive sciences, the EEG provides the data for many advanced analysis strategies, like source localization and connectivity analysis. EEG recordings have a low amplitude and are very sensitive to movement artefacts that can be caused by head movements (e.g. electrode displacement), eye and eyelid movements and by muscle activity (face and neck muscles). An analysis of contaminated EEG data can lead to misinterpretations of the results. Consequently, artefact removal is an important pre-processing step. Many studies have focused on methods that aim at the reduction of artefacts' influence on EEG data.

A high number of approaches that focus on artefact removal exist and most of them are specialized on a type of artefact (ocular, heartbeat, movement). Methods that use a co-registered reference signal are applicable when recordings

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from the source of the artefact are available. Signals such as EOG (reference signal for eye movements, i.e. cornea-retinal dipole movement, retinal dipole movement and eyelid movements), the ECG (for the designation of the heartbeat) and surface EMG recordings (EMG interferences and movements) can be used as reference.

Regression-based algorithms are frequently used for ocular and heartbeat artefacts and can be found in EEG analysis toolboxes. Ocular artefacts are more difficult to correct than heartbeat ones because of their varying shape (types and intensity of eye movements) and their random occurrence. In contrast to the quasi periodic sequence of the ECG-interference. Frequently used EOG removal algorithms estimate (e.g. least-square regression) the portion (correction coefficients) of the artefact that is in the EEG and removes it by subtraction [1].

The EMG and its envelope can be used as reference signal to detect contaminated EEG epochs. Surface EMG and EEG signals strongly overlap in the higher frequency bands and the corresponding artefact amplitude can be higher than those of the EEG. Thompson et.al [2] considers that a low pass filtering is enough when the brain activity of interest is below 15 Hz and also that one can avoid using the contaminated channels.

Often, a co-registration of a reference signal is not possible or the available signals are not suitable as a reference signal. In this case, methods such as blind source separation (BSS) approaches and spatial filtering can be used.

Blind source separation methods used for artefact correction are Canonical Correlation Analysis (CCA) [3], Principal Component Analysis (PCA) [4], Independent Component Analysis (ICA) [5, 6].

The Independent Component Analysis (ICA) was successfully used alone in several studies as artefact removal technique [5 - 9] and also in combination with the Wavelet Transform (WT) [10 - 12].

In this paper, the classic ICA approach and the Robust Artefact Removal (RAR) method proposed in [12], which is based on WT and ICA, are applied on highly contaminated epileptic EEG data for the removal of ocular and muscle artefacts. The objective of this methodological study is to select the approach that is most suitable for our data set. A description of the methods as well as a comparison of their results is made.

2. Independent component analysis

ICA aims at separating individual signals from mixtures assuming that the original source signals are statistically independent. This assumption is the crucial point of the ICA. Two variables are statistically independent if information on the value of one variable does not give any information on the value of the second variable, and vice versa. Furthermore, if two random variables are independent, they are also uncorrelated, but not vice versa [9]. When applied to EEG data, the brain sources are linearly separated from the artefact sources, offering the possibility to reject the artefact components and to reconstruct the data.

The artefact removal procedure starts with the decomposition of the signal into a set of independent components (ICs). Thereafter, the ICs that correspond to artefacts are identified and set to zero (elimination). The back projection of the remaining ICs results in a reconstruction of the signal which is largely freed from artefacts.

One crucial step is the correct identification of the components that correspond to artefacts. When a reference signal is available, the most common method is to calculate the correlation between the ICs and the reference; high correlations indicate artefacts. In the case that a reference signal is not available, typical artefact signal characteristics, such as time-frequency or/and topographic (scalp topography) patterns [6], can be used to identify the artefactual components. A semi-automatic identification of artefact ICs is the correlation of ICs inverse weights (IC maps) with those of a user-defined template [5].

The usefulness of ICA for artefact removal has been demonstrated by a high number of applications. It can be noted that ECG and eye artefacts may be corrected by ICA. Muscle and eye artefacts were successfully treated by using CCA and ICA [3, 7]. Strong gait-related movement artefacts can be removed by means of a combined processing strategy consisting of a template-regression method and ICA. These selected examples already show the broad spectrum of ICA applications [8].

3. Wavelet transform and ICA

However, the ICA artefact removal has one drawback: those ICs that are identified as 'artefacts' may include EEG activity, i.e. their rejection would yield a loss of meaningful brain activity.

The combination of ICA and WT was proved to overcome this problem [10 - 13]. The WT is applied to the ICs, (all or selected ones) in order to identify and reduce, by denoising, only the artefact activity of the independent components. In some studies, all independent components are denoised, by applying a fixed threshold [10, 13], reducing the high amplitude artefacts. Another approach is to apply the Wavelet denoising method only on those ICs which are identified as artefacts. Criteria like sparsity (Eq. 1) [12] and kurtosis (Eq. 2) [11] are used to automatically identify movement or ocular artefacts. The criteria are based on the statistical properties of the artefacts: EMG is characterized by high amplitude and short duration compared to EEG, and EOG have mainly a peaky distribution.

$$sparsity(s^{(j)}) = \frac{\max\left[\left|s_i^{(j)}\right|\right]}{std\left[s_i^{(j)}\right]}\log\left(\frac{std\left[s_i^{(j)}\right]}{median\left[\left|s_i^{(j)}\right|\right]}\right), \tag{1}$$

where $s^{(j)} = \left(s_1^{(j)},\ldots,s_N^{(j)}\right)$ represents the *j*th component, *i* the time index and *N* is the number of samples.

$$kurt(s) = E(s^4) - 3\left[E(s^2)\right]^2, \tag{2}$$

where E is the statistical expectation. A high value for kurtosis describes a highly peaked distribution.

The method used in this study is called robust artefact removal (RAR) method and was proposed by Zima et al. in [12]. It is an automatic sequential procedure that removes short-duration, high-amplitude movement artefacts from long-term EEG recordings. The method uses ICA and Wavelet denoising, applied several times on EEG data segments that overlap. Only ICs identified as artefacts using the sparsity criteria are denoised. The artefact free EEG is obtained by combining the resulting tentative reconstructions. In [12] the method is tested for neonatal EEG recordings and the results are promising.

4. Data

The EEG data were recorded during pre-surgical evaluation of the patients at the University Hospital Vienna, Epilepsy Monitoring Unit, following a standard protocol that was described by Mayer et al. [14]. A group of 18 children with a seizure recording of 10 min (5 min before and after seizure) were selected for analysis. A number of 23 gold disc electrodes placed according to the extended 10-20 International System with additional temporal electrodes was used. The patients suffer from mesial/lateral Temporal Lobe Epilepsy (TLE).

5. Results

In this section representative results (one subject) which have been achieved by using ICA and RAR are described.

For the Independent Component Analysis, the FieldTrip toolbox [15] was used. The epileptic EEG signals were decomposed and the resulting independent components were visually inspected. Ocular and movement artefacts were identified for all subjects. The components most affected by one or both artefacts were rejected. From the mathematical point of view, the rank of the reconstructed data matrix decreases with the number of rejected components and can affect a multivariate analysis of the data. Thus, a maximum of 3 components were selected to be rejected for each subject. An example of ocular and movement artefact components identified for one subject is depicted in Fig. 1.

In this example, the 3rd component is clearly associated with ocular artefacts, as the topography (frontal scalp area) and the EOG-like pattern indicates. The 4th and 7th components are identified as movement artefact, due to the high amplitude and spike-like patterns.

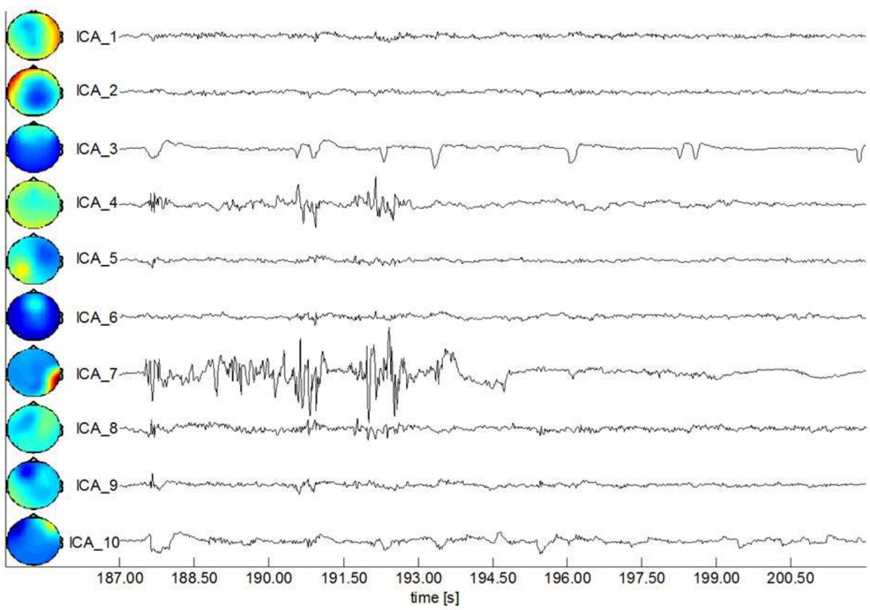

Fig. 1. Example of ICA decomposition. Components which are most probably associated with artefacts are 3rd, 4th and 7th. The analysis interval is 15 s

Also, the associated topographic representation of the source points to a homogenous distribution in the case of the 4th component and to the temporal area for the 7th component, which is known to be more sensitive to movement artefacts. The reconstructed EEG signals, after rejecting these three independent components, are presented in Fig. 2B together with the original data in Fig. 2A. The rejection of the ocular artefacts is most effective for the frontal channels that usually pick up such activities.

The EEG at electrode TP10 shows the highest degree of movement artefact contamination. In Fig. 2B the results of artefact rejection are shown. It can be demonstrated that the movement artefacts have been successfully removed.

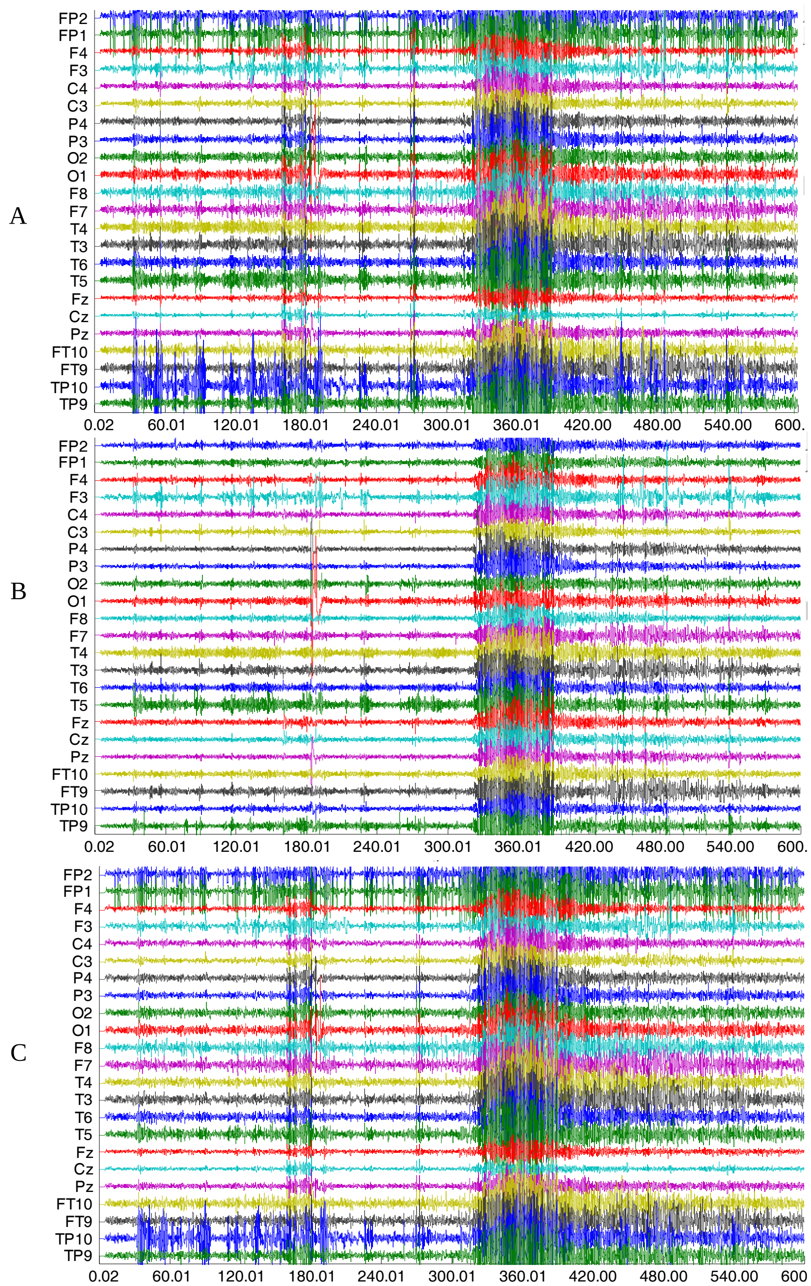

Fig. 2. Original EEG (A), after ICA based artefact rejection (B) and after RAR approach (C). Time [s] on the x-axis

The examination of all EEG channels indicates the capabilities and the limits of the removal approach. An overall improvement of the data can be observed. However, movement artefacts are still present in all channels, but with a strongly reduced amplitude. In contrast, the EEG particularly at electrode O1 shows no improvement with regard to the vehement impulse-like artefact because the IC associated with this artefact has not been excluded.

The following conclusion can be drawn: artefact removal by means of ICA is an optimization process between the minimization of the artefact influence and the preservation of the natural EEG activity, i.e. the higher the number of rejected components, the lower the contamination, and simultaneously, the greater the degree of EEG activity elimination. This is more or less common to all methods of artefact rejection. The combination between ICA and wavelet denoising could be a possible methodological solution to optimize the relation between rejection quality and preservation degree for EEG components. This approach was also applied to the TLE data and its results have been compared with those of the ICA approach.

The RAR method is made available as open source software [12]. RAR focus on the rejection of movement artefacts which are characterized by high amplitude and short duration. The results for the same subject are presented in Fig. 2C. The results demonstrate that RAR’s specialization leads to a selected removal of impulse-like (at electrode O1), high-amplitude artefacts, whereas all other contaminations (movement and ocular artefacts) are persistent. Only a slight overall improvement can be observed. This is an example for just one subject.

Since every recording is different (i.e. for each subject), not all subjects are affected by artefacts. However, an analysis was performed for selected channels for different subgroups that presented similar artefacts. One channel that was severely contaminated with ocular artefacts in 10 (out of 18) children is FP2. The data after artefact rejection using both methods is presented in Fig. 3. The data after applying the RAR method (Fig. 3A) shows the same ocular artefact pattern as the original data (not shown) whereas a clear rejection of the ocular artefacts can be observed for the artefact free data after the ICA approach (Fig. 3B). The same effect can be seen in Fig. 4, where movement artefacts are present for two subjects (channel O1). A decrease of the EEG amplitude is achieved after artefact rejection with the RAR method (Fig. 4C) as compared to the original EEG data (Fig. 4A), but the movement artefact is still present, in contrast to the artefact free data as a result of the ICA approach (Fig. 4B). An interesting effect of the RAR approach was observed when analysing the Fourier spectrum (Fig. 5Ca-b). The method acts like a low-pass filter, setting all frequencies higher than a certain threshold, to zero.

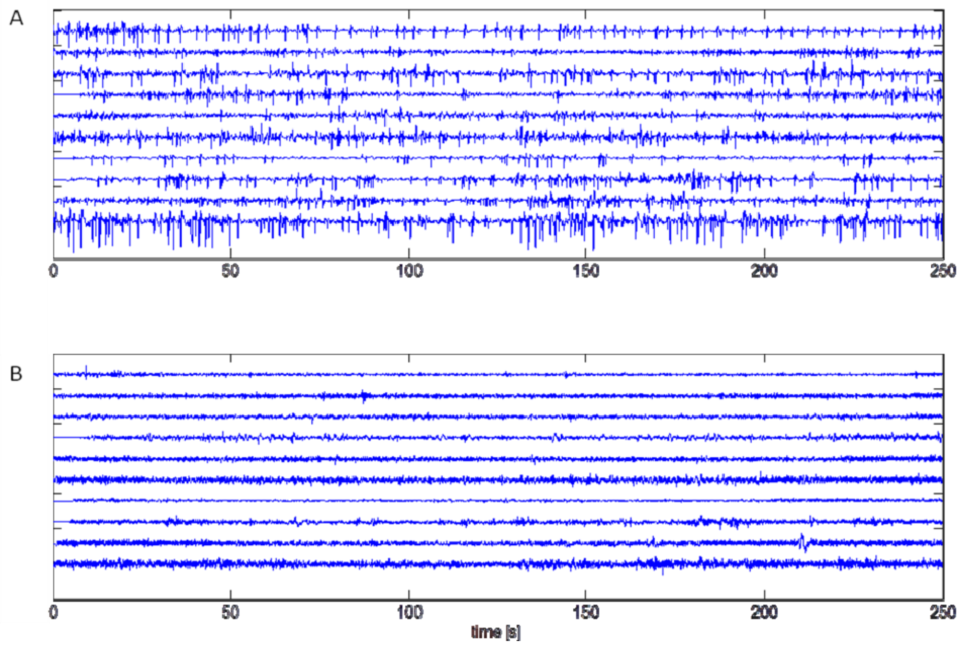

Fig. 3. EEG for 10 subjects at electrode FP2: after RAR method for artefact rejection (A) and after ICA approach (B). Strong ocular artefacts are still present in (A).

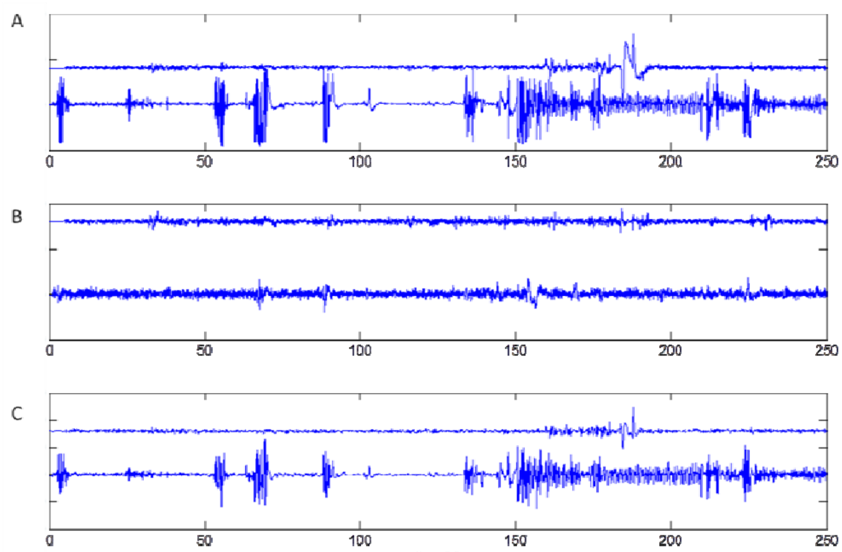

Fig. 4. EEG for 2 subjects at electrode O1: original data (A), after ICA approach for artefact rejection (B) and after RAR method (C). Contamination with movement artefacts.

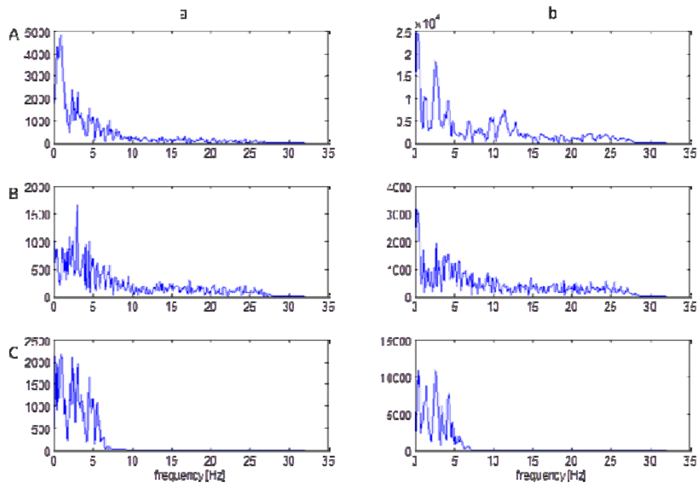

Fig. 5. Spectrum for one subject: original data (A), after ICA approach for artefact rejection (B) and after RAR method (C), at electrodes FP2 (a) and O1 (b).

However, if the artefact rejection is a pre-processing step for connectivity analysis, filtering the data is not recommended, since it results in spurious and missed causalities [16]. For the ICA approach, the artefact free data has a broad spectrum (Fig. 5Ba-b) and the method has only minor influences on the connectivity analysis results [17]. It is obvious that for the TLE-EEG and similarly contaminated EEG data, the RAR approach is not appropriate.

6. Conclusions

This article presents the results of two advanced approaches for artefact removal applied to EEG data recorded from a group of TLE patients. The artefact rejection is an inevitable processing step for connectivity analysis which must be performed with big care and consequence. This paper proves that the RAR approach is not suitable for highly contaminated data and also, that one should investigate the effects of the artefact rejection on the spectrum of the data, if connectivity analysis is the next step. On the other hand, the ICA approach is more suitable for data contaminated with ocular and movement artefacts and also, the artefact-free data can be further used for connectivity analysis, without severely impairing the results.

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