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REG-ICA: A hybrid methodology combining Blind Source Separation and regression techniques for the rejection of ocular artifacts

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ABSTRACT

There are so far two main methodological approaches for rejecting ocular artifacts from electroencephalographic (EEG) and magnetoencephalographic (MEG) signals: regression- and Blind Source Separation (BSS)-based techniques, both having merits, as well as, some serious limitations. In this piece of work, a hybrid methodology that combines the main advantages of these two methods is proposed. We hypothesize that the artifactual independent components (ICs) extracted by a BSS method include more ocular and less cerebral activity than the contaminated EEG signals. We thus propose to apply a regression algorithm to the ICs rather than directly to the recorded signals. The analysis was carried out with synthetic mixtures of real EEG and electroocculographic (EOG) recordings. A BSS method, the extended INFOMAX version of Independent Component Analysis (ICA), was initially used to decompose the artificially contaminated EEG signals into spatiotemporal ICs. Then, a regression scheme, based on a stable version of the Recursive Least Squares algorithm, sRLS, was applied to the artifactual components in order to remove only the ocular artifacts, maintaining the underlying neural signals intact. The processed ICs were then projected back, reconstructing the artifact-free EEG signals. The performance of the proposed technique was compared with two automatic techniques; a regression technique based on Least Mean Square (LMS) algorithm and a BSS-based artifact rejection technique called wavelet-ICA (W-ICA) on the artificially contaminated data. For comparison, two metrics were used to assess the different methods' performance: the first quantified how successful each technique was in removing the ocular artifacts from the EEG recordings, and the second one quantified how much each technique distorted the ongoing brain activity in both time and frequency domains. Confirming our main hypothesis, results have shown that the artifactual ICs contained more ocular and less cerebral activity ($p < 0.04$) (artifact to signal ratio (ASR) = 1.83 ± 3.65) in contrast to the contaminated electrode signals (ASR = 0.69 ± 3.40). Our results reveal that the proposed methodology, namely REG-ICA, removes the ocular artifacts more successfully than W-ICA ($p < 0.01$) or LMS ($p < 0.01$). It also distorts less the brain activity in the time domain when compared to W-ICA and LMS. In the frequency domain, it distorts the brain activity less than the W-ICA in all frequency bands, and less than the LMS for the delta, beta, and gamma bands. Our results suggest that the proposed methodology is evidently an attractive alternative to other already proposed artifact rejection methodologies.

1. Introduction

Artifacts are the outstanding enemy of high quality electroencephalography (EEG) and magnetoencephalography (MEG). Some of the most troublesome artifacts observed in the EEG or MEG signals are due to the ocular activity [1]. Ocular artifacts appear mostly at anterior sites [2] as high voltage patterns caused by eye-blinks or as low frequency components produced by eye movements [3]. An effective way to deal with the electroocculographic (EOG) artifacts is by asking subjects to restrict their eye movements fixating on a stable point. This fixation, however, may suppress and eventually harm the subject's ongoing cognitive processes, thereby affecting the neuroscientific interpretation of the results. For example, such fixation instructions have been shown to affect the Contingent Negative Variation (CNV), N1 and P300 [4–6] components of the Event Related Potentials (ERPs). Moreover, this restriction is sometimes not feasible, especially in experiments performed in children, disabled people, and uncooperative subjects or taking place in real environmental setups [7,8]. Another common way to deal with ocular artifacts is by recognizing and rejecting the contaminated

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EEG/MEG epochs. Their recognition is generally accomplished by detecting voltage increases in the EOG channels above a certain threshold (~100 μV during light stimulation or ~30 μV in total darkness) [9]. The elimination of bad trials can however lead to unacceptable loss of data.

A variety of artifact rejection techniques have been proposed for the detection and correction of EOG artifacts. These techniques are used to recover the cerebral activity lying under the artifactual segments, and they can be separated into two main categories according to their mathematical background: the regression- and the Blind Source Separation (BSS)-based artifact rejection techniques. The regression-based algorithms compute the backward propagation coefficients in order to define the amplitude relationship between the EEG and EOG channels, and finally they subtract the proper amount of EOG activity from the EEG signals [10–12]. Although this methodology is quite simple, its performance is seriously affected by the well-known bidirectional contamination problem, which is due to the fact that the EOG signals also capture underlying neural activity originating from the prefrontal cortex. So the EOG and EEG recordings in the prefrontal region have common cerebral patterns, leading to their removal by regression scheme.

The second class of the artifact rejection tools is based on the BSS methods assuming that the artifactual signals are independent from the ongoing cerebral activity. Exploiting the central limit theorem, the BSS methods are capable of separating a mixture of signals originating from different sources to independent components (ICs), and they can, therefore, be used to separate the artifactual signals from the signals induced by the cerebral activity. The main and inevitable disadvantage of this methodology is that an artifactual component may also contain neural activity aside from pure artifacts [14,29–31]. In this sense, the removal of the contaminated ICs, followed by a signal reconstruction may lead to distortions of the underlying cerebral activity. In BSS methods, specialists are usually called to identify the artifactual components, remove them and reconstruct the signals so as to be free of ocular artifacts [13]. Alternatively, algorithms offering an automatic labeling of the artifactual components can be used [25–27]. Although such an automatic selection of the artifactual ICs is much faster than the visual inspection approach and does not require the involvement of highly trained specialists, it is deemed to be risky, since artifactual components may be marked as normal and vice versa [28].

In the light of the above, the aim of this paper is to introduce a new artifact rejection methodology that effectively "tackles" the major drawbacks of both BSS and regression-based techniques by combining their advantageous features. Our assumption lies with the fact that the ocular artifacts are concentrated in just a few ICs [14]. Since the components tend to be statistically independent in pairs and they represent the activated independent sources, the mutual information of every pair of ICs tends to be minimal. So, as long as the cerebral and ocular activities are derived from different/independent sources, the cerebral activity included in the artifactual ICs tends also to be minimal. So, it is expected that the amount of the cerebral activity included in the contaminated ICs is much lower compared to that existing in the contaminated EEG signals. It can, therefore, be assumed that the artifactual components contain less cerebral activity common to EOG signals. In this manner, it is proposed that the contaminated EEG signals should be initially decomposed into ICs using a BSS method (i.e. the extended INFOMAX–Independent Component Analysis (Extended-ICA) [15]), and then, only, the recognized artifactual ICs should be filtered by means of a regression-based algorithm (i.e. the stable Recursive Least Squares (sRLS) [11]). In this way, only patterns related with the EOG signals are rejected, while the rest of the activity in the ICs remain relatively unaltered, thereby keeping a greater portion of neural activity undistorted.

The idea of filtering the artifactual ICs is not novel; it has already been proposed for image and signal processing [38–40], while Castellanos and Makarov have used it to process EEG signals [14]. Their suggestion was based on the assumption that the amount of the cerebral activity included in the contaminated ICs is much lower compared to that existing in the direct signals. In the present study, we provide clear evidence that this speculation has scientific merit. The novelty of our approach lies with the fact that the contaminated by ocular artifacts ICs are filtered using a regression algorithm.

The remaining parts of this paper are structured as follows. In the next section the details of the proposed methodology, namely REG-ICA, are provided and followed by a presentation of the metrics used to evaluate the performance of the methodology. In the fourth section, relative merits of the approach in removing ocular artifacts are discussed while in the final section possible further extensions are discussed.

2. Materials and methods

2.1. Dataset definition

2.1.1. EEG recordings used in the computation of the ASR index

Real EEG data were obtained from 27 healthy subjects with normal vision: 14 males (mean age: 28.2 ± 7.5) and 13 females (mean age: 27.1 ± 5.2) during a visual experiment (for more details see [16]). A total of 108 datasets were obtained which were then carefully inspected in order to exclude datasets with high amounts of external noise (like bad electrode tangencies, electrodes movements or shiftings), thereby leaving a total of 87 datasets suitable for the purpose of our analysis. Each dataset had 2 min duration. Nineteen scalp electrodes placed according to the international 10–20 system (Fig. 1), with odd indices referenced to the left and even indices to the right mastoids respectively. Central electrodes (Fz, Cz, Pz) were referenced to the half of the sum of the left and right mastoids. Signals were digitized at a rate of 200 Hz, band pass filtered at 0.5–40 Hz and notch filtered at 50 Hz. These datasets were used for the calculation of ASR (see Section 2.5.1), since the signals contain both ocular and neural activity naturally mixed.

2.1.2. EEG, during eyes-closed sessions, used in the artificially contaminated data

EEG data were also obtained from the above subjects during an eyes-closed session (before and after the aforementioned experiment). The EEG electrodes were placed and filtered like before. Fifty-four datasets were obtained in total. The duration of each dataset was 30 s. These datasets additionally included EOG signals, which were recorded by four electrodes placed above and below the left eye and another two on the outer canthi of each eye. This process gave rise to two bipolar signals, namely, vertical-EOG (VEOG), which is equal to the upper minus lower EOG electrode recordings and horizontal-EOG (HEOG), which is equal to the left minus right EOG electrode recordings. These two EOG signals were filtered in the frequency band between 0.5 and 5 Hz [17]. The obtained datasets where carefully inspected in order to ensure that there is no significant contamination by ocular artifacts. These datasets were later used in Section 2.1.4.

2.1.3. EOG used in the contamination procedure

Separate EOG signals were also obtained from an eyes-open session before and after the visual paradigm described in Section 2.1.1. The EOG electrodes were placed as before. The two obtained bipolar EOG signals last 30 s and were pre-processed like in Section 2.1.3. These signals were used in order to contaminate the datasets of

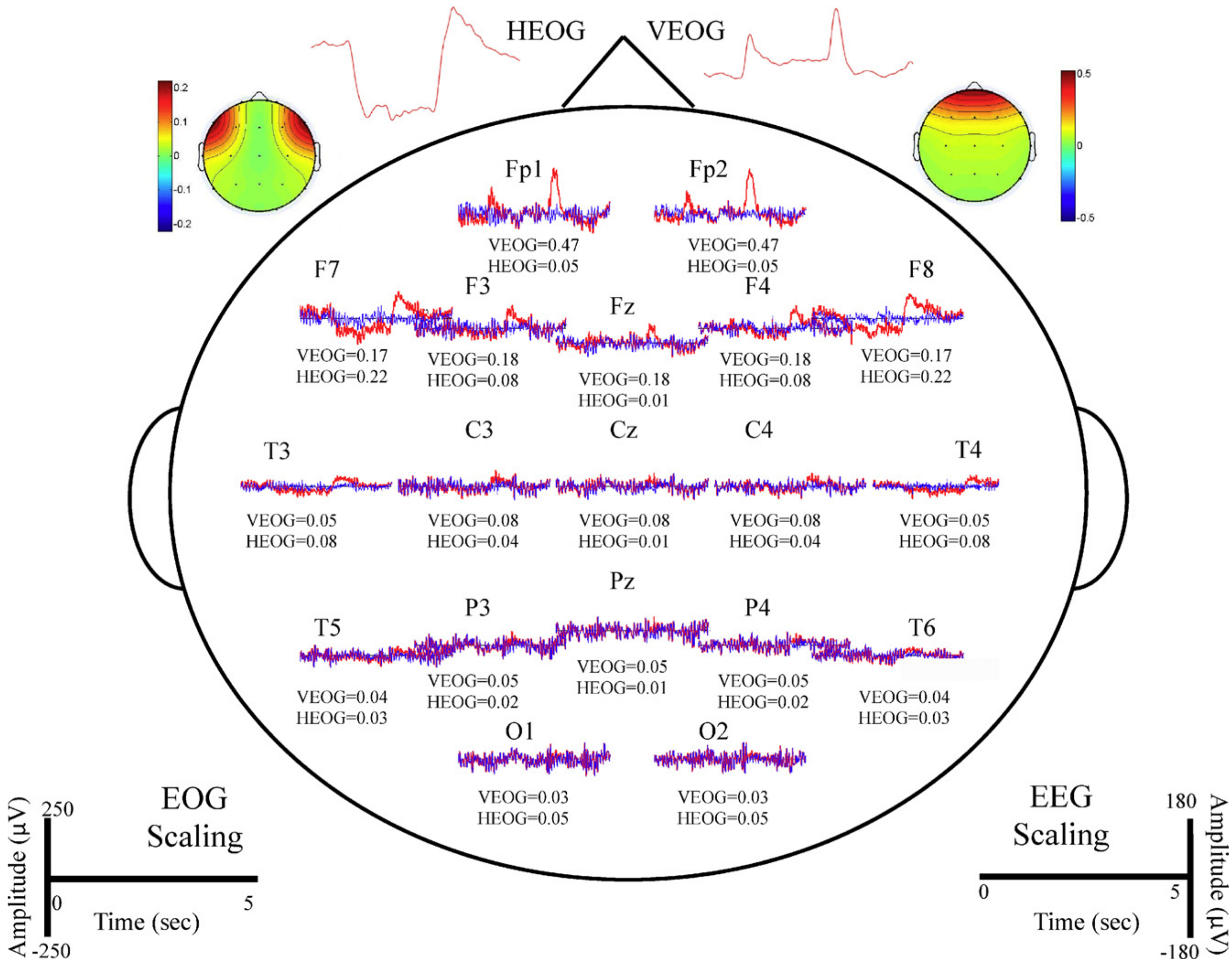

Fig. 1. Contamination procedure – pre-contaminated (free of artifacts) (blue) and contaminated (red) EEG signals are depicted in scalp electrode positions. Contamination coefficients, as proposed by [17] for both VEOG and HEOG activity are provided at each electrode site. On the top part, HEOG and VEOG signals are illustrated alongside with scalp distributions of their associated contamination factors. As it can be clearly noted, anterior sites are more contaminated in contrast to posterior ones for VEOG, while the HEOG activity is most troublesome in lateral electrode positions.

Section 2.1.2 and to generate the artificially contaminated EEG data (see Section 2.1.4).

2.1.4. Artificially contaminated EEG data

In order to generate the "artificially contaminated EEG signals" (used for evaluating the performance of REG-ICA), we have used the Elbert's contamination model [9]:

$$CEEG_{i,j} = PEEG_{i,j} + a_j VEOG + b_j HEOG \tag{1}$$

where *CEEG* are the artificially contaminated EEG signals and *PEEG* are the signals described in Section 2.1.2. The *VEOG* and *HEOG* are the EOG signals obtained from the eyes-opened session (see Section 2.1.3). Vectors a_j, b_j denote the contamination coefficients for VEOG and HEOG, respectively, initialized according to [17]. Finally index *i* indicates the subject's number, while *j* denotes the electrode (Fig. 1).

2.2. Blind Source Separation

A BSS model assumes that a set of recordings of *p* random variables $\mathbf{u}(t) = [u_1(t), \ldots, u_p(t)]^T$ is linear mixtures of *q* independent source signals:

$$\mathbf{u}(t) = \mathbf{A} \cdot \mathbf{s}(t) + \mathbf{n}(t) \tag{2}$$

where $\mathbf{A}$ is a $[p \times q]$ matrix and $\mathbf{n}(t)$ denotes an additive vector of white noise. A BSS method finds the ICs without a priori knowledge of the mixing process or the source signals, provided that (i) the number of source signals is less than or equal to the number of recordings and (ii) the mixing matrix, $\mathbf{A}$, is full column-ranked.

2.3. Regression analysis

Each regression-based artifact rejection technique, uses the linear model of Eq. (3) to calculate the relationship between the observed EOG and EEG signals and then tries to approximate the "real" EEG by subtracting the EOG signals from the observed EEG (Eq. (4)):

$$OBS_i = EEG_i + a_i VEOG + b_i HEOG \tag{3}$$

$$\hat{EEG}_i = OBS_i - \hat{a}_i VEOG - \hat{b}_i HEOG \tag{4}$$

where OBS_i and EEG_i are the observed and the real EEG signals in the *i*th electrode. *VEOG* and *HEOG* are the vertical and horizontal EOG signals respectively. The contamination coefficients in the *i*th electrode are denoted with a_i and b_i, and the indicator $\hat{}$ indicates approximated variables.

Adaptive filters are based on regression analysis. Their goal is to adapt the filter coefficients $(\hat{a}_i, \hat{b}_i)$ and adjust them as closely as possible to the real contamination coefficients (a_i, b_i) (Fig. 2).

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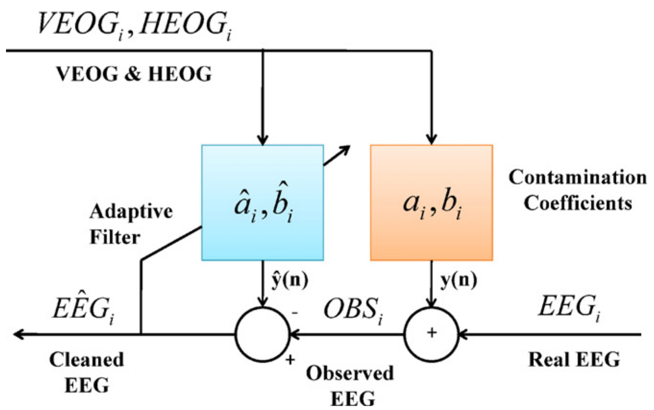

Fig. 2. Regression-based (adaptive filter) artifact rejection technique block diagram – VEOG and HEOG are multiplied by the contamination coefficients and are then added to the real EEG resulting in the observed EEG. An adaptive filter, also known as a Wiener filter, tries to adjust its coefficients in some iteration steps, in order to approximate the real ones. After this approximation the clean EEG is obtained using Eq. (3)).

It stands that:

$$\lim_{\substack{\hat{a}_i \to a_i \\ \hat{b}_i \to b_i}} E\hat{E}G_i = EEG_i \tag{5}$$

2.4. Evaluating the proposed hybrid methodology: the REG-ICA approach

Our methodology consists of two parts. The first one is concerned with the BSS method used for the decomposition procedure, while the second one, with the regression algorithm used for cleaning the ICs (Fig. 3).

A widely used version of ICA decomposes signals to statistically independent components using the INFOMAX principle [15]. According to this approach, maximizing the joint entropy $H(y)$ of the output of a neural processor minimizes the mutual information among the ICs. An extended version of the INFOMAX ICA [13], for super – sub Gaussian signals, was employed here, in order to extract the ICs. Our approach lies with the assumption, that the ICs are contaminated by EOG artifacts according to the linear model described in (3), so an adaptive filter based on a stable version of the Recursive Least Squares (sRLS) algorithm [11] may be used to filter the ICs. So, the algorithm receives the contaminated EEG channels as input and the EOG (here VEOG and HEOG) as a reference. Extended-ICA is used to decompose EEG signals into ICs. Then, the sRLS algorithm, with the parameters mentioned in Table 1, is used to filter only the contaminated ICs; finally all ICs (cleaned or not) are re-projected back, thereby constructing the cleaned EEG signals. Table 1 summarizes the steps of the proposed methodology.

2.5. Quantification measures

2.5.1. Artifact to signal ratio (ASR)

In order to conclude if the artifactual ICs contain less cerebral and more artifactual activity compared to the directly contaminated EEG signals, the ASR index was adopted. The ASR index was calculated for all electrodes of each EEG dataset from Section 2.1.1. The maximum value was chosen to represent the electrode's ASR value. The Extended-ICA was applied to the filtered EEG signals, and the ASR index was calculated for all ICs. The maximum value was chosen to represent the IC's ASR value.

The ASR was calculated using the formula:

$$ASR = 10\log_{10}\frac{E_{ARTIFACT}}{E_{SIGNAL}} \tag{6}$$

where $E_{ARTIFACT}$ is the total energy of the contaminated segments, while the E_{SIGNAL} is the total energy of the rest of the signal. In this approach, the greater the ASR value is, the more the artifactual (compared to cerebral activity) signal content is.

2.5.2. Root mean square error (RMSE)

To quantify the amount of EEG distortion in the time domain, as well as, the ability of each method to remove ocular artifacts, the root mean square error (RMSE) index was calculated:

$$RMSE = \sqrt{\sum_{i=1}^{N}(inEEG_i - outEEG_i)^2} \tag{7}$$

where the *inEEG* denotes the pre-contamination EEG dataset (Section 2.1.2) and the *outEEG* stands for the cleaned artificially contaminated EEG signals (Section 2.1.4). The lower the RMSE value, the better rejection of EOG artifacts is, at least as far as the distortion in time domain is concerned.

2.5.3. Power spectral density (PSD)

In order to quantify the degree of spectral distortion across the different frequency bands, delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma (30–40 Hz), the following

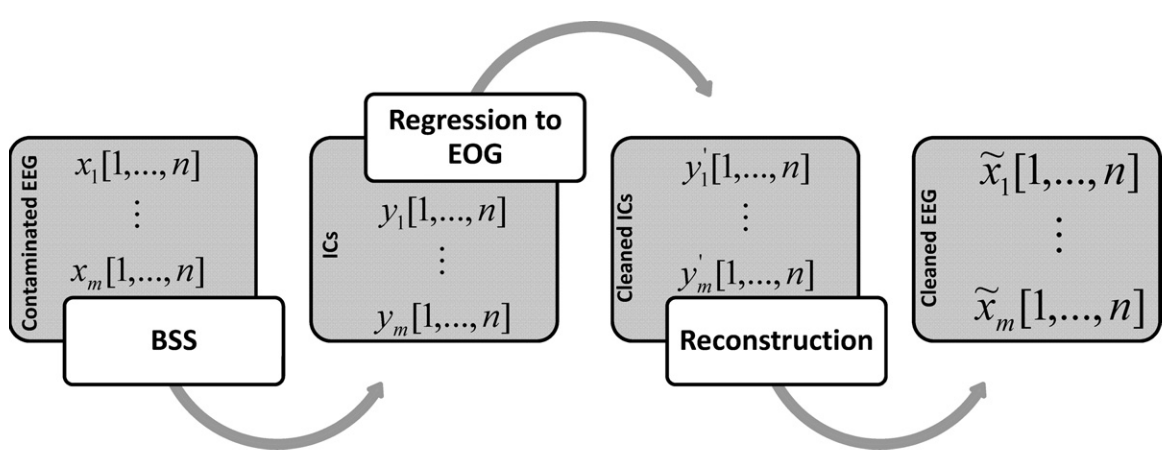

Fig. 3. Schematic representation of the proposed methodology. Contaminated EEG signals (x_i, far left) are decomposed using a BSS method to statistically Independent Components (IC) (y_i, second left). The artifactual ICs are cleaned using a regression algorithm (y'_i, second right) and then they are reconstructed forming the EEG signals free from ocular artifacts ($\tilde{x}_i$, far right).

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Table 1
Summary of the proposed REG-ICA methodology.

Input: Contaminated EEG; EOG channels as a reference (here VEOG, HEOG)
Output: Clean EEG
1. Apply ICA to decompose EEG signals to statistically independent components (computation of the mixing matrix)
2. Filter the ICs with the sRLS adaptive filter (remove only ocular artifacts)
sRLS parameters:
p = the order of adaptive filter (here $p = 3$)
λ = forgetting factor (here $\lambda = 0.9999$)
σ = value to initialize $P(0)$ (here $\sigma = 0.01$)
3. Reconstruct the signals by multiplying the ICs with the inverse of the mixing matrix

formula was used:

$$|\Delta P| = \left|P_{inEEG} - P_{outEEG}\right| \quad (8)$$

P denotes the power spectrum density (PSD) estimated using the Welch method. The parameters used as input in the Welch algorithm are: 400 sample points (sp) as the length of the window, 1 sp overlap and 200 Hz sampling rate. Finally the average PSD across all subjects was computed for each frequency band. As in the RMSE case, the lower the ΔP values get, the lower the distortion in the current frequency band is.

2.5.4. Mutual information

The mutual information (MI) index was finally adopted for the quantification of the mutual dependence of the pure EEG signals and the artifact-rejected EEG datasets using the next formula:

$$MI(inEEG, outEEG) = \sum_{y \in inEEG} \sum_{x \in refEEG} p(x, y) \log\left(\frac{p(x, y)}{p_1(x)p_2(y)}\right)$$

where $p(x, y)$ is the joint probability distribution function, and $p_1(x)$ and $p_2(y)$ are the marginal probability distribution functions of *inEEG* and *inEEG* respectively.

2.6. Evaluation of performance and statistical analysis

In order to evaluate the performance of the proposed artifact rejection scheme, namely REG-ICA, we have compared it with two artifact rejection techniques from either category (regression and BSS based). The LMS adaptive filter was chosen from the regression based class, since it was proved to have a better performance among other widely used artifact rejection techniques of either category [18], while the wavelet-ICA (W-ICA) [14] was chosen to represent the BSS-based methodology, because it lies on the same philosophy like REG-ICA and it seems to be very promising.

Two criteria were used for the evaluation/comparison: how successfully algorithms remove ocular artifacts, and how much the EEG signals are distorted after the artifact rejection procedure. Shapiro–Wilk and Kolmogorov–Smirnov tests were performed in order to check whether our variables have Gaussian distribution. Either of the two tests revealed that all variable distributions are not normal (for all variables related to the comparison criteria, both tests conclude in $p < 0.01$). For this reason, we have used non-parametric statistics in order to compare the performance of the aforementioned algorithms. More specifically, we have used the asymptotic 2-tailed Mann & Whitney U test for the comparison of the mean values having either equal or unequal variances [45].

On the other hand, one-way ANOVA was used to conclude whether there is a statistically significant difference between the mean ASR values of the contaminated ICs and the contaminated electrodes' signals or not. One-way ANOVA was used because the Shapiro–Wilk and Kolmogorov–Smirnov tests have shown that both variables, regarded the ASR values, have Gaussian distributions. For all of the above analyses the SPSS v.17.0 package was used with the threshold for the statistical significance set to 95%, while all extreme values of all variables were excluded.

3. Results

3.1. Artifact to signal ratio

The mean ASR for the contaminated electrode signals is 0.69 ± 3.4 while the ASR for the artifactual ICs is 1.83 ± 3.65 (Fig. 4). One-way ANOVA also revealed that there is a statistically significant difference ($F(3.58) = 4.16$; $p < 0.04$) between the above mentioned ASR mean values. This means that the contaminated ICs are probably less correlated with EOG signals, thereby eliminating the bidirectional contamination problem and supporting our main hypothesis.

3.2. Comparison results

In this section the results from the quantification measures are provided. These results concern the artifact rejection techniques applied in the artificially contaminated EEG datasets (Section 2.1.4). The performance of REG-ICA is compared to that of LMS and W-ICA in both rejecting the ocular artifacts and distorting the EEG signals in the time and frequency domains. Results concerning the non-linear characteristics of the signals are also provided. Table 2 provides the mean ± std values for the RMSE, ΔP of PSDs in the five different bands and the MI. The p-values, extracted by the Mann & Whitney U test, are also included in the table, thereby indicating whether the difference between the REG-ICA and the other two artifact rejection techniques is statistically significant.

The mean ± std values for all the quantification metrics and for all three algorithms are presented. The last two columns also contain the p-values, extracted by the Mann & Whitney U test, revealing the statistically significant difference between the REG-ICA with LMS and W-ICA respectively. REG-ICA has statistically significant differences for all of the quantification metrics (except those of ΔP in theta and alpha bands) in contrast to LMS (Fig. 5), while it outperforms the W-ICA for all of the above quantification measures.

According to the RMSE results, REG-ICA (4.46 ± 2.55) removes the ocular artifacts from the EEG signals more successfully, when compared to LMS (4.84 ± 2.62) and W-ICA (9.32 ± 4.50). Further statistical analysis revealed that the RMSE difference between REG-ICA and either of the two compared algorithms is statistically significant ($p < 0.01$). Moreover RMSE was also adopted in order to quantify the introduced distortion in the time domain, where the results are similar like before.

Fig. 4a depicts the great difference, in time domain, between the REG-ICA and the W-ICA. As it can be seen, W-ICA does not remove entirely the eye-blink or the horizontal activity just before the blink. It does not give a close approximation of the pre-contamination EEG signals (Pure EEG) either.

In contrast to W-ICA, LMS gives a better approximation of the pre-contamination EEG signals (Fig. 4b), but REG-ICA also outperforms it (Table 2). Mann & Whitney U tests revealed that their difference is statistically significant for all the quantification metrics, except those of ΔP in Theta and Alpha bands (Fig. 5). Fig. 4b also presents that both REG-ICA and LMS are close enough, but the

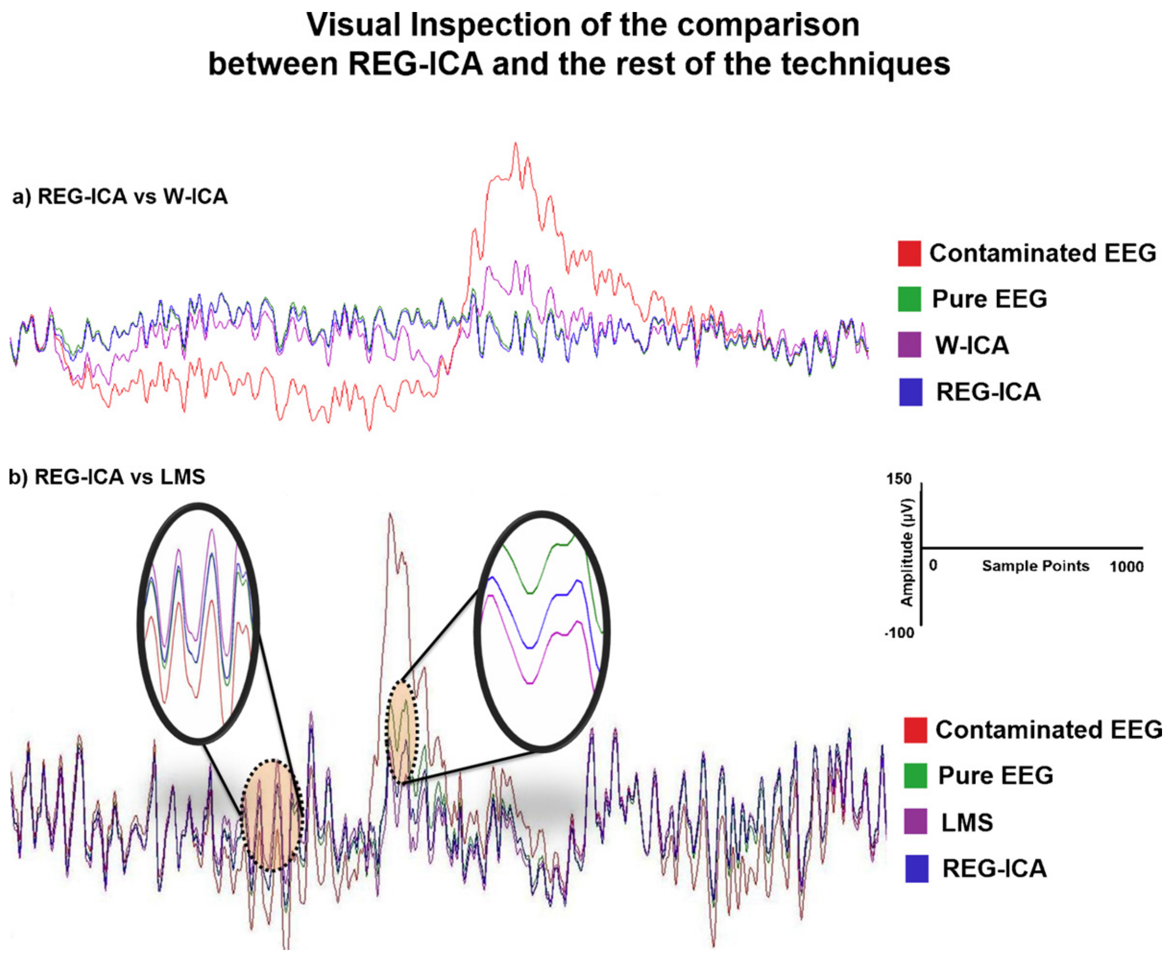

Fig. 4. (a) REG-ICA vs. W-ICA – as it can be seen the top part, W-ICA does not decontaminate neither the eye blink nor the horizontal activity just before the blink. In contrast to this, REG-ICA gives a better approximation of the Pure EEG signals. It has to been mentioned that Pure EEG signals are not clearly observable in the top part of the figure as they overlap with the REG-ICA. (b) REG-ICA vs. LMS – both REG-ICA and LMS give a good approximation of the Pure EEG signals in both contaminated and uncontaminated segments. In order to depict their small difference we have used two zoom panels, one for an artifact free area and one for a contaminated segment, where it is clearly observed that REG-ICA is closer to the Pure EEG signals as compared to LMS.

zoom panels disclose that REG-ICA gives, qualitatively speaking, a closest approximation of the Pure EEG signals.

4. Discussion

In this piece of work, we have proposed an artifact rejection methodology that combines two existing approaches for artifact rejection while attempting to compromise their individual main drawbacks. The proposed approach can be easily modified and extended making use of other future proposed, BSS and/or regression algorithms.

A typical regression-based artifact rejection technique is lying with the assumption that the underlying brainwave activity is uncorrelated with the EOG signals; an assumption which is generally invalid [20,21]. As a result of this invalid assumption, regression-based techniques eliminate from the signals those neural potentials, which are common to both EOG and EEG electrodes placed in frontal and prefrontal regions. The idea behind the proposed methodology is that ocular artifacts are concentrated in few ICs, where the ASR is much higher than in the contaminated EEG signals. This means that the artifactual ICs include less activity originating from the cortex compared to the contaminated signals. So the underlying brainwave activity of the ICs is less correlated (compared to the signals recorded by electrodes) with the EOG recordings. It is thus preferable to apply a regression algorithm on the artifactual ICs rather than directly on the raw electrode signals, in order to limit the bidirectional contamination problem. This idea was firstly exploited by Castellanos and Makarov [14] and despite

Table 2
Summarized results concerning the assessment of the proposed approach (REG-ICA) against the LMS and the W-ICA in terms of RMSE, ΔP of PSD (in five frequency bands), and MI.

Quantification metrics	REG-ICA (mean ± std)	LMS (mean ± std) (p-value)		W-ICA (mean ± std) (p-value)	
RMSE (μV)	4.46 ± 2.55	4.84 ± 2.62	$p < 0.01$	9.32 ± 4.50	$p < 0.01$
ΔP in Delta Band (dB/Hz)	1.07 ± 2.20	2.84 ± 3.98	$p < 0.01$	7.91 ± 12.87	$p < 0.01$
ΔP in Theta Band (dB/Hz)	0.15 ± 0.19	0.17 ± 0.32	$p < 0.317$	1.59 ± 1.79	$p < 0.01$
ΔP in Alpha Band (dB/Hz)	0.14 ± 0.18	0.16 ± 0.28	$p < 0.2$	9.03 ± 10.18	$p < 0.01$
ΔP in Beta Band (dB/Hz)	0.012 ± 0.016	0.027 ± 0.03	$p < 0.01$	0.51 ± 0.63	$p < 0.01$
ΔP in Gamma Band (dB/Hz)	0.003 ± 0.003	0.011 ± 0.011	$p < 0.01$	0.06 ± 0.09	$p < 0.01$
MI	2.65 ± 0.49	1.99 ± 0.56	$p < 0.01$	0.95 ± 0.25	$p < 0.01$

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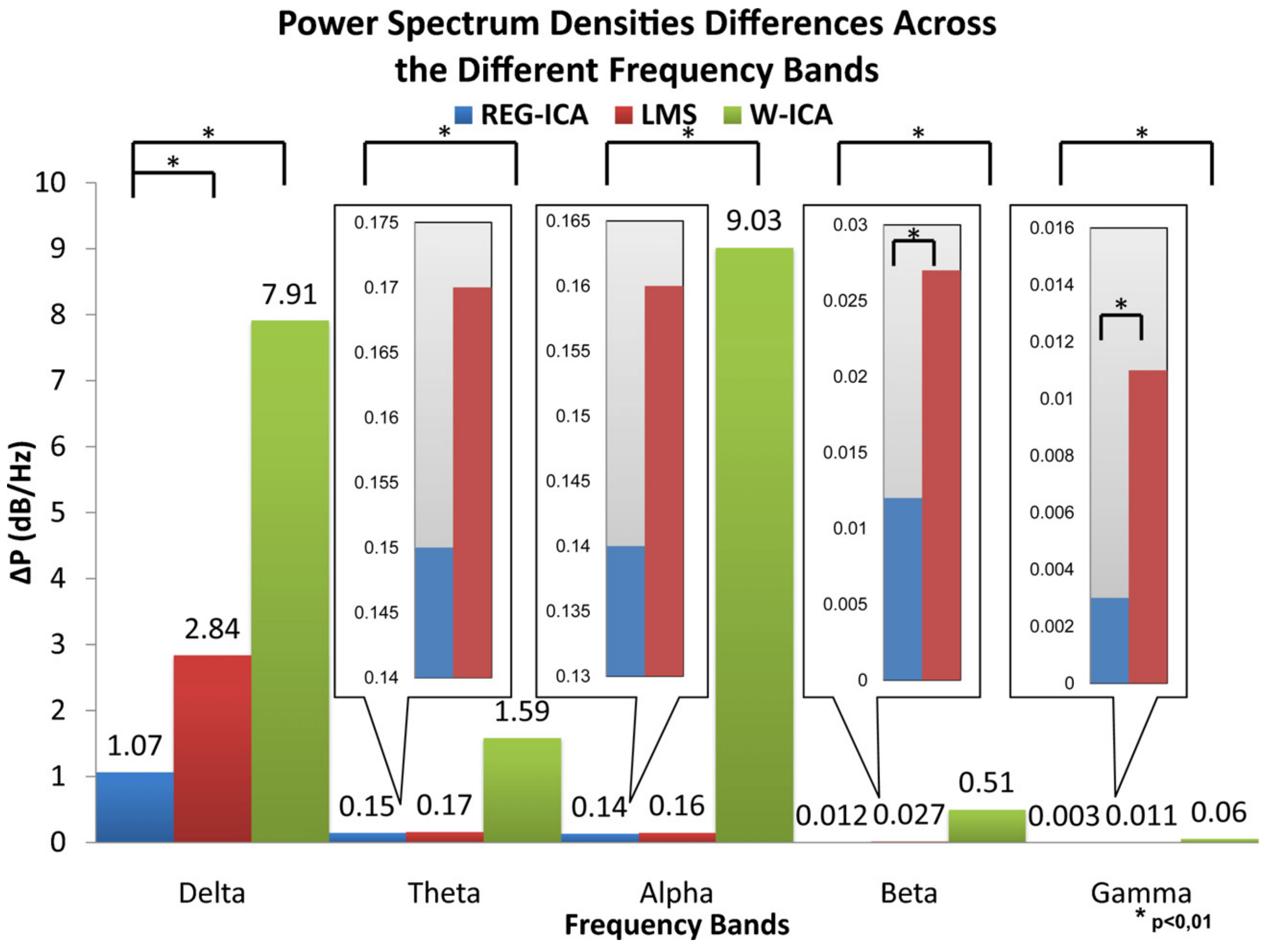

Fig. 5. PSD distortion – the herein proposed algorithm distorts less the PSDs of all but the theta and alpha frequency bands. The double asterisk above the columns depicts that the difference among the two compared algorithms is statistically significant with $p < 0.01$.

its logical basis it has never been investigated any further. The current study comes to provide further evidence about the soundness of that idea, since the ASR values are much higher in the contaminated ICs rather than in artifact affected electrodes, while ANOVA revealed that there is a statistical significance in these differences ($p < 0.04$).

REG-ICA filters only the artifactual components using a regression algorithm with EOG signals as the input references. Thus, only the artifacts related to the EOG signals are rejected, while the remaining activity of the contaminated ICs, which is mainly derived by the cerebral cortex, is projected back, forming in that way EEG signals with more neural information in contrast to the classical approach of the BSS methodology, where the reconstructed EEG signals are missing the neural information included in the rejected artifactual components. In order to evaluate the performance of the proposed methodology, two criteria were used: the first quantifies the ability of each artifact rejection technique to successfully remove the ocular artifacts captured by the EOG signals, while the second one quantifies the distortion that each artifact rejection technique introduces to the EEG signal. For this evaluation, the Extended-ICA algorithm was used for the decomposition procedure and the sRLS adaptive filter for the decontamination of the components. The main reason why Extended-ICA was selected is the reliability of its extracted ICs [33]. According to [34], the ICs extracted by the Extended ICA are reliable, since there is a linear correlation among the (sample points)/(channel^2) with the reliability of the ICs. This study supports that if $\log_{10}$ (samples points per channel^2) > 2.8, then the 70% or more of the total number of the ICs are reliable. In our analysis, it stands that $\log_{10}$ (samples points per channel^2) = 4.1969, so this index, according to the linear dependence mentioned above, supports that our ICs are fairly reliable. Another reason why Extended-ICA was used in this study is that it is a widely used algorithm for the rejection of ocular artifacts and its performance seems to be more than enough for the purposes of this research [23,24]. On the other hand sRLS was employed because our previous work has shown that LMS removes better the ocular artifacts from the EEG signals in contrast to the sRLS algorithm [18].

Current analysis was based on the artificially contaminated EEG datasets, which are datasets of preference for artifact rejection studies, as the EEG signals lying under the artifacts are known and the performance of each artifact rejection technique can be easily and accurately quantified. The construction of the artificially contaminated data was based on the Elbert model [9]. EEG signals from eyes-closed sessions are generally preferable for constructing artificially contaminated data, because they lack of eye-blinks, which are the most frequent and troublesome among other ocular artifacts [19]. Moreover, the reorientation of the eye-ball dipole produces signals of much lower amplitudes in total darkness rather than in light stimulation [9]. It is, however, important to state that the EEG recordings during the eyes-closed session are not artifact-free, and still contain some low-frequency eye movements [32]. A reason why we preferred to use EEG signals during an eyes-closed session is that it seems to be the most realistic approach for generating EEG data with minimal artifact contamination. On the other hand, the other two alternatives will be either to record and analyze EEG signals during an eyes-open condition or to generate artificial signals from the scratch. We avoided to process EEG signals when eyes were open since the human eye produces signals with lower amplitude in darkness, rather than in light stimulation [9]. In this sense, the EEG signals from the eyes-closed session were finally preferred because they do not have so frequent artifacts as an eyes-opened condition (eye-blinks), while the possible ocular artifacts during the eyes-closed session (vertical and horizontal eye movements) do not produce high amplitude signals like the eyes-opened state. However, the eyes-opened state was preferred in order to record the EOG signals used for the generation of the artificially contaminated data, because the subjects produced ocular movements and blinks in natural way. The recorded EOG signals have been filtered with a band pass filter between 0.5 and 5 Hz [17]. To this extend other studies [36,37] come in conflict with [17] by using a low pass filter in 7.5 Hz, but until now there is no clear evidence as to what is the optimal low pass frequency to be used. So further research is needed in order to conclude such best practices for the pre-processing of the EOG signals.

RMSE is the Euclidean metric which depicts the distance between the pre-contaminated and the artifact-rejected EEG signals. This measure can support the assessment of each algorithm's performance in both rejecting ocular artifacts as well as quantifying the introduced distortion in the time domain. Our results suggest that REG-ICA (4.46 ± 2.55) has a better performance in the artifact rejection procedure, since it successfully removes the ocular artifacts, while at the same time keeping the neural signals more intact in the time domain when it was compared to the LMS (4.84 ± 2.62) and W-ICA (9.32 ± 4.50) algorithms. Moreover, the Mann & Whitney U tests come to enhance the dominance of REG-ICA, in contrast to either of the other two mentioned algorithms, supporting that their difference is statistically significant ($p < 0.01$). In addition, REG-ICA distorts less all the brain rhythms, compared to LMS and W-ICA. Mann & Whitney U tests revealed also that the difference between REG-ICA and LMS is statistically significant ($p < 0.01$) only for Delta, Beta and Gamma bands, while the same test supports that REG-ICA's eminence compared to W-ICA is statistically significant ($p < 0.01$) for all brainwaves. The MI index was also estimated in order to investigate how each artifact rejection algorithm distorts the signal non-linear characteristics. Our results suggest that REG-ICA keeps more useful information undistorted after the artifact rejection process in contrast to the other algorithms (LMS and W-ICA). All these come to enhance our hypothesis that the herein proposed methodology distorts less the brain signals, in both time and frequency domains, with respect to their non-linear characteristics.

This is one of the few studies concerning an artifact rejection technique, in which statistical analysis is used to evaluate the performance of the proposed methodology. What usually is reported is a qualitative inspection which indicates the relative merits of the proposed algorithm(s), or minimally quantified results in terms of mean values, without, however, addressing the statistical significance of the performance [12,25–27].

W-ICA was used in the presented assessment because it recovers the cerebral activity underlying the artifactual components, like REG-ICA does. However, this method passes all the wavelet coefficients of the ICs through a thresholding procedure, which cuts out only the high magnitude voltages (like eye-blinks) [14], this methodology suffers a lot, from this thresholding procedure, in cases where high magnitude voltages are not derived from artifactual sources, but originate from true brain responses (like epileptic EEG signals). On the contrary, our methodology overcomes this problem by employing the regression filtering procedure with the EOG channels as reference inputs. Thus, only artifacts related with EOG activity are removed. Our results suggest that REG-ICA outperforms the W-ICA algorithm, and this is probably due to the selection of the employed threshold for the elimination procedure of the extracted wavelet coefficients [41]. The adaptation of this threshold may enhance the performance of the W-ICA, but this is against its automatic ability. Moreover, the authors of W-ICA [14] indicate that other thresholding strategies could possibly provide better tuning of the W-ICA to the particular peculiarities of other artifacts, emphasizing that their proposed threshold yields a good performance concerning the ocular and heart beat artifacts.

5. Limitations and future work

Although all the BSS-based artifact rejection techniques have the ability to reject the ocular artifacts without the need of EOG signals, REG-ICA demands the EOG recordings in order to reject only the ocular artifacts. However, all the BSS-based artifact rejection techniques introduce a substantial distortion on neural activity, so to this extent, we postulate, that it is preferable to use more channels for artifact rejection purposes, like REG-ICA does, than distorting the recorded brain signals. Moreover the availability of the EOG signals enables us to use a constraint BSS algorithm enhancing the decomposition of the signals, which probably leads to a better solution of the bidirectional contamination problem.

A limitation of the presented artifact rejection technique lies with the use of Extended-ICA for the decomposition procedure. The application of the Extended-ICA in long lasting data is limited due to computer memory capacity problems produced by its complexity. Another aspect, concerning the use of the Extended-ICA, that should be further checked, is its use for real time applications. In our analysis we have used the Extended-ICA in 2 min EEG segments with nineteen channels, and its mean convergence time was 251.0466 s. Despite this, the relationship between the input signals ((number of channels) $\times$ (sample points)) with ICA's convergence time remains unknown yet, so we cannot conclude from our results whether the Extended-ICA can be used for online EEG signal processing or not. So further research, in short term EEG signals, is needed, in order to conclude if Extended-ICA can be applied in real time applications. On the other hand, the ICA's adoption for an offline analysis does not seem to be a problem, as long as reasonable amounts of data are available for decomposition alongside with cutting edge equipment.

We envisage that the roadmap to a more robust technique has not been entirely satisfied with the methodology presented herein. One has to investigate the performance of several BSS methods and the performance of different regression algorithms in order to fully tabulate the relative merits and finalize a decision. To a next level, one has to compare the "gold-standard" version of REG-ICA methodology with other artifact rejection techniques. This comparison can take place with simulated data developed with new and promising models [35,36], as well as, with real EEG data in realistic scenarios. For example, since REG-ICA has been evaluated in this study and the results support its efficacy, it can be further assessed in realistic scenarios like BCIs, where a classification increase will indicate more discriminant characteristics leading to the conclusion that ocular artifacts have been rejected more successfully. In the same way, Kook et al. [43] have assessed the performance of their artifact rejection strategy, which has been developed in order to improve the classification of multi-channel evoked potentials.

Moreover, other researchers [44] evaluate their own ICA-based artifact rejection technique using an ERP paradigm. They support the efficacy of their technique by supporting that it can preserve ERP contributions, evoked by visual stimuli. It is, therefore, in our immediate future plans is to investigate if REG-ICA can preserve ERP contributions in a better way than the above ICA-based artifact rejection technique does. The results presented in [16] have been extracted using the technique proposed in [44] for the rejection of ocular artifacts. So a similar kind of analysis is planned for the same data as in [16], with the only difference that REG-ICA will be

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used for the decontamination of the EEG signals. What we expect to see is lower *p*-values, which means that REG-ICA removes the EOG artifacts better, and at the same time keeps neural activities more intact, thereby suggesting that REG-ICA may be really useful for the artifact rejection purposes in ERP studies.

More efforts are also needed in order to upgrade REG-ICA to an automatic methodology. Until now, the presented methodology has two layers, one concerning the BSS method used for the decomposition of the signals, while the second one refers to the regression algorithm used for the decontamination of the artifactual components. In order to make REG-ICA capable to reject ocular artifacts automatically, a new layer should be introduced, dealing with the automatic recognition of the artifactual components. So, the existing algorithms, which automatically detect the artifactual components, should be further assessed and compared in order to conclude which one separates the contaminated ICs from the normal ones, in the best possible way. Exploiting the demanding usage of the EOG signals, more detection algorithms which make use of the EOG signals, like the one presented in [26], can be included in the aforementioned assessment.

6. Software and data download

The artificially contaminated dataset used in the current work, alongside with a plugin for EEGLAB [46] which implements several versions of REGICA methodology is available at http://lomiweb.med.auth.gr/gan/ in the "Download" Menu.

7. Conclusions

Concluding, the primary criteria introduced in this work, together with the current analysis, compose the main ingredients of a complete future investigation, which also necessitates the comparison of a range of different BSS, regression and automatic identification algorithms in order to reach a "gold-standard" in the successful and automatic removal of ocular artifacts, in parallel to keeping neural signals intact. The proposed methodology faces the problems related to the EEG signals distortion, during the EOG artifact rejection process by using existing methodologies. Results suggest that the contaminated ICs are less correlated with the EOG signals, compared to the affected electrode signals, limiting with that way the bidirectional contamination problem. On the other hand, filtering and not entirely removing an artifactual IC ensures that a greater portion of neural activity still remains intact. So it is preferable to apply a regression-based artifact rejection technique on the contaminated ICs rather than in the contaminated raw signals themselves.

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