How Many Channels are Enough? Evaluation of Tonic Cranial Muscle Artefact Reduction using ICA with Different Numbers of EEG Channels

Azin S. Janani
College of Science and Engineering
Flinders University
Adelaide, South Australia

Tyler S. Grummett
College of Science and Engineering
Flinders University
Adelaide, South Australia

Hanieh Bakhshayesh
College of Science and Engineering
Flinders University
Adelaide, South Australia

Trent W. Lewis
College of Science and Engineering
Flinders University
Adelaide, South Australia

John O. Willoughby
College of Medicine and Public Health
Flinders University
Adelaide, South Australia

Kenneth J. Pope
College of Science and Engineering
Flinders University
Adelaide, South Australia

***Abstract*—Scalp electrical recordings, or electroencephalograms (EEG), are heavily contaminated by cranial and cervical muscle activity from as low as 20 hertz, even in relaxed conditions. It is therefore necessary to reduce or remove this contamination to enable reliable exploration of brain neurophysiological responses. Scalp measurements record activity from many sources, including neural and muscular. Independent Component Analysis (ICA) produces components ideally corresponding to separate sources, but the number of components is limited by the number of EEG channels. In practice, at most 30% of components are cleanly separate sources. Increasing the number of channels results in more separate components, but with a significant increase in costs of data collection and computation. Here we present results to assist in selecting an appropriate number of channels. Our unique database of pharmacologically paralysed subjects provides a way to objectively compare different approaches to achieving an ideal, muscle free EEG recording. We evaluated an automatic muscle-removing approach, based on ICA, with different numbers of EEG channels: 21, 32, 64, and 115. Our results show that, for a fixed length of data, 21 channels is insufficient to reduce tonic muscle artefact, and that increasing the number of channels to 115 does result in better tonic muscle artefact reduction.**

Keywords— Independent Component Analysis, muscle reduction, number of channels, electroencephalogram, electromyogram

I. INTRODUCTION

Electroencephalogram (EEG) is an important biological signal and has a key role in brain research, brain disease diagnosis, and brain computer interfaces (BCI) [1, 2]. These scalp measurements are susceptible to various non-neural biological contamination, especially electromyogram (EMG) [1]. EMG activity can be categorised as phasic or tonic activity. Phasic muscle activity is associated with overt movements of the head, jaw, facial muscles, etc. They are high in amplitude and isolated in time, so can be recognised visually or by simple algorithms. Tonic muscle activity is associated with maintaining the posture of the head and neck. The signals are low in amplitude but are present at all times, even in relaxed conditions. Recent research on pharmacologically paralysed subjects reveals that scalp measurements are contaminated by tonic cranial and cervical muscle activity from as low a frequency as 20 hertz, and the artefacts exceed the neural signals in power by up to 20 decibel at 100 hertz [3-5].

One of the main issues in EEG research, therefore, is to discard or to reduce the effect of muscle activity on brain signals. Several methods have been implemented with the purpose of providing EMG-free EEG. Among them, Independent Component Analysis (ICA) [6-8] has been widely shown to be successful in reducing muscle contamination, and is implemented in several commonly used EEG analysis toolboxes such as EEGLAB [9] and FieldTrip [10].

Using a linear transformation, ICA separates a set of signals (EEG channels) into a set of components, equal in number to the input EEG channels, that are maximally independent [11, 12]. Components can then be classified as neurogenic or myogenic based on characteristics such as their temporal properties, spectral slope, or topography.

ISBN 978-90-827970-1-5

Typical clinical EEG recordings use 21 channel caps, with research recordings commonly using (approximately) 21, 32, 64, or 128 channels. The number of different muscles and brain regions, plus their spatial separation, suggests that the number of sources certainly exceeds 21, and may even exceed 128 [6, 13]. ICA separation is known not to be perfect, with most of the derived components being a mixture of sources rather than "pure EEG" or "pure EMG" [13-15]. So, it seems that the number of EEG channels used in ICA may have a significant effect in the classification of components and hence in the quality of muscle signal reduction. We test this hypothesis using our unique database of paralysed conscious subjects.

II. METHOD

A. Paralysis dataset

Our unique dataset is composed of scalp measurements recorded from six subjects (one female and five males) accomplishing a series of tasks twice, once before and once during pharmacologically-induced paralysis. This results in two sets of data, one set contaminated with muscle activity (EMG-contaminated), and the other set recorded under the same conditions but with no muscle activity (EMG-free). The experimental tasks include: baseline eyes closed, baseline left eye open, serial subtraction, oddball paradigm, exposure to a strobe light at three different frequencies (16 hertz, 40 hertz, and 59 hertz), and an auditory verbal learning task. This experiment is described in more detail in [4, 5]. The total recording time was 12 minutes with the sampling rate of 5000 hertz. 115 channels of EEG were recorded with a left-ear reference, and labelled using the 10-5 international system [16].

B. Pre-processing

Using code written in MATLAB (The Mathworks, Natick, MA, USA), all the pre-processing and processing of recorded data was performed offline. All data were resampled to 1000 hertz, passed through a high pass filter with 0.5 hertz cut-off frequency to reduce electrode drift, and re-referenced to the common average head reference.

C. ICA pruning with different numbers of EEG channels

From the various ICA algorithms, we selected the Information maximisation algorithm (Infomax) [17], which is a popular choice in neuroscience and provides a good separation of components in a reasonable time [14].

To evaluate the effect of number of EEG channels in muscle reduction, we applied the selected ICA algorithm on EMG-contaminated data four times; each time with a different number of input EEG channels. Each application of ICA results in a set of components which are equal in number to the number of input EEG channels, and an associated weight matrix that describes the linear transformation between channels and components. Infomax was applied to the original 115-channel data, and to subsets of channels corresponding substantially to the 10-10 (64 channels), extended 10-20 (32 channels) and 10-20 (21 channels) systems [10].

We followed the procedure explained in [6] separately for each application of ICA on the EMG-contaminated data. The spectral gradient of each component was calculated by fitting a straight line to the log-log spectrum between 7 hertz and 75 hertz. We selected the conservative threshold to ensure all brain-containing components were preserved [6]. Then, components whose spectral gradient was greater than the threshold were labeled as muscle-containing components and were discarded (set to zero). Finally, pruned EEG signals were reconstructed by multiplying the components and inverse of weight matrix (the mixing matrix). We label these pruned EEG signals according to their number of channels: e.g. pruned-64, pruned-21 etc.

D. Comparisons and statistical analysis

The power spectra of all EMG-contaminated, pruned, and EMG-free signals were calculated using Welch's modified periodogram [18] using one-second Hanning windows. Spectral power was then averaged in bands related to neural activity that also contained significant muscle artefact. The selected bands are gamma1 (25-35 hertz), gamma2 (35-45 hertz), gamma3 (52-98 hertz), and muscle (102-198 hertz). In these bands, we examined baseline and cognitive tasks to see if (1) muscle artefact was reduced, and (2) neurophysiological responses were retained.

We considered two groups of channels: central channels (Fz, Cz, C1, C2, Pz), and peripheral channels (T7, T8, F7, F8, O1, O2). To test our observations statistically, we compared EMG-contaminated, EMG-free and pruned spectra within each group of channels and for the four frequency bands.

Statistical analyses were performed using a 1-way parametric ANOVA test or its nonparametric equivalent (Kruskal-Wallis), depending the outcome of a Lilliefors test for normality of the data. Where multiple tests were performed, Bonferroni correction was applied. Where a significant effect was found, a modified Bonferroni correction was applied to the multiple post hoc comparisons. All tests used a threshold for significance of $p = 0.05$.

III. RESULTS

A. Tonic muscle artefact removal

Fig. 1 displays the topographic maps of relative spectra of EMG-contaminated to EMG-free, and pruned signals to EMG-free signal in the four frequency bands of interest. The scale from dark blue to dark red indicates how much a region is affected by muscles. Dark red areas are highly contaminated by cranial muscle EMG whereas dark blue areas are almost muscle-free.

It can be observed that the average power of EMG-contaminated spectra at peripheral channels was about 300 times greater than EMG-free spectral power, but after pruning by ICA this decreased to about 100 times and 35 times using 21 and 32 channels respectively. Visually, ICAs

ISBN 978-90-827970-1-5 © EURASIP 2018

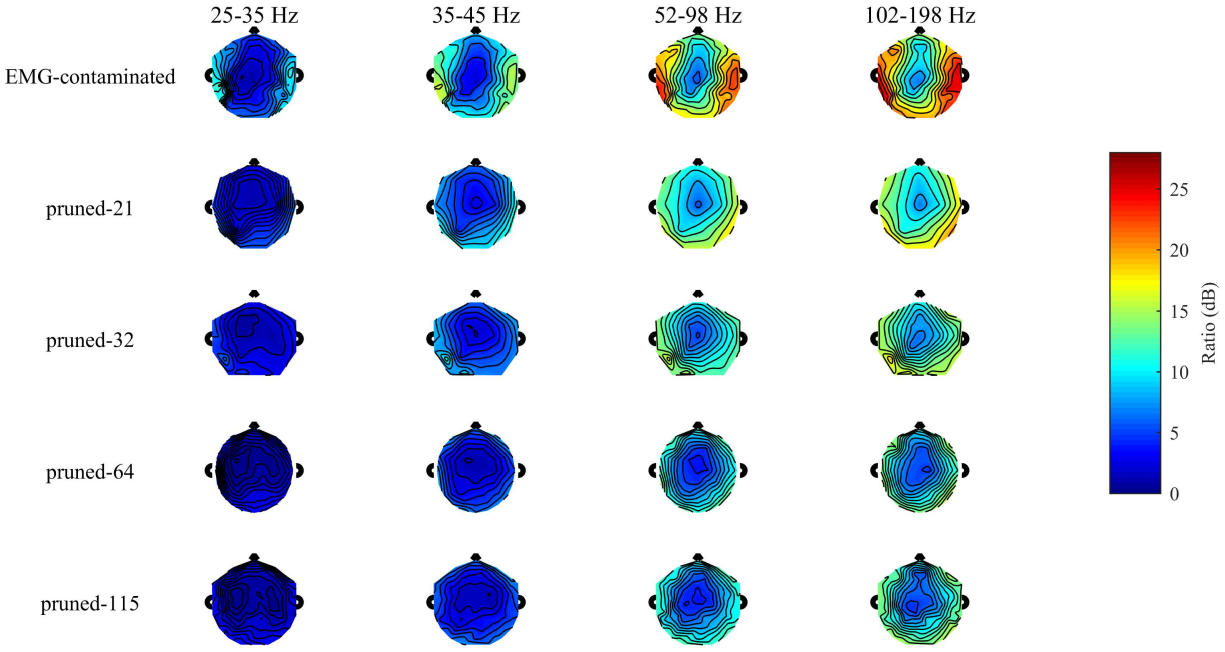

Fig. 1. Topographic maps of relative spectra of EMG-contaminated and pruned signals relative to EMG-free (rows) in the four frequency bands of interest (columns). Note that the difference is mostly in peripheral channels.

with 64 and 115 input channels nearly halve the power of ICA with 32 input channels, especially at peripheral channels where cranial muscles are mostly located. However, it is difficult to see a difference between pruned-64 and pruned-115.

Fig. 2, for each group of channels, shows the spectra of EMG-contaminated, EMG-free and pruned signals averaged across channels. The orange and the dark blue color are corresponding to EMG-contaminated and EMG-free data respectively. Better pruning has spectra closer to EMG-free spectra.

Statistical analysis revealed that there is no statistically significant difference between EMG-contaminated and EMG-free signals in central channels in the low frequency bands (gamma1 and gamma2). Hence, we would expect no difference with pruned signals in these situations either. This

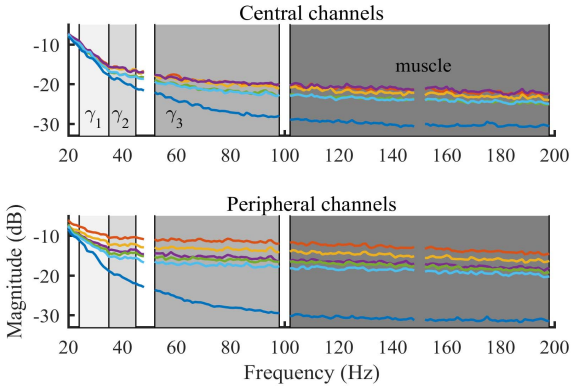

Fig. 2. Average of 6 subjects' power spectra in central channels: Fz, Cz, C1, C2, Pz (top), and peripheral channels: T7, T8, F7, F8, O1, O2 (down) during baseline eyes closed task. Refer to Fig. 4 for the legend.

result is consistent with the expectation that muscle power is least at low frequencies and in central channels.

Pruned-21 signals are not statistically significantly different to EMG-contaminated signals in any combination of the frequency bands and channel groups, i.e. the pruning does not achieve a significant reduction in muscle power. Pruned-32 achieves statistically significant difference to EMG-contaminated only in peripheral channels in the lower frequency bands (gamma1 and gamma2). Pruned-64 achieves statistically significant difference to EMG-contaminated in peripheral channels in the three lower frequency bands (gamma1, gamma2 and gamma3), and in central channels in the higher frequency bands (gamma3, muscle). Pruned-115 signals are statistically significantly different to EMG-contaminated signals in both peripheral and central channels at the higher frequency bands (gamma3 and muscle), and in only the peripheral channels at the lower frequency bands (gamma1 and gamma2). These results are consistent with pruned-115 outperforming the other methods.

B. Retention of neurophysiological responses

We investigated the effect of the number of EEG channels used in ICA pruning on the measurement of neurophysiological responses, such as the Berger effect (difference in alpha rhythm between eyes open and eyes closed), Visual Steady State Response (VSSR), and Evoked Response Potential (ERP).

1) Berger effect

EEG power in the alpha band (8-13 hertz) in the occipital region during a relaxed, eyes open condition is consistently lower than in a relaxed eyes closed condition. This effect is known as Berger effect [19].

ISBN 978-90-827970-1-5 © EURASIP 2018

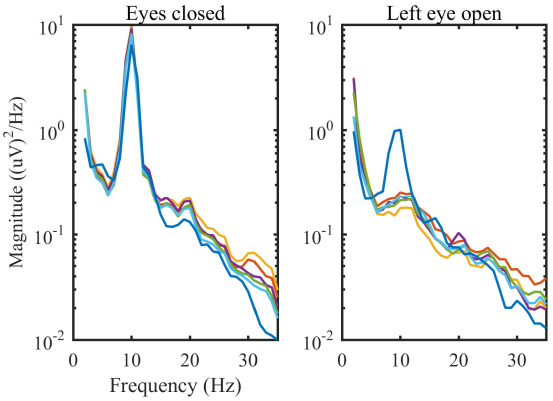

Fig. 3. Average of six subjects' eyes closed (left) and eyes open (right) spectra at Pz. Eyes open shows a clear reduction in EEG power in the alpha band (8-13 hertz). Refer to Fig. 4 for the legend.

Fig. 3 shows the mean of six subjects' eyes closed and eyes open spectra at one of the occipital channels (Pz). The power of the alpha band has decreased significantly in the eyes open task comparing to eyes closed task. Note that the EMG-free and EMG-contaminated data were recorded at different times and all pruned spectra are from EMG-contaminated data.

Fig. 4 shows the averaged relative spectra of the six subjects at Pz. The clear peak around 10 hertz is due to the reduction of power in the eyes open task. Despite the apparent differences in alpha power ratio, statistical analysis revealed no significant difference between EMG-contaminated, pruned and EMG-free signals (chi-sq = 0.88, p = 0.97).

2) Evoked response potentials

The effect of each pruning method was evaluated on the evoked response potential (ERPs) during an auditory oddball task. Fig. 5 illustrates mean ERP at channel Fz for 5 subjects.

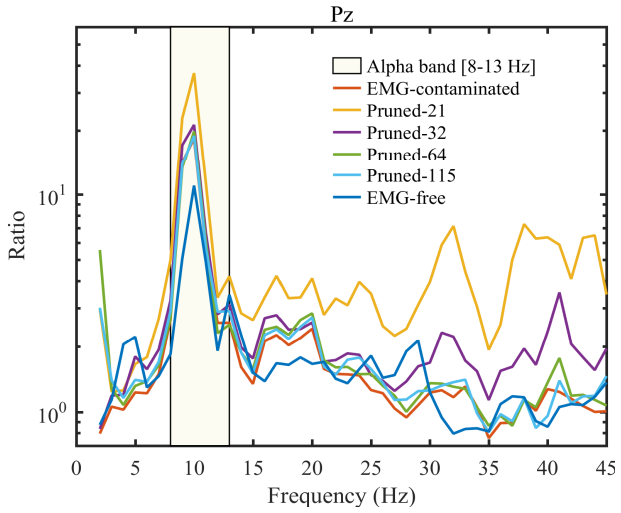

Fig. 4. Mean of six subjects' relative spectra (eyes closed to eyes open) at channel Pz. There is no statistical difference in alpha power between any of the contaminated, pruned and EMG-free signals.

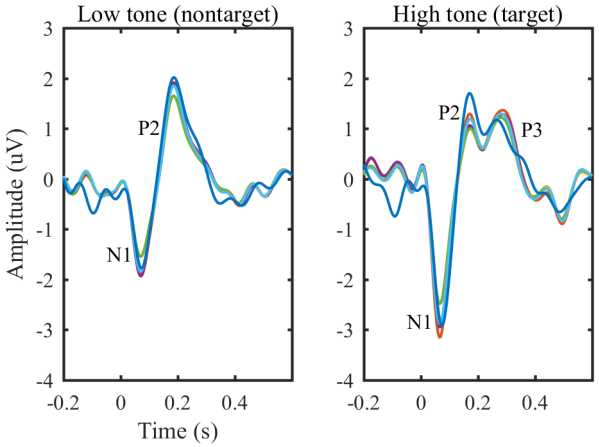

Fig. 5. Averaged evoked-response potentials (ERPs) of five subjects in an oddball task at channel Fz. The N1, P2, and P3 components to non-target low tone (left) and target high tone (right) have been preserved in all pruning approaches. Refer to Fig. 4 for the legend.

It is clear that the N1 and P2 components, which are responses to any tone, and the P3 component, which is the response to the target high tone, have been preserved in all pruning methods.

To test this observation statistically, an ANOVA was performed for each component (N1, P2, and P3) to compare their power in all signals. The results showed no significant difference between any signals (N1: chi-sq = 3.34, p = 0.64; P2: F = 0.62, p = 0.68; P3: chi-sq = 0.29, p = 0.99). This result shows that none of the pruning approaches affected the measurement of ERPs.

3) Visual steady state responses

When subjects undertake a photic stimulation task with a specific frequency, the brain's neurophysiological response to that stimulation is a peak in the power spectra at the same frequency. This is called a Visual Steady State Response (VSSR).

Fig. 6 shows the mean of six subjects' power spectra at Pz in response to photic stimulation at 16 hertz, 40 hertz and 59 hertz. The 16 hertz VSSR is visually apparent in all signals, whereas at 40 hertz there is no clear peak in the EMG-contaminated and pruned-21 spectra, and at 59 hertz there is no clear peak in the EMG-contaminated spectrum. Three separate ANOVAs (three frequencies) revealed no significant difference between EMG-contaminated, EMG-free and pruned signals in their spectral power at 16 hertz, 40 hertz and 59 hertz (16 Hz: F = 0.67, p = 0.64; 40 Hz: chi-sq = 6.51, p = 0.25; 59 Hz: chi-sq = 3.96, p = 0.55). These results are consistent with preservation of brain activity in all pruning approaches.

IV. CONCLUSION

We evaluated the relationship between the number of EEG channels used in ICA and the reduction of tonic cranial muscle contamination. Although ICA pruning based on 21 channels of EEG showed good results in reducing phasic

ISBN 978-90-827970-1-5 © EURASIP 2018

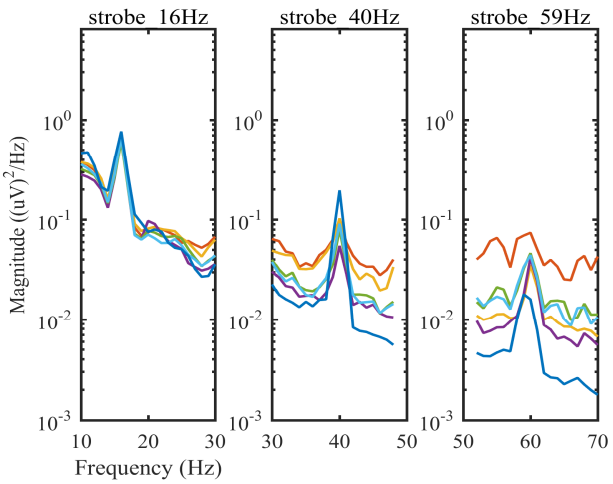

Fig. 6. Mean of 6 subject's power spectra at Pz in response to photic stimulation at 16 hertz, 40 hertz and 59 hertz. The amplitude of the steady state response is retained. Refer to Fig. 4 for the legend.

muscle contamination [20, 21], our results show that its application achieves no significant reduction of tonic muscle contamination. Moreover, using ICA with 32 EEG channels can only significantly reduce tonic muscle contamination at lower frequency bands (below < 45 hertz) and in peripheral channels. Application of ICA with 64 and 115 EEG channels results in a significant muscle reduction even at higher frequencies (above 45 hertz) and in all channels. The only difference between them is that, ICA with 64 EEG channels is insufficient for tonic muscle reduction at frequencies above 100 hertz peripherally. Additionally, the application of ICA with 21, 32, 64 and 115 channels has no effect on the measurement of brain neurophysiological responses.

Hence, the application of ICA to reduce tonic muscle artefact while retaining neurophysiological responses cannot be achieved with 21 channels. As the number of channels increases, the amount of artefact reduction increases, as does the range of frequencies achieving significant reduction. This is at the cost of additional computation expense and time. Hence, the choice of number of channels should depend on the purpose of analysis. For example, studies at low frequencies (below 45 hertz), ICA with 32 channels is sufficient. Studies which need to reduce the effect of tonic muscle contamination at higher frequencies, especially peripherally, should use a higher number of EEG channels.

REFERENCES

[1] C. Zhang, L. Tong, Y. Zeng, J. Jiang, H. Bu, B. Yan *et al.*, "Automatic artifact removal from electroencephalogram data based on a priori artifact information," *BioMed research international,* vol. 2015, 2015.

[2] V. Vinhas, E. Oliveira, and L. P. Reis, "Realtime dynamic multimedia storyline based on online audience biometric information," in *New Directions in Intelligent Interactive Multimedia*: Springer, 2008, pp. 545-554.

[3] K. J. Pope, S. P. Fitzgibbon, T. W. Lewis, E. M. Whitham, and J. O. Willoughby, "Relation of gamma oscillations in scalp recordings to muscular activity," *Brain Topogr,* vol. 22, no. 1, pp. 13-7, Jun 2009.

[4] E. M. Whitham, T. Lewis, K. J. Pope, S. P. Fitzgibbon, C. R. Clark, S. Loveless *et al.*, "Thinking activates EMG in scalp electrical recordings," *Clin Neurophysiol,* vol. 119, no. 5, pp. 1166-75, May 2008.

[5] E. M. Whitham, K. J. Pope, S. P. Fitzgibbon, T. Lewis, C. R. Clark, S. Loveless *et al.*, "Scalp electrical recording during paralysis: quantitative evidence that EEG frequencies above 20Hz are contaminated by EMG," *Clinical Neurophysiology,* vol. 118, no. 8, pp. 1877-1888, 2007.

[6] S. Fitzgibbon, D. DeLosAngeles, T. Lewis, D. Powers, T. Grummett, E. Whitham *et al.*, "Automatic determination of EMG-contaminated components and validation of independent component analysis using EEG during pharmacologic paralysis," *Clinical Neurophysiology,* vol. 127, no. 3, pp. 1781-1793, 2016.

[7] B. W. McMenamin, A. J. Shackman, L. L. Greischar, and R. J. Davidson, "Electromyogenic artifacts and electroencephalographic inferences revisited," *Neuroimage,* vol. 54, no. 1, pp. 4-9, 2011.

[8] A. J. Shackman, B. W. McMenamin, H. A. Slagter, J. S. Maxwell, L. L. Greischar, and R. J. Davidson, "Electromyogenic artifacts and electroencephalographic inferences," *Brain topography,* vol. 22, no. 1, pp. 7-12, 2009.

[9] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods,* vol. 134, no. 1, pp. 9-21, 2004.

[10] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, "FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Computational intelligence and neuroscience,* vol. 2011, p. 1, 2011.

[11] A. Delorme, T. Sejnowski, and S. Makeig, "Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis," *Neuroimage,* vol. 34, no. 4, pp. 1443-1449, 2007.

[12] K. J. Pope and R. E. Bogner, "Blind Signal Separation I. Linear, Instantaneous Combinations: I. Linear, Instantaneous Combinations," *Digital Signal Processing,* vol. 6, no. 1, pp. 5-16, 1996.

[13] A. Mognon, J. Jovicich, L. Bruzzone, and M. Buiatti, "ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features," *Psychophysiology,* vol. 48, no. 2, pp. 229-240, 2011.

[14] D. Dharmaprani, H. K. Nguyen, T. W. Lewis, D. DeLosAngeles, J. O. Willoughby, and K. J. Pope, "A comparison of independent component analysis algorithms and measures to discriminate between EEG and artifact components," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, 2016, pp. 825-828: IEEE.

[15] A. Delorme, J. Palmer, J. Onton, R. Oostenveld, and S. Makeig, "Independent EEG sources are dipolar," *PloS one,* vol. 7, no. 2, p. e30135, 2012.

[16] R. Oostenveld and P. Praamstra, "The five percent electrode system for high-resolution EEG and ERP measurements," *Clinical neurophysiology,* vol. 112, no. 4, pp. 713-719, 2001.

[17] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural computation,* vol. 7, no. 6, pp. 1129-1159, 1995.

[18] P. D. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Transactions on audio and electroacoustics,* vol. 15, no. 2, pp. 70-73, 1967.

[19] K. Kirschfeld, "The physical basis of alpha waves in the electroencephalogram and the origin of the "Berger effect"," *Biological cybernetics,* vol. 92, no. 3, pp. 177-185, 2005.

[20] T.-P. Jung, S. Makeig, C. Humphries, T.-W. Lee, M. J. Mckeown, V. Iragui *et al.*, "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology,* vol. 37, no. 2, pp. 163-178, 2000.

[21] T. Radüntz, J. Scouten, O. Hochmuth, and B. Meffert, "EEG artifact elimination by extraction of ICA-component features using image processing algorithms," *Journal of neuroscience methods,* vol. 243, pp. 84-93, 2015.

ISBN 978-90-827970-1-5