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Research article

A practical guide to the selection of independent components of the electroencephalogram for artifact correction

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ABSTRACT

Background: Electroencephalographic data are easily contaminated by signals of non-neural origin. Independent component analysis (ICA) can help correct EEG data for such artifacts. Artifact independent components (ICs) can be identified by experts via visual inspection. But artifact features are sometimes ambiguous or difficult to notice, and even experts may disagree about how to categorise a particular component. It is therefore important to inform users on artifact properties, and give them the opportunity to intervene.
New Method: Here we first describe artifacts captured by ICA. We review current methods to automatically select artifactual components for rejection, and introduce the SASICA software, implementing several novel selection algorithms as well as two previously described automated methods (ADJUST, Mognon et al. Psychophysiology 2011;48(2):229; and FASTER, Nolan et al. J Neurosci Methods 2010;48(1):152).
Results: We evaluate these algorithms by comparing selections suggested by SASICA and other methods to manual rejections by experts. The results show that these methods can inform observers to improve rejections. However, no automated method can accurately isolate artifacts without supervision. The comprehensive and interactive plots produced by SASICA therefore constitute a helpful guide for human users for making final decisions.
Conclusions: Rejecting ICs before EEG data analysis unavoidably requires some level of supervision. SASICA offers observers detailed information to guide selection of artifact ICs. Because it uses quantitative parameters and thresholds, it improves objectivity and reproducibility in reporting pre-processing procedures. SASICA is also a didactic tool that allows users to quickly understand what signal features captured by ICs make them likely to reflect artifacts.

1. Introduction

The electroencephalogram (EEG) recorded from electrodes placed on the scalp can provide information about underlying brain activity, but attempts to interpret the recorded signal are invariably hindered by the presence of artifacts, i.e. electrical signals of non-neural origin.

One major issue in interpreting scalp EEG is that the signal recorded at each electrode reflects a mixture of several sources of activity of various origin within and outside of the brain. A widely used method that allows one to isolate and subtract independent sources of activity is independent component analysis (ICA). This method has been introduced to EEG analysis by Makeig et al. (1996), and popularized in the EEGLAB (Delorme and Makeig, 2004), a widely used software package running under MATLAB (The Mathworks). ICA allows isolation of statistically independent sources, called independent components (ICs) as linear combinations of electrodes. Each IC is characterized by a topography (set of inverse weights, describing the projection of the independent source onto the electrode cap), and a time course, which can be thought of as the signal that would have been recorded with an electrode located directly at that source. Because ICs are linear combinations of the original electrode signal, they can be treated in many respects like single electrodes. In particular, they can be subtracted easily from the signal just like one would discard a bad electrode after recording. After removal of a bad electrode, the signal is free of the artifacts that occurred at that electrode. Likewise, after subtraction of an artifactual IC, the remaining signal is free from artifacts that were captured entirely by that IC.

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This method of component subtraction is widely used to remove artifacts such as eye blinks or muscle activity from EEG recordings (e.g. Delorme et al., 2007; Jung et al., 2000a,b; Mantini et al., 2007; McMenamin et al., 2010; Urrestarazu et al., 2004). Some ICs capture a large amount of non-brain sources that recur in the signal, such as eye and muscle movements, heart beats, high impedance electrodes, or line noise (Jung et al., 2000a). However, although visualisations of IC activations and the effect of their subtraction make a compelling case for the usefulness of this approach in separating artifacts from neural signal, it is usually left to the user to scrutinise the ICA output and judge which ICs capture artifacts. Although selecting artifact ICs should be based on objective criteria, a comprehensive review of the signal features present in classical artifact types is to our knowledge missing in the literature. We will here define and illustrate precisely the features of the most common artifact types, and explain how these features are reflected in various statistical measures that can be computed on ICs, in order to provide investigators with a proper means of deciding which ICs capture artifacts and which ones do not.

The features of artifactual ICs can be visualized using various representations. EEGLAB offers a number of handy visual representations of IC properties that allow a trained observer to accurately identify artifactual ICs, but some features are not immediately obvious from these representations and time-consuming scrutiny and extensive experience is required. A number of automated procedures exist (e.g. Campos Viola et al., 2009; Delorme et al., 2007; Mognon et al., 2011; Nolan et al., 2010; Winkler et al., 2011) that compute objective statistical measures from ICs, and use these measures to automatically decide whether a component is artifactual or not. However, because of the high variability in EEG signals, these methods are inevitably prone to type I and type II errors. Furthermore, although some artifacts are unequivocally considered a nuisance (e.g. badly connected electrode noise), and have to be removed from the signal before analysis, others may be more controversial (e.g. Olbrich et al., 2011), and not every experimenter may want to discard them. We thus promote here an intermediate method, using the objective measures computed by several methods and enhanced EEGLAB visual representations to allow users to decide whether or not individual ICs reflect artifacts and need to be removed from the data or not.

In this paper, we first describe the relevant signal features related to the most common EEG artifacts – ocular artifacts, tonic muscle artifacts, loose electrode connections (high impedance), and exceptional high amplitude events – and show how these features can be mapped onto a number of visually recognizable attributes in visual representations of the signal and on objective statistical features of the signal. Some of these measures have been introduced before in plugins for EEGLAB (ADJUST Mognon et al., 2011; and FASTER Nolan et al., 2010). Second, we introduce the SASICA plugin (Semi-Automated Selection of Independent Components of the electroencephalogram for Artifact correction) for EEGLAB that provides a convenient visualization of all of these measures and allows refining selections manually if needed (Fig. 1). We thereby provide the user with all required information for understanding the reasons why a given component might be removed from the data. Finally, we evaluate all methods against expert classifications for a total of 21 experimental datasets, and illustrate the impact of (in)appropriately identifying and removing artifactual components on signal quality.

2. Methods

2.1. Signals captured by ICA

Several categories of signals are readily isolated by single ICs. Specifically, ICs can capture (1) a source of neural activity, (2) variations of potential due to blinks, (3) eye movements (saccades), (4) muscle contraction, or (5) line noise or a misconnected (high impedance) electrode, commonly referred to as a “bad channel”.

Importantly, ICA may also fail to separate signals, and many components (often a majority) do not fit a single category. In essence, separating distinct classes of ICs is thus a signal detection problem in which the experimenter needs to avoid two mistakes: missing to-be-detected artifact ICs (type II error) and falsely reporting other non-artifactual ICs (type I error). In the context of artifact correction, the former mistake would imply under-correction while the latter would imply over-correction. Another challenge is to solve this task using objective criteria that can be readily communicated, for example in publications.

All automated methods reviewed here have their own heuristic to identify at least some of these ICs. In the following, we describe all the features of each category of IC, as well as a number of statistical measures designed to reveal these features. We include measures computed by SASICA, CORRMAP (Campos Viola et al., 2009), ADJUST (Mognon et al., 2011), and FASTER (Nolan et al., 2010). We present a summary of all measures offered by these methods in Table 1. We refer the interested reader to the original papers for details on each method.

2.1.1. Neural activity

The success of ICA in EEG analysis is largely due to the plausibility of the solution returned by ICA. Indeed, in most cases, when performed on a full-rank long enough dataset, the topography and time course of at least a handful of components compellingly allow identifying them as capturing selective neural activity. These components are often dipolar, i.e. they are well modeled by one, or sometimes two, dipolar sources (Delorme et al., 2012), and their topography is regular and smooth. Moreover, they often rank amongst the strongest components in the dataset (i.e. those explaining most variance in the signal, and sorted first in EEGLAB), they often contain a peak at physiological frequencies (e.g. alpha, beta, delta or theta), and may show a strong evoked response to sensory stimuli. These properties are listed in Fig. 2A for reference.

The dipolar nature of the components can be measured by first fitting a dipolar source to the component (as implemented in the DIPFIT toolbox distributed with EEGLAB; applied to all components of all datasets tested in this article), and then measuring the residual variance after removing the fitted data. Residual variance is often very low for accurately modeled components (see results, Fig. 2B-D). Therefore, this measure is used routinely within EEGLAB to select neural components for analyses conducted on component time courses. However, it should be noted that some components with low residual variance may be artifactual. For instance blink or saccade components can be very well modeled by dipoles placed in the eyes of the subjects (see Fig. 3A, 5% residual variance of a dipole fit, see Section 2.2.2.5 on residual variance for explanation). Some pure tonic muscle components may also be well modeled by a dipole placed close to the scalp, where muscular activity arises (e.g. Fig. 4B, 9% residual variance). Furthermore, several spatially separated sources of neural activity working in synchrony will not be well modeled by a dipole (e.g. Fig. 2E, 31% residual).

It is often the case that components neatly isolating neural activity rank amongst the first twenty components in a dataset. This feature is an empirical observation that has to our knowledge not been measured so far. In the 8 training datasets used in this article, 50% of the components rated as neural by the experts ranked amongst the 13% largest components. Nevertheless, artifacts can also be of strong amplitude (e.g. blinks), so this feature may not be discriminant for deciding whether a component is neural or artifactual.

ICs capturing neural activity often contain a peak in the Alpha (8–12 Hz, Fig. 2B), Beta (15–30 Hz, Fig. 2C), delta (1–4 Hz), or Theta