Detection and correction of artefacts in EEG for neurofeedback and BCI applications

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Award date:
2012
Detection and correction of artifacts in EEG for Neurofeedback and BCI applications

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August 2008
TPM / Philips Research

ID nr: 0520395
Report nr: N/KFM 2008-02
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Technical note TN-PR 2008/00409

Issued: 8/2008

Artifact detection and correction in Neurofeedback and BCI applications

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Philips Restricted

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Concerns: Report

Period of Work: September 2007 - August 2008

Notebooks:

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Title: Detection and correction of artifacts in EEG for Neurofeedback and BCI applications

Author(s): Ivo Erkens, Gary Garcia Molina, Ad Denissen

Reviewer(s):

Technical Note: TN-PR 2008/00409

Additional Numbers:

Subcategory:

Project: Direct Neural Access for Content Manipulation (2005-145)

Customer:
Keywords: Ocular artifact detection, ocular artifact correction, Ambulatory EEG, ICA, BCI, Neurofeedback

Abstract: Scalp recorded electroencephalogram signals (EEG) can nowadays be recorded by pocket-size devices, giving rise to several new consumer based applications of EEG, e.g. brain computer interfaces (BCIs) and neurofeedback (NF). Using EEG ambulatory systems such as these, creates new challenges for EEG data analysis, especially concerning artifact handling. In a clinical setting, EEG can be recorded in a controlled environment, while the subject is in rest, and using additional sensors, e.g. EOG electrodes or eye tracker systems. For user-friendly applications, controlling the environment and the user, and using obstructive sensors for recording, are not possible. This requires a new perspective in the evaluation of artifact handling in EEG.

In this thesis artifact handling is considered from an ambulatory-system point of view. Artifacts are classified in accordance with their impact on possible BCI and NF applications. Artifact detection performance is measured based on individual electrode signals, yielding a topographic view of artifact detectability. A method for artifact correction is chosen based on practical considerations pertaining to implementation. The influence of recording settings on correction performance is explored. A validation of artifact correction is given, based on averaged signals.

Ocular artifacts have a significant impact on the analysis of EEG. The fact that they cannot be avoided, appear often (up to 15 times for eye blinks and possibly more often for movement), and have a large signal to artifact ratio (SAR) (up to -10 for frontal electrode sites and approximately 1 for the central area of the scalp), makes the correction of these artifacts necessary. The performance of three threshold-based detection methods is found to be highly subject dependent. The locations of the electrodes used for detection have a great influence on detection performance, which is closely related to SAR.

For the correction of ocular artifacts from EEG recordings for BCI and NF applications, independent component analysis (ICA) is chosen as the preferable method. Key in accurate ICA artifact estimation is the location of the electrodes that are used as input. The importance of using frontal electrodes outweighs the importance of a high number of electrodes. The minimum sample rate needed for accurate ocular artifact estimation is 128 Hz. The most efficient and effective approach to correct artifacts, is to first construct a training file for each ocular artifact type. From these training files a filtering matrix is constructed, which will subsequently be used to correct artifacts as they are detected. Even under optimal conditions ICA correction is incomplete and residual artifacts remain.
Conclusions: Among the possible artifacts than can influence ambulatory EEG applications, ocular artifacts are the most relevant. They cannot be avoided, either by using state-of-the art equipment, or by the subject itself, and have significantly high SARs at relevant electrode locations.

The performance measure of artifact detection methods varies across subjects. An experiment using just 4 subjects revealed significant dissimilarities. It has been shown that there is no method that provides the best results for every subject, i.e. for a different subject, a different method can perform best. Detection methods perform better in areas with large SARs.

For the correction of ocular artifacts in EEG recorded for user-friendly ambulatory applications, ICA was found to be the preferred method. Evaluation has shown the considerable importance of including frontal electrodes to improve ICA performance. A sample rate of 128 Hz has been found to be sufficient for good artifactual source estimation.

The implementation of ICA should clearly be based on a training file approach. This method is both more efficient, and more effective for artifact correction.

ICA correction was found to be incomplete in the experiments performed in this thesis. Residual artifacts were found after averaging corrected data. The most likely explanation for this phenomenon is the non-linear propagation of artifacts.
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Chapter 1

Introduction

1 context

The first experiments involving the measuring of electrical activity from a brain were done in 1875 by the English physiologist Caton [1]. His research was confined to studying animals because state-of-the-art technology required the placement of electrodes directly on the surface of the brain. It was not until 1929 that the German psychiatrist Hans Berger made a major breakthrough by recording electrical potential fluctuations with electrodes placed on the intact scalp of a human being. Since then, the electroencephalogram (EEG) has been recognized as a very useful diagnostic tool and is used for a variety of clinical purposes, e.g. sleep pattern assessment and recognizing epileptic seizures. Today, EEG can be measured by means of pocket size devices, creating opportunities for consumer based EEG products. One example of such an application, is a brain computer interface (BCI). A BCI is a communication system that translates brain activity into commands for a computer or other device. Another example is neurofeedback (NF), where the user is provided with information on his own brain activity, in order to improve his state of mind.

2 Challenges

Recording EEG for these consumer based applications, creates several new challenges that were not an issue for the clinical use of EEG. Firstly, the user will have a much higher freedom of movement, which may give rise to a number of artifacts. The detection and possible correction of these artifacts, are the main topics of this thesis. Furthermore, the equipment used to record the EEG, must not pose too great an inconvenience to the user, leading to several constrictions on the recording hardware. Design is also very important and design will also create limitations on the equipment. Finally, the fact that these applications will have to perform online, creates the need for fast processing of the EEG data, including artifact detection, artifact handling, and data analysis.
3 Contributions

The main contributions of this thesis may be summarized as follows.

- Inventory and classification of artifacts that can influence the signals of an ambulatory EEG system

- Evaluation of artifact detection methods. Instead of using the full set of EEG and EOG electrodes to measure artifact-detection performance (usual approach), each electrode is considered individually. This provides information on the topography of artifact detectability, which is important for product design.

- Choice of the most suited correction method (Independent Component Analysis), based on evaluation of the currently available correction methods, while considering specific restrictions, such as ambulatory EEG recording, and limited computation complexity

- Evaluation of the influence of recording settings (electrode positioning, sample rate, number of electrodes) on correction performance.

- Validation of correction by comparing the average energy of corrected signals with baseline values.

- Establishment of an optimal artifact-correction approach using data recorded during training.

4 outline

This thesis is organized into seven chapters. A brief overview of the basics of EEG recording is presented in chapter 2. The artifacts that may occur during the measurement are treated in chapter 3. An evaluation of several methods to detect these artifacts is given in chapter 4. The last two chapters deal with the correction of these artifacts. In chapter 5 several correction methods are evaluated, and in chapter 6 the most suited of these methods, independent component analysis, is validated. Finally the conclusions are presented in chapter 7.
Chapter 2

EEG and its applications

In this chapter some of the basic properties of EEG are briefly discussed in sections 1 and 2. In section 3 all the relevant matters involved in recording the EEG are described, including the measurement system that has been used in this work. Several EEG applications, that are currently under development at Philips, are mentioned in section 4. The influence of artifacts on EEG and the consequences for applications is discussed in section 5.

1 Physiological origins of EEG

The central nervous system is comprised of nerve cells and glia cells. The nerve cells, or neurons, are organized in a laminar pattern, with glia cells located between them. A neuron consists of a cell body (soma), dendrites (receptor or afferent pathway), and axons (efferent pathway), as shown in Fig. 2.1. Contact with other nerve cells is provided by several thousand synapses that cover the soma, the dendrites, and the axon of each cell. Across the cell membrane a resting potential may be measured of 60-70 mV, with negative polarity at the intracellular space. This membrane potential can be influenced by the occurrence of an action potential. If an action potential travels along the presynaptic fibre ending in an excitatory synapse, an excitatory postsynaptic potential (EPSP) will occur in the next (postsynaptic) neuron, depolarizing the membrane. If several of these action potentials travel along the same fibre, there will be a summation of EPSPs. If this summed potential crosses the neuron’s membrane threshold, a new action potential will be triggered at the postsynaptic neuron. When the action potential travels in a fibre ending in an inhibitory synapse however, hyperpolarization will occur, called inhibitory postsynaptic potential (IPSP). During EPSP and IPSP the membrane potential changes through ionic current flows, both through and along the membrane. The ions involved are mostly sodium (\(Na^+\)) and potassium (\(K^+\)). The ESPS and ISPS are the primary origins of EEG signals recorded at the scalp. Because the EEG recording electrodes are relatively far away from the source of these neuron potentials, the potentials measured at the scalp are two to three orders of magnitude smaller than at intracellular levels. Furthermore, the signal recorded at an electrode on the scalp, represents the averaged effect behavior of many neurons, with numbers ranging in the millions. Large amplitudes in the EEG therefore require synchronous rhythmic activity in the neuronal populations.
2 Main oscillation frequencies

EEG is usually classified based on the energy content of certain frequency bands. Although the precise definition of these bands varies slightly, the following ranges are widely used [3]:

- Delta band (0.1-3.5 Hz) Activity in this band is associated with deep sleep and anesthesia, and is also present during various meditative states involving willful and conscious focus of attention in the absence of other sensory stimuli.
- Theta band (4 - 7.5 Hz) Originates from interactions between cortical and hippocampal neuronal groups. It appears in periods of emotional stress and during rapid eye movement sleep.
- Alpha band (8 - 13 Hz) Prominent during resting conditions and disappears when a sensory stimulus is presented or during concentration and when making mental efforts.
- Beta band (14 - 30 Hz) Typically shows in periods of intense activity of the nervous system.
- Gamma band (above 30 Hz) Associated with attention, perception and cognition.

By determining the relative energy in these frequency bands, information can be obtained on the mental state of a subject, such as attention, memory encoding, motor imagery, and perception.

3 EEG acquisition

The most common way to record EEG, is non-invasively through electrodes that are placed on the scalp, usually kept in place by a headcap. A common standardization of EEG electrode positioning is the 10-20 system [4]. In this system electrode positions are based on relative distances with respect to certain landmark points on the scalp. The midline of the head is defined as the line running over the scalp, connecting the nasion and the inion (Fig. 2.3).
Along this midline electrode are equidistantly positioned at 20% of the total distance. A similar segmentation with 10% distances is defined for the positions of the electrodes that lie on lines perpendicular to the midline, see Fig. 2.3. To record an electrencephalographic signal, at least two electrodes are required, since the potential measured by an electrode has to be referenced against the potential at a reference position [5].

The choice of the reference position is very important since only the difference in electrical potential is defined. Several different references are used in EEG recording. An often used position is the ear or mastoid, which have a relatively low electrical activity. If the focus is on local differences in electrical activity, the reference electrode can be placed close to the electrode of interest [6]. It is also possible to use averaged referencing, where the electrical activity of the electrodes is referenced against the average electrical activity of multiple simultaneously recorded electrodes. Using a single reference electrode is referred to as common referencing.

### 3.1 Experimental setup

The EEG recording equipment used in this work is a Biosemi system (figure Fig. 2.2). It is equipped with 32 pin-type active electrodes, that are positioned in accordance with the 10-20 system (see Fig. 2.3). The active electrodes have a sintered Ag-AgCl tip, integrated with a first stage amplifier, providing low noise, low offset voltages and stable DC performance, without any skin preparation [7, 8]. A special gel is used to increase conduction between electrodes and the scalp. An active-electrode has a low output impedance, reducing problems with regards to capacitive coupling between the cable and sources of interference, as well as artifacts by cable and connector movements. The electrodes share a common connector with 140 cm cable length which is connected to an AD-box.
Referencing

Referencing is handled by two electrodes: the common mode sense (CMS) active electrode, and the driven right leg (DRL) passive electrode. These two electrodes form a feedback loop, which drives the average potential of the subject (the common mode voltage) as close as possible to the ADC reference voltage in the AD-box, where the ADC reference can be considered as the amplifier zero. The DRL is placed in between the Cz and C4 electrodes. The standard location for the CMS is in between the Cz and C3 electrodes In this thesis however, another reference point has been chosen. The CMS-reference electrode was placed approximately 3 cm below the Oz electrode near the inion. This was done to better represent the global propagation of ocular artifacts, which are the main focus of this thesis. These large amplitude artifacts, travel from the anterior part of the head to the posterior, and while they propagate through the brain they are attenuated. If the reference electrode is placed midway between the posterior and anterior, the amplitude of these artifacts will appear to change signs as they pass the reference location (Fig. 2.4): the reference electrode forces the amplitude to be zero halfway, and any further decrease in amplitude will subsequently be manifested as an increasingly larger negative amplitude relative to the reference electrode. Since this is a very non-intuitive way of representing artifact propagation, a different reference location was selected for conceptual clarity. It was chosen on the midline of the scalp, for reasons of symmetry. Since this location is the farthest from the source of ocular artifacts, these artifacts will also be almost completely attenuated, making it a good grounding location.
Figure 2.4: Schematic representation of the propagation of an ocular artifact (eye blink) along the central axis of the scalp. When it reaches the reference location, the signal is zero by definition. Further attenuation of the peak is manifested as an increasingly larger negative peak.

Measurement routine

The recording hardware is equipped with software to control measurements. It monitors electrode impedance and allows software based re-referencing to any electrode. Measurements are performed as follows:

- The subject is asked to sit in a comfortable chair.
- The electrode headcap is placed on the scalp of the subject, making sure it fits tightly.
- The gel cavities in the headcap are filled with the gel after which the electrodes are placed. Electrode impedance is kept low.
- During the recording of the EEG, the subject is asked to sit still, and not move his head.
- The EEG is recorded and digitally stored for further processing.

EEG is usually divided into segments of a certain duration for analysis. When this segment, or epoch, contains the measured voltage of several electrodes, this will be referred to as a recording. If only a single electrode is considered, this will simply be called a signal, to prevent confusion. The recorded EEG is processed in Matlab using the EEGLab toolbox [10]. All signals were bandpass filtered between 1 and 60 Hz using a third order Butterworth filter. This frequency band was chosen in accordance with the relevant EEG frequencies in BCI and neurofeedback applications. To attenuate power line noise a notch filter at 50 Hz was applied.

Baseline EEG

As described previously, EEG is an ongoing, continuous signal that is never silent, and looks different from person to person. Because the EEG is subject specific, many features cannot be expressed in absolute values, but they must be expressed relative to a subject’s baseline EEG. This baseline serves as a reference, and should therefore be recorded under resting conditions. To record the baseline, subjects were asked to keep their eyes open and keep their gaze fixed on a point while avoiding blinks. Subjects were asked to keep their eyes open, to avoid alpha waves, and keep their gaze fixed at a single point, and to blink as little as possible. From the recording of the required length, the epochs containing ocular artifacts were rejected manually.
4 Applications

In the past, EEG has primarily been used in a clinical setting. Recently there has been an increasing interest in using EEG for consumer-like applications. Examples of such applications (on which this thesis is focused) are: brain computer interfaces (BCIs) and neurofeedback (NF). They will be introduced in the following sections.

4.1 Brain computer interface

A BCI is a direct brain-computer communication system, which allows the user to control a device by merely thinking [9]. It was first conceived to help people that are suffering from severe neuromuscular disorders, by providing them with new ways of communication. Currently, the scope of BCI research is much broader, and it is even being used in the video gaming industry. The subject controls the device by performing mental activities (MAs), which are associated with certain actions. The nature of these MAs depends on the BCI application, and may include cursor positioning, spelling programs, or controlling a robot. The BCI identifies the MAs by detection of certain features in the EEG of the user.

One type of BCI is based on a MA called evoked response. It makes use of external visual or auditory events (e.g. blinking objects on a computer screen, flashing elements on a grid, or brief sounds), which elicit transient signals in the EEG that are characterized by voltage deviations known as event related potentials (ERPs) [11, 12]. When the user pays attention to a particular stimulus, an ERP that is time locked with that stimulus appears on his EEG, which is detected by the BCI. By associating actions with these stimuli, the user can gain control of the BCI by focussing his attention on the stimulus corresponding to the desired action. An example of evoked response based BCI is based on the P300 response. If infrequent or particularly significant auditory, visual, or somatosensory stimuli are mixed with routine stimuli, these will typically evoke a positive peak in the EEG at about 300 milliseconds after the stimulus presentation. This can be detected by the BCI, which presents the user with different stimuli, previously associated with specific actions. The P300 is prominent only in the response elicited by the desired choice, which allows the BCI to determine the user’s intent. For a P300 based BCI, electrodes near the C3 and C4 electrodes are of importance. Analysis consists of averaging over several trials in the time domain.

Another type of evoked response that can be used for BCI is the steady state visual evoked response (SSVER). When a flickering light of variable frequency (2-90 Hz) is presented to the user, this will elicit a SSVER in his EEG, which is characterized by an oscillation at the same frequency as the stimulus. When actions are associated with targets flickering at different frequencies, the user can control the BCI by gazing at the target corresponding to the desired action. Common methods to detect SSVERs consist of examining the averaged spectral content in the visual processing region, namely electrodes O1, O2, and Oz.

Another type of BCI is based on operant conditioning, where the user can acquire control of the BCI by feedback on his MAs. An example of such a BCI is based on event-related desynchronization (ERD) [13]. The user imagines the movement of his hands which causes the attenuation of the power in the 8-13 Hz band in the signals recorded at electrodes on the motor cortex. Through this amplitude decrease, which can be detected by comparing the left and right hemisphere, the BCI can distinguish between left or right movement, without any actual movement being involved. This can be used for, e.g. cursor positioning. While two electrodes are in principle sufficient to detect ERDs, using more electrodes may increase the detection accuracy.
4.2 Neurofeedback

The aim of neurofeedback is to provide the user with information on his brain activity, with the intent to influence this activity in a positive manner [14]. The general idea is that the user is capable of controlling his MA to some extent, and can do this in a constructive manner, provided he receives feedback about it. At Philips, neurofeedback systems based on auditory feedback are being investigated. A headset, equipped with a portable EEG recorder with two electrodes at C3 and C4, is used to measure the user’s brain activity. From these signals, the user’s stress levels are deduced, and this information can be communicated to the user through music, e.g. volume changes. The current prototype measures the user’s mental state by comparing the energy in the alpha band to the energy in a band from 1-42 Hz.

5 Artifacts

Brain activity is not the only source of electrical activity in the EEG. Several other parts of the body, e.g. heart, eyes, muscles, all produce their own electrical potentials that are always mixed, to varying extent, with the cerebral activity in the EEG. These non-cerebral sources are measured in the EEG as artifacts, and induce large amplitude distortions. The environment in which the EEG is acquired can also be the source of several artifacts, e.g. power line noise, and amplifiers [15]. If an epoch contains an artifact it is usually rendered unusable for analysis. This makes artifact handling an essential part of any EEG application, and several different methods are used. A very pragmatic manner of dealing with artifacts, is prevention. In a clinical setting, environmental conditions are usually carefully controlled. Recording rooms are often made free of electromagnetic influences, and subjects are asked to lie down and to refrain from moving, during measurements. To reduce ocular artifacts, subjects are frequently asked to keep their eyes closed and not move their gaze direction. For ambulatory BCI and NF applications, controlling the environment and the user in such a manner is not an option. Therefore, recording artifacts is unavoidable, and validation of the recorded EEG is necessary [16].

A prerequisite for developing an artifact handling procedure is a thorough understanding, categorization, and classification of artifacts. It is important to know how often an artifact occurs, at what position on the scalp, and to what extent it distorts the cerebral EEG. An assessment of these matters is given in chapter 3.

Once the relevant artifacts are identified, they have to be detected before they can be handled. There are many detection methods in use today, each with their own advantages and disadvantages. Artifact detection will be discussed in chapter 4.

After an epoch containing an artifact is detected, there are two possible options in dealing with it. The most straightforward and most commonly used option is rejection of the epoch, i.e. dismissing the epoch for further analysis. However, for certain applications rejection may prove unacceptable. Both P300 and SSVER BCI require the averaging of several trials of EEG. When the trials containing artifacts are rejected, the total number of trials that are needed will increase. This could significantly lower the bit rate of the BCI. For ERD based BCIs, the ultimate goal is to recognize the user’s intent, from a single trial. If this trial would contain an artifact, rejection is not an option, since all information would be lost. For the neurofeedback device, an epoch containing an artifact could lead the programme to mistakenly derive that the user is stressed, and as a reaction it would pause the music unnecessarily. The user would therefore receive
incorrect feedback from the device, lowering effectiveness. Since rejection of all contaminated epochs is undesirable, correction of the artifact may be a solution. In the last decades several different approaches to artifacts correction in EEG have been developed. They will be discussed in chapter 5. The key in artifact correction is to remove the artifact from an epoch to such an extent that the relevant information can be extracted, without removing any of that relevant information. Chapter 6 gives a detailed analysis of the correction method that was chosen in this thesis.
Chapter 3

Artifact classification

EEG artifacts can be divided into two separate classes: environmental (non-biological) artifacts, and user generated (biological) artifacts. To the first class belong power line noise, and artifacts caused by the recording equipment, e.g. electrode pop and amplifiers. Biological artifacts include eye blinks, eye movement, muscle activations, jaw clenching, the heart, and movement of the subject [15]. These artifacts may all adversely influence the effectiveness of the EEG applications described in the previous chapter. The extent to which an artifact may interfere with an applications, depends on the magnitude of the artifact, the electrode site, and the frequency of occurrence of the artifact. In this chapter, an evaluation of these matters will be given for each artifact type, where main focus will be on ocular artifacts.

1 Non-biological artifacts

Most problems with non-biological artifacts can be solved by using proper recording procedures. Active electrodes reduce movement artifacts and electrode pops can be prevented by using appropriate circuitry [17]. Power line noise is reduced by assuring electrode impedance is low and the remainder can be filtered out using a notch filter (see also chapter 2). If the right equipment is used, and the experiment is setup correctly, the non-biological artifacts can be greatly attenuated. As far as they are present, they depend on the hardware that is used for recording the EEG. In this thesis, these artifacts are not considered.

2 Muscle activation

Facial muscles and muscles in the neck can also cause artifacts in the EEG. Figure 3.1 shows two examples, namely eyebrow raising and jaw clenching. Both artifacts appear as large amplitude, high frequency distortions, as can also be seen in the power spectral density (PSD) graph in Fig. 3.2. The eye brow raising artifact is a representative example of facial muscle artifacts, which are all in the high frequency range. Clearly, jaw clenching is a very strong artifact, making it remarkably difficult to extract any useful information from the EEG. Although muscle artifacts can certainly distort the EEG, they can voluntary be avoided, as far as healthy subjects are concerned. They are therefore not studied further in this thesis.
Figure 3.1: The time domain representation of eyebrow raising (left) and jaw clenching (right), occurring at $t = 1.5$ s. The artifacts are characterized by large amplitude waves in the high frequency range. The jaw clenching artifact is much stronger than the eyebrow raising artifact, which is representative of other facial muscle artifacts. The scales are in $\mu V$.

Figure 3.2: The PSD of jaw clenching and eyebrow raising, with the baseline PSD as a reference.
3 Ocular artifacts

Ocular artifacts are caused by a difference in electrical charge between the cornea and the retina \[18\]. Electrically active cells on the retina keep a charge difference intact, causing the cornea to be positively charged with respect to the retina. This phenomenon is often referred to as the corneo-retinal dipole. Under controlled and stable light conditions, the difference in electrical charge between cornea and retina is fairly stable. Therefore, potential fluctuations caused by the eyes will only appear in the EEG when the eyes move or blink. When the eyes move, altering gaze direction causes the position of the cornea and retina change with respect to the rest of the head. This dipole movement causes a change in the electrical potential throughout the head. During an eye blink, potential change is caused by the eyelid moving over the positively charged cornea. Eye movement and blinking never happen completely independent from one another: during eye movement small eyelid movements occur, and blinking causes small eye movement \[19\]. Eye blinks and eye movement will be characterized in the following. It is important to point out however, that the shape of biological artifacts is subject dependent, and there are even differences between artifacts produced by the same subject. Furthermore, the ocular artifacts are voluntarily created by the subjects. Voluntarily created artifacts may differ slightly from involuntarily created artifacts \[20\]. The classification given in the next sections, should therefore be interpreted as a general description, and not as a definition of the respective artifacts.

3.1 Eye blinks

Humans blink roughly every four or five seconds, i.e. 12 to 15 times a minute. The physical act of blinking lasts about 100 ms. The distortion of the EEG caused by the eye blink however, lasts significantly longer. Figure 3.3(a) shows 4 seconds of EEG with a voluntary blink artifact at \(t = 0\) for electrode Fp1. This electrode was chosen because the blink artifact is most pronounced in the frontal electrodes. As it is symmetrical with respect to the left and right hemisphere, Fp1 was chosen arbitrarily in stead of Fp2. The blink artifact appears as a peak with amplitude considerably greater than that of baseline. The shape of the artifact is partially occluded by the cerebral EEG. Figure 3.3(b) shows the averaged signal of 150 epochs from a single subject, all containing an eye blink, aligned with respect to the top of their peaks. By averaging, the non-artifactual baseline EEG cancels, revealing the true shape of the artifact. The standard deviation is also shown to indicate the spread in the data. For \(-0.5 > t > 0.5\), the averaged signal is practically zero, which is expected for averaged baseline EEG, as it can be seen as a random signal. At \(t = -0.5\) the average signal starts to deviate from zero towards a valley with its minimum at \(t = -0.1\). The valley is followed by a sharp peak whose maximum amplitude varies per blink. The average value for this subject (healthy male, 25 yrs old) is 105 \(\mu V\) with a standard deviation of 30 \(\mu V\), however, these values may differ greatly for other subjects. Another valley appears after the peak, making the complete blink artifact last up to 1 second. Although the size of an eye blink artifact is variable, the general shape if fairly constant.

A frequency domain representation of an eye blink is shown in 3.3(c). This graph shows the average power spectral density (PSD), based on the discrete Fourier transform (DFT) of the 150 signals, using a 1 second epoch \((-0.5 < t < 0.5)\). The DFT was calculated using a fast Fourier transform (FFT) in Matlab with a Hamming window. As a reference, the average PSD of 150 baseline epochs is also shown. The sharp rise at 1 Hz is caused by the fact that all signals are band passed filtered between 1 and 60 Hz, as described in chapter 2. The PSD shows an increase in the power spectral density for frequencies below 20 Hz. Most of the artifactual energy is contained in the delta and theta band.
Figure 3.3: The general characteristics of the eye blink artifact. (a) The time domain representation of a 4 second epoch with a voluntary blink occurring between \(-0.5 < t < 0.5\). (b) The average of 150 blinks and the standard deviation. The amplitude of the peak may vary greatly from one blink to the next, and is subject specific. (c) The frequency domain representation. The energy of the eye blink artifact is mostly contained in the range below 20 Hz. (d) The average blink at different locations on the scalp, from the anterior to posterior sites.
Figure 3.4: The average eye blink artifact for 4 different subjects. Clearly the shape and magnitude of the artifact differs between subjects.

Figure 3.3(d) depicts the manner in which the eye blink artifact is mitigated as it propagates through the brain. It shows the average eye blink at different electrode sites, traveling from the front of the head to the back. The artifact attenuates rapidly as it propagates through the brain, scull and scalp, and is barely visible as it reaches the occipital region (O1).

To give an indication of the subject dependency of ocular artifacts, Fig. 3.4 shows the average eye blink artifact for 4 different users. From this figure it becomes apparent that eye blinks may differ in shape, height, and width.

3.2 Eye movement

Eye movement artifacts are more difficult to model than eye blinks. Whereas a blink is almost always performed in the same manner, eye movements have more degrees of freedom. The shape of the eye movement artifact is influenced by starting angle, angle change (proportional to distance between starting point and end point), and speed. These degrees of freedom would give rise to any number of different eye movements, each with a different shape. To be able to characterize eye movements in this thesis, they were limited to two orthogonal classes: horizontal and vertical movement. Horizontal movement is defined here as follows: the subject is sitting in front of a computer screen, the distance from his eyes to the screen approximately 50 cm. On the screen, two points are indicated, 30 cm apart, on a horizontal axis crossing the center of the screen. The subject is asked to keep his head facing the screen, and move only his eyes to direct his gaze from one point to the other. For vertical movement, the two indicator points were 25 cm apart on a vertical axis crossing the center of the screen. The subject is asked to change his gaze from one indicator to the other at regular intervals, thereby creating a movement artifact (left to right, right to left, upward, or downward). Because horizontal and vertical movement create distinctly shaped artifacts, they will be discussed separately in the next sections.
Horizontal eye movement

Contrary to eye blinks, horizontal eye movements are most pronounced at the F7 and F8 electrodes. Their averaged signal for these electrodes is plotted in Fig. 3.5. As can be seen, the horizontal eye movement artifact is antisymmetrical, both with respect to the left and right hemisphere, and with respect to the direction of the movement. Starting the movement from the right and moving gaze towards the left, manifests itself as a negative peak, followed by a positive peak at the F7 electrode (a), which is mirrored at the F8 electrode (b). Reversing the movement causes a sign change (c,d). All movement artifacts were aligned with respect to their maximum for F8 and their minimum for F7. Only 25 single-session recordings were used to average each graph, because only recordings could be used that were free of any other artifacts. Especially blinks appeared frequently, rendering a large number of recordings unusable.

Figure 3.6(a) shows the power spectral density of the eye movement artifact (left to right at F8) and its attenuation as it moves away from the eyes. Only one direction is shown because of the similarity between the two directions for these properties. The attenuation of the artifact is very similar to the eye blink, as shown in Fig. 3.6(b).
Vertical eye movement

For vertical eye movement, the two directions of movement cause very differently shaped artifacts, as can be seen in Fig. 3.7. An upward movement (Fig. 3.7(a)), generates an artifact very similar to an eye blink, though smaller in size. A downward movement artifact resembles that of a horizontal movement (Fig. 3.7(b)), although it is symmetrical. The spectral content of the two opposite movements are also dissimilar (Fig. 3.7(c) and (d)). Vertical eye movements are more pronounced at the Fp1 and Fp2 electrodes. The attenuation of the artifacts is very similar to that of the other artifacts, and is therefore not shown.

3.3 Signal to artifact ratio

To get a better picture of artifact influence at different scalp locations, the signal to artifact ratio (SAR) can be used. The SAR is defined as the ratio between the total energy of the EEG from cerebral sources and the total energy from artifactual (ocular) sources, at a certain electrode site:

\[
SAR = 10 \cdot \log \frac{\sum_{i=1}^{N}(EEG_c(i))^2}{\sum_{i=1}^{N}(EEG_o(i))^2} = 10 \cdot \log \frac{\text{Energy}_{EEG_c}}{\text{Energy}_{EEG_o}}. \tag{3.1}
\]

Here, \( EEG_c \) is the cerebral EEG, \( EEG_o \) is the EEG from ocular sources and \( i \) is the sample number out of a total of \( N \). The difficulty is in determining the part of the EEG that is due to cerebral sources, and the part that is due to ocular sources, as they are both mixed in the recorded EEG, and there is no direct way to separate them.

This problem can be overcome by using baseline EEG as an estimate for pure cerebral EEG. If this baseline is measured without the occurrence of any ocular artifacts, its energy can be used as \( EEG_c \) in equation 3.1. Naturally this is not an ideal method, since baseline EEG will always be contaminated by artifacts. However, it is assumed here, that if the subject is sitting still, and refrains from either moving or blinking his eyes, artifacts will be sufficiently reduced to allow baseline EEG to approximate pure cerebral EEG. The energy of an ocular artifact could now be defined as the difference between the energy of an epoch containing an artifact and a
Figure 3.7: The time and frequency representation of the vertical eye movement artifacts at electrodes Fp1 and Fp2.
Figure 3.8: The SAR of the ocular artifacts shown as topographic plots. All artifacts are strongest at the frontal electrodes, blinks and vertical movement at Fp1 and Fp2, horizontal movement at F7 and F8. Eye blinks attenuate faster than eye movement artifacts. In the central region of the scalp, artifact energy is of the same order of magnitude as baseline (cerebral) energy.

baseline epoch. An epoch containing an artifact contains both artifactual and baseline EEG, and by subtracting this baseline energy, the energy belonging solely to the artifact remains. The SAR now becomes:

\[
SAR = 10 \cdot \log \frac{\text{Energy}(EEG_b)}{\text{Energy}(EEG_a) - \text{Energy}(EEG_b)},
\]

(3.2)

where \( EEG_b \) is baseline EG and \( EEG_a \) is EEG containing an artifact. Naturally, the epochs containing baseline and the ones containing artifacts have to be recorded separately from each other and therefore there is no direct correlation between any given baseline epoch and an artifactual epoch. Therefore, calculating SAR in the manner described above, is only valid if the average energy is taken across several epochs, for both artifactual and baseline EEG. To calculate the SARs for each of the ocular artifacts 100 one-second long epochs, containing an artifact were used. Furthermore, 100 baseline epochs of 1 second were recorded and visually inspected to ensure they were free of artifacts. The energy (between 1 and 60 Hz) was taken for each epoch and then averaged. Bootstrapping was used to verify that 100 averages were enough to get an adequate average of the energies.

The SAR for each of the ocular artifacts is shown in Fig. 3.8. The SARs are shown here as topographic plots, to give a convenient representation of artifact propagation. The frontal electrodes have the lowest SAR, indicating that the artifacts are most pronounced there. Eye
blinks have a lower SAR at Fp1 and Fp2 compared to eye movements, however, they also attenuate more rapidly. This can be explained by the fact that during a blink only the eyelid moves (by approximation) instead of the entire eye, which is located deeper in the head. Whereas blinks and vertical movement artifacts are strongest at the most frontal electrodes Fp1 and Fp2, horizontal eye movement has the largest amplitude at electrodes F7 and F8. This is due to the fact that the fields of the two moving dipoles cancel each other out on an axis, equidistant from both dipoles, i.e. the midline.

Although all artifacts attenuate rapidly, in the central region of the scalp (the area around C3 and C4) they are of approximately the same magnitude as baseline EEG. This means that in this region, which is important for many BCI and NF applications, the cerebral EEG is indeed distorted by ocular artifacts. The results shown in Fig. 3.8 show agreement with studies using simulations [21].

4 Conclusion

The relevance of an artifact depends on the magnitude of the artifact, the electrode location, and the level of occurrence of the artifact. Non-biological artifacts depend on the hardware that is used to record the EEG, and since no BCI or NF hardware was available at the time this work was done, these artifacts were not studied further. Muscle activation artifacts, although they have a great impact on the EEG practically everywhere on the scalp, can easily be avoided by the user. They will therefore also not be treated in this thesis.

The occurrence level of ocular artifacts is quite high, for eye blinks up to 15 times a minute, and for eye movement this number may be much higher, depending on the activity performed by the user. Given a length of approximately 1 second per artifact, ocular artifacts can contaminate 25% or more of the recorded EEG, and can therefore be of high impact on EEG analysis. The rapid attenuation of the artifacts, makes the location of interest a very important factor in determining their impact. The SAR shows that artifacts are of the same order of magnitude at the electrodes that are relevant for BCI and NF applications (area around C3 and C4). Given the high occurrence level of eye blinks, the length of their impact period, and their involuntary nature, ocular artifacts potentially have a great impact on EEG analysis. Therefore the focus of the remainder of this thesis will be on the detection and correction of these artifacts.
Chapter 4

Artifact detection

The previous chapter showed that ocular artifacts can significantly distort EEG, which poses a problem for BCI and NF applications. It is therefore important that epochs that contain these artifacts, are either rejected for analysis, or corrected prior to analysis. Whether an epoch is to be rejected or corrected, detection of the artifact is a prerequisite. This chapter deals with the matter of artifact detection. Several artifact detection methods found in literature are described in section 2. In most studies however, ocular artifacts are detected using the electro-oculogram (EOG). The EOG is the electrical activity of the eyes, measured by electrodes that are placed close to the eyes. Using EOG sensors is not desirable for user-friendly ambulatory BCI and NF applications, as electrodes placed near the eyes would create too much inconvenience for the user. Therefore, the detection methods are re-evaluated, without the use of EOG. Detection performance is measured, using the receiver operator characteristics curve, which is introduced in section 1. Since BCI and NF devices will ideally use as few electrodes as possible, evaluation will be based on single electrode detection, i.e. the performance of each detection method is measured for each electrode individually. The setup of the experiments is given in section 3 and the results are presented in section 4.

1 Performance measure for detection methods

EEG recordings are usually evaluated in epochs, whose length depends on the application. Consequently, artifact detection operates on these epochs. A detection algorithm has to determine if a given epoch contains one or more artifacts. It can therefore be considered a classifier, assigning a label (artifact or no artifact) to each epoch. Since different detection algorithms are considered in this chapter, a performance measure is required to compare them. A means to evaluate the success rate of a classifier is the receiver operating characteristics (ROC) curve, which is a technique for visualizing, organizing and selecting classifiers, based on their performance. Each epoch (referred to as an instance) that is to be evaluated by the classifier, belongs to one element of the set \{p, n\} of positive or negative class labels [22]. The positive (negative) class contains the epochs with (without) an artifact. The purpose of a classifier is to assign each instance to the predicted classes \{Y, N\}. Given an instance that has been assigned by a classifier, there are four possible outcomes. If the instance is positive (p), and it is classified as positive (Y), it is designated a true positive (TP). When it is classified negative (N) it is called a false negative (FN). If the instance is negative (n) and it is classified negative it is counted as a true negative (TN), if it is classified as a positive it is counted as a false positive (FP). Given a classifier and a set of instances, a two-by-two confusion matrix can be constructed, representing...
the dispositions of the instances. This confusion matrix can be seen in table 4.1.

<table>
<thead>
<tr>
<th>True class</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p</td>
<td>n</td>
</tr>
<tr>
<td>Hypothesized class</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>True Positives</td>
<td>False Positives</td>
</tr>
<tr>
<td>N</td>
<td>False Negatives</td>
<td>True Negatives</td>
</tr>
</tbody>
</table>

Table 4.1: The confusion matrix for a classier.

From this matrix, two relevant parameters can be derived. The true positive rate of a classier is calculated as:

$$t_{p rate} = \frac{TP}{TP + FN},$$  \hspace{1cm} (4.1)

Thus, $t_{p rate}$ is the fraction of the total actual positives that were correctly classified as such. The false positive rate of the classier is given by:

$$f_{p rate} = \frac{FP}{FP + TN},$$  \hspace{1cm} (4.2)

and represents the negatives that were incorrectly classified as positives, as a fraction of the total negatives.

The relative trade-off between the benefits for a classier (true positives) and the costs (false positives), can be visualized in an ROC graph. ROC graphs are two-dimensional graphs in which $t_{p rate}$ is plotted on the y-axis and $f_{p rate}$ on the x-axis. An example of an ROC graph can be seen in Fig. 4.1.

Each point in the ROC graph represents a classier applied to a set of instances. Several points in the ROC graph are important to note. Point (0,0) represents the strategy of never assigning a false positive, at the cost of never assigning a true positive. The opposite strategy, of unconditionally issuing true positives, yields 100% false positives as well, represented by the point (1,1). Perfect classification is represented by the point (0,1). Generally, a point in ROC space can be considered better than another, if it is to the northwest ($t_{p rate}$ higher, $f_{p rate}$ lower, or both). Furthermore, classifiers appearing on the left-hand side of the graph (point B), can be considered to be conservative, i.e. they make positive classifications only based on relatively stringent restrictions. They make few false positive errors, and as result have low true positive rates. Classifiers that appear near point C, can be thought of as more convenient. Due to their weaker restrictions they will more quickly assign a true positive, the consequence of which are more false negatives. The dashed line ($x = y$) represents the strategy of random guessing. Any classifier lying in the lower right triangle (point A) performs worse than random guessing, and should therefore be negated, producing a point in the upper left triangle.

If a classier uses a threshold to assign classes to an instance, the value of this threshold will influence the point in ROC space that classier will occupy. A threshold of zero, will yield the point (1,1), as all instances will be labeled positive. The point (0,0) is obtained by using an infinitely high threshold, effectively assigning no instances to the positive set. By varying the
threshold, the classifier will trace a curve through ROC space, which is characteristic for the classifier.

A very useful property for comparing classifiers is the area under the ROC curve (AUC). The AUC reduces ROC performance to a single scalar value representing expected performance \([23]\). The AUC can be calculated by using trapezoidal integration [24]:

\[
AUC = \sum_{i=1}^{N-1} \left( tp_{rate} \cdot frate_{rate} + \frac{1}{2} (tp_{rate+1} \cdot frate_{rate}) \right),
\]

where \(\Delta tp_{rate} = tp_{rate+1} - tp_{rate} \), \(\Delta frate_{rate} = frate_{rate+1} - frate_{rate} \), and \(N \) is the number of points on the ROC curve.

2 Methods for artifact detection

Several different detection methods can be used for artifact detection [25, 26, 27]. Delorme et al. [28] show that time and frequency domain thresholds work very well for ocular artifacts. They are described below, after which an extension of the time domain threshold will be introduced.

2.1 Time domain threshold

Time domain threshold detection (TDT) is the most commonly used artifact detection method. For each epoch, the maximum amplitude is determined, with respect to the mean of the signal. If this amplitude is larger than a certain threshold value, the epoch is said to contain an artifact. If the maximum value is lower than the threshold, it is designated as clean. To obtain the ROC
curve, the threshold was varied between 0 and 400 $\mu V$. The upper limit was chosen higher than the highest peak amplitude, corresponding to an infinitely high threshold.

### 2.2 Frequency domain threshold

Frequency domain thresholding (FDT) is similar to time domain thresholding, with the exception that the threshold is applied to the power in a certain frequency band. The procedure is as follows: a FDT is calculated of a single epoch of a signal, multiplied by a Hamming window. From this FDT, the energy in the frequency range from 1 through 7 Hz is determined, as this is the band where artifactual EEG is most dissimilar from baseline EEG, as was shown in the previous chapter. If the energy in this range is larger than the threshold, varied between 0 and 1500 $\mu V^2$, the epoch is classified as artifactual.

### 2.3 Extended time domain threshold

Time domain threshold detection makes no use of the consistency that ocular artifacts exhibit. Ocular artifacts are not simply large amplitude distortions, they are also accompanied by negative voltage valleys. These valleys appear within a certain time window around the positive peaks. This information can be used to improve the time domain threshold detection routine. By taking the minimum value within range of 300 ms around the positive peak, and applying a threshold between 0 and 400 $\mu V$, to the difference between the maximum and minimum values, detection may be improved. This method will be referred to as extended time domain threshold detection (ETDT).

### 3 Acquisition

The detection methods were all first tested for each ocular artifact type separately. For each artifact (blinks, horizontal and vertical eye movements) a recording of 4 minutes was made, where the subject creates the respective artifact every four seconds, i.e. every four seconds, the subject will blink, move his eyes from left to right (and 4 seconds later from right to left), or move his eyes up (and 4 seconds later down). Since eye blinks cannot be avoided for long periods of time, the movement artifact recordings will also contain eye blinks. The recordings were preprocessed according to the standard procedure (described in chapter 1) and subsequently divided into 1 second epochs, with 0.5 second overlap. Each epoch was then manually assigned to the $\{p,n\}$ set by the experimenter, based on visual inspection of the time domain signals. This process was simplified by the fact that artifacts appear every four seconds. Nonetheless, errors may occur due to misclassification by the experimenter. A common problem in classifying epochs are artifacts that are partially contained in an epoch (though clearly present). The epoch edge can often cut an artifact in two, making it’s assignment somewhat arbitrary. In this work, an epoch is considered to contain an artifact, if more than approximately 40% of the signal is artifactual. An ocular artifact can therefore encompass several epochs. All this will influence the performance measure of the classifier, as it is calibrated with respect to a set that is assumed to be accurate, though in practice is not. Analysis of the recording yielded 478 epochs per recording of which approximately 25% was labeled as artifactual, which conforms with expectations, as the artifacts last approximately 1 second, and appear every 4 seconds.

After the detection methods were evaluated for each artifact type individually, their performance was evaluated using a recording which contained all ocular artifact types. This recording was
created by concatenating the three separate recordings. The beginning and ending of each recording was smoothed to make sure that no large amplitude differences appear where the recordings were attached to each other. The result was one recording of 12 minutes, containing all three artifact types in equal amount. To test the robustness of the detection methods, all the experiments were performed for 4 different subjects, (all healthy, one female and three male, ages between 24 and 34). The results of the performance analysis are given in the next section.
4 Detection performance results

In this section, the performance measures for the three detection methods will be presented, based on the ROC curves and the AUCs. This will first be done for each artifact type individually. Finally all artifacts are detected in a single recording, yielding different results. The detection methods were tested on the EEG of 4 different subjects.

4.1 Eye blink detection

The ROC curves for eye blink detection are shown in Fig. 4.2. Each graph shows the ROC curves of a subject, for each of the three detection methods, at the Fp1 electrode. This electrode was chosen because detection of the eye blink is easiest at the frontal electrodes. The graphs clearly show the subject dependency of artifact detection. While TDT and ETDT perform nearly perfect for subject 1, they perform significantly worse for the other subjects. FDT performs approximately equally well for all subjects, and is the best method for subjects 2 and 3. It does however never reaches perfect prediction, and for subjects 1 and 4 the other methods perform better. In general, ETDT outperforms TDT for eye blink detection. For subjects 2, 3, and 4 detection clearly tends to the more conservative part of the ROC curve. For these subjects, using a relatively high threshold will lead to a good \( tp_{rate} \), without leading to a high \( fp_{rate} \).

An explanation for the difference in performance for the different methods can be found in the respective shapes of the averaged eye blink artifacts of the different subjects. When they are compared to each other (Fig. 3.4), the blink of subject 1 shows the shallowest valleys before and after the main peak. For this subject, epochs that end just before the main peak are relatively artifact free, whereas the same epochs for subject 2 or 3 would most likely be designated artifactual, as the depth of the valley is much more pronounced for these subjects. Detecting these valley parts of the eye blink is relatively difficult for simple TDT. This is why ETDT performs better. Apparently, the frequency content of the valley epochs, is distinct enough to detect them with FDT, which is why this method performs with such consistency. The epochs containing the main peak, are clearly easy to detect, given the near perfect performance for subject 1.

For BCI and NF, not all electrodes may be available, and therefore an evaluation of detection performance for each electrode separately is required. A convenient way to represent the relative performance at different scalp locations, is a topographic plot of the AUC of each detection method. In the topographic plot, the AUC (varying between 0.5 and 1) is indicated by color. Such plots are shown in Fig. 4.3 for subject 1, as this subject yielded the best results. The graphs show that all detection methods perform well at the anterior electrodes, and performance deteriorate rapidly towards the posterior sites, where the detection methods hardly perform better than random guessing (AUC = 0.5). As is expected, the topographic plots resemble those of the SAR for eye blinks.
Figure 4.2: The ROC curves of the three detection methods, at electrode Fp1, for 4 different subjects. The numbers in parentheses are AUC values. Detection method performance depends on the subject. Both TDT and ETDT show near-perfect classification for subject 1, where FDT performs worse in comparison. For subjects 2 and 3, FDT is the better classifier. In general, FDT is the most robust detection method.
4.2 Horizontal eye movement detection

For horizontal eye movements, the F7 and F8 electrodes showed the largest SAR. As a result, detection of horizontal movement is also the easiest near these electrodes, as shown in Fig. 4.4 for electrode F7. For horizontal eye movement, all three detection methods work approximately equally well. The difference in performance across the 4 subjects is much smaller than that of blinks. Apparently eye movement artifacts show less variation in shape or size, leading to a more consistent, and overall better detection. The AUCs for horizontal movement are larger than for eye blinks. The topographic plots of the AUCs of subject 1 in Fig. 4.5 show very clearly the peak in detection performance of the artifacts around the F7 and, by symmetry, F8 electrode.

4.3 Vertical eye movement detection

The ROC curves for vertical eye movement are shown in Fig. 4.6. The AUC plots show that vertical eye movement detection is easier at the frontal electrodes, as was expected based on the SAR. Detection performance is relatively consistent between subjects, although FDT seems to perform worse for subject 1 than for the other subjects. For subjects 2 and 3, vertical movement detection performs better than blink detection.

4.4 General ocular artifact detection

So far each type of ocular artifact has been detected separately, in order to evaluate performance of the detection methods for each artifact type. In practice however, all ocular artifacts will naturally occur during a recording and any detection procedure should be able to detect all of them using a single, albeit subject specific, threshold. As different artifacts are detected with optimal results at different threshold values, using one threshold for all of them will adversely affect detection performance. To see to what extent this applies to each detection method, they were tested on a recording containing all ocular artifacts.

The results can be seen in Fig. 4.8. Only electrode Fp1 is shown here, but the results for F7 are comparable, as depicted in Fig. 4.9. Given the fact that all artifact types had to be detected using the same threshold, the detection methods perform relatively well for each subject. For all subjects, ETDT does not perform worse than TDT. The AUC plots show an averaged effect of Fp1/Fp2 and F7/F8 being the ideal detection electrodes, which can be expected.
Figure 4.4: The ROC curves of the three detection methods at electrode F7, for horizontal eye movement detection. The numbers in parentheses are AUC values. All methods perform comparably and better than for eye blinks.

Figure 4.5: The topographic plots of the AUC of subject 1, of the three detection methods for horizontal eye movement. All detection methods perform best in the area around electrodes F7 and F8, as is expected from their SAR plots.
Figure 4.6: The ROC curves of the three detection methods, at the Fp1 electrode for vertical eye movement detection. The numbers in parentheses are AUC values.

Figure 4.7: The topographic plots for subject 1 of the AUC of the three detection methods for vertical eye movement.
Figure 4.8: The ROC curves of the three detection methods for all ocular artifact types. The numbers in parentheses are AUC values.

Figure 4.9: The topographic plots of the AUC of the three detection methods for all types of ocular artifacts for subject 1.
5 Discussion and conclusion

The shape and size of eye blink artifacts are subject dependent, resulting in large variation in detection performance across subjects. This is evident even with few (e.g. 4) subjects. Furthermore, different subjects showed different best performing methods, making it difficult to determine which detection method is preferable. In general ETDT performed better than TDT. Any actual detection algorithm will have to be fine-tuned to the specific user, both for the detection method that should be used, and for the threshold value. Also, testing the detection methods on more subjects is recommendable.

By examining performance at each electrode site, valuable information is gained for application design. The topographic plots of the AUC clearly showed that although ocular artifact detection works very well at the frontal electrodes, detectability decreases rapidly farther away from the anterior sites. This may have a large impact on the detection performance of the applications that are considered in this work, as using frontal electrodes may not be desirable. By knowing the performance for different artifact types, the detection algorithm can be fine-tuned to that artifact type that has the largest influence on the application.
Chapter 5

Artifact correction

Epochs that contain artifacts can either be rejected for analysis, or they can be corrected. As described in chapter 2, artifact rejection may prove unviable for some applications, as it may lower the bit rate to an unacceptable level. Artifact correction can solve this problem. The goal of artifact correction is to extract the clean, or true, EEG (the EEG from exclusively cerebral sources), from the recorded EEG, which is a mixture of EEG from cerebral and artifactual sources. This can generally be modeled as follows:

\[
EEG_r(t) = EEG_c(t) + \sum_{k=1}^{K} EEG_k(t),
\]

(5.1)

Where \( EEG_r(t) \) is the recorded EEG, \( EEG_c(t) \) is the cerebral EEG, and \( EEG_k(t) \) is the artifactual EEG from the \( k^{th} \) artifact source. There are several different methods to estimate \( EEG_c(t) \) from \( EEG_r(t) \). Several of these methods are presented in section 1 and their merits are discussed in section 2. Section 3 gives a more information on the implementation of the preferable correction method: independent component analysis.

1 Correction methods

Detection methods can generally be divided into two groups: methods that use only the EEG as input, e.g. component based methods, and those that require additional input, e.g. linear regression, camera tracking. In this section several of these correction methods are introduced, where main focus will be on component based methods.

1.1 Linear regression

Linear regression methods use EOG recordings to correct ocular artifacts from EEG. EOG is usually recorded by two pairs of electrodes. The electrodes of one pair are placed just above and below the eye, and the difference in their potentials is commonly referred to as vertical EOG, VEOG. The potential difference measured by the pair of electrodes positioned on opposite sides next to the eye is called horizontal EOG, HEOG. Linear regression is based on the assumption that the recorded EEG signals are a linear, time-invariant superposition of different sources \[29\]. A linear model is used to approximate the relationship between the recorded EOG, the observed EEG, and the cerebral EEG \[30\].
\[ EEG_{ri}(t) = \alpha_{1i} F(HEOG)(t) + \alpha_{2i} F(VEOG)(t) + EEG_c(t), \] (5.2)

where \( EEG_{ri}(t) \) denotes the recorded EEG from electrode \( i \) at time \( t \), HEOG(t) and VEOG denote the respective recordings EOG recordings at time \( t \), and \( EEG_c(t) \) is the cerebral EEG from electrode \( i \) at time \( t \). Here, \( F(\cdot) \) denotes a procedure dependent filter. Multiple regression may be used to estimate \( \alpha_{1i} \) and \( \alpha_{2i} \). The estimated cerebral EEG is then found by applying

\[ EEG_{ci}(t) = EEG_{ri}(t) - \alpha_{1i} F(HEOG)(t) - \alpha_{2i} F(VEOG)(t). \] (5.3)

A problem in using regression methods lies in the fact that the EOG will always contain some cerebral EEG, which will also be subtracted. This forward propagation may corrupt the corrected EEG.

1.2 Camera tracking

In [31] a novel way, using an eye tracker, to correct eye movement artifacts in EEG is described. The data from this camera system cannot be corrupted by any electrophysiological signals, making it an accurate correction method. The orientation of the eye is derived from the horizontal and vertical position of the pupil. The method is based on three assumptions:

- Changes in ocular orientation have instantaneous effects on electric potential.
- Ocular orientation is statistically independent of brain activity, as reflected in the EEG.
- The relation, between the orientation of the eye and the electrical potential caused by the eye, is adequately parameterized by first and second order combinations of eye orientation.

Eye tracker based correction showed better results compared to other correction methods.

1.3 Component based methods

Component-based correction methods use the information contained in multiple electrode recordings to estimate the ocular artifact [32]. Basically, component based analysis is nothing more than alternatively representing data by transforming it. It is a very powerful mathematical technique that is widely used for multivariate data analysis. In recent years, it has been explored as an EEG correction tool, having the advantage that no EOG recordings are necessary. In the following the principle behind component based analysis, and its use as a correction method for ocular artifacts is explained.

General model

Component based analysis is closely linked to the so called cocktail-party problem, which considers \( n \) people speaking simultaneously in a room. Their voices are recorded by \( n \) microphones, located at random locations in the room. The microphones measure \( n \) time signals, denoted by \( x_1(t), x_2(t), \ldots, x_n(t) \). Each of the recorded signals is a weighted sum of the speech signals emitted by the speakers, denoted by \( s_1(t), s_2(t), \ldots, s_n(t) \). This is modeled as a linear system:

\[ x_i(t) = a_{i1}s_1(t) + a_{i2}s_2(t) + \ldots + a_{in}s_n(t), \text{ for all } i = 1, \ldots, n \] (5.4)
where \( a_{ij} \) are parameters that depend on the distances of the microphones from the speakers. The model used here is a generative model, it describes how the observed data are generated by a process of mixing the components \( s_j(t) \). These components are latent variables, i.e. they cannot be directly observed. Only the random variables \( x_i(t) \) are observed, from which both the mixing coefficients, and the components \( s_j(t) \) have to be estimated. This must be done under as general assumptions as possible. Any time delays that may occur in the mixing are neglected.

It is more convenient to use vector notation here, instead of sums. The random vector \( \mathbf{x} \) has the mixtures \( x_1(t), ..., x_n(t) \) as elements, and the random vector \( \mathbf{s} \) has the elements \( s_1(n), ..., s_n(n) \). The \( n \times n \) mixing matrix with elements \( a_{ij} \) is denoted by \( \mathbf{M} \). All vectors are understood as column vectors. Using his vector-matrix notation, the mixing model can be written as:

\[
\mathbf{x} = \mathbf{M}\mathbf{s}.
\]  

(5.5)

When it is more convenient to refer to the columns \( \mathbf{a}_j \) of \( \mathbf{M} \), the model can also be written as:

\[
\mathbf{x} = \sum_{i=1}^{n} \mathbf{a}_i s_i.
\]  

(5.6)

Inversely, the components \( s_i \) are given by:

\[
\mathbf{s} = \mathbf{W}\mathbf{x},
\]  

(5.7)

where \( \mathbf{W} \) is the inverse of \( \mathbf{M} \), called the unmixing matrix. Component analysis techniques can now be seen as methods to estimate both \( \mathbf{M} \) and \( \mathbf{s} \), by posing certain restrictions on \( \mathbf{M} \) and \( \mathbf{s} \). These restrictions depend on the method. Two such methods are principal component analysis and independent component analysis. For a more detailed description of these methods, see [32].

**Principal component analysis**

Principal component analysis (PCA) uses the assumption that the components \( s_j \) are uncorrelated to solve (5.7). Two random variables \( y_1 \) and \( y_2 \) are said to be uncorrelated, if their covariance is zero:

\[
cov(y_1, y_2) = E\{y_1y_2\} - E\{y_1\}E\{y_2\} = 0.
\]  

(5.8)

Here \( E\{\cdot\} \) denotes the expectation operator. Given a set of multivariate data, PCA will give a smaller set of variables with less redundancy, which would give as good a representation as possible. In PCA, redundancy is measured by correlations between data elements, meaning that only second order statistics are used. In the PCA transform, the vector \( \mathbf{x} \), with \( n \) elements, is first centered by subtracting it’s mean \( E\{\mathbf{x}\} \). Then \( \mathbf{x} \) is linearly transformed to another vector \( \mathbf{y} \) with \( m \) elements, \( m < n \), so that redundancy induced by the correlations in the elements is removed. This is done by finding a rotated orthogonal coordinate system such that the elements of \( \mathbf{x} \) in the new coordinates become uncorrelated. At the same time, the variances of the projections of \( \mathbf{x} \) on the new coordinate axes are maximized, so that the first axis (principal component) corresponds to the maximal variance, the second axis corresponds to the maximal variance in the direction
orthogonal to the first axis etcetera. Dimensionality in the data set is then reduced by retaining those characteristics of the data set that contribute most to its variance, i.e. keeping lower-order principal components and ignoring higher-order ones.

**Independent component analysis**

Independent component analysis (ICA) makes much stronger assumptions on the sources $s_j$ than PCA. It assumes that all the sources are mutually independent to estimate $W$. Statistical independence can be defined as follows: for any functions $h_1$ and $h_2$, the random variables $y_1$ and $y_2$ are said to be independent if

$$
E\{h_1(y_1)h_2(y_2)\} = E\{h_1(y_1)\}E\{h_2(y_2)\}.
$$

(5.9)

This means that they originate from two different physical processes that are in no way related to each other.

A second restriction for the independent components (ICs) is that all but one component must have non-Gaussian distributions. The key property of ICA is that it uses higher order statistics (i.e. higher than second order) to estimate the ICs. However, for Gaussian distributions higher order cumulants are zero. Thus, ICA is essentially impossible if the observed variables have Gaussian distributions. It is not necessary however, to know what the actual distributions are, as long as they are not Gaussian. For time dependent signals (such as EEG signals), the non-Gaussianity requirement can be loosened as long as the ICs have different autocovariances. The time dependency of the signals also brings forth the condition of instantaneous linear mixing of the source signals at the sensors. For ICA to work, this condition must be satisfied. However, as most of the energy in EEG signals lies below 1 kHz, the quasistatic approximation of Maxwell equations holds, and each time instance can be treated separately. Therefore, the propagation of the EEG signals is immediate, and instantaneous mixing is valid.

The third restriction is that the mixing matrix $A$ is square. This means that the number of independent components is equal to the number of observed mixtures. This restriction is imposed to simplify the estimation, and to ensure that the matrix is invertible.

The ICA model in (5.5) also holds some indeterminacies. Firstly, the variances (energies) of the ICs cannot be determined. The reason is that, both $s_i$ and $M$ being unknown, any scalar multiplier in one of the sources $s_i$ can always be canceled by dividing the corresponding column $a_j$ of $M$. As a consequence, the magnitudes of the independent components are usually fixed in such a way that each has unit variance: $E\{s_i^2\} = 1$. The matrix $M$ will take this restriction into account. This still leaves the sign of each component undetermined: they could each be multiplied by -1 without affecting the model. As long as one is aware of this however when analyzing the components, it does not pose a problem. The second ambiguity of ICA is the indeterminacy of the order of the components. The order of the terms in equation (5.6) can be freely changed because again, $s$ and $A$ are unknown. Any IC can therefore be called the first one.

**ICA by maximum likelihood estimation**

There are many ways to estimate the ICA model. A very popular approach is maximum likelihood estimation. Consider the probability density $p_x$ of the mixture vector $x = Ms$:
\[ p_x(x) = |\text{det}B| p_s(s) = |\text{det}B| \prod_{i} p_i(s_i), \quad (5.10) \]

where \( B = M^{-1} \), and \( p_i \) denote the densities of the independent components. This can be expressed as a function of \( B = (b_1, \ldots, b_n)^T \) and \( x \), giving

\[ p_x(x) = |\text{det}B| \prod_{i} p_i(b_i^T x). \quad (5.11) \]

Assuming there are \( T \) observations of \( x \), denoted by \( x(1), x(2), \ldots, T \). The likelihood can be obtained as the product of this density evaluated at the \( T \) points. This is denoted by \( L \) and considered as a function of \( B \):

\[ L(B) = \prod_{t=1}^{T} \prod_{i=1}^{n} p_i(b_i^T x(t)) |\text{det}B|. \quad (5.12) \]

Usually the logarithm of the likelihood is used, as it is algebraically simpler. It is given by

\[ \log L(B) = \sum_{t=1}^{T} \sum_{i=1}^{n} \log p_i(b_i^T x(t)) + T \log |\text{det}B|. \quad (5.13) \]

The maximum likelihood estimator is usually found from equating the derivative of (5.13) to zero, and solving the equation. An estimation principle based on the likelihood, developed by Bell and Sejnowski, is the infomax principle \[35\]. This is based on maximizing the output entropy, or information flow, of a neural network with nonlinear outputs. The ICA toolbox \[10\] that was used for ICA calculations is based on the infomax principle.

## 2 Correction method evaluation

The linear regression methods described in section 1.1 requires the recording of EOG alongside EEG. This involves accommodating at least two EOG electrodes near the eye of the user. For the ambulatory devices described in chapter 2 this is not acceptable, since these electrodes would hinder the user and compromise an efficient product design. Linear regression methods are therefore not an option. Likewise, camera tracking is not an option for the described applications. Placing a camera in front of the front of the user would be very cumbersome for ambulatory systems.

The solution clearly must be found in component based methods, as they require no additional sensors. PCA is computationally more simple, as it uses only second order statistics, making it easier estimate the orthogonal PCA components. In general however, there is no reason why neurobiologically distinct EEG sources should be spatially orthogonal to each other. Therefore, PCA should not in general effectively separate the artifactual EEG from the cerebral EEG components \[36\].

ICA makes use of the stronger assumption of independence, which for EEG artifact correction implies that the different artifact sources are independent from the cerebral sources. Although there is no strong theoretical basis to support this assumption, empirical evidence suggest that it holds very well. This would suggest that ICA is the better choice for artifact correction in
EEG. Jung et al. have shown that ICA does indeed outperform PCA for this purpose [37]. Nevertheless Wallstrom et al. show that PCA can be successful, especially for shorter epochs (only a few seconds), where ICA generally requires more data [30]. Both studies do however use EOG electrodes for artifact estimation.

Based on the mentioned studies, and the fact that artifact estimation will be significantly more difficult without EOG electrodes, ICA was chosen as correction method for this thesis. The fact that ICA requires relatively more data, will not prove to be a problem, as will be shown towards the end of the next chapter.

3 Artifact correction by ICA

The independent component analysis model described above, can be used to estimate artifact components from EEG recordings. The general principle behind this, is the assumption that artifactual EEG potentials are generated independently from cerebral EEG potentials. As a result, one or more of the independent components will resemble the artifact, and others will resemble cerebral EEG signals. The EEG recording can be corrected by removing the artifactual component, and then reconstructing the recording. This can be done by building a filtering matrix.

Consider the following procedure: A recording of EEG is acquired, with length $L_{\text{epoch}}$ in seconds, using $n$ electrodes. This recording is denoted as $\mathbf{r} = [r_1(j), r_2(j), \ldots, r_n(j)]^T$, where $r_i(j)$ is the signal recorded by the $i^{th}$ electrode, and $j$ is the sample number. This recording contains an ocular artifact, either blinking or eye movement, see also Fig. 5.1 (left). ICA is performed on this recording, resulting in the unmixing matrix $\mathbf{W}$ from equation 5.7 and consecutively the $n$ ICs $(s_1, s_2, \ldots, s_n)$, shown in Fig. 5.1 (middle). Suppose the $i^{th}$ component resembles an artifact, and will be designated $s_{\text{art}}$. To remove $s_{\text{art}}$, the mixing matrix $\mathbf{M}$ is first calculated as $\mathbf{M} = \mathbf{W}^{-1}$. Now, the elements of the $i^{th}$ column of $\mathbf{M}$, being the weight factors corresponding to $s_{\text{art}}$, will all be set to zero, effectively nullifying $s_{\text{art}}$. The artifact component now has weight zero at all the electrode sites, canceling it’s effect. A filtering matrix is now constructed using the modified mixing matrix $\mathbf{M}_{\text{mod}}$ and the unmixing matrix:

$$\mathbf{F} = \mathbf{M}_{\text{mod}} \mathbf{W}. \quad (5.14)$$

This filtering matrix can then be used to correct the original recording by simply multiplying the filtering matrix with the recording,

$$\mathbf{r}_c(j) = \mathbf{F} \mathbf{r}(j), \quad (5.15)$$

where $\mathbf{r}_c(j)$ is the corrected data. This is shown in Fig. 5.1 (right). Applying this filter matrix has the same effect as simply making the artifact component zero and then reconstructing the recording with the mixing matrix. Using a filtering matrix was chosen here for conceptual clarity.
Figure 5.1: An example of ICA artifact correction, using 10 electrodes containing an eye blink. The original recording (left) contains an eye blink artifact at $t = 2$ s. All 10 electrodes are fed into the ICA, yielding 10 independent components (middle). The first component is the artifact component. A filtering matrix is constructed, designed to effectively remove the artifact component, to correct the recording (right).
Chapter 6

ICA validation

As shown in the previous chapter, ICA is the best correction method for removing ocular artifacts from the BCI and NF devices that are considered in this thesis. In this chapter a thorough evaluation of ICA as a correction method for ocular artifacts in EEG will be given. In section 1 several validation methods for EEG correction techniques are discussed. Section 2 deals with the influence that recording settings have on ICA correction performance. The actual validation of ICA will be given in section 3 where two different techniques to apply ICA correction will be treated. All the results that are shown in this chapter are based on the correction of eye blinks, however, they can be extrapolated to eye movement as well. The conclusion and some recommendations are given in section 4.

1 Validation methods

Two features are paramount in validating the performance of a correction method. Firstly, the removal of the artifacts should be as complete as possible, or at least to a satisfactory level, i.e. the artifact terms $EEG_k(t)$ in (5.1) should be estimated accurately. Secondly, removal of the artifactual EEG should not lead to overcorrection, i.e. removal of relevant parts of the cerebral EEG ($EEG_c(t)$ in (5.1)). A major problem in assessing these features is that no obvious method of validation is available. This is due to the fact that no accurate means of measuring either uncontaminated cerebral EEG, or pure artifactual EEG, exists. Therefore, there is no criterion against which to measure the success of the correction method, and any performance measure will consequently always be less than ideal.

Several methods to validate correction methods are given in literature. In [38, 39] a visual inspection of the corrected EEG is suggested as the best method. Corrected waveforms should have face validity, i.e. they should look reasonable. This does require the input from an expert to analyze the corrected EEG, which may lead to inconsistencies. Nonetheless, useful information may be derived from visual inspection of corrected signals.

Another possible validation method is the correlation between EOG and uncontaminated EEG [38], which should be low for good correction. Apart from the fact that this validation method ignores the genuine correlation between EOG and EEG, the use of EOG recordings is not an option for the devices in this thesis, as mentioned before.

In many studies, the problem of the indeterminacy of the cerebral EEG is circumvented by using simulated EEG data to validate correction methods [21, 29, 40]. Data simulation usually consists of the simultaneous linear mixing of EEG and separately measured EOG signals. Since in this case the original clean EEG is known, it can easily be compared to the corrected EEG.
Performance measures consist of the error in either the time or frequency domain, between the corrected EEG and the original clean EEG. Although this method allows for a good comparison between different correction methods, it is less suited for the validation of a correction method, since any non-linearities in the EEG will not be taken into account. There is also no means to determine to what extent the simulated EEG resembles actual EEG. The ideal performance test would be to actually test ICA correction on the device that are being considered in this thesis. Since they were not available at the time this work was done, this was not an option. None of the validation methods described in literature are suited for ICA validation. Therefore, a different performance measure based on averaging and comparison to baseline EEG is introduced in section 3.

2 Influence of recording settings

When validating ICA as a correction method, it important to know what properties have influence on the outcome of ICA. The success of ICA estimation of the artifactual sources depends mainly on the amount of relevant information that is fed into ICA. The larger the amount of information, the better ICA is capable to estimate the independent sources. However, since ICA correction is intended to be used in BCI and NF devices, low computational load is desirable, and therefore efficiency will also have to be considered. Relevant parameters that are inherent to the recording settings are therefore:

- The electrode configuration, which depends on the purpose of the device, e.g. detecting ERDs or SSVEPs, described in chapter 2. From an acquisition point of view, more electrodes lead to better resolution. However, from a design point of view, it might be desirable to have as few electrodes as possible, e.g. NF applications that work with only electrodes C3 and C4. The effect of using fewer electrodes on the outcome of ICA correction will be evaluated in section 2.1.

- The sample rate of the device. A low sample rate requires less computation time and less processing power, and is therefore preferable. A sample rate that is too low however, may lead to aliasing. This trade-off will be considered in section 2.2.

These two properties will both be compared to optimal conditions to see how lowering the amount of information will influence ICA correction.

2.1 Electrode Configuration

One of the most important parameters that determine the outcome of ICA is the electrode configuration that is used for recording EEG. As explained in section 1.3, the number of components that ICA will generate, is equal to the number of channels that are fed into ICA. If the number of channels is insufficient, ICA will not be able to fully separate the artifactual source from the cerebral sources. Therefore, changing the number of electrodes can considerably affect the outcome of ICA correction. Equally important are the locations of the electrodes, since ocular artifacts are most prominent in the frontal electrodes, as shown in chapter 3. This means that the artifactual EEG will be easier to separate from cerebral EEG in the frontal electrodes. The Biosemi system used in this study is equipped for a maximum of 32 electrodes, which will be taken as a best case reference point. A large number of combinations can be made with these 32 electrodes, and the actual configuration of electrodes depends strongly on the application. Therefore, the effect of electrode configuration on the outcome of ICA, is studied here in a very
The eye blink component for the three different electrode configurations.

general manner, focusing on the importance of frontal electrodes. The difference is examined, between using all electrodes, using only the frontal electrodes (Fp1, Fp2, AF3, F7, F3, F8, F4, Fz), and not using any of the frontal electrodes. To do this, ICA was run with these three electrode configurations, using a recording of 4 seconds containing an eye blink artifact. The signal was filtered as described in chapter 2. From the generated independent components of each session, the blink component, \( s_{\text{blink}}(t) \), was manually selected and normalized. The results are shown in Fig. 6.1 for \( t = -1 \) to 1.

The resulting \( s_{\text{blink}}(t) \) from using all electrodes is shown as the solid blue line. It shows a peak, with its maximum at \( t = 0 \), which is also the location of the top of the eye blink in the original recording. The shape of the peak in the artifact component also matches that of the blink artifact in the recording. The rest of the component contains signal that resembles cerebral EEG, which should not generally be filtered out. Ideally, the artifact component would contain only artifactual signal. How much relevant information is contained in this component depends on the purpose of the EEG recording. A general evaluation could be made, by looking at the amplitude of the signal. The absolute amplitude of the independent components has no meaning in ICA, as explained in section 1.3. The mixing coefficients in the mixing matrix determine the weight factor for each electrode. The column of the mixing matrix corresponding to the artifact component can be used to reconstruct this component for all the electrodes, thereby restoring information on the amplitude of the artifactual signal. Evaluating the reconstructed component for electrode Fp1, showed that the amplitude ranged from -10 to 10 \( \mu V \). This is the same order of magnitude as the amplitude of baseline EEG. This means some EEG information will be lost, although what information that is exactly could be determined here.

The frontal electrode configuration, the dashed green line, shows good compliance with the 32 electrode case. This makes sense, since the eye blink is most pronounced in these electrodes, and apparently, nine electrodes are sufficient for extracting the blink component. When the front electrodes are left out of the ICA calculation, the blink component can still be identified as represented by the red line in Fig. 6.1. The peak at \( t = 0 \) has roughly the same shape as the other two, however the rest of the signal contains relatively more baseline EEG. This would mean that if this component were filtered out in order to correct the artifact, this baseline which
could contain valuable information, would also be thrown away. Therefore, even though more electrodes were used (23 in stead of 9), the resulting blink component was less good. This reveals the significance of the electrode configuration and the importance of including several of the front electrodes in ICA correction, to ensure adequate component separation. In the following sections, all electrodes will be used for ICA correction.

2.2 Sample rate

The sample rate is also an important property to evaluate. From a design point of view, a low sample rate is preferable, as this would lower the computational load for data processing. ICA however benefits from a large input of data, and therefore a higher sample rate might be necessary for good correction performance. The trade of between these two point of views will be examined here.

Given the fact that most relevant information in EEG is contained in the frequency spectrum below 60 Hz, and taken into account that all recordings are low-pass filtered at this frequency, it is expected that the sample frequency need not be higher than 128 Hz. After all, this is the nyquist rate (in powers of 2), \( F_{\text{nyquist}} = 2F_{\text{max}} \), where \( F_{\text{max}} \) is the maximum frequency of interest. The Nyquist rate gives the lower bound for the sample frequency that can be used to sample the signal without aliasing [41].

The sample rate of the Biosemi system is 2048 Hz, making it the maximum value, which will again be taken as a reference. To determine the effect of using a lower sample rate, the following experiment was performed. An EEG recording of 4 seconds, containing one eye blink at \( t = 0 \) s was measured at a sample frequency of 2048 Hz. This recording was then downsampled to lower frequencies, (1024, 512, 256, 128, 64, and 32 Hz respectively) using the Matlab resample function, which is based on a polyphase filter implementation. The recording was not downsampled below 32 Hz because it is not likely that any application will have such a low sample rate. After all, a sample rate of 32 Hz can be used to measure frequencies up to 16 Hz. For all these recordings the ICA components were calculated, and the components pertaining to the blink were selected manually, and compared to the reference component.

Part of the components, for the relevant frequencies only, are plotted in Fig. 6.2. It clearly shows that even the lowest sample frequency (32 Hz) recording shows good compliance with the reference case (2048 Hz). The shape of the peak (between \( t = -0.05 \) and 0.1 s) is matched point by point, although several points between 0.1 and 0.4 s are slightly off. This can be explained by considering the Nyquist rate. The solid line shows a sinusoidal wave pattern in this period with a frequency of roughly 20 Hz, introducing aliasing for a sample rate of 32 Hz. Downsampling to only 64 Hz yields a better result, and a sample frequency of 128 Hz leads to a blink component that is virtually identical to the reference case. Therefore, the sample frequency need not be higher than 128 Hz, for the purpose of eye artifact correction under these conditions. For this reason, all signals recorded in the experiments described in this chapter have been downsampled to 256 Hz, in order to save computation time, while maintaining sufficient resolution.

3 Validation

Once the influence of recording settings on ICA is determined, actual validation of ICA is possible, using optimal settings. The manner in which artifacts are corrected also has an influence on ICA performance. In this section, two different approaches on ICA correction and their properties are evaluated.
Figure 6.2: Part of the recording for Fp1, with different sample frequencies. Between $t = 0.1$ and 0.4 the 32 Hz case is slightly off, but the peak is estimated equally well for all sample rates

- The first uses new data for each individual artifact that is encountered to construct a filtering matrix
- the second uses a single filtering matrix based on a training file, to correct all artifacts.

The aim is to find the best approach, based on the validation of ICA correction.

### 3.1 Individual correction approach

One possible approach to correcting artifacts could be the following: the EEG signal is scanned online for artifacts, and as soon as an artifact is detected, a recording of a certain length containing the artifact is selected. ICA can then be used to calculate a filtering matrix for the specific recording which can then be used to correct the signal. This is schematically depicted in Fig. 6.3. This procedure could then be repeated for every artifact that is detected. This method understandably requires a lot of computation time, as the ICA subroutine will have to be used repetitively. Computation time could be reduced, by decreasing the amount of samples that are fed into ICA, i.e. taking a shorter epoch containing the artifact. This will however have an adverse effect on the effectiveness of ICA in finding the artifact component. The trade off between speed and quality of correction will be discussed here more closely.

#### Methods

In order to validate to what extent ICA is successful in removing ocular artifacts, a performance measure is required. Ideally, a correction method would be evaluated by comparing the corrected signal to the clean EEG signal. However, in experimentally recorded EEG, the clean EEG signal is not known, because it is mixed with the signals of artifactual sources. Some studies use simulated EEG, where a modeled artifact source is added to baseline EEG. A disadvantage of this approach is that these models never fully describe real EEG artifacts. Since the goal of this
Figure 6.3: Schematic depiction of the correction procedure for three electrodes. After an artifact is detected as indicated by the red arrow, an epoch, containing the artifact, of length $L_{\text{epoch}}$ is selected. ICA is performed on all three signals, yielding three independent components. The first one clearly is the estimation of the artifact, based on its shape. A filtering matrix is constructed so that the first component is taken out. This filtering matrix can then be used to reconstruct the corrected signals, by simply multiplying the matrix with the original signals. This entire procedure is repeated for every single artifact that is detected.

study is to evaluate ICA in a real life scenario, a different approach was chosen for validation. The success rate of correction will be evaluated by comparing the energy of the corrected signal to that of baseline EEG.

Consider a subject, who’s EEG is being measured while he is sitting comfortably in a chair, and who is asked to blink every few seconds. Arguably, the average energy of the measured EEG should, after it is successfully corrected for the eye blinks, be the same as the average energy of EEG that is measured from the same subject while he does not blink his eyes. Assuming that the neuronal activity involved in eye blinking is negligible and that a sufficient amount of epochs are used for averaging. The difference in energy between corrected and baseline EEG can thus be taken as performance measure of ICA correction. For clarity, only eye blinks are considered, and only the energy of electrode Fp1, because eye blinks are most pronounced in this electrode, as was shown in chapter 3. Due to symmetry of the eye blink artifact, electrodes Fp1 and Fp2 are equivalent, and Fp1 was chosen arbitrarily here. All 32 electrodes were however used to construct the filtering matrices. The data set that was constructed contains 150 recordings of 4 seconds, each containing one eye blink. The epochs were selected from a recording were a subject is asked to blink every 4 seconds, paced by means of a beep. The eye blinks are all aligned so that the tops of their peaks coincide at $t=0$, the center of the epoch (the epoch runs from $t=-2$ to 2s). Energy is taken in a 1 second interval, chosen symmetrically around the top of the peak for all 150 trials:

$$E = \frac{1}{f_s} \sum_{i=-0.5f_s}^{0.5f_s} s_i^2$$  \hfill (6.1)

Here, $f_s$ is the sample frequency, and $s_i$ the $i^{th}$ sample of the corrected signal. The median of the energy after correction is compared to the median energy of 300 baseline epochs with a length of 1 second. The median is chosen rather than the mean to be robust for outliers.

According to Delorme et al. [10], the ICA algorithm used here requires a sample input input of several times $n^2$, were $n$ is the number of electrodes. Arguably, the sample rate is of importance.
in considering this number as it was shown before that increasing the number of samples by increasing the sample rate does not lead to better ICA artifact source estimation. To determine the influence of the amount of samples that is used for ICA on its effectiveness, the length of the records that were used for ICA was varied between 1 and 4 seconds, and for each record, the filtering matrix was calculated and used to correct the blink artifact. The ICA epoch was always chosen with the top of the peak in the center.

**Results**

Fig. 6.4 shows a box plot of the energy that remains after correction, for different epoch lengths of the recordings that were fed into the ICA. The box plot shows the median (red line), the first to third quartile (blue box), the smallest and largest value that are not an outlier (black whiskers) and the outliers (red circles). The box plots for baseline EEG are plotted in green, as a reference. The plot for an epoch length of 1 second shows the least good results, judging by the artifact energy that remains after correction. The median energy is approximately $350 \mu V^2$, which is the value for the highest measured value for baseline EEG. Obviously, ICA correction does not succeed very well in extracting the artifact component if the entire epoch is only 1 second long. This is not an unexpected result, as the eye blink artifact itself lasts approximately 1 second. This means that ICA does not have enough baseline signal to compare to the artifactual signal. Including an extra second of signal in the ICA epoch improves the result of correction significantly. The majority of the calculated energies of the 2 second epoch are within the range of baseline values, although there are several outliers. The graph shows that the distribution of energies further improves, i.e. goes towards baseline, as the epoch length is increased further. This improvement seems to level off around 4 seconds. The 4 second epoch shows good compliance with the baseline EEG, with the exception of only a few outliers.

The relative quality of the ICA correction can also be visualized by plotting the average eye blink components for each epoch length. This has been done in Fig. 6.5. It shows the four components, which all vary in length, for a 1 second interval. The average signal for Fp1 from the recordings that were used for ICA to create the blink components is shown for comparison.

The shape of the blink components reveals why the 4 second epoch performs better than the other epochs: the shape of the eye blink is estimated better for this epoch length. Although all 4 cases have roughly the same peak shape, the valeys at $t = -0.1$ and $t = 0.17$, that characterizes an eye blink are most pronounced for the 4 second epoch, leading to a better correction. The graph also shows however, that in the interval between $t = 0.1$ and $t = 0.4$ not even the 4 second epoch component truly resembles the shape of the actual blink. A significant difference between recording and estimation exists, which will lead to incomplete correction. The difference between the 3 and 4 second case is negligible, indicating that increasing the interval beyond 4 seconds will not improve correction.

Using the distribution of the energy of the corrected signal as a performance measure, one might have concluded that ICA correction works very well, except for a few outliers. While this energy approach certainly is a good indicator of the performance of ICA, it obviously does not tell the whole story. After all, the fact that the energy of a signal is within the range of baseline EEG, does not necessarily mean that the eye blink is completely filtered out as Fig. 6.5 suggests. To verify this, the corrected signals themselves were evaluated.

Figure 6.6 shows the point by point average signal of all the corrected signals. The graph shows a residual artifact from roughly $t = 0.25$ s before, up to $t = 0.5$ s. This means that on average, a small part of the eye blink still remains in the signal after correction. This residual artifact is visible in all electrodes, although it diminishes towards Oz, because this is where the reference
Figure 6.4: The box plots of the energies of the 4 different epoch lengths \((N = 150)\). The box plots show the median (red line), the first to third quartile (blue box), the smallest and largest value that are not an outlier (black whiskers) and the outliers (red circles). The baseline reference is depicted in green.

Figure 6.5: The average of 30 independent blink components for the different epoch lengths. The dotted black line is the average signal at the Fp1 electrode of the recordings on which the components are based.
The averaged signal after correction of the 150 eye blink recordings. It clearly shows a residual artifact where the eye blink used to be.

electrode is located. Moreover, the amplitude of the residual artifact is of the same order of magnitude as that of the amplitude of baseline EEG. Had correction worked fully, the leftover baseline EEG would have a mean very close to zero for all t, as it would cancel itself out. The average signal could of course be due to a few bad corrections, with relatively large residual blinks, where the majority of the corrections is indeed good. To investigate this possibility, all 150 corrected recordings were manually inspected and only those that did not clearly show a residual blink were selected. The time average of these signals however, still showed the residual blink of roughly the same amplitude. All this shows, that even after correction, the signals still have some part of the eye blink left in it, and that ICA correction is never complete. A discussion of why this is the case, is given at the end of this chapter, after a different approach for ICA correction is treated.

3.2 Training based correction approach

In the previous, a method for online artifact correction was described, involving the calculation of a new filtering matrix for each artifact that is detected. Boudet et al. [42] suggest a different approach, where a single ICA filtering matrix is used for the correction of all artifacts in a recording. This filtering matrix will be based on a training session, which is recorded before the regular EEG recording and contains all the artifacts that are to be corrected (see also Fig. 6.7). Using one ICA filtering matrix to correct all ocular artifacts has the obvious advantage that it has a much smaller computational load, making it very attractive for online applications. The time-consuming calculation of the ICA components and the resulting filtering matrix has to be performed only once, after which the correction only requires multiplying the signals with the filtering matrix. This does bring up the fundamental issue of using the ICA spatial filtering
Figure 6.7: Schematic of the training method of artifact correction. In this approach, a training session is first recorded, prior to the actual recording session, containing artifacts that are to be corrected in the actual recording session. Based on this training record, a single filtering matrix is constructed using ICA (top box). During the actual session, whenever an artifact is detected, the signals are multiplied with the training-based filtering matrix, thus correcting them (bottom box).
matrix based on one set of data, on a different set of data. The question is whether the matrix based on one artifact, e.g. an eye blink, can be used to correct a different eye blink. However, since the source of each eye blink (or other eye artifact) can be assumed to be the same, namely the eyes, this should not prove a problem, and the ICA filtering matrix should be interchangeable from one artifact to another. For this assumption to be justified, each electrode will naturally have to stay on a fixed place on the scalp after the training session. Another requirement for using a single ICA filtering matrix, is that the filtering matrix has to be of sufficient quality. Since all ocular artifacts will be corrected with this one filtering matrix, it is imperative that it yields good results, i.e. that it will filter out as much of the artifacts as possible, while throwing out as little non-artifact EEG data as possible. As was described in the previous, the result of one filtering matrix may differ significantly from the next, which may result in bad correction. Using a training file does however have the advantage that the training recording can be relatively long, and contain several artifacts of the same type. After all, the training has to be performed only once. This means there is more data available to feed to the ICA which may lead to a better result than using the individual ICA, and a more reliable performance. These matters will be considered in the following sections.

Methods and results

To be able to compare this method to the individual method described in section 3.1, the same set of 150 blink records was used in this section. The filtering matrices were obtained from training data, recorded separately from the test data, but during the same measurement session. This was done to ensure all the electrodes remained at the same location. From the training data, training recordings were selected, containing 1, 2, 3, and 4 blink artifacts respectively. At least 4 seconds of signal was included per artifact, taking into account the results from section 3.1. The result of correction from four training sets can be seen in Fig. 6.8.

Once again, the box plot of the energy of the 150 corrected blink recordings are shown together with the box plot for baseline EEG. The training set containing a single artifact performs the least well, as is to be expected. The training sets with multiple artifacts all perform well, both for the median energy and outliers. Indeed, they perform much better than the individual approach, depicted in Fig. 6.4.

Since each ICA performance can turn out differently, the result of one training set may be different from that of another set. This is even true if training sets contain the same amount of artifacts. Since in the training approach, all artifacts will be corrected with a single filtering matrix, it is imperative to have knowledge on how much the result will fluctuate from one training set to another. Therefore, the process of correcting the 150 eye blinks has been repeated 20 times for each type of training set.

Figure 6.9 shows the distribution of the median energies of different trials. It is important to point out that the standard deviation for the training data is obtained in a different manner than before. For each training trial, the 150 artifact recordings were corrected and the median was calculated. This was then repeated at least 20 times for each type. The box plot represents the spread in this median energy, from one trial to the other. The box plot for using a single artifact in the training file shows the largest spread, indicating that the outcome of the correction fluctuates the most. This case also shows outliers. Clearly the effectiveness of an individual filtering matrix cannot be guaranteed by using a single artifact. If the training file contains two artifacts however, the average results become much more constant. Increasing the number of artifacts beyond two, does little or nothing to improve the effectiveness of correction.

To see how complete correction is for the training based approach, Fig. 6.10 shows the averaged...
Figure 6.8: The box plots of the energies of the 4 different amounts of artifacts included in the training file. The box plots show the median (red line), the first to third quartile (blue box), the smallest and largest value that are not an outlier (black whiskers) and the outliers (red circles). The baseline reference is depicted in green.

Figure 6.9: The box plots indication the variation of the average outcome of a training session. For each box, the training session has been repeated 20 times and the median was calculated each time.
Figure 6.10: The averaged signal after training based correction of the 150 eye blink recordings.

signal after correction. Clearly, part of the artifact remains for this approach as well. An explanation for this phenomenon is given in the next section. If the training session approach is compared to the individual approach of the previous section, it becomes clear that the training based approach is the preferable method for online artifact correction. It is faster, more effective and more reliable. The only drawback is the fact that a training is required before each recording session. However, as was shown, only two artifacts per type are required to get the most effective correction performance.

Because of time restrictions, the results of the correction procedure were discussed here only for eye blink artifacts, using a single filtering matrix. The same procedure can be used to correct eye movements. This requires the construction of a filtering matrix for each artifact type, after which one filtering matrix can be constructed that can correct all trained artifact types. This can be done by simply multiplying the separate filtering matrices:

$$F_{total} = F_1 \cdot F_2 \cdot \ldots \cdot F_n.$$  

(6.2)

4 Discussion and recommendations

The importance of electrode configuration in ICA was clearly shown, where electrode positioning outweighs electrode quantity. Using frontal electrodes is paramount for accurate artifact estimation without compromising non-artifact EEG retention. The sample rate should not prove to be a restricting factor for artifact correction, as even very low rates (32 Hz) show acceptable results. This is most likely due to the low frequency content of ocular artifacts.

Using a training session to calibrate a filtering matrix is not only far more efficient for online correction, it also shows better and more reliable performance. It is therefore the recommended...
correction procedure. ICA is however not an ideal correction tool, neither in terms of removing artifacts nor in retaining non-artifact EEG. Even under optimal circumstances, ICA does not succeed in completely filtering out eye blink artifacts. An explanation for this phenomenon can be found in the propagation of the eye blink through the brain tissue. ICA assumes that this propagation is linear, i.e. the eye blink has a fixed shape, and is attenuated as it travels towards the posterior. This is represented by a single artifact component and the different weight factors for each electrode. To see in what degree artifact propagation is linear, the average of the 150 eye blink recordings is shown for 4 different electrode sites (Fp1, AF3, F3, FC1), in Fig. 6.11. The average eye blink has been normalized with respect to the peak maximum for each electrode, correcting for attenuation. This plot shows that if the top of the peak is kept constant, the valley at t=1.8s changes size as the artifact travels through the brain. This means that the blink artifact changes shape and cannot be represented by a single component for every electrode. It would be possible for ICA to estimate a second artifact component, which could compensate the shortcomings of the first one. However, after visual inspection of all the components of several recordings, no such components were found. This indicates that ICA in fact does not estimate this extra artifact component, at least not in this setup. This reveals a fundamental shortcoming of linear ICA for artifact correction.
Chapter 7

conclusion

The most important conclusions of this thesis are the following:

- Among the possible artifacts than can influence ambulatory EEG applications, ocular artifacts are the most relevant. They cannot be avoided, either by using state-of-the art equipment, or by the subject itself, and have significantly high SARs at relevant electrode locations.

- The performance measure of artifact detection methods varies across subjects. An experiment using just 4 subjects revealed significant dissimilarities. It has been shown that there is no method that provides the best results for every subject, i.e. for a different subject, a different method can perform best. Detection methods perform better in areas with large SARs.

- For the correction of ocular artifacts in EEG recorded for user-friendly ambulatory applications, ICA was found to be the preferred method. Evaluation has shown the considerable importance of including frontal electrodes to improve ICA performance. A sample rate of 128 Hz has been found to be sufficient for good artifactual source estimation.

- The implementation of ICA should clearly be based on a training file approach. This method is both more efficient, and more effective for artifact correction.

- ICA correction was found to be incomplete in the experiments performed in this thesis. Residual artifacts were found after averaging corrected data. The most likely explanation for this phenomenon is the non-linear propagation of artifacts.

Future directions:

- Non-linear blind source separation methods can be used as an alternative to linear ICA, in order to reveal the artifact dynamics, and derive correction methods that do not leave residual artifacts

- To evaluate whether or not ICA is a sufficiently effective correction method, a final test is needed, where performance is measured by evaluating the performance of the actual application before and after input-signal correction.

- The experiments for artifact detection and correction should be repeated for a larger number of subjects.
Chapter 8

Acknowledgements

My graduation project at Philips has been a great experience for me. I found working in a corporate environment very challenging, and most satisfying. I would like to thank my supervisors, first of all Gary Garcia. Even though you were sometimes abroad, you were always available for questions, and I will never forget our sometimes noisy skype sessions! I would like to thank Ad Denissen as well, with whom I had the pleasure to share an office. Your cheerful presence made my stay at Philips fun as well as interesting. Of course I should not forget my backup supervisors Vojkan Mihajlovic and Mark Jaeger. Your input has been very valuable, thank you for that. I would also like to thank all the people who were kind enough to be a subject for my experiments. Furthermore I would like to thank all my colleagues at Philips, and all the members of the Philips Intern Committee, it has been fun! Pieter Wijn I would like to thank for letting me find my own way over at Philips, and for making sure I did not forget about the Physics. Finally, I would like to thank, once again, my family for all their loving support. Thank you all.
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