Dealing with the cochlear implant related artefact in electroencephalographic research

A COMPLETE OVERVIEW OF ALL THE REQUIRED PRE- AND POST-PROCESSING STEPS

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Preface

My name is Fergio Sismono and I am a Bachelor student in Life Science and Technology at the University of Groningen. I am specializing in the major Biomedical Technology and in May 2015 it was finally time for me to start looking for a subject for writing my thesis. A lot of things intrigued me at that moment, and I thought really well about what interested me the most. I wanted to find something that I would truly enjoy researching and writing about.

It is very common in the Biomedical Technology department for students to do a design assignment instead of writing a thesis. In a design assignment, the student goes through all the steps of product development and finally develops a medical product specifically tailored for an existing problem in the medical world. However intriguing this may seem, I have done many group assignments where I had to develop a medical product together with a team and I thought it was time for me to learn something new. So I wrote to several research groups and planned several meetings in order to discuss the topics they needed help with, and the opportunity for me to do my thesis in their respective fields.

One of the people I e-mailed was professor Deniz Baskent from the Audiology department of the UMCG in Groningen. She introduced me to dr. Anita Wagner, who was doing very interesting EEG research on people that have been implanted with a cochlear implant hearing device. As I have a background in programming (studied Computer Science in my first year) I thought this was a great opportunity for me to develop these skills in practice. I accepted the opportunity to do my research there and now, a few months later, I look back and I could say I've had a wonderful and very educational experience.

Anita, thank you for giving me the opportunity to do my research with you, and thank you for helping me out whenever I had questions. Thank you for your good guidance and feedback on the papers I wrote and on the data I analysed. I wish I had more time to work on this project, but unfortunately the time has come for me to finish.

I hope I will find a way to apply the skills I have learned here in the future to come. I still have a lot to learn, but it does not end here, as I will start my Master's in Biomedical Engineering in a few months from now. I see this experience as the very start of my career and I am very excited about the things the future will bring me.

For everyone else that is reading this thesis, I hope that after reading this paper, you will be a little more educated about what it means to work with EEG data, and you will have a better understanding of the things involved whenever you hear about someone working with EEGs.

I sincerely hope you enjoy reading this paper.

Fergio Sismono – Groningen, June 2015

Summary

The cochlear implant (CI) related artefact remains a problem researchers are faced with nowadays when analysing the electroencephalographic (EEG) data of subjects implanted with a CI. The CI related artefact can change when different stimuli are used in an experiment, and can even vary a great deal across participants in the same experiment due to different settings on their devices. This makes it very difficult for EEG researchers to reliably identify and remove the artefact from their data, preventing further analysis in their experiments.

In this thesis paper, the complete process of cleaning up EEG data from CI participants will be explained step-by-step in order to come to a full understanding of what it means when working with contaminated EEG data. From filtering to the calculation of event-related potentials, every step is equally important and can have its own effects on the final brain potential figure.

Special attention will be given to the CI related artefact, and it will be visualised to give a general idea of its appearance and properties. Different methods of minimizing the CI artefact from previous successful studies will be discussed, including ICA (independent component analysis) and a single-channel approach.

Contents

1. Introduction

This thesis was written in conjunction with my Bachelor Research Project on *"Minimizing the Cochlear Implant Artefact in a Spoken-Word Event-Related Potential Experiment"*. Previous studies and other types of literature will be discussed in this paper in order to come to a full understanding of the process of cleaning up EEG data. In this chapter, a brief introduction will be given about EEG research and all its associated matters.

1.1 EEG AND THE EVENT-RELATED POTENTIAL TECHNIQUE

Ever since the recording of the first electroencephalogram, also known as EEG, in 1924 many have used this technique to visualize certain cognitive processes in the brain. The EEG is composed of electrical signals originating from post-synaptic activity in the brain and is measured from different locations on the scalp. The raw data acquired from these measurements cannot directly be used as evidence for task processing in the brain, as the data will only contain electrical signals and without the right context, nothing can be concluded about the origin or meaning of the signals without first processing them in some way [figure 1].

Figure 1: a typical EEG recording showing the electrical activity in an 18-channel recording.

A simple, yet effective technique to analyse these recordings is the event-related potential technique, also commonly abbreviated as ERP technique or ERP. Shortly summarised, the method involves presenting a stimulus and simultaneously recording a trigger on the timeline of the EEG. During analysis, the raw data can be time-locked to these triggers and averaged over many trials. These averages can be plotted to visualise the response of the brain to these stimuli. For example a stimulus can be recorded and played back to a participant in the experiment. Every time this sound is played back, the EEG will record the brain activity of the participant (which will consist of small fluctuations in the raw EEG signal) as well as the trigger at the moment the sound is played back. This can be repeated many times to create what is called *epochs* or *trials*, and these events can be averaged over many instances in order to create one single figure that displays the neural response to that certain stimulus. An example of such an ERP is shown in figure 3.

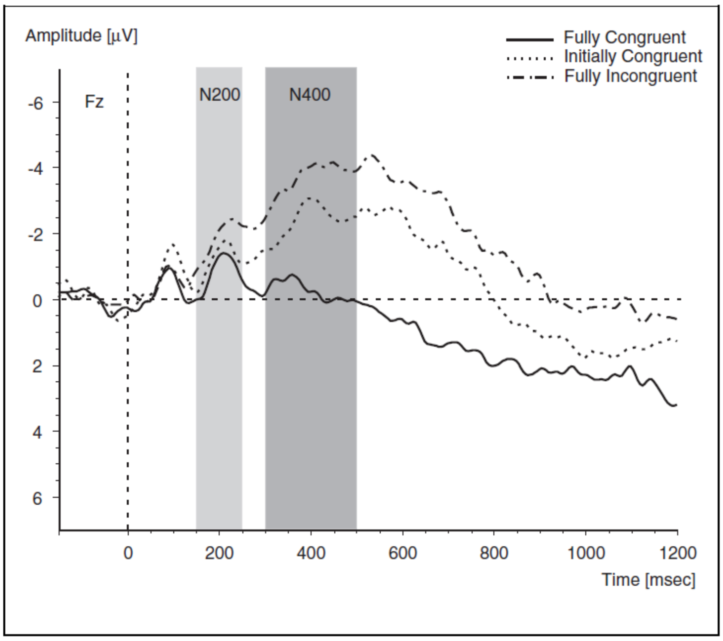

Figure 2: a grand average (ERP average of many participants) event-related potential from a speech-related experiment by Van den Brink in 2001 [3]. In this study the participants were presented with sentences from either fully congruent, initially congruent or fully incongruent sentences. The differences between the peaks are evidence of the effect of context on spoken word recognition and the latency at which these cognitive processes occur in the brain.

This method has been used for decades [1] and has evolved over the years to become a reliable and relatively inexpensive method of capturing the brain response. The table below describes the advantages and disadvantages of ERP compared to other techniques commonly used in analysing brain response. ERPs are non-invasive, cheap, and provide excellent temporal resolution.

Table 1.1
Comparison of invasiveness, spatial resolution, temporal resolution, and cost for microelectrode measures (single-unit and local field potential recordings), hemodynamic measures (PET and fMRI), and electromagnetic measures (ERPs and ERMFs)

Parameter	Microelectrode Measures	Hemodynamic Measures	Electromagnetic Measures
Invasiveness	Poor	Good (PET) Excellent (fMRI)	Excellent
Spatial resolution	Excellent	Good	Undefined/poor (ERPs) Undefined/better (ERMFs)
Temporal resolution	Excellent	Poor	Excellent
Cost	Fairly expensive	Expensive (PET) Expensive (fMRI)	Inexpensive (ERPs) Expensive (ERMFs)

Figure 3: The advantages and disadvantages of brain analysing techniques (Table 1.1 from "Introduction to the Event-Related Potential Technique" [2]).

When recording an EEG with an electrode cap, the electrodes will unfortunately not only record the signals from the brain. Many electrical signals from other sources will contaminate the recorded data. In practice, it is highly unlikely that the EEG data of an experiment is clean from *artefacts* without processing the data first by using computer software. Therefore, it is important that when using ERPs in an experiment setup, the EEG data is considered completely clean before computing the ERPs and drawing any scientific conclusions. The classic electrical artefacts contaminating data from EEG experiments are blinks, muscle contractions, eye-movements and background noise. Their characteristics and the removal of these artefacts will be explained shortly in this paper.

When studying neural potentials from people implanted with a cochlear hearing device, a completely new artefact is introduced: the cochlear implant (CI) artefact. An artefact caused by the electrical signal produced by the cochlear implant.

1.2 AIM OF THIS STUDY AND THE RESEARCH QUESTION

In my Bachelor Research Project, EEG data from a speech recognition experiment, regarding people implanted with a cochlear hearing device, was cleaned from the artefact that the device caused on the EEG recordings. The aim of this literature study is to fully describe the process in which this was accomplished, including any pre- and post-processing actions performed, and to justify these steps based on the literature and previous studies. The research question is as follows:

"Which steps in pre- and post-processing of raw EEG data are necessary in order to acquire the event-related potentials from a spoken-word recognition experiment regarding subjects implanted with a cochlear implant?"

In the coming chapters, the research question will be answered by explaining each of the steps in chronological order. Firstly, the software and techniques used for the standard pre-processing will be explained. Then, a chapter on artefact rejection will explain what blink, muscle contraction and eye-movement artefacts are, as well as how they were removed. Afterwards, an explanation of the Independent Component Analysis (ICA) algorithm and how it was used to remove the Cochlear Implant artefact will be given. Finally, the results of this experiment will be discussed by comparing them to findings of closely related studies.

2 Software processing

2.1 EEGLAB AND FIELDTRIP

In order to be able to perform analysis of EEG data, the software tools used can play a very important role in the research setup. Nowadays, numerous EEG analysis programs are available, developed in countries from all over the world, and choosing which software to use is an important step in successful EEG research. The program the researcher chooses can depend on many factors, such as how fast the software is, the analyzing techniques that the researcher plans to use, or even the relative ease of use. In this study, two different toolboxes were used: EEGLAB and FieldTrip.

The open source EEGLAB toolbox, developed by Arnoud Delorme and Scott Makeig in 2004 [4], provides a variety of functions for EEG processing and is fully implemented in the MATLAB programming environment. The toolbox implements a Graphical User Interface (GUI) [fig. 4], that allows the user to easily perform advanced processing techniques without having extensive knowledge about programming. The main advantages of EEGLAB are the GUI, the relative ease of use, and the fast and the easy-view plots of the EEG data. For researchers new to EEG, the toolbox is an informative way to get to know their data and can be used for basic analysis relatively quickly once it is picked up. The disadvantage of EEGLAB, however, is that the program can be slow when performing some functions such as filtering, where the process can take up to one hour for datasets of over 1 GB. Previous studies have successfully used the built-in independent component analysis (ICA) functions from EEGLAB in the recovery of ERPs from CI contaminated data [5,6] and even a full semi-automatic correction tool for the selection and removal of CI artefacts has been developed and tested [7,8].

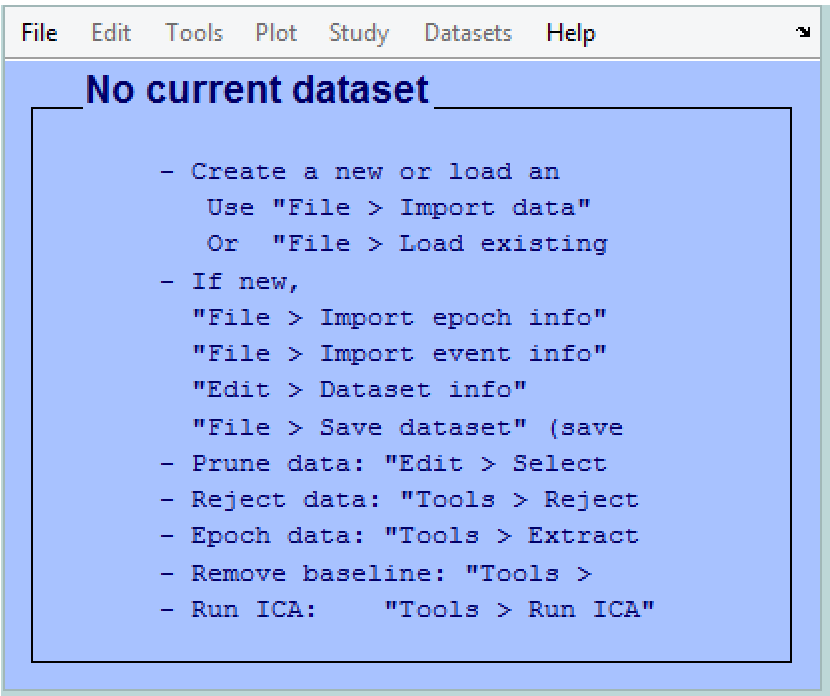

Figure 4: The EEGLAB Graphical User Interface

Similar to EEGLAB, FieldTrip is also an open source toolbox fully implemented in MATLAB. Developed by the Radboud University of Nijmegen, Netherlands, FieldTrip provides many functions for use in EEG software processing, such as advanced plotting, ICA, averaging and automated pre-processing of datasets [9]. The main disadvantage for new EEG researchers, is that FieldTrip does not provide a GUI. However, compared to EEGLAB, it is much faster and it allows the user to create scripts for the more or less routine processing of experimental data. The toolbox is more difficult to use for beginning programmers, but provides more advanced options and tools for processing and will become easier and more time efficient to use in the long run, especially for experienced programmers.

Although both have their advantages and disadvantages, the researcher is not forced into choosing between the two. Both platforms provide cross-compatibility through the functions called *eeglab2fieldtrip.m* and *fieldtrip2eeglab.m*, respectively. In this study, EEGLAB has been used for loading in the datasets, filtering the data using a high and low-pass filter, and cleaning the data of (both CI and other) artefacts using its built-in extended ICA. The data were exported to FieldTrip for the fast, routine processing of the cleaned data and the calculation and evaluation of the ERPs.

2.2 FILTERING

The first step in software processing of the collected EEG data is choosing whether or not to filter the data. Incorrectly filtering the data can introduce new artefacts and distorting the data may have severe effects on the final ERPs, whereas not filtering the data at all can leave in a lot of background noise [10-12]. Therefore, appropriate filter design is a step that should be carefully considered.

Filtering by using the FIR filter in EEGLAB and the consequences of excessive filtering have been demonstrated in a paper of Rousselet [10]. He had also shown that in a sample of 158 ERP studies, both the median and the modes of these studies were at 0.1 Hz for high-pass and 30 Hz for low-pass.

Based on these findings, the settings of the FIR filter used on all of the datasets in this study were filtered using the basic FIR filter in EEGLAB. The high-pass filtering and low-pass filtering were done separately, as sometimes the filters would not work when both are done at the same time. The high-pass filtering was first done at a setting of 0.1 Hz, and afterwards, the data was again low-pass filtered at 30 Hz. These two steps were performed on the datasets of all participants, as to remove the background noise from the data before any further analysis was done.

3 Artefact rejection

This chapter is dedicated to the removal of artefacts that are common in all sorts of EEG research. As previously stated, the most notable artefacts on EEG data are blinks, muscle contractions, and eye-movements. The identification of these artefacts can be done by either visual inspection (manual selection of bad trials), automatic detection, or semi-automatic detection (the same as automatic detection, but with a visual inspection of the trials marked for removal) [13]. After the contaminated trials are identified and selected, they can be either removed manually or cleaned with the ICA algorithm. It was found that in this experiment setup, the combination of both manual rejection of trials and ICA cleaning provided a good way to minimize artefact-related contamination of the EEG data.

3.1 THE REMOVAL OF ARTEFACTS USING INDEPENDENT COMPONENT ANALYSIS

Independent component analysis is an algorithm that is widely used in EEG research nowadays as it provides a way to minimize artefacts without the loss of relevant data. Based on statistical analysis, the ICA is able to convert a collection of data vectors into a set of components that are maximally independent from each other. One of its many practical applications is blind-source separation; the separation of a mixed signal into its source signals without any pre-knowledge of these sources.

First applied on EEG data by Makeig et al. in 1996 [14], the ICA was able to separate the mixed signal of an EEG recording into the signals it is composed of by computing these independent components (ICs). The ICs would then be visualised by plotting their time-course averages and scalp map projections. Any artefact-related ICs can then be identified and excluded from the original dataset, hereby effectively minimizing the effect of these contaminations. The practical application of this method is well documented in the literature [15], and is very commonly used nowadays in EEG research of many kinds.

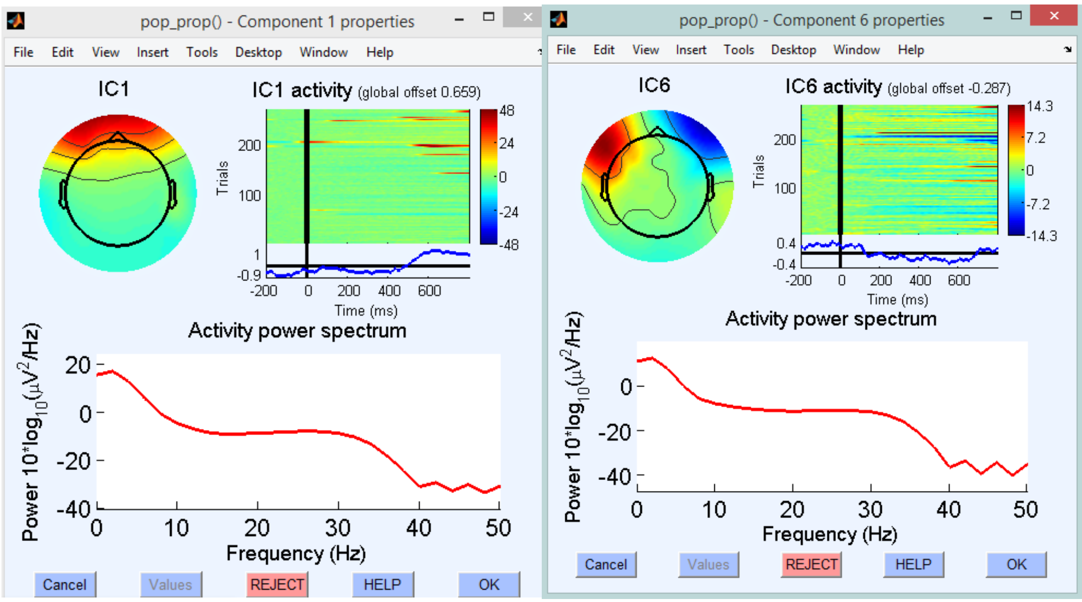

Figure 5: Two eye-related artefact ICs are shown in this figure. On the left an IC related to blinks in the data (identified by the characteristic topography above the eyes) and on the right an IC related to horizontal eye-movements (opposite polarity above the eyes).

The EEGLAB toolbox provides a way to apply ICA to EEG within the comfort of a Graphical User Interface. Using its built-in function *runica()*, the program can perform automated ICA on loaded datasets containing either continuous or segmented EEG data. In this study, the ICA was performed on separate trials in the EEG data in order to reduce computing times.

Even though the ICA is capable of separating the sources that contaminate the signal, the algorithm is not always able to achieve this in practice. As described by Makeig when he first published about EEGLAB (including also an explanation of its ICA) [4], the underlying components may not always be successfully separated if they are not temporally independent of each other. ICs therefore always have to be evaluated by a trained observer, making this a very subjective method. Though when used correctly, ICA provides a reliable way to minimize a wide variety of artefacts, while preserving as many brain-related signals as possible. Especially when limited data is available, ICA performs well when compared to other methods such as regression and PCA [16].

3.2 MANUAL REMOVAL OF ARTEFACTS

Any trials that are severely contaminated when compared to the rest of the trials can be removed prior to the ICA. If there are signals from less sources, it is expected that the ICA will perform better when trying to separate the remaining sources. In our case, this was observed in the ICs when some prior manual cleaning was done to the datasets as opposed to no cleaning at all. The trials that were removed during this visual inspection of all individual trials were mostly eye blinks and eye-movements [fig. 6]. As shown in figure 6, these artefacts are easy to spot when doing a manual examination of the acquired EEG data, and can quickly be marked and removed.

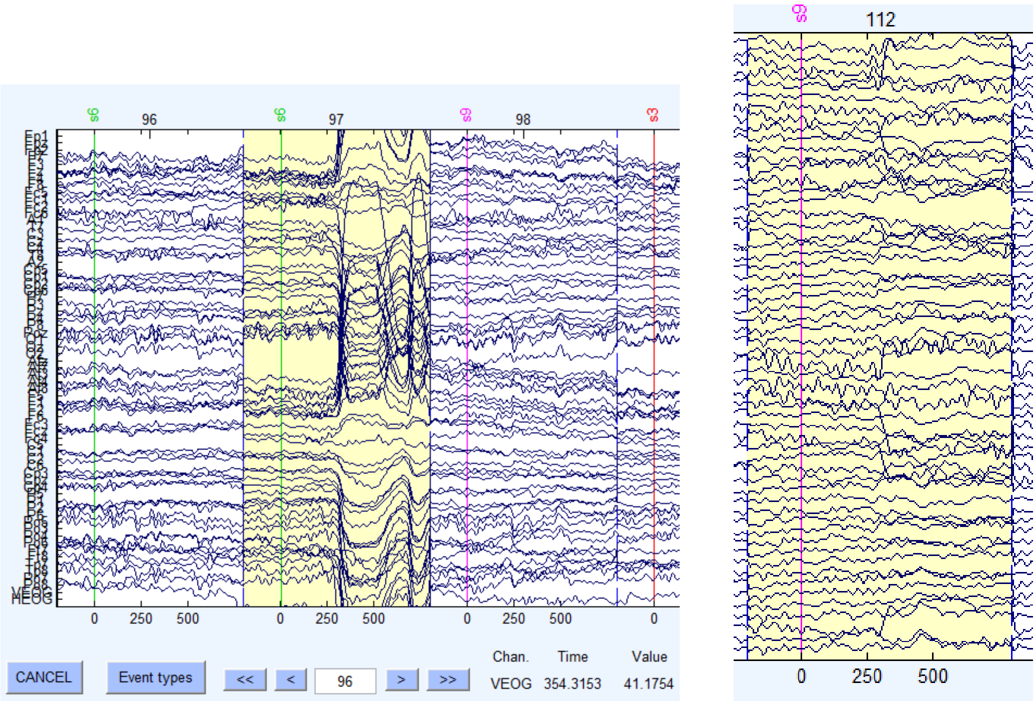

Figure 6: Two images are shown here. On the left a blink in the EEG data: the trial number 97 showed a blink that interfered and contaminated all channels. On the right an eye-movement artefact occurring around 250 ms after stimulus onset and appearing on all channels as an elevated voltage potential. Blinks are more easy to spot than eye-movement artefacts and trials were always completely removed when they were spotted. Eye-movements were only removed if they were clearly visible and occurring across all channels.

4 The cochlear implant artefact

The pre-processing steps that are needed for CI participants are found to be generally the same as normal hearing subjects. The same filter and re-referencing settings can be used, as well as a manual inspection for the removal of the classic artefacts. However a main issue when working with CI participants is that an additional artefact related to the cochlear implant is often observed, which cannot be removed using these techniques. In our study, ICA was not only used to remove classical artefacts, but also proved useful in minimizing the CI-related artefact.

4.1 VISUALISATION OF THE CI ARTEFACT

In order to be able to successfully remove the CI-related artefact and to conclude that it is not present (or minimized) in the averaged time-lock analysis, it is first necessary to understand how the CI artefact manifests itself. There are numerous previous studies that describe the artefact when a pure tone stimuli is used, but not a lot is known about the artefact in a speech-related experiment. These two can differ greatly, as pure tones have a constant amplitude, whereas speech contains amplitude modulations.

A study performed by Xiaoxia Li et al. in 2010 [17] shed some light on this issue. All of the working components (sound processor, receiver/stimulator and implant load board) of a *Nucleus Freedom* cochlear implant were connected to a tissue model. This tissue model, in the form of a chicken carcass, was fitted with a 64-channel NeuroScan system in order to record the CI artefact without any interfering neurological components.

The results of this experiment showed that the settings on the device greatly influenced the manifestation of the CI artefact, but information about the settings of the CI users was not readily available to us during our experiments. However, in their experiment they were able to demonstrate the difference between pure tone stimuli and speech stimuli [fig. 7].

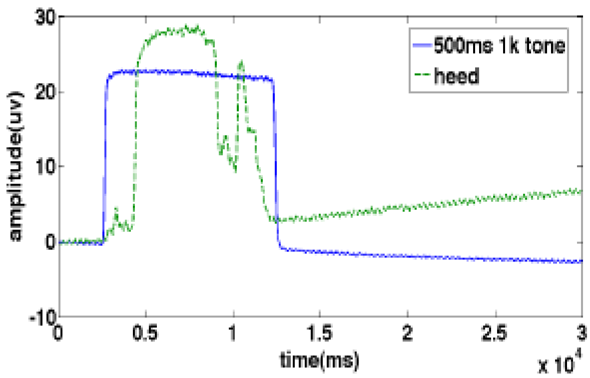

Figure 7: The difference between the CI artefact induced by speech and pure tone stimuli. The pure tone stimuli used was a 500ms long 1 kHz tone and the speech stimuli were the word “heed” being presented. (From Xiaoxia et al., 2010 [17]).

Even though the CI-artefact can look very different in a more realistic setup, this gives a general idea regarding what to expect when observing the datasets from CI subjects.

4.2 MINIMIZING THE CI ARTEFACT USING A SINGLE CHANNEL APPROACH

In our study, a 64-channel NeuroScan system was used mainly for the application of ICA. ICA needs as many electrode channels as possible, or the algorithm will not be able to separate the sources from the mixed signal reliably. A 64-channel system is however very expensive, and for many other EEG experiments hardware like this will not be readily available.

An alternative method to ICA, proposed by Mc Laughlin et al. [20], provides a possibility to remove the CI related artefact using a single-channel approach. They had found that the CI related artefact consisted mainly of two components: a high frequency component and a low frequency component (similar to the 'pedestal' artefact in fig. 7). The high-frequency artefact was found by them to be completely attenuated by a low-pass filter of 30 Hz (also applied by us), leaving only the low frequency artefact. This problem was then solved by creating a mathematical model to estimate the low frequency artefact based on the pulse amplitude.

Their experiment was done in order to examine LAEPs (late auditory evoked potentials) induced by pure tone stimuli. Applying a similar method in speech related experiments is possible, but would be far more difficult in practice. The CI artefact in pure tone stimuli experiments will have a predictable amplitude, whereas the amplitude of the artefact in a speech related experiment is more likely to have constant modulations. Therefore an adaptable model would be required, and mostly in the interest of time it was decided not to perform this method during the project.

4.3 MINIMIZING THE CI ARTEFACT USING INDEPENDENT COMPONENT ANALYSIS

Similar to the application of ICA for removal of classical artefacts as described in paragraph 3.1, ICA can also be used in order to identify and remove CI artefact related ICs. This way, the CI artefact can be effectively reduced, allowing for the analysis of ERPs in contaminated EEG recordings.

One of the main reasons why this approach was used to minimize the CI-related artefact was due to the amount of previous studies successfully being able to do this in a similar way. To give some examples: ICA has been used to minimize the artefact in the analysis of CAEPs (cortical auditory evoked potentials) in children [18], it has been compared to the optimized differential technique [6], and has also successfully been used in the analysis of AEPs (auditory evoked potentials) [5,19].

Furthermore, even a semi-automatic CI correction tool has been developed by Viola et al. [7,8]. The main difficulty of using ICA is the selection of independent components that are related to the artefacts, as they can be very difficult to identify in practice. This semi-automated correction tool allows a more objective way of selecting independent components that are related to the CI-artefact. Due to technical difficulties with getting the outdated program to function properly, and considerations in the interest of time, this method has not been tested during this study.

Even though these studies were performed using pure tone stimuli and not speech stimuli (as was the case in our study), they do provide us with some information and criteria for the selection of CI artefact related ICs. One major attribute of CI-related ICs is that they are characterized by a centroid figure in their scalp map topography [fig. 8]. Additionally, when looking at the temporal activity of these ICs (top right in figure 8), most of the activity occurs in the region of stimulus onset and can be either dipolar or monopolar.

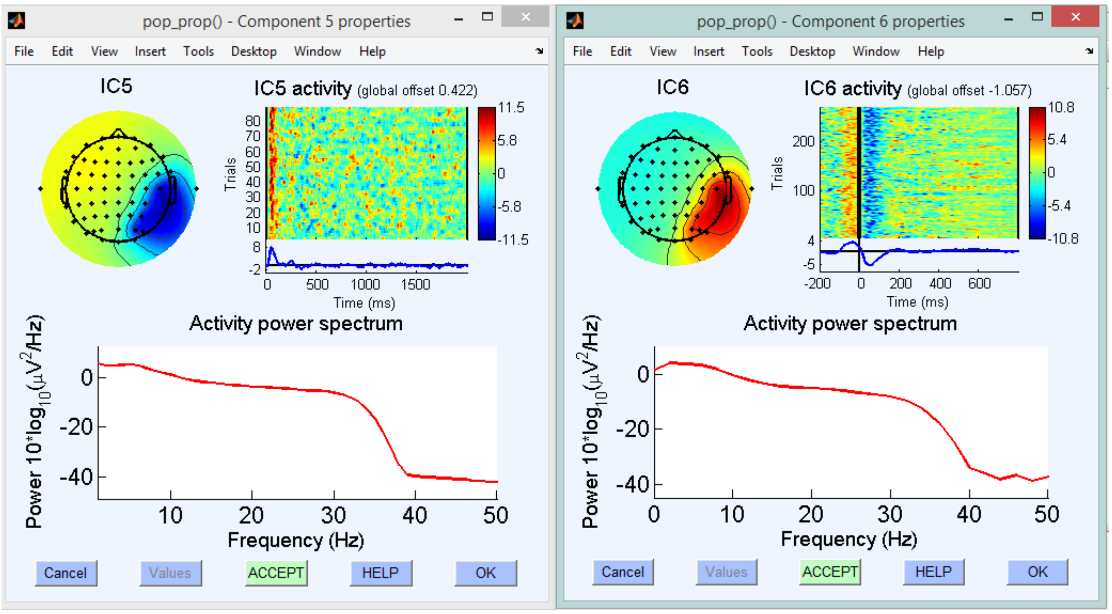

Figure 8: The centroid figure (the blue and red shapes on the scalp map) often present in CI-related ICs. Both images are ICs from the same experiment, but with a different trigger stimulus.

Unfortunately these two criteria alone do not allow the isolation of all the elements contributing to the CI-artefact, but they do allow the recovery of the event-related potentials from the contaminated dataset, which was sufficient for our experiment.

The ICs found during the ICA most likely represent the low-frequency artefact as described in the Mc Laughlin paper, and the high-frequency artefact was already attenuated by using the 30 Hz low-pass FIR filter. Based on these assumptions, it is expected that we have indeed been able to successfully minimize the CI related artefact using commonly applied pre-processing steps and independent component analysis.

5 Conclusion

In this literature study done in conjunction with my Research Project on minimizing the CI related artefact in an event-related potential experiment using speech stimuli, it has been demonstrated that the steps in pre-processing of CI subject data are generally the same as the steps required in the data of people without a CI. With the additional step of using independent component analysis in the data of CI participants, all datasets could be cleaned and prepared for further analysis.

Using an FIR filter of 0.1 - 30 Hz attenuates background noise as well as the high-frequency CI related artefact, without negatively influencing the final ERPs, and subsequently removing all severely contaminated trials opens up the path for ICA. With ICA, all remaining artefacts could be successfully minimized in order to allow the analysis of ERPs.

The ICA approach however remains to be a subjective method as the evaluation and selection of independent components is a task that has to be manually performed by a trained researcher. Therefore, the ICA approach may prove not to be a successful method for other researchers in similar future experiments.

Additionally, one other major drawback of ICA is that the algorithm itself will sometimes not be successful in separating the CI related component from the neural signal, resulting in mixed components (both neural and CI related). The removal of these components will not only minimize the CI related artefact, but also minimize neurological information and may eventually negatively affect the final ERPs. Future research will have to verify this, but caution is advised when removing components that have neurological properties as well as CI component properties.

The single-channel approach may provide a solution to these problems, but developing a similar system for speech related experiments will take more time and testing than was available during this project. This is mainly due to the complexity of the amplitude modulations in speech stimuli, and the variance of the artefact among different CI devices and settings.

The ICA approach did however, perform well for most participants in our speech experiment and allowed us to retrieve the ERPs from our contaminated data. Even in electrode channels very close to the implant location we were able to uncover peaks that were previously not visible.

The ICA may not be flawless, but in our case proved more than sufficient up until now. Unfortunately, clean data of only two CI participants were available for the duration of this project. The experiment however is still ongoing and this method will continue to be tested on future participants, hopefully validating the effectiveness of this approach.

6 Literature

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