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Comparison of Independent Component Analysis, Linear Regression and Adaptive Filtering for Artifact Removal in SSVEP Registration

***Abstract**. Artifacts pose a significant challenge in the analysis of EEG signals. In this study, the authors investigated the impact of artifacts on the detection of steady-state visually evoked potentials (SSVEPs). The article explored various techniques for physiological artifact elimination, including linear regression, adaptive filters, and independent component analysis (ICA). The effectiveness of the algorithms was evaluated using classification accuracy as a metric. The results indicate that the most promising outcomes were achieved with independent component analysis.*

***Streszczenie.** Artefakty odgrywają znaczącą rolę w analizie sygnałów EEG. Autorzy zbadali wpływ artefaktów na detekcję potencjałów wywołanych SSVEP. Artykuł przedstawia różne techniki eliminacji artefaktów fizjologicznych – regresję liniową, filtrację adaptacyjną oraz analizę składowych niezależnych (ICA). Efektywność algorytmów została oceniona z wykorzystaniem metryki jaką była skuteczność klasyfikacji. Wyniki wskazują, że najbardziej obiecujące wyniki osiągnięto dzięki analizie składowych niezależnych (ICA).*
*(**Porównanie analizy składowych niezależnych, regresji liniowej i filtracji adaptacyjnej na użytek usuwania artefaktów w rejestracji SSVEP**).*

Keywords: artifacts, ICA, linear regression, adaptive filtering
Słowa kluczowe: artefakty, ICA, regresja liniowa, filtracja adaptacyjna

Introduction

Electroencephalography (EEG) is a commonly used method for studying brain activity in medical diagnostics. Unfortunately, direct analysis of EEG signals can be very challenging or even impossible in some cases due to the presence of disturbances caused by natural physiological activity. The disturbances in EEG signals are called artifacts. Electrooculographic (EOG) artifacts are caused by the eye movements of the subject (blinking, sideways eye movements, eyelid clenching). Electrocardiographic (ECG) artifacts result from the natural electrical activity of the heart muscle. The largest group of artifacts is electromyographic (EMG) artifacts caused by various muscle activities of the human body, such as swallowing or breathing. Other artifacts can also occur in EEG signals, such as technical artifacts caused by improperly placed electrodes, power fluctuations, or damaged measurement cables. It can be observed that there are numerous types of artifacts. Developing methods for eliminating physiological artifacts in EEG recordings is crucial in many research areas. Extracting useful information from EEG signals would allow for the development of highly valuable tools for brain-computer interfaces and medical diagnosis.

There are many methods for artifact elimination that have been extensively described in the literature [1-7, 14, 15]. The first of these methods is independent component analysis (ICA). The ICA method is based on decomposing the signal into independent components and eliminating those components that contain artifact-related information. Then, using the remaining components, the signal is reconstructed. The ICA method requires expert knowledge, as the automatic selection of artifact-containing components cannot always be applied [8]. Another method used for artifact removal is regression [9]. It involves removing artifacts using information from the channel (or channels) where the artifact is recorded. Another method for artifact elimination is adaptive filtering [11], which relies on adjusting linear filters using adaptive algorithms. Examples of such filters are the least mean squares (LMS) and recursive least squares (RLS) filters.

The article presents attempts to eliminate artifacts from real EEG signals using ICA, regression, and adaptive filtering. For thi ***Porównanie analizy składowych niezależnych, regresji liniowej i filtracji adaptacyjnej na użytek usuwania artefaktów w rejestracji SSVEP**)*.s purpose, the authors created a database containing EEG signals (3 electrodes) and EMG/EOG signals (8 electrodes) recorded during the observation of a pulsating LED with frequencies of 7 and 8 Hz for four users. Creating such a database allows for comparing artifact removal methods by evaluating the classification accuracy of SSVEPs.

Materials

In order to assess the effectiveness of artifact removal methods, it was crucial to collect suitable EEG signals. To achieve this, an experiment was devised where volunteers were exposed to flashing LED stimuli while deliberately introducing artifacts. To record a database comprising both clean EEG signals and EEG signals contaminated with EOG and EMG artifacts, a cap and the g.tec g.USBamp signal amplifier were employed. The signal was recorded with a sampling frequency of 256 Hz. The electrodes were placed on the subject's head using conductive gel to ensure proper positioning. The study utilized three EEG electrodes to record brain activity - O1, Oz, O2 - and eight EMG/EOG electrodes for capturing the muscle and eye activity of the subject. The EMG electrodes were placed on the face and neck. The distribution of electrodes is illustrated in Figure 1. SSVEPs were evoked using a 1cm diameter red LED diode emitting pulses at a specific frequency. Frequencies of 7 Hz and 8 Hz were used during the registration of SSVEPs. These frequencies were selected because they were found to significantly disrupt both the EEG signal and the SSVEPs. The SIGLENT SDG830 function generator was used to generate the stimulating pulses.

All the studies were conducted on adult individuals whose age did not exceed 40 years. Written consent was obtained from the participants. The acquisition scenarios (including instructions for the participants) were created using the OpenVibe program. This program also allowed for the recording of EEG signals. It was decided to conduct detailed investigations on three types of artifacts - facial grimacing, jaw clenching, and neck tension. As a reference, segments of signals were recorded without any artifacts. In further studies, the signal was divided into one second windows. Manual selection of windows with artifacts was performed (10 for each artifact type), as well as automatic selection (30 consecutive windows). Based on these selected windows, spectrum analysis was performed for windows (subsets) before and after signal cleaning. Example averaged spectra of the signals with selected artifacts for one of the users (10 subsets, SSVEP 7 Hz) are presented in Figure 2

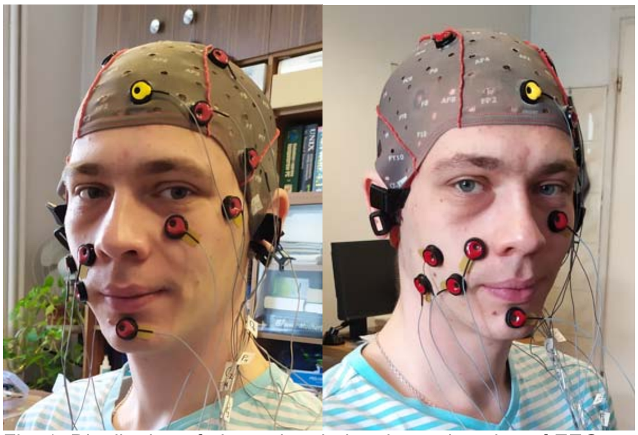

Fig. 1. Distribution of electrodes during the registration of EEG and EMG signals

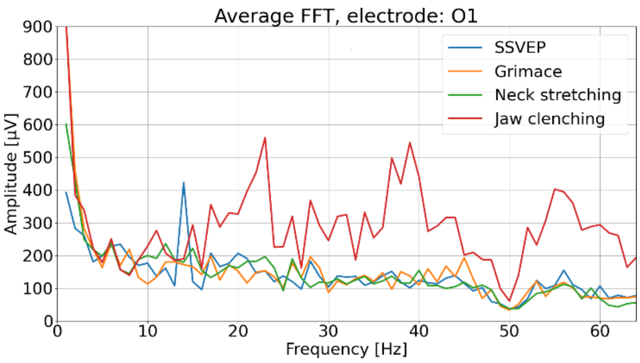

Fig. 2. Averaged spectra of signals with selected artifacts (for 10 one-second windows)

It can be observed that the SSVEP for the second harmonic (14 Hz) is clearly visible in the artifact-free signal. However, in the presence of artifacts, the peak becomes much less prominent. Analyzing the occurrences of individual harmonics of the investigated SSVEP frequency will help assess the quality of the artifact removal method. After cleaning, the peaks should be much more visible. In Figure 2, the influence of the artifacts on the signal spectrum can be noticed. Jaw clenching was found to be the most disruptive type of artifact.

Methods

To eliminate artifacts, we utilized three methods - ICA, regression, and adaptive filtering (LMS and RLS). These methods differ in their approach and operation. For instance, in the regression and adaptive filtering methods, the auxiliary EMG/EOG electrodes are defined as the sources of artifacts. In the case of ICA, cleaning is achieved by rejecting selected components of the signal, which requires expert knowledge.

The linear regression method [1, 3, 10] has been widely used for removing EOG artifacts in the 1990s due to its simplicity and low computational requirements. This method requires a reference channel and assumes that each EEG measurement channel is a combination of a clean source signal and a portion of the reference signal containing artifacts. The goal of regression is to estimate the optimal propagation coefficient for each electrode, allowing for proper artifact removal. The correction of the contaminated signal involves subtracting the reference signal multiplied by the determined propagation coefficient. As a result, we obtain a cleaned signal. In the case of multiple regression, the signals measured at individual EEG electrodes are influenced by more than one reference signal originating from EMG/EOG electrodes. During the study, all EMG/EOG electrodes were used as reference electrodes. The authors focused on cleaning the EEG signal recorded on the O1, Oz, and O2 electrodes. During the cleaning process, it was observed that applying sliding windows along the signal and averaging it yielded better results than cleaning the entire signal at once. Therefore, a window of one second length was selected, and it was shifted by one sample along the signal. Regression was performed for each window, and the obtained results were averaged.

The independent component analysis (ICA) method for artifact removal [1, 2, 3] involves decomposing the signal recorded by the electrodes into independent components, among which are those that correspond to the sources of artifacts. Then the signal is reconstructed by mixing the components obtained in the ICA decomposition, excluding the components responsible for the artifact sources. As a result, artifact-free signals are obtained. ICA is a method that requires expert knowledge. Due to the use of 11 different electrodes, the signal was decomposed into 11 ICA components. Subsequently, the components showing the highest correlation and statistical similarity to artifacts were discarded. For most of the cleaned EEG signal, this amounted to around 7 or 8 components.

The idea behind adaptive filtering [1, 3, 11, 16] is to adjust the filter coefficients based on feedback information about the input signal and the desired output signal. Adaptive filtering algorithms employ various methods and criteria for adapting the filter coefficients, such as minimizing the mean squared error using recursive methods (RLS filters) or gradient methods (LMS and NLMS filters). The most commonly used adaptive filtering algorithms are LMS (Least Mean Squares), RLS (Recursive Least Squares), and NLMS (Normalized Least Mean Squares). The LMS algorithm is simple but may have slower convergence. RLS provides faster convergence and better adaptation to non-stationary signals but has higher computational complexity due to the calculation of inverse matrices. Additionally, RLS may be more susceptible to highly interfering signals, leading to overfitting. NLMS normalizes weights based on the energy of the input signal, providing better robustness against interference. In the study, the focus was on RLS and NLMS filters. In the case of adaptive filtering, a key parameter was the selection of the forgetting factor μ. Small values of the forgetting factor result in little influence of previous samples on the current estimation of the RLS filter. The larger the value of μ, the greater the influence of previous samples on the estimation. In the conducted experiments, a coefficient of 0.99 was used. In the case of the NLMS filter, the coefficient μ controls the learning rate of the adaptive filter. It is a positive value that determines how much the current weight update depends on the prediction error and the norm of the input vector. In our case, the chosen coefficient for NLMS was 0.5. In both filters, reference electrodes were required, which were selected in the same manner as in the case of regression.

Results and discussion

A major challenge in evaluating the effectiveness of artifact removal algorithms is that we do not know how the signal should look after cleaning. The authors decided to use several measures to assess the effectiveness of artifact removal. The first measure was visual evaluation, where the presence of visible artifacts after cleaning was assessed. The next measure was spectral analysis concerning the quality of evoked potential identification and the statistics for the cleaned signals (mean, standard deviation, minimum /maximum values, and skewness). The final measure of assessing the effectiveness of signal cleaning was the accuracy of SSVEPs classification using the cleaned signal segments. Linear discriminant analysis (LDA) was used for this purpose. Based on these measures, an attempt was made to identify the most effective artifact removal method. For the purpose of visualization, the focus was on jaw clenching. This artifact is particularly difficult to remove, as it disrupts the signal across a wide frequency range and varies in character depending on the individual user. Figure 3 illustrates the effect of cleaning a segment of the actual signal (REAL) contaminated with the jaw clenching artifact. The application of each described method (REG, ICA, NLMS, and RLS) is shown. The quality of cleaning can be compared by analyzing the temporal waveforms of the signals. For some methods (ICA, RLS), a smoothing effect on the signal waveform during the occurrence of the artifact, i.e., between 14.5 and 15.5 seconds, is observed. This suggests effective artifact removal using these methods, but further confirmation of their effectiveness requires evaluation using other metrics as well.

For comparative purposes, statistics of the signal were also calculated before cleaning and after applying the cleaning methods. Table 1 presents the statistical values for the cleaned signal segments shown in Figure 3. The data in Table 1 confirm the observations made during the analysis of the temporal waveforms. The ICA method significantly reduced the amplitude of the analyzed signal (from the maximum value 55.6 μV to 20.0 μV). Additionally, the standard deviation was reduced (from 11.82 to 5.94). The skewness of the signal remained unchanged. In the case of the NLMS method, a reduction in standard deviation is evident (from 11.82 to 8.13).

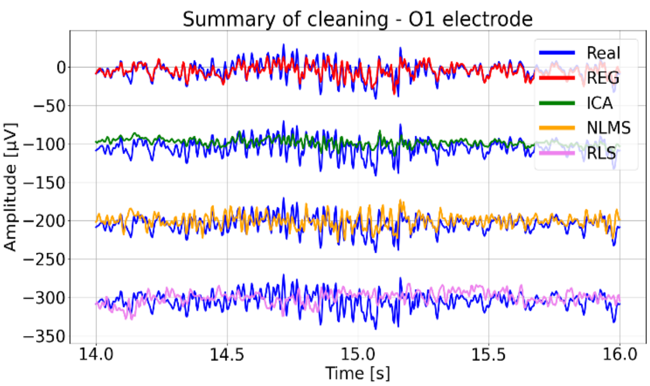

Fig. 3. Temporal waveforms comparison of selected signal cleaning methods for the jaw clenching artifact

Table 1. Cleaned signal statistics for electrode O1

	Clearing method				
	Real	***Regression***	***ICA***	***NLMS***	***RLS***
Mean	0.19	0.25	-0.04	0.15	-0.04
Std	11.82	9.09	5.94	8.13	7.50
Min	-41.32	-35.38	-16.97	-34.33	-33.86
Max	55.59	32.08	19.98	41.19	35.15
Skew	0.07	-0.07	-0.03	0.05	-0.11

The spectra of the signals were computed, and then the classification of 1-second segments was performed for each artifact and the actual signal. For classification purposes, the FFT bins for 7 Hz and 8 Hz were selected. The LDA algorithm was used for classification. The classification accuracy results for individual windows were averaged and presented in a bar graph shown in Figure 4.

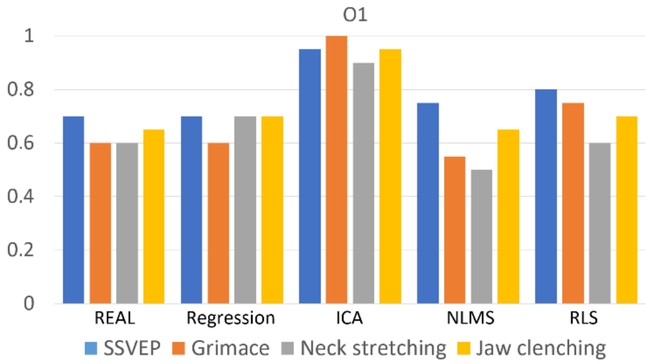

Fig. 4. Comparison of the average classification accuracy of LDA for SSVEPs in signals cleaned using different artifact removal methods

The graph in Figure 4 confirms the superior performance (highest classification accuracy) of the ICA method compared to the classification accuracies in the actual signal (REAL). The accuracy increased for each type of artifact and SSVEP (signal without artifacts). The highest increase in classification accuracy after the cleaning was observed for the facial grimace artifact, with an increase from 0.6 before signal cleaning to 1 after signal cleaning. Improvement or maintenance of accuracy was also observed for the RLS method (most notably for SSVEP, increasing from 0.7 to 0.8) and linear regression (jaw clenching, increasing from 0.65 to 0.7). However, in the case of the NLMS method, a decrease in accuracy compared to the actual signal was observed for two artifacts (facial grimace, decreasing from 0.6 to 0.55, and neck tension, decreasing from 0.6 to 0.5). Figure 5 presents the spectra of the signals cleaned using ICA (the spectra before cleaning are visible in Figure 2). It is noticeable that the SSVEP peaks are enhanced, which contributed to the improvement in the classification accuracy of the evoked potentials compared to the actual signal before cleaning. There is also a significant reduction in the amplitude of the spectral peaks associated with the jaw clenching artifact, indicating its effective removal. In the case of other artifacts, the difference is smaller but still noticeable.

The effects of successful artifact removal using ICA are noticeable. In other studies [12, 13], the method also yielded satisfactory results. However, it is difficult to directly compare them as the authors used different equipment and focused on different types of artifacts.

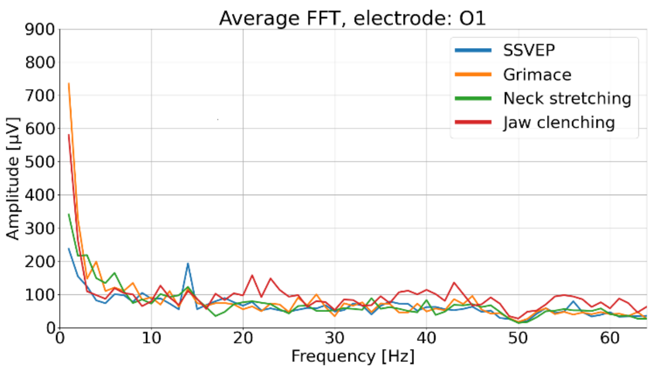

Fig. 5. Averaged spectra of selected artifacts (from Figure 2) after cleaning (for 10 one-second windows)

Conclusions

Different artifact removal methods were tested, including linear regression, ICA, and two types of adaptive filters - RLS and NLMS. Some of the artifact removal methods, although eliminating disturbances associated with artifacts, also led to a decrease in the classification accuracy of evoked potentials, indicating the removal of essential information. The conducted research indicates that the most effective method in terms of SSVEP classification is ICA. However, it requires expert knowledge regarding the studied artifacts and is computationally complex. Nevertheless, it allows for signal cleaning from all electrodes, which can be useful in certain applications. The NLMS method proved to worsen the classification accuracy for artifacts related to facial grimacing and neck tension. On the other hand, the RLS filter performed significantly better, showing an improvement in SSVEP classification accuracy for each artifact. In the case of linear regression, improvement was observed for neck tension and jaw clenching artifacts, while the classification accuracy for facial grimacing artifact remained unchanged. In terms of speed and simplicity, the RLS adaptive filter proved to be the best method. In ongoing work, the authors are exploring the use of CNNs to remove EMG/EOG artifacts.

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