EEG and Eye-Tracking Integration for Ocular Artefact Correction

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Abstract: Electroencephalograms (EEG) are a widely used brain signal recording technique. The information conveyed in these recordings can be an extremely useful tool in the diagnosis of some diseases and disturbances, as well as in the development of non-invasive Brain-Machine Interfaces (BMI). However, the non-invasive electrical recording setup comes with two major downsides, a. poor signal-to-noise ratio and b. the vulnerability to any external and internal noise sources. One of the main sources of artefacts are eye movements due to the electric dipole between the cornea and the retina. We have previously proposed that monitoring eye-movements provide a complementary signal for BMIs. He we propose a novel technique to remove eye-related artefacts from the EEG recordings. We couple Eye Tracking with EEG allowing us to independently measure when ocular artefact events occur and thus clean them up in a targeted manner instead of using a "blind" artefact clean up correction technique. Three standard methods of artefact correction were applied in an event-driven, supervised manner: 1. Independent Components Analysis (ICA), 2. Wiener Filter and 3. Wavelet Decomposition and compared to "blind" unsupervised ICA clean up. These are standard artefact correction approaches implemented in many toolboxes and experimental EEG systems and could easily be applied by their users in an event-driven manner. Already the qualitative inspection of the clean up traces show that the simple targeted artefact event-driven clean up outperforms the traditional "blind" clean up approaches. We conclude that this justifies the small extra effort of performing simultaneous eye tracking with any EEG recording to enable simple, but targeted, automatic artefact removal that preserves more of the original signal.

1 INTRODUCTION

Electroencephalogram (EEG) recordings are widely used nowadays for different neurological applications, such as diagnosis of epilepsy or sleep disorders, or brain machine interfaces. (Iber, Ancoli-Israel, Chesson., *et al.*, 2007; Giannitrapani and Kayton, 1974; Saatchi, Oke, Allen, *et al.*, 1995). The EEG trace is known to be highly variable, in part due to transient physiological conditions and state of the brain as well as noise inside the nervous system (e.g. Faisal, 2010, Sengupta et al, 2013, Neishaborui and Faisal , 2014; for general overview see Faisal et al., 2008) but mainly due to noise and artefacts from any kind of non-neuronal genereated electro-magnetic fields. Noise artefacts are caused by external (e.g. AC line noise, mobile phones, electric motors) or biological electromagnetic activity from muscle contractions of the face and the eyes, as well as movement of the eye-ball itself. Ocular artefacts are most relevant since the influence of the eye dipole (potential difference between the Retinal Pigment Epithelium and the cornea) in the recording is very high, due to the proximity to the electrodes. The influence of eye blinks specifically is very high as it causes a large change in the signal, both due to the influence of the eye lid and the reflex rotation of the eye ball downwards and inwards (Iwasaki, Kellinghaus, Alexopoulos, *et al.*, 2005).

Eye Tracking technology, and mostly the video-based recording of eye gaze, have recently become by a factor of up to 1,000 less costly (Abbott and Faisal, 2012) and rapid "walk-up" calibration (Abbott et al, 2013) is enabling this technology to be more widely used in several applications (e.g. medical diagnostics or robotic control). Moreover, video-based eye tracking is not affected by external electrical fields and as such is independent from EEG noise sources.

Most of the current approaches to Ocular

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Artefact removal are “blind” and include removal of blink regions (Yoo, Basa and Lee, 2007), wavelet decomposition (Kumar, Arumuganathan, Sivakumar, *et al.*, 2008), Independent Components Analysis (Vigário, 1997) or use Electrooculogram recordings (EOG) to then subtract this from the EEG (Jervis, Coelho and Morgan, 1989). “Blind” approaches have the downfall of the artefact removal being performed generically to the whole signal, so there is a step in identifying what is and what is not an artefact, which is prone to error. By having an eye tracking recording we eliminate this error and are sure of when an artefact is ocurring. Moreover, it enables the specific ocular artefacts to be characterised for use in other removal approaches, such as the Wiener filter.

In this study we use the Eye Tracking information to detect regions of Ocular Artefacts and use that to perform local correction, thus minimizing the influence of the corrective measures in the rest of the signal. This will provide a non corrupted but clean signal, that can then be used in EEG applications such as Brain Machine Interfaces or Medical Diagnosis.

2 METHODS

A simple gaze fixation protocol was used to record EEG and Eye-tracking signals simultaneously. Subjects were instructed to stare at a white dot presented on a screen without moving their head. No instructions were given regarding blinking, allowing the subjects to blink freely. Figure 1 represents the experimental setup.

Eye Tracking was performed with an SMI Red-m Eye Tracker (SensoMotoric Instruments GmbH, Teltow, Germany), a binocular, remotely mounted Eye Tracker. EEG data was collected with a BrainProducts ActiCHamp amplifier and a 32 active-electrode set with an ActiCap (Brain Products GmbH, Gilching, Germany). Eye Tracking was performed at 120 Hz and EEG recordings were sampled at 500 Hz. Impedance of Electrodes against the skin was reduced to levels always below 15 kΩ, to ensure EEG signal quality. Eye Tracking was performed at a distance of 50-70 cm from the cameras.

The EEG data was then pre-processed by a bandpass filter between 0.1-50 Hz, resampled to 120 Hz and Common Average Re-referenced. Eye Gaze data (retrieved from the Eye Tracker) was used to find blink regions and extract blink markers.

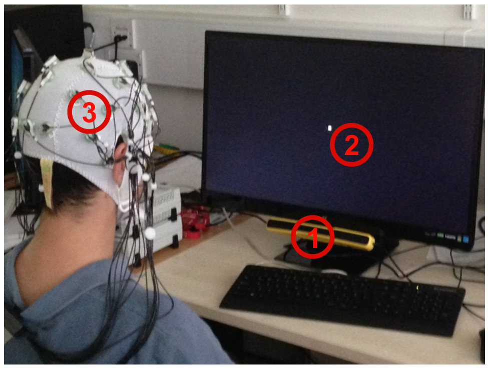

Figure 1: Experimental Setup. 1 is the Eye Tracker, 2 is the stimuli screen and 3 is the electrode cap.

2.1 Experimental Setup

The task was set up in Matlab with the help of the PsychoPhysics Toolbox (Brainard, 1997). Participants were asked to sit at a distance of 50-70 cm from the Eye Tracker and Monitor, to ensure tracking (as per the Eye Tracker’s technical information sheet). Time to relax was given to patients while performing the setup of the EEG apparatus and participants were instructed to sit comfortably and focus only on the screen. External interference was minimized to avoid distractions that could result in inadvertent saccadic movements.

Data was collected from 12 subjects with an average age of 25 years.

2.2 Analysis Methods

Several methods were studied in order to find the most suitable for ocular artefact correction, including Independent Components Analysis (ICA), Wavelet Decomposition and Wiener Filtering. The traces resulting from these methods were then analysed and compared.

2.2.1 Independent Components Analysis

ICA is an algorithm that maximizes the independence of different components of a signal by finding a linear coordinate system that creates signals that are statistically independent (Lee, 1998). ICA is used for Blind Source Separation. As ocular artefacts do not correspond to neural activity (i.e. they have a different source), ICA seemed a suitable approach to ocular artefact correction in EEG signals.

The ICA algorithm used is present in the EEGLAB toolbox for Matlab and uses the *infomax* learning rule (Bell and Sejnowski, 1995). This rule minimizes the mutual information in the components in the output, thus maximizing their statistical independence.

The original *infomax* condition fails to separate sub-Gaussian sources due to the sigmoid function used; a solution to this problem was proposed by Bell and Sejnowski and consisted of a flexible sigmoid function (Bell and Sejnowski, 1995), but empirical results have shown that sometimes it is not possible to find independent components with this approach, alongside it being highly demanding in terms of computational load.

To evaluate the Gaussianity of a distribution, a measure of its kurtosis can be used. Kurtosis is defined as the 4th order cumulant and gives a measure of the shape of a distribution. A cumulant is used to describe and in some cases approximate a normal distribution; these are similar to moments in the sense that two distributions with identical moments will also have identical cumulants.

To overcome the problems of the original rule proposed by Bell and Sejnowski, an extended version of their algorithm was created: in this version the algorithm switches according to the kurtosis of the distribution of the data points. This means that according to the sign of the kurtosis, the learning rule is updated and this way it is possible to overcome the original problem. Simulations run on datasets with multiple sources and a variety of sub- and super-Gaussian distributions show that this extended version of the *infomax* algorithm is able to separate the sources (Lee, Girolami and Sejnowski, 1999).

The original learning rule with a natural gradient is defined as (Bell and Sejnowski, 1995):

$$\Delta W \propto (I - \tanh(u) \times u') \times W \tag{1}$$

where u represents the estimated sources, I denotes the identity matrix and $u = W \times x$, x being the mixed components signals. The extended learning rule, proposed in (Lee, Girolami and Sejnowski, 1999) is defined as:

$$\Delta W \propto [I - K \tanh(u)\, u' - uu'] \tag{2}$$

where k_i are elements of the N-dimensional diagonal matrix K. This matrix is related to the kurtosis of the data, so if $k_i = -1$ the data is sub-Gaussian and if $k_i = 1$ the data is super-Gaussian.

2.2.2 Wiener Filter

The Wiener Filter approach creates an optimal linear filter based on the signal and noise power spectra, as stated in the equation:

$$y(n) = x(n) + \omega(n) \tag{3}$$

where $x(n)$ is the EEG neural signal and $\omega(n)$ is the ocular artefact (both in time domain). Since we can retrieve the artefact positions in the signal through the Eye Tracker, an "average artefact" can be obtained by averaging the signal pieces that contain an artefact, and thus the Wiener Filter kernel can be calculated and applied to the signal.

Let's assume that $x(n)$ and $\omega(n)$ are stationary and uncorrelated – a valid assumption, considering these signals have different origins and therefore should not have any strong correlation. This can be translated into the fact that the expectation is zero:

$$E[x(n), \omega(n)] = 0 \tag{4}$$

The goal is to find an optimal filter that minimizes the error between the signal $x(n)$ and the estimated signal $\hat{x}(n)$:

$$\min\left(E\left[\left(x(n) - \hat{x}(n)\right)^2\right]\right) \tag{5}$$

and

$$\hat{x}(n) = g(n) * y(n) \tag{6}$$

where $g(n)$ denotes the filter and $*$ represents convolution. By using the orthogonality principle (Papoulis and Pillai, 2002) it is possible to obtain the filter that minimizes the mean square error:

$$\begin{aligned} E[e(n), y(n)] &= E\left[\left(x(n) - \hat{x}(n)\right), y(n)\right] \\ &= E[x(n), x(n)] - g(n) \\ &\quad * E[y(n), y(n)] = 0 \end{aligned} \tag{7}$$

When converted to Fourier Space, the above equation will turn into an algebraic equation:

$$G(\omega) = \frac{P_x(\omega)}{P_x(\omega) + P_w(\omega)} \tag{8}$$

where $P_x(\omega)$ represents the power spectral density of the signal (with no artefacts), $P_w(\omega)$ is the power spectral density of the artefact extracted and $G(\omega)$ is the filter function. $P_x(\omega)$ and $P_w(\omega)$ were computed by extracting a mean artefact and mean clean signal and then calculating the power spectral density of each.

After the computation of this filter function and in order to apply it to the whole signal, either the filter function has to be inversely transformed to be in a time basis or the signal has to be transformed to be in Fourier space. The signal is then convolved (time) or multiplied (Fourier) with the filter and the noise should be removed.

2.2.3 Wavelet Decomposition

Wavelets and wavelet decomposition are tools used in signal processing to analyse, correct and characterize signals. Wavelet functions define the basis over which the signal is going to be decomposed.

From the several different types of wavelets in existence in signal processing it is possible to choose some whose properties adjust better to a specific purpose or case. In the case of artefact correction, wavelets that mimic the artefact will be more suitable, since the coefficients of the transform will be higher in the artefact zones.

The Discrete Wavelet Transform (DWT) consists of the decomposition of a signal into a wavelet basis, thus attributing coefficients that relate the signal to the wavelet form. The main equation that describes this process is (Kumar, Arumuganathan, Sivakumar, *et al.*, 2008):

$$\Psi_{j,k}(t) = 2^{j/2}\,\Psi(2^j t - k) \tag{9}$$

where Ψ represents the wavelet function. The process of obtaining the wavelet coefficients of a signal can be performed at different levels, each one of them defined by the binary decimation factor $\mathfrak{D}_0$ (Nason and Silverman, 1995):

$$(\mathfrak{D}_0 x)_j = x_{2j} \tag{10}$$

where x represents the signal. This implies that $\mathfrak{D}_0$ chooses every even number of a sequence.

The main issue of the Discrete Wavelet Transform (DWT) is that it is not time-invariant, and thus the translation invariance property is lost, i.e. the translated DWT of a signal is not the same as the DWT of a translated signal.

Stationary Wavelet transform is a variation of the usual Discrete Wavelet transform. The advantage relies on the independence of the choice of origin for the wavelets, which is achieved by applying appropriate high and low pass filters to the data at each level, thus producing two sequences at the next level. This way there is no decimation, instead the filters are changing at each level by zero-padding in a well-defined way. The details of the filter adaptation are described in (Nason and Silverman, 1995). The Stationary Wavelet Transform (SWT) contains the coefficients of the Discrete Wavelet Transform but shifted according to the choice of the origin of DWT. There is no restriction on the localisation as the stationary wavelet transform fills the gaps between coefficients in decimated DWT (Nason and Silverman, 1995).

In the case of artefact correction of the EEG, (Kumar, Arumuganathan, Sivakumar, *et al.*, 2008)show a simple way to correct the eye blink artefacts from the EEG using Stationary Wavelet Transforms and Symlet Wavelets (part of the.

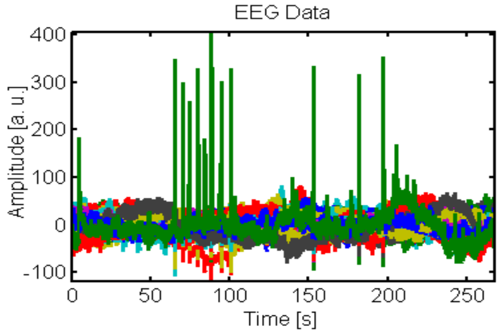

Figure 2: EEG recording. Different colours represent different channels; the spikes in the signal are blink artefacts.

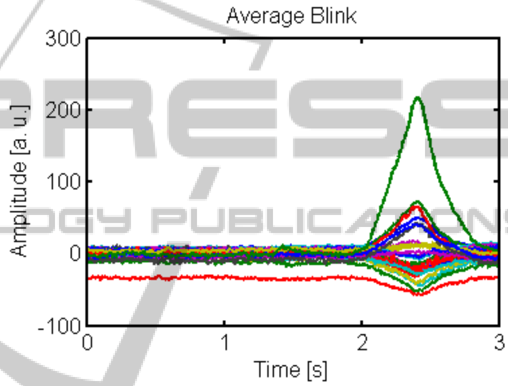

Figure 3: Average Blink for one subject. The artefact extracted is quite large and thus can influence the use of the data.

Daubechies (Daubechies, 1990) family) of level 3. In this paper they show a method to correct the artefacts with a simple threshold of the wavelet coefficients.

3 RESULTS

In order to visualize the influence of the artefacts in the signal, all 31 channels of the recording are shown in Figure 2. The same recording is shown in this paper for the sake of comparison, and it is only illustrative of the data collected.

The Eye Tracker data was aligned with the EEG recording and thresholded to yield a set of artefact markers. The extraction and average of blink artefacts through the use of these markers is represented in Figure 3.

Event-driven Independent Components Analysis:

ICA was applied to 1500 points in the data around the artefact; 30 channels were used to guarantee fullrank data. After projection of Independent Components to the original data space, Artefact components were identified and subtracted from the data. The result is shown in Figure 4 and Figure 5.

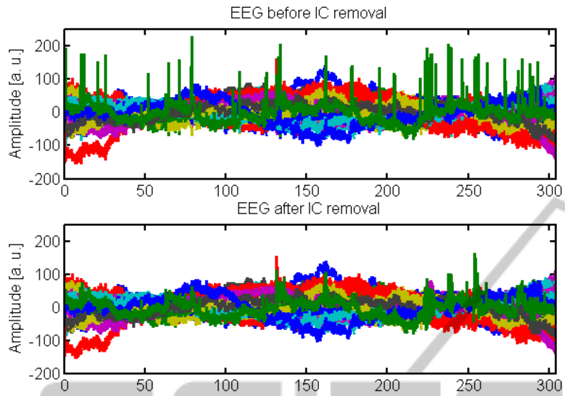

Figure 4: Top: EEG signal before artefact correction; Bottom: Same signal after correction of artefacts with ICA. The artefacts that correspond to the spikes in the upper plot are reduced in the bottom plot. The black window represents the region that was zoomed for the detail plot in Figure 5.

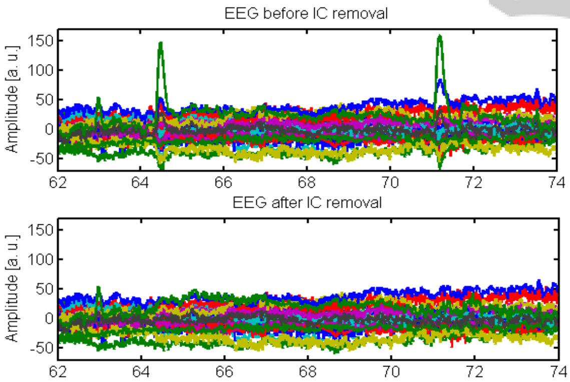

Figure 5: Detail plot of two blink artefacts. Top: before correction; Bottom: after correction with ICA.

Event-driven Wiener Filtering:

To calculate the filter kernel, the EEG signal with the artefacts and without artefacts was separated and averaged; both signals were zero-padded to the length of the signal and the power spectral density was calculated and then used in the filter function calculation (Izzetoglu, Devaraj, Bunce, *et al.*, 2005; Kailath, Sayed and Hassibi, 2000; Jingdong Chen, Benesty, Yiteng Huang, *et al.*, 2006). The result of the filtering is shown in Figure 6 and Figure 7.

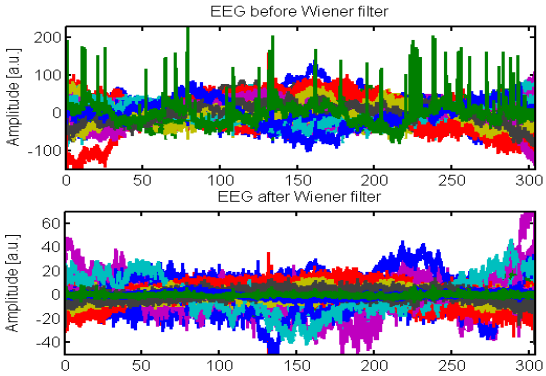

Figure 6: EEG signal before and after correction of artefacts with Wiener filter. Top: signal before artefact correction; Bottom: signal after artefact correction. The black window represents the region of the signal that is zoomed in the detail plot (Figure 7).

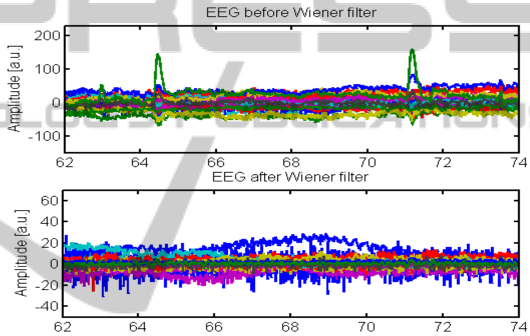

Figure 7: Detail plot of the EEG signal. Top: signal before artefact correction; Bottom: signal after artefact correction with Wiener filter.

Event driven Wavelet Decomposition:

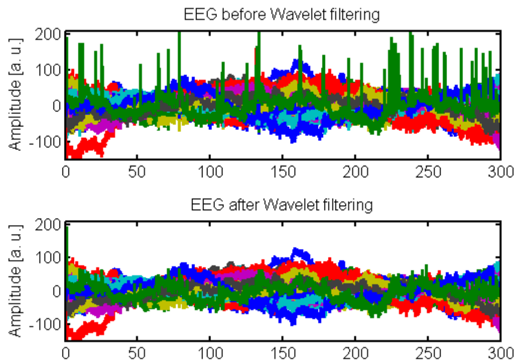

Figure 8: EEG signal before and after correction of artefacts with Wavelet Decomposition. Top: signal before artefact correction; Bottom: signal after artefact correction. The black window indicates the region of the signal that is zoomed in the detail plot (Figure 9).

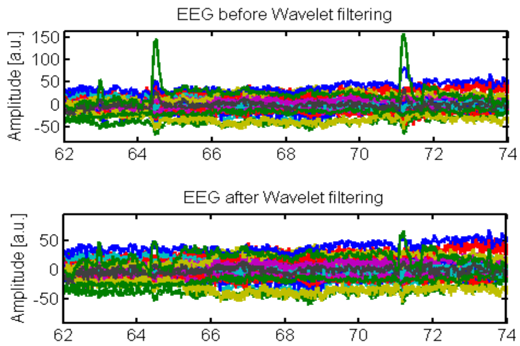

Figure 9: Detail plot of the EEG signal. Top: signal before artefact correction; Bottom: signal after artefact correction with Wavelet Decomposition.

Stationary wavelet decomposition was used to correct the artefact; Symlet wavelets were chosen due to their resemblance to the ocular artefact (Kumar, Arumuganathan, Sivakumar, *et al.*, 2008) and 8 levels of decomposition were applied to 1500 data points around the ocular artefact. Figure 8 and Figure 9 show the results of this method.

"Blind" Independent Components Analysis:

Another method applied to the data in order to prove the pertinence of our methods, was a standard ICA clean up, where we have a sliding window over the data, calculating Independent Components and eliminating those that resemble an artefact. This approach is blind and as such has no knowledge of how a blink artefact looks like or even their locations. Results are shown in Figure 10 and Figure 11.

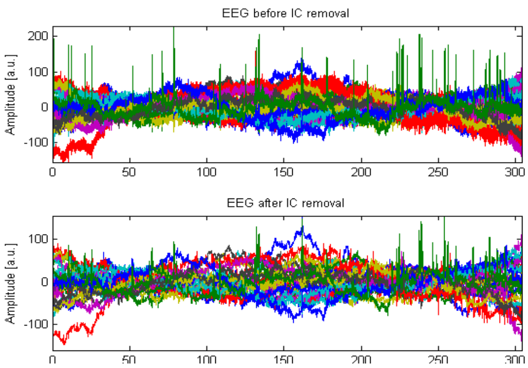

Figure 10: EEG signal before and after correction of artefacts with Blind ICA. Top: signal before artefact correction; Bottom: signal after artefact correction. The black window indicates the region of the signal that is zoomed in the detail plot (Figure 9).

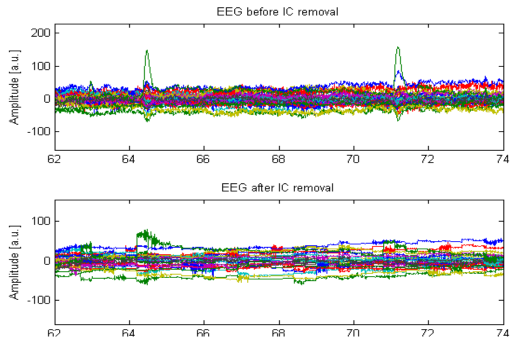

Figure 11: Detail plot of the EEG signal. Top: signal before artefact correction; Bottom: signal after artefact correction with Blind ICA.

4 DISCUSSION

In this work we studied the effect of using an Eye Tracker in Ocular Artefact correction of EEG data. We implemented standardised signal processing methods such as ICA or Wavelet Decomposition, as well as a Wiener Filter, a method not generally used in EEG artefact correction.

Our results show that all 4 methods are successful in correcting the artefacts, although Event-Driven ICA seems to yield the best signal after correction. This is an expected finding considering that the origins of the artefact and the signal are different, and thus Blind Source Separation techniques such as ICA have great potential in achieving the best signal output. When compared to the other methods, Blind ICA clearly is stricter with the data and sometimes leads to an over-correction. In Figure 11 we can clearly see that the data, although it might preserve most of its frequency spectrum, has been severely affected by the corrective measure.

There is high inter- and intra-subject variability on the EEG recordings; shape of head, changes in electrode impedance or subject behaviour can influence the data recordings, by introducing artefacts and non-linear trends in the signal. Moreover, attention or drowsiness can influence the Eye Tracking (Di Stasi, McCamy, Catena, *et al.*, 2013).

The Wiener Filter is the method that is more prone to failure, as it relies on an effective extraction of the average artefact. Moreover it will filter out all the frequencies represented in the artefact, which are low (duration of about 200 milliseconds) (Caffier, Erdmann and Ullsperger, 2003) and thus can eliminate relevant information from the signal

(Harmony, Fernández, Silva, *et al.*, 1999; Whitham, Pope, Fitzgibbon, *et al.*, 2007; Iber, Ancoli-Israel, Chesson., *et al.*, 2007).

One improvement that could be performed to the Wavelet Decomposition method is the use of a more complex adaptive thresholding technique, since the one used for this analysis combines only the mean and variance of the signal to obtain a threshold; other methods have been tested in "blind" approaches (Stein, 1981; Krishnaveni, Jayaraman, Anitha, *et al.*, 2006) and thus could be implemented in this study.

The ICA technique could be implemented as an online correction technique, though it would lead to some delay in the output of results. Wavelet and Wiener filter methods can only be used for post-processing and not for online correction with the approaches described in this work.

As further work we would like to appoint the validation of these techniques and their pertinence in artefact correction. A validation approach was attempted, with a Movement Imagery task and a simple K- Nearest Neighbours classifier. The goal was to examine the classifier's accuracy for different methods of ocular artefact correction, but in the experiments the number of ocular artefacts was correlated with the Movement Imagery epochs (number of blinks increased in Movement Imagery and lowered in Rest epochs), thus proving this validation method as unable to accurately find the best corrective algorithm.

The potential benefits of a clean EEG signal that can be expected are among a better understanding of neural signals and better use for these, such as in Brain Machine Interfaces that can be used to help patients suffering from Locked in Syndrome, as an example. Online implementation is although required for this purpose, but the usage of an eye tracker that is not affected by external electromagnetic fields (unlike, for example, electrooculograms or magnetic search coils (Schlag, Merker and Schlag-Rey, 1983)). Our work suggests simple steps towards a cleaner EEG signal, hopefully with more usable neural information being conveyed in it and useable in real-time.

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