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6 Methods for the Estimation and Removal of Artifacts and Overlap in ERP Waveforms

Durk Talsma and Marty G. Woldorff

In an ideal world, one would have no need for artifact detection mechanisms at all. Event-related potentials (ERPs) are calculated using the approach of averaging the recorded EEG activity of many repetitions of the same stimulus condition (often referred to as "trials"), which assumes that for any given repetition, the recorded EEG consists of a signal part (ERP) and a noise part (background EEG). The noise part is assumed to be uncorrelated with the signal, and therefore, given an infinite number of trials, the noise part should cancel out and the remaining ERP would be a reflection only of the event-related brain activity.

Unfortunately, such an ideal world does not exist. In reality, various recording artifacts do tend to correlate with the signal; some artifacts are always of the same polarity (and thus do not cancel out during signal averaging), subjects may blink their eyes or make movements at consistent times relative to the onset of a visual stimulus (causing large time-locked amplitude deflections on the frontal EEG channels), and it is never possible to record an infinite number of trials to lose these artifacts completely. Moreover, as we will see later in this chapter, the very nature of the experimental design required for specific scientific questions, namely that of ERP components from adjacent trials that are overlapping onto the current one, may introduce a more subtle type of distortion (Woldorff, 1993). As we will discuss later, overlap can be a specific problem when stimulus presentation rates are high.

Above we distinguished three different elements contributing to any given single trial: signal (ERP), noise (background EEG), and artifacts. Although not explicitly mentioned, it follows intuitively from this description that whereas cerebral activity generates the signal and the background EEG noise, artifacts are typically generated by external sources, such as eyes, muscles, or recording equipment. We therefore propose the following working definition of an artifact:

Artifacts are occurrences of any given electrical activity that can be recorded by EEG equipment, which is not originating from cerebral sources, and either clearly distinguishable from the recorded background EEG or substantially large enough to modify the observed ERP waveform from its true waveform.

According to this definition, overlap is not a true artifact, because brain activity generates the overlapping ERP components. However, this activity is unwanted, because it is activity that is not the result of processing the current trial type, but of processing the preceding or succeeding trial.

Because artifacts can distort the observed ERP waveform, it is necessary to find some way to estimate and remove these artifacts from the EEG signal. One method is based on the principle of detecting artifacts and excluding trials on which they are detected. In general, this method is effective; however, one should keep in mind that when using very strict criteria, the rejection method may result in a large number of false alarms because naturally occurring high-amplitude EEG waves may trigger the artifact detection algorithm, therefore excluding a large number of trials and, hence, yield again a very poor signal-to-noise ratio. For this reason, artifact removal based on the exclusion of artifact-contaminated trials should strive for a careful balance between the severity of the artifacts rejected and the number of trials included in the final average. The spike, drift, and eyeblink detection algorithms we discuss below are good examples of this group of methods.

Other methods are based on the principle of not only detecting the presence of artifacts, but also on estimating the relative size of the artifact and correcting (i.e., removing) it. One obvious advantage of these methods is that correcting artifacts leaves more trials available for averaging, and thus makes it possible to obtain a better signal-to-noise ratio of the observed ERP. A disadvantage of this method, however, is that if the estimations of the artifact are poor, the errors induced by subtracting these can be large enough to substantially distort the observed ERP. This group of methods includes the eyeblink correction and overlap removal methods.

This chapter discusses three different types of artifacts and presents methods to remove them. In order of increasing complexity, we will discuss the following types of artifacts: (1) instrumentation artifacts, (2) eye movement artifacts, and (3) overlap from adjacent trials.

Instrumentation Artifacts

A number of sources can generate instrumentation artifacts. Instrumentation artifacts consist, among others, of high-frequency transient activity or high-frequency background noise; or low-frequency drifts that can be caused by slow polarization of electrodes, cephalic skin potentials (e.g., Picton & Hillyard, 1972), or badly placed electrodes. In many cases, these artifacts are in the frequency range that is outside that of interest in ERP research (which is typically from about 0.1 to about 20 Hz). When this is the case, applying an off-line digital bandpass filter (i.e., applied after the fact) might be sufficient to reduce the noise contributed by the artifact to acceptable levels

(see chapter 5 of this volume). When this is not the case, the
eliminate—or at least greatly attenuate—these types of artifact

Transient Activities

Fisch (1991) identifies a number of different artifacts that, alt
ences in amplitude, frequency of occurrence, and scalp distri
common characteristic for automatized detection of these arti
mostly consist of high-amplitude spikes that are easily detecta
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graphic (ECG) activity, blood-flow pulse waves, and electrode
We base the description of each artifact in the following sectio
chapter 6.

Muscle Activity Muscles can cause transient high-amplitude
generated by scalp and face muscles in frontal and temporal
may be recorded by electrodes nearly anywhere on the scalp
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relax, drop the jaw or open their mouth slightly, or change t
type of artifact occurs on a single electrode, pushing on or rea
sometimes stop it.

Movement Head and body movements or movement of e
artifacts even when all electrodes make good mechanical and
types of artifacts are often erratic and not repetitive, unless th
cal. This type of artifact can result from tremor, chewing or su
movements.

Electrocardiographic Activity ECG activity can be picked u
recordings with wide interelectrode distances, especially in
and to the left ear. The artifact may appear in all channels i
used and it is being picked up at that reference, or it can b
Small artifacts may reflect the *R*-wave of the ECG, whereas
additional ECG components. The *R*-wave usually appears ma
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and directed diagonally from right to left and from anterior t

Pulse-Wave Artifacts Periodic waves of smooth or triangu
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(see chapter 5 of this volume). When this is not the case, there are other methods to eliminate—or at least greatly attenuate—these types of artifacts from the ERPs.

Transient Activities

Fisch (1991) identifies a number of different artifacts that, although marked by differences in amplitude, frequency of occurrence, and scalp distribution, share one useful common characteristic for automatized detection of these artifacts. In particular, they mostly consist of high-amplitude spikes that are easily detectable using a peak-to-peak amplitude test. These artifacts are caused by muscle activity, movement, electrocardiographic (ECG) activity, blood-flow pulse waves, and electrode or equipment problems. We base the description of each artifact in the following section mainly on Fisch 1991, chapter 6.

Muscle Activity Muscles can cause transient high-amplitude spikes, which are mainly generated by scalp and face muscles in frontal and temporal regions; however, they may be recorded by electrodes nearly anywhere on the scalp surface. This type of artifact can often be reduced, or even completely eliminated, by asking the subjects to relax, drop the jaw or open their mouth slightly, or change their position. When this type of artifact occurs on a single electrode, pushing on or reapplying the electrode can sometimes stop it.

Movement Head and body movements or movement of electrode wires can cause artifacts even when all electrodes make good mechanical and electrical contact. These types of artifacts are often erratic and not repetitive, unless the movement is rhythmical. This type of artifact can result from tremor, chewing or sucking, breathing, or head movements.

Electrocardiographic Activity ECG activity can be picked up in the EEG mainly in recordings with wide interelectrode distances, especially in linkages across the head and to the left ear. The artifact may appear in all channels if a common reference is used and it is being picked up at that reference, or it can be in just a few channels. Small artifacts may reflect the R-wave of the ECG, whereas larger artifacts can reflect additional ECG components. The R-wave usually appears maximally over the left posterior scalp regions, because the main cardiac dipole producing the R wave is positive and directed diagonally from right to left and from anterior to posterior.

Pulse-Wave Artifacts Periodic waves of smooth or triangular shape may be picked up by an electrode on or near a scalp artery as the result of blood pulse waves producing slight changes of the electrical contact between electrode and scalp. Fisch (1991) reports that this is more likely to happen with electrodes in the frontal or temporal areas than with electrodes in the posterior scalp regions.

Electrode- or Equipment-Related Artifacts Most artifacts in this category are distinguished from cortical activity in that they seem to be superimposed on cortical recordings and/or appear only in channels connected to one electrode. Although some of these have characteristic shapes, others might resemble cerebral activity. A common artifact in this category is "electrode popping," which is due to a sudden change of electrode contact, causing large amplitude changes that rise and fall abruptly. Other electrode artifacts drift more slowly and may resemble cerebral slow waves (see below). Because this type of artifact is mainly due to faulty electrodes or equipment, the first step in avoiding these types of artifacts is to check all the connections: the electrode may be detached or loose, the lead wire may be broken, or the conductive paste may have dried. Next, check the electrode impedance. In addition, check that all connections between electrodes and amplifier are sufficiently dry. We have experienced that a residual amount of moistness in the connectors linking the electrocaps to the switchboard (as a result of washing the caps after a previous recording session) can cause substantial drifts on a number of channels. Finally, carefully consider using disposable sponge disks (to redistribute the pressure of cap-mounted electrodes on the subject's head), as we have experienced that these can lift the electrodes from the scalp and cause frontal channels to drift.

Spike Detection When the number of trials containing spikes is low, relative to the number of clean trials, and the onset of the artifact is random with respect to the onset of the event of interest, selective averaging will by itself largely reduce the distortion of the ERP waves due to spike occurrence. For example, if a typical ERP consists of averaging together 100 trials and a spike has an average amplitude of 50 µV, then after averaging, the contribution of each single spike to the final average is reduced to 0.5 µV, assuming that these spikes do not overlap in time. Although this example shows that selective averaging can seriously reduce amplitude deflections from spike artifacts in EEG data, even averaging a full 100 trials will reduce the effect of spike artifacts to an amplitude difference that is of the same magnitude of amplitude as a typical ERP effect.

To illustrate this, we present data from a single subject originally collected for a study on non-spatial intermodal attention (Talsma & Kok, 2001). Figure 6.1 shows this subject's ERP response to a visual stimulus. In this particular recording, some of the trials were contaminated by large-amplitude spike artifacts, but they were very low in number. More specifically, on 4 out of 105 trials, spikes with amplitude changes of up to 160 µV between two consecutive samples (4 ms) were detected, due to a popping reference electrode. These spikes were detected using a relatively simple peak-to-peak amplitude detection algorithm (see appendix II) configured to detect amplitude

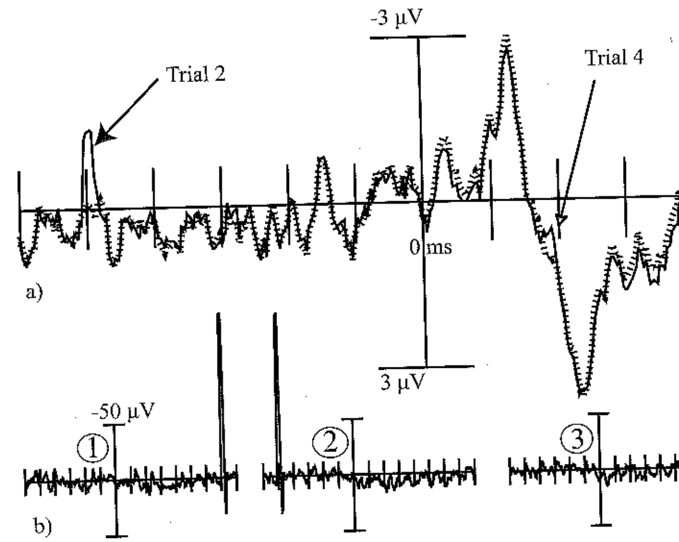

Figure 6.1
Example of the effectiveness of excluding trials containing spike
Comparison of an ERP waveform with spike trials included (soli
Including trials containing spike artifacts in this example can lead
in the final averages. (*b*) examples of four individual trials contai
the distortion caused by each of these spike-trials. Notice that tria
same spike, but shifted in time, due to the relatively high stimulus

deflections of more than 50 µV per 4 ms. As figure 6.1 sho
the average results in spike-related distortions of about 1 µ
It is best to reject trials when spikes with high amplitude
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amplitude artifacts will generally not help improve this c
cause the quality of the ERP waveform to decrease becau
number of rejected trials. Because of this, sometimes an
determining the spike rejection criteria on the basis of th
signal. An example of such a method excludes trials fro
electrical activity exceeds that of two or more standard de
Although this method appears to work reasonably well,
rejections of trials when low background activity in th
method to use low rejection criteria.

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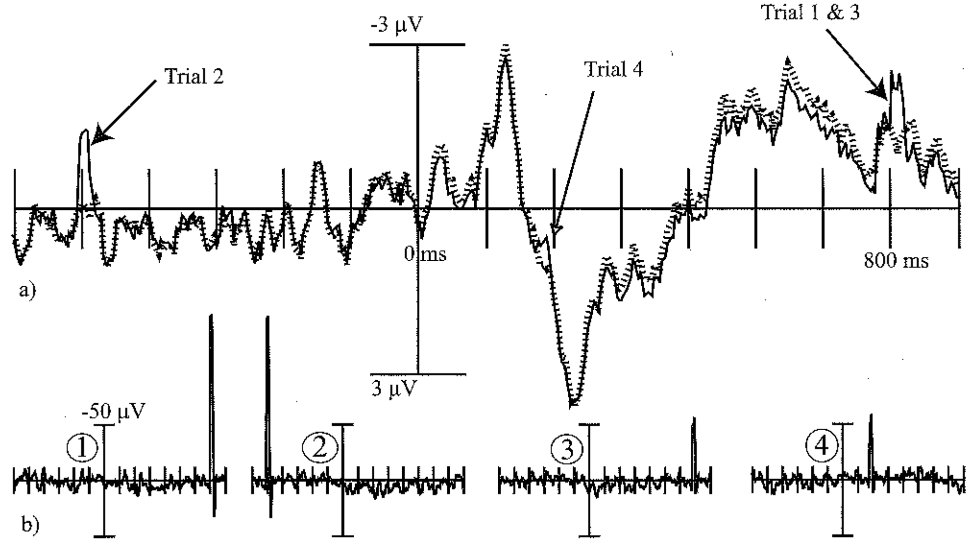


Figure 6.1
Example of the effectiveness of excluding trials containing spike artifacts on ERP averages. (*a*) Comparison of an ERP waveform with spike trials included (solid) and excluded (dotted line). Including trials containing spike artifacts in this example can lead to distortions of about 1–2 μV in the final averages. (*b*) examples of four individual trials containing spikes. Panel (*a*) indicates the distortion caused by each of these spike-trials. Notice that trials 1 and 2 actually contain the same spike, but shifted in time, due to the relatively high stimulus presentation rate.

deflections of more than 50 μV per 4 ms. As figure 6.1 shows, including spike trials in the average results in spike-related distortions of about 1 μV in the averaged ERP wave.

It is best to reject trials when spikes with high amplitudes are present (i.e., more than 150 μV). It is difficult to give an exact criterion for spike rejection, because the relative distortion of the averaged ERP waveforms depends on both frequency and amplitude of spike occurrence. In general, excluding a few trials with high-amplitude spikes will help improve the quality of the ERP waveform, but excluding many trials with low-amplitude artifacts will generally not help improve this quality further—it may even cause the quality of the ERP waveform to decrease because of an unacceptably high number of rejected trials. Because of this, sometimes an alternative method is useful, determining the spike rejection criteria on the basis of the statistical properties of the signal. An example of such a method excludes trials from further analysis on which electrical activity exceeds that of two or more standard deviations of the mean voltage. Although this method appears to work reasonably well, it is still susceptible to false rejections of trials when low background activity in the recorded EEG causes this method to use low rejection criteria.

As an alternative, when the duration of the artifact is short—not more than a few milliseconds—one could also consider correcting the artifact by interpolating around the occurrence of the artifact. In general, the estimated interpolation error will be small, compared to the error caused by the artifact. Therefore the signal-to-noise ratio of ERPs composed of artifact-interpolated trials will be larger than that of ERP averages composed of either all the trials (with no correction or rejection), or than that of ERP averages composed of only the artifact-free trials (i.e., after rejection of the trials with artifacts).

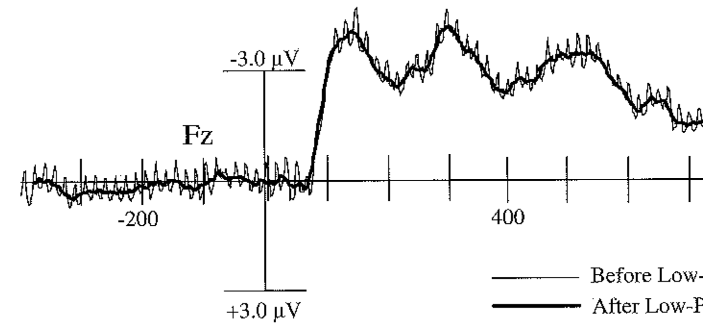
Periodic Noise

The next type of basic recording artifacts we cover consists of periodic noise. We subdivide this group of artifacts into two different categories. The first consists of exogenous artifacts, mainly caused by sources of interference outside the subject (i.e., from the recording equipment or the electrical environment). The second source of periodic "artifact" is endogenous to the subject and consists primarily of unwanted rhythmic brain activity with a disproportionately large amplitude.

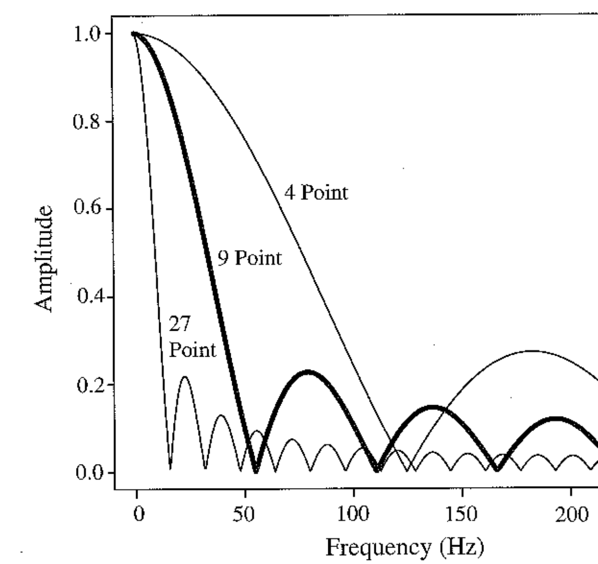
Interference The most common artifact due to interference comes from power lines and equipment. This interference has a frequency of 60 Hz in North America, and of 50 Hz in most other countries. This artifact is most typically picked by electrodes with poor connections, that is, by electrodes with high impedances, which causes the wires running from these electrodes to function as antennae, picking up environmental electrostatic noise. Although faulty or high-impedance electrodes may pick up this artifact, and they may appear in one or a few channels, inordinately strong interference can cause artifacts even with good recording electrodes and equipment; these artifacts are then likely to appear in all channels of all recordings made in this particular setting. Interference artifacts may be introduced either electrostatically by unshielded power cables and regardless of current flow, or electromagnetically by strong currents flowing through cables and equipment such as transformers or electromotors. Shielding the offending power cables and using a shielded room for the recording can reduce electromagnetic interference by proper wiring of the power cables. An effective method of removing line noise is by applying a low-pass moving average (see figure 6.2). Figure 6.2b shows the frequency response of a number of moving average filters with lengths of 4, 9, and 27 points. We can compute the frequency response of such a moving average filter using the following equation

$$H[f] = \frac{\sin(\pi f M)}{M \sin(\pi f)}$$

where H is the frequency response function and M is the length of the moving average filter. The frequency f runs between 0 and 0.5 times the sample frequency. For $f = 0$,



a) The effect of line noise removal on ERPs



b) Frequency-response functions at 500 Hz sample rate

Figure 6.2
Effectiveness of line-noise removal. (*a*) Shown here is a grand avera
by averaging 19 single-subject ERPs. Each single-subject ERP was com
single trials. In the unfiltered data (thin line), a high-frequency nois
ent, even in the grand average waveform, because stimulus presenta
60-Hz refresh cycle of the computer screen. Low-pass filtering, usin
filter, effectively removed this high-frequency noise component. (*b*) F
4-, 9-, and 27-point moving average filters, for a digital signal sample
ing average fully attenuates frequencies at 56 Hz and strongly at
60 Hz.

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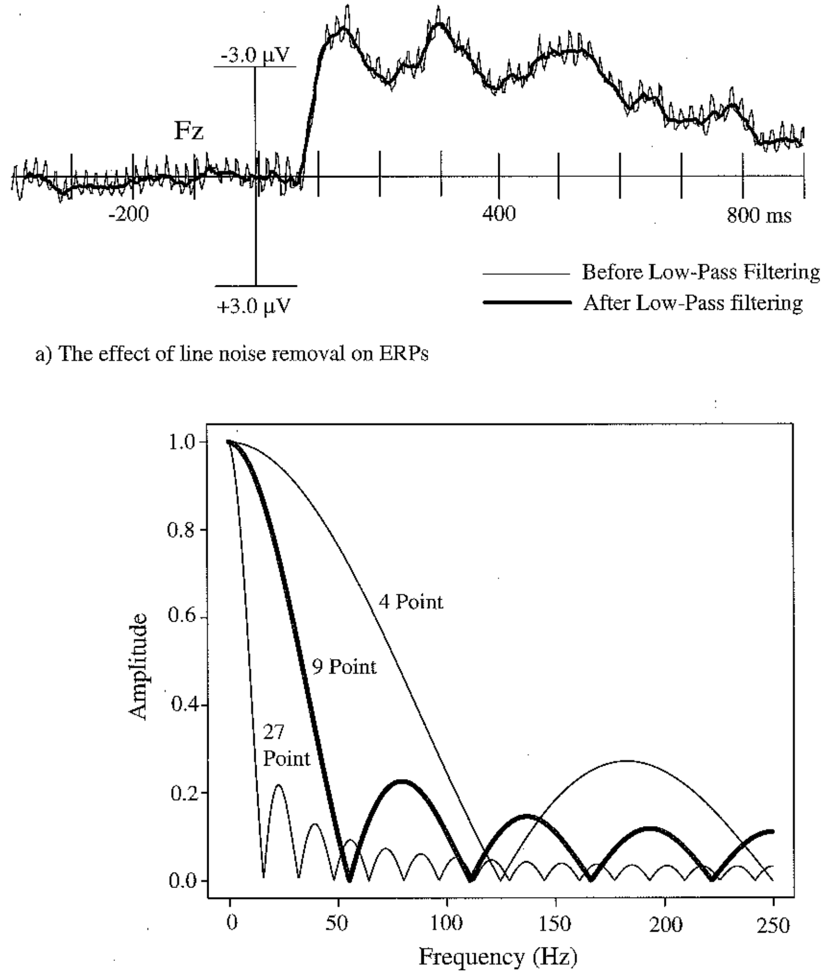

a) The effect of line noise removal on ERPs

b) Frequency-response functions at 500 Hz sample rate

Figure 6.2

Effectiveness of line-noise removal. (*a*) Shown here is a grand average ERP, which was obtained by averaging 19 single-subject ERPs. Each single-subject ERP was composed of approximately 100 single trials. In the unfiltered data (thin line), a high-frequency noise component is clearly present, even in the grand average waveform, because stimulus presentation was time locked to the 60-Hz refresh cycle of the computer screen. Low-pass filtering, using a 9-point moving average filter, effectively removed this high-frequency noise component. (*b*) Frequency response curves for 4-, 9-, and 27-point moving average filters, for a digital signal sampled at 500 Hz. A 9-point moving average fully attenuates frequencies at 56 Hz and strongly attenuates frequencies around 60 Hz.

use $H[f] = 1$. As figure 6.2b shows, using a 9-point moving average will fully attenuate frequencies at 56 Hz and strongly reduce frequencies in the band around 60 Hz, effectively removing line-noise artifacts.

Rhythmic Activity Although technically not an artifact according to our working definition, rhythmic EEG activity can pose a number of problems to an experimenter that are similar in nature to real artifacts. Therefore, we conclude this section on periodic noise with a brief discussion of these EEG waves and the specific problems they pose in ERP research.

One of the most common brain rhythms consists of sinusoidal waveforms in the frequency band between 8 and 12 Hz, known as the alpha band, and which peaks at 10 Hz. These alpha waves are observed mostly over parietal and occipital recording sites and more so when subjects have their eyes closed or are drowsy. Thus, they can be an indication of a subject's fatigued state. Alpha activity takes many trials to average out, because it is of high amplitude and because of the tendency of alpha waves to sometimes synchronize with stimulus presentation. The presence of alpha waves differs strongly from subject to subject, and when a subject is producing a particularly large amount of alpha activity, it may be necessary to discard him or her from inclusion in the analysis.

Large alpha waves might be a particular problem when ERPs are composed of limited numbers of trials. For example, in many attention studies, subjects are required to respond to an infrequent number of so-called target stimuli. Because targets are infrequent, ERPs to these targets are therefore composed of only a low number of trials. Therefore, these ERPs are generally more difficult to interpret, because of the lower signal-to-noise ratio.[1] This is particularly a problem when large alpha waves are found, because the residual alpha wave activity in the targets will be substantially larger than the alpha activity still present in more frequent non-target ERPs (see figure 6.3).

Residual alpha activity in ERP averages can be reduced by jittering the stimulus presentation, in ranges of 100 ms, or multiples of 100 ms. By jittering the stimulus presentation from trial to trial, the onset of the ERP response will be random with respect to the phase of the alpha wave in the background of the ERP. Because the dominant frequency in the alpha band is around 10 Hz, one cycle of the alpha wave will take about 100 ms to complete. Therefore, randomly jittering the stimulus presentation over such a 100 ms range will, on average, have the stimulus presentation occur equally on each phase of the alpha wave, causing the background alpha activity to cancel out during averaging.

Slow Drifts and Amplifier Saturations

Slow-wave activity such as those related to anticipatory processes ([CNV]; Walter et al., 1964), directing of attention (Hopf & Mangun, 2000), or working memory processes

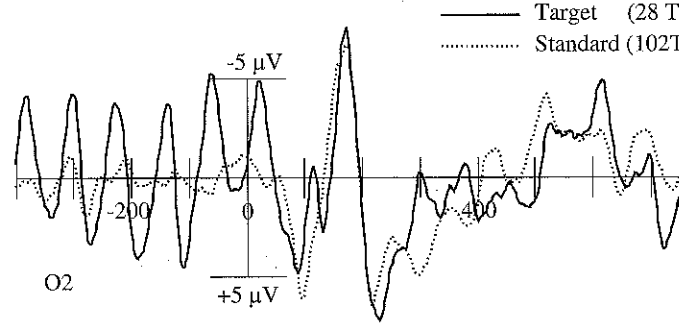

Figure 6.3
Illustration of excessive rhythmic brain activity (large alpha wav
waveforms to a visual target stimulus composed of 28 artifact fre
standard, consisting of 102 artifact free trials. Notice that because
only one-third of the trials as the standard ERP, the signal-to-nois
and the contribution of background activity is still present, obfusca
such as the P1 or the N1.

(Klaver et al., 1999) typically has the same frequency conte
skin potentials or incorrectly placed electrodes. Slow drifts a
EEG recordings are made in DC mode, that is, when no hig
ing data acquisition. This type of recording is typically mad
such as described above, is of interest. Therefore, if such is
detect large linear drifts in these recordings and reject thos
channel yields a linear trend that exceeds a previously es
detection can be done through linear regression by minin
tion, to determine a and b

$$\chi^2(a,b) = \sum_{i=1}^{N}\left(\frac{y_i - a - bx_i}{\sigma_i}\right)^2$$

in which x represents the observed time series, b any li
observed time series x, and a an intercept (DC value) at x_0.
6.1, the value of b can be compared to a preset thresho
exceeded, this trial can be rejected.

Figure 6.4 shows ERP data from a single subject that wa
study on spatial intermodal attention (Talsma & Kok, 2002
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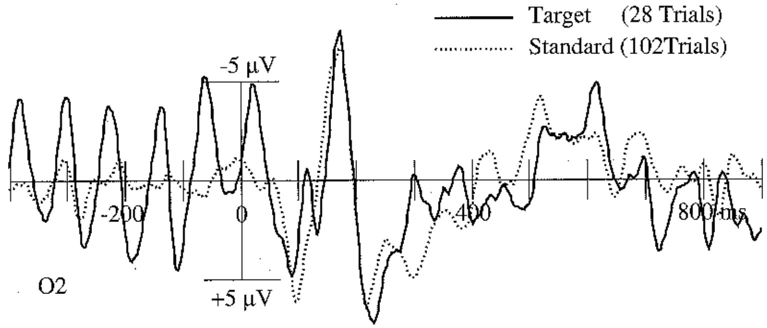


Figure 6.3
Illustration of excessive rhythmic brain activity (large alpha waves). Plotted here are the ERP waveforms to a visual target stimulus composed of 28 artifact free trials, vs. a similar attended standard, consisting of 102 artifact free trials. Notice that because the target ERP is composed of only one-third of the trials as the standard ERP, the signal-to-noise ratio is significantly reduced and the contribution of background activity is still present, obfuscating the true ERP components such as the P1 or the N1.

(Klaver et al., 1999) typically has the same frequency content as slow drifts caused by skin potentials or incorrectly placed electrodes. Slow drifts are mainly a problem when EEG recordings are made in DC mode, that is, when no high-pass filter is applied during data acquisition. This type of recording is typically made when slow wave activity, such as described above, is of interest. Therefore, if such is the case, it is necessary to detect large linear drifts in these recordings and reject those trials in which any given channel yields a linear trend that exceeds a previously established threshold. Trend detection can be done through linear regression by minimizing the following equation, to determine a and b

$$\chi^2(a,b) = \sum_{i=1}^{N}\left(\frac{y_i - a - bx_i}{\sigma_i}\right)^2 \tag{6.1}$$

in which x represents the observed time series, b any linear trend present in the observed time series x, and a an intercept (DC value) at x_0. After minimizing equation 6.1, the value of b can be compared to a preset threshold and if this threshold is exceeded, this trial can be rejected.

Figure 6.4 shows ERP data from a single subject that was originally recorded for a study on spatial intermodal attention (Talsma & Kok, 2002). In this particular recording a substantial amount of drifting channels were observed, because of a loosely connected reference electrode. Figure 6.4 shows an auditory ERP generated by averaging 182 trials, including trials containing drifting channels. This full ERP is compared to

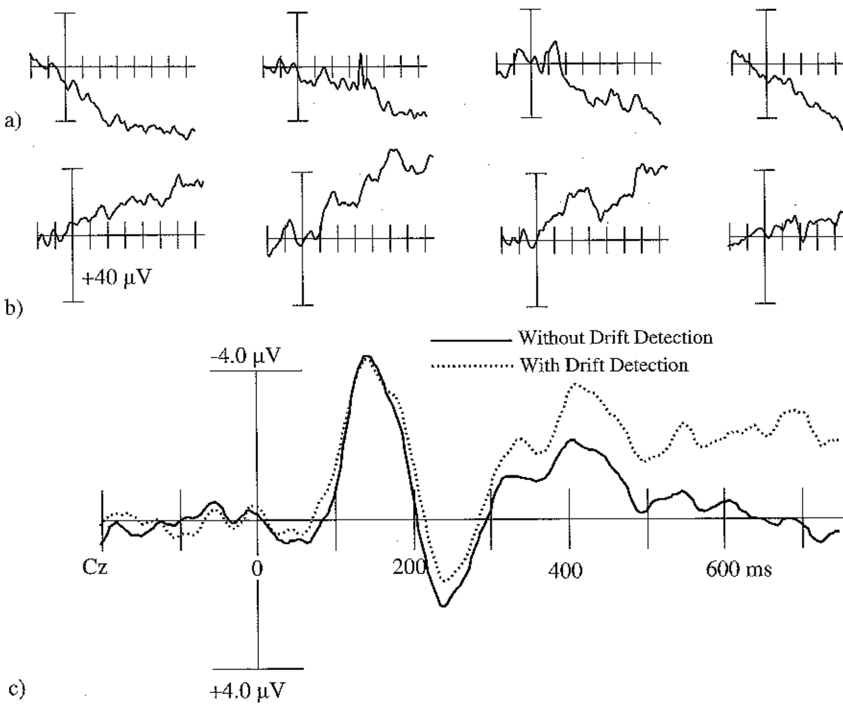


Figure 6.4
Effectiveness of drift removal using linear trend detection on ERP waveforms. (*a*) Example of four individual trials containing a large positive-going drift; (*b*) example of four similar trials, but now drifting negatively; (*c*) difference in the resulting single-subject ERP, resulting from excluding trials with large drifts.

the same ERP response, where 77 trials with either a positive or negative linear trend of more than 10 µV/s were excluded from the average, thus leaving 105 drift-free trials.

This example illustrates two important aspects of drift detection: (1) Despite the fact that slow channel drift was exceptionally high in this particular recording, and also despite the fact that the degree of drift on affected trials was high, the difference in observed ERP between including and excluding drifting trials is relatively small. The reason for this is that in this example the direction of drift (positive or negative) was random with respect to stimulus presentation and therefore positive and negative drifts largely cancelled out. (2) Even though the difference in ERP signal resulting from excluding drifting channels is relatively small in our example, it is still somewhere in the order of 1 to 2 µV, which is in the same order of magnitude as a typical experimental ERP effect, and therefore there would be an advantage of rejecting or correcting for drifting channels. When using a drift detection mechanism as described above, one

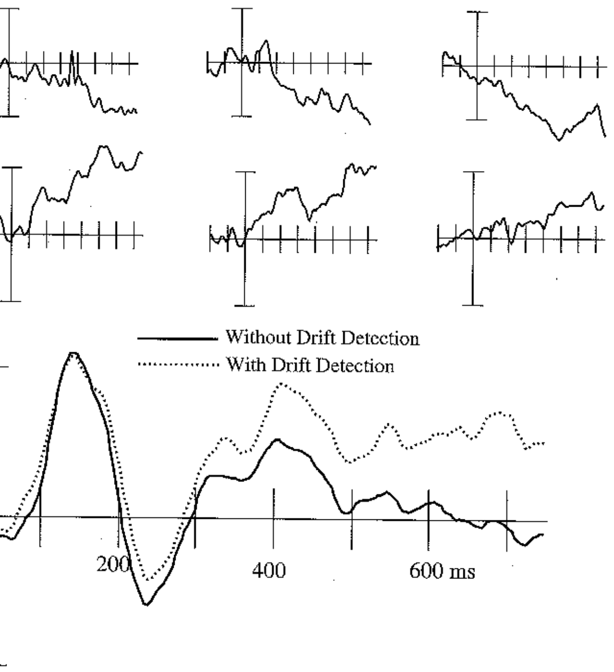
should make sure to use a substantially long time window (
culate the drift, because otherwise the drift detection algorit
amplitude changes. Instead of rejecting trials containing la
choose to correct these trials by subtracting the estimated
served data.

One should take a number of issues into consideration whe
nels. First, in some cases, channels can show a rapid drift in
then followed by a much slower drift into the opposite polar
ing channels, the experimenter should make sure to detect b
itive drifts. Otherwise the "drift free" ERPs will generally be d
could be even worse, because negative- and positive-going
anymore. We will give an illustration of this below, when we
of not correctly detecting the post blink-return drift in the
figure 6.5).

Another problem related to drifting channels is amplifier
Saturation occurs when a continuously increasing (or decre
the edge of the amplification or digitization range, at whic
clipped off at the maximum (or minimum) digitization valu
line. Again, this problem is most frequently encountered wh
mode (i.e., without the use of a hardware high-pass filter). An
can be detected by scanning the digitized output signal for re
same digitization unit. However, line noise can cause small
output, making the strict versions of the above-described test
to scan for flat lines using a blocking/flat line algorithm tha
variations in signal that may occur even during blocking, su
describes. The main difference between the peak detection al
and the flat line detection algorithm is that the latter report
when the peak-to-peak amplitude is smaller than the thres
reports a positive identification when the observed peak-to
than this threshold. Obviously, one should use this functi
recorded signal stays within a very small amplitude range, su
tial period of time (e.g., 500 ms).

Eye Movements and Eyeblinks

Two distinctly different processes generate ocular artifacts c
and saccades. The eyeball is polarized, with the cornea be
to the retina. Saccade potentials are caused by rotation of
whereas blink potentials are caused by the eyelid sliding
charged cornea, permitting current to flow up toward the fo



using linear trend detection on ERP waveforms. (*a*) Example of four
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which is in the same order of magnitude as a typical experi-
refore there would be an advantage of rejecting or correcting
n using a drift detection mechanism as described above, one

should make sure to use a substantially long time window (preferably 1 or 2 s) to calculate the drift, because otherwise the drift detection algorithm is susceptible to local amplitude changes. Instead of rejecting trials containing large drifts, one could also choose to correct these trials by subtracting the estimated linear trend from the observed data.

One should take a number of issues into consideration when detecting drifting channels. First, in some cases, channels can show a rapid drift into one direction, which is then followed by a much slower drift into the opposite polarity. When detecting drifting channels, the experimenter should make sure to detect both the negative and positive drifts. Otherwise the "drift free" ERPs will generally be distorted by a net drift that could be even worse, because negative- and positive-going drifts do not cancel out anymore. We will give an illustration of this below, when we discuss the consequences of not correctly detecting the post blink-return drift in the vertical EOG channel (see figure 6.5).

Another problem related to drifting channels is amplifier or digitization saturation. Saturation occurs when a continuously increasing (or decreasing) EEG signal reaches the edge of the amplification or digitization range, at which point the true signal is clipped off at the maximum (or minimum) digitization value and will appear as a flat line. Again, this problem is most frequently encountered when data is recorded in DC mode (i.e., without the use of a hardware high-pass filter). Amplifier saturation artifacts can be detected by scanning the digitized output signal for repeated occurrences of the same digitization unit. However, line noise can cause small fluctuations in the digital output, making the strict versions of the above-described test fail. Therefore, it is better to scan for flat lines using a blocking/flat line algorithm that allows for the very small variations in signal that may occur even during blocking, such as the one appendix III describes. The main difference between the peak detection algorithm from appendix II and the flat line detection algorithm is that the latter reports a positive identification when the peak-to-peak amplitude is smaller than the threshold, whereas the former reports a positive identification when the observed peak-to-peak amplitude is larger than this threshold. Obviously, one should use this function to check whether the recorded signal stays within a very small amplitude range, such as 1 μV, for a substantial period of time (e.g., 500 ms).

Eye Movements and Eyeblinks

Two distinctly different processes generate ocular artifacts originating from eyeblinks and saccades. The eyeball is polarized, with the cornea being positive with respect to the retina. Saccade potentials are caused by rotation of this corneoretinal dipole, whereas blink potentials are caused by the eyelid sliding down over the positively charged cornea, permitting current to flow up toward the forehead region (Lins et al., 1993b; Matsuo, Peters, & Reilly, 1975). The potentials both of these processes generate are typically large, and therefore these eye movements and blink related activities should always be recorded in an electro-oculogram (EOG) using electrodes near the eyes (Picton et al., 2000). Typical EOG recordings consist of the recording of a vertical EOG (vEOG), expressed as a differential recording between two electrodes placed at locations directly above and below the eyes, and a horizontal EOG (hEOG), which is the difference of two electrodes placed at the outer canthi of the left and right eye. In some cases, a radial EOG (rEOG) is obtained, which is the average amplitude of the two vertical EOG electrodes, referenced against a distant electrode location, such as Pz or Oz. The rEOG is generally not employed in EOG correction (e.g., Croft & Barry, 2002), but some think it is necessary to account for eye movement in the plane perpendicular to both horizontal and vertical planes (Elbert et al., 1985) and others use it to account for the eyelid component of blinks (Croft, 2000). Although ocular artifacts most strongly affect frontal electrodes, diminishing in amplitude as one moves posteriorly back over the scalp, they can still be observed on electrodes located as far away from the eyes as O1 or O2.

Because ocular artifacts are of such large amplitude, one should inform subjects about the effect of artifacts on EEG recordings. In many EEG studies, therefore, subjects are instructed to fixate their eyes on a central point throughout length of a block of trials and to try to minimize blinking during a trial as much as possible. When subjects comply with this, the number of ocular artifacts on any given run is typically low (on the order of 10 percent of all trials). Trials that do contain EOG artifacts can then be handled in a number of different ways, as described below.

Approaches to Handling EOG Artifacts

Rejection of Contaminated Trials A common procedure in dealing with ocular artifacts is to reject trials in which the electrical activity at the EOG or other frontal channel exceeds a certain criterion level. When subjects have complied with the instructions described in the previous section, the number of EOG-contaminated trials is relatively low, and these trials can be rejected from further analysis. In many cases, there are good reasons for excluding trials containing ocular artifacts; in experiments studying visual processes, one wants to be sure that on each trial subjects were actually perceiving the stimuli from the correct location, that is, that they fixated at the designated location, and also that they perceived the stimulus correctly (i.e., that their eyes were actually open during stimulus presentation). Therefore, one should reject trials in which subjects did not properly fix their eyes, or closed their eyes during visual stimulus presentation. Such trials may not reflect the brain processes the experimenter intended to measure (Simons, Russo, & Hoffman, 1988).

The rejection method is relatively straightforward, but the
problems in this method. Although it is relatively easy to r
short period of time, it is generally impossible not to blin
a block of trials. In addition to instructing subjects that th
experimenter should also emphasize that subjects should
secondary task that takes up so many resources that it imp
on the primary task or reduces ERP waveforms in amplitude
1973). Especially fast-rate ERP designs have trials that overla
It is therefore unavoidable that a number of trials will contai
to be rejected from further analysis. Although this proble
small with healthy young adults, the problem of recording
age groups, such as small children or seniors, or in patient
deficit/hyperactivity disorder (ADHD) or autistic children,
problematic.

Researchers have reported a number of additional problem
method. First, the ocular artifacts can show a considerable v
the smaller blinks and saccades are generally difficult to det
2001). Croft and Barry (2002) argue that in order to achieve
tained with common EOG correction methods, the rejection
would have to be set to values as impractically low as 2.6
channels, any vertical EOG activity exceeding 2.6 μV would
mation error equal to or larger than the error induced b
methods. Along similar lines, Verleger (1993) argues that it
whether or not a given trial is contaminated by blink or eye

Finally, incorrectly rejecting eyeblink trials may lead to
more distorted than not rejecting any eyeblink trials at all.
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change, as the eyelid moves across the cornea. This initial
followed by a much slower blink-return drift of the EOG sig
ing level. In this example we show a grand-average audito
2001). We performed eyeblink detection by scanning fo
changes that exceeded 50 μV in a moving time window of
The left column of figure 6.5 compares the results from co
with the results obtained by averaging all the trials (i.e., inc
Here we started detecting eyeblinks on every trial in a mov
500 ms before stimulus onset. The center and right two colu
the reason for starting blink detection a few hundred mi
onset. Here, blink detection started at stimulus onset, and
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Reilly, 1975). The potentials both of these processes generate herefore these eye movements and blink related activities ed in an electro-oculogram (EOG) using electrodes near the Typical EOG recordings consist of the recording of a vertical as a differential recording between two electrodes placed at nd below the eyes, and a horizontal EOG (hEOG), which is trodes placed at the outer canthi of the left and right eye. In rEOG) is obtained, which is the average amplitude of the two eferenced against a distant electrode location, such as Pz or not employed in EOG correction (e.g., Croft & Barry, 2002), essary to account for eye movement in the plane perpen- l and vertical planes (Elbert et al., 1985) and others use it to omponent of blinks (Croft, 2000). Although ocular artifacts al electrodes, diminishing in amplitude as one moves poste- , they can still be observed on electrodes located as far away z.

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OG Artifacts

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The rejection method is relatively straightforward, but there are also some inherent problems in this method. Although it is relatively easy to refrain from blinking for a short period of time, it is generally impossible not to blink for the entire length of a block of trials. In addition to instructing subjects that they should not blink, the experimenter should also emphasize that subjects should not make blink-control a secondary task that takes up so many resources that it impairs the subject's behavior on the primary task or reduces ERP waveforms in amplitude (see, e.g., Weerts & Lang, 1973). Especially fast-rate ERP designs have trials that overlap in time (see also below). It is therefore unavoidable that a number of trials will contain ocular artifacts and have to be rejected from further analysis. Although this problem is in general relatively small with healthy young adults, the problem of recording artifact-free ERPs in other age groups, such as small children or seniors, or in patient groups such as attentional deficit/hyperactivity disorder (ADHD) or autistic children, can be considerably more problematic.

Researchers have reported a number of additional problems with the EOG rejection method. First, the ocular artifacts can show a considerable variation in amplitude, and the smaller blinks and saccades are generally difficult to detect (see, e.g., Talsma et al., 2001). Croft and Barry (2002) argue that in order to achieve the same accuracy as obtained with common EOG correction methods, the rejection criteria for EOG artifacts would have to be set to values as impractically low as 2.6 μV. That is, at frontal EEG channels, any vertical EOG activity exceeding 2.6 μV would already cause an ERP estimation error equal to or larger than the error induced by EOG artifact correction methods. Along similar lines, Verleger (1993) argues that it is impossible to determine whether or not a given trial is contaminated by blink or eye-movement artifacts.

Finally, incorrectly rejecting eyeblink trials may lead to ERP waves that are much more distorted than not rejecting any eyeblink trials at all. Figure 6.5 shows an example of this. Eyeblink EOGs are typically characterized by a relatively large initial voltage change, as the eyelid moves across the cornea. This initial amplitude change is then followed by a much slower blink-return drift of the EOG signal to the baseline recording level. In this example we show a grand-average auditory ERP (data from Talsma 2001). We performed eyeblink detection by scanning for peak-to-peak amplitude changes that exceeded 50 μV in a moving time window of 100 ms (see appendix II). The left column of figure 6.5 compares the results from correctly rejecting blink trials with the results obtained by averaging all the trials (i.e., including the eyeblink trials). Here we started detecting eyeblinks on every trial in a moving window starting about 500 ms before stimulus onset. The center and right two columns of figure 6.5 illustrate the reason for starting blink detection a few hundred milliseconds before stimulus onset. Here, blink detection started at stimulus onset, and although this enabled the detection of any blinks following stimulus onset, the procedure failed in detecting

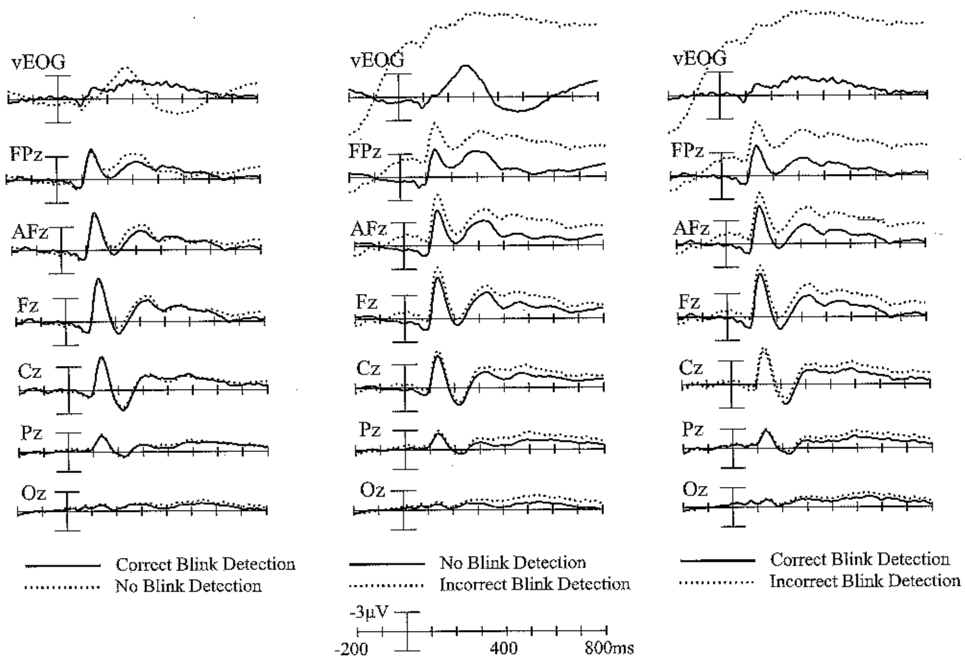

Figure 6.5
Example of eyeblink artifacts on ERPs. Shown here are the results of correct and incorrect eyeblink detection on the vertical EOG channel and the effect of eyeblink activity on the midline ERPs from anterior to posterior electrode positions. (*Left*) The effect of correctly rejecting eyeblink contaminated trials. When eyeblink trials were included (dashed line) EOG activity was larger than when these trials were excluded (solid line). Consequently, the ERPs are distorted by this ocular artifact. (*Center*) Effect of incorrectly conducted eyeblink detection. When blink detection started at stimulus onset (dashed line), the blink detection algorithm failed to catch the post blink return drift in the signal, resulting in a large negative drift in the signal around stimulus onset, which led to a distortion of the ERP wave that was much larger than the distortion caused by not rejecting any blink-contaminated trial (solid line). (*Right*) Comparison of correctly and incorrectly rejected eyeblinks.

blinks that had occurred right before stimulation. Because
tude test was not sensitive enough to detect the post-blink
exclusion of only those trials where blinks occurred directly
in ERP averages that were much more distorted than either
activity from the average (center column), or ERPs excludin
column).

To avoid problems such as these, researchers have prop
tion methods (see, for example, Brunia et al., 1989, for a co
methods). The most widely used method for removing ocu
cordings subtract part of the monitored EOG signal from
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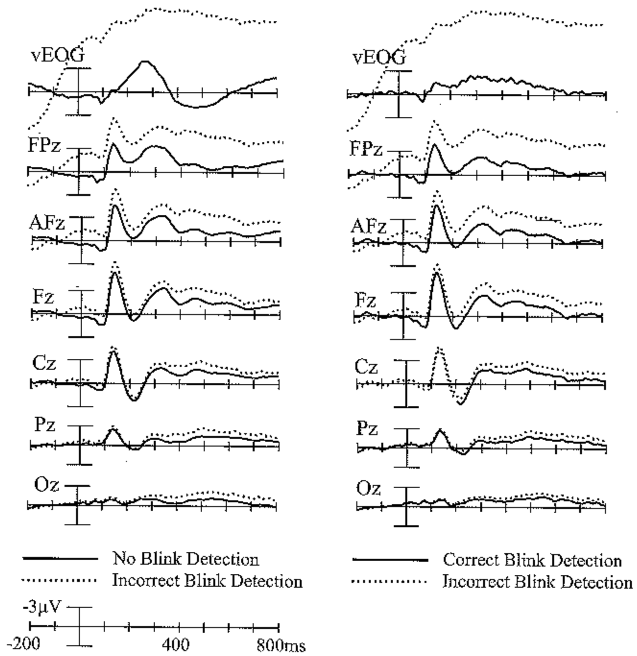
true EEG plus a linearly scaled fraction of the EOG. This fra
tor) represents how much of the EOG signal spreads to the E

For effective artifact correction, one must solve two proble
gation factors for each electrode site, and performing the c
propagation factors accurately it is important to have en
activity. Blinks produce consistently large potentials and ar
to compute propagation factors using the recorded data. Bec
of eyeblink artifacts is distinctly different from the scalp dist
to saccades, one should calculate separate propagation facto
blinks. Although eye movements in recorded data may be sr
to affect ERP averages, they may nevertheless be too small t
tion of propagation factors. If this is the case, it is best to
factors using separate calibration recordings in which consi
of about 15 degrees are generated in left, right, up, and dow

There are a number of approaches to estimating the pr
tracting the EOG activity from EEG recordings. These a
frequency domain based regression, dipole source modeling
nent analysis (ICA). In the following sections we discuss ad
of each of these methods.

Regression Methods Linear regression is a technique to de
two sets of variables. One can use linear regression to pr
recordings by estimating the linear relation between EEG a
pendix I for a mathematical description of the use of linear
correction). It is one of the earliest developed methods fo
from EEG recordings. Regression can correct EEG recording
time domain (Gratton, Coles, & Donchin, 1983; Verleger,
the frequency domain (Gasser, Sroka, & Möcks, 1985; Woe
gen, 1983).[2] Although both methods are based on the



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l (solid line). (*Right*) Comparison of correctly and incorrectly rejected

blinks that had occurred right before stimulation. Because the peak-to-peak amplitude test was not sensitive enough to detect the post-blink return drift, the selective exclusion of only those trials where blinks occurred directly after stimulation resulted in ERP averages that were much more distorted than either ERPs excluding no blink activity from the average (center column), or ERPs excluding all blink activity (right column).

To avoid problems such as these, researchers have proposed a number of correction methods (see, for example, Brunia et al., 1989, for a comparison among different methods). The most widely used method for removing ocular artifacts from EEG recordings subtract part of the monitored EOG signal from each EEG signal. This approach is based on the assumption that the EEG recorded on the scalp consists of the true EEG plus a linearly scaled fraction of the EOG. This fraction (or propagation factor) represents how much of the EOG signal spreads to the EEG recording electrode.

For effective artifact correction, one must solve two problems: computing the propagation factors for each electrode site, and performing the correction. To compute the propagation factors accurately it is important to have enough variance in the eye activity. Blinks produce consistently large potentials and are usually frequent enough to compute propagation factors using the recorded data. Because the scalp distribution of eyeblink artifacts is distinctly different from the scalp distribution of artifacts related to saccades, one should calculate separate propagation factors for eye movements and blinks. Although eye movements in recorded data may be small but consistent enough to affect ERP averages, they may nevertheless be too small to allow an accurate estimation of propagation factors. If this is the case, it is best to estimate these propagation factors using separate calibration recordings in which consistent saccades of the order of about 15 degrees are generated in left, right, up, and down directions.

There are a number of approaches to estimating the propagation factors and subtracting the EOG activity from EEG recordings. These approaches include time or frequency domain based regression, dipole source modeling, and independent component analysis (ICA). In the following sections we discuss advantages and disadvantages of each of these methods.

Regression Methods Linear regression is a technique to describe the relation between two sets of variables. One can use linear regression to predict the distortion of EEG recordings by estimating the linear relation between EEG and EOG recordings (see appendix I for a mathematical description of the use of linear regression in ocular artifact correction). It is one of the earliest developed methods for removing ocular artifacts from EEG recordings. Regression can correct EEG recordings for ocular artifacts in both time domain (Gratton, Coles, & Donchin, 1983; Verleger, Gasser, & Möcks, 1982) and the frequency domain (Gasser, Sroka, & Möcks, 1985; Woestenburg, Verbaten, & Slangen, 1983).[2] Although both methods are based on the same underlying regression model, differences in implementation can lead to small but consistent differences between the various methods.

Time Domain Regression Simple time domain linear regression is the basis of a number of correction methods that have been successfully applied in ERP research (e.g., Gasser, Sroka, & Möcks, 1986; Verleger, Gasser, & Möcks, 1982). A problem with this basic method, however, is that correlations between EEG and EOG that are not due to ocular artifacts may bias the estimation of the propagation factors. For example, one may observe similar event-related activity on both EEG and EOG channels, which will bias the estimation phase of the propagation factors. For this reason, Gratton, Coles, and Donchin (1983) developed an improved method that is based on the simple regression method, but differs in that it subtracts any event-related activity from both EEG and EOG recordings and uses only event-unrelated EEG and EOG activity to estimate the regression coefficients.

Frequency Domain Regression One limitation of the simple regression model is that it cannot account for frequency-dependent and delayed (phase-shifted) transfer from EOG to EEG (Brillinger, 1975; Kenemans et al., 1991). In contrast, a multiple-lag time domain (multiple) regression model describes both transfer characteristics. Researchers have used such models in many multiple lag time domain EOG correction algorithms (Kenemans, Molenaar, & Verbaten, 1991; Kenemans et al., 1991). The mathematical operation used to correct EEG signals in the multiple regression method, known as convolution, is equivalent to a multiplication in the frequency domain. Generally, the convolutions involved in time domain multiple-lag regression require considerably more computation time than the equivalent multiplications in the frequency domain (fast Fourier transformations included; see Beauchamp & Yuen, 1979). Although computation time is currently much less a consideration as it was more than twenty years ago, it still follows that multiple-lag ocular artifact correction is best performed in the frequency domain.

Figure 6.6 (see color plate 1) illustrates the frequency domain regression method. Shown here is an ERP waveform of one senior participant of an aging study described by Talsma (2001, chapter 8). Although still an active society member at the age of 79, this person had severe problems controlling his eyeblink. Using the rejection method would have resulted in the exclusion of all trials. Figure 6.6 shows an auditory ERP. The vertical eye channels contain a considerable amount of electrical activity, which is transferred onto the EEG recordings, specifically channels FP1, FPz, and FP2. After correction, the undistorted auditory ERP remains intact, whereas the distortion due to eyeblinks has been removed. The method used in this example is based on a description by Kenemans et al. (1991).

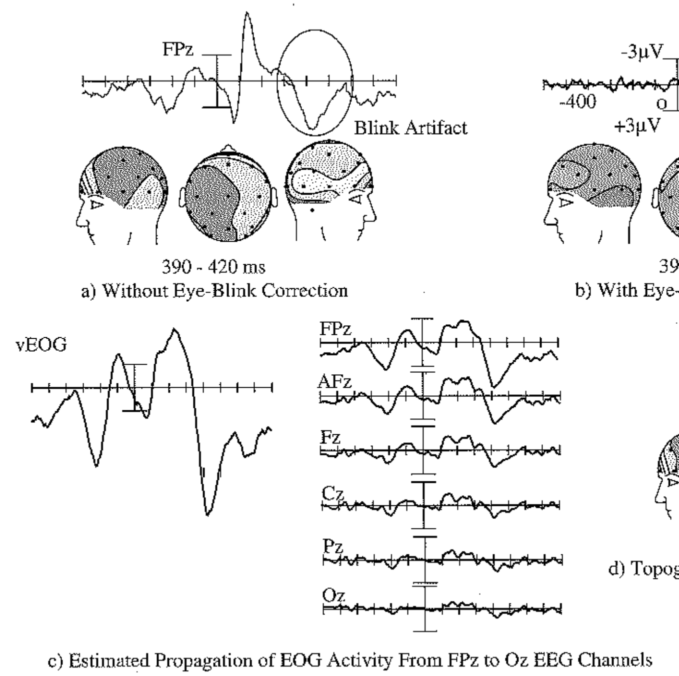

Figure 6.6
Example of ocular artifacts on ERPs with and without correction,
regression method. (See plate 1 for color version.)

Dipole Source Modeling Scherg and Berg (1995) and Ber
that the traditional regression methods can distort the s
recordings so much that frontal sources (including the audit
modeled adequately. There are two reasons for this argume
and Berg (1995), the EOG reflects only part of the true ocu
EEG activity also transfers to the EOG channels (Iacono &
the regression methods may remove not only ocular activit
activity at frontal channels. As an alternative to regressior
dipole modeling solution, which estimates the eye activity
EEG. Instead of considering propagation factors between E
ponents or "characteristic topographies" are computed for
These source components are then combined with a dipo
1994; Lins et al., 1993a) or principal components analysi
description (Ille, Berg, & Scherg, 1997) of the brain activi
that is applied to the data matrix to generate waveforms

ementation can lead to small but consistent differences be-
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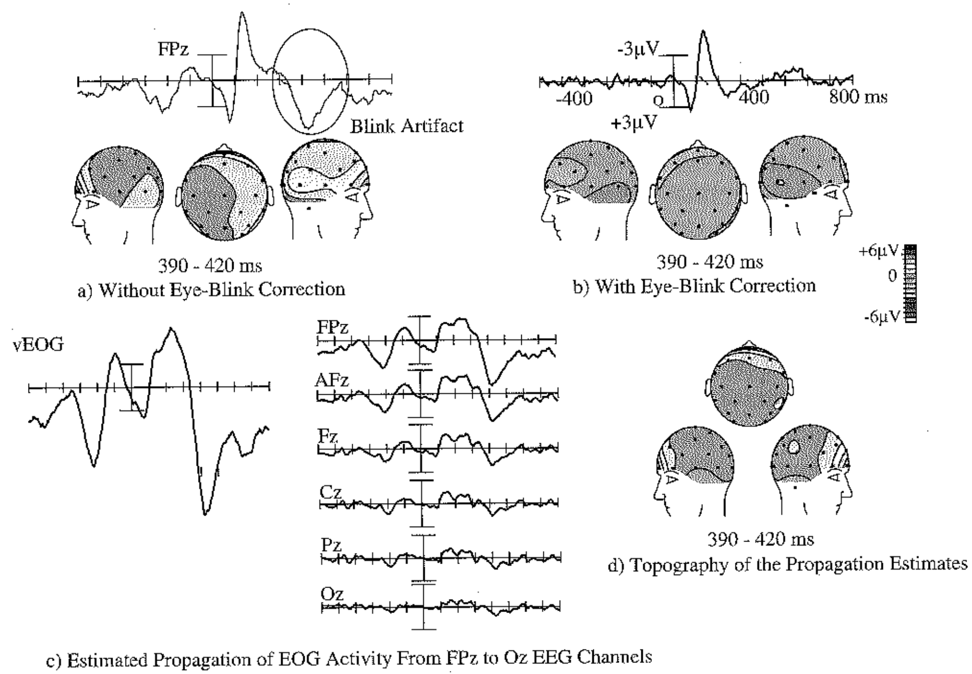

Figure 6.6
Example of ocular artifacts on ERPs with and without correction, using the frequency domain regression method. (See plate 1 for color version.)

Dipole Source Modeling Scherg and Berg (1995) and Berg and Scherg (1991) argue that the traditional regression methods can distort the spatial distribution of EEG recordings so much that frontal sources (including the auditory areas) can no longer be modeled adequately. There are two reasons for this argument: (1) according to Scherg and Berg (1995), the EOG reflects only part of the true oculo-electric activity; and (2) EEG activity also transfers to the EOG channels (Iacono & Lykken, 1981). Therefore, the regression methods may remove not only ocular activity but also part of the EEG activity at frontal channels. As an alternative to regression they therefore propose a dipole modeling solution, which estimates the eye activity independent of the frontal EEG. Instead of considering propagation factors between EOG and EEG, source components or "characteristic topographies" are computed for each type of eye activity. These source components are then combined with a dipole model (Berg & Scherg, 1994; Lins et al., 1993a) or principal components analysis (PCA)-based topographic description (Ille, Berg, & Scherg, 1997) of the brain activity to produce an operator that is applied to the data matrix to generate waveforms that are estimates of the overlapping eye and brain activity. The estimated eye activity is then subtracted from all EEG (and EOG) channels using the propagation factors defined by the source components.

According to the authors of the BESA dipole localization program, this method has a number of advantages over the traditional regression approach. First, they claim that it generates a better estimate of ocular activity than that provided by EOG channels. Second, it allows them to use the EOG channels for their EEG information. Third, if separate source components are generated for different types of ocular artifacts, their estimated waveforms provide an estimate of these different types of ocular artifacts independently.

Disadvantages of this method are, however, that it relies heavily on the use of dipole localization software and involves a labor-intensive construction of an adequate dipole model for estimating and separating the underlying ERP and EOG activities. The method also requires using a considerable number of periocular electrodes for estimating ocular activity, which cannot be used for recording brain activity at other locations. This may especially be a problem when recording with a limited number of electrodes (e.g., 32 or fewer).

Independent Component Analysis Independent components analysis (ICA) is a new, data-driven method for extracting individual signals from mixtures of signals (see e.g., Stone, 2002, for a good introduction of the ICA technique). More specifically, ICA can separate mixtures of signals recorded from *N* channels into a maximum of *N* separate components. Although ICA is still a fairly new technique, it has been used in analyzing a wide variety of problems (e.g., Jung et al., 2000, 2001), including separating eye movement activity from EEG recordings (Jung et al., 2000). ICA is similar to the spatial PCA approach (Ille, Berg, & Scherg, 1997) in that both ICA and PCA find spatial components representing ocular artifacts. Corrected EEG can than be obtained by removing these components through inverse computation. ICA differs from PCA in that it can detect components that are statistically independent, but not necessarily uncorrelated, whereas PCA components are by definition always uncorrelated. For this and other reasons, PCA cannot completely separate artifacts from cerebral activity, especially when both have comparable amplitudes (Lagerlund, Scharbrough, & Busacker, 1997), whereas ICA would be theoretically capable of doing so.

A limitation of ICA, however, is that the algorithm assigns ocular artifacts arbitrarily to one of the detected independent components. Therefore ICA requires the visual inspection of each solution to determine which component represents the estimated ocular artifact that is to be removed. In addition, ICA is a very novel technique that still needs to be validated and compared to some of the more established methods.

Overlapping ERP Components

Electromagnetical event-related brain activity typically consists
can last up to 1 or more seconds. Of these components, the P300
high amplitude and is usually followed by a negative slow wave
which can last for up to one or more seconds. Many experiment
relatively slow rate (i.e., less than one stimulus per second), to pr
adjacent trials overlapping. At higher presentation rates, ERPs
stimuli can overlap in time, which can result in distortion of th
dorff, 1993).

There are many experimental situations, however, that require
lus presentation (reviewed in Woldorff, 1995). In studies of s
example, a relatively low rate of stimulus presentation makes it
tively focus on one relevant stimulus type and ignore others. H
tion rates, on the other hand, seem to enable a more selective
This view is also strongly supported by empirical data indicatin
entiation of processing of attended and unattended stimuli is
requires a faster rate of stimulus presentation (Hansen & Hillyar
1973; Parasuraman, 1978; Schwent, Hillyard, & Galambos, 19
& Hillyard, 1987; Woldorff, Hackley, & Hillyard, 1991; Wold
Woldorff et al., 1993; Woldorff et al., 1998).

At high rates of stimulus presentation, however, there exists
form distortion that needs to be dealt with. In this section w
approaches one can take to minimize or remove the distortio
lapping ERPs. More specifically, we will describe the ADJAR ite
deconvolution method and the "no-stim" subtraction meth
overlap correction methods use Fourier transforms (Hansen,
Linear Model (Brillinger, 1981) to model the distortion due t
trials.

Approaches to Estimate Overlap

To date, researchers have taken various approaches to resol
lapping ERP responses. One approach has been to increase th
filter settings, which effectively attenuates the longer latency,
of the ERPs. This technique artificially "forces" the response
to appear to be finished, by the time the next stimulus is p
filtering may achieve a reasonable solution when only t
waves of the ERP are of interest, but may be of limited value
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Overlapping ERP Components

Electromagnetical event-related brain activity typically consists of components that can last up to 1 or more seconds. Of these components, the P300 can be of particularly high amplitude and is usually followed by a negative slow wave returning to baseline, which can last for up to one or more seconds. Many experiments present stimuli at a relatively slow rate (i.e., less than one stimulus per second), to prevent ERP waves from adjacent trials overlapping. At higher presentation rates, ERPs elicited by successive stimuli can overlap in time, which can result in distortion of the ERP averages (Woldorff, 1993).

There are many experimental situations, however, that require a high rate of stimulus presentation (reviewed in Woldorff, 1995). In studies of selective attention, for example, a relatively low rate of stimulus presentation makes it very difficult to selectively focus on one relevant stimulus type and ignore others. High stimulus presentation rates, on the other hand, seem to enable a more selective focusing of attention. This view is also strongly supported by empirical data indicating that the early differentiation of processing of attended and unattended stimuli is enhanced by, or even requires a faster rate of stimulus presentation (Hansen & Hillyard, 1984; Hillyard et al., 1973; Parasuraman, 1978; Schwent, Hillyard, & Galambos, 1976; Woldorff, Hansen, & Hillyard, 1987; Woldorff, Hackley, & Hillyard, 1991; Woldorff & Hillyard, 1991; Woldorff et al., 1993; Woldorff et al., 1998).

At high rates of stimulus presentation, however, there exists the potential for waveform distortion that needs to be dealt with. In this section we describe a number of approaches one can take to minimize or remove the distortions resulting from overlapping ERPs. More specifically, we will describe the ADJAR iterative post-experimental deconvolution method and the "no-stim" subtraction method in detail. Additional overlap correction methods use Fourier transforms (Hansen, 1983), or the General Linear Model (Brillinger, 1981) to model the distortion due to overlap from adjacent trials.

Approaches to Estimate Overlap

To date, researchers have taken various approaches to resolve the problem of overlapping ERP responses. One approach has been to increase the high-pass cutoff of the filter settings, which effectively attenuates the longer latency, lower frequency portion of the ERPs. This technique artificially "forces" the response to be finished, or at least to appear to be finished, by the time the next stimulus is presented. Such high-pass filtering may achieve a reasonable solution when only the early high-frequency waves of the ERP are of interest, but may be of limited value when the longer latency waves are of interest, or when these waves contain significant power in the higher frequencies. Therefore, if studying these longer latency waves, one needs to apply one or more techniques to actually estimate the overlap from adjacent responses and subtract the estimated overlap from each waveform. In this section we will discuss two basic methods for estimating and removing overlap. We should emphasize that the use of either of these methods should be taken into consideration while designing the experiment, because a number of criteria will have to be met in order to successfully estimate the overlap from adjacent trials.

In general, one can considerably reduce the problem of overlap by fully randomizing and first-order counterbalancing the stimulus sequence. This procedure ensures that each trial type will contain approximately the same overlap as each other trial type. Therefore, contrasting two trial types that are each distorted with exactly the same overlap with each other will reveal the true difference between these two trial types. There are, however, some caveats in this method: (1) Woldorff (1993, 103–105) discovered that under certain circumstances stimulus randomization does not control for differential overlap. More specifically, when the experimental condition varies between runs (e.g., attend left vs. attend right), thereby changing the responses to the adjacent trial types, the observed overlap may not necessarily be the same for all trial types, even if the stimulus presentation sequence was fully randomized. (2) Sometimes, ERPs from two separate stimuli will be combined (e.g., one auditory [A] and visual [V] stimulus) and compared to ERPs elicited by the simultaneous presentation of a multi-object stimulus (e.g., one audiovisual multisensory object). One can combine ERPs when the ERP waves of interest represent independently evoked perceptual processing of these stimuli only (e.g., Giard & Perronet, 1999; Molholm et al., 2002; Teder-Sälejärvi et al., 2002; Talsma & Woldorff, in revision). When this assumption is valid, the combined waveform can be compared to a similar multi-object response. When overlap distorts these ERP waveforms, however, the assumption of sensory processing only is violated and the summated waveforms will contain twice the overlap distortion as the multi-object ERPs waveforms and therefore obfuscate the effects of interest. (3) Although randomization can enable the extraction of the differential response between two trials, the raw ERPs of both types will still be distorted by overlap.

Interstimulus Interval Jittering At stimulus rates where successive ERP waveforms overlap, every response included in the average (except the first and the last in the sequence) will have superimposed upon it portions of the ERP response to the preceding stimulus and portions of the response to the succeeding stimulus. Randomly varying or jittering the ISIs around a mean value can partially cancel or "smear out" these overlapping responses, thereby mitigating the distortion of the final average. An empirical rule of thumb is that the effective jitter range needs to be larger than the period of the slowest dominant waves in the overlapping responses (Woldorff, 1993). Given a

few assumptions, the effect of ISI jitter on the overlap from a
approximated as a low-pass filtering operation on the adjacer
negative or positive time shift (see Woldorff, 1993, for a full d

Postexperimental Deconvolution (ADJAR) As described abo
tween successive trials acts as a low-pass filter, which mitigates
overlapping ERP components. However, as with a high-pass fi
earlier, this approach still leaves a residual amount of overla
One mathematical framework of methods estimating this r
use of the distribution of ISIs between successive stimuli. Th
the adjacent response (ADJAR) technique (Woldorff, 1993), e
waveforms by convolving preceding and succeeding ERP res
tive ISI adjacent event distributions (figure 6.7, plate 2).

Advantages of the ADJAR technique are that it allows for
volution, which makes it suitable to apply to a large number
In addition, ADJAR requires a relatively minor number of ch
mental designs. In general, to successfully correct ERP data u
ensure that ISIs are reasonably well jittered. It also helps to ha
reasonably well randomized, but this is not critical (see below
technique is suitable for deconvolving various subranges o
tions, which allows the analysis of extremely rapid stimulus s
makes use of the actual event distribution of the trial seq
overlap, instead of a theoretical distribution, ADJAR will w
bers of trials are present in different conditions. Finally ADJA
distributions are skewed, or when stimulus sequences are n
example, in "S1/S2" paradigms, a stimulus of one type (i.e.,
by a stimulus of another type (i.e., an imperative stimulus), bu
type (i.e., two cues) never follow each other.

ADJAR has proven relatively difficult to implement. In ad
deconvolution process is computationally intensive and the
process (although theoretically the time domain convolutio
frequency domain multiplication). Finally, because of the low
of jittering ISIs and the convergence of the iterative approach
the removal of overlap from low-frequency responses, such a
waves.

Inclusion of "No-Stim" Trials As an alternative to the
deconvolution, one can choose to estimate the distortion on
substantially large enough proportion of "no-stim" trials in

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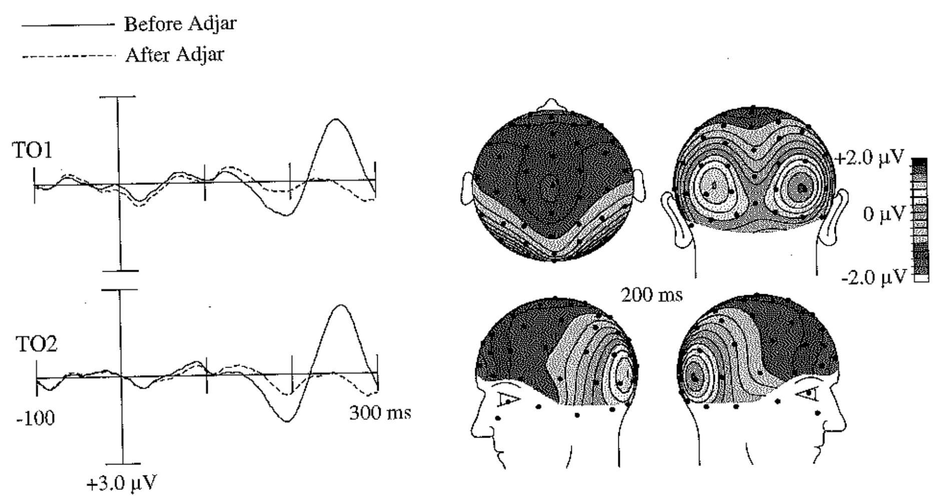
few assumptions, the effect of ISI jitter on the overlap from adjacent responses can be approximated as a low-pass filtering operation on the adjacent response with either a negative or positive time shift (see Woldorff, 1993, for a full discussion).

Postexperimental Deconvolution (ADJAR) As described above, jittering the ISI between successive trials acts as a low-pass filter, which mitigates the distortion caused by overlapping ERP components. However, as with a high-pass filtering method described earlier, this approach still leaves a residual amount of overlap in the ERP waveforms. One mathematical framework of methods estimating this residual distortion makes use of the distribution of ISIs between successive stimuli. This framework, known as the adjacent response (ADJAR) technique (Woldorff, 1993), estimates overlapping ERP waveforms by convolving preceding and succeeding ERP responses with their respective ISI adjacent event distributions (figure 6.7, plate 2).

Advantages of the ADJAR technique are that it allows for postexperimental deconvolution, which makes it suitable to apply to a large number of experimental designs. In addition, ADJAR requires a relatively minor number of changes to existing experimental designs. In general, to successfully correct ERP data using ADJAR, one should ensure that ISIs are reasonably well jittered. It also helps to have the stimulus sequence reasonably well randomized, but this is not critical (see below). In addition, the ADJAR technique is suitable for deconvolving various subranges of the ISI event distributions, which allows the analysis of extremely rapid stimulus sequences. Because ADJAR makes use of the actual event distribution of the trial sequences that estimate the overlap, instead of a theoretical distribution, ADJAR will work when unequal numbers of trials are present in different conditions. Finally ADJAR also works when event-distributions are skewed, or when stimulus sequences are not fully randomized. For example, in "S1/S2" paradigms, a stimulus of one type (i.e., a cue) is always followed by a stimulus of another type (i.e., an imperative stimulus), but two stimuli of the same type (i.e., two cues) never follow each other.

ADJAR has proven relatively difficult to implement. In addition, the time domain deconvolution process is computationally intensive and therefore a time-consuming process (although theoretically the time domain convolutions could be replaced by a frequency domain multiplication). Finally, because of the low-pass filter characteristics of jittering ISIs and the convergence of the iterative approach, ADJAR does not handle the removal of overlap from low-frequency responses, such as CNVs, or negative slow waves.

Inclusion of "No-Stim" Trials As an alternative to the ADJAR post-experimental deconvolution, one can choose to estimate the distortion on ERP waves by including a substantially large enough proportion of "no-stim" trials in the experimental design.



a) The effect of removing an overlapping visual stimulus on ERP waveforms

b) The scalp topography of the overlapping visual ERP as estimated and removed by ADJAR

Figure 6.7
Illustration of the use of the ADJAR overlap correction technique in a multisensory experiment. Auditory and visual stimuli were presented in close temporal proximity. (*a*) Shown here is the ERP response to an auditory stimulus that was followed in time by a visual stimulus (between about 75–125 ms). The delayed visual response can clearly be seen in the uncorrected ERP waveform (solid line). After ADJAR correction, the contribution of the visual stimulus has been removed (dashed line). (*b*) The scalp topography of the difference between corrected and uncorrected ERP waveforms. This scalp topography is typical of a visual ERP waveform, showing that ADJAR was successful in removing the visual ERP, but maintaining the auditory ERP. (See plate 2 for color version.)

This approach borrows from the functional imaging (fMRI) literature, where no-stim trials were first introduced to provide a way to estimate the overlap from the slow, event-related, hemodynamic response signals (blood oxygen dependent, or BOLD signals) used in functional MRI (Buckner et al., 1998; Dale & Buckner, 1997; Burock et al., 1998). No-stims can best be thought of as points in time that are randomly inserted into the stimulus stream, and which have the same randomization as the regular stimuli, but without the actual occurrence of a stimulus. In such a case, the time-locked averages to no-stim trials will contain on average the same response overlap from adjacent trials as any other trial type will contain. When the proportion of no-stims and the jitter rate of the ISI between trial types satisfy the conditions Busse and Woldorff specify (2003), one can assume that the no-stim events do not evoke a response themselves. Therefore, selectively averaging the no-stim events will only reflect the

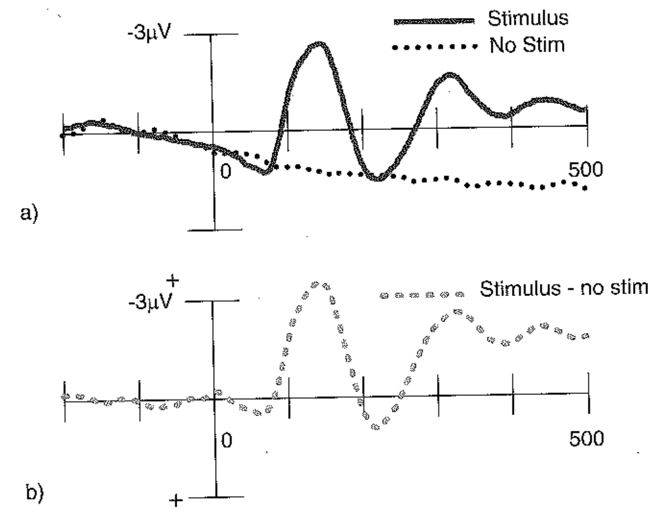


Figure 6.8
Illustration of the effectiveness of subtracting time-locked averages "n
locked averaged ERPs elicited by real stimuli. In this example, ERPs w
types in one condition of a multisensory integration condition. Panel
time-locked averaged ERP waveforms to the real stimulus trials and to
shows the same ERP waveform after subtracting the response to the n
slanted baseline, which is equally present for the both stimulus trials
panel (*a*), has disappeared in panel (*b*).

summated response overlap from adjacent trials. Thus, sub
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the response overlap, revealing the true ERP waveform to the

As an example, we present data from a study on the in
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The no-stim approach can have several advantages over AI
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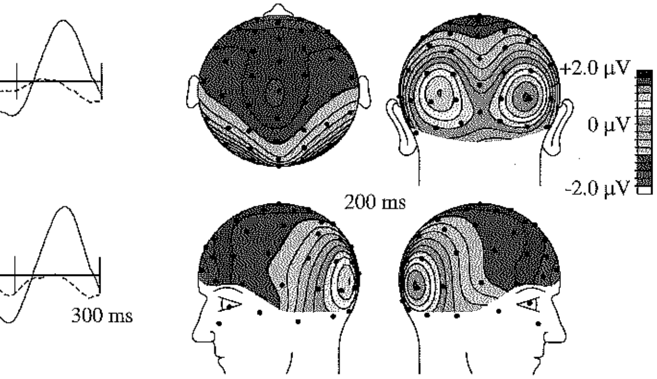

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b) The scalp topography of the overlapping visual ERP as estimated and removed by ADJAR

e ADJAR overlap correction technique in a multisensory experiment.
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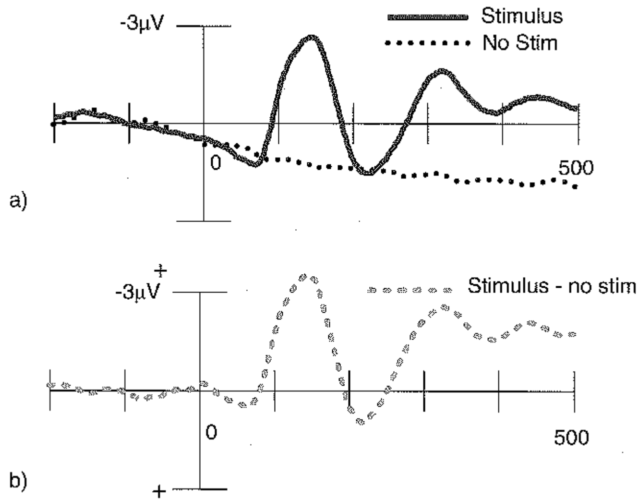

Figure 6.8
Illustration of the effectiveness of subtracting time-locked averages "no-stim" trials from the time-locked averaged ERPs elicited by real stimuli. In this example, ERPs were collapsed across all trial types in one condition of a multisensory integration condition. Panel (*a*) shows superimposed the time-locked averaged ERP waveforms to the real stimulus trials and to the no-stim trials. Panel (*b*) shows the same ERP waveform after subtracting the response to the no-stim trials. Notice that the slanted baseline, which is equally present for the both stimulus trials and for the no-stim trials in panel (*a*), has disappeared in panel (*b*).

summated response overlap from adjacent trials. Thus, subtracting the average no-stims ERP from the observed ERP averages from the other trial types will subtract out the response overlap, revealing the true ERP waveform to these other trial types.

As an example, we present data from a study on the interaction between multisensory integration and attention (Talsma & Woldorff, in revision). To test the effectiveness of estimating overlap using the no-stim method, visual-only, auditory-only, and multisensory ERPs were collapsed (to obtain a very high signal to noise ratio) for one attention condition (attend left); no-stim ERPs from the same attention condition were subtracted from this waveform. Figure 6.8a clearly shows that baseline activity (resulting from overlapping responses) is equally present in both ERPs evoked by stimulus trials as well as ERPs evoked by no-stim trials. Subtracting the no-stim ERPs from the stimulus ERPs therefore eliminates any baseline activity from the stimulus ERPs.

The no-stim approach can have several advantages over ADJAR. First of all, subtracting out no-stim ERP responses is a mathematically simple procedure, which is also easy to implement in existing ERP software. However, the use of this method needs to be carefully planned in the design stage of the experiment. Because no-stims pick up any overlapping ERPs in exactly the same way as normal ERPs would, the no-stim method is also able to correct for overlap from all types of low-frequency activity, including late negative slow waves, or stimulus preceding, anticipatory negativities.

There are, however, also a number of limitations to the no-stim method. First, it is necessary to include a relativly high number of no-stim trials in the design to get a clean estimate of the overlap. There are two reasons for this. First, as with regular ERPs, the signal-to-noise ratio of no-stim ERPs is directly proportional to the square root of the number of trials. Therefore, one needs to have at least the same number of no-stim trials as there are regular trials in one condition, to obtain an estimate of the overlap that has the same signal-to-noise ratio of the ERP waves. Second, as Busse and Woldorff (2003) show, the total number of no-stim trials should be a considerable proportion of the total number of trials, to avoid the no-stim trials from evoking an omitted stimulus response. These authors showed that this is even more true at rates of one stimulus per second or faster, as the omitted stimulus response is even more likely to be elicited at such rates. For these reasons, it is not advisable to use no-stims in long experiments, because the inclusion of a substantial number of no-stims would make an already long experiment even longer.

For reasons given above, the no-stim method works best in fully randomized and counterbalanced designs. When experimental designs are not fully counterbalanced, the assumption that all stimulus types are equally distorted by overlap is violated, and therefore, subtracting no-stim ERPs from real stimulus ERPs will not accurately remove the adjacent-response overlap and reveal the true ERPs. In such circumstances, ADJAR or other deconvolution approaches would be more advisable.

Comparison of ADJAR versus No-Stims

From the description of the two main overlap removal techniques it follows that each technique has its own strengths and weaknesses. Whereas ADJAR is flexible and adaptable, it is relatively hard to configure or implement correctly. The no-stim subtraction method, by contrast, is more limited to specific types of experiments and has certain requirements, but is easy to use. It also may be better at estimating overlap caused by very slow potentials. There are many situations where either method is applicable, and there is no principal requirement to limit oneself to one method.

Conclusion

This chapter has discussed a number artifacts and methodological problems that are commonly dealt with in ERP research. More specifically, we have discussed recording artifacts, such as spikes, drifts, and noise from power lines, ocular artifacts, including

blinks and saccades, and finally, we have discussed a number
arise as the stimuli are presented more rapidly and the ERPs el
in the sequence overlap in time and distort the averages.

Common recording artifacts, such as spikes and drifting ch
through mathematically easy procedures that are generally fai
ing from the average any trials containing these artifacts. We
that in certain cases it is possible to correct trials containing
further illustrated that the amplitude of artifacts on single trial
After averaging, the amplitude of spike and drift artifacts ar
However, the amplitudes of these artifacts are still large enoug
as experimental effects. Therefore, one should carefully determ
in artifact exclusion or artifact correction procedures.

Similarly, ocular artifacts are commonly dealt with by remo
they are detected. There are, however, a number of useful alt
moval approach. The first of these methods consists of compu
electro-ocular activity into the EEG through linear regression
different algorithms based on this technique. Simple regressio
and frequency independent transfer between EOG and EEG.
the other hand, is able to handle delayed and frequency deper
to EEG. These two techniques both operate in the time dor
regression techniques are mathematically equivalent to the
lag regression method, but are computationally more efficien
method.

An alternative to the regression technique is to model b
activity by using a dipole model. The ocular activity can ther
spatial dipolar pattern, which can be subtracted from the s
plained by the cortical dipoles. Similarly, one can use indepen
to estimate a statistically independent spatial pattern that ca
EEG channels.

Finally, at fast rates of stimulus presentation, the ERPs to
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mber of no-stim trials should be a considerable proportion
ls, to avoid the no-stim trials from evoking an omitted stim-
ors showed that this is even more true at rates of one stimu-
as the omitted stimulus response is even more likely to be
these reasons, it is not advisable to use no-stims in long
nclusion of a substantial number of no-stims would make an
ven longer.
e, the no-stim method works best in fully randomized and
When experimental designs are not fully counterbalanced,
imulus types are equally distorted by overlap is violated, and
tim ERPs from real stimulus ERPs will not accurately remove
rlap and reveal the true ERPs. In such circumstances, ADJAR
proaches would be more advisable.

sus No-Stims

e two main overlap removal techniques it follows that each
ngths and weaknesses. Whereas ADJAR is flexible and adapt-
configure or implement correctly. The no-stim subtraction
ore limited to specific types of experiments and has certain
to use. It also may be better at estimating overlap caused by
are many situations where either method is applicable, and
rement to limit oneself to one method.

d a number artifacts and methodological problems that are
ERP research. More specifically, we have discussed recording
rifts, and noise from power lines, ocular artifacts, including

blinks and saccades, and finally, we have discussed a number of problems that might arise as the stimuli are presented more rapidly and the ERPs elicited by adjacent trials in the sequence overlap in time and distort the averages.

Common recording artifacts, such as spikes and drifting channels, can be detected through mathematically easy procedures that are generally fairly successful at excluding from the average any trials containing these artifacts. We have argued, however, that in certain cases it is possible to correct trials containing such artifacts. We have further illustrated that the amplitude of artifacts on single trials might be considerable. After averaging, the amplitude of spike and drift artifacts are substantially reduced. However, the amplitudes of these artifacts are still large enough to be falsely identified as experimental effects. Therefore, one should carefully determine the parameters used in artifact exclusion or artifact correction procedures.

Similarly, ocular artifacts are commonly dealt with by removing any trials on which they are detected. There are, however, a number of useful alternatives to the trial removal approach. The first of these methods consists of computing the propagation of electro-ocular activity into the EEG through linear regression. There are a number of different algorithms based on this technique. Simple regression assumes instantaneous and frequency independent transfer between EOG and EEG. Multiple regression, on the other hand, is able to handle delayed and frequency dependent transfer from EOG to EEG. These two techniques both operate in the time domain. Frequency domain regression techniques are mathematically equivalent to the time domain multiple lag regression method, but are computationally more efficient than the time domain method.

An alternative to the regression technique is to model both cortical and ocular activity by using a dipole model. The ocular activity can then be estimated through a spatial dipolar pattern, which can be subtracted from the spatial pattern that is explained by the cortical dipoles. Similarly, one can use independent component analysis to estimate a statistically independent spatial pattern that can be subtracted from the EEG channels.

Finally, at fast rates of stimulus presentation, the ERPs to successive stimuli in the sequence can overlap, thereby distorting the ERP averages. We discussed two methods to estimate and remove such overlap. The ADJAR approach is an iterative deconvolution technique that subtracts better and better estimates of the adjacent-response overlap from the ERPs. The second method relies on including no-stim trials in the randomized sequence that do not evoke ERPs themselves, but whose time-locked averages reflect the same overlap from adjacent trials as do the other stimulus types. Both of these methods has its specific strengths: ADJAR is a more general approach, but not so easy to implement and slow to converge for removing very slow wave overlap. The no-stim method imposes certain design restrictions (e.g., inclusion of a number of additional trials of null events) and assumptions (no elicitation of omitted stimulus responses), but it can be very useful under certain circumstances, such as removing slow wave overlap.

Appendix I: Ocular Artifact Removal Using Linear Regression

In its most elementary form, time domain regression methods perform a simple linear regression between signal and artifact. Consider for example the following equation,

$$y_t = hx_t + e_t \tag{6.2}$$

which represents the linear relation between two signals x (EOG) and y (EEG), which vary as a function of time. Time is indexed by t, ranging from 0 to $T-1$ (T being the number of samples) and e_t represents the error made when predicting y_t from x_t. Minimizing the mean square of e_t (across t), we find a least square estimate for h in equation 6.2:

$$h = \frac{w_{xy}}{w_{xx}} \tag{6.3}$$

where w_{xy} is the covariance between x and y, and w_{xx} denotes the variance of x. Using the value of h from equation 6.3 the EOG artifact in signal y can now be corrected by subtracting hx_t from y_t.

Equation 6.2 can be extended and turned into a multiple regression model by including as predictors past and future values of x:

$$y_t = \sum_{u=-T}^{T} h_u x_{(t-u)} + e_i \tag{6.4}$$

where u indexes the lag for prediction. Equation 6.4 represents a general model for multiple lag regression. As for equation 6.2, we can solve equation 6.4 using a least square estimate:

$$H = W_{xx}^{-1} W_{xy} \tag{6.5}$$

where H is a vector containing the h_u, for u ranging from $-U$ to U. W_{xx} is a symmetrical $(2U+1) \times (2U+1)$ matrix, containing the covariances between x_t and x_{t-u}, $u = -U, \ldots, U$—i.e., the autocovariance function of x. W_{xy} is a vector containing the covariances between x_t and $y_{(t-u)}$, $u = -U, \ldots, U$, i.e. the cross-covariance function of x and y. After obtaining H from equation 6.5, the observed EEG signal can be corrected for ocular artifacts by convolving the observed EOG signal with the regressors H and subtracting the estimated artifact from the observed EEG signal, e.g.:

$$EEG_{t,corr} = EEG_{t,obs} - \sum_{u=-T}^{T} h_u EOG_{(t-u)} \tag{6.6}$$

Appendix II: Sample C++ Code for Spike Detection

Excessive amplitude fluctuations in EEG signals can be det straightforward moving peak-to-peak amplitude test. The follo used to perform such a test. This function scans if the EEG sig the value of `maxAmpDiff` within a moving time window of detected amplitude fluctuation exceeds the maximally allo tion, the function stores the observed maximum amplitude `*amplitude` while also returning the first sample number at curred. Otherwise, the function returns 0 to indicate that the has passed the test.

```
int detectSpikes (double *data,
                  double maxAmpDiff,
                  int duration,
                  int start,
                  int end,
                  double *amplitude)
{
      double ampDiff;
      int index;

      for (int j = start; j < (end-duration); j++)
      {
            for (index = 0; index <= duration; ind
            {
                  ampDiff = fabs (data [j] - dat
                  if (fabs (ampDiff >= maxAmpDif
                  {
                        *amplitude = ampDiff;
                        return j;
                  }
            }
      }
      *amplitude = 0;
      return 0;
}
```

This function can scan for artifacts of different amplitude ar one of the following arguments:

```
double *data: A vector containing EEG data.
double maxAmpDiff: The maximum peak-to-peak am
                   allowed within the envelope.
```

e very useful under certain circumstances, such as removing

act Removal Using Linear Regression

orm, time domain regression methods perform a simple linear al and artifact. Consider for example the following equation,

(6.2)

ear relation between two signals x (EOG) and y (EEG), which ne. Time is indexed by t, ranging from 0 to $T-1$ (T being the e_t represents the error made when predicting y_t from x_t. Min- e of e_t (across t), we find a least square estimate for h in equa-

(6.3)

nce between x and y, and w_{xx} denotes the variance of x. Using ation 6.3 the EOG artifact in signal y can now be corrected by

extended and turned into a multiple regression model by ast and future values of x:

(6.4)

for prediction. Equation 6.4 represents a general model for As for equation 6.2, we can solve equation 6.4 using a least

(6.5)

taining the h_u, for u ranging from $-U$ to U. W_{xx} is a sym- $+1)$ matrix, containing the covariances between x_t and x_{t-u}, autocovariance function of x. W_{xy} is a vector containing the nd $y_{(t-u)}$, $u = -U, \ldots, U$, i.e. the cross-covariance function of x from equation 6.5, the observed EEG signal can be corrected nvolving the observed EOG signal with the regressors H and l artifact from the observed EEG signal, e.g.:

$$h_u EOG_{(t-u)} \quad (6.6)$$

Appendix II: Sample C++ Code for Spike Detection

Excessive amplitude fluctuations in EEG signals can be detected using a relatively straightforward moving peak-to-peak amplitude test. The following C++ code can be used to perform such a test. This function scans if the EEG signal fluctuates more than the value of `maxAmpDiff` within a moving time window of length duration. If the detected amplitude fluctuation exceeds the maximally allowed amplitude fluctuation, the function stores the observed maximum amplitude variation in the variable `*amplitude` while also returning the first sample number at which this violation occurred. Otherwise, the function returns 0 to indicate that the EEG signal in this epoch has passed the test.

```
int detectSpikes (double *data,
                  double maxAmpDiff,
                  int duration,
                  int start,
                  int end,
                  double *amplitude)
{
    double ampDiff;
    int index;

    for (int j = start; j < (end-duration); j++)
    {
        for (index = 0; index <= duration; index++)
        {
            ampDiff = fabs (data [j] - data[j + index]);
            if (fabs (ampDiff >= maxAmpDiff))
            {
                *amplitude = ampDiff;
                return j;
            }
        }
    }
    *amplitude = 0;
    return 0;
}
```

This function can scan for artifacts of different amplitude and duration by modifying one of the following arguments:

```
double *data: A vector containing EEG data.
double maxAmpDiff: The maximum peak-to-peak amplitude fluctuation
              allowed within the envelope.
```

```
int duration: The length of the time window used for the peak-to-
              peak amplitude test.
int start: The first EEG data point that is tested.
int end: The last EEG datapoint that is tested.
```

Appendix III: Sample C++ Code for Flat Line Detection

Extended periods of little or no EEG activity (e.g., indicating amplifier saturations or blocking) can be detected using a modified version of the peak-to-peak amplitude test described in appendix II. The following C++ code can be used to perform such a test. This function is similar to the spike detection algorithm; however, it scans the EEG signal to see if it fluctuates less than the value of `minAmpDiff` within a moving time window of length duration. If the detected maximum amplitude fluctuation stays within the minimally allowed amplitude fluctuation for the entire window, the function stores the recorded maximum amplitude variation in the variable `*amplitude` while also returing the first sample number at which the violation occurred. Otherwise, the function returns 0 to indicate that the EEG signal in this epoch passed the test. The advantage of a method such as this over scanning for the occurrence of repeated series of identical digitization units is that this method will allow for small fluctuations due to line noise.

```
int detectFlatline (double *data
                    double minAmpDiff,
                    int duration,
                    int start,
                    int end,
                    double *amplitude)
{
    double ampDiff;
    double localMax = 0;
    int index;
    for (int j = start; j < (end-duration); j++)
    {
        for (index = 0; index <= duration; index++)
        {
            ampDiff = fabs (data[j] - data[j + index]);
            if (fabs(ampDiff) > localMax)
                localMax = fabs(ampDiff);
        }
        if (fabs (localMax <= minAmpDiff))
        {
            *amplitude = ampDiff;
                return j;
        }
    }
    *amplitude = 0;
    return 0;
}
```


This function can scan for artifacts of different amplitude a
one of the following arguments:

```
double *data: A vector containing EEG data.
double minAmpDiff: The minimum peak-to-peak a
               required within the time window
int duration: The length of the time window u
               peak amplitude test.
int start: The first EEG data point that is te
int end: The last EEG datapoint that is teste
```

Acknowledgments

We wish to thank Chad Hazlett, Tineke Grent-'t Jong, Wa
for their helpful comments on earlier drafts of this chapt
Durk Talsma also wishes to thank various colleagues in A
assistance in implementing some of the algorithms discusse

Notes

1. There are additional interpretation difficulties related to target s
by motor response related ERP components. These problems are,
this chapter.

2. Time domain refers to the most common method of represent
the time domain, electrical voltages are represented as a function
Any time series X_t (where $t = 0, \ldots, t = N$) can be decomposed i
wave frequencies F_f (where $f = 0, \ldots, f = N/2$). The representatic
quencies is known as the frequency domain representation of a s
time domain and frequency representation can be done throu
known as the discrete Fourier transform.

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& Unwin.

```
he length of the time window used for the peak-to-
eak amplitude test.
first EEG data point that is tested.
st EEG datapoint that is tested.
```

+ Code for Flat Line Detection

e or no EEG activity (e.g., indicating amplifier saturations or
d using a modified version of the peak-to-peak amplitude test
. The following C++ code can be used to perform such a
ilar to the spike detection algorithm; however, it scans the
uctuates less than the value of `minAmpDiff` within a moving
uration. If the detected maximum amplitude fluctuation stays
owed amplitude fluctuation for the entire window, the func-
maximum amplitude variation in the variable `*amplitude`
st sample number at which the violation occurred. Otherwise,
indicate that the EEG signal in this epoch passed the test. The
uch as this over scanning for the occurrence of repeated series
nits is that this method will allow for small fluctuations due

```
 (double *data
  double minAmpDiff,
  int duration,
  int start,
  int end,
  double *amplitude)

f;
ax = 0;

start; j < (end-duration); j++)

ex = 0; index <= duration; index++)

pDiff = fabs (data[j] - data[j + index]);
 (fabs(ampDiff) > localMax)
   localMax = fabs(ampDiff);

 (localMax <= minAmpDiff))

mplitude = ampDiff;
```



```
                    return j;
              }
        }
        *amplitude = 0;
        return 0;
  }
```

This function can scan for artifacts of different amplitude and duration by modifying one of the following arguments:

```
double *data: A vector containing EEG data.
double minAmpDiff: The minimum peak-to-peak amplitude fluctuation
              required within the time window.
int duration: The length of the time window used for the peak-to-
              peak amplitude test.
int start: The first EEG data point that is tested.
int end: The last EEG datapoint that is tested.
```

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Notes

1. There are additional interpretation difficulties related to target stimuli, such confounds caused by motor response related ERP components. These problems are, however, beyond the scope of this chapter.

2. Time domain refers to the most common method of representing EEG or ERP waveforms. In the time domain, electrical voltages are represented as a function of time, known as a time series. Any time series X_t (where $t = 0, \ldots, t = N$) can be decomposed into a series of sine and cosine wave frequencies F_f (where $f = 0, \ldots, f = N/2$). The representation of a signal as a series of frequencies is known as the frequency domain representation of a signal. The conversion between time domain and frequency representation can be done through a computational technique known as the discrete Fourier transform.

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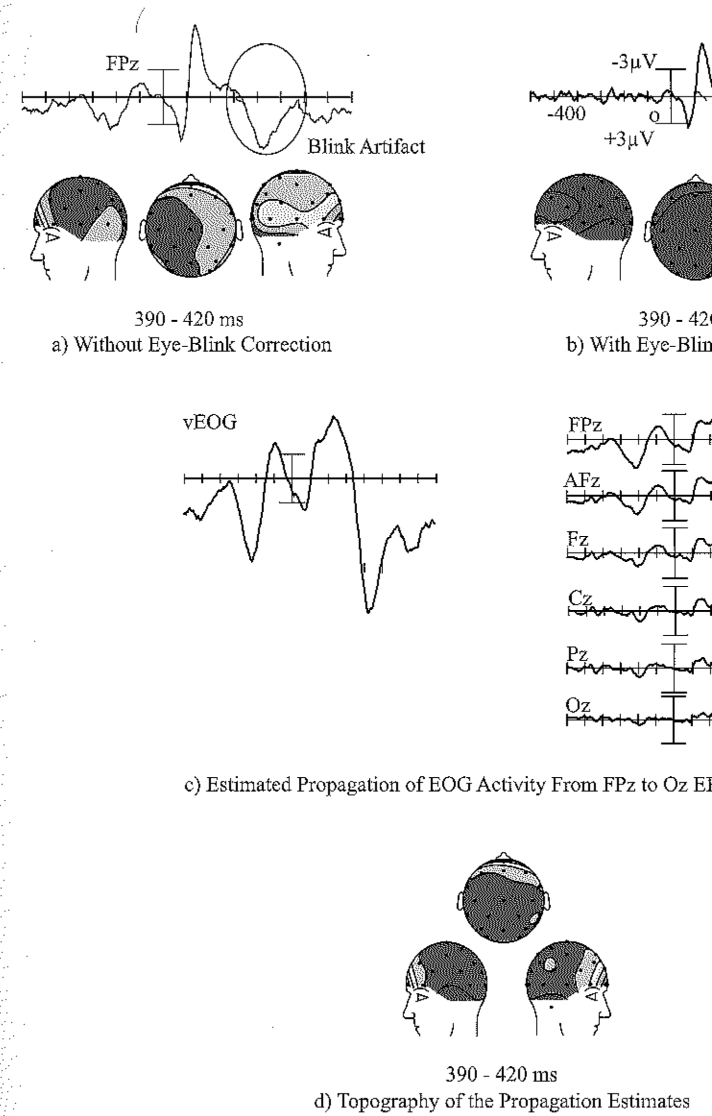

Plate 1
Example of ocular artifacts on ERPs with and without correcti
domain regression method. See chapter 6.

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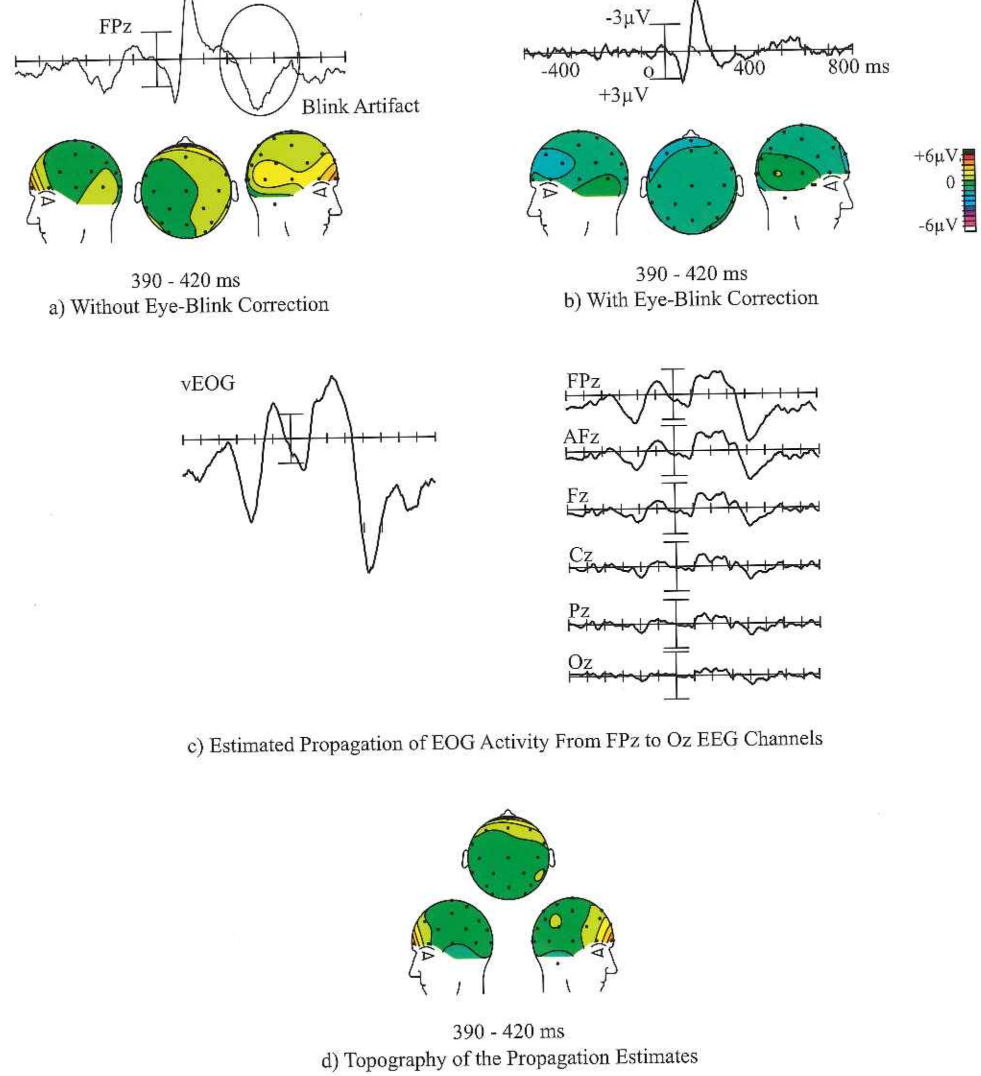
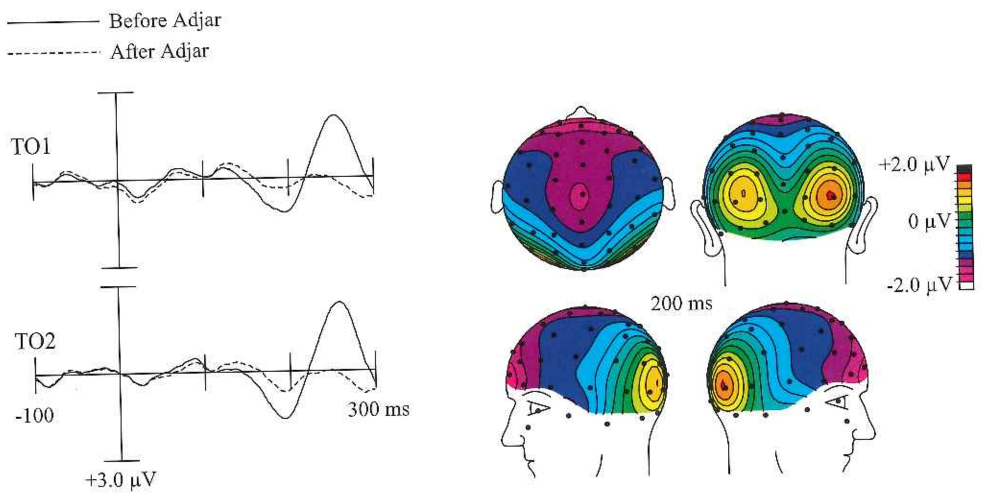


Plate 1
Example of ocular artifacts on ERPs with and without correction, using the frequency domain regression method. See chapter 6.



a) The effect of removing an overlapping visual stimulus on ERP waveforms

b) The scalp topography of the overlapping visual ERP as estimated and removed by ADJAR

Plate 2

Illustration of the use of the ADJAR overlap correction technique in a multisensory experiment. Auditory and visual stimuli were presented in close temporal proximity. *(a)* Shown here is the ERP response to an auditory stimulus that was followed in time by a visual stimulus (between about 75–125 ms). The delayed visual response can clearly be seen in the uncorrected ERP waveform (solid line). After ADJAR correction, the contribution of the visual stimulus has been removed (dashed line). *(b)* The scalp topography of the difference between corrected and uncorrected ERP waveforms. This scalp topography is typical of a visual ERP waveform, showing that ADJAR was successful in removing the visual ERP, but maintaining the auditory ERP. See chapter 6.

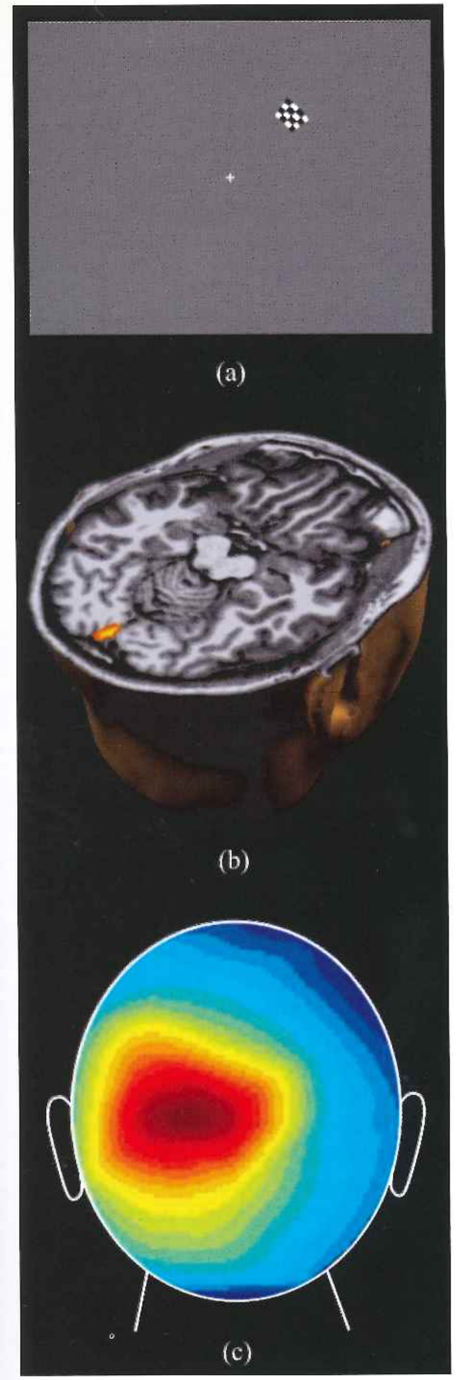


Plate 3

(a) Stimulus display w
ter and checkerboard
in the upper right v
along each edge. *(b)*
MRI, with reconstruc
ments below a select
The head volume is
view is from posterio
activity in left ventr
by the stimulus is
red outline, as asses
(fMRI). *(c)* Posterio
topography elicited
onset. Red, yellow,
progressively decrea
respectively. The lef
mum is due to the u
activity. See chapter