Beamforming and Blind Source Separation Have a Complementary Effect in Reducing Tonic Cranial Muscle Contamination of Scalp Measurements

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

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 electroencephalograms (EEG) are susceptible to cranial and cervical muscle contamination from frequencies as low as 20 hertz, even in relaxed conditions. Reliably recording cognitive activity, which is in this range, is impossible without removing or reducing the effect of muscle contamination. Our unique database of paralysed conscious subjects enabled us to test the effect of combining beamforming and blind source separation in reducing tonic muscle contamination of scalp electrical recordings. Using the beamforming technique, muscle sources are separated automatically based on their location; while using blind source separation, muscle components are separated based on their spectral gradient. Our results show that applying the beamforming technique on data pruned by a blind source separation technique (or vice versa) can reduce tonic muscle contamination significantly more than applying either of them separately, especially at peripheral locations. Hence, these approaches complement each other in reducing muscle contamination of EEG.**

Keywords— beamforming, blind source separation, muscle contamination, electroencephalograph, neurophysiological response

I. Introduction

Contamination of electroencephalogram (EEG) signals due to cranial and cervical muscle activity (EMG) is an unavoidable issue in experimental and clinical studies [1, 2]. The extent of muscle contamination depends on the location of the muscle and the strength of muscle contraction, hence there is no stereotype for EMG contamination [3]. Phasic muscle contractions of cranial, facial, and `neck muscles produce signals of high amplitude overlapping the frequency bands of interest in EEG [4]. Generally, the amplitude of phasic EMG contamination is sufficiently high that the artefact can be detected easily by eye or mathematical algorithm, then the contaminated part of data is discarded from all channels [2, 4, 5]. To reduce the occurrence of phasic contractions in EEG recordings, subjects are asked to sit or lie down in a relaxed position.

However, even during a "relaxed" condition, sitting or reclining, many cranial and cervical muscles are activated, albeit more weakly, e.g. to keep the mouth closed, the head up, and facial gesture expressed. These on-going, gentle, involuntary contractions to maintain muscle tone (tonic muscle contractions) produce EMG contamination continuously. Hence traditional muscle artefact rejection by discarding blocks of time cannot be used for tonic muscle contamination. Additionally, studies conducted on paralysed conscious subjects indicate that tonic muscle signals exceed cognitive signals in strength from 20 hertz. For example, their power can differ by 23 decibels peripherally at 100 hertz [6, 7].

Blind source separation (BSS) separates measurements into components, characterised by a de-mixing matrix in the linear case. With EEG measurements, the aim is to achieve separation of muscle and brain sources into different components. Several implementations of BSS have been used for pruning muscle from EEG, with Independent Components Analysis (ICA) [8-10] and Canonical Correlation Analysis (CCA) [11, 12] being the most common. Recently, Chen et al. [13] proposed that Independent Vector Analysis (IVA), an extension of ICA when there are more than two datasets, can also be used. Alternatively, non-blind decomposition algorithms can be

ISBN 978-90-827970-1-5 © EURASIP 2018

used in place of a BSS algorithm. Beamforming has been used to separate scalp electrical signals into source signals located within the head. This technique significantly reduces muscle contamination in the source signals [14], and also in reconstructed sensor signals [15].

None of the aforementioned methods works perfectly in reducing tonic muscle contamination, and there is still residual cranial muscle activity in pruned EEG data [8, 15]. However, as the BSS and beamforming approaches target different features of the sources, we hypothesise that their combination will be complementary. Hence, we test if combinations of BSS and beamforming approaches reduce muscle contamination more than individual approaches.

II. METHOD

A. Dataset

Our unique dataset consists of scalp electrical recordings from six subjects (five males and one female) performing a series of tasks twice, once before and once during pharmacologically-induced paralysis. Hence, we have two sets of data, one set containing EMG artefact (EMG-contaminated), and the other collected under the same conditions but with no EMG artefact (EMG-free). The experimental tasks include: baseline eyes closed, baseline eyes open, oddball paradigm, the auditory verbal learning task, serial subtraction, and exposure to a strobe light at three different frequencies (16 hertz, 40 hertz, and 59 hertz). More information about the experiment can be found in [7]. The total recording time was 12 minutes and the sampling frequency was 5000 hertz. 115 channels of EEG were recorded, with left-ear as the reference.

B. Pre-processing

All the pre-processing and processing of recorded data was performed offline using code written in MATLAB (The Mathworks, Natick, MA, USA). EEG channels were labelled based on the 10-5 international system. All data were resampled to 1000 hertz, were passed through a high pass filter with 0.5 hertz cut-off frequency to reduce electrode drift, and were re-referenced to the common average head reference.

C. ICA pruning

We used the information maximisation algorithm (Infomax), as it is a commonly chosen implementation of ICA in neuroscience. It can achieve a good separation of components in a reasonable time [16].

Pruning muscle artefact from the scalp recordings followed the process described in [8]. Firstly, Infomax was applied separately to the EMG-contaminated and EMG-free data, yielding two sets of components and two mixing matrices. Secondly, the spectral gradient of each component was calculated by fitting a straight line to the log-log spectrum between 7 hertz and 75 hertz. Thirdly, the maximum gradient of EMG-free components was set as a threshold. Fourthly, EMG-contaminated components with a spectral gradient greater that the threshold were labelled as muscle-containing components and were rejected. Finally, scalp EEG was reconstructed using the preserved components and the mixing matrix, yielding signals we call pruned-ICA.

D. CCA-BSS

CCA-BSS removes muscle artefact from scalp EEG. Components are identified using CCA applied to a dataset and a delayed version of itself, then the components are classified as muscle or brain based on their correlation coefficients. The delay of one sample is used to identify whether a component is muscle-like or brain-like, as muscle is modelled as similar to white noise and hence has a low autocorrelation coefficient at lag one, whereas brain is a slower, more correlated signal and hence has a high autocorrelation coefficient at lag one. However, classical CCA-BSS requires the user to specify the threshold for the classification of components, and hence the process is not automatic. The recently proposed extended CCA-BSS approach [17] uses a two milliseconds delay to determine the lag between the datasets, and classifies components completely automatically based on both their correlation coefficients and spectral gradients [8].

In this paper, we used the extended CCA-BSS approach with the conservative gradient threshold [17] to ensure that we are preserving all of the brain-containing components. Components with correlation coefficients below the correlation threshold were discarded as noise or muscle, and components with spectral gradients above the gradient threshold were rejected as muscle. Lastly, scalp EEG was reconstructed using the retained components. We call these signals pruned- CCA.

E. IVA pruning

IVA is an extension of ICA from one dataset to multiple datasets, that can be used to remove muscle artefact from scalp recordings by using a delayed version of the recordings as the second dataset [13]. Like other BSS approaches, IVA estimates a set of components for each dataset. However, rather than treat each dataset separately, components across the datasets are collected into source components matrices (SCM). In the EEG pruning case considered here, that produces one SCM per EEG channel, each SCM containing two components as there are two datasets (scalp EEG recordings and their delayed version). IVA then minimises entropy across all components and maximises mutual information within SCMs. This yields components that are maximally independent within datasets and maximally dependent to its corresponding components across datasets. Thus, the aim with IVA is to combine the advantages of both the CCA and ICA approaches. CCA only achieves decorrelation not independence of components with datasets, but does provide correlation information for component classification that ICA cannot.

IVA requires a model for the probability density function of the SCMs. We selected IVA-GL, as it is robust and has the best performance [13, 18]. After applying IVA-GL on both EMG-contaminated and EMG-free data, the spectral gradients of all derived components were calculated and the threshold was set as described in section II.C. Components whose gradients were greater that the specified threshold were rejected as muscle-containing components. Finally, surface EEG was reconstructed using the retained components. We call these signals pruned-IVA.

F. Beamforming pruning

It has been shown that minimum-norm beamformers such as sLORETA can reduce the effect of tonic cranial muscle contamination of EEG signals at the sensor level. Following [15], we constructed a generic standard volume conduction model of the head with three volumes, scalp, skull, and brain, and a set of dipoles placed either inside the brain volume or the scalp volume. Then, by calculated lead-fields using the head model, dipole location (voxels) and electrode location, source signals at each voxel were estimated. Finally, surface EEG signals were reconstructed (forward model) using sources just within the brain volume (putatively brain) and their corresponding lead-fields. We call these signals pruned-sLORETA.

G. Combination of beamforming and BSS

To test the complementary effect of BSS and beamforming approaches in reducing tonic muscle contamination of EEG, the EEG data pruned by each of BSS methods were also pruned by the sLORETA method. Additionally, this was repeated with the order of the two prunings reversed. The resulting doubled-pruned data is named with the first-applied method listed first. For example, the EEG data pruned by ICA and then sLORETA is called pruned-ICA-sLORETA, while the EEG data pruned by sLORETA and then ICA is called pruned-sLORETA-ICA. Consistently, IVA pruning failed on pruned-sLORETA data due to numerical conditioning, hence no data is presented as pruned-sLORETA-IVA.

H. Comparisons and statistical analysis

Using Welch's modified periodogram, the power spectra of all EMG-contaminated, pruned and EMG-free signals were calculated. For statistical analysis, the power in defined bands were calculated. Following [15], we used bands defined as gamma1 (25-35 hertz), gamma2 (35-45 hertz), gamma3 (52-98 hertz), and muscle (102-198 hertz). Comparisons were made in baseline tasks, and in tasks that elicit a neural response. This allowed us to test for the efficacy of artefact removal and for the retention of neurophysiological signals.

Depending on the normality of data, tested by the Lilliefors test, paired parametric t-tests or non-parametric Wilcoxon signed rank tests were applied to perform statistical comparison between all possible pairs of EMG-contaminated, EMG-free, and pruned signals in each band. The tests were modified Bonferroni corrected to account for the multiple comparisons.

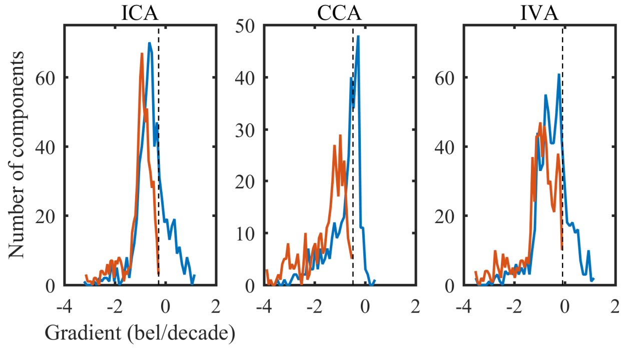

Fig. 1. Histograms of the gradients of EMG-contaminated (blue) and EMG-free (orange) components derived by applying ICA (left), CCA (middle) and IVA (right).

III. RESULTS

A. The selection of thresholds

Fig. 1 shows the histogram of the gradients of the derived components by three different BSS approaches (ICA, CCA, and IVA) for EMG-contaminated and EMG-free signals. The threshold for rejecting the muscle-containing components is set at the maximum gradient of EMG-free components. Hence, the thresholds for the ICA, CCA, and IVA methods were set at -0.28, -0.48, and -0.1 bel/decade respectively.

B. Tonic muscle artefact removal

Fig. 2 compares the mean of six subject's EMG-contaminated, pruned and EMG-free power spectra averaged within two groups of channels during baseline eyes closed task. Fz, FCz, Cz, C1, C2, CPz, and Oz comprised the central channels (ie the top of the head), and T7, T8, F7, F8, O1, and O2 comprised the peripheral channels (around the cranial-base).

The central channels are distant to muscle, whereas the peripheral channels are directly above muscles. The highest

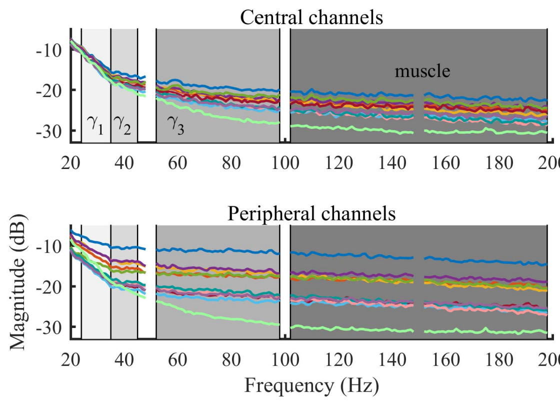

Fig. 2. Average of six subjects' power spectra in central channels: Fz, FCz, Cz, C1, C2, CPz, Oz (top) and peripheral channels: T7, T8, F7, F8, O1, O2 (down) during baseline eyes closed task. Refer to Fig. 4 for legend.

and the lowest (bright green) to EMG-free signals. Better prunings are closest to the EMG-free signals. Visually, it appears that all pruning methods improve on EMG-contaminated data, but do not achieve the ideal pruning that is defined by EMG-free data. Additionally, at peripheral channels, the amount of muscle reduction achieved by double-pruning methods exceeds that achieved by using a single pruning method.

The statistical analysis results showed that at all four frequency bands within peripheral channels, all single-pruned approaches were statistically less effective than all double-pruned approaches. Also, this was mostly true at central channels, where muscle artefact is less, but in some comparisons pruned-sLORETA was no different to some double-pruned methods, and in some comparisons pruned s-LORETA-ICA was no different to some single-pruned methods. These observations suggest BSS and beamforming pruning approaches are complementary and do yield improved results over individual methods.

Comparisons between double-prunings and EMG-free data show no difference at gamma1 and gamma2, centrally and peripherally. This is consistent with the double-prunings closely approximating EMG-free data. At higher frequencies, where the power in muscle artefact is larger, there are statistically significant differences in power peripherally for all methods, and centrally for all methods except pruned-CCA-sLORETA and pruned-IVA-sLORETA. This is consistent with those methods outperforming the other double-pruning methods.

Pruned-sLORETA is the only single-pruning method that showed no significant difference to EMG-free data in some comparisons, again consistent with it outperforming the other single-pruning methods.

C. *Retention of neurophysiological responses*

A good artefact removal algorithm should not additionally remove desired signals. Hence, we investigated the effect of the double-pruning methods on brain neurophysiological responses, namely the Berger effect, auditory evoked-response potentials and visual steady-state responses.

1) *Berger effect*

The power of occipital EEG spectra at frequencies 8-13 hertz (alpha band) is considerably lower when the eyes are open than when the eyes are closed, known as the Berger effect. Fig. 3 displays the spectra of the two tasks, and Fig. 4 displays their ratio (relative spectra), in an occipital channel for all signals. The amplitude reduction around 10 hertz with the eye open is clear.

Statistical analysis revealed no significant differences between any pair of EMG-contaminated, EMG-free and pruned signals. This result is consistent with none of the pruning approaches substantially affecting measurement of this low frequency cognitive response.

2) *Auditory oddball*

Fig. 5 shows the average evoked-response potentials in an oddball task. The brain responses to any tone (N1/P2

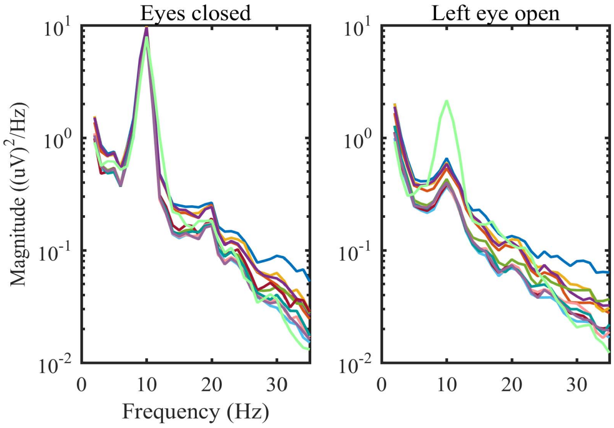

Fig. 3. Average of six subjects' eyes closed spectra (left) and eye open spectra (right) at Oz. Alpha activity, the peak around 10 Hz, is noticeably smaller with the eye open. Note that the spectra the EMG-free data was recorded at a different time while all the pruned spectra are from EMG-contaminated data. Refer to Fig. 4 for legend.

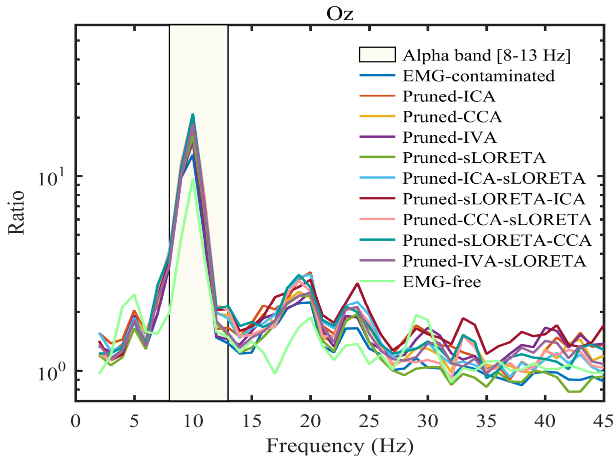

Fig. 4. Average of six subjects' relative power spectra (eyes closed to eyes open) at Oz. Alpha activity, the power at frequencies 8-13 Hz, is not statistically significantly different in any pair of EMG-contaminated, EMG-free, and pruned signals.

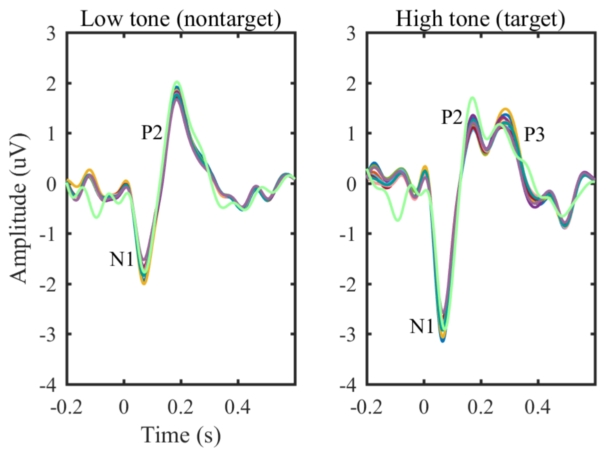

Fig. 5. Average evoked-response potentials (ERPs) to the non-target low tone (left) and the target high tone (right) at Fz in an oddball task. N1/P2 complex is retained in all prunings in both cases, as is the P3 neural response to the target. Refer to Fig. 4 for legend.

ISBN 978-90-827970-1-5 © EURASIP 2018

complex) and to target tones (P3) are apparent in all traces. Statistical analysis shows no significant difference in the amplitudes of N1, P2, and P3 between all pairs of EMG-contaminated, EMG-free and pruned signals.

3) Photic stimulation

The brain response to photic stimulation at a specific frequency is a peak in power spectra at the same frequency. Fig. 6 shows the average of power spectra in photic stimulation tasks (strobe at 16 hertz, 40 hertz and 59 hertz with eyes closed) at Oz. The statistical analysis reveals no significant difference between any pairs of EMG-contaminated, EMG-free and pruned signals at any of the stimulation frequencies. These observations are consistent with all pruning approaches reducing cranial muscle contamination while retaining brain activity.

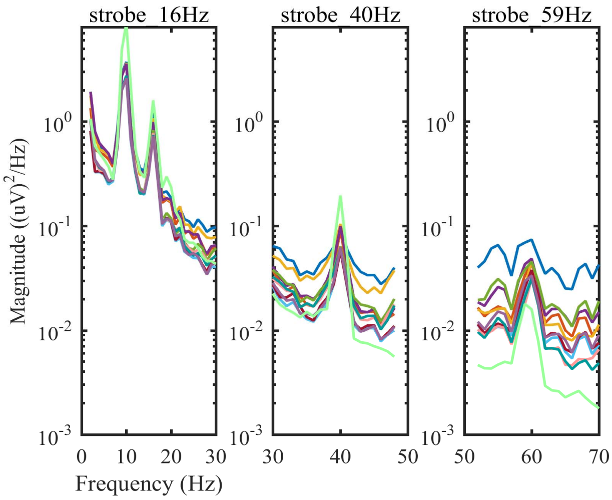

Fig. 6. Averaged of six subject's power spectra at Oz in response to photic simulation at 16 hertz, 40 hertz and 59 hertz. The amplitude of the steady state response is retained. Refer to Fig. 4 for legend.

IV. CONCLUSION

Muscle components typically have spectra that increase between 7 and 75 hertz, whereas brain components' spectra decrease in this frequency band. Hence components derived by BSS approaches can be separated based on their spectral characteristics. Additionally, the beamforming technique has location information, hence muscle sources can be discarded based on their location. So, these two approaches, using different features, can complement each other. We tested this using data from paralysed subjects, which provides an EMG-free ideal to compare to. In almost every comparison, the combined approaches reduced muscle artefact statistically significantly more than any single approach. Moreover, the muscle reduction at lower frequency bands was sufficient to yield signals that were not statistically significantly different to EMG-free signals. This significant result was achieved without affecting the measurement of brain activity, as brain neurophysiological responses were retained.

REFERENCES

[1] M. J. Fu, J. J. Daly, and M. C. Cavusoglu, "A detection scheme for frontalis and temporalis muscle EMG contamination of EEG data," *analysis,* vol. 5, p. 6, 2006.

[2] I. I. Goncharova, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "EMG contamination of EEG: spectral and topographical characteristics," *Clinical Neurophysiology,* vol. 114, no. 9, pp. 1580-1593, 2003.

[3] J. A. Urigüen and B. Garcia-Zapirain, "EEG artifact removal—state-of-the-art and guidelines," *Journal of neural engineering,* vol. 12, no. 3, p. 031001, 2015.

[4] S. P. Fitzgibbon, D. DeLosAngeles, T. W. Lewis, D. M. Powers, E. M. Whitham, J. O. Willoughby *et al.*, "Surface Laplacian of scalp electrical signals and independent component analysis resolve EMG contamination of electroencephalogram," *Int J Psychophysiol,* vol. 97, no. 3, pp. 277-84, Sep 2015.

[5] W. J. Freeman, M. D. Holmes, B. C. Burke, and S. Vanhatalo, "Spatial spectra of scalp EEG and EMG from awake humans," *Clinical Neurophysiology,* vol. 114, no. 6, pp. 1053-1068, 2003.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, and S. Van Huffel, "Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram," *IEEE transactions on Biomedical Engineering,* vol. 53, no. 12, pp. 2583-2587, 2006.

[12] J. Karhunen, T. Hao, and J. Ylipaavalniemi, "A generalized canonical correlation analysis based method for blind source separation from related data sets," in *Neural Networks (IJCNN), The 2012 International Joint Conference on*, 2012, pp. 1-9: IEEE.

[13] X. Chen, H. Peng, F. Yu, and K. Wang, "Independent Vector Analysis Applied to Remove Muscle Artifacts in EEG Data," *IEEE Transactions on Instrumentation and Measurement,* 2017.

[14] J. F. Hipp and M. Siegel, "Dissociating neuronal gamma-band activity from cranial and ocular muscle activity in EEG," *Frontiers in human neuroscience,* vol. 7, p. 338, 2013.

[15] A. S. Janani, T. S. Grummett, T. W. Lewis, S. P. Fitzgibbon, E. M. Whitham, D. DelosAngeles *et al.*, "Evaluation of a minimum-norm based beamforming technique, sLORETA, for reducing tonic muscle contamination of EEG at sensor level," *Journal of neuroscience methods,* vol. 288, pp. 17-28, 2017.

[16] 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.

[17] A. S. Janani, T. S. Grummett, T. W. Lewis, S. P. Fitzgibbon, E. M. Whitham, D. DelosAngeles *et al.*, "Improved artefact removal from EEG using Canonical Correlation Analysis and spectral slope," *Journal of neuroscience methods,* vol. 298, pp. 1-15, 15 March 2018.

[18] J. Laney, K. P. Westlake, S. Ma, E. Woytowicz, V. D. Calhoun, and T. Adalı, "Capturing subject variability in fMRI data: A graph-theoretical analysis of GICA vs. IVA," *Journal of neuroscience methods,* vol. 247, pp. 32-40, 2015.