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Simultaneous EEG and fMRI: Recording, Analysis, and Application

Markus Ullsperger (ed.), Stefan Debener (ed.)

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CHAPTER

3.1 3.1 Using ICA for the Analysis of Multi-Channel EEG Data

Stefan Debener, Jeremy Thorne, Till R. Schneider, Filipa Campos Viola

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Abstract

Independent component analysis (ICA) is a linear decomposition technique that aims to reveal the underlying statistical sources of mixed signals. The EEG signal consists of a mixture of various brain and non-brain contributions. Accordingly, a valid and powerful unmixing tool promises a better, more accessible representation of the statistical sources contributing to the mixed recorded signal. ICA, being potentially such a tool, may help in the detection of signal sources that cannot be identified on the raw data level alone using other, more conventional techniques. The application of ICA to EEG signals has become popular, as it provides two key features: it is a powerful way to remove artifacts from EEG data, and it helps to disentangle otherwise mixed brain signals. This chapter is concerned with evaluating and optimizing EEG decompositions by means of ICA. First, it discusses typical ICA results with reference to artifact- and brain-related components. Then, it elaborates on different EEG pre-processing steps, considered in light of the statistical assumptions underlying ICA. As such, the motivation for the chapter is to provide some practical guidelines for those researchers who wish to successfully decompose multi-channel EEG recordings.

Keywords: EEG data, independent component analysis, ICA, artifacts, unmixing, EEG-informed fMRI analysis

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Introduction

It has been known for several decades that electric potential recordings provide a wealth of information about brain function. Electroencephalogram (EEG) signals inform about various types of processes, from basic brain function via sensory processing to higher order cognition such as language, memory or awareness, to name a few. Accordingly, the EEG technique provides a "window of the mind" (Nunez and Srinivasan, 2006). However, what types of information the EEG signal might contain that can help us to advance our understanding of the relationship between mind, brain, and behavior is not well understood (Sauseng and Klimesch, 2008). Here we take the view that the statistical decomposition of multi-channel EEG signals provides an important means to gain a better recognition and understanding of the various types of processes that are reflected in the EEG signal. Specifically, this chapter is concerned with the application of independent component analysis (ICA) to EEG data. ICA is a linear decomposition technique that aims to reveal the underlying statistical sources of mixed signals. That the EEG signal consists of a mixture of various brain and nonbrain contributions can hardly be questioned. Accordingly, a valid and powerful unmixing tool promises a better, more accessible representation of the statistical sources contributing to the mixed recorded signal. ICA, being potentially such a tool, may therefore help in the detection of signal sources that cannot be identified on the raw data level alone using other, more conventional techniques. An example illustrating this claim is shown in Figure 3.1.1. Here, the electrical signal of an unborn baby's heartbeat was recovered from multi-channel electric potential recordings taken from a pregnant woman's abdomen. Note that the infant's heartbeat was not evident from the raw data, which was dominated by the mother's heartbeat. Neither was it recoverable using other techniques such as filtering or averaging. So, under favorable circumstances, ICA can identify even small signal sources that otherwise would be missed.

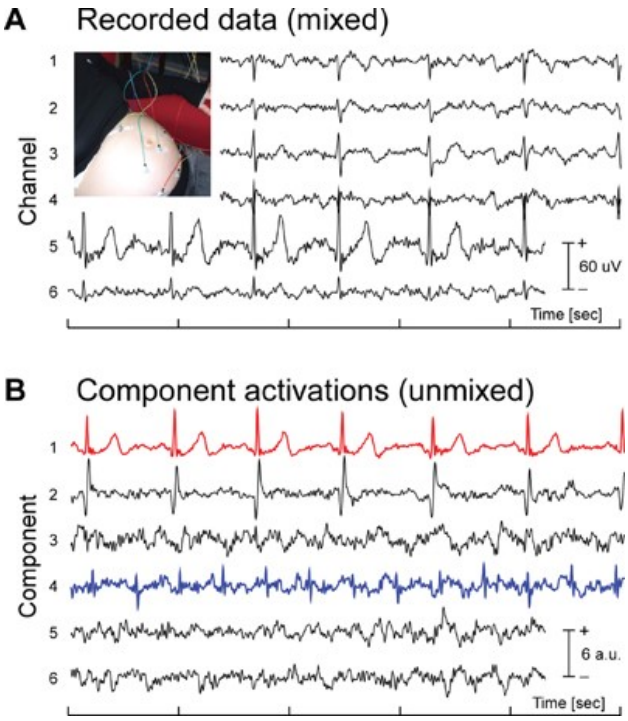

Figure 3.1.1. Example illustrating the blind decomposition of mixed multi-channel biopotential recordings into statistical sources. A: Data were recorded from six electrodes attached to a pregnant woman's abdomen. Shown is a 5-second section, dominated by the mother's electrical heartbeat activity. B: Same section of data after decomposition with ICA. Shown are maximally temporally independent time courses, with component 1, in red, reflecting the mother's electrical heartbeat activity, and component 4 reflecting the unborn baby's heartbeat that was not visible from the mixed channel recordings shown in A.

Excellent books covering the mathematical details and different implementations of ICA have been published (Hyvärinen et al., 2001; Stone, 2004); the application of ICA to multi-channel EEG recordings has been reviewed (Onton et al., 2006); and a conceptual framework for using ICA for the study of event-related brain dynamics exists (Makeig et al., 2004a). Indeed, the application of ICA to EEG signals has become popular, as it provides two key features: it is a powerful way to remove artifacts from EEG data (Jung et al., 2000a; Jung et al., 2000)b, and it helps to disentangle otherwise mixed brain signals (Makeig et al., 2002). In some fields of EEG research, such as EEG-fMRI integration, these two key characteristics have clearly fostered progress in the field (Debener et al., 2006). Not surprisingly, this book contains several chapters on ICA for EEG-fMRI integration, so the topic will not be considered further here. Instead, the present chapter is concerned with a more basic issue, namely, evaluating and optimizing EEG decompositions by means of ICA. We will first show typical ICA results and discuss these with reference to artifact- and brain-related components. After this we will discuss different EEG preprocessing steps, considered in light of the statistical assumptions underlying ICA. Accordingly, we will present examples showing that the quality of ICA decompositions depends at least partly on the adequate preprocessing of the EEG data and discuss examples that help to evaluate decomposition quality. As such, the motivation for this chapter is to provide some practical guidelines for those researchers who wish to successfully decompose multi-channel EEG recordings.

Basic ICA Model

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ICA decomposes multi-channel recordings into a weighted (linear) mixture of different processes or signal sources. Let us call the recorded EEG data a 2-D matrix X consisting of a number of channels (rows) and time points (columns). The outcome of a complete form of ICA is a square matrix W of the size of the number of channels. W enables the modeling, or recovery, of the independent component activity time courses, A, such that

$$A = WX \tag{1}$$

A is revealed by matrix multiplication of W with the raw data X and has the same size as X. However, A now refers to independent components (ICs), not channels, and the columns represent the activity profiles from ICs that are maximally temporally independent from each other. The recorded data X can be fully reconstructed by multiplication of the inverse of W with A. Thus, W^{-1} is known as the mixing matrix:

$$\mathrm{X} = \mathrm{W}^{-1}\mathrm{A} \tag{2}$$

The left-hand part of Equation 2 is usually referred to as the channel or signal space, meaning that the values stored in X have a proper physical unit (μV for EEG recordings). The right-hand part of Equation 2 can be considered the source space. For practical reasons outlined below, it is important to keep in mind that the data in the source space are arbitrarily scaled. However, arbitrary scaling does not mean that sign and magnitude information are lost, just that the sign and magnitude information for each IC are distributed between W^{-1} and A. For this and several further reasons, it is generally helpful to consider both the inverse weights and the activations for the functional interpretation of each IC: just as EEG data in the raw signal space usually require the consideration of temporal and topographical information for interpretation, ICA results similarly require an interpretation.

For each IC, the rows of matrix W^{-1} contain the weights at each recording channel and may be best considered a spatial filter. This provides the topographical information for an IC of interest, that is, the contribution of each channel to the respective IC time course stored in A, and could be plotted as a map. So, while A reflects the activity profile that changes over time, W^{-1} stores the spatial weights that apply equally to all time points. This is illustrated in Figure 3.1.2, providing a more comprehensive illustration of Equation 2.

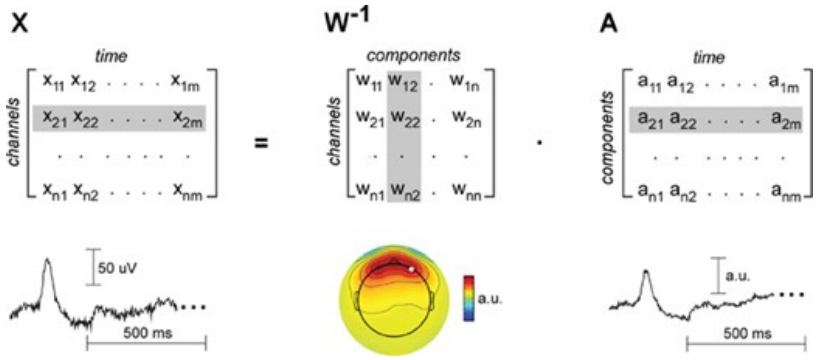

Figure 3.1.2. Linear decomposition of multi-channel EEG data (X). Inverse weights (W^{-1}) represent the spatial pattern of each source time course. Matrix-multiplication of W^{-1} with the maximally temporally independent time courses (in A) gives the mixed channel data, a process called back-projection. For illustration purposes, one component/channel vector is highlighted in grey and shown below the corresponding matrices.

In order to obtain the actual contribution of one or several ICs to the raw signal, it is possible to back-project single ICs of interest. Similarly, ICs that are identified as artifacts can be removed by back-projection of all but those ICs. This can be done by making use of Equation 2 and zeroing out the columns (in W^{-1}) or the rows (in A) of those ICs that are not to be considered further. Figure 3.1.3 shows an example. The segment of raw EEG data shown, matrix X, contains two eye blinks plus ongoing oscillations in the EEG alpha frequency range. Unmixing of these data by means of ICA reveals IC time courses (A) and maps (W^{-1}). It can be seen that the first component, IC 1, captures the eye blinks, whereas IC 3 and IC 4 seem to represent oscillations in the alpha frequency range. Note the similarity between the eye blink topography shown in the raw data and the map of IC 1, as well as the time course of this component with the time course of the eye blinks. Back-projection of all but the first two components returns corrected EEG data (X_c), as shown in the upper right part of Figure 3.1.3. A comparison of the eye blink topographies before and after artifact correction enables a quality check. In the present example, the map after eye blink correction does not
p. 123 suggest residual eye blink activity, indicating very good correction ↳ quality. Note also that occipital alpha oscillations can now be observed during the eye blink interval. This interpretation would not have been possible without accurate eye blink correction.

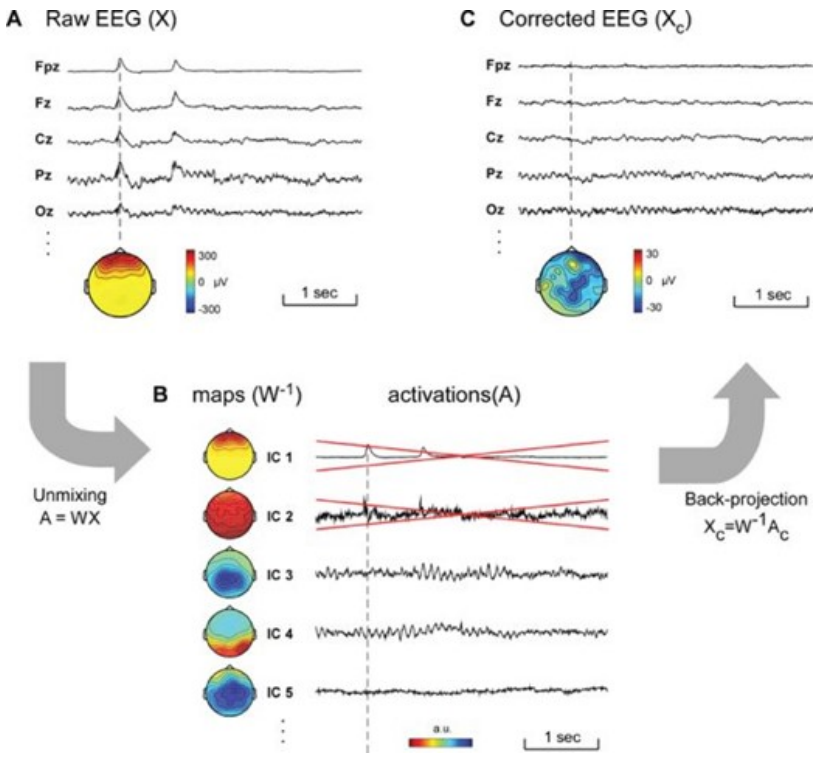

Figure 3.1.3. Illustration of artifact removal by means of ICA. A: Section of selected channels from a multi-channel EEG recording is shown, with ongoing EEG oscillations in the alpha range evident at occipital electrodes and two eye blinks at fronto-polar channels. B: Unmixing of the EEG data into a set of independent components. Each component can be described on the basis of a spatial pattern (map) and a time course (activation). C: Back-projection of all but components 1 and 2 reveals artifact-corrected EEG data.

More generally, a comparison between the original data X and the back-projected data X_c provides several opportunities. For instance, it enables the quantification of the amount of variance accounted for by one IC, or a group of ICs, in the raw data. This procedure has been used to identify the contribution of ICs to event-related potential (ERP) components of interest (e.g., Debener et al., 2005a). Moreover, further quality checks can also be done by comparing measures derived from X and X_c. For instance, the signal-to-noise ratio (SNR) improvement for an ERP component of interest could be determined by comparing the SNR of the ERP based on trial averages of X versus the SNR of the ERP based on trial averages of X_c (e.g., Debener et al., 2007). An additional advantage of back-projected data is that they are scaled in physical units, thus solving the sign and magnitude ambiguity that needs to be considered at the source level. Therefore, for practical reasons, it can be convenient to perform further processing on back-projected data instead of source data, even if only one IC per decomposition is of interest (e.g., Debener et al., 2005a).

While more advanced ICA algorithms—that often promise solutions to some of the problems outlined in the next section—are under development and have been published, they have not yet been tested on EEG data rigorously enough to justify their consideration here. Infomax ICA on the other hand has been extensively applied to EEG data and seems to be among the most powerful ICA algorithms (e.g., Delorme et al., 2007a). Therefore, all further statements and illustrations refer to the well-established and freely available infomax ICA algorithm.

ICA Assumptions

Like other statistical procedures, the application of ICA rests on several statistical assumptions. Are these assumptions reasonably fulfilled for EEG data? It is our experience that a consideration of these assumptions can improve the outcome of the ICA decomposition. Indeed, many failures and disappointments with ICA may arise from suboptimal EEG recording or preprocessing. Accordingly, the argument put forward here is that EEG preprocessing steps can be adjusted to ensure as good as possible compliance of the EEG data with ICA assumptions. The possible relationship between EEG preprocessing and ICA model assumptions will be discussed and illustrated below, after a brief summary of the most relevant ICA assumptions.

Imagine the situation where several groups of people are in a room and talk to each other, all in the presence of background noise. Background noise might be the humming of an air conditioning unit, some jazz music, and the sound of a cocktail-shaker—hence the name cocktail party problem. Let us also assume that we are recording this mixture of sounds by placing a number of microphones positioned at different places in the room. It would certainly be very hard, if not impossible, to follow any single conversation by listening to the sounds recorded by the different microphones. This is because each microphone will have picked up sounds from all sources, albeit with a different level.[1] So, which assumptions must be fulfilled, such that ICA can correctly identify these different sound sources from the cocktail party recordings, and how similar is the cocktail party scenario to EEG?

More Sensors than Sources

To solve the cocktail party problem, there must be at least as many microphones in the room as there are
p. 124 sound sources. ↳ Ideally, the number of microphones should be equal to the number of sound sources. The problem of course is that for real recordings of biological signals, we don't know how many sources there are that contribute to the recordings. This is particularly the case for the decomposition of EEG signals. How many EEG electrodes are needed for ICA? What types of problems can arise from either undercomplete (i.e., there are more sensors than sources), or overcomplete scenarios (i.e., there are more sources than sensors)? We will show ICA examples from 30, 68, and 128 channel recordings and illustrate some practical aspects of the assumption that there are at least as many sensors as sources in each case.

Spatial Stationarity (Fixed Sources-Sensor Configuration)

Another assumption is that the location of the sources does not change relative to the location of the
p. 125 microphones. Different scenarios that could potentially violate this ↳ assumption should be considered, such as the relocation of microphones during the recording, or the movement of signal sources (such as guests at the cocktail party). If either of this happens, ICA is not very effective and a decomposition would likely return unsatisfactory results. Does this problem apply to EEG or magnetoencephalography (MEG)? In the case of multi-channel EEG recordings, individuals may touch the electrode cap during the recording. The cap can also be dislocated as a result of gross head movement, facial expressions, pulling on the electrode cables, or bad fit. It is our experience that some electrode cap systems and configurations are more susceptible to various forms of dislocation than others. Fortunately, for MEG, the sensors are fixed in a helmet, making it impossible for the relative position between the sensors to change. Here, the source of the problem is rather that the position of the head relative to the helmet can change as a result of head movement. Clearly, this scenario would also violate the spatial stationarity assumption. The second scenario is the movement of signal sources and seems to be a problem for EEG/MEG recordings in only a very few, limited recording situations. Some sleep patterns and certain epileptic sources have been reported to contribute moving projections to the EEG signal, and those data can pose a problem for ICA. However, most neural signals picked up by EEG and MEG are generated by pyramidal neurons, which do not move. Thus, this latter issue seems much less of a problem. However, sensor dislocation (EEG) and head movement (MEG) should be avoided or kept at a minimum to facilitate good ICA decompositions. Finally, single channel drifts, as sometimes occur in EEG recording, can be seen as violating the spatial stationarity (and the more signals than sources) assumption, as they would result in stationarity distortions of the "true" underlying signals and can add complexity to the whole dataset.

Linear Mixing

The signals received by each microphone are considered as an instantaneous linear mixture of a number of source signals. The assumption of instantaneous mixing is indeed a problem for acoustic signals, because it takes some time for a sound to travel a distance, meaning that microphones placed further away pick up a signal from a sound source later than those nearby. However, for EEG/MEG, this issue seems negligible. Based on the laws of conductance, the assumption of instantaneous superposition is usually considered to be fulfilled for EEG/MEG.

Independence of Sources

Now let us assume that the host of the cocktail party uses two cocktail shakers perfectly simultaneously and synchronously. Would ICA be able to separate these two sounds? Indeed, the independence assumption is often criticized as being not very plausible for EEG/MEG data, as some form of organized temporal structure is probably present in large-scale, inter-regional brain activity. It seems unlikely that large-scale brain areas contributing to the EEG have "nothing to do with each other." A more plausible view would be to assume some form of functional coupling or connectivity between distant cortical regions, and this seems to be in contrast to the independence assumption. However, as long as two sources are not perfectly coupled during the recording, they may express some degree of temporal independence, and this amount of partial independence (or partial connectivity) may be sufficient for ICA to achieve a good degree of unmixing. Several publications report that ICA can deal with even those artifacts that appear to be perfectly phase-locked to event-related potentials (ERPs) of interest (Debener et al., 2008). Moreover, the success of ICA in recovering dipolar patterns of brain activity, as shown below, suggests that large-scale brain regions may not be perfectly coupled (with the possible exception of some homologous brain areas), but rather express some dynamics in their coupling.

Non-Gaussian Distribution

Another assumption is that (at least some) sources must not contribute a perfectly Gaussian distribution. Mixed signals such as EEG data are often characterized by Gaussian distributions. This can be explained by the central limit theorem, which states that the sum of a number of independent random variables is characterized by a more Gaussian distribution than that of the independent variables. The opposite interpretation is however not justified: Just because we are recording a signal with a Gaussian distribution we cannot infer that this signal consists of a mixture of non-Gaussian sources. Therefore, as with the independence assumption, it seems impossible to tell whether this assumption is reasonable. However, given the practical value of ICA and the quality of many ICA decompositions, we conclude that the assumptions of independence and non-Gaussian distribution seem to be reasonably plausible for EEG data.

ICA Outcome

In this section, we will first illustrate some typical artifact and brain ICs that can often be identified across laboratories, recording set-ups, subjects, and experiments. Subsequently, we will discuss potential problems that can arise when the reliability of ICA solutions is low.

ICs Representing Artifacts

According to the model outlined above, ICA should separate EEG artifacts from brain activity patterns. Some of the most common artifacts typically identified by ICA are shown in Figure 3.1.4. Eye blinks, for instance,
p. 126 can often be easily identified by their characteristic topography (W^{-1}) and time ↳ course (A), but provide limited spectral information (Viola et al., 2009). Whether these and other artifact ICs show event-related activity such as an evoked response usually depends on the task. The presentation of visual stimuli for instance often induces event-related eye blinks, which could then be characterized by an eye-blink IC ERP. The examples shown in Figure 3.1.4 are taken from an auditory experiment while the participant watched a silent movie. Accordingly, lateral eye movements and eye blinks were rather common, as illustrated in the single-trial visualization, the ERP image, but did not evoke much event-related activity. Note that even with the occurrence of artifacts that seem perfectly phase-locked to ERPs, ICA has been demonstrated to be of significant help (e.g., Debener et al., 2008).

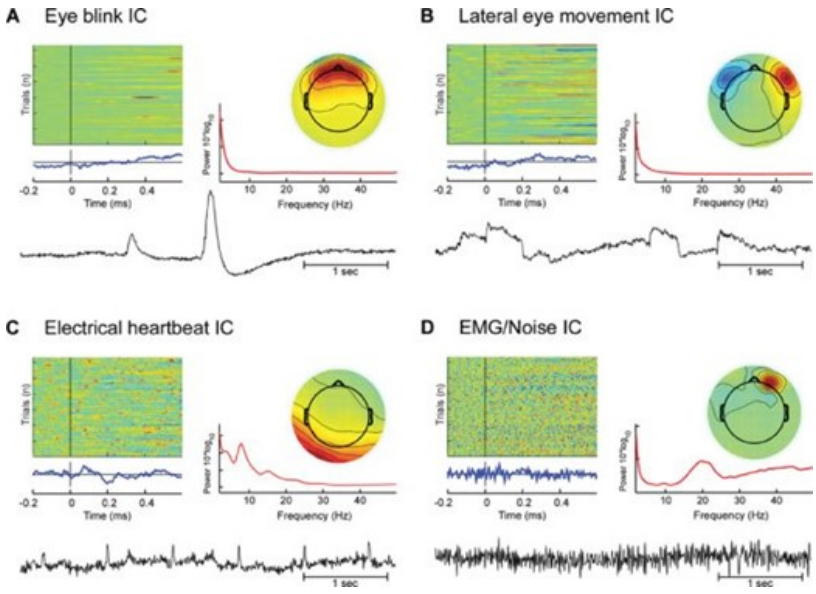

Figure 3.1.4. Typical EEG artifacts as identified by ICA. A: Eye blink artifact components. Shown are the IC map, the single-trial activity as an image, the time-domain average, i.e., the ERP (blue) and the spectrum (red), along with a representative section of ongoing activity (below). B: Same for lateral eye movements. C: Same for electrical heartbeat artifact. D: Same for muscle/noise activity.

Technically, ICA allows all artifacts that can be safely identified to be removed by back-projection. This requires, of course, the correct identification of artifact ICs. However, the decomposition of high-density EEG recordings often results in more than one IC representing the same type of artifact. This general problem might indicate overfitting, or an undercomplete decomposition, that is, the separation of the identical source process on different ICs (see Gómez-Herrero et al., 2005; Särelä and Vigário, 2004, for in depth discussion and examples). Alternatively, it might suggest that different types of eye blinks (e.g., voluntary and spontaneous) were identified due to their slightly different time courses. Another common artifact that is usually represented by a single IC results from lateral eye movements. The lateral eye movement IC is easy to identify by the characteristic time course and topography, and is often found to be highly correlated with bipolar horizontal electrooculogram (HEOG) recordings.

Also very common in EEG recordings are ICs reflecting electromyogram (EMG) or muscle activity, which are sometimes hard to distinguish from channel noise or overfitting problems. ICA from high-density EEG recordings typically reveals a number of these ICs, sometimes clearly representing different muscle groups and/or different EEG channels. The distinction between EMG and channel noise seems not easy, since both
p. 127 contribute high frequency activity to the EEG ↳ signal. In our experience, EMG ICs tend to express a more tangential dipolar pattern, whereas channel-noise IC maps specifically point (radially) to a single channel.

One artifact type that receives less attention in EEG/ERP research is related to electrical heartbeat activity. ICA often represents this activity in one IC (or sometimes two), as shown in Figure 3.1.4C. It is plausible to expect that the location and orientation of the heartbeat dipole is reflected in an asymmetry of the IC map. The characteristic R peaks represented by the IC time course often go undetected in the mixed channel signal, probably due to their relatively small contributions to the ongoing EEG signal. However, while electrical heartbeats may not show substantial event-related activity patterns in typical ERP experiments, they may nevertheless represent a serious source of artifact, in particular for a topographical analysis in the frequency domain: The highly characteristic, asymmetric topography of this component, together with its broad-band spectral contribution, suggests that measures such as posterior EEG alpha asymmetry, which have been used to study individual differences, could be substantially biased by this artifact and thus profit from its removal.

If the focus is on artifact removal, a good strategy seems to be to remove those ICs that can be classified as representing artifacts. The necessary classification of these components could be done by visual inspection of various component properties, such as those shown in Figure 3.1.4. More objective and efficient component identification approaches have been developed (e.g., Viola et al., 2009), but we nevertheless recommend a careful visual inspection of the ICA outcome, since the separation of artifacts from brain-related activity is not always satisfactory. However, the use of ICA for artifact removal often achieves good data quality in ERP research, which enables, for instance, the dipole source localization of single subject data (e.g., Hine, 2008), the recovery of ERPs that otherwise would be completely buried in artifact (e.g., Debener et al., 2008) or the study of trial-by-trial event-related brain activity (e.g., Makeig et al., 2002). The following section will present a few examples of ICs reflecting brain activity.

ICs Representing Brain Activity

Various examples have been published demonstrating the potential of ICA for the identification of event-related brain activity patterns (e.g., Debener, et al., 2005a; Debener et al., 2005b; Delorme et al., 2007b; Makeig et al., 2002; Onton et al., 2005). These studies have combined ICA with single-trial EEG analysis, thereby exploring brain dynamics beyond the evoked fraction of the signal that is preserved in the ERP. Summarizing this growing body of work is clearly beyond the scope of this chapter. Instead, we will illustrate the basic view that some ICs represent brain-activity as clearly as others represent artifact. Based on this assumption, ICA should disentangle not only different artifacts, but also different brain processes from each other.

To briefly illustrate the capability of ICA for achieving this, data from an audiovisual speech discrimination experiment recorded in our lab are shown in Figure 3.1.5. This experiment included multisensory audiovisual (AV) as well as unisensory auditory (A) and visual (V) trials. ICA decomposition was performed for concatenated single-trial data that included the trials from all three experimental conditions A, V, and AV, with the main purpose of removing artifacts. However, inspection of the other, nonartifact ICs clearly suggested that some were specifically related to auditory or visual processing. Two representative ICs are shown in Figure 3.1.5. The top row of this figure shows the channel data and scalp maps at the peak latency of the P1 VEP (left) and the peak latency of the AEP N1 (right). Panel B shows IC 6, which explained about one third of the VEP in the P1 latency range 70 to 126 ms, but did not contribute to the AEP in the N1 range 88 to 166 ms. This suggests that IC 6 represented mainly visual event-related activity. The bottom panel shows the same analysis for another component, IC 1, which contributed little to the VEP variance in the P1 latency range, but more than 50% of the AEP in the N1 range.

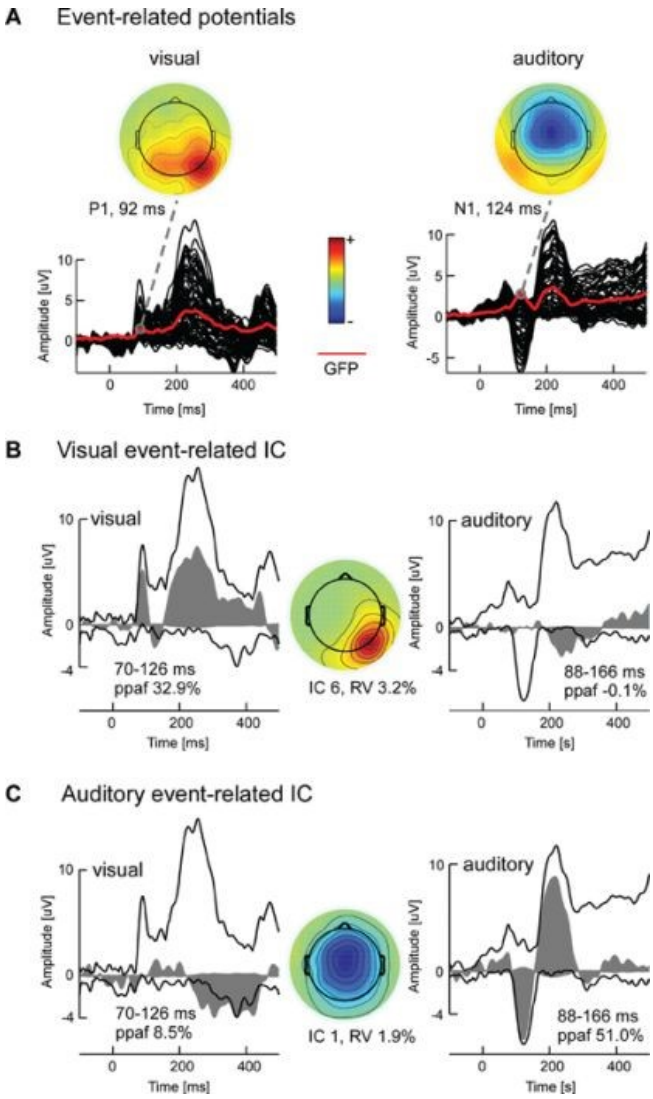

Figure 3.1.5. Two example ICs representing event-related brain activity. A: ERPs from a single subject in response to acoustic and visual stimulation. Shown are VEPs and AEPs, respectively, for all recorded channels (black traces) and the topography for the indicated VEP at the P1 peak latency (92 ms) and for the AEP at the N1 peak latency (124 ms). B: Contribution of IC 6 to the VEP (left) and AEP (right), indicated by showing the channel ERP envelope (the minima-maxima across all recording channels, black traces) and, in grey, the envelope of the back-projection of this component, explaining approximately 32% of the total variance of the VEP in the 70-126 ms interval. The same IC does not contribute to the AEP N1 interval (88-166 ms). C: Contribution of IC 1 to the VEP (left) and AEP (right). This component explained 51% of the variance in the N1 latency range (88–166 ms), but did not contribute substantially to the VEP in the 70–126 ms interval. PPAF = percentage of power accounted for; GFP = global field power; RV = residual variance.

Note the substantial similarity between the channel-based evoked potentials at the ERP peak latencies and the respective IC 1 and IC 6 maps. Again, these ICs were defined across all experimental conditions, but explained condition-specific variance, which can be taken as important information for the functional interpretation of ICs reflecting event-related brain activity. Of further importance is the notion that these ICs can be studied on the single-trial level, thereby allowing the assessment of event-related activity beyond the phase-locked portion (not illustrated here). And finally, inspection of further ICs indicates that several ICs commonly contribute to the scalp-ERP, although it often seems the case that few ICs explain a large amount of variance, whereas many others contribute little each. Accordingly, a number of ICs usually represent event-related activities, among which some may be condition-specific, as shown in Figure 3.1.5, whereas others may contribute similarly to different conditions.

ICA Reliability

p. 128 A very important practical consideration is that the stability or reliability of any ICA decomposition cannot be taken for granted. Unlike principal components analysis (PCA), which always returns identical decompositions when applied repeatedly, ICA can produce different results from repeated application to identical data. This is because the unmixing weights (W) are learned over repeated iterations, which use randomly chosen samples from the training data submitted (X). As a result, the outcome may differ to some extent. It is therefore important to consider the factors that contribute to the reliability of ICA decompositions.

First, reliability depends on the amount of data submitted to the algorithm. ICA requires a sufficient number of training data to produce near identical solutions for the repeated decomposition of the identical data. It is difficult to estimate how much data are needed but high density data require more training data than low density data, because n^2 weights need to be trained (where n refers to the number of channels). An
p. 129 illustration of the effect of the number of training ↳ data on the reliability of ICA is given in Figure 3.1.6. A rule of thumb has suggested at least $20*n^2$ data as a minimum number of training data (Onton et al., 2006).

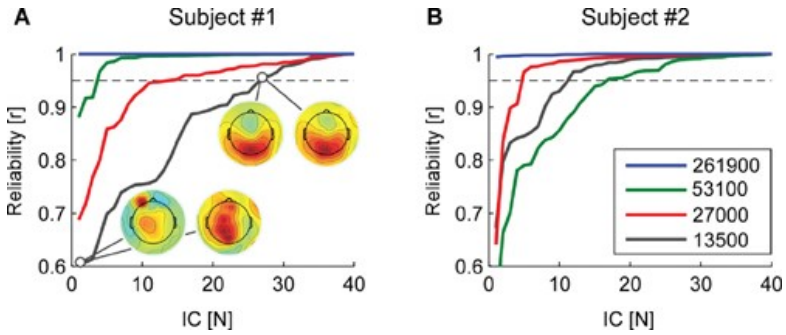

Figure 3.1.6. Effect of the number of training data on ICA reliability for two representative subjects (A, B). Time courses reflect the degree of correlation between the ICA maps of a first and second decomposition of the identical data, sorted in ascending order. Blue line reflects decomposition of all epochs (after rejection of those containing nonstereotype artifacts, see below), other lines a subsample of approx. 20% (green), 10% (red) and 5% (grey) of all data. For the 5% condition from subject #1, two pairs of IC maps are shown, illustrating maps with very high and very low reliability. Note that only the decomposition of all epochs (blue line) revealed near-perfect reliability for both subjects and all ICs.

According to the rule of thumb mentioned above, for a 68-channel dataset at least 92480 data points (training data) would be necessary to achieve a reliable decomposition. To test this we applied ICA twice to identical data, and correlated the weights from the first and second applications to identify maximum correlations for each component. This was done for 40 dimensions and the concatenated epochs that remained after rejection of epochs containing atypical activity (Delorme et al., 2007a). The correlation procedure was repeated for all data (261900), which exceeded the $20*n^2$ criterion, and subsamples of the data epochs, representing about 20, 10, and 5% of the available data points, thus not passing this criterion. This enabled us to study the effect of the length of the training data on the reliability of ICA. Shown are the reliability values for each IC, sorted in ascending order. As can be seen for subject 1 (Figure 3.1.6A), all ICs trained on the total data were retest reliable, as evidenced by correlation values of r >.99. The 20% subsample of these data (green line) also indicated good retest reliability, with 37 out of 40 ICs showing correlations of r >.95. However, the results for the 10% (red) and 5% (gray) subsamples show that retest-reliability was further reduced to an unacceptable level. In the 5% dataset, only 17 ICs could be considered retest reliable, if one applies the r >.95 criterion, strongly indicating an insufficient amount of data.

The results shown in Figure 3.1.6A clearly support the common statement that ICA needs "a lot" of training data to achieve a stable decomposition. However, the conclusion that "more is always better" may be a bit premature. To illustrate this, data from another representative subject are shown in Figure 3.1.6B. As for subject 1, the decomposition of the total data from subject 2 revealed near perfect retest reliability. However, a comparison of the 20% dataset (green line) with the 10% and 5% subsamples shows that retest reliability was higher for the smaller compared to the larger number of training data (Figure 3.1.6B). In the 10% dataset (red line), 36 ICs correlated with r >.95, whereas in the 20% dataset, only 24 ICs met this criterion. Accordingly, it can be speculated that, in addition to the quantity of the data, the quality of the data plays an important role as well. It is likely that the data from subject 2 contained sections that were not in accord with the ICA assumptions. For the 100% dataset, which also included these sections and was of the size of approximately $56*n^2$, this did not affect retest reliability. In other words, for very large numbers of training data, temporally constrained violations of ICA assumptions seem to be tolerable. However, the 20% dataset, which was of the size of approximately $11*n^2$, was apparently substantially affected by these data sections. This illustrates that in cases where large numbers of training data are not available, a better retest reliability may be achieved by using fewer but more consistent data for ICA decomposition. Similarly, ICA decompositions of ERPs tend to return disappointing results, probably because not enough training data is provided. It can also be argued that most of the information that could be used to define independence might be lost in the average (Makeig et al., 2004a). Finally, the rule of thumb mentioned above should in our opinion be considered in light of the low-pass filter used, not the sampling rate. Using a low low-pass filter in combination with a high sampling rate may not help in achieving good reliability, because this does not add information to the existing data. Instead, the frequency of the recording low-pass filter may be considered to estimate the required number of samples for a reproducible decomposition. In any case, it is recommended that the reliability of data of interest be assessed (Groppe et al., 2009). This could be done by simple correlation statistics as outlined here, or by using more advanced tools such as ICASSO (http://www.cis.hut.fi/projects/ica/icasso/).

Good Components, Bad Components

Keeping the reliability problem in mind, it is important to note that most ICA solutions of EEG data are
p. 130 rarely fully considered and analyzed. That is, in most practical cases, ↳ researchers tend to choose some ICs, but do not usually consider all available components. This raises the important question as to whether those ICs of scientific interest are retest reliable or not. In the former case, the issue of training data quantity becomes less significant practically, but in the latter case, it would raise substantial concerns about the usage of ICA. Figure 3.1.6A shows two pairs of ICs from the 5% training dataset, one pair expressing high retest reliability (here r =.96) and one with low retest reliability (r =.61). As can be seen, the reliable pair expressed a dipolar-like topography, that is, a map that could be reasonably well modeled by a single dipole or by two symmetric dipoles. Dipolarity has been used as a criterion for the selection of ICs representing brain activity (e.g., Makeig et al., 2004a; Makeig et al., 2004b; see also Figure 3.1.5), and it is therefore of interest to consider the relationship between the dipolarity and reliability of ICs. Are dipolar ICs more reliable than non-dipolar ones? In order to explore this issue, we repeatedly decomposed a 128 channel EEG recording in several different ways, the results of which are summarized in Figure 3.1.7. Each model was repeated once (dotted lines), and six different models are shown (in different colors). Here, either all data (A + B; 777352 data points) or the first (A; 384774 data points) or second (B; 389578 data points) half of the recording were used. Additionally, different numbers of dimensions were considered by employing PCA reduction to either 120 or 96 components. Shown are the sorted dipolarity values for each model, as revealed by single equivalent current dipole modeling using the DIPFIT EEGLAB plug-in and a spherical head model (www.sccn.eeglab.edu).

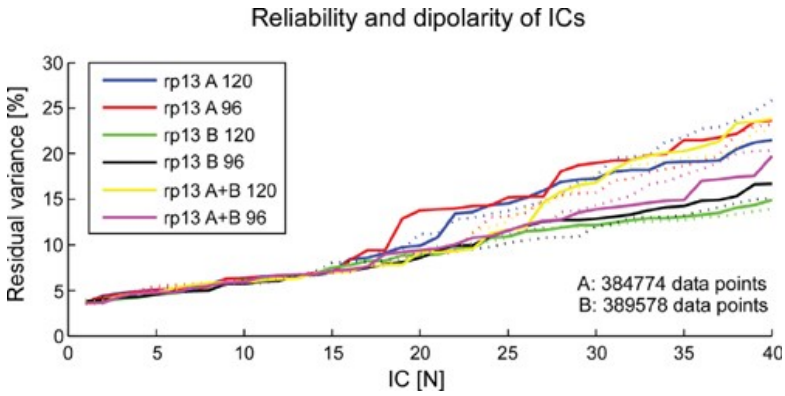

Figure 3.1.7. Relationship between the reliability and dipolarity of independent components, illustrated for a single subject 128 channel EEG recording. Plotted is the residual variance (RV) of 40 independent components, in ascending order, for several different ICA models. Solid lines refer to the first, dotted lines to the repeated decomposition of the identical model/data, with color indicating different models. A=data of the first half of a 128 channel EEG recordings, B=data of the second half of the recording, A+B=all data. 120, 96=number of components decomposed. Note that for the dipolar ICs (those with residual variance >10%), lines overlap each other near perfectly.

As can be seen, the lines substantially overlap each other for those ICs expressing a high dipolarity (i.e., low residual variance, RV). This holds for the different models as well as for the replication of the identical model (solid versus dotted lines). We repeatedly observed this pattern in several subjects, and interpret this as evidence for the view that dipolar ICs tend to be more reliable than non-dipolar ICs. Accordingly, the focus on dipolar ICs seems a reasonable strategy. High dipolarity of ICs representing brain activity seems to indicate a successful and reliable unmixing process.

EEG Preprocessing and ICA Outcome

According to the model outlined above, ICA should separate EEG artifacts from brain activity patterns. Moreover, ICA should also separate different brain activity patterns originating from different areas of the brain from each other (see Onton et al., 2006, for discussion). Accordingly, ICs reflecting brain activity can be assumed to express an equivalent current dipolar pattern to the EEG signal, representing the contribution from one cortical area (or in some cases two homologous areas), and a maximally temporally independent activity profile. IC 6 in Figure 3.1.5 shows one example of a dipolar IC probably representing brain activity from right occipital cortex and contributing predominantly to the visual evoked potential. In addition to the issue of training data quantity discussed in section 3.2.5, what other factors might favorably affect ICA quality?

Rejection of Nonstereotype Artifacts

One strategy recommended by several labs employing ICA regularly is the rejection of nonstereotyped artifacts, such as those due to gross head movement, cable movement, or swallowing. All these contributions usually occur only for small sections of EEG recordings, but may unfavorably change the "More signals than sources" ratio of ICA. Accordingly, the data should be "pruned" from those nonstereotype sections before they are submitted to ICA. In contrast, more common and frequent EEG
p. 131 artifacts such as eye blinks or eye movements seem repeatedly to express the ↳ same source signal to the EEG, and it can therefore be considered a good investment to spend a few ICs on modeling (and thereby potentially removing) their activity patterns. Note that nonstereotyped artifacts are not specifically identified by a simple amplitude criterion, as this would find eye blinks for instance as well. Also, some nonstereotyped artifacts may not necessarily contribute high-amplitude signals to the EEG. It is therefore recommended to use more advanced artifact identification algorithms, such as those operating on the probability of amplitude distributions (Delorme et al., 2007a).

Removal of Channel Drifts

Given the enormous dynamic range of modern EEG amplifiers, many researchers tend to record EEG data now with the filters wide open. In the low frequency range, this usually comes at the expense of recording high amplitude drifts in the >1 Hz frequency range, which may be largely caused by electrode potentials or sweating artifacts, among other things. We find that these low-frequency contributions, which are often spatially unstable and fluctuate substantially over time, have an adverse effect on ICA quality. This may be because these low-frequency contributions add spatially nonstationary signals to the EEG, and compromise the "More sensors than sources" assumption. It is therefore recommended that those portions are removed by application of a suitable high-pass filter or by de-trending of the data. In our experience, this tends to return more reliable, and more dipolar ICs. At first glance, this recommendation may prevent using ICA for DC-recorded EEGs and the study of slow potentials (e.g., Schicke et al., 2006). However, a solution to this problem would be to train the ICA weights on high pass filtered data and apply the results to the unfiltered data. This approach would allow, for instance, the use of ICA for eye blink removal in DC EEG recordings.

Decomposition of Continuous Data Versus Concatenated Single Trials

Much less clear is the issue of whether continuous EEG recordings or concatenated single trials should be submitted to ICA. In light of the reliability issue, one might argue for the decomposition of continuous recordings, as this would, for most experimental paradigms, result in more data points and thus the likelihood of improved ICA reliability. However, following the assumptions of the additive ERP model, neural sources that cause ERP deflections may be regarded as contributing activity to the EEG recording specifically for rather small intervals that are phase-locked to some events of interest. Accordingly, if the aim is to identify ICs that refer to classical ERP components, it might be advisable to constrain ICA training to these intervals of interest, which could be done by concatenating the corresponding single trials or epochs. However, doubts have been expressed over the adequacy of the additive ERP model, and it is not yet known whether the additive model is more valid than alternative accounts (e.g., Sauseng and Klimesch, 2008). One of these alternative accounts would state, in contrast, that there is no clear distinction between sources contributing to the ongoing EEG and those contributing to the event-related EEG (e.g., Makeig et al., 2004a). According to this view, EEG alpha oscillations for instance should be modeled as carefully as possible to study how they might contribute to visual evoked potentials (Makeig et al., 2002). Accordingly, concatenated long epochs or even the continuous recordings should be submitted to ICA, as this increases the likelihood of returning a better identification and separation of ICs representing ongoing alpha activity. In short, no clear recommendation can be given for the decomposition of epoched versus continuous data, as this depends on the research question asked and is linked to the view a researcher may have about event-related brain function.

Low-Pass Filtering and Down Sampling

One of the commonly mentioned disadvantages of ICA is that it can take considerable time for the algorithm to converge to a solution. Among other issues, the size of the training data is an important determinant of computation time, and therefore, reducing the number of training data—within the limits of reliable solutions—is a practical consideration. One way to achieve a substantial speed-up would be to down-sample the recorded data, which are usually recorded over-sampled, in order to prevent aliasing problems. Thus, if the focus is on ERPs and/or other low frequency EEG activity, it may be advisable to down-sample EEG data recorded at 1000 Hz (with a 200 Hz analog low-pass filter) to a sampling rate of 250 Hz, after further low-pass filtering (e.g., 80 Hz). As a result, a substantial reduction in computation time can be expected. However, it should be noted that the degree of low-pass filtering can have a negative effect. While low-pass filtering yields an important noise reduction, very substantial low-pass filtering has also been reported to increase the likelihood of over-fitting the input data (Gómez-Herrero et al., 2005). Care should be taken to not remove too much information from the EEG data by using a too narrow passband before ICA decomposition.

Removal of Bad Channels

Another practical consideration is the management of bad channels, that is, electrodes that have lost good contact to the scalp or show other forms of malfunctioning during the recording. It seems to be the case that some EEG cap and electrode systems are more prone to creating bad channels than others, and it would of course be best to use systems and procedures that avoid the occurrence of bad channels. However, unforeseen circumstances may counteract this standard, raising the question of how ICA outcome could be
p. 132 affected by inclusion of bad channels. The signal contributed ↳ by bad channels can be seen as further inflating the dimensionality of EEG data and also increasing the risk of nonstationarity. Thus, activity from bad channels should be removed before ICA decomposition, as it can massively deteriorate otherwise good decomposition results. If bad channel replacement is implemented by means of spatial interpolation, it should be kept in mind that the dimensionality of the data set is reduced by the number of the interpolated bad channels. The resulting rank-deficiency can cause problems for ICA algorithms to converge, and the procedure of bad channel interpolation may therefore be combined with a subsequent dimensionality reduction step to prevent this.

Conclusion

Over the past decade, ICA has become increasingly popular in EEG/MEG research. Besides the significant achievements that have been made by using ICA, the increased experience with this technique requires us to draw some practical conclusions, simply because the success of ICA should not overshadow the potential limitations inherent in it. First, using ICA does not necessarily guarantee an unmixing into physiologically plausible components. Although it is sometimes forgotten that this argument does not selectively apply to ICA, the plausibility of independent components is a matter of interpretation and not given inherently by the data. Second, unmixing multi-channel EEG/MEG data with ICA does not necessarily return a reliable decomposition. We have discussed some of the main factors that seem to contribute to the reliability of ICA decompositions. In particular, we argue that different preprocessing steps should be selected and adjusted keeping the ICA model assumptions in mind. This allows one to appreciate that, when adequately chosen, preprocessing can help to produce more reliable solutions. Third, there is at least preliminary evidence that these two issues, interpretability and reliability, are closely related. In terms of physiological plausibility, it makes sense to assume dipolar or near dipolar independent components (see Makeig et al., 2004a, for discussion), and independent components contributing with a dipolar spatial pattern to the EEG tend to be more reliable than non-dipolar ones. Dipolar components are also more robustly observed across subjects than non-dipolar ones. However, it is not yet fully understood how dipolarity and reliability of independent components relate to each other, and this issue clearly requires further research. And finally, more recent ICA algorithm developments may also help to further optimize the amount of information that can be identified in, and used from, EEG/MEG recordings. Careful comparison and validation studies are needed to advance our knowledge on which algorithm performs best for a given type of data or problem. It is unlikely that any single algorithm is superior to all others for all practical questions that can be addressed with ICA-based EEG/MEG analysis. However, future developments will bring better algorithms and better validation criteria and it is evident that, while not perfect, ICA can be expected to continue providing a significant contribution to cognitive brain research.

Note

1. Here, for the sake of simplicity, we ignore the problem of sound travel time delays which greatly complicates the unmixing process. A similar problem does not however exist for EEG recordings.

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