A Comparison of Independent Component Analysis Algorithms and Measures to Discriminate between EEG and Artifact Components

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Abstract— **Independent Component Analysis (ICA) is a powerful statistical tool capable of separating multivariate scalp electrical signals into their additive independent or source components, specifically EEG or electroencephalogram and artifacts. Although ICA is a widely accepted EEG signal processing technique, classification of the recovered independent components (ICs) is still flawed, as current practice still requires subjective human decisions. Here we build on the results from Fitzgibbon et al. [1] to compare three measures and three ICA algorithms. Using EEG data acquired during neuromuscular paralysis, we tested the ability of the measures (spectral slope, peripherality and spatial smoothness) and algorithms (FastICA, Infomax and JADE) to identify components containing EMG. Spatial smoothness showed differentiation between paralysis and pre-paralysis ICs comparable to spectral slope, whereas peripherality showed less differentiation. A combination of the measures showed better differentiation than any measure alone. Furthermore, FastICA provided the best discrimination between muscle-free and muscle-contaminated recordings in the shortest time, suggesting it may be the most suited to EEG applications of the considered algorithms. Spatial smoothness results suggest that a significant number of ICs are mixed, i.e. contain signals from more than one biological source, and so the development of an ICA algorithm that is optimised to produce ICs that are easily classifiable is warranted.**

I. INTRODUCTION

EEG recordings measure the electrical activity on the scalp, hence the sensor signals are a cumulative sum of signals of neural origin (EEG) superimposed with activity from various non-neural sources, i.e. artifacts. Removal of such artifacts has been shown to greatly improve data interpretation and analysis, as it allows the underlying cerebral activity to be more easily detected and understood [2]. One commonly used technique for the removal of artifacts is Independent Component Analysis (ICA), a statistical method that exploits independence to isolate sources from the measured source mixtures [3].

Though using ICA for artifact removal is widely accepted, there is presently no proven automated classification of ICs [4]. Manual and semi-automated methods of classification are subjective and time consuming and there is no "truth" available to verify the decisions. To address these issues, fully automated classification methods have been developed, and comparisons are made to expert decisions [5, 6].

A promising new automated approach is the spectral slope algorithm [1], which identifies EMG contaminated components by measuring the slope of each IC's power spectrum. Using an EMG-free dataset of scalp recordings collected under neuromuscular paralysis, a maximum slope of ICs that do not contain muscle can be identified. ICs from EMG-contaminated datasets with higher slopes are therefore presumed to contain EMG. Automated artifact removal using spectral slope was shown to preserve and/or enhance the detection of expected neurogenic activity; reduce spectral power in typical EMG frequencies to approach the spectral power seen in EMG-free data; and generally produce results comparable to manual classification [1].

Here we further explore the development of automatic component classification methods. We present two new measures (peripherality and spatial smoothness), and compare them to the spectral slope algorithm. This is performed for three different ICA algorithms (FastICA, Infomax and JADE) to determine which algorithm is best suited to EEG component classification.

II. METHODS

A. EEG Data

Two datasets comprising of paralysis and pre-paralysis data were used to compare the measures and algorithms. They consisted of 115 channels of continuous EEG (5 kHz sampling), using a left ear reference [7].

Specifically, this data contains EEG recordings taken from six subjects performing six tasks: resting eyes-open, resting eyes-closed, photic stimulation at 16 Hz, oddball testing, a mental arithmetic task and an auditory discrimination task [7]. Tasks were performed without paralysis, then repeated under neuromuscular paralysis [7].

B. Processing

Data were processed using programs written in Matlab (The Mathworks, Natic, MA, USA). Scalp channels were

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relabelled to the international 10-5 system [8] and analysed separately using three ICA algorithms: Joint Approximate Diagonalization of Eigenmatrices (JADE) [9, 10], Information Maximization (Infomax) [11, 12] and FastICA [13, 14]. Task data were concatenated to provide sufficient data for reliable calculation of components. Three measures that may discriminate between neural and artifact components were calculated.

1) Spectral Slope

Spectral slope [1] measures the gradient (straight line fit) of the log-log power spectrum of an IC between 7 and 75 Hz, a putative frequency range for muscle. ICs of muscular origin are expected to have positive slopes, whereas ICs of neural origin are expected to have negative slopes [15].

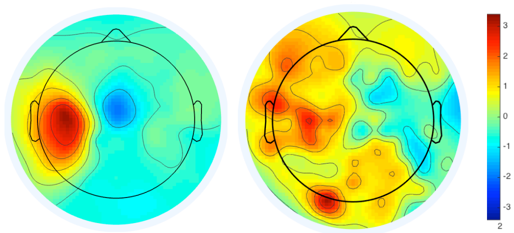

Figure 1. Scalp topographies or spatial maps of (left) a component with a peripherally-originating source, and (right) a mixed component.

2) Peripherality

Columns of the mixing matrix specify the strength of an IC in each electrode, and can be displayed as scalp topographies (Figure 1). Weighting these strengths by the distance of an electrode from the vertex of the head and summing gives a measure that will be large for sources that originate near the periphery of the cap, and be small for sources that originate near the centre of cap. Figure 1 (left) shows a peripheral source, likely of muscular origin. To account for phase reversals and the scaling ambiguity of components, the absolute value of the strengths were normalised before the weighted summation.

3) Spatial Smoothness

The number of sources (neural plus artifactual) in scalp recordings is large, almost certainly exceeding the number of electrodes [1]. Hence at least some ICs will be a mixture of sources rather than a single source. Such ICs will have scalp topographies that do not have a single focus, such as Figure 1 (right). Whether to retain or discard such components is unclear, and may depend on the application. However, identifying such components would seem to be valuable.

Spatial smoothness computes the relative difference in magnitude between pairs of electrodes weighted by the distance between the electrodes, and sums over all pairs. It is expected that heavily mixed sources will have large local variations in magnitude and hence a large value for spatial smoothness, whereas components with a single source will have small local variations and hence a small value for spatial smoothness.

III. Results

Execution time for ICA algorithms is often significant. Here we found JADE was the fastest, FastICA took approximately 1.5 times as long as JADE, and Infomax took approximately 5 times as long as JADE.

Figure 2 shows histograms of the three measures for pre-paralysis (orange) and paralysis (blue) on all ICs using FastICA. Figure 3 shows broadly similar results for Infomax. The results for JADE, Figure 4, are similar for spectral slope but less clear for the other two measures.

The spectral slope result is similar to that in Fitzgibbon et al. [1], showing the spectral slope of a significant number of pre-paralysis ICs exceeding the spectral slope of (almost) all paralysis ICs. Pre-paralysis ICs generally show larger values for peripherality, though the difference between the histograms is less than for spectral slope. Paralysis ICs have clearly smaller values of spatial smoothness (i.e. have smoother topographies) than pre-paralysis ICs.

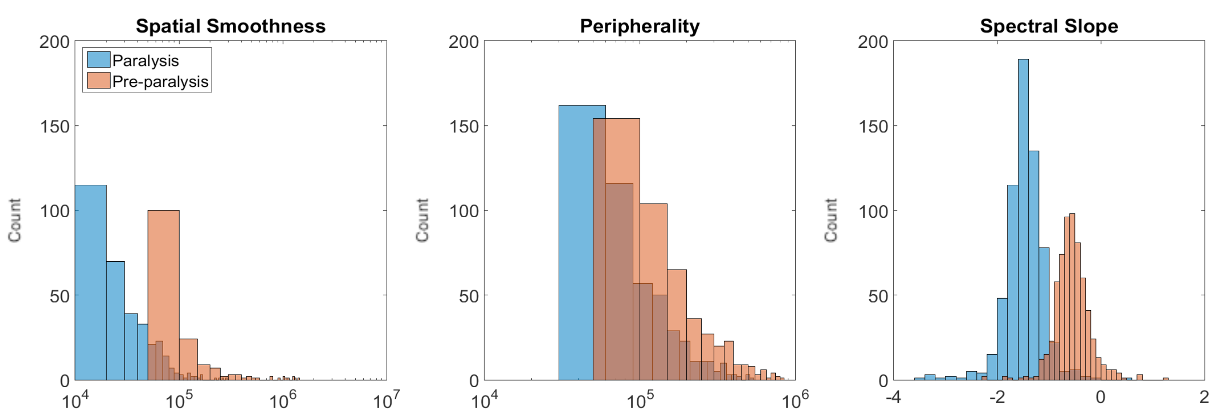

Figure 2. Histograms of (left) spatial smoothness, (centre) peripherality, and (right) spectral slope measures of ICs calculated using FastICA. EMG-contaminated data is shown in orange, whilst EMG-free data is shown in blue.

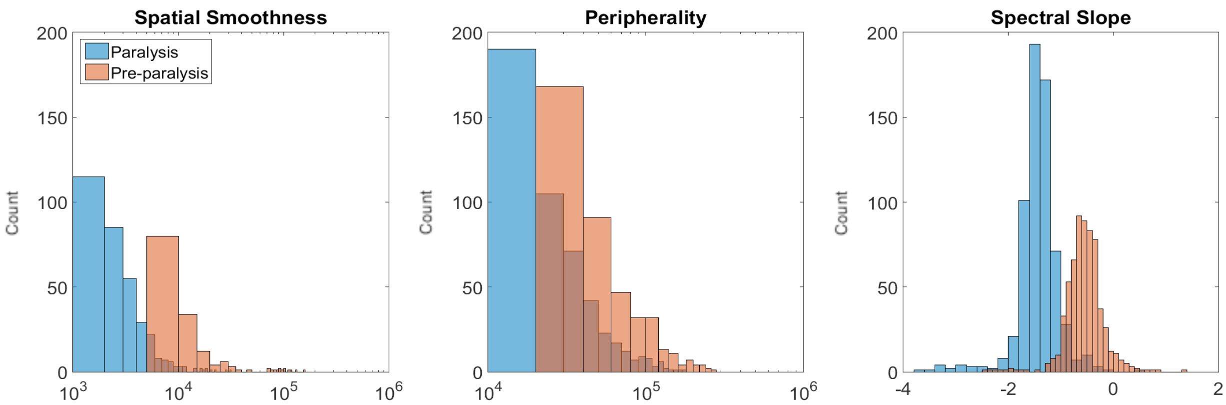

Figure 3. Histograms of (left) spatial smoothness, (centre) peripherality, and (right) spectral slope measures of ICs calculated using INFOMAX. EMG-contaminated data is shown in orange, whilst EMG-free data is shown in blue.

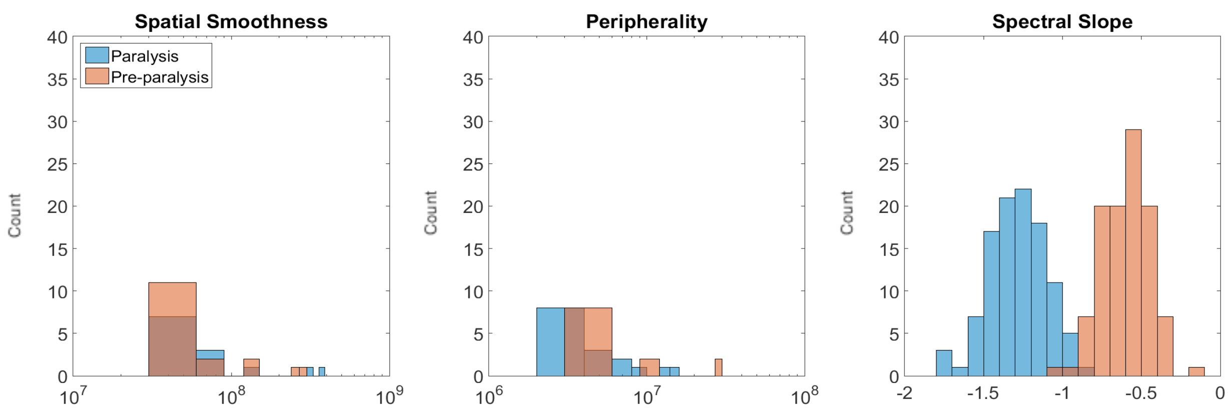

Figure 5. Histograms of (left) spatial smoothness, (centre) peripherality, and (right) spectral slope measures of ICs calculated using JADE. EMG-contaminated data is shown in orange, whilst EMG-free data is shown in blue.

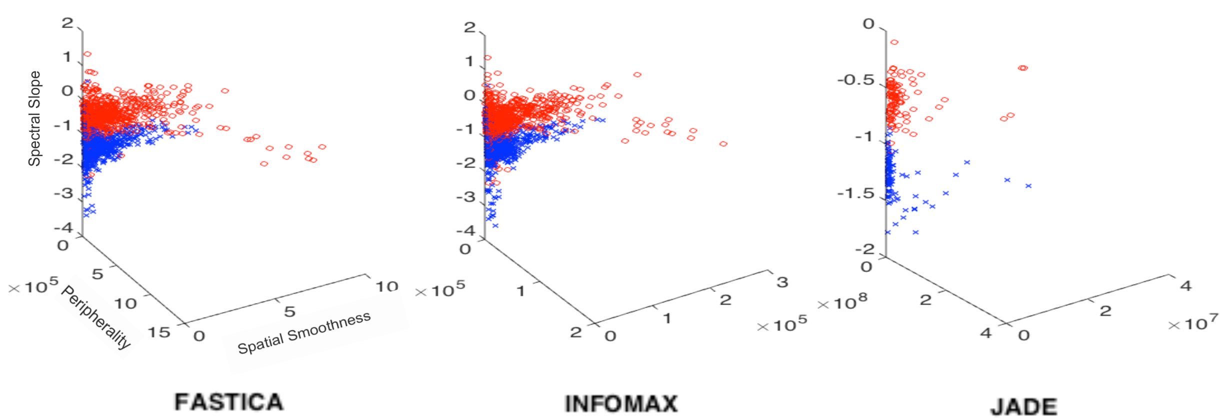

Figure 4. Scatter plots for (left) FastICA, (centre) Infomax and (right) JADE. EMG-contaminated values are shown in red, and EMG-free in blue.

Figure 5 (left) shows a scatter plot of the three measures for pre-paralysis ICs (red circles) and paralysis ICs (blue crosses) for FastICA. Figure 5 (centre) and (right) show similar scatter plots for Infomax and JADE respectively. The extension of the red circles beyond the blue crosses to the right corresponds to the proposed thresholding of Fitzgibbon et al. [1]. A non-vertical threshold would correspond to using information from all three measures, and could be chosen to select more ICs than just using spectral slope alone.

IV. DISCUSSION

The results for FastICA and Infomax are quite similar, suggesting equivalent performance of the two algorithms. Given the difference in execution times, FastICA would be preferred. The results for JADE suggest that the resultant ICs were more mixed than for the other algorithms. It may be possible to improve the unmixing by adjusting convergence parameters of the algorithm, at the cost of extended execution time, though this was not investigated.

From the histograms for FastICA and Infomax, spatial smoothness looks as if it could produce similar EMG-identification results as spectral slope. Peripherality exhibits a greater overlap in the histograms of pre-paralysis and paralysis ICs, and so would be unlikely to achieve as good performance. This is consistent with neural sources being both close to the center of the head and at the periphery of the cap (e.g. temporal and occipital cortices), whereas muscular sources will be at the periphery.

However, the scatter plots provide evidence that the combination of all three measures is likely to achieve better results than a single measure. For example, a low smoothness provides evidence for an IC being a single source, and spectral slope can then provide evidence of whether it is of neural or muscular origin.

It is worth noting that as the paralysis dataset is comprised of EMG-free and EMG-contaminated data, a quantitative assessment of how well the measures classify artifactual components of muscular origin can be made. However the assessment of artifacts of non-muscular origin cannot be facilitated by the dataset. Objective identification of non-muscular artifact, e.g. ocular, cardiac, non-biological, is still an open question.

V. FUTURE WORK

An important next step would be to combine multiple measures to achieve more "pruning" of EMG contamination without compromising the retention of neural activity. Fitzgibbon et al. [1] shows that using spectral slope alone does not result in spectra approaching that of paralysis data.

The ICA algorithms tested here all utilize higher-order statistics to measure the independence of the ICs. Several other ICA algorithms use temporal correlations, e.g. SOBI [16], or a combination of higher-order statistics and temporal correlations, e.g. TCHOBI [17]. A difficulty in using these algorithms is that the input data must be uniformly sampled without breaks, i.e. the temporal correlations cannot be disturbed. This may make it difficult to find sufficient data for reliable convergence of the algorithms, particularly if the number of electrodes is large. This is the reason these algorithms were not included. We suggest a more thorough comparison should include these algorithms.

The more challenging aim would be to integrate the use of the measures into the ICA algorithm itself and develop a new ICA algorithm or algorithms that are optimized to produce outputs that are not only independent, but are also more clearly of sources of only one type, e.g. neural, muscular, ocular etc. Such an algorithm would be of significant benefit in opening up the use of EEG in many areas, e.g. brain-computer interfaces where artifact currently limits its application, particularly if such an algorithm can run in real time.

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