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Automatic determination of EMG-contaminated components and validation of independent component analysis using EEG during pharmacologic paralysis

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HIGHLIGHTS

- We present a conceptually simple, spectral-based, heuristic to automatically identify independent components that are predominantly EMG.
- Spectra with slopes above a certain threshold are used to define EMG-contaminated components, which are then removed.
- We validate its effectiveness using EMG-free data recorded under pharmacological neuromuscular paralysis.

ABSTRACT

Objective: Validate independent component analysis (ICA) for removal of EMG contamination from EEG, and demonstrate a heuristic, based on the gradient of EEG spectra (slope of graph of log EEG power vs log frequency, 7–70 Hz) from paralysed awake humans, to automatically identify and remove components that are predominantly EMG.
Methods: We studied the gradient of EMG-free EEG spectra to quantitatively inform the choice of threshold. Then, pre-existing EEG from 3 disparate experimental groups was examined before and after applying the heuristic to validate that the heuristic preserved neurogenic activity (Berger effect, auditory odd ball, visual and auditory steady state responses).
Results: (1) ICA-based EMG removal diminished EMG contamination up to approximately 50 Hz, (2) residual EMG contamination using automatic selection was similar to manual selection, and (3) task-induced cortical activity remained, was enhanced, or was revealed using the ICA-based methodology.
Conclusion: This study further validates ICA as a powerful technique for separating and removing myogenic signals from EEG. Automatic processing based on spectral gradients to exclude EMG-containing components is a conceptually simple and valid technique.
Significance: This study strengthens ICA as a technique to remove EMG contamination from EEG whilst preserving neurogenic activity to 50 Hz.

1. Introduction

Because of its non-invasive nature, its high-temporal resolution, and its comparative low-cost, the scalp-recorded

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electroencephalogram (EEG) is an important diagnostic and research tool in humans. Unfortunately, cerebral activity measured by scalp sensors is highly susceptible to contamination by biological artefacts such as electromyogram (EMG), electro-oculogram (EOG) and electrocardiogram (ECG), and non-biological contaminants such as 50 Hz or 60 Hz electromagnetic line interference.

There exist methods for dealing with some forms of contamination. For example, EOG artefacts can be filtered from scalp recordings using a variety of correction techniques (Gratton, 1998), and line interference can be removed by notch-filters. Similarly, it is common practice to discard data in periods of time where overt movement (e.g., eye movement, swallowing, coughing) causes transient high amplitude EMG signals that dominate the scalp recordings.

Of greater difficulty is persistent EMG contamination that is always present due to continuous, variable and usually mild contraction of the postural muscles and the muscles of facial expression (Goncharova et al., 2003) and jaw (Yilmaz et al., 2014). Persistent EMG contamination shares the same spectral and spatial characteristics as transient EMG contamination caused by overt movement, but is of lower power and cannot reliably be identified visually in scalp recordings. In addition to persistent EMG, all mental efforts are likely to increase EMG activity and any task requiring a motor response will be further confounded by non-specific cranial muscle activation associated with movements such as keypresses and saccades (Whitham et al., 2008). Quantification of persistent EMG (Whitham et al., 2007, 2008; Pope et al., 2009; Yilmaz et al., 2014) demonstrates that: (1) EMG begins to have an impact on spectra from frequencies below 20 Hz; (2) in the important 20–80 Hz range (Engel et al., 1992; Aoki et al., 1999; Bertrand and Tallon-Baudry, 2000), EMG exceeds EEG power 10-fold; and (3) in circumferential scalp electrodes, by 100 Hz, EMG power can exceed EEG power by more than 200 fold. Furthermore, single motor unit potentials, e.g., in temporalis muscle, can be detected in electrodes across the scalp, including circumferentially (Whitham et al., 2007, 2008; Pope et al., 2009; Yilmaz et al., 2014). In short, non-time-locked beta and gamma EEG cannot reliably be measured in humans.

The class of algorithms known as independent component analysis (ICA) is effective at separating signals from an arithmetic mixture of signals using higher-order statistical properties (Delorme and Thorpe, 2001; Delorme et al., 2007; Fitzgibbon et al., 2007). ICA identifies electrical signals that appear at different amplitudes in multiple electrodes and which are statistically independent (as used here in a temporal, not a spatial sense) from other signals; ideally each electrical signal corresponds to a separate source. Standard ICA algorithms produce the same number of sources as input signals, here, EEG channels. The ICA de-mixed activity of a 20-channel scalp recording looks like a 20-channel recording, except that each 'channel', now an independent component (IC), has characteristics more like clean EEG, or EMG, or ECG, or eye-movement, etc. If the ICs that are EEG-like are remixed in the proportion that they were found in the original channels (their weights), and the other non-EEG-like channels discarded, EEG is obtained as if recorded with the non-EEG sources absent. The approach is widely-accepted as a method for separating neurogenic and myogenic signals (Jung et al., 1998a,b, 2000; Fitzgibbon et al., 2007) and other contaminants (Delorme and Thorpe, 2001; Delorme et al., 2007; Fitzgibbon et al., 2007; Viola et al., 2009).

EMG removal depends on two key steps; (1) the ability of the algorithm to reliably produce signals that are, exclusively or mainly, EEG or EMG, and (2) the ability of the investigator to identify which signals are of brain origin and which are contaminant. Correct identification of the origin of the separated ICs typically combines visual inspection with heuristics based on known characteristics of the signal types. Furthermore, most heuristics seek to identify transient EMG associated with overt muscle contraction. Persistent EMG contamination is a largely ignored or underappreciated problem.

Here we evaluate a conceptually simple heuristic for identifying persistent EMG, based on the gradient of the power spectrum of ICs. EEG spectral power is commonly accepted to decrease with frequency at a rate of approximately 1/frequency, extensively discussed in Buzsaki (2006), although $1/f^2$ spectra have been identified in intracranial recordings broadening the spectral character of EEG (Milstein et al., 2009). Conversely, spectral power of muscle in the 10–70 Hz range increases with frequency (Goncharova et al., 2003). In this study, we tested a heuristic that excludes ICs with spectral gradients greater than a certain threshold. Specifically, components with spectra whose power decreases faster than the threshold are kept, whilst components where spectral power decreases slower than the threshold are rejected as being predominantly EMG. We utilise EEG data from unparalysed and paralysed subjects to quantitatively evaluate the choice of the gradient threshold. We evaluate this heuristic for the identification and removal of persistent EMG components in normal scalp recordings and show that the removal of components contaminated with EMG does not degrade cortical signals.

2. Methods

2.1. Experimental plan

Existing data from three healthy experimental groups, all utilised in prior publications (Whitham et al., 2007, 2008; DeLosAngeles, 2010), were used to calibrate and validate the EMG pruning procedure. The first group (dataset 1, from Whitham et al., 2007) comprised subjects who had EEG recorded during eyes-closed, eye-open, auditory oddball testing (Picton, 1992), and photic stimulation-induced steady state EEG responses (Herrmann, 2001) before and after total neuromuscular paralysis, thus providing EMG-contaminated (unparalysed) and EMG-free (paralysed) EEG data. The recording of tasks when unparalysed preceded recording of tasks when paralysed by approximately 20 min. The second group (dataset 2, from DeLosAngeles, 2010) had EEG recorded during auditory steady-state stimulation and the third group (dataset 3, from Whitham et al., 2008) was a large sample of healthy participants ($n = 93$) who had EEG recorded during eyes opened and closed. The second and third groups were not paralysed and therefore only provided EMG-contaminated EEG data. The Clinical Research Ethics Committee of the Flinders University and Flinders Medical Centre approved all experiments and all subjects gave written informed consent.

We examined all three datasets before and after applying the automatic EMG-removal procedure and compared the brain signals (power spectra, alpha responsiveness to eye-opening, auditory oddball responses, visual or auditory steady state responses) from EMG decontaminated data to EMG contaminated data to determine if the EMG-removal process had also eliminated brain signals. In dataset 1 we were also able to compare brain signals after EMG decontamination with EMG-free data recorded under paralysis. For datasets 1 and 2 we also included data that were decontaminated using a manual ICA procedure and confirmed its effectiveness. Manual pruning of dataset 3 would have been impractically laborious; however, we were easily able to apply the automatic pruning procedure and compare the brain signals from decontaminated to contaminated data.

2.2. Dataset 1: baseline state, photic stimulation and oddball paradigm

The subject demographics and EEG parameters for dataset 1 are detailed in Table 1. Scalp recordings were obtained from subjects