Performance Evaluation of Methods for Correcting Ocular Artifacts in Electroencephalographic (EEG) Recordings

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Abstract: The presence of ocular artifacts (OA) due to eye movements and eye blinks is a major problem for the analysis of electroencephalographic (EEG) recordings in most applications. A large variety of methods (algorithms) exist for detecting or/and correcting OA's. We identified the most promising methods, implemented them, and compared their performance for correctly detecting the presence of OA's. These methods are based on signal processing "tools" that can be classified into three categories: wavelet transform, adaptive filtering, and blind source separation. We evaluated the methods using EEG signals recorded from three healthy persons subjected to a driving task in a driving simulator. We performed a thorough comparison of the methods in terms of the usual performances measures (sensitivity, specificity, and ROC curves), using our own manual scoring of the recordings as ground truth. Our results show that methods based on adaptive filtering such as LMS and RLS appear to be the best to successfully identify OA's in EEG recordings.

1 INTRODUCTION

Electroencephalographic (EEG) recordings reflect the neuronal and electrical activity within the brain. They are obtained from electrodes placed on the scalp. They are often contaminated by signals from other sources, called artifacts. (Artifact is also used to denote the local deformation of the signal of interest, here the EEG.) One distinguishes between physiological artifacts and technical artifacts. The most frequent physiological artifacts are due to the activity of the eyes, the heart, and the muscles. The most common physiological artifacts are the ocular artifacts (OA's), due to the movements of the eyeballs and eyelids. Technical artifacts are mostly due to electrode placement problems and body movements.

All artifacts result in an EEG recording that may be quite different, generally locally, from the true underlying EEG signal reflecting the brain activity. It is thus critical to do something about OA's.

The three usual ways of dealing with OA's are prevention, rejection, and removal. Prevention consists in reducing the occurrences of OA's by giving proper instructions to patients. However, some OA's are involuntary and unavoidable. Rejection consists in rejecting the epochs affected by OA's. Of course, rejection implies that the OA's be first detected. Although simple, rejection has the major drawback of dropping a significant amount of valuable data. Removal consists in removing as best as possible the OA's to produce a signal that is as close as possible to the true, underlying EEG signal. Removal may require that the OA's be first detected. Since removing the OA's corrects the signals, the term "correction" can also be used in place of the term "removal". Any correction method can be turned into a detection method by thresholding the difference between the raw signal and the cleaned one.

When dealing with OA's, it is useful to record the electrooculographic signals (EOG), which allow the observer (and the algorithms) to establish a "correlation" between the OA's in the EEG and the features in the EOG.

Our interest in the handling of OA's arose from the study of drowsiness for subjects actively involved in a task, such as driving. Indeed, until they fall asleep, these subjects have their eyes mostly open. Therefore, the EEG signals recorded for studying the evolution of drowsiness are affected by OA's due to eye movements and eye blinks. This

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should be contrasted with the study of sleep, where subjects have their eyes closed. (However, note that the eyes and the eyelids can move even when the eyes are closed.)

Several methods have been proposed in the literature for cleaning EEG's from OA's. Comprehensive reviews are found in (Croft and Barry 2000) and (Kandaswamy et al. 2005). However, we have not found any published paper comparing a significant number of the proposed methods in terms of a common performance measure. The present paper performs such a comparison.

2 MATERIAL AND METHODS

2.1 Data Recordings

We acquired data at the "Centre d'Etudes des Troubles de l'Eveil et du Sommeil" (CETES) of the University Hospital of Liège in the context of the study of driver drowsiness. Subjects were presented with a driving task in a simulator. We recorded the following polysomnographic (PSG) signals: EEG (for electrodes Fz, Cz, Pz, C3, C4, A1, A2), EOG, and EMG. The subjects received the instruction to drive at a constant speed of 80 km/h on a one-way road, where there were no other vehicles. This task lasted about two hours. The PSG signals were recorded with an Embla system at a sampling rate of 500 Hz. They were partitioned into butting (and thus non-overlapping) epochs of 1024 samples. The methods described below, except the last one, were successively applied to each of these epochs. The last method was applied on one whole EEG recording.

2.2 Methods Compared

We identified 12 potentially useful methods in the literature. We organized these methods according to the seven signal processing "tools" they use (DWT, SWT, LMS, RLS, H^{∞}-TV, ICA, SOBI), which we further organized into three broad categories (of tools), i.e. wavelet transform (WT), adaptive filtering (AF), and blind source separation (BSS) tools. The abbreviations are spelled out below. Table 1 shows the tools used by the 12 methods. For example, Method 4 uses both the SWT and LMS tools.

Table 1 shows that Methods 1 and 2 use only WT tools, that Methods 3, 5, and 7 use only AF tools, and that all BSS tools are used in combination with WT tools. Methods 4, 6, and 8 - 12 use two tools, each from a different category.

Table 1: Methods compared, and the "tools" they use.

	Tools						
	WT		**AF**			**BSS**	
Methods	DWT	SWT	LMS	RLS	H^{∞}-TV	ICA	SOBI
1	■						
2		■					
3			■				
4		■	■				
5				■			
6		■		■			
7					■		
8		■			■		
9		■				■	
10		■					■
11	■					■	
12	■					■	

We now successively consider the broad categories (WT, AF, BSS) of tools, and, for each, we provide the description of the methods that use these tools. These descriptions generally do not refer explicitly to the method indices of Table 1.

2.2.1 Wavelet Transform (WT) Tools

The wavelet transform (WT) (Mallat 1999) is one of the leading techniques for analyzing non-stationary signals like EEG's. The major asset of wavelet analysis is its capability to decompose waveforms into components that are well localized in time and in frequency (or, equivalently, in scale).

The continuous WT (CWT) constructs a "family" of wavelets by scaling and translating a function called the mother wavelet.

The discrete WT (DWT) results from the discretization of the CWT on a dyadic grid.

Translation invariance is important in many applications such as change detection and denoising. The stationary WT (SWT) is a WT algorithm designed to overcome the lack of translation invariance of the DWT (Nason and Silverman 1995). Translation invariance is achieved by removing the down-samplers and up-samplers present in the DWT.

2.2.1.1 Detection of OA's with DWT

Krishnaveni et al. applied a wavelet-based thresholding algorithm to identify zones of OA's (Krishnaveni et al. 2006). They based their method on (Venkataramanan et al. 2004), i.e. they used the Haar wavelet to precisely detect the moment when the state of the eye changes from open to closed and vice versa.

The technique is based on the difference in frequency contents between the EEG recording ([0-20] Hz) and the OA signals ([0-16] Hz). The raw EEG signal is decomposed with the Haar DWT. The detail wavelet coefficients (WCf's) are then cancelled and this results in a step function with a falling edge indicating a change from open to closed eyes, or with a rising edge indicating a change from closed to open eyes.

The edges of the approximation are classified into artifact or non-artifact edges according to their relative amplitude.

2.2.1.2 Correction of OA's with SWT

Krishnaveni et al. consider the OA's as a noise part of the EEG recording, and they apply a wavelet-based thresholding algorithm to remove them (Krishnaveni et al. 2006). Soft-thresholding is the most popular thresholding technique, and it has been theoretically justified by Donoho and Johnstone. These last authors suggest to choose optimal thresholds by minimizing the Stein Unbiased Risk Estimator (SURE) at each decomposition level (Donoho and Johnstone 1995).

Soft-thresholding functions are continuous with discontinuous derivatives. However, continuous derivatives of first and higher orders are often desired for optimization problems. A new class of soft-like-thresholding functions with continuous derivatives was proposed (Xiao-Ping and Desai 1998). The method consists in applying the SWT with Coiflet3 as mother wavelet for levels 3 to 6, selecting the optimal threshold for each level by minimizing the SURE, applying soft-like-thresholding, and applying the inverse SWT.

Since OA's occupy the lower frequency band ([0-16] Hz) of the typical EEG, the threshold selection and the thresholding are only performed on the decomposition levels 3 to 6. Coiflet3 is chosen as the mother wavelet since it resembles the shape of an eye-blink OA. This implies that large WCf's be generated in OA zones and that small WCf's be generated in areas corresponding to non-OA zones. Reducing the amplitude range of the large coefficients should then result in the removal or reduction of the OA's.

2.2.2 Adaptive Filtering (AF) Tools

Adaptive filters (AF's) belong to the category of optimal filters (Klados et al. 2009; Correa and Leber 2011): they adapt their coefficients to the disturbance in the input signal, and subtract the result from the input signal. The adaptive process involves an optimization controlled by the error signal between the input signal and the filter-output signal. We tested three AF algorithms: (1) the least mean square (LMS) algorithm, which minimizes the mean squared error, (2) the recursive least squares (RLS) algorithm, which minimizes a cost function that is a linear combination of squared errors, and (3) the H^{∞} Time-Varying (H^{∞}-TV) algorithm, which minimizes the infinite norm of a linear combination of squared errors (Puthusserypady and Ratnarajah 2006).

We implemented these three AF's as presented in Tables 1-3 of (Klados et al. 2009).

The application of AF's can be combined with the use of the SWT (Kumar et al. 2008). The procedure consists in applying the SWT with the Symlet3 mother wavelet up to eight levels, applying the AF to the WCf's, and applying the inverse SWT to the error signal.

2.2.3 Blind Source Separation (BSS) Tools

Blind source separation (BSS) techniques are based on a linear decomposition of the measured signals into sources, also called components. Applied to EEG and EOG recordings, these methods segregate the artifactual activities into separate sources. Therefore, the reconstruction of the recorded EEG with these sources removed leads to a reduction of OA's. These techniques can be used with several EEG channels.

The most common BSS methods are the independent component analysis (ICA) and the second-order blind identification (SOBI).

ICA is a statistical technique in which measured signals are linearly transformed into sources that are maximally independent from each other (Hyvärinen and Oja 2000).

Numerous ICA algorithms exist. FastICA and Infomax are the most popular ones. Infomax (Bell and Sejnowski 1995) is effective in separating sources that have super-Gaussian probability density functions, but it fails to separate sources that have negative Kurtosis. Unless explicitly stated otherwise, we have used FastICA.

SOBI (Belouchrani et al. 2002) divides a set of measured signals into sources by exploiting the possible time coherence between the sources. It minimizes the cross-correlations between each component and other components shifted in time, across a set of time delays.

2.2.3.1 Correction of OA's by Combining a BSS Tool with High-order Statistics

The two methods we describe here are based on the same scheme. The first one is that of (Ghandeharion and Erfanian 2010) where the BSS tool is ICA. The second one uses SOBI instead of ICA.

The methods first decompose the EEG and EOG recordings (two channels) into sources, by applying either of the BSS transforms. They then identify the artifactual source (in the way described below) and remove it. They finally produce the output signal by applying the appropriate inverse transform to the remaining (non-artifactual) sources.

The artifactual source is identified as follows. For each of the above sources, one computes seven statistical measures, with four directly on the sources and one on each set of SWT coefficients for levels 3 to 5. The four measures on each source are (1) the mutual information, (2) the projection strength, (3) the correlation, and (4) the kurtosis. The measure on the selected SWT coefficients is the kurtosis. One then flags for each measure the couple source/measure with maximum measure values. Any source with four flags is deemed to be artifactual.

2.2.3.2 Correction of OA's by Simultaneously using ICA and DWT

The main drawback of ICA is that the number of measured signals must be larger than the number of sources for correctly decomposing the different types of artifacts. Therefore, ICA has difficulty in separating the OA sources from the true PSG sources. Moreover, the spectrum of some OA's is located in a narrow frequency band. Since ICA works in the time domain and since DWT has a good frequency resolution, the combination of ICA and DWT is particularly well adapted.

Automatic wavelet independent component analysis (AWICA) (Mammone et al. 2012) combines DWT and ICA on multichannel PSG recordings to improve the performance of source separation. This method consists in the six following phases executed on each epoch:

- Each recorded PSG channel is decomposed by DWT with the Daubechies4 mother wavelet. The four frequency bands characterizing the brain activity are represented by the wavelet components (WC's).
- An automatic procedure is applied to measure the level of "artifactuality" of the WC's. Two measures are used to this end: the kurtosis (Kt) and the Renyi's entropy (ReE). This last measure allows one to quantify the randomness. The Kt and the ReE of the WC's are computed and then normalized to zero mean and unit variance with respect to every WC. If one of these normalized measures exceeds a fixed threshold, the WC is marked as being a critical wavelet component (CWC).
- ICA is applied to all CWC's. The critical wavelet independent components (CWIC's) are so extracted.
- The set of CWIC's is partitioned into non-overlapping windows. If the Kt or the ReE of one CWIC exceeds a fixed threshold in more than 20% of the non-overlapping windows, it is marked and rejected.
- An inverse ICA is applied so that artifact-free WC's are recovered.
- The inverse DWT is applied to reconstruct the cleaned EEG signals (channels).

2.2.3.3 Correction of OA's by Combining ICA and Wavelet Denoising in a Robust Way

The method called Robust Artifact Removal (RAR) is presented in (Zima et al. 2012) as a method for removing short-duration, high-amplitude artifacts from long-term neonatal EEG recordings.

It consists in three major phases: (1) partitioning the EEG recording (one channel) into contiguous epochs in three different ways; (2) independent processing (as described below) of each partition; (3) combining the three artifact-free reconstructions for obtaining a reconstruction that is freer of artifacts.

Phase (2) consists of five processing steps: (1) ICA, (2) artifact detection, (3) wavelet denoising of artifact sources by using DWT and soft-thresholding, (4) replacement of the artifact sources by their noise part, estimated in previous step, (5) inverse ICA.

For ICA, we use the implementation of (Tichavský and Yeredor 2009) of the algorithm BGSEP (Pham and Cardoso 2001). This algorithm is based on second-order statistics as in the SOBI algorithm, but uses the non-stationarity of the measured signals.

The identification of high-amplitude artifact sources is based on their duration, which is short in comparison to the partition length. The authors call such sources "sparse" in the time domain. They define the sparsity of a signal as a value proportional to its maximum amplitude and logarithmically proportional to the inverse of its median. A source with sparsity exceeding a fixed threshold is marked as an artifact.

The specific combination of the three reconstructions, called "adaptive folding", allows one to reduce the possible remaining artifacts by averaging, epoch-by-epoch, the reconstructions containing the fewest artifacts. The presence, or not, of artifacts is decided based upon the differences and the maximum absolute values of the reconstructions.

2.3 Method of Performance Evaluation

For memory, Method 1 is a detection method, and all others are correction methods. No obvious evaluation method is available for estimating the performance of a correction method. Indeed, we do not have an accurate means of measuring the true EEG signal. For this reason and for the purpose of evaluating the performance of the methods, we decided to “turn” the 11 correction methods into detection methods. This transformation is done by subtracting the corrected EEG signal from the raw EEG signal and thresholding the result.

To quantify the detection performance of the 12 methods, we defined the ground truth by manually segmenting many 2s epochs of 1024 samples each into true OA zones and true non-OA zones. For this, we used a tool included in the Matlab toolbox Fieldtrip (Oostenveld et al. 2011).

The top part of Fig. 1 illustrates the “true” segmentation of, say, one epoch performed manually by an observer into OA zones and non-OA ($\overline{\text{OA}}$) zones. The bottom part illustrates the corresponding “computed” segmentation performed automatically by some method. The boundaries of the true and computed zones define intervals that can each be labeled as true positive (*tp*), true negative (*tn*), false positive (*fp*), and false negative (*fn*). We transform this labeling into the customary *tp*, *tn*, *fp*, and *fn* numbers by simply adding the lengths of the intervals that have the same, corresponding label.

These four numbers define a confusion matrix. However, the fundamental measures of performance that we use to compare the 12 methods are:

- The *tp* rate, which is the ratio between *tp* and the number of positives, i.e. *tp* + *fp*;
- The *fp* rate, which is the ratio between *fp* and the number of negatives, i.e. *tn* + *fn*.

The *tp* rate is also called the sensitivity and “1- the *fp* rate” the specificity. We use the common receiver operating characteristic (ROC) curves for representing these measures.

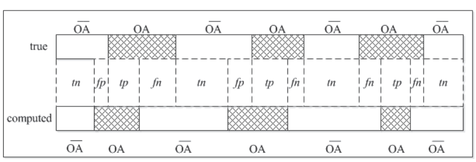

Figure 1: Evaluation: segmentations into true (top) and computed (bottom) OA zones and non-OA ($\overline{\text{OA}}$) zones.

3 RESULTS

Figure 2 shows the results of the 12 methods on one epoch of 1024 samples from one EEG recording.

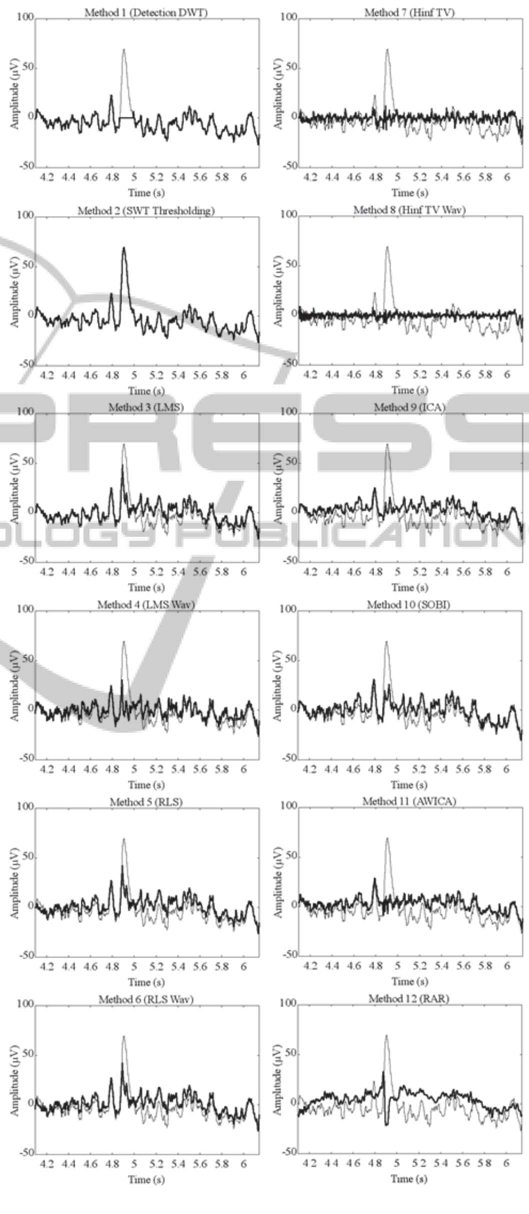

Figure 2: Results of the 12 methods on one epoch of 1024 samples from one EEG recording. The thin (thick) lines show the raw (cleaned) EEG signals.

Method 1 detects correctly the OA zone.

Method 2 is not capable of correcting EEG signals for OA’s. This observation is in contradiction with the results presented in (Krishnaveni et al. 2006). Our conclusion is that this method should not be expected to work because the method is one of denoising, and therefore applicable only to white noise. However, OA’s cannot be considered to be white noise! Therefore, we decided to ignore this method in our performance evaluation. The results of the LMS and RLS methods (Methods 3 and 6) are very similar: the spike due to the OA is weakened. In the results of H^{∞}-TV (Methods 7 and 8), the OA spike is clearly reduced, but useful data is also perturbed. The results of the BSS methods (Methods 9 to 12) are quite similar: the OA peak has disappeared.

Figure 3 shows the ROC curves of the 11 retained methods on the same EEG recording (i.e. with Method 2 ignored). The four best ROC curves are given by the LMS and RLS methods (Methods 3 to 6).

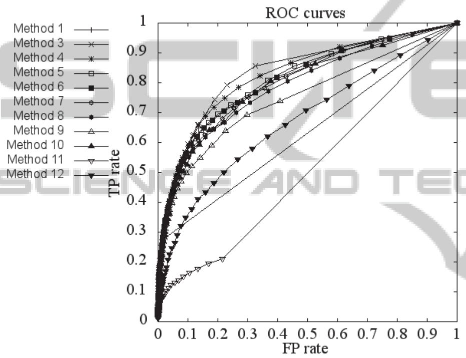

Figure 3: ROC curves for the 11 retained methods.

The sensitivity and the specificity have antagonistic behaviors. Therefore, another way of comparing the performances of the methods is to consider the sum of the sensitivity and the specificity. Then, the larger the sum is, the better the performance is. Table 2 lists the sensitivity, the specificity, and their sum. The rows of the four best methods are shown in gray with the performance increasing from light to dark gray.

4 DISCUSSION

Method 1, which is a detection method based on a thresholding of wavelet approximation coefficients, does not seem to correctly identify all OA zones in the considered EEG recording (in comparison to the reference). Indeed, Method 1 has one of the lowest-positioned ROC curve in Figure 3. In addition, we see from Table 2 that the sensitivity barely reaches 0.275. This means that only 27.5% of OA’s are correctly detected. However, the method has a high specificity.

Figure 2 shows that all other methods – which are correction methods –, except for Method 2, are able to remove a substantial amount of OA from the EEG recording. In each graph of this figure (except for that of Method 2), one can observe that the spike due to the OA is clearly reduced. However, as indicated earlier, it is difficult to evaluate the performance of the correction methods because we cannot measure directly the activity of the brain and of the eyes separately. We will thus discuss the results of these methods of correction in terms of their ability to identify correctly the OA zones in the EEG recording.

In general, methods based on adaptive filtering show better results than those based on BSS methods. Indeed, Table 2 indicates that the sum of the values of sensitivity and specificity is higher for Methods 3 to 8 than for Methods 9 to 12. This is confirmed by the ROC curves shown in Figure 3, where one can observe that the curves for Methods 3 to 8 are located closer to the upper-left corner than those for Methods 9 to 12. Table 2 and Figure 3 indicate that Methods 7 and 8 can correctly identify the OA zones. However, visual inspection of the corresponding graphs of Figure 2 reveals that these methods also remove a lot of useful data. Methods 3 to 6 (LMS- and RLS-based algorithms) are thus the four best methods to successfully identify OA zones in the EEG recording.

From Table 2 and Figure 3, one can also conclude that combining the LMS and RLS algorithms with the SWT does not improve the results as compared to using LMS and RLS alone.

Table 2: Best compromise in sensitivity and specificity for the 11 retained methods.

Methods	***Sensitivit***	***Specificity***	***Sens.+ spec.***
Method 1	0.275	0.985	1.260
Method 3	0.791	0.768	1.559
Method 4	0.717	0.813	1.530
Method 5	0.642	0.858	1.500
Method 6	0.647	0.847	1.494
Method 7	0.587	0.882	1.469
Method 8	0.578	0.882	1.460
Method 9	0.639	0.775	1.414
Method 10	0.641	0.828	1.469
Method 11	0.123	0.956	1.079
Method 12	0.501	0.779	1.280

5 CONCLUSIONS

Ocular artifacts (OA’s) are often present in EEG recordings. They mask the true, underlying EEG signal. As a result, the OA’s make the analysis of EEG recordings more difficult and, more importantly, they can lead to incorrect analysis and wrong conclusions. To avoid losing valuable data, it is critical to develop robust methods for cleaning out EEG recordings from OA's. For the purpose of evaluating the state of the art in the detection and elimination/reduction of OA's, we implemented 12 promising methods found in the literature. We evaluated the performance of all the methods in terms of their ability to correctly detect OA zones in EEG recordings, as compared to a ground truth established visually. Results suggest that methods based on adaptive filtering such as LMS and RLS, as well as their combination with the SWT are the best methods to successfully detect OA zones in EEG recordings. These methods have higher values of sensitivity and specificity, and better ROC curves, than the other correction methods.

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REFERENCES

Bell, A., Sejnowski, T., 1995. An information-maximization approach to blind separation and blind deconvolution. In *Neural Computation, 7(6):1129-1159.*

Belouchrani, A., Abed-Meraim, K., Cardoso J. F., 2002. A blind source separation technique using second-order statistics. In *Signal Processing, IEEE, 45(2): 434-444.*

Correa, M. A. G, Leber, E. L., 2011. Noise removal from EEG signals in polisomnographic records applying adaptive filters in cascade. In *Adaptive Filtering Applications. L.G. (Ed.).*

Croft, R. J., Barry, R. J., 2000. Removal of ocular artifact from the EEG : a review. In *Clinical Physiology, 30(1): 5-19.*

Donoho, D. L., Johnstone, I. M., 1995. Adapting to unknown smoothness via wavelet shrinkage. In *Journal of the American Statistical Association, 90(432): 1200-1224.*

Ghandeharion, H., Erfanian, A., 2010. A fully automatic ocular artifact suppression from EEG data using higher order statistics: improved performance by wavelet analysis. In *Medical Engineering and Physics, 32(7): 720-729.*

Hyvärinen, A., Oja, E., 2000. Independent component analysis: algorithms and applications. In *Neural Networks, 13:411-430.*

Kandaswamy, A., Krishnaveni, V., Jayaraman S., Malmurugan N., Ramadoss K., 2005. Removal of ocular artifacts from EEG: a survey. In *IETE Journal of Research, 51(2): 10.*

Klados, M. A., Papadelis, C., Lythari, C., Bamidis P. D., 2009. The removal of ocular artifacts from EEG signals: a comparison of performances for different methods. In *4th European Conference of the International Federation for Medical and Biological Engineering. J. Sloten, P. Verdonck, M. Nyssen and J. Haueisen, Springer Berlin Heidelberg, 22:1259-1263.*

Krishnaveni, V., Jayaraman, S., Anitha, L., Ramadoss, K., 2006. Removal of ocular artifacts from EEG using adaptive thresholding of wavelet coefficients. In *Journal of Neural Engineering, 3(4):338-346.*

Krishnaveni, V., Jayaraman, S., Aravind, S., Hariharasudhan, V., Ramadoss, K., 2006. Automatic identification and removal of ocular artifacts from EEG using wavelet transform. In *Measurement Science Review, volume 6, section 2, no. 4.*

Kumar, P. S., Arumuganathan, R., Sivakumar, K., Vimal, C., 2008. Removal of artifacts from EEG signals using adaptive filter through wavelet transform signal processing. In the *9th IEEE Int'l Conference on Signal Processing.*

Mallat, S., 1999. A wavelet tour of signal processing, (second edition). *Academic Press.*

Mammone, N., La Foresta, F., Morabito, F. C., 2012. Automatic artifact rejection from multichannel scalp EEG by wavelet ICA. In *Sensors Journal, IEEE, 12(3):533-542.*

Nason, G. P., Silverman, B. W., 1995. The stationary wavelet transform and some statistical applications.

Oostenveld, R., Fries, P., Maris, E., Schoffelen, J.M., 2011. Fieldtrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. In *Computational Intelligence and Neuroscience.*

Pham, D.T., Cardoso, J.F., 2001. Blind separation of instantaneous mixtures of non stationary sources. In *IEEE Transactions on Signal Processing, 49: 1837-1848.*

Puthusserypady, S., Ratnarajah, T., 2006. Robust adaptive techniques for minimization of EOG artefacts from EEG signals. In *Signal Processing, 86(9): 2351-2363*

Tichavský, P., Yeredor, A., 2009. Fast approximate joint diagonalization incorporating weight matrices. In *IEEE Transactions on Signal Processing, 57: 878-891.*

Venkataramanan, S., Kalpakam, N. V., Sahambi J.S., 2004. A novel wavelet based technique for detection and de-noising of ocular artifact in normal and epileptic electroencephalogram. In the 6th *Nordic Signal Processing Symposium 2004.*

Xiao-Ping, Z., Desai, M. D., 1998. Adaptive denoising based on SURE risk. In *Signal Processing Letters, IEEE, 5(10):265-267.*

Zima, M., Tichavský, P., Paul, K., Krajča, V., 2012. Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions. In *Physiological Measurements, 33(8):39-49.*