CHAPTER 1

The recording and analysis of event-related potentials

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Introduction

This chapter reviews the techniques for recording and analyzing event-related brain potentials. An ‘event-related potential’ or ERP is an electrical change recorded from the brain in association with something that occurs either in the external world or within the brain itself. Human ERPs are usually recorded from electrodes placed on the human scalp. These potentials can provide a non-invasive means to evaluate the activity of the human brain as it perceives stimuli, makes decisions and controls behavior.

An ERP may be ‘evoked’ by an external stimulus, or ‘emitted’ by the brain as it makes a decision or initiates a response. Evoked potentials are further classified as ‘exogenous’ or ‘endogenous’ on the basis of whether they are determined mainly by the physical characteristics of the stimulus or by the psychological effects of this stimulus (Sutton, Braren, Zubin et al., 1965). Emitted potentials are all endogenous. In recent years, there has been a tendency to use the term ‘event-related potentials’ to mean the endogenous potentials, but this was not its original meaning (Vaughan, 1969).

The nomenclature for ERPs is usually based on the different peaks of the recorded waveforms. These peaks are typically described in terms of their polarity and peak-latency. For example, P100 is a positive peak occurring with a latency of 100 ms. Since latency may vary among individuals and among different recording situations within the same individual, the wave is often generically identified by its typical latency. For example, P300 is a late positive wave that occurs when an improbable target stimulus is detected in a train of standard stimuli (Picton, 1992). Its typical peak-latency when a young adult subject performs a simple discrimination between target and standard is 300 ms. The actual peak-latency is longer for older subjects and longer if the signal is more difficult to detect. Another system of nomenclature is based on a sequential numbering of the peaks. For example P1, N1, P2, N2 and P3 form a sequence of positive and negative peaks in the ERP waveform following a detected target tone. This approach removes the confusion of the same peak having different latencies in different situations. However, it may itself be confounded when similar peaks occur at different scalp locations or when multiple small deflections are superimposed upon a larger wave. This can lead to hierarchies of deflections, such as N1a, N1b, and N1c or P3a and P3b. Some parts of the ERP do not have a specific peak and have received rather non-specific names such as ‘Slow Wave’. Other components of the response have been named by their assumed function. The ‘contingent negative variation’ (CNV) is a slow negative wave that develops between two stimuli when a subject realizes the association between the stimuli and begins to expect the second stimulus following the first. The ‘Bereitschaftspotential’ is a slow negative wave that develops before a motor act and is associated with ‘readiness’. The ‘processing negativity’ is a negative wave that is superimposed upon the ERP when attention leads to further processing. No system of nomenclature is without problem. As we know
more about the ERPs, the nomenclature will become more rational and consistent. Ultimately we should be able to identify a component of the ERP on the basis of its source within the brain and its function in cognition.

Three basic procedures are necessary to evaluate ERPs (Fig. 1). First, the electrical potentials must be recorded from the scalp. Second, they must be analyzed to provide meaningful measurements. Third, the results of the analysis must be displayed for visual assessment. At the present time, recording is mainly analog and analysis mainly digital. Analog-to-digital conversion is the interface between these two.

ERPs can be displayed in many different ways. The most common display plots the potentials recorded from a particular scalp location over time. Either negativity or positivity at the scalp relative to a reference electrode can be plotted upward. The general convention of electroencephalography is to plot ‘negative up’ whereas most other disciplines plot ‘positive up’. All illustrations in this chapter are plotted positive up.

This chapter reviews the procedures used to record and analyze human ERPs. It is impossible to describe every technique in detail, but the most important principles are summarized and illustrated. The intent is to provide the reader with the necessary information to record reliable and meaningful ERPs and to understand the methods used by others to make these recordings.

Recording procedures

Recording electrodes

The ERPs generated in the human brain are usually recorded as electrical fields on the scalp. Techniques for recording ERPs from intracerebral electrodes (Stapleton and Halgren, 1987) are not discussed in this chapter. For scalp recordings, the connections between the subject and the recording equipment are made through electrodes attached to the scalp. Since everything depends upon these crucial connections,
some knowledge about the biophysics of electrodes (Geddes, 1972; Geddes and Baker, 1989) is essential to any understanding of how the ERPs are recorded.

When a metal electrode is immersed in an electrolyte, an electron exchange occurs causing metal ions to enter into solution or ions in the electrolyte to combine with the metal. This exchange causes an electrode potential which varies with such factors as the type of metal and the temperature. In addition, a layer of ions builds up immediately adjacent to the metal with a second layer of oppositely charged ions just beyond the first. This ‘electrical double layer’ acts like a capacitor when current flows between the electrode and the electrolyte. This causes the electrode interface to act as a high-pass filter. The filtering effect varies with the size of the electrode and the type of metal in the electrode. What is less recognized is that the filtering effect also varies with the amount of current passing through the electrode and thus with the input impedance of the amplifier. Some years ago, Cooper (1963) published data showing very significant distortion of recorded signals with many commonly used EEG electrodes. As pointed out by both Cooper, Osselton and Shaw (1980) and by Geddes and Baker (1989) much of the distortion was due to the low input impedance (750 kΩ) of the amplifiers and the resultant large currents passing through the electrodes. With modern high-impedance amplifiers this distortion is much less. Figure 2 shows sustained potentials recorded with some commonly used electrodes.

A simple way to evaluate the filtering effects of the recording electrodes is to record the horizontal electro-oculogram (EOG) from electrodes near the external canthi when a subject gazes to one side for a period of time. If the EOG recording returns to baseline (or not) at the same rate as a step-change in voltage applied directly to the input of the amplifier, one can conclude that the time constant of the EOG recording is the same as the time constant of the amplifier. The electrodes therefore do not cause any extra high-pass filtering over and above that of the amplifier (Cooper et al., 1980; Polich and Lawson, 1985).

The electrical double layer can be eliminated by using a ‘reversible’ electrode. In such an electrode, the passage of current does not significantly alter the electrolyte composition in the vicinity of the electrode. The most commonly used reversible electrode is a silver electrode (Ag) upon which has been deposited a layer of silver chloride (AgCl), or an electrode that consists of a ‘sinter’ mixture of Ag and AgCl. Because of the high concentration of AgCl in the electrode there is no significant change in the concentrations of the Ag⁺ or Cl⁻ ions when small amounts of current pass through the electrode. If properly maintained (Tassinari, Green, Cacioppo et al., 1990), these reversible Ag/AgCl electrodes are very stable and can be used to record slow potential changes in the brain lasting for many seconds.

![Fig. 2. Electrode characteristics. This figure shows the results of an experiment to evaluate the characteristics of electrodes used in recording electrical activity from the scalp. The experimental set-up is shown in the upper right section of the figure. A pulse of current is injected into a saline bath by a constant-current generator. The current pulse lasts 3 s. The potential field set up in the saline is measured by two electrodes (dark circles) connected to a DC amplifier that has an impedance of either 1 MΩ or 100 MΩ. On the left of the figure are shown the potentials recorded using different kinds of electrodes when the amplifier input impedance was 1 MΩ. The silver/silver chloride (Ag/AgCl) electrode accurately portrays the current pulse. The silver (Ag), tin (Sn) and gold (Au) electrodes all show high-pass filtering characteristics. The platinum (Pt) electrode, unlike the other electrodes was a needle electrode with a very small surface area. This shows very significant high-pass filtering characteristics. At the bottom right of the figure are shown the results for the silver and platinum electrodes when the amplifier was changed from one with an input impedance of 1 MΩ (thin line recordings) to one with an input impedance of 100 MΩ (thick line recording). With the high-impedance amplifier the electrodes are able to portray the electrical field more accurately.](image-url)
Connecting electrodes to the scalp requires a conducting medium, some preparation of the skin and some means of fixing the electrode in place. The conducting medium is usually an electrolyte solution that has been made into a paste or jelly so that it will not easily evaporate or drain away during the recording. There are two kinds of conducting medium: in one the electrolyte (usually sodium chloride) is highly concentrated and in the other the electrolyte is similar in its concentration to subcutaneous tissue or sweat. The concentrated electrolyte has the advantage of higher conductivity, whereas the isotonic electrolyte does not set up diffusion potentials at the interface between the electrolyte and the scalp. The concentrated electrolyte is preferable unless scalp potentials are being specifically measured.

Electrodes work best when they are completely separated from the skin by the conducting medium. Otherwise, several different interfaces can serve as sources of potential: electrode-skin, electrode-jelly, jelly-skin. Large potentials can then be generated by slight changes in the surface area of these interfaces caused by movement of the electrode. This can be prevented by keeping the electrodes away from the skin by means of a sponge filled with electrode jelly or a plastic housing filled with jelly.

The preparation of the scalp prior to electrode application involves two steps. First, the hair must be moved from beneath the electrode. Although it need not be cut, the hair must be parted so that it does not prevent the electrolyte from connecting the electrode to the skin. The hair may be kept away by mechanical pressure or by collodian. Second, the skin beneath the electrode must be abraded so that the electrode is properly connected to the subcutaneous tissue. Not abrading the skin causes a greater pick-up of electromagnetic artifacts because of the high impedance of the electrode circuit. Large changes in the resting potentials generated by intact skin may also contaminate the recording.

The skin is electrically very complex. It generates a standing potential between its external surface and the subcutaneous tissue. The trans-epidermal potentials for the intact scalp are about 25 mV with the surface negative in relation to the subcutaneous tissue (Picton and Hillyard, 1972). The trans-epidermal impedance of the unabraded scalp is approximately 25 kΩ. Sweating induced by heat or by psychological stress reduces the impedance of the skin and changes the transepidermal potential. Scalp sweat glands are most highly concentrated in the temples and behind the ears (Picton and Hillyard, 1972). In these areas, large skin potentials can occur and significantly distort slow ERPs. In order to decrease these skin potentials, the scalp beneath the electrodes should be abraded using a blunt needle or some abrasive paste. To eliminate them the skin should be punctured with a sterile needle.

Abrading or puncturing the skin to reduce electrode impedance carries the risk of infection. The electrodes must therefore be disinfected after every use with sodium hypochlorite (household bleach), glutaraldehyde (less corrosive than bleach) or some other effective technique (Putnam, Johnson and Roth, 1992).

The integrity and conductivity of the electrode-scalp connection should be tested by measuring the inter-electrode impedance when a very small alternating current is passed through the electrodes. It is essential to use alternating rather than direct current in order not to polarize the electrodes. Inter-electrode impedance is usually recorded in the frequency range of the EEG at 10 or 30 Hz. The measured impedance will be affected by the surface area of the electrode and the way in which the skin is prepared. For surface electrodes with a conducting area of about 1 cm² the impedance should be less than 10 kΩ for recording frequencies of greater than 1 Hz, and less than 3 kΩ for recording frequencies below 1 Hz. Unprepared scalp has an impedance of about 50 kΩ between two surface electrodes.

The electrodes are attached to the scalp by some adhesive material or by mechanical pressure. A commonly used adhesive is collodian. This can glue the hair down as well as fix the electrode to the scalp. A disadvantage of collodian is that the acetone needed to remove it can dissolve the plastic housing of some electrodes. Double-sided adhesive collars can connect electrodes to skin. These adhesive collars can be used on the scalp if the hair is initially glued down with a collodian-soaked gauze pad with a hole in the center.
to allow the electrode to connect to the scalp. Some electrode pastes are made up so that they are themselves adhesive. Such pastes may be used if the recording time is short. For recording times lasting longer than 1 h, these pastes may dry out and lose their conductivity.

Various means of holding electrodes in place mechanically have also been developed. Recent examples are the elastic cap (Blom and Anneweldt, 1982) and the geodesic net (Tucker, 1993). These methods can locate the electrodes as well as hold them in position. However, malfunctioning electrodes are difficult to change. These methods are particularly useful when recording from a large number of sites.

Recording montages

Simultaneous recordings from multiple scalp locations are essential for understanding the ERPs. For some simple sensory evoked potentials, the locations of the scalp fields generated in the sensory pathways and the nature of possible artifacts are sufficiently well known that a single-channel recording from a pair of scalp electrodes can be used. For most ERPs, however, multiple electrodes are necessary.

Electrodes should be located on the scalp in standard positions. In order to compensate for the different sizes and shapes of the human head, the ‘Ten-Twenty’ system of electrode placement was developed (Jasper, 1958). This identifies the inion, nasion and preauricular points and locates electrodes on the basis of simple percentages (10, 20 and 50) of the lines linking these reference points. Extra electrodes can be located at positions halfway between those of the original Ten-Twenty system. Figure 3 shows a nomenclature for electrode positions that was proposed by the American Electroencephalographic Society (1991). In this system, T7/T8 and P7/P8 replace previous inconsistent terms for these locations. The relationship of the scalp locations to underlying cortical structures has been recently reviewed (Steinmetz, Fürst and Meyer, 1989). The location of these electrodes relative to a sphere fitted to the head has been evaluated using MRI scans (Towle, Bolanos, Suarez et al., 1993; Lagerlund, Sharbrough, Jack et al., 1993). Electrode locations can be digitized in three dimensions (de Munck, Vijn and Spekreijse, 1991; Echallier, Perrin and Pernier, 1992). Using these techniques, one can fix the electrodes more or less arbitrarily on the scalp and measure their positions afterwards. One can also evaluate the shape of the skull for fitting various head models.

The number of scalp electrodes needed to define the scalp distribution of an ERP waveform depends upon how rapidly the potential changes from point to point on the scalp. Sampling theory requires that at least two samples be taken from any one cycle of a signal (Bendat and Piersol, 1971; Oppenheim and
A linked-ear (or linked-mastoid) reference basically combines the activity from the two ears. Unfortunately, the amount of activity from each ear in the combined recording depends upon the impedance at each ear electrode. Since these impedances may vary during the experiment, the virtual location of the linked-ear reference is unknown. Furthermore, it is theoretically possible to short circuit some of the currents between the ears (Nunez, 1981, pp. 188–193), although in practice this seldom occurs (Miller, Lutzenberger and Elbert, 1991). This reference can be improved by using 10 kΩ resistors (greater than the allowed difference in skin resistance between the two ears and less than the input impedance of the amplifier) in series with each of the ear electrodes. A better approach would be to make all recordings using one ear (for example A1) as a reference and to include one channel that records the difference between the two ears (A2 – A1). An algebraic linked-ear reference recording (which might be desirable for displaying and comparing data with earlier studies) can then be calculated by subtracting half the inter-ear recording from the single-ear reference recording:

\[ X - (A1 + A2)/2 = (X - A1) - (A2 - A1)/2 \]

Even better would be a midline scalp reference for symmetry reasons: if something is wrong with an electrode, the data set becomes obviously asymmetric. The ‘remontaging’ capabilities of digital systems allow the computation of any reference including the algebraic linked-ear reference, provided recordings are made from each ear.

A balanced non-cephalic reference was initially proposed by Stephenson and Gibbs (1951). Recordings using a neck or chest reference are usually contaminated by large EKG artifacts. The balanced non-cephalic reference records from the center-tap of a potentiometer (20–50 kΩ) linking an electrode over the seventh cervical vertebra with an electrode over the right sterno-clavicular joint. The potentiometer is adjusted to cancel the EKG as much as possible. Woods and Clayworth (1985) have used a variant of this non-cephalic reference that records from four electrodes around the base of the neck linked through...
a two-dimensional potentiometer. This reference has the same problem as the linked-ear reference: its virtual location is unknown. The EKG artifact contaminating records referred to a single neck electrode (with known location) can be suppressed by correction methods discussed later.

Figures 4 and 5 show auditory evoked potentials recorded using different references. The original recordings were made using a non-cephalic reference and the other montages were derived algebraically. Figure 4 shows the potentials recorded in response to an unattended auditory stimulus. The major waves in the response are the N1 and P2 waves and the sustained potential (SP). On the montages using linked-mastoid or non-cephalic references, all these waves are recorded with maximum amplitude at the vertex and midfrontal regions with no inversions of field polarity at other locations. The montages using the nose or average reference show clear polarity inversions below the Sylvian fissure (located just above the T7 and T8 electrodes).

The search for an ‘inactive’ reference electrode has long concerned electroencephalographers. Unfortunately, fields generated within the brain spread

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**Noncephalic**  
![Noncephalic](image_url)

**Linked Mastoids**  
![Linked Mastoids](image_url)

**Nose**  
![Nose](image_url)

**Average**  
![Average](image_url)

**Fig. 4.** Different recording montages for the auditory evoked potentials. This figure shows the ERPs recorded following a standard stimulus occurring with a probability of 80% in a train of unattended auditory stimuli. Each stimulus was a tone burst of 400 ms duration presented to the right ear. The frequency was either 1000 or 2000 Hz (counterbalanced for the target and standard stimuli). The potentials displayed in the upper left of the figure show the actual recordings made using a linked sternovertebral ‘non-cephalic’ electrode. In these tracings (and all others in this chapter), positivity at the scalp relative to the reference is shown as an upward deflection. The recordings were made from the nose, Fpz, F5, Fz, F6, left mastoid, T7, C3, Cz, C4, T8, right mastoid, P5, Pz, P6, and Oz. The recordings in the upper right show what would have been recorded if linked mastoids had been used as the reference. The recorded fields are not much changed from those recorded from the non-cephalic reference. The recordings at the lower left show the results that would have been obtained if the nose electrode had been used as a reference. There is a clear polarity inversion of the N1, P2 and SP waves above and below the Sylvian fissure located just above the T7 and T8 electrodes. The waveforms in the lower right show the results of using an average reference. There are again clear polarity inversions over the Sylvian fissure.
through volume conduction to all areas of the scalp. There is therefore no location on the scalp that does not record some electrical activity. Linked-ear or non-cephalic electrodes pick up electrical activity from the base of the brain. The average reference is the best estimate of an inactive reference (Bertrand et al., 1985). However, this reference must be based on an adequate sampling from all surfaces of the brain. Electrodes should be not only be located over the upper regions of the scalp but should also be placed on the neck, face and lower scalp to record from the inferior surface of the brain; one must not forget this ‘dark side’ of the brain. Recent controversies concerning the distortions that might result from the use of an average reference (Desmedt and Tomberg, 1990) probably relate to a biased sampling of the surface fields with an inadequate number of recording sites for the inferior surface of the brain.

Amplification

The electrodes are connected to an amplifier either through a capacitor or directly (direct coupling or DC). DC recordings are used for studying very slow potential shifts. These studies require special amplifiers that can represent slow changes in potential without themselves adding their own slow drifts (such as those caused by temperature fluctuations) to the recordings. Direct-coupled amplifiers usually have some provision for balancing out the sustained potential of the recordings so that the signal can be amplified to show small fluctuations riding on this resting potential. Capacitor-coupled amplifiers filter out any sustained potential difference between the recording electrodes and attenuate slow fluctuations in this potential. Most event-related potentials can be recorded using capacitor coupling.

All recordings are ‘differential’ in that they record the difference in potential between two electrode locations. The brain electrical activity recorded from the scalp is very small compared to other electrical activity that may be picked up by the recording electrodes. Any activity common to both electrodes can be cancelled by using a differential amplifier. The ‘common mode rejection ratio’ (CMRR) of an amplifier measures this cancellation by recording the amount of ac-
tivity remaining when identical signals are connected to the two inputs of the amplifier (Elbert, 1991). For recording human ERPs, the CMRR must be at least 100 dB (100,000 to 1) and preferably greater than 120 dB.

The subject should be connected to a ‘ground’ which serves as a large sponge for accumulated charge. This connection drains off charge that may develop in the subject through capacitive inductance from power lines or other sources of high voltages. The ground thus decreases common mode signals and further improves the CMRR of the recording. However, it can also allow leakage or fault currents from the amplifier to return to ground through the patient (Cadwell and Villareal, 1992). Modern instruments therefore often use an ‘isolated’ ground which uses electronic components to prevent dangerous leakage currents. A pre-amplifier that is electrically isolated from the main amplifier can decrease the risk of leakage currents through the recording electrodes (rather than through the ground connection). These pre-amplifiers can be powered by battery and can transmit signals to the main amplifier using a transformer or an optical coupler.

Although modern amplifiers are far more consistent than earlier amplifiers, it is still essential to monitor and maintain their calibration. This is usually done by inserting a brief voltage pulse into the amplifiers and monitoring the recorded output. The voltage pulse should be similar in amplitude and duration to the ERPs being recorded. Optimally one should evaluate as much of the recording system as possible. The calibration pulse should therefore be inserted into the electrode connections rather than into the input of the amplifier and the final amplitude should be measured after averaging on the computer rather than at the output of the amplifier. If one uses a step-change in voltage one can calibrate the frequency response of the system as well as its amplification by performing a Fourier transform of the recorded signal.

**Analog-digital conversion**

Once amplified, the analog signal is converted into digital form for computational processing (Fig. 6). The analog-digital (A-D) conversion occurs at a determined rate (samples per second) and for a certain period of time (sweep). The converter has a range of voltages that it can represent and a resolution whereby this range can be represented.

The rate of conversion has to be fast enough to catch the highest frequencies of the signals being studied. The sampling rate must be more than the Nyquist ‘rate’ which is twice the highest frequency present in the signal. It is essential that frequencies higher the Nyquist ‘frequency’ (one half the sampling rate) not be entered into the conversion. Such high frequencies may show up in the digitized data under the alias of their lower harmonics (Fig. 7). The ideal anti-aliasing filter would be set at one half the A-D conversion rate and would completely remove all higher frequencies. Unfortunately, real filters have a finite slope to their cut-off. The anti-aliasing filter should therefore have a cut-off setting (–3 dB) at one quarter the A-D conversion rate and a relatively high slope (12 dB/octave or more).
such a ±5 V range the converter can discriminate signals that are 10/4096 V or 2.4 mV different. Because of the amplification that occurs prior to the A-D converter, this represents a much smaller value in terms of the actual signal. However, it is often less than the resolution desired in the final waveform. Provided that the input signal moves through more than two A-D levels, averaging will increase the amplitude resolution of the recording. The difference between the digitized signal and the real signal is considered ‘quantization error’ (Fig. 8). This has a root-mean square amplitude equal to $0.29r$ where $r$ is the size of the resolution unit (Bendat and Piersol, 1971). Averaging treats this as another source of random noise.

It is essential that the input signal be amplified to extend over most of the range of the A-D converter. If not, the effective resolution of the A-D converter is significantly reduced. For example, if one connects the normal tape-recorder output of an EEG machine (maximum voltages ±1.4 V) to an A-D converter with a range of ±5 V the effective resolution of the converter is reduced by almost 2 bits. When recording slow changes in the D-C potential one may wish to use a very high-resolution A-D converter (e.g. 16 bits). This will allow the signal to wander around

The A-D conversion of multiple channels usually requires one A-D converter to switch from one channel to another by ‘multiplexing’. The way in which this multiplexing is performed depends upon the converter and its programming (Bührer and Sparrer, 1991). Many converters use a programmed rate for A-D conversion and another faster rate to switch from one channel to the next in a ‘triggered scan’ mode. A very simple multiplexer switches through the multiple channels at a regular rate that equals the desired rate for each channel times the number of channels. For most applications, the delay between one channel and the next is not significant. However, it may distort some measurements that compare the phase of signals between channels (Lutzenberger and Elbert, 1991). The optimal approach is to use a ‘simultaneous sample-and-hold’ circuit that samples all channels at the same time and then reads the values sequentially.

The resolution of most A-D converters used in ERP research is 12 bits. This means that the analog waveform is converted to numbers between 0 and 4095 ($2^{12} - 1$). The converter acts over an amplitude range that is typically ±5 V, although this varies from one converter to the next and may be adjustable. With
the range of the converter without blocking but still allow sufficient resolution of the signals of interest, which are small fluctuations on top of the large slow changes.

**Signal analysis**

**Averaging**

ERPs recorded from the scalp combine 'signal' (the ERPs) and 'noise' (other electrical activity). Because the signal is usually smaller than the noise, it is often difficult or impossible to distinguish the ERP in a single sweep. The 'signal-to-noise ratio' must be increased before the ERP can be analyzed or measured. The most common technique for enhancing the signal-to-noise ratio is averaging (Picton and Hink, 1974; Vaughan, 1974; Glaser and Ruchkin, 1976, pp. 177–219; Rockstroh, Elbert, Canavan et al., 1989, pp. 13–34; Challis and Kitney, 1990).

Averaging is performed in temporal relation to some identifiable repeating event. The recorded waveforms are aligned in time with this event and then averaged. During averaging the ERP remains constant whereas the noise decreases with each repetition of the event. Averaging is thus based upon three assumptions (Glaser and Ruchkin, 1976):

(i) the signal and noise linearly sum together to produce the recorded waveform;

(ii) the signal waveform is the same for each repetition of the event;

(iii) the noise waveforms are sufficiently irregular from event to event that they can be considered as statistically independent samples of a random process.

For the purposes of averaging, the ideal noise is 'stationary', meaning that different segments of the noise have similar means and variances, and 'independent' from trial to trial, meaning that the data points in one trial do not covary with those of other trials. Averaging will reduce such an ideal noise to a residuum that is directly proportional to the root-mean-square of the original noise and inversely proportional to the square-root of the number of repetitions. This is the 'square-root' rule of averaging. Figure 9 illustrates the process of averaging using some human ERP data.

In real situations, however, the background noise does not always fulfill the assumptions of averaging. The noise is often non-stationary because of occa-

![Fig. 9. Process of averaging. This figure illustrates the averaging of auditory evoked potentials recorded in response to a detected target stimulus. The subject listened to a train of tone bursts presented to the right ear. The standard stimuli with a tonal frequency of 1000 kHz occurred with a probability of 80% and the targets with a frequency of 1200 kHz occurred with a probability of 20%. The responses were recorded between vertex and balanced non-cephalic chest reference with an A-D conversion rate of 250 kHz and a filter bandpass (-3 dB) of 0.1–10 Hz. The single-trial ERPs in the first column were selected from the set of responses to target stimuli on the basis of a lack of muscle or ocular artifacts and an absence of rhythmic background activity. In the second column, groups of four responses have been averaged together. In the upper part of each of the four paired tracings, the responses have all been added together; in the lower tracings they have been alternately added and subtracted to give a estimate of the residual unaveraged background noise, the (±) average. The third column shows the average of all 16 responses, again with a (±) average in the lower tracing. By the time all 16 responses have been averaged together, the response is significantly larger than the residual noise. In the upper right corner of the figure are superimposed two averages of 8 responses each to illustrate the replicability of the response. These tracings have been labelled using a sequential nomenclature of N1, P2, N2 and P3. The amplitude scaling of the responses (shown at the bottom of the columns) has been adjusted so that the range of the averaged noise remains approximately constant. Thus, when four responses are combined together and the noise levels reduced by 2, the vertical size of the responses is doubled. This illustrates the square root rule of averaging.]

13
sional trials in which the noise is of much higher amplitude than usual. For example, some trials may contain a high level of muscle artifact because of movement, swallowing or coughing. If these trials only occur occasionally, rejecting them from the averaging will significantly improve the process of averaging. If the trials occur quite frequently, one can consider them as part of the background noise and increase the number of trials averaged in order to obtain a reasonable signal-to-noise ratio. Another problem is that the different samples of noise may not be independent because rhythmic activity may be similar from one trial to the next. One approach to this problem is to randomize the interstimulus interval over a range that is greater than the period of any rhythm in the background noise. Another is to use an interstimulus interval that is not equal to any multiple of the period of the rhythmic noise.

The temporal relations between the event and the signal vary with the experiment. For sensory evoked potentials, the signal waveforms follow the sensory stimulus. Motor-related potentials are generated by electrical activity in the motor areas of the brain that precede a muscle movement. In order to record these potentials, one must record the motor event (EMG activity in a muscle, the pressing or releasing of a button, etc.) and average backward in time from this event, i.e. 'opisthochronic' (bent back in time) averaging. For cognitive ERPs, the relation between the event and the potentials is more difficult to determine. For these potentials, one can use an external event (or absence thereof) that is linked in time to the cognitive event. For example, a decision about a sensory stimulus could be linked in time to the occurrence of the sensory stimulus or to the pressing of a button in response to that decision.

The arithmetic mean is the most common measure of 'central tendency'. Alternative measures are the 'median' and the 'mode'. If arranged in order of magnitude, one half of the observations lie on either side of the median. The mode is the value that occurs most frequently. Both the median and the mode are less affected by extreme values than the mean. They may therefore be useful when such extreme values occasionally occur in the data. The background noise in recording ERPs is usually normally distributed and

![Image](image.png)

**Fig. 10.** Averages and variances. In the upper left of this figure are superimposed the 16 waveforms that were averaged together in Fig. 9. One can obtain some feeling for the 'mode' of the response by blurring one's eyes and picking out the darkest portion of the superimposed tracings. Below these superimposed tracings are given the mean and the median. In the upper right, the two waveforms show the distribution of the mean waveform plus or minus one standard error. The middle tracings show the confidence limits (obtained using two-tailed t-statistics) for the mean response plotted versus zero with the mean response superimposed. The bottom tracing shows the regions of the waveform where the amplitude of the response relative to zero is beyond the confidence limits at that latency.
the median and mode are therefore similar to the mean. Since the median and the mode are more difficult to calculate and less tractable to statistical assessment, the mean is almost invariably used in recording ERPs. Figure 10 shows that the median waveform for the data averaged in Fig. 9 is very similar to the mean waveform.

The signal-to-noise ratio may be increased by augmenting the number of repetitions. However, ERP may change with time because of boredom, fatigue or learning. These changes distort the averaged waveform and therefore counter any enhancement of the signal-to-noise ratio brought about by increasing the number of trials. The number of repetitions can be increased without increasing the duration of the recording by decreasing the interstimulus interval. However, for most ERPs, this also results in a decrease in the amplitude of the response. One must therefore attempt to select a stimulus rate that maximizes the recording efficiency.

Signals in noise

Although the noise is reduced by averaging, it never reaches zero. There is always some residual noise in the recording (Turetsky, Raz and Fein, 1988). How does one know how much of the averaged waveform represents the signal and how much represents residual noise? The answer requires some estimate of what the residual noise in the recording would be if there were no signal present. A simple and effective way to assess noise levels is to repeat the recording two or more times; the more similar the waveforms, the better they represent the signal (Wong and Bickford, 1980; Picton, Hink, Perez-Abalo et al., 1984; Picton, 1987). The similarity of the replications can be quantified by calculating a correlation coefficient. The difference between replications is another reasonable estimate of the residual noise. It can be calculated by averaging one of the replications with the inverted version of the other, i.e. the (+) reference (Schimmel, 1967). The residual noise can then be quantified by calculating the variance or the standard deviation of the (+) reference. Standard deviations (the square root of the variance) are easier to understand because they use the same units as the amplitudes. However, signal-to-noise ratios are usually expressed in terms of energy or variance.

Several techniques are available to determine whether the averaged response is significantly different from zero. The noise levels in the averaged response may be assessed by measuring the variance of the single-trial data at each point in the recording. If one is confident that the background noise is stationary through the recording sweep, one can estimate the variance at each point from calculations based on only one point in the waveform (Elberling and Don, 1984). Unfortunately, since ERPs may occur concomitantly with changes in the background noise these single-point calculations may not be generalizable to other latencies. Given the variance, confidence limits can be determined for the mean measurement at each point in time using Student’s \( t \). If the confidence limits of the mean do not include zero, one can be confident (at the level for which the limits were calculated) that a response is present. This is illustrated in Fig. 10. Unfortunately, an ERP waveform spans many points and a small number of mean ERP values may be ‘significantly’ different from zero by chance alone. For example, if the confidence limits are calculated at \( p < 0.05 \) one would expect approximately one in twenty values to differ from zero even if there were no signal present. Guthrie and Buchwald (1991) have described a way to evaluate these multiple tests. Given the auto-correlation statistics for a waveform, one can estimate the chances of obtaining a number of significant results in a row.

Blair and Karniski (1993) have described another approach to assessing the significance of averaged waveforms. The justification for this procedure derives from permutation theory. If the null hypothesis is true (that the waveform is not significantly different from zero) then the ordering of the time points is arbitrary. The \( t \)-statistics are calculated for each time point when the order of the time points are permuted through all possible combinations from trial to trial. For example, the calculations can associate time points 1, 2 and 3 of the first trial with time points 1,3 and 2 or time points 2, 1 and 3 of the second trial. These calculations yield a large set of \( t \)-statistics, only one of
which is the actual result. One can thus determine the exact probability of having obtained the actual $t$-statistic. This approach is extremely demanding in terms of the amount of calculation. However, it has clear advantages over the Guthrie–Buchwald test in that it requires no estimate of the correlation statistics for the waveforms.

Another approach is the ‘Residual Orthogonality Test’ of Achim, Richer, Alain et al. (1988a). If all data values collected during one trial are multiplied by the corresponding values collected during another trial, the sum of all of these products has an expected value of zero if no signal was present in both trials. If $N$ waveforms are combined together there are $(N - 1)/2$ possible pairs of waveforms. The sum of the products can be calculated for each possible pair and the mean of the sums of products is compared to zero by a Student $t$-test with $[(N - 1)/2] - 1$ degrees of freedom. If the mean sum-of-products is significantly greater than zero by this test, one can conclude that a signal is present in the data. This test is computationally simpler than the previous test, although it will not show the temporal location of the significant results within the recorded waveform.

These statistical techniques are very helpful in many aspects of ERP research. As well as determining whether an average ERP waveform recorded from a single subject in a single experimental condition is significantly different from zero, these approaches can be used to assess combined (‘grand mean’) data from different subjects. They can also be used to study the differences between ERP waveforms. The simplest way is to calculate a ‘difference waveform’ by subtracting one waveform from another and then to compare the difference waveform to zero. These statistical tests are also helpful when trying to model recorded waveforms in terms of components (Achim et al., 1988a). The tests can assess whether the residual activity (unexplained by the modelling) contains signals that are significantly different from zero (and therefore need to be explained by further modelling).

**Latency jitter**

ERPs do not completely fulfill the formal assumptions of the averaging process. The signal may not always be constant. The trial-to-trial variability of the ERP may be an important parameter when evaluating cerebral function and several techniques have been proposed to measure it (Möcks, Gasser and Tuan, 1984; Fein and Turetsky, 1989). Variability is greater for ERPs that are more susceptible to cognitive control. During averaging, variability in either the amplitude or latency (or both) of the ERP can significantly distort the average. If only the amplitude of the signal varies, the averaged waveform will accurately reflect the wave shape of the individual signals and the averaged waveform will be the average of the individual signals. Latency changes are far more problematic. In general, the averaged waves will spread out in time and the amplitude of the average response will be smaller than the average amplitude of the individual signals (Ruchkin, 1988). The larger the latency variability and the sharper the waveform, the greater will be the resultant distortion.

It is sometimes possible to prevent the distortion of the response due to latency variability. If the signal-to-noise ratio is large enough, the latency of a waveform can be estimated on each individual trial. The waveforms can then be shifted in order to compensate for the latency variability prior to averaging. In one method (Woody, 1967; Harris and Woody, 1969; Purves and Boyd, 1993), the latency differences from trial to trial are estimated by computing a cross-correlation function between the recorded waveform and a template. The time lag at which the cross-correlation coefficient is largest is taken as the latency on that particular trial. The waveforms are then aligned by their estimated latencies and averaged. The average waveform then replaces the original template and the whole cycle is repeated again until the resultant waveform becomes stable. This process is illustrated in Fig. 11. The choice of the initial template is not critical but if the initial template is a good estimate of the signal, the number of iterations required for convergence to the final waveform will be smaller. If the latency jitter is not too large, the uncompensated average waveform can be used as the initial template. A judicious pre-filtering of the data can improve the procedure by increasing the signal-to-noise ratio on
the single-trial waveforms. Because the largest wave in the single-trial waveforms is the main determinant of the alignment, this technique is most useful when the ERP is characterized by one major wave and smaller waves that either vary in the same way as the large wave or are not relevant to the analysis. If the signal waveform contains several components that vary independently in latency, the Woody approach will not work well. Another approach for compensating latency jitter picks out the peaks in each recording and lines these up separately prior to combining the recordings (McGillen, Aunon and Childers, 1981).

Dynamic time warping is a technique that can alter the timing of one waveform to fit to the timing of another waveform (Picton, Hunt, Mowrey et al., 1988). It has been used extensively in the evaluation of speech sounds where the relative timing of the different parts of the speech waveform (consonants and vowels) can vary with such things as accent and speed of talking. As well as comparing a waveform with a template, warping may also be used to combine waveforms together to form a composite waveform that is midway between the two originals in terms of selected parameters. The technique is diagrammed with model waveforms in Fig. 12. Its application to actual ERP waveforms is illustrated in Fig. 13.

The process for comparing waveforms involves several steps. First, each waveform is converted into a set of measurements \((X_i \text{ to } X_j \text{ and } Y_i \text{ to } Y_k)\) at selected time points. Next, a specified set of variables is described for each time point. In the diagrammatic Fig. 12, only amplitude \((a)\) is used. In our evaluation of the ERPs, we used both the amplitude \((a)\) and the slope \((s)\) of the waveform at each time point since both parameters were subjectively important in the visual analysis of the responses. In order to find a non-linear alignment of the waveforms that will make them as similar as possible in terms of their amplitudes and slopes, we define a dissimilarity measure between the \(j^{th}\) point of waveform \(X\) and the \(k^{th}\) point of waveform \(Y\) as the sum of the absolute differences in \(a\) and \(s\):
Fig. 12. Dynamic time warping. This is a diagrammatic representation using highly simplified data. In the upper left of the figure are shown two waveforms X and Y. These are digitized at the dots and plotted along the X and Y axes of the difference matrix \( d \) beginning (for both axes) at the lower left corner. The difference matrix shows the absolute differences between any point of one waveform and any point on the other. From this matrix, an ‘accumulated difference’ matrix \( D \) can be calculated. Any position in this matrix shows the lowest accumulated difference obtained by adding up the difference scores along any path to that position from the lower left corner that moved in a rightward or an upward step. As these accumulated differences are calculated, one also stores a matrix of ‘pointers’ showing for each position the direction from which the optimum path has come to that position. The ‘optimum path’ can then be traced back from the upper right corner of the matrix to the lower left corner. The optimum path shows the amount of warping necessary to fit one waveform to the other. If the path goes along the diagonal, no warping is necessary. If the path goes vertically, waveform \( Y \) must be compressed in time to become similar to \( X \); if the path goes horizontally, waveform \( Y \) must be expanded. The lower left section of the figure shows a ‘fan-graph’ linking the points on one waveform to the homologous points on the other, and a warp-average waveform that combines the \( X \) and \( Y \) waveforms on the basis of the warp path.

\[
d_{j,k} = |a(X_j) - a(Y_k)| + w|s(X_j) - s(Y_k)|
\]

where \( w \) is a weighting variable that can adjust the relative contributions of the amplitude and slope to the alignment.

We then need to find the alignment that minimizes the sum of this dissimilarity measure along the waveforms. If we plot \( X \) horizontally with time increasing from left to right and plot \( Y \) vertically with time increasing from bottom to top, possible alignments can be represented as paths extending from point 1,1 in the lower left corner to point \( J,K \) in the upper right corner. The task is to find the path over which the summed dissimilarity measure is minimum.

An individual step in a path can be vertically upwards (from \( j,k \) to \( j,k+1 \)), or horizontally rightwards.
(from \(j,k\) to \(j+1,k\)). Let us define the minimum summed dissimilarity measure from 1,1 to \(j,k\) to be the sum of the dissimilarity measurement at point \(j,k\) and the lower of the summed dissimilarity measurements below or on the left:

\[
D_{j,k} = d_{j,k} + \text{MIN}[D_{j,k-1}, D_{j-1,k}] \quad (j,k > 1)
\]

where the function MIN selects the minimum of its two arguments.

By applying these relations recursively from point 1,1 to point \(J,K\), the total dissimilarity along the optimum alignment path, \(D_{J,K}\), can be found. The optimum path can be determined by constructing a \(J \times K\) matrix whose \(j,k\)th element indicates which of the two possible points immediately preceded \(j,k\) along the optimum path passing through \(j,k\). The optimum path is revealed by tracing back from \(J,K\) along the set of ‘pointers’ defined by this matrix.

The optimum path through a summed dissimilarity matrix of dimensions \(N \times N\) consists of \(2N\) connected points. This path can be used in three ways. First, we can calculate the warp-average of the two waveforms by averaging the amplitudes of each waveform at the temporal locations indicated by the points on the optimum path. This gives a warp-average with twice as many time points as either original waveform. This waveform can be collapsed back to the original number of points, by sequentially averaging pairs of values in the waveform. Figure 13 shows the process of combining two ERP waveforms by means of dynamic time warping.

Second, the technique can be used to measure the difference between waveforms. The distance of the path from the diagonal measures the latency differences. The minimum summed dissimilarity measurement \(D_{J,K}\) measures the difference between the waveforms once they have been optimally compensated for latency differences.

Third, warping techniques can be used to compare waveforms to a normal template. The normal template can be constructed by warp-averaging a set of normal waveforms. The distance the optimum path moves away from the diagonal can measure the amount of time compression or dilation needed to fit the individual waveform to the normal template, i.e. how temporally abnormal the individual waveform is.

Unfortunately, dynamic time warping may make mistakes. It assumes that the signals are not obscured by noise and will warp both signal and noise together. Figure 14 shows the results of latency compensation using either Woody filtering or warp averaging. The warp-averaging clearly indicates the P2-N2 portion of the waveform more clearly than either simple averaging or Woody filtering. However, it is difficult to determine whether this represents jittered waveforms in the signal or simply random background noise. Earlier waveforms in the warp-average appear to represent noise since they occur at a latency near 0 ms. It is possible that using data from multiple electrode locations in the dissimilarity equations will improve the signal-to-noise ratios and allow warping across single-trials in a single subject. In the meantime, warping is probably more applicable to combining already-averaged data from different subjects.

![Fig. 14. Latency compensation techniques. This figure compares the results of both the Woody and the warping techniques for combining single trials to simple averaging. Each technique was applied to the single-trial responses shown in Fig. 9. The Woody approach increases the amplitude of the P3 wave (downward arrow). The warping technique accentuates the waveforms in the region of the P2 wave (downward arrow). However, it may also accentuate waves that are not part of the response but part of the background noise (upward arrow).](image-url)
Artifacts

The process of averaging proceeds most smoothly and most predictably when the noise is similar from one trial to another. However, human subjects have a definite need to swallow, blink and move intermittently. During these activities, the background noise in the scalp recordings is increased by potentials generated in the muscles, eyes and electrodes. The residual noise level of the average response is increased in proportion to the number of trials contaminated by such 'artifactual' potentials, and in proportion to the amplitudes of these potentials. These artifacts may be attenuated by increased averaging. However, some artifacts may become more or less time-locked to the stimulus. The cerebral ERP may then be distorted by an overlapping non-cerebral ERP. Such artifacts cannot be removed by increased averaging and either the contaminated trials must be rejected prior to averaging or the average waveform compensated for the effects of the artifacts. Many different artifacts can contaminate scalp-recordings of brain electrical activity (Barlow, 1986; Kenemans, Molenar and Verbaten, 1991). These are basically of two kinds: those resulting from the electrical noise in the subject's surroundings, and those deriving from the subject in the form of non-cerebral physiologic potentials.

Electrical contaminants of the ERP recording can derive from many possible sources (Lindsey and Wicke, 1974, pp. 64–76). Simple electrostatic potentials induced in a subject by such things as friction with clothing can change with movement and cause large artifacts in the scalp-recorded activity. Potentials may also be induced in the subject or the recording electrodes by the electromagnetic fields surrounding power lines, electrical transformers and electrical motors. Such artifacts can be reduced by moving the subject as far as possible from the source of the artifact, adequately grounding the subject, and/or by shielding the recording area with a material of high electrical conductivity and magnetic permeability. Once the pick-up of electrical noise has been minimized by the preceding techniques, its effect on the average ERP recording can be further reduced by several techniques. Notch-filtering can be used to remove line noise from the recording, provided such filtering does not distort the ERP. If distortion of the ERP might result from this filtering, the stimuli can be presented at intervals equal to an odd number of half-periods of the line noise, so that with averaging the noise will continually cancel itself out.

The generators of the sensory stimuli can cause electrical artifacts at the same time as the sensory stimuli being presented to the subject. Such artifacts will occur repeatedly and consistently with each stimulus and cannot be removed by averaging. These potentials can be decreased by shielding the stimulator or by moving the stimulus away from the subject: visual stimuli can be transmitted to the subject through fibre optics, and auditory stimuli through acoustic tubes. Large electrical artifacts occur when electrical currents are directly injected into the subject as stimuli for the somatosensory evoked potentials. Artifacts from this source can be decreased by minimizing the current necessary for stimulation (for example, by placing the electrodes as close as possible to the nerve being stimulated) and by using a large low-impedance ground electrode between the stimulating and recording electrodes.

The human eyes provide major sources of non-cerebral physiologic activity that can contaminate human ERP recording (Lins, Picton, Berg et al., 1993a). There is a standing potential of several millivolts between the cornea and the retina of the normal human eye, with the cornea being positive. Eyeblinks cause a positive potential in the anterior scalp regions by connecting those areas to the positive potential at the cornea (Matsuo, Peters and Reilly, 1975). Eye movements contribute a positive potential to those areas of the scalp towards which the eyes are moved (Hillyard and Galambos, 1970).

The muscles of the scalp, neck and face may show slow reflex responses to the stimuli being presented to the subject. Such 'microreflexes' (Bickford, 1972) are particularly evident when intense stimuli are used and when the muscles are under some degree of resting tension. The reflexes tend to occur mainly in the 8–80 ms region after a stimulus, and the recorded potentials in this latency range are often extremely difficulty to interpret. The cerebral ERPs at this latency can be
shown to have different scalp distributions from the muscle reflexes and to continue to be present with the muscle relaxation of moderate to deep sleep. It is impossible, however, to determine at these latencies whether small changes in the recorded waveform are due to actual changes in the cerebral ERP or to the superposition of muscle artifact.

Voluntary movement of the muscles of the face and tongue can also cause large electrical fields that will be picked up from scalp electrodes. These pose particular problems for the study of speech-related potentials (Szirtes and Vaughan, 1977; Brooker and Donald, 1980). Such artifacts should be closely monitored during the experiment with facial and submental electrodes, and contaminated trials must be eliminated from averaging.

Changes in the skin-potentials generated in the scalp beneath the recording electrodes can markedly distort the measurement of cerebral slow potentials (Picton and Hillyard, 1972). The most efficient way of preventing such problems is to scratch the skin under the recording electrodes so that inter-electrode impedance measurements are less than 1 kΩ in the 0–50 Hz frequency range.

Several techniques are available to prevent or attenuate the effects of artifactual potentials (Picton, Linden, Hamel et al., 1983). Provided there is no locking of the potentials to the stimulus, the simplest approach is to average over a larger number of responses. However, this may entail a fair amount of time. If the noise levels are twice as large as usual, the averaging would have to continue over four times as many trials in order to obtain the usual signal-to-noise ratio.

Other techniques can decrease the effect of artifact-contaminated trials on the average response. Since prevention is always better than cure, the best approach is to decrease the number of artifact-contaminated trials by carefully instructing the subject to relax and to blink or move as little as possible during the recording. For those trials that are nevertheless contaminated, there are three therapeutic approaches: 'surgical', 'medical' and 'rehabilitative'.

The 'surgical' approach is to cut out those trials that have obvious artifacts. These trials can be recognized by measuring the amplitude or some other parameter of the signal on each trial. If the amplitude increases above a set value (often the limits of the A/D converter), the trial is rejected from the averaging process. When the artifactual contamination is smaller than the EEG noise, such rejection protocols can be based on separate recordings wherein the artifacts are large. For example, although blink artifacts may not be very large in a recording from the vertex, the blink-rejection protocol can be based on the larger potentials recorded simultaneously from electrodes near the eye. Unfortunately, sometimes the surgery kills the patient by leaving too few trials for adequate averaging. If too many trials are rejected and if the artifactual potentials are not time-locked to the stimulus, it may be more efficient not to reject the high-noise trials but just to continue the averaging over many more trials. This may perhaps be supplemented by procedures to attenuate the effects of the high-noise trials.

There are several 'medical' procedures for decreasing the effect of high levels of random noise on the averaging process. One approach is to use 'weighted averaging' (Hoke et al., 1984; Elberling and Wahlgreen, 1985). Prior to averaging the individual trials are multiplied by a factor that is inversely proportional to the amplitudes recorded on that trial. This can be accomplished by the computer or by an automatic-gain-control amplifier. The amplitude of the average response is not calibrated, but it can be calculated if the factors used on the individual trials are known. Another approach is to allow the A/D converter to saturate at levels just outside the expected limits of the noise on low-noise trials. This process of 'clipping' is helpful if there are not too many artifact-contaminated trials. These medical approaches do not work if the artifactual potentials are time-locked to the ERP.

A 'rehabilitative' approach to artifact-contaminated trials is to allow the artifacts but to compensate for their effect on the recording (Barlow, 1986). This can only be done if there is a recording of the artifact that is relatively independent of the recorded signal. For example, eliminating the artifact from the EKG in scalp recordings can be done by monitoring the EKG from electrodes on the thorax. By triggering on the R-wave of this recording one can average EKG artifact
(pre- and post-R-wave) at each scalp electrode. This averaged EKG artifact can then be subtracted from the single-trial EEG recordings prior to any averaging of the ERP.

As another example, the electro-oculogram (EOG) can be measured from electrodes close to the eye and the recordings from other locations compensated for the effects of eye movements by subtracting from them a scaled version of the EOG (Elbert, Lutzenberger, Rockstroh et al., 1985; Brunia, Möcks, van den Berg-Lenssen et al., 1989). One difficulty in calculating an appropriate compensation factors is that blinks and eye movements propagate differently across the scalp. The potential associated with a blink falls off more rapidly away from the eye than does the potential associated with a saccadic eye movement (Hillyard and Galambos, 1970; Corby and Kopell, 1972; Lins et al., 1993a). Separate compensation factors must therefore be calculated for blinks and saccades. These factors are based on the ratios of the potentials recorded in peri-ocular electrodes to those simultaneously recorded at the different scalp electrodes. The major problem with this approach is that it is usually not possible to record the artifactual potentials independently of the EEG signals. Subtracting a scaled version of the artifact therefore always subtracts as well some portion of the EEG. It is particularly difficult to remove the effects of ocular artifacts from the EEG recorded from the frontal regions of the scalp. Source analysis can overcome this difficulty and we shall return to this problem later in the chapter.

Filtering

Filtering is another way to improve the signal-to-noise ratio of the recording. An optimal or 'Wiener' filter attenuates the background noise in inverse proportion to the signal-to-noise ratio at any particular frequency (de Weerd, 1981a). Since an ERP waveform usually contains a complex mixture of frequencies, such optimal filtering can significantly distort the waveform. The filtering of ERPs therefore usually just passes the frequencies present in the ERP and eliminates the other frequencies. This combines high-pass filtering (which passes frequencies higher than a cut-off setting and attenuates lower frequencies) and low-pass filtering into a band-pass filter.

Filtering can involve either analog or digital procedures. Analog filtering is usually controlled by adjusting circuit elements in the amplifier. The main purpose of analog filtering is to condition the signal for A-D conversion by removing slow frequencies that might cause the amplified signal to exceed the amplitude range (‘block’) the A-D converter and fast frequencies that might cause aliasing if they are faster than the Nyquist frequency. Analog filters are characterized by a cut-off frequency and a cut-off slope. The cut-off frequency is usually the frequency at which the filtered power is half (–3 dB) the unfiltered power (or the filtered amplitude is 0.71 times the unfiltered amplitude). This cut-off frequency \( f_c \) can also be expressed as a time constant which equals \( 1/(2\pi f_c) \). Thus, a high-pass filter with a cut-off (–3 dB) of 0.1 Hz has a time constant of 1.6 s. Time constants are most commonly used to describe high-pass filters. These filters record a step-change in voltage away from zero as exponentially returning to zero. The time constant equals the time taken for the voltage to fall back to 37% of the initial step value. Unfortunately, some instruments describe the cut-off frequency as the frequency at which the filtered amplitude is one-half (rather than 71%) the unfiltered amplitude. The cut-off slope of a filter is usually expressed in dB/octave.

The most commonly used filter is the Butterworth filter which is constructed with a resistor, a capacitor and an operational amplifier. This has a slope of 6 dB/octave if only one resistor and capacitor are used (single-pole design). Higher slopes can be obtained by linking together the resistor-capacitor circuits to form double or higher pole filters. However, the slope remains finite and there is never complete attenuation of the frequencies outside the passband. The Butterworth filter has a flat amplitude response within the passband but alters the phase of the frequencies being attenuated. The amount of phase shift varies with the frequency and can significantly distort an ERP waveform if the filter attenuates frequencies that contribute significantly to the response. If the frequency cut-off of a four-pole Butterworth filter is close to the dominant frequency contributing to a peak in the waveform, the
generally recommended that analog filtering before A-D conversion pass as broad a range of frequencies as possible. Any further filtering should be performed digitally. Analog filters can cause significant distortion of the ERP waveform (Duncan-Johnson and Donchin, 1979). Now that digital filtering is readily and easily available, there is really no need to use analog filtering for signal-to-noise enhancement (Picton et al., 1984; Elbert, 1991; Wolf, 1991).

Digital filtering can be applied either before or after averaging. Filtering each recording is computationally demanding and only necessary if information from the single-trial is required. An example would be using the single-trial recordings for latency-compensated averaging. If one is not using the single-trial data, it is far more efficient to apply the digital filtering after averaging. Nevertheless, rapidly acting and easily programmable digital signal processing boards are now making on-line digital filtering much more available.

Fig. 16. High-pass filtering. This figure shows the effect of a Butterworth filter designed to pass frequencies greater than 1 Hz. The figure is set up similarly to the previous figure. In the upper right, the effects of filtering twice include a significant attenuation of the amplitude of the P300 wave and a decrease in its latency (downward arrow). Furthermore there is an artificial large negative wave with a peak latency of about 500 ms in the filtered waveform (upward arrow). This is the result of phase changes in the energy contributing to the P300 and the small aftergoing negative wave that follows the P300. As shown in the lower right section of the figure, zero-phase filtering causes much less distortion of the waveform.
Digital filtering in the frequency domain can be performed after computing the frequency spectrum of the recorded waveform using the Fourier transform. The filter consists of a set of weights for each of the different frequencies present in the recording. For example, a simple band-pass filter will have a weighting of 1 for all frequencies within the band and a weighting of 0 for all other frequencies. Each point in the frequency spectrum of the recorded waveform is multiplied by the appropriate weighting function. The filtered waveform is then reconstructed using the inverse Fourier transform. The Fourier transform assumes that the sampled waveform repeats itself ad infinitum. 'Windowing' allows one to fit the data to this assumption (Harris, 1978; Wolf, 1991): each point in the waveform is multiplied by the corresponding point of a windowing function that begins and ends at zero. Windowing will distort the waveform, particularly at its beginning and end. We have found that the 'extended cosine bell' provides a reasonable approach to filtering ERP waveforms since it only affects the initial and final portions of the waveform. One can adjust the recording sweep so that the most important region of the waveform occur at the middle of the sweep where the distortion is least.

Digital filtering in the time domain can be much more efficient than in the frequency domain. In the time domain, the number of calculations can be truncated without significant loss of information. A finite impulse response (FIR) filter consists of a set of weighting coefficients \( W(i) \) for the time points adjacent to each time point in the recorded waveform \( S(t) \). The value at a particular point in time in the filtered waveform \( F(t) \) equals the sum of the weighted adjacent time points from \( B \) points before to \( A \) points after the point of calculation:

\[
F(t) = \sum_{i=-B}^{A} W(i) S(t+i)
\]

These filters can be designed so as not to cause any phase distortion of the waveform. The requirements for phase-invariance are that \( A = B \) and that \( W(i) \) is symmetrical around zero. If a particular digital filter is asymmetrical, it can be converted to a zero-phase filter by applying it in both forward and backward directions. This cannot be performed directly on-line since it must act on the basis of 'future' data; it can, however, be performed on stored data, even when these are only temporarily retained in a buffer store.

Arbitrary weighting functions can be used for filtering. A common weighting function is a 'boxcar' filter (Ruchkin, 1988). The weighting function of this filter contains an odd number \( (N) \) of points between \( \pm (N-1)/2 \) with the weighting being constant \( (1/N) \) for these points and zero elsewhere. Application of this filter causes low-pass filtering of the waveform with the \(-3 \text{ dB} \) frequency cut-off determined by the number of points in the boxcar \( (N) \) and the time per address \( (t) \): \( 0.44/(Nt) \) when \( N \) is greater than 7. However, the amplitude function of this filter is not simple (Fig. 17).

A better approach to determining the time domain weighting function is to apply the inverse Fourier transform to a desired filter function (Wolf, 1991; Cooke and Miller, 1992; Press, Teukolsky, Vetterling et al., 1992). This will provide a set of weights that are symmetrical about the point to be calculated and that extend \( N/2 - 1 \) points on either side (where \( N \) is the number of points in the recorded waveform). In order to increase the efficiency of the filter, the number of time points can be truncated and the truncated weighting function tapered using a windowing function. Figure 18 shows the application of such an 'optimal FIR filter' to ERP data. These filters can significantly improve the signal-to-noise ratio of a recording, allowing some ERP measurements to be made on single-trial waveforms (Farwell, Martinerie, Bashore et al., 1993).

Since the frequency content of an ERP waveform can vary with latency, it may be appropriate to filter the waveform differently at different latencies. Such 'time-varying' filters have been used to record the early auditory evoked potentials (de Weerd, 1981b). The periods over which the different filter characteristics operate and the actual filter characteristics for each of these time periods may be determined a priori or may be determined on the basis of an initial averaging of the recorded data. An interesting, although arbitrary, time-varying filter is a boxcar filter in which the width of the boxcar increases with the latency of the
signal. Since the frequency content of an ERP waveform often decreases with increasing latency, this simplistic time-varying filter may be relatively efficient in preserving the signal at the expense of noise. This ‘expanding boxcar’ filter is illustrated in Fig. 17.

If the ERP does not change or changes only slowly from trial to trial, it is possible to use two-dimensional filters to evaluate the waveforms (Sgro, Emerson and Pedley, 1985). Sequential single-trial waveforms or small sub-averages of these responses are stacked in a two-dimensional array. One dimension is determined by the sweep time and the other dimension is determined by the event repetition. The data can then be filtered in both dimensions. Noise that varies from trial to trial will be removed by filtering in the event dimension. Filtering in the sweep dimension will be similar to all of the previously described techniques. The selection of the filter parameters along the event dimension will determine how rapidly the recordings will respond to changes in the ERPs (Turetsky, Raz and Fein, 1989).

Özdamar and Delgado (1993) have proposed a filtering technique of ‘spectral enhancement averaging’. This technique is based on the fact that much of the electrophysiological noise in recording ERPs is quasistationary and its characteristics do not change appreciably within the period of stimulation. Recordings are therefore made both before and after the event. The recording in the pre-event period represents noise. The frequency spectrum of this noise can then be com-
pared to the frequency spectrum of the post-event response and an optimal filter constructed to remove noise from the post-event recording. This procedure works well if the noise spectrum is significantly different from the response spectrum.

Measurement of ERP waveforms

Problems of measurement

The scientific evaluation of ERP recordings requires that they be measured. What to measure is then the crucial question. The most common approach evaluates the amplitudes and latencies at identified peaks and troughs in the ERP waveform. Unfortunately the identification of these peaks and troughs is often not simple. The measuring algorithm must follow unambiguous rules. For example, in a particular experiment, the P300 wave may be identified as the most positive point in the waveform between 250 and 500 ms after the stimulus. The problem of multiple peaks within this latency range can be handled by using rules to choose among (or combine) the identified peaks or by submitting the data to sufficient low-pass filtering that only one peak remains within the latency range.

Peak-picking cannot fully evaluate the shape of an ERP waveform. If one has some knowledge of what the waveform is supposed to look like prior to the measurement, one can cross-correlate the recorded waveform with a template. The point at which the correlation is the highest gives the latency difference between the recorded response and the template and the correlation value at that point in time measures the similarity of the response to the template.

Another approach to the evaluation of ERPs involves discriminant analysis. If the recordings are known to belong to one of two separate classes (for example, ‘ERP-present’ versus ‘ERP-absent’, or one type of stimulus versus another), they can be identified as more similar to or the other class by using a simple discriminant function derived from the analysis of a training series of ERPs of known classification (Squires and Donchin, 1976; Glaser and Ruchkin, 1976, pp. 220–230; Donchin and Heffley, 1978). Discriminant functions can be sufficiently powerful to allow the correct discrimination of single-trial ERPs.

Fabiani, Gratton, Karis et al. (1987) have assessed the reliability of various means to identify and measure the P300 wave. They found that the signal-to-noise ratio was the most important determinant of reliability, and that filtering was the most important way to improve the signal-to-noise ratio of the recording. Reliability was further enhanced by combining data across different latencies (by means of a waveform template
or discriminant function) or across different recording locations (by means of a spatial vector filter that we review later in the chapter).

The crucial question remains, however, the identification of the ‘components’ of the waveform. Picking peaks is a simplistic and often misleading view of the components of an ERP. Information is processed in the brain in many different regions. As processing occurs, fields are generated that can be recorded from the scalp. Since the fields from different regions overlap, many different processes occurring in many different regions of the brain can contribute to any peak of activity recorded at the scalp. What is needed are techniques to determine the true structure of the response, with each component representing a particular type of processing in a particular region of the brain. The following sections will discuss some published techniques for measuring ERP waveforms. After this, we return to the problem of determining the ERP components.

**Frequency-based approaches to ERPs and background activity**

ERP waveforms can be looked at in terms of frequency rather than time. Frequency-based approaches have been used extensively in recording sensory evoked potentials (Regan, 1989). Of particular importance are the steady state evoked potentials. If stimuli are presented at rates that are sufficiently rapid that the response to one stimulus overlaps with response to preceding stimuli, the response becomes periodic at the rate of stimulation. Frequency-based approaches to steady state responses can be very efficient and objective when evaluating stimulus-determined ERPs (Picton, Vajsar, Rodriguez et al., 1987; Victor and Mast, 1991). However, they have not been used extensively in evaluating endogenous processes.

The background activity of the EEG is usually considered as ‘noise’ when evaluating ERPs. This electrical activity is generated in areas of the brain that are not acting in any precisely time-locked way to the stimulus. Some of these activities may be irrelevant to the processing of the stimulus. However, it is likely that other activities may indicate processing that is relevant to the brain’s evaluation to the stimulus. For example, there may be some attenuation of background rhythmic activity associated with processing. If this rhythmic activity is not precisely time- and phase-locked to the stimulus, there will be no change in the average ERP waveform. Studying changes in background rhythmic activities by means of frequency analysis (Challis and Kitney, 1991a,b) may help to map out the patterns of cerebral processing that occur without precise time-locking.

Furtscheller, Steffan and Maresch (1988) have proposed techniques to measure the topography of ‘event-related desynchronization’. Electrical activity is recorded from different scalp locations in association with some time trigger much like the ERPs. The recorded waveform over brief intervals of time during the sweep is then converted to frequencies using a Fourier transform and the power is calculated at different frequency bands. The power values are then averaged across sweeps. This allows one to determine the levels of the background activity in different frequency bands independently of whether they change in phase from sweep to sweep. A final average then presents a waveform that shows the variation in power in a certain frequency band over time during the recording sweep. The general finding is that activation of a cortical region is associated with an attenuation of the background rhythmic activities in that region. This is attributed to the neurons in the area firing independently of one another rather than synchronously oscillating together.

Frequency analysis is only one way of characterizing the background activity. There are several other ways of describing the characteristics of the background activity. Recently, there have been some initial studies of the chaotic dimensionality of background activity (Pritchard and Duke, 1992; Skinner, Molnar, Vybiral et al., 1992).

**Maps of the scalp distribution of an ERP**

Scalp-recorded potentials have both temporal and spatial dimensions. They are sampled in time at the rate of the A-D converter and in space at the locations of the scalp electrodes. The usual initial presentation
of the data is by means of multiple waveforms showing voltage as a function of time at each of the recording electrodes. These waveforms do not easily convey the scalp distribution of the recorded potentials. More appropriate to the spatial domain are maps that plot the voltage levels over the different regions of the scalp (Duffy, Burchfiel and Lombroso, 1979; Duffy, 1986; Pfurtscheller, 1991). These maps can be very helpful provided one is aware of the conventions by which they are plotted.

Scalp distribution maps are plotted on a two-dimensional projection of the three-dimensional scalp surface. Various kinds of projection are possible. For viewing the scalp from above, we have found the best projection to be an azimuthal equidistant projection. In this projection, the scale is linear along all of the lines radiating from the ‘pole’ at the center of the map (Cz). The projection can be extended down below the ‘equator’ at the Fpz-T8-Oz-T7-Fpz circumference to show data from the lower hemisphere. The maps in this chapter are all plotted using this type of projection and extend down to 20° below the equator.

Maps are made continuous by interpolating values in the regions between the points at which accurate measurements are obtained. A simple interpolation uses the ‘nearest neighbor’ algorithm (Duffy et al., 1979; Buchbaum, Rigal, Coppola et al., 1982). The potential at any one point \( V_x \) is considered a function of the potentials recorded at the nearest measurement sites:

\[
V_x = \sum_{i=1}^{N} \left( d_{i}^{-m} V_i \right) / \sum_{i=1}^{N} d_{i}^{-m}
\]

where \( V_i \) is the potential at the neighboring electrode and \( d_i \) is the distance to that electrode. The algorithm will vary with the number \( N \) of the nearest neighbors that are being used and with the power \( m \) of the distance rule whereby each neighbor contributes to the interpolated measurement. The most common algorithms use four nearest neighbors and a linear \( m = 1 \) distance rule. These algorithms sometimes cause significant aberrations in the maps. Lines may show up at the edges between different neighborhoods (‘cliffs’), and the region between adjacent electrodes in an area of maximum voltage may be inappropriately low (‘cleavage’).

Other interpolation algorithms can provide maps that do not show these discontinuities. Spline interpolations result in smoothly changing contours (Pfurtscheller, 1991). Three-dimensional interpolations are more accurate than simple two-dimensional (planar) interpolations (Soufflet, Toussaint, Luthringer et al., 1991). Given the spherical shape of the surface being mapped, spherical splines (Perrin, Pernier, Bertrand et al., 1987, 1989) are probably the most appropriate although other spline equations are possible. Figures 19 and 20 show spline-interpolated maps of the scalp-recorded waveforms plotted in Figures 4 and 5. These and the other maps in this chapter were obtained using the algorithms of Perrin et al.

If the scalp distributions of an ERP waveform recorded under different experimental conditions (or at

![Fig. 19. Scalp distribution maps for the auditory evoked potential. These maps present the scalp distributions at selected latencies during the waveforms plotted in Fig. 4. The maps are based upon the average reference recordings and are plotted using an azimuthal equidistance projection extending down below the Fpz-T7-Oz-T8 equator to about the level of the mastoid electrodes. The thick line in the maps represents zero voltage. The dashed lines represent contours for negative voltages and the thin lines represent contours for positive voltages, both plotted at intervals of 1 μV. At 105 ms there is negative wave (N1b) recorded maximally at the vertex whereas a later negative (N1c) occurs maximally in the left temporal region. The P2 wave is maximally recorded from the vertex. The sustained potential (SP) is maximally recorded from fronto-central regions with a scalp distribution somewhat more anterior than that of the N1b wave.](image)
amplitude differences between experimental conditions. A simple strategy for normalizing the data across different conditions is to find the maximum and minimum values in each condition, subtract the minimum from each data point and divide the result by the difference between maximum and minimum (McCarth and Wood, 1985).

Maps of scalp potentials should be evaluated with caution (Picton, 1988). First, most of the data in maps are interpolated and may not accurately reflect the actual surface potentials. Statistical comparisons that evaluate all of the interpolated positions can therefore be very misleading. If one wishes to compare scalp distributions, one should use only the data recorded at actual electrode sites and these data should be appropriately normalized prior to comparison (McCarth and Wood, 1985). Second, one must be very careful to determine the latencies of the components of the waveform in the different experimental conditions and to compare the maps at the appropriate latencies. If one does not compensate for changes in the latency of a wave and arbitrarily compares maps at the same latency, one may mistakenly infer from the different maps that the intracerebral generators of the wave have changed. Third, maps may be misleading as well as beautiful. Since colors are not perceived along a linear dimension, color differences can highlight changes in potential from one level to another that may not be significant. Fourth, maps of potentials are not maps of sources. The maxima and minima of a scalp map do not necessarily occur over the areas of cortex that are most active. Indeed, for tangentially oriented dipole generators (Fig. 21), the maxima and minima are on opposite sides of the location of the generator and at some distance therefrom.

Maps are best interpreted in terms of the underlying sources that generate the maps. As we discuss later in this chapter, the sources for scalp-recorded potentials can be considered in terms of equivalent dipoles. Activation of an area of cortex may generate a field with a current source on one side of the cortex and a current sink on the other. This creates a dipole field that can be recorded at the scalp. The location and orientation of the dipole field determine the distribution of potentials that it generates at the scalp (Fender, 1987).
Fig. 21. Scalp distribution of dipole fields. At the top of this figure are shown dipoles located in various regions of the brain. All dipoles are oriented within the coronal plane. The second line of the figure shows the distribution of the scalp potentials associated with these dipoles. The bottom line of the figure estimates the current source density (csd) at the surface of the scalp. Note the similarity between the middle two potential maps and the dissimilarity of the csd maps. Note also the absence of any clear csd map when the dipole is located at the center of the head (rightmost column).

Figure 21 shows the potential distributions (and current source densities) that are recorded at the scalp when dipole sources have different locations and different orientations within the brain. The figure illustrates the differences between deep and superficial dipoles and among dipoles that are oriented tangentially, radially, or obliquely.

There are several ways to describe the distribution of potentials across the scalp. One important measure is the 'global field power' (Lehmann and Skrandies, 1980; Lehmann, 1987). This combines all possible potential differences which can be measured between any two electrodes in the full electrode array:

\[
\sqrt{\frac{1}{2N} \sum_{i=1}^{N} \sum_{j=1}^{N} (u_i - u_j)^2}
\]

where \(N\) is the number of electrodes, and \(u_i\) represents the observed voltage at an electrode location referenced to the common reference. If the measurement is scaled down by the square root of the number of electrodes used, it becomes independent of the number of electrodes and represents the root-mean-square of the voltages measured at all electrodes (relative to an average reference). Peaks in the global field power over time represent peaks of activity in the generators of the field potentials recorded at the scalp. However, they do not necessarily each represent the activity of single generators since several different sources may be contributing to a global field power maximum. Evaluations of the dipole nature of the field at points of maximum global field power may therefore give an overly simplistic account of the possible generators.

Gratton, Coles and Donchin (1989) have proposed using a 'vector filter' to identify and measure an ERP component on the basis of its scalp distribution. A set of weights, one for each scalp location, is used to estimate the magnitude of the component at each time point. The P300 wave is usually recorded with maximal amplitude in the parietocentral regions and with lower amplitudes in the occipital and frontal regions. When evaluating the P300, one can set up the vector filter so that the parietocentral measurements are more highly weighted than the frontal or occipital locations. This differs from the traditional procedure of peak-picking in which a weight of one is associated with the selected scalp location (often the point where the amplitude is maximal) and a weight of zero given to the other scalp locations. The set of weights used in the vector filter can be based upon the average scalp distribution of the peak being measured or they can be selected a priori to satisfy some requirement of the measurement (such as discriminating between target and standard responses). The vector filter represents an abstract approach to source analysis. One can conceive a source within the brain that might generate scalp-recorded fields with the weightings of the vector filter. We return to this possibility in the upcoming section on source analysis.

In sum, maps help us to visualize the surface distribution of our measurements. They provide us with the measurements in space at one point in time just like an ERP waveform provides us with measurements in time at one point in space. A full understanding of the data requires evaluation in both the spatial and temporal dimensions.
Current source density

The potentials over the surface of the scalp show a spatially smeared representation of currents coming from the brain. The flow of current out of the skull diffuses through the more conductive subcutaneous tissue of the scalp. One can decrease the effect of this circumferential current flow by computing the second spatial derivative of the scalp field. This estimates the effective sources and sinks of radial current ('current source density'). This can be done by using an approximation to the Laplacian operator, with each electrode referred to the average of its nearest neighbors (Hjorth, 1975). There are several techniques available to derive the current source density from the potential distribution (Pascual, Gonzalez, Valdés et al., 1988; Gevins, 1989; Nunez, 1989). The second spatial derivative can also be calculated directly from spline-interpolated maps (Perrin, Pernier, Bertrand et al., 1989). This technique provides accurate maps of the current source density, although one must be careful when considering coherence measurements between electrode locations (Biggins, Fein, Raz et al., 1991) Figure 21 shows maps for both the scalp potential and its second-spatial derivative.

The estimates of the current source density can sometimes help to distinguish between scalp maps that result from a deep-seated dipole generator and scalp maps that result from a more superficial generator. For example, the widespread frontocentral scalp distribution of the sustained potential in Fig. 19 might suggest an origin in a deep-seated dipole generator. However, the current source density for these scalp recorded potentials (Fig. 22) show foci of activity in the temporal regions with clear dipole fields above and below the Sylvian fissures. This suggests that the scalp-recorded potentials are generated by bilateral tangential generators in the supratemporal plane. We return to these potentials when we discuss source analysis later in this chapter.

As well as estimating the current source density at the surface of the scalp, one can calculate the actual distribution of potentials at the surface of the brain beneath the skull (Gevins, Le, Brickett et al., 1991; Ford, Sidman and Ramsey, 1993). These techniques are important but one must not then conclude that the fields at the surface of the brain indicate the activity only in the subjacent cortex. Volume conduction from sources below the surface (in the cortical sulci and in subcortical nuclei and tracts) still occurs. The surface fields represent the overlapping activity of fields generated by multiple sources, both near the surface and far away.

Event-related covariance

Gevins and his colleagues (Gevins, 1989; Gevins, Cutillo, Bressler et al., 1989; Gevins and Cutillo, 1993) have looked at multi-electrode data from the point of view of the relations between the different recordings. The basic principle of this approach is that the time envelope of the macropotentials of two functionally related regions of the brain should show similar patterns of activity at delays that reflect the time when each region processes incoming informa-
tion. This similarity in waveform could be measured as a lagged covariance between individual ERP components recorded from each region. The procedure for measuring event-related covariances involves several steps. First, recordings are made from multiple electrode locations over the scalp. The Laplacian derivation for the resulting potential fields is calculated. This provides a reference-free estimate of the current entering and exiting the scalp at each electrode location.

Cross-covariance functions are computed between all pairwise combinations of non-peripheral recording sites. These covariance functions are computed for analysis windows centered on ERP peaks and for lag times up to one-half period of the highest frequency present in the filtered waveform. The significance of the cross-covariance estimate is determined by what might have been obtained if there were no ERP signal present in the waveform. This estimate is based upon randomly selecting the analysis windows in each single-trial recording before averaging and calculating the cross-covariances. The analyses provide a set of statistical relations between different areas of the scalp. These are plotted as arrows, with the direction of the arrows indicating the time lag of maximum covariance and the width of the arrows indicating the significance of the cross-covariance. The mapped arrows suggest patterns of relationships between different regions of the brain as it performs different tasks.

However, as Gevins notes, the results of these analyses must be viewed with some caution. The basic assumption that the recording at each electrode location represents activity in the directly underlying cortex is not necessarily true. Volume conduction in the brain means that potentials can be picked up at some distance from their generation. Laplacian derivations may attenuate the effects of deeper sources on the scalp potentials, but they cannot completely dissociate deep and superficial sources (Turetsky and Fein, 1991). Furthermore, they do not directly localize the activity from tangential sources: current source density maps from a tangential dipole generator show activity on either side of the source location rather than exactly above the source location. The maximum and minimum of the current source density is closer to the source location than the maximum and minimum of the electrical field, but neither the maximum nor the minimum is located directly over the source.

A second problem with the technique involves the interpretation of a relationship between the waveforms recorded at two different locations. These may be similar because one neuronal population is 'driving' the other. If so, the connections subserving this relationship (cortico-cortical or thalamocortical) are not clear. Furthermore, the waveforms recorded at two sites may derive from one rather than two cortical regions. Volume conduction to the different electrode locations would then explain the similarities in the waveforms. For radial currents, the covariance related to volume conduction will be maximal at zero-time lag. The Laplacian derivation may 'deblur' the smearing of the voltages across the scalp and decrease these zero-time covariances. However, the Laplacian will continue to show dipole fields when tangential currents are active. Recordings from one side of a tangential source will show similar patterns to recordings on the other side of the source with a time lag approximately equal to one half-period of the major frequency content of the recorded activity.

Recently, Gevins et al. (1991) have used a realistic head model to 'deblur the scalp EEG' and backproject an estimated activity profile onto the cortical surface. However, the deblurring can introduce artifactual sources on the cortical surface, particularly if there is spatial undersampling with respect to the real potential distribution on the cortex and at the boundaries of the electrode coverage. Furthermore, the potential topography on the cortical surface still presents a superposition of the activity of all brain sources (both at the cortical surface and in other cerebral locations), although less blurred than the potential distribution on the scalp.

A final caution involves the evaluation of the significance of the correlations between different areas. The technique as presently performed evaluates both the signal-to-noise amplitude ratio as well as the correlation between the signals recorded at different scalp locations. A better control would be signals that have the same amplitude and frequency content as the signals being evaluated but lack the relationships between the areas. It is also difficult to relate waveforms
over a duration that is close to the period of the dominant frequency in the waveform. Most correlation statistics use longer durations for comparison.

**Multiple measurements**

A final approach to interpreting ERPs involves multivariate analysis. Two major techniques are used. In one, quantitative EEG measurements and ERPs are recorded from two different groups of subjects (usually a normal group and a group with some well-defined disorder) and a discriminant function is determined that best separates the two groups. Data from other subjects can then be analyzed according to this discriminant function to determine the group to which they are more similar. This technique has been used to evaluate the evoked potentials and EEGs in children with dyslexia (Duffy, Denckla, Bartels et al., 1980). One difficulty with this technique is the generalization of the results to subjects who are recorded in different situations or who may not fit exactly into the groupings on which the discriminant functions are based.

Another technique involves clustering multiple ERP and quantitative EEG measurements into groups with similar characteristics (John, 1977; Prichep and John, 1986; John, Prichep and Easton, 1987; John, Prichep and Almas, 1992). The results of such an analysis provide a neurophysiological taxonomy. The subtypes of patients demonstrated by these 'neurometric' techniques may be related to different diagnostic categories, to different prognoses or to different responses to treatment. Discriminant functions may then help to classify patients into one or other subgroup. The idea of neurometrics is good. The electrical activity recorded from the brain contains a great deal more information than we can interpret using present techniques. This information probably contains rules for diagnosis and prognosis that may be discernible by cluster analysis.

However, it is sometimes difficult to determine the validity of the discriminant functions or clusters provided by these analyses. Multivariate procedures are very powerful and will distinguish groups of measurements on the basis of any of the variance in the data. Although some distinctions may therefore reflect valid groupings in terms of diagnosis and prognosis, others may be related to noise in the recordings. The diagnostic application of these procedures is only worthwhile if it is meaningful with respect to treatment or prognosis and if it is reliable in different recording situations. Some of the discriminations obtained by cluster analysis have been difficult to confirm in other laboratories (Yingling, Galin, Fein et al., 1986). Although others have been replicated in multiple studies (Prichep and John, 1986), the discriminations are often valid for groups of patients and not always accurate for single patients.

One problem with neurometric techniques is that they are far removed from the original data. Just as when analyzing the ERPs, one must pay even more careful attention to the EEG signals than when recording the spontaneous EEG, when evaluating the discriminant functions one must pay even more careful attention to recording EEGs and ERPs than when simply looking at the waveforms. Only ERPs that have been demonstrated to have a very high signal-to-noise ratio and that have been carefully monitored to make sure that there are no artifactual contaminants should be submitted to these analyses. When the data are noisy, one may wind up creating a taxonomy that has no basis in reality. Another source of 'noise' in the analyses derives from the fact that data recorded in one laboratory differ from data recorded in another laboratory. The differences may be subtle but, because the discriminant functions are based on many measurements, these differences may interfere with any meaningful application of a taxonomy derived in one laboratory to data obtained in another.

**Component analysis**

**Nature of components**

ERP data recorded from the scalp have five dimensions: three in space, one in time and one in voltage. Furthermore, these waveforms are usually recorded from different subjects and under different experimental conditions. The analysis of these data has as its goal some understanding of cerebral processing. We
wish to know how this processing might differ among individuals and among different states within an individual. This is no easy task.

A simple approach to the ERP is to measure the latencies and amplitudes of various peaks and troughs in the waveform. Such measurements can provide a clear characterization of the waveform and can be used to demonstrate significant differences among experimental conditions. However, the measurements may sometimes become ambiguous. ('Does this peak represent wave 2 or a delayed wave 1?'). Furthermore, the peaks may or may not represent some particular activity in the brain. Many different generators may be active at the same latency and the peak may result from the superposition of their different fields. In addition, a change in the latency and/or the amplitude of a peak does not necessarily indicate a similar change in some intracerebral process. Such changes could be caused by the addition of some other activity, the fields of which add to or subtract from those causing the original peak.

Much effort has therefore been devoted to determining the 'components' of ERP waveforms. Donchin, Ritter and McCullam (1978) proposed that a component was a 'source of controlled, observable variability'. This definition entails that the ERP represents a linear superposition of a set of basic waveforms or components. Each of these components can be independently affected by the experimental manipulations. This model fits very easily with the procedures of principal component analysis or PCA (Glaser and Ruchkin, 1976, pp. 233–290; Donchin and Heffley, 1978; Hunt, 1985; Dunteman, 1989; Guthrie, 1991; Möcks and Verleger, 1991). The PCA technique was originally developed to evaluate large multivariate data sets coming from psychometric testing. The idea was that the results were determined by a small number of causative factors, each contributing with a different weight to each of the results. The goal of PCA was to 'explain' the large set of data by a small number of components, each representing something such as a personality factor. The major difference between these data and ERP waveforms is that the ERPs show temporal and spatial relations that are not present in the psychometric data. Nevertheless, the technique can be applied to ERP waveforms with appropriate hope and caution.

Principal components analysis

The basic rationale of PCA is that when a group of variables vary together, there exists some underlying 'component' causing the observed correlation or covariance. The goal of PCA is to explain a substantial part of the variance in a set of variables on the basis of a few underlying dimensions or components. The components are uncorrelated linear combinations of the original variables. For example, a set of measurements of $p$ variables, described as a vector of $p$ dimensions $(x_1, x_2, \ldots, x_p)$, can be linearly transformed into a one-dimensional component $y_1$:

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p$$

using a set of weights $a_{11}, a_{12}, \ldots, a_{1p}$. If there are $n$ observations of the $p$ variables, we can set up a $p \times p$ matrix for the correlation matrix and calculate the $a$ weights to maximize the variance of $y_1$ (denoted by $\lambda_1$) over the $n$ observations, given the constraint that the sum of the squared weights equals 1:

$$\sum_{i=1}^{p} a_{1i}^2 = 1$$

This will also maximize the sum of the squared correlations of this principal component $y_1$ with the original variables first. A second principal component $y_2$ is calculated to maximize its variance over the $n$ observations, to maintain the sum of its squared weights at 1, and to be uncorrelated with the first component. These procedures continue until there are $p$ principal components ordered so that the first accounts for most of the variance present in the original measurements and successive components account for less and less of the variance.

Geometrically, the first principal component is the best fit line to the $n$ measurements in the $p$ dimensional variable space (Figs. 23 and 24). It minimizes the sum of the squared distances of the $n$ measurements from the line, distance being defined in a direc-
Fig. 23. Geometrical properties of PCA. The top of the figure shows ERPs to target tones presented in an oddball paradigm. The waveforms are all from one subject and show ERPs recorded from 16 electrode positions. The lower left quadrant shows a scatterplot of the potentials at A (110 ms) and B (130 ms). The cigar-shaped cloud of dots indicates that the variables at the two points vary together (cova) strongly. The first principal component (C1) is oriented along the larger axis of the cloud and by itself contains 98% of the variance of the two original axes. The second principal component (C2) is oriented 90° (orthogonally) from the first and contains the rest of the variance (only 2%). Component 1, therefore, reflects an underlying process that is producing the covariance between A and B (the N1 wave). The lower right quadrant shows the scatterplot of the potentials at A and C (420 ms). The shape of the cloud of dots is more complex and extends significantly in two directions. Component 1 is oriented along the larger axis of the cloud and accounts for 85% of the variance. Component 2 still accounts for 15% of the variance indicating that 2 different processes underlies these two sets of variables: the P3 wave (C1) and the N1 wave (C2). In this last case, there was not much advantage in running a PCA because the new axes (C1 and C2) are very similar to the original axis (A and C).

A point in a set of waveforms varies together with the other time points when we vary the conditions. These indices of association are organized into a square matrix with the number of rows and columns equal to the number of time points. Calculating the indices by simple multiplication yields a cross-products matrix. Subtracting the mean waveform from each individual waveform before multiplication will give a covariance matrix. If, in addition, we standardize each time point prior to the calculation of the indexes so that all time points have the same variance, we will have a correlation matrix. It is important to understand how these manipulations affect the results of the analysis. PCA uses the variance between the time points across experimental manipulations to extract the components. A cross-products matrix contains the total variance of the data. A covariance matrix contains the variance re-
The main statistics resulting from a PCA are the weight vectors or ‘latent vectors’ \( a_1, a_2, \ldots, a_p \) associated with each component, and its variance \( \lambda \) (Fig. 24). The elements in the latent vector indicate the relative amount of variance in the variables explained by the principal component. It is often easier to interpret a principal component when the weights of the latent vector are transformed to correlations between the variables with the principal component. This can be done by multiplying each weight by the square root of the component variance \( \sqrt{\lambda} \). These correlations of the variables with the principal components are called ‘loadings’. One way to interpret a component is to evaluate the pattern of its loadings.

Another useful outcome of a PCA are the principal component ‘scores’ (Fig. 24). The scores estimate how large the components would be in the different experimental conditions if they had been measured directly. They are therefore very helpful in interpreting how a component varies with the experimental manipulations. We can compute scores by using the latent vectors. Thus, the score on component 1 for a particular ERP in a particular condition is

\[
\sum_{i=1}^{p} a_i x_i
\]

where \( x_1, x_2, \ldots, x_p \) are the actual ERP measurements for that condition.

**Decomposition of recorded data**

One of the most interesting properties of PCA for the analysis of ERPs is its ability to decompose the variables into additive contributions from the components. PCA may thus ‘dissect’ a set of scalp-recorded waveforms into simpler components that can be easier to interpret. Furthermore, one might be able to use the recomposed waveforms for one or more components in a source analysis to localize sources in the brain.
The matrix of principal component scores \((Y)\) can be expressed as

\[ Y = A'X \]

where \(A'\) is the matrix of latent vectors arrayed in rows and \(X\) is the matrix of original variables arranged in columns. For ERPs, \(X\) is the matrix of recorded waveforms of all subjects, conditions and electrode locations with each column representing one digitized ERP waveform. \(A'\) provides linear combinations of these waveforms (i.e. differently weighted mixtures with the weights being the latent vectors) which are also called ‘basic waveforms’. These are the rows of the matrix \(A'\).

Since \(A'\) is an orthogonal matrix, \(A'\) multiplied by its transpose \(A\) equals an identity matrix \(I\). Since we can multiply both sides by \(A\) to give

\[ AY = AA'X = X \]

therefore,

\[ X = AY \]

Thus, the original matrix of variables \(X\) is equal to the matrix of latent vectors arranged in columns multiplied by the matrix of scores. This equation can be further developed as

\[ X = A_r Y_r + A_d Y_d \]

where \(A_r Y_r\) are the components retained and \(A_d Y_d\) are the components discarded.

The above equation indicates that we can approximate \(X\) by using the first few components. The more components we use the better the approximation. It also indicates that we can ‘reconstruct’ the contribution from one or more components to the original data set (as we illustrate later in Figs. 33, 34 and 35) or eliminate the contribution of one or more components from the original data set.

**Rotations**

The analysis yields only one of many ways that the ERP data set can be explained in terms of components. Basically, the cloud of data points are explained in terms of their projections onto a small number of orthogonal axes. One can rotate the axes to explain the data in a different way (Tabachnik and Fidell, 1989) and to make the components easier to interpret (Fig. 25). An orthogonal rotation shifts the coordinate axes while maintaining the orthogonality between them. Thus, the rotated components remain uncorrelated. Oblique rotations allow for correlation between factors. Orthogonal rotations may be easier to describe and interpret. However, they strain reality, unless the researcher is pretty sure that the underlying processes are close to independent.

An unrotated analysis usually yields components weighted over a large number of latencies. In ERP research, one generally considers components as highly active at some latencies and not at others. Such components can be obtained by rotating the axes. The most commonly used orthogonal rotation is the ‘Varimax’ rotation. This simplifies components by maximizing the variance of the loadings within components, across variables (time in the case of ERPs). Loadings that are high become higher and loadings that are low become lower. The Varimax solution is unique. Quartimax, another kind of orthogonal rotation, does for the variables what Varimax does for the loadings. It simplifies variables by maximizing the dispersion of the loadings within variables, across components. Varimax operates on the columns of the loading matrix whereas Quartimax operates on the rows. Since one generally wants simple components rather than simple variables, Varimax is much more popular. Oblique rotations vary with the amount of allowed correlations between components. The amount of correlation permitted within components is determined by the experimenter.

**Factor analysis**

Both PCA and ‘factor analysis’ (FA) have the aim of reducing the dimensionality of a data set. However, there are differences between the techniques. PCA is a procedure to decompose the variables without an underlying model. It does not distinguish be-
Fig. 25. Rotation of components. This figure illustrates the rotation of the principal components from a three-variable PCA. The variables are the potentials at points A (110 ms), B (130 ms) and C (320 ms) of one of the waveforms shown in Fig. 23. Only the two first principal components, explaining 99% of the variance, were retained. The top of the right column shows the unrotated component loadings plotted against time. A scatterplot of the unrotated component loadings is shown at the bottom of the column. Both components load quite highly at all time points. The middle column shows the component loadings after a Varimax rotation. The components are still orthogonal. Component 1 now loads highly at 320 ms and component 2 at 110 and 130 ms. Note that component 1 still loads a little at 110 and 130 ms and component 2 a little at 320 ms. The right column shows the component loadings after an oblique rotation. The components are no longer orthogonal and there is now some correlation between them. Components 1 and 2 now load almost exclusively at 320 ms and 110/130 ms, respectively.

Illustration using ERPs from a single scalp location

We illustrate the application of PCA with some simple examples. The data for the first example come from an experiment similar to that performed by Squires, Squires and Hillyard (1975) and analyzed by Squires, Donchin, Herning et al. (1977). This experiment demonstrated that the P300 wave following a detected target might be composed of several different positive components: P3a, P3b and the Slow Wave.

Auditory evoked potentials were recorded from the vertex in reference to linked mastoids under four different conditions. The stimuli were 30 ms tones of either 1000 or 1200 Hz presented to the right ear at a rate of 1/s and at an intensity of 60 dB above normal hearing threshold. The tonal frequency of the stimuli was determined at random with one of the stimuli improbable ($p = 0.2$) and the other more probable ($p = 0.8$). This is the classic ‘oddball’ paradigm. The
improbable stimulus was considered the ‘target’ and the probable stimulus the ‘standard’. Which stimulus was which was counterbalanced across the experiment and the data were collapsed to remove any effects of tonal frequency. The subject either read a book or listened to the stimuli in order to detect and count the number of improbable stimuli (targets). The two experimental manipulations (probability and attention) yielded four different ERP waveforms. Eight subjects participated in the experiment providing a total data set that consisted of 32 ERP waveforms. Each ERP waveform was collapsed to 75 voltage values occurring every 8 ms for a total sweep duration of 600 ms.

If scalp-recorded waveforms are a summing together of different components, subtraction techniques may help to demonstrate these constituents. Subtracting the ‘read’ ERP from the ‘count’ ERP should leave whatever is added to the waveform by paying attention to the stimuli. Subtracting the ERP to the probable stimulus from the ERP to the improbable stimulus should leave the ERP waveforms related to the detection of the improbable target (whether conscious or not). These subtraction processes are shown in Figs. 26 and 27.

PCA evaluates the covariation among data points in the ERP waveform as the ERP changes from subject to subject and from experimental condition to experimental condition. The first component is calculated to explain the greatest amount of variation in the data set. Subsequent components are then sequentially calculated to account for the variance in the data that remains unexplained by already calculated components. Ultimately, there are as many components as there are variables. However, if the variables are correlated, the later components will account for little of the variance and can be disregarded. This leaves a small number of components to explain the data. For the data set described in the previous paragraph, we found that five components explained 93% of the variance. The loadings for these components are diagrammed in Fig. 28. It is important to realize that the component loadings indicate the correlation of the different time point measurements with the component and have no meaning in terms of the polarity of the actual waveform.

Fig. 26. Target-standard difference waveforms. At the top of the figure are superimposed the ERPs to the target (p = 0.2) stimuli (thick line) and the standard (p = 0.8) stimuli (thin line). The ERPs are the grand mean responses recorded at the Cz location from eight subjects who detected a 1200 Hz target in a train of 1000 Hz standards (or vice versa). The tones occurred once every second and had a duration of 30 ms. Beneath the superimposed ERPs are plotted the difference waveforms obtained by subtracting the standard response from the target response. The difference waveforms show a small mismatch negativity (MMN). When the stimuli are being attended this leads into a large N2-P3b complex.

Fig. 27. Attend-ignore difference waveforms. This figure represents the same waveforms as shown in the preceding figure. However, in this figure, the difference waveforms are obtained by subtracting the ERPs recorded when the subjects read a book and ignored the stimuli from those obtained when the subjects attended the stimuli. The difference waveforms show a small negative wave called Nd or the ‘negative difference wave’. For the target stimuli the Nd is larger and leads into the N2-P3b complex.
scores high on the ERPs evoked by attended improbable stimuli and low on the ERP waveforms evoked by the ignored stimuli or by the attended probable stimulus. The pattern of these scores can be evaluated using an analysis of variance (ANOVA) modelled on the experimental design. For this experiment, we used a two-way (probability and attention) ANOVA with repeated measures across the eight subjects. The ANOVA results show that component 1 is affected by an interaction between attention and probability; it is large when the stimulus is both attended and improbable and small otherwise. Component 2 shows the same pattern as the first component. Component 3 is mainly affected by stimulus probability, and components 4 and 5 are modulated by attention. If one combines these relations to the experimental manipulations to the time course of the components, one might consider components 4 and 5 to represent the sensory evoked potential (N1-P2), component 3 the ‘mismatch negativity’ or MMN, and components 1 and 2 the P300 wave.

A major difficulty with both PCA and simple subtraction techniques occurs if a component changes in latency from one condition to another or from one subject to another. The latter case is well illustrated in our present example. Figure 29 also shows the ERPs to the attended target from each of the eight subjects in the experiment. Both the N1 and the P300 waves vary significantly in latency among the subjects. Each wave is therefore represented by two components (1 and 2 for P300, 4 and 5 for N1).

Illustration using ERPs from multiple scalp locations

ERPs can be recorded from many different electrodes as well as from different subjects in different experimental conditions. The ERP data set then has four dimensions (time points, subjects, experimental conditions, electrodes). In actual fact, the electrodes represent points in three-dimensional space. We have so far shied away from considering how ERPs recorded from different electrodes might fit into a PCA. The difficulty is that we may find a component that changes its scalp distribution from one experimental condition to another. Such a component is very diffi-
Fig. 29. Component scores. These measurements derive from the PCA described in Fig. 28. The top half of the figure presents graphically the mean scores for each component at each experimental condition. The bottom half shows the results of a two-way (probability by attention) analysis of variance (ANOVA) with repeated measures of the component scores. Five ANOVAs were performed, one for each principal component. The component scores give another clue for interpreting the components. Indeed, components 1 and 2 are significantly increased in the attend-target condition, which is consistent with the interpretation that both components represent the P3b wave. Component 3 is significantly affected by probability in both ignore and attend condition. This is consistent with the interpretation of component 3 as mismatch negativity processes. Component 4 is significantly modulated by attention in both standard and target conditions which supports the interpretation of this component as representing wave N1a. Component 5 is also modulated by attention but this was not statistically significant.

cult to understand in terms of what might be going on in the brain (Picton and Stuss, 1980). A change in scalp distribution must be explained by at least two different underlying processes rather than by a single underlying generator process that is more or less active. One way to interpret these effects might be to model PCA components in terms of intracerebral generators. The PCA component may represent a ‘functional’ component composed of two or more ‘anatomical’ components.

There is therefore no reason not to perform the PCA on data from multiple scalp locations. The analysis can provide information about the component structure of the recorded data that is not available in single-channel analyses. If we had used three scalp electrodes (Fz, Cz, Pz) rather than just one in the analysis of the previously described data set, we would have obtained (like Squires and his colleagues) a somewhat different component structure. The single-channel PCA did not clearly distinguish P3a and P3b components. The P3a probably shares the same variance pattern as the MMN. Our analysis also did not show a ‘Slow Wave’ component. Since this is usually recorded as a negative wave anteriorly and a positive wave posteriorly and shows little activity at Cz, it is missed in a PCA limited to the Cz waveforms. Since the Slow Wave can change its scalp distribution with different experimental conditions (Fitzgerald and Picton, 1981), it may itself may reflect two different processes, one generating the anterior negative wave and the other generating the posterior positive wave.

Our second PCA example is similar to the first except that the stimuli had a longer duration (400 ms) and a wider target-standard frequency change (1000 and 2000 Hz). In this experiment, we recorded from 16 different electrode positions. As before, the stimuli were presented only to the right ear. The use of multiple electrodes makes it possible to perform a PCA on data from a single subject in a such simple paradigm. This removes the problem of latency differences
among different subjects, although it does not remove the problem of latency variability among different conditions in the same subject. Figure 30 shows the raw data of one subject. Figure 31 shows the unrotated and Varimax rotated component loadings of the first five components. Figure 32 shows the component scores. By observing the patterns expressed in the loadings (in what time period each component loads higher) and the scree (how electrode position and experimental manipulations modulate each component), it is possible to interpret the components.

Component 1 loads highest between 300 and 450 ms. The scores indicate that the response to target stimuli is strongly modulated by attention. This is most evident at the parietal and central regions. Another observation is that the scores for all conditions seem shifted negatively at the frontal regions of the head. Component 1 is, therefore, modelling at least two different processes. Figure 33 shows recomposition waveforms of component 1 for the target stimuli. In the ignore condition, there is a negative wave with higher amplitude at the frontopolar and frontal regions, representing the sustained potential. In the attend condition, there is a positive wave with larger amplitude at the parietal and central regions, representing the P3b wave.

Component 4 loads highest between 200 and 300 ms (Fig. 33). The score patterns do not show clear effects of target or attention. The recomposed waveforms show a positive wave peaking around 250 ms with a more anterior scalp distribution than the P3b wave (Fig. 33). This response might therefore have something in common with wave P3a.

Component 2 loads highest after 400 ms but it also has two smaller peaks around 130 and 230 ms. Inspection of the scores again shows two patterns: the responses to both the ignore and the attend conditions are affected by probability, especially at anterior head regions. Furthermore, for the attend-target condition the component reverses polarity from negative at the front to positive at the back of the head. Figure 34 shows the recomposed waveform for component 2.
Fig. 31. Principal components in the oddball task. This figure shows the component loadings resulting from a PCA of the data shown on the previous figure. The loadings express the amount of correlation between the components and the recorded data across the variables (time points). Initially, the analysis gives us the unrotated loadings. The left half of the figure shows the first five unrotated components, explaining 93% of the variance of the recorded data. Since the unrotated loadings are quite spread out in time and have both positive and negative values, they are often difficult to interpret. To simplify the loadings we performed a Varimax rotation. This keeps the components orthogonal but rotates them in the multidimensional component space to maximize the variance of the loadings within the components across time. It simplifies the components by making them load highly in fewer time points. Component 1 loads highest near 350 and represents a combination of P3b and sustained potential. Both these processes occur at the same latency and the experimental manipulation does not have sufficient power to dissociate them. Component 4 loads highest at 250 ms and may represent the P3a wave. Component 2 loads highest after 400 ms but also has two smaller peaks at 130 and 230 ms. This component appears to combine the Slow Wave and the mismatch negativity. Component 3 and component 5 peak, respectively, at 120 ms and 160 ms and probably represent waves N1b and N1c.

The late part of this component can be readily identified as the Slow Wave. The earlier waves could be different parts of the mismatch negativity.

Component 3 loads highest around 120 ms. The pattern of the scores shows some modulation by probability in the frontocentral regions of the scalp. The recomposed waveforms (Fig. 35) can be readily identified as wave N1b. The scalp distribution shows higher amplitude at the midline central and frontal regions. Component 5 loads highest around 160 ms.

The pattern of the scores is unhelpful, but the recomposed waveforms reveal a negative wave larger in the posterior temporal region contralateral to the stimulated ear. This could correspond to the wave N1c (or N145). This wave may be produced by a radially (and slightly posteriorly) oriented generator in the lateral surface of the temporal lobe and it often has higher amplitude on the side contralateral to the ear been stimulated (Scherg et al., 1989).

Fig. 32. Analysis of component scores. This figure shows the component scores for the first three components in the previous figure. Graphs are plotted at each electrode to represent the scores in the four experimental conditions. The lines represent the stimulus probability; thin lines the standard (r = 0.8) and thick lines the target (r = 0.2). The horizontal axis represents the subject’s task: ignore the stimulus (left) and attend to the stimulus (right). The vertical axis represent the actual values of the scores: positive up and negative down, the horizontal axis being zero. Component 1 is strongly affected by stimulus probability but only in the attend condition. It is negative at the front in the ignore conditions and positive at the back in the attend-target condition. Component 1 seems to represent at least two processes: the P3b wave and the auditory sustained potential. Component 2 also shows two patterns: first, both the ignore and attend conditions are modulated by stimulus probability, especially at the front of the head; second, in the target condition there is an inversion of polarity, from negative at the front to positive at the back of the head. The first pattern could represent MMN processes and the second the Slow Wave. Component 3 is modulated by stimulus probability in the frontocentral regions in both the attend and the ignore condition, and seems to represent the N1b wave. The scores for components 4 and 5 were not very helpful in interpreting the components and are not illustrated.
Fig. 33. Recomposition of the waveforms for the P3a and P3b components. This figure shows the contribution of components 1 and 4 to the recorded waveforms. The recomposition is done by multiplying the transpose of the latent vector of each component by the vector of component scores. Only target waveforms are shown. When the subject ignores the stimuli, component 1 produces a negative wave between 200 and 500 ms with maximum amplitude at the front of the head (upward arrow). This can be readily identified as the sustained potential. Component 4 waveforms shows a positive wave peaking at about 250 ms with maximum amplitude near the vertex (actually larger in the left central area). This may represent the P3a process. When the subject attends to the stimuli, component 1 waveforms show a large positive wave peaking at around 350 ms with larger amplitude at the midparietal region. This is the P3b wave. Component 4 waveforms for the attend condition show similar waveforms to those in the ignore condition except that they now are larger on the right. The symmetry was idiomatic to this subject and is of uncertain significance. This case illustrates how a PCA component can represent two different processes appearing in different experimental conditions (component 1 representing both the sustained potential and the P3b wave).

Cautions in interpreting PCA components

The use of PCA in ERP research is as much an art as a science. Basically, the analysis attempts to discern meaningful components in a data set that does not properly fit the assumptions of the analysis. One problem in the analysis is the residual noise that remains in the recordings after filtering and averaging. Some of this noise may be correlated among the data points. The PCA will attempt to explain the variance of this noise in the components that it distinguishes. One should never attempt a PCA on very noisy data. Even with relatively clean data, one should realize that residual noise may still affect the components.

ERP data recorded in an experiment are usually organized into three modes: subjects, electrodes and experimental manipulation. To fit all three modes to one homogeneous data set involves brute force and may lead to significant problems. Since the variance related to experimental manipulations may be smaller than that related to subject or electrode differences, this variance may be allocated to subject or electrode components when the number of components is truncated. One way to restrict the PCA to the experimental manipulation may be to remove the variance that is not related to these manipulations prior to the PCA (Möcks and Verleger, 1991). This ‘data cleaning’ would also remove the residual noise in the recordings. Another approach, still in development, would be to use a parallel factors approach to analyzing the data (Field and Graupe, 1991).

A major problem with the PCA is that it cannot easily handle components that change in latency since it assumes that the data at different time points always
measure the contributions of the different components in the same way. Variation in ERP latency is common. One usually does not perform PCAs on data when the experimental manipulation significantly changes the latency of a component. However, latency differences between subjects can distort the PCA even when the experimental manipulations do not affect latency. It is possible that the time-warping techniques discussed earlier may be helpful in eliminating inter-subject latency differences prior to PCA. Latency differences caused by the experimental manipulations could be removed as well, but one would then have to have some way of assessing the effects of the experimental manipulations on latency, perhaps by submitting the component loadings to a reverse time-warping.

An important interpretational difficulty with PCA concerns the indeterminacy of the component structure. Rotations of the component axes can provide an infinite number of component sets (one of which is the Varimax), each representing the data equivalently in terms of least-squares fit. Deciding which rotation optimally represents the data requires the exercise of criteria (such as waveform shape or relation to other data sets) that are outside of the data set being analyzed.

PCA is based on the orthogonality of the components and some rotations maintain this orthogonality. Since there is no reason to assume that cerebral components act orthogonally, the orthogonally rotated solutions may not properly represent their activity. Wood and McCarthy (1984) used simulations to show that the evaluation of ERP data by means of PCA and

Fig. 34. Recomposition of the waveforms for the mismatch negativity and Slow Wave component. This figure shows the recomposition of the contribution of component 2 to the recorded waveforms. The waveforms for all four conditions are presented. Note that this component is very inactive in response to the standard stimuli. However, it becomes large in response to the targets. The waveforms has two small negative peaks at 130 and 230 ms that are larger at the front of the head (arrows). These can be interpreted as mismatch negativity processes (with the earlier peak representing some enhancement of the N1 caused by the change in the tonal frequency from standard to target). There is also a large slow wave beginning at 400 ms. In the ignore-target condition this wave is always negative and larger at the front of the head. In the attend-target condition this wave is larger and reverses polarity across an imaginary line passing between the anterior temporal and the mid-temporal electrodes, the central and the mid-temporal electrodes, and the central and parietal electrodes: negative anterior to this line (upward arrow) and positive posterior to this line (downward arrow). This is the Slow Wave. It is possible that two different cerebral processes generate the Slow Wave: one process, independent of attention, would generate the negative wave at the front of the head. The other, active only when one attends to the stimuli, would generate the posterior positivity.
Fig. 35. Recomposition of the waveforms for the N1b and N1c components. This figure presents the contribution of components 3 and 5 to the recorded waveforms. Only the attend-target condition is shown. Component 3 waveforms show a negative wave peaking at 120 ms, with maximum amplitude at the vertex (arrow) and reversing polarity between the central and the midtemporal electrodes. This is the N1b wave. Component 5 waveforms show a smaller negative wave peaking at 160 ms and with larger amplitude at the posterior temporal regions (arrow), maximum at the left hemisphere (the stimuli were delivered to the right ear). This pattern is compatible with wave N1c. Wave N1b is probably generated near the primary auditory cortex. The field generated by bilateral activation of these regions is maximum at the vertex. Wave N1c is probably generated more laterally, at the superior gyrus of the temporal lobes. The field generated by the activation of these areas is more laterally oriented and often asymmetrical.

Varimax could misallocate variance among the components. This was most likely due to correlations between their components, since the PCA does not uniquely allocate this shared variance (Möcks and Verleger, 1991).

Given these present limitations, PCA must be used in an exploratory manner. It provides a relatively simple way of looking at an extensive data set. The components have meaning only as they relate to other information about how the brain works. PCA should not be used to demonstrate the existence of components unless they make sense. One particular difficulty with PCA components is their relationship to intracerebral generators. Those PCA components that are related to the experimental manipulations of cognition may represent 'cognitive processes' in the brain. These cognitive processes may involve several different brain regions and each active brain region may contribute to several cognitive processes. It is to these active brain regions or ‘sources’ that we now direct our analysis.

Source analysis

Concept of sources

The components that are derived from a PCA are somewhat abstract. They represent components of the experimental variance and lack clear physical instantiation. Source analysis attempts to determine actual intracerebral generators for scalp-recorded events. It is a component analysis that is constrained by physical rules governing the generation of electric fields at the surface of a volume conductor, rather than by statistical rules requiring orthogonality or maximum variance.

Before going into details of source analysis, it is important to understand the concept of the ‘equivalent source’ which describes the generator of a particular ERP component in relation to the physiology and anatomy of the human brain. In recent years, positron emission tomography (PET) has provided overwhelming evidence for the functional organization of the brain by showing enhanced metabolism in circumscribed brain areas during sensory, motor and cognitive processing (Posner, Petersen, Fox et al., 1988; Petersen, Fox, Snyder et al., 1990; Zatorre, Evans, Meyer et al., 1992; Roland, 1993). Functional magnetic resonance imaging (MRI) has shown similar foci of increased activity (Belliveau, Kennedy, McKinstry et al., 1991; McCarthy, Blamire, Rothman et al., 1993). For ERP source analysis, these findings suggest a model of brain function with a finite number of discrete active areas (Roland, 1993). Each active brain area could act as an equivalent source and generate electrical activity at the scalp.

In contrast to PET and functional MRI, ERPs have a less accurate anatomical resolution since they are recorded from only a small number of scalp locations. Therefore, an image reconstruction of the brain electrical activity is only possible with severe constraints and very limited spatial resolution (Scherg and Ebersole 1992; Scherg and Ebersole 1993). However, PET averages the brain activities over tens of seconds and yields a static image of the magnitude of the local metabolic change, whereas ERPs contain a wealth of temporal information in addition to the geometrical information.
Each equivalent source of an ERP component can be characterized by geometrical variables (location and orientation of the activated brain area) as well as by the time course of activation (source waveforms). The information about the timing of processes in different brain regions is essential to any understanding of how these regions interact. This is the main advantage of the ERPs.

*Source dipoles*

When a neuron is activated by synaptic input, ions flow across the activated area of the membrane (Nunez, 1981). This ionic current flows through the extracellular spaces to return passively to the neuron at inactive regions of its membrane (Fig. 36). Regions where there is a net current outflow into the extracellular space are called current ‘sources’. Regions with a net current inflow into the neuron are called current ‘sinks’. According to the laws of electrostatics, there is as much source current from a neuron as sink current into it. If there is significant asymmetry to the structure of the neuron and/or the location of its activation, the centers of gravity of the source and sink regions will be spatially separated. This will compose a dipole field in the extracellular space. The classic example is the synaptic activation of the cell body of a pyramidal cell in the cerebral cortex. Excitatory synaptic input causes current flow into the cell resulting in an extracellular current sink. Most of the current returns to the extracellular space through the apical dendrite, forming a current source at the level of the dendrite. The fields set up in the extracellular space from this dipole will spread beyond the region inhabited by the neuron as an ‘open’ field. Under other conditions of synaptic input and neuronal structure, the flow of current in the extracellular spaces around the neuron will be in all directions. For example, if the cell body of a stellate cell is activated, the return current flow involves all of the dendrites of the cell. In these conditions, there is no spread of current beyond the region of the neuron and the field is considered ‘closed’. One can conceive of the current flow in the symmetrically oriented dendrites as creating multiple dipole fields all oriented in different directions and cancelling themselves out.

When many neurons in a region of the brain are activated they will each generate their own extracellular fields and these fields will superpose. Under certain conditions these superposed fields will generate open fields that can be measured beyond the region of the activated neurons. Some of these conditions involve the pattern of activation. The magnitude of the total field will be greater if the activation is more synchronous and if the individual fields are similar from neuron to neuron. Other conditions depend upon the structure of the neuronal tissue. The magnitude of the total field will be greater if the neuronal structure is asymmetrical and if the neurons are oriented in a similar way throughout the tissue. Large open fields occur with the activation of the cell bodies of pyramidal cells in the cortex when they are excited by incoming thalamocortical connections. Current flows into the pyramidal cells near the level of their cell bodies and out at the level of their apical dendrites. The surface of the cortex becomes positive relative to the
depth. At a distance from a region of activated neurons, the electrical field can be considered in terms of equivalent dipoles (Fig. 37). For a flat layer of cortex, the equivalent dipole is located within the cortex at the center of the activated area. For an activated curved area of a gyrus, the equivalent dipole is located at the center of a plane connecting the edges of the activated area, i.e. at some depth below the gyrus (Peters and de Munck, 1990).

Using equivalent dipoles to represent the activity of the brain requires some choice of level. At the one extreme, one can consider dipoles for each activated neuron. At the other extreme, one can consider one equivalent dipole for the activation of the whole brain. From the point of view of human ERPs, we are interested in the workings of volumes of the brain that have a size of one to several cubic centimeters. Although these levels of analysis will not portray the complexity of the different generators within each cortical area (Mitzdorf, 1987; Vaughan and Arezzo, 1988), they are feasible in terms of the measurements that we can make, tractable in terms of interpreting how different regions of the brain might interact, and meaningful in terms of localizing areas of function and dysfunction.

Instantaneous and spatiotemporal modelling

Whether or not we use the temporal information of the ERP waveform will determine the type of source model: spatiotemporal or instantaneous. Spatiotemporal source analysis attempts to determine the geometrical and the temporal aspect of each generator for example by estimating a source activity waveform or source potential in addition to the location and orientation of an equivalent dipole source (Scherg and von Cramon 1985, 1986; Achim, Richer and Saint-Hilaire, 1988b, 1991; Baumgartner, Sutherling, Shi et al.,
have become available for individually adjusting four-shell head models (Berg and Scherg, 1994b).

Dipoles are characterized by five geometrical parameters (three locations, two orientations) and the dipole strength or magnitude which is one parameter in instantaneous models and a waveform in spatiotemporal models. These parameters are illustrated in Fig. 38. If one knows the electrical properties and geometry of the volume conductor and the location and orientation of a source within it one can estimate the potential topography that will be recorded from the surface. This is the forward problem. Its solution is approximated by placing a dipole at a certain location

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Fig. 38. Source parameters. This figure illustrates how source analysis can describe the parameters of a dipole source. For simplicity, only one dipole is shown (a blink dipole). A source dipole is defined by its location, orientation and strength. Location is expressed by three parameters: eccentricity, azimuth (theta) and longitude (phi). Eccentricity is the distance from the source to the center of the head model. It is often expressed as a percentage of the radius of the head model used. Theta is the angle formed with the vertical axis by the line joining the source location to the center of the head. Phi is the angle formed with the coronal plane by a line joining the source and the center of the head. Orientation is expressed by two parameters: theta and phi. These are measured using the same references as the angles used to express location. The sign convention for theta is that a positive sign indicates right-sided location or right-going orientation and a negative sign indicates left-sided location or left-going orientation. For phi, a negative sign means clockwise rotation and a positive sign means anti-clockwise rotation from the coronal plane. The strength of the dipole as a function of time is given by the dipole source potentials.
within a spherical multi-shell head model and computing the predictions of the model for the scalp potential at each electrode. The inverse problem is to calculate the dipole parameters from a given scalp topography (instantaneous model) or a set of different scalp topographies (spatiotemporal model). If we consider any overdetermined model with a finite number of discrete equivalent sources and lesser degrees of freedom than the data (e.g., single instantaneous or spatiotemporal models), a mathematical solution can be obtained using a least-squares fit or maximum likelihood criterion. In contrast, the instantaneous 'minimum norm' or current density images are underdetermined and ill-posed because a much larger number of source parameters is estimated than available from one time slice.

From the finite number of possible discrete models, however, one has to be selected which has the appropriate number of sources such that each source matches one of the active brain areas. The appropriateness of a discrete model can be checked a posteriori using an additional probe source (Scherg 1992; Scherg and Ebersole 1993). For physical reasons, the probe source waveforms must reveal the activity of the brain area where the probe is placed. If the probe source waveforms are within the noise level at any brain region not contained in the model to be tested, then the model is appropriate with respect to the limited spatial resolution (about 2 cm) of source analysis. This procedure can be used with discrete models containing an increasing number of sources as described below (Scherg, 1992).

One parameter that is sometimes difficult to determine in the process of source analysis is the number of sources. A lower limit for the number of sources needed by the model can be obtained by performing a PCA over the epoch of interest. The number of waveforms on the PCA that are recognizably different from noise provides the minimum number of sources to account for the scalp-recorded waveforms. However, such a PCA cannot differentiate between sources that are identical in waveform but separate in space, a situation that may occur quite often in the brain if there is symmetrical activation of the two hemispheres.

The instantaneous methods of dipole source analysis are severely limited in the number of sources that can be determined. Since each dipole has six parameters and since the analysis is limited to only one time point, the maximum number of sources that can be determined is equal to the number of electrode locations divided by 6. Thus, a 16-channel recording can provide no more than two dipole sources and a 32-channel recording no more than five dipole sources. However, ERP data contain biological noise and the overlap of the instantaneous dipole fields at one time slice yields a new topography for which the fit with more than one dipole field may be unstable or subject to location errors resulting from the noise and the imprecision of the model with respect to individual head geometry and conductivities (Zhang and Jewett, 1993).

Spatiotemporal analysis overcomes some of these limitations by considering the different scalp topographies over time with varying magnitudes of the underlying generator activities. Thus, the number of sources that can be possibly determined from one signal epoch is limited by both the number of electrodes and the degrees of freedom in the time signals. In return for this increased number of sources, one cannot change the location and orientation of the sources from moment to moment. At first glance, this seems an unnecessary restriction. However, a stationary dipole can represent the activity from a specific brain region to the scalp. Furthermore, it attributes a defined meaning to the source waveform in that it reflects the compound source activity of this brain area, provided that each active area is modelled by an equivalent source and that the errors of head model misspecification are small within the applied model (Zhang and Jewett, 1993).

It might be useful to consider the procedures of spatiotemporal source analysis in more detail (Scherg, 1990). The general principles underlying the technique are illustrated in Fig. 39 which uses as an example the sources that are active during a visual ERP (Plendl, Paulus, Roberts et al., 1993). The elements of the spatio-temporal source model and the mathematical formulations for the forward and inverse solutions are depicted in Fig. 40.
Fig. 39. Basic principles of source analysis. During an ERP waveform several sources \((s_n)\) may generate electrical fields that can be recorded from the scalp. The electrical activity recorded at a scalp electrode \((u_k)\) is the sum of the activities from all the sources. The voltage generated at the scalp by these sources will depend on the location and orientation of the sources and upon the geometry and impedance of the head. These factors can be combined into a coefficient \((c_{nk})\) specific to the source and the electrode. The diagram illustrates these principles using the main sources that are active during the ERP evoked by a half-field patterned visual stimulus (Plendl et al., 1993). The posteriorly oriented first source represents activity in the striate cortex; the laterally oriented second source represents activity in the peristriate cortex; and the inferiorly oriented third source represents activity in the medial inferior surface of the occipital lobe.

The first process involves setting up the ‘forward’ and ‘inverse’ solutions. For this we need a head model that provides a reasonable estimate of the topography of the scalp-recorded potentials due to an intracerebral dipole. We then postulate a finite number of dipoles sources \((n = 1,\ldots,N)\) with particular locations and orientations. For each dipole, the transfer (or forward) coefficients can be calculated from the head model to predict the potential at each of the electrodes \((k = 1,\ldots,K)\). These transfer coefficients \((c_{nk})\) are assembled into a matrix \(C\) with dimensions \(N \times K\). This matrix consists of \(N\) forward coefficient vectors or source ‘topographies’ each having a dimension \(K\). The last element of the source model is given by the magnitudes of the equivalent dipoles which vary over time \((t = 1,\ldots,T)\). These dipole magnitudes are called ‘source waveforms’ or ‘dipole source potentials’ because they reflect the compound activity of the underlying source region. The \(N\) source waveforms are assembled into a matrix \(S\) with dimensions \(N\times T\).

According to the principle of superposition, the electrical activity occurring over time at a particular scalp location \(u_k(t)\) is the sum of the activities generated from all sources within the brain. The analysis assumes that sources are active throughout the recording sweep and that these sources do not move in their location or orientation during this sweep. For a given set of dipole sources, a given head model and a given set of source waveforms, we can predict the voltage distribution at the scalp electrodes:

\[
\begin{align*}
    u_1(t) &= c_{11}s_1(t) + c_{21}s_2(t) + c_{31}s_3(t) + \cdots + c_{N1}s_N(t) \\
    u_2(t) &= c_{12}s_1(t) + c_{22}s_2(t) + c_{32}s_3(t) + \cdots + c_{N2}s_N(t) \\
    &\vdots \\
    u_K(t) &= c_{1K}s_1(t) + c_{2K}s_2(t) + c_{3K}s_3(t) + \cdots + c_{NK}s_N(t)
\end{align*}
\]
In order to distinguish between the voltages predicted by the model and the actual voltages recorded from the scalp we use $U'$ for the predicted voltages and $U$ for the actual voltages. The preceding equations for the forward solution can then be expressed in matrix terms:

$$U' = C \times S$$  \hspace{1cm} \text{(forward model)}$$

When recording ERPs from the scalp, we do not normally know the source waveforms. However, if we have measured the scalp distribution of the voltages over time (matrix $U$), we can obtain a best estimate of the source waveform matrix by inverting the equation of the forward model and replacing the model matrix $U'$ by the real data matrix $U$:

$$S = C^{-1} \times U \hspace{1cm} \text{(inverse model)}$$

Once $S$ is obtained, we can backproject the source activity to the scalp and calculate the model data matrix $U'$ using the equation for the forward model. The difference between the model data $U'$ and the real data $U$ can then measure the quality of the model. This difference can be expressed as the ‘residual variance’ or RV (Scherg, 1984) which is the sum of the squares of all the elements in the difference matrix divided by the sum of the squares in the data matrix:

$$RV = \text{variance}(U' - U) / \text{variance}(U)$$

or by the ‘goodness-of-fit’ ($G$):

$$G = 1 - RV$$

The second process involves setting up a ‘minimization’ procedure which varies the parameters of the dipole configuration in order to fit the model $U'$ to the data $U$. With each change, the $C$ matrix is recomputed since some of the dipole parameters have been altered. This corresponds to testing different source hypotheses with modified locations and/or orientations of the dipoles. The pseudo-inverse of $C$ is calculated and used as a linear operator to decompose the data matrix $U$ into a new source activity matrix $S$. The backprojection of $S$ to the scalp gives a new version of the model data matrix $U'$. The new $U'$ matrix can then be compared to the data matrix $U$ and the goodness-of-fit compared to the old $U'$ matrix. We can then iteratively change the source locations and orientations to improve the fit of the modelled data to the recorded data using a specific cost function and a minimization procedure such as the simplex algorithm (Fender, 1987).

The most common criterion or cost function to be minimized is RV. More useful is a combination of RV and other factors which enhance the separation of ac-
tivity in the source waveforms and prevent instability in the iterations (Scherg, 1984; Scherg and Berg, 1991). Such instability occurs if the spatial vectors \( \mathbf{c}_n \) (or topographies) of two or more dipoles interact, i.e. they become linearly dependent. One way to avoid this is to measure the amount of ‘energy’ in the sources. This criterion calculates the total variance in the source waveforms. Minimizing this total variance avoids situations wherein two dipoles interact. A large amplitude at one source can be compensated by a large amplitude at another source with opposite orientation leaving only a small potential on the surface of the scalp. Another important criterion is the ‘variance’ criterion which evaluates the variance in a particular source waveform over a particular period of time and helps to concentrate the activity of the source within a marked interval. In this manner, we can use physiological hypotheses about the sequence of activation in different brain areas to limit sources to sequential time periods. The application of these criteria is illustrated diagrammatically in Fig. 41.

Once the number of dipole sources being fit to the data exceeds three or four, the number of possible combinations of the six dipole parameters becomes extremely large. For each possible combination, a residual variance may be calculated. Finding the true minimum of this variable is computationally difficult. Choosing starting values is important. Selecting a search algorithm that does not get stuck in local minima is essential (Fender, 1987). Algorithms that use ‘simulated annealing’ (Gershon, Cardenas and Fein, 1993) may be the most efficient. Perhaps most important is to provide ‘constraints’ (Scherg and Berg, 1991). The procedure should not have to look at solutions that are physiologically impossible (such as sources in the visual striate cortex being activated early in the course of an auditory evoked potential) and should not have to compare solutions that differ within the limits of accuracy of the head model (such as sources that differ in location by less than 0.5 cm).

One powerful constraint is to limit the source analysis to the sulci and gyri of the cerebral cortex (Dale and Sereno, 1993). The rationale is that cortical sources account for most of the scalp-recorded electrical fields because of their open-field structure and their proximity to the scalp.

Other techniques are variants of solving the set of equations of the spatiotemporal source model presented above. One such technique, ‘multiple signal classification’ (MUSIC), first used to locate different sources for sounds, was applied to the source analysis for magnetic recordings by Mosher et al. (1992). MUSIC assumes that the scalp-recorded ERPs are generated by sources that are not correlated over time, i.e. by sources that would be determined through a PCA of the surface waveforms. The analysis then proceeds to find the most likely locations in the brain for sources that would generate these components of the surface recorded activity. The MUSIC procedure starts from the decomposition of the recorded data into orthogonal components by means of a PCA. These components can be considered to constitute a multidimensional space with each dimension representing one of the components. Using a regional source at a given location within the brain one can compute the probability that the source is completely described in the multidimensional PCA space. A high probability is obtained if the spatial topographies of the regional source form a subspace of the PCA space or, in other words, if there is a high correlation between the re-

![Diagram](https://via.placeholder.com/150)

**Fig. 41.** Criteria for source analysis. This figure diagrammatically illustrates the different criteria that can be used in the iterative process of source analysis. The major criterion is the residual variance. This is the variance of the difference between the modelled and the recorded waveforms expressed as a percentage of the recorded waveform variance at each time point. The minimum energy criteria attempts to decrease covariance between source waveforms. The timing criterion can be used to concentrate the variance of a source waveform into a particular latency region.
Regional source and PCA spaces. Three-dimensional probability maps can then be drawn for these correlations, and sources located at probability maxima within the scanned volume. The principles of MUSIC are illustrated in Fig. 42, and the results of a MUSIC analysis of the early somatosensory evoked potential is illustrated in Fig. 43. Although it is an excellent way of finding sources for scalp-recorded activity when the different sources are not related, MUSIC does not work well if similar source waveforms occur in different regions of the brain. It can be quite misleading when there is synchronous activation of the two hemispheres: in such cases, MUSIC points to a single midline source. MUSIC is helpful when the sources for the ERP are asymmetrical, as in the early somatosensory evoked potential (Fig. 43).

Regional source imaging (Scherg, 1992; Scherg and Ebersole, 1993) is another special variant of multiple dipole imaging. A regional source consisting of three collocated orthogonal dipoles can image the current flow of a localized brain volume in any direction (Scherg and von Cramon, 1986). The volume of the brain is divided up into a set of discrete voxels and regional sources are used to scan the brain at these voxels. At the end of the scanning process, those voxels are selected for which each regional source images a maximal amount of variance while having the least amount of covariance with the other regional sources. If the number of regional sources exceeds the number of underlying areas of activity, one or more regional sources begin to show source waveforms of low amplitude, indicating little contribution from these brain regions. The inactive sources thus act like probes to check brain regions for the presence of source currents. The goodness-of-fit of a regional source does not change with rotation of the local coordinate system. Hence, once the active regions are located by the scanning process, local axes can be selected for each regional source so that the first dipole reflects the initial activity, the second dipole the next (orthogonal) activity and the last dipole the remaining activity in the local volume of brain.

Instead of starting with multiple regional sources in different areas of the brain, one can sequentially add

![Fig. 42. Principles of Multiple Signal Classification (MUSIC). ERPs recorded from the scalp can be considered as data in a multidimensional space with the number of dimensions equal to the number of scalp electrodes. PCA (lower right) provides a subdivision of this multidimensional data space into a signal subspace (with dimensions equal to the number of accepted components) and a noise subspace. The three topographies of a regional source form another three-dimensional subspace (upper right). The MUSIC procedure scans the brain in discrete steps across horizontal slices using a regional source. At each location, the correlation coefficient between the regional source waveforms and the PCA waveforms are computed by projecting the regional source topographies onto the PCA signal subspace. Logarithmic contour plots of the probabilities of these correlation coefficients (right) for each horizontal slice reveal areas with a high source probability. Areas with probabilities greater than 0.98 are shaded. Maxima (crosses) in the three-dimensional correlation space are found by comparing the distribution in one slice with the adjacent upper and lower slices. Since they are derived from three-dimensional comparisons, these maxima may not fit with the maximum probability region in a single slice.](image_url)
Fig. 43. Application of MUSIC to the analysis of early somatosensory ERPs. These maps represent the probability that a source at a particular location within the brain can explain the principal components of the early (10–40 ms) somatosensory evoked potential recorded from the scalp using 32 electrodes following left median nerve stimulation. The probability maps are plotted for cross-sections of the brain in at 5 mm steps from 30 mm below the center of the brain to 60 mm above. The shaded areas of the map represent locations where there is a source probability of greater than 0.98. The crosses represent maxima in the three-dimensional probability calculations. Three possible source locations are identified. One (section –30) is located near the center of the brain and probably represents a brainstem generator. A second source (section 25) is located within the right cerebral hemisphere and may represent thalamocortical activity or activation of the cortex in the Rolandic fissure. A third source (section 40) is active at the surface of the brain in the right central region and represents activation of the primary somatosensory area. These data are derived from Scherg (1993).

Regional sources until adding a further regional source results in source waveforms that are not significantly different from noise, that covary with source waveforms already present or that do not explain any significantly greater amount of the variance in the scalp recordings. Once one has located the regions of the brain that are active (and dropped those regions that are not significantly active), one can then begin to fit the activity within a region.

Strategies for spatiotemporal source analysis

Finding the multiple source solutions for a scalp recorded ERP is a complex procedure. The number of possible locations and orientations for the underlying sources is so large that no computer can calculate all possible permutations and combinations in any reasonable time. Strategies are therefore necessary for determining reasonable solutions within reasonable times.

It is usually advantageous to have some idea at the beginning of the recording how many sources might be needed to explain the recorded activity. A principal component analysis of the recordings will provide components that vary in their timing, and in the amount of variance that they can explain. If one has some estimate of the noise levels in the recordings one can assume that one needs at least as many sources as there are principal components to explain the non-noise variance. The principal component analysis may also give some idea of the regions of the recorded activity that are explained by different components and some suggestion of their waveforms. However, since there may be correlations between different sources in
different regions of the brain, it is likely that there will be more sources present in the data than components in the PCA and that the source waveforms will be significantly different from the PCA basic waveforms.

Once one has some idea of the number of sources, one needs to know where to start looking for them. Judicious choice of starting parameters speeds up any iterative modelling process. One approach to setting the initial parameters involves making physiological hypotheses. If one believes that certain regions of the brain are active during the ERP, one can use dipole sources in these regions as a starting point in the analysis. Another approach is to use the multiple signal classification (MUSIC) technique. MUSIC derives from PCA and locates regions in the brain that are the most likely sources for the components. These locations could then serve as the initial locations for dipole sources in the analysis (Fig. 43).

A moving dipole fit to the recorded waveforms may help in suggesting the locations of possible sources for the recordings. At times when only one source is active or when one source is predominant, the single dipole will be located in or near the location of that source. Rotation of the moving dipole in one location may suggest that different cortical regions with different orientations are being activated sequentially. Figure 44 shows a moving dipole fit to the early somatosensory evoked potential.

Another approach to analysis is to fit prominent peaks in the recording. Although these peaks may result from the overlapping of different generators, there is also a reasonable probability that they mainly reflect one particular generator source. One can therefore pick peaks in the waveform at particular locations or peaks in the global field power and fit point dipole sources at these latencies.

There is no unique solution to the inverse problem (Snyder, 1991). However, if one can demonstrate a solution that explains the recorded data as well as can be expected from the noise levels of the data, if the solution is robust to small perturbations in its parameters within the accuracy of the head model and the spatial resolution of the recording, and if the solution makes sense in terms of the known physiology and anatomy of the brain, we can be reasonably sure that the solution is correct. Furthermore, using probe sources we can exclude the possibility that another solution exists with sources located in completely different regions of the brain. The other possible solutions to the inverse problem must therefore be similar to the proposed solution in terms of the locations and orientations of the sources and the time course of the source waveforms. However, for multiple activities in a small and complex brain region such as the visual cortex, ambiguities may remain with respect to the decomposition of the scalp waveforms into meaningful source waveforms and orientations. In such situations, detailed comparisons with the underlying individual neuroanatomy may be needed. Any published source
solution should therefore provide some estimate of the goodness-of-fit, evaluate the tolerance limits of the solution and describe the supporting anatomy and physiology.

Source analysis of the auditory evoked potentials

There has been some controversy concerning the intracerebral origins of the late auditory evoked potentials that can be recorded from the human scalp. A sequence of waves (P1-N1-P2-N2) occurs at the onset and offset of a sound. This sequence of waves is maximally recorded from the vertex in reference to a linked-mastoid or non-cephalic electrode, and is often called the 'vertex potential'. During the continuation of the sound there is a sustained potential (SP) that is recorded as a negative wave in the frontocentral regions (Picton, Woods, Stuss et al., 1978b). The SP negativity is somewhat more anterior in its scalp distribution than the N1 component (Picton, Woods and Proulx, 1978a). There were two main hypotheses for the intracerebral origin for these waves: bilateral activation of the auditory cortices of the temporal lobes (Vaughan, 1969; Vaughan and Ritter, 1970) or widespread activation of the association areas, particularly those in the frontal lobes (Picton, Hillyard, Krausz et al., 1974). Recordings from the temporal regions of the scalp showed two negative waves, one earlier and one later than the vertex-recorded N1 peak. These were termed N1a and N1c to distinguish them from the vertex N1b (McCallum and Curry, 1980). Wolpaw and Penry (1975) proposed that these waves might be generated in the temporal regions and that the scalp recording therefore might indicate the activation of both temporal regions and more widespread association cortices. Point by point analysis of the scalp distribution of the late auditory evoked potentials suggested multiple intracerebral sources for these responses (Wood and Wolpaw, 1982). Näätänen and Picton (1987) therefore proposed that several generators contributed to these responses: some in the temporal lobes and some in the frontal lobes.

Source analysis of the late auditory evoked potentials suggests that all major generators for these responses are in the temporal lobes. The initial source analysis (Scherg and von Cramon, 1985, 1986) used a coronal chain of electrodes and demonstrated two dipole sources in each temporal lobe. A vertically oriented source accounted for the N1b wave recorded from the vertex and a laterally oriented source accounted for the N1c wave recorded from lateral scalp electrodes. However, these recordings were limited to a coronal chain of electrodes and could not properly evaluate possible contributions from the frontal regions. Scherg, Vajsar and Picton (1989) analyzed auditory evoked potentials recorded from 14 scalp electrodes and confirmed that the main sources for the scalp recordings were located in the temporal lobes. Figures 45 and 46 illustrate these source analyses using data from a subset of the original recordings (Scherg and Picton, 1991).

Figure 45 shows how the recordings can be analyzed using regional sources. Two regional sources were placed, one in each temporal region. The locations of the sources were then iteratively changed to minimize the residual variance between the modeled response and the actual scalp-recorded waveforms. The resultant source waveforms show symmetrical activation of the temporal lobes. The vertically oriented sources contribute to the N1b wave, the laterally oriented sources contribute to the lateral N1c wave and the anteriorly directed sources appear to be contributing to both N1b and the sustained potential. There is some similarity between the source waveforms for the anteriorly and vertically oriented sources. Placing a 'probe' regional source in the frontal regions did not pick up much additional source activity although there were some tiny waves present in the region of the N1-P2 complex. Trying to fit the probe source in the frontal lobe resulted in it moving down and back into the temporal lobes. The activity being picked up by this probe therefore indicates some inadequacy of the fitting of the temporal regional source rather than any additional source activity in the frontal lobe.

The next step of the source analysis released the three sources within each temporal lobe from their orthogonal constraints. Using the 'variance' criterion, the vertical and laterally oriented sources were fit using different regions of time: 50–250 ms for the vertically oriented source and 100–200 ms for the laterally
Fig. 45. Regional source imaging This figure illustrates the use of regional sources in the analysis of the late auditory evoked potentials. Two regional sources (thick lines) were placed in each hemisphere and the locations of these regional sources were fit using a simple residual variance criterion. The regional sources locate themselves reasonably symmetrically at the upper part of the temporal lobe in each hemisphere. Placing a third regional source (thin lines) in the frontal lobes shows only small waveforms at the same latencies as those picked up by the temporal lobe sources and does not significantly change the other source waveforms. Attempting to fit the frontal regional source causes it to move back and down into the temporal lobe. The tiny deflections in the source waveforms in the frontal regional source therefore probably do not indicate source activity in the frontal lobes. Rather they indicate that the temporal lobe sources can probably be adjusted to fit the data better.

oriented source. The anteriorly directed sources were adjusted to fit the sustained potential occurring later in the waveform (350–400 ms) without any constraints on their duration. This procedure ultimately led to the final source analysis given in Fig. 46. Vertically oriented sources in the temporal lobes are the main generators for the vertex recorded N1b component. Laterally oriented sources at the edge of the Sylvian fissure appear to be the major generators for the N1c component recorded from lateral electrodes. The sustained potential has a duration that begins with the N1b wave and lasts through the stimulus. Its generator is located on the supratemporal plane somewhat more anterior in location and somewhat more anteriorly oriented than the N1b generator.

What do these results indicate about possible frontal lobe sources for the auditory evoked potentials? It is possible that these are only active when the interstimulus intervals are long (Nääätänen and Picton, 1987). Since the data used in the source analyses were recorded with short interstimulus intervals the frontal generators may have been relatively inactive. It is also possible that generators in the frontal lobe contributed to the recordings but that, because only 14 scalp electrodes were used, it was difficult for the source analysis to distinguish a small frontal source from a larger underlying temporal source. Recent recordings with 32 channels have suggested that there may indeed be some small frontal generators of the auditory vertex potential (Giard, Perrin, Echallier et al., 1994).

**Source analysis of the Bereitschaftspotential**

The Bereitschaftspotential is a slowly developing negative wave that occurs prior to the performance of a simple motor act. Since this negative wave is maximally recorded from the regions near the vertex (Deecke, Scheid and Kornhuber, 1969; Shibasaki, Barrett, Halliday et al., 1980), it may be generated in the supplementary motor area located on the medial surface of the frontal lobe (Deecke and Kornhuber, 1978). Just before the initiation of the movement there
Fig. 46. Sources for the auditory evoked potential. This figure shows the final source analysis for the late auditory evoked potentials. Three sources in each temporal lobe explain most of the variance in the data. Vertically oriented sources (1 and 2) contribute mainly to the scalp N1b wave. Laterally oriented sources (3 and 4) contribute mainly to the N1c wave recorded in the temporal regions. The sustained potential (SP) gets its major contribution from sources 5 and 6 which are oriented upward and anteriorly and are located somewhat in front of the N1b generator. The sustained potential generator is active throughout the stimulus and contributes in part to the scalp-recorded N1b wave as well as to the scalp-recorded SP. The residual variance (RV) is very low during the ERP, but is high before and after the ERP when the procedure is modelling residual EEG noise.

is an enhancement of the negativity that is maximally recorded from the regions over the motor cortex specific to the movement. It is therefore possible that initiation of the movement occurs in the supplementary motor area and leads finally to activation of the movement through the motor cortex. The large potentials recorded from the central regions following the movement probably represent afferent input from the moving limb.

Bötzel, Plendl, Paulus et al. (1993) have recently performed a source analysis of the Bereitschaftspotential recorded using 32 scalp electrodes (Figs. 47–49). An initial step in the analysis was to test the hypothesis that the supplementary motor area was a major source for the scalp-recorded Bereitschaftspotential. A dipole source was therefore located in the region of the supplementary motor area and its orientation adjusted to fit the scalp recordings. This source was unable to model the scalp-recorded waveforms very well. If two sources were used and their locations freed, they moved to the lateral rather than medial frontal cortices. These two sources illustrated on the right of Fig. 48 modelled the scalp recordings much more effectively than the single source. The sources are quite

Fig. 47. Scalp distribution of the Bereitschaftspotential. This figure shows the scalp distribution of both potential and current source density for different latencies in the recording of the Bereitschaftspotential associated with extension of the right middle finger. The latencies show the beginning of the Bereitschaftspotential, the motor potential and the reafferent somatosensory evoked potential. These data derive from Bötzel et al., 1993.
Fig. 48. Sources for the Bereitschaftspotential: hypothesis-testing. This figure represents the results of testing the hypothesis that the supplementary motor area on the medial surface of the frontal lobe is a major generator for the Bereitschaftspotential associated with extension of the left middle finger. Placing a single dipole in this region and fitting its location and orientation results in the source waveforms and residual variance shown on the left. On the right are shown what happens when two dipoles are used to fit the recorded data. These place themselves symmetrically in the two hemispheres some distance away from the supplementary motor area. The fit for this two-dipole solution is much better than the fit for the single dipole solution.

deep within the frontal lobes. This probably results from the synchronous activation of a number of pre-motor areas in the frontal lobes, located both on the surface of the gyri and within the sulci (particularly the central sulcus). Further sources can be fit to explain the potentials recorded immediately before and after the movement (Fig. 49). A response to the movement can be generated in the post-central cortex and there is some suggestion of activity in the precentral gyrus that might explain the pre-motion positivity and some parts of the post-motion recording.

Fig. 49. Sources for the Bereitschaftspotential This figure presents two further solutions for the source analysis in Fig. 48. On the left, a third dipole has been added to explain the potentials following the movement. This locates itself in the region of the somatosensory cortex. The fit is much better than the two-dipole solution shown in the previous figure, particularly in the interval after the movement. On the right is shown the effects of adding a fourth dipole to explain the premotion positivity. This dipole suggests a tiny premotion positivity in the precentral gyrus. However, this 4-dipole solution does not explain the recorded data significantly better than the 3-dipole solution and the 3-dipole solution may be taken as final.
What then is the role of a supplementary motor area in the initiation of movement? It is possible that there is not much need for the supplementary motor area to be active in the simple automatic movements that are being performed during the recording of the Bereitschaftspotential. The supplementary motor area may only be necessary if the movement is complex or requires conscious control. Another possibility is that the supplementary motor area is active bilaterally even for a unilateral movement. Bilateral activation would generate equivalent dipoles in the medial frontal cortex of both frontal lobes. The fields from such dipoles would overlap and, since they would be in opposite directions, these fields could cancel each other out to a large extent and not be detected in the scalp recordings. The effects of such partial cancellation have been demonstrated by simulations (Scherg and Berg, 1991). There is some suggestion that cancellation may indeed occur since patients who have lesions of one hemisphere show larger Bereitschaftspotentials (Deecke, Lang, Heller et al., 1987).

Uses of source analysis

Determining the locations and time courses of the sources for scalp-recorded fields and using this information to understand human brain function is the primary role of source analysis. Source analysis, however, is not a simple procedure. It requires a fair knowledge of all of the constraining circumstances. It also requires some creativity in adjusting sources both to fit the recorded waveforms and to make sense in terms of their time course. Even the technique of regional source analysis requires final human intervention to determine the patterns of activity in individual dipole sources that are represented on the three orthogonal axes of the regional source. Presently, fully automated procedures for source analysis are not available although they are theoretically possible on the basis of regional source analysis or on the basis of iterative spatio-temporal minimum-norm methods converging to a multiple source solution. Furthermore, the deviation of the approximate head models from real individual heads requires substantial human intervention to match the information concerning source locations and orientations with the real underlying anatomy.

An important second use of source analysis is to test hypotheses about human brain function. If one believes that certain regions of the brain are active during certain types of information processing and that these activities are contributing to the ERP, one can test this hypothesis by placing source dipoles in these areas of the brain.

Source analysis can be used quite effectively in evaluating patients with abnormal ERPs. One can set up a normal template for the sources of a scalp-recorded ERP by analyzing the mean data from a group of normal subjects. This template would consist of a set of source parameters (locations and orientations). One can then evaluate the ERPs recorded from normal subjects using these template sources. These evaluations will provide a set of normal source waveforms for each source. Confidence limits can be calculated for these source waveforms. One can then evaluate the ERPs from a patient using the template sources and determine whether the source waveforms in the patient differ significantly from the source waveforms of normal subjects (Scherg and von Cramon, 1986, 1990).

A fourth use of source analysis is to set up ‘source filters’. If one knows that an area of the brain is active during the recording of an average ERP, one might be able to use the source parameters to analyze single-trial waveforms. In this way, one might be able to monitor the timing and the magnitude of activity at the source on a single trial. In effect, this is the idea of the vector filter (Gratton et al., 1989) that made concrete in terms of a source within the brain rather than abstract in terms of the scalp distribution of the recorded potentials. This ‘source filter’ technique can also be used to evaluate activity in different regions of the brain during the spontaneous EEG. The underlying principle of such filters is the linear spatial deconvolution or deblurring of the scalp EEG by means of a ‘software lens’ (Freeman, 1980) or ‘FOCUS’ (Scherg and Ebersole, 1994) into the brain that yields an approximate image of the compound electrical activities of different brain regions. Such images can be obtained by fixed multiple source configurations and used for a
fast deconvolution of digital EEG recordings (Scherg and Ebersole, 1994).

**Source approaches to compensating for ocular artifacts**

A final use of source analysis is to compensate for non-cerebral artifacts. Artifactual contaminants of the ERP records have a specific scalp distribution that depends upon the location of the sources that generate them. These sources can be modelled in the same way as the intracerebral ERP generators and used to remove the effects of the artifactual potentials on the recordings. We shall illustrate this by describing how source analysis can compensate for ocular artifacts.

Electrical potentials generated by the eyes are often a serious problem when recording ERPs (Hillyard and Galambos, 1970). In ERP recordings, ocular artifacts may distort the average waveform significantly if they are specifically evoked by the stimuli. Even when they are not time-locked to the stimuli, they may be difficult to remove by averaging because of their large amplitude. The major ocular potentials occur with movements of the eyelids during blinks and of the eyes during eye-movements. These ocular potentials derive from the sustained electrical potential difference between the cornea and the fundus of the eye. This causes an ocular dipole with the cornea positive and the fundus negative.

When the eyes move, the regions of the head towards which the cornea moves become more positive and the regions of the head towards which the negatively charged fundus moves become negative. The resting corneofundal dipoles point approximately in the direction of gaze. The changes in the electrical fields generated by rotation of these dipoles can be represented by ‘differential’ dipoles which equal the vector difference between the starting and ending positions of the ocular equivalent dipoles.

Blink potentials are generated simply by the movement of the eyelid over the cornea. The eyelid acts as a sliding electrode connecting the frontal regions of the scalp to the positively charged cornea (Matsuo et al., 1975). As the eyelid slides over the cornea, the flow of current through the lid increases without any change in the orientation of the corneofundal dipoles. The resultant dipole is oriented forward and a little upward. Both blinks and upward eye movements generate a positive wave at the forehead. However, since their dipoles are differently oriented, the potentials associated with vertical eye movements propagate further back on the scalp than blink potentials (Hillyard and Galambos, 1970).

The electrical potentials deriving from ocular movements can be monitored by recording the electro-oculogram (EOG) from electrodes placed near the eyes. Since the eyes move in two dimensions, it is necessary to record both vertical and horizontal EOG channels. The field changes during blinks can be estimated in the vertical EOG or can be evaluated using a third dimension for the EOG recordings (Elbert et al., 1985).

There are several ways to reduce the ocular artifact in a recording. The most obvious is to ask the subject to try not to blink or move the eyes during the recording. Periods wherein the subject blinks or moves the eyes are eliminated from the analysis. However, there are several problems with this approach. First, it may be difficulty or even impossible for some subjects (children, psychiatric patients) not to move their eyes. Second, some ocular potentials may be too small to be recognized and yet sufficiently time-locked to significantly distort averaged data (Picton, 1987). Third, periods containing frequent blinks may be associated with different functional cerebral states from periods with infrequent blinks (Stern, Walrath and Goldstein, 1984). A related problem is that subjects who pay attention to not blinking or moving their eyes may not be able to pay as much attention to the experimental task as subjects who ignore their eyes (Verleger, 1991). Fourth, eye movements may be integral part of the experimental paradigm, for example in experimental designs that use a ‘reading’ condition.

Several techniques have been proposed to remove ocular artifacts after they have occurred. The common assumption of these techniques is that the EEG signal recorded at the scalp is composed of a ‘true’ EEG signal plus an ocular artifact. The ocular artifact recorded at each electrode site depends upon both the amount of ocular activity occurring and the position of
the recording electrode in relation to the eyes. The ocular activity that reaches each scalp location will be some fraction ('propagation' or 'compensation' factor) of the ocular activity recorded near the eyes.

Propagation factors are evaluated by performing a linear regression between the digitized data points of the EOG channels and the data points recorded at each electrode site. The propagation factors are the slopes of the best-fit straight lines of the resulting regression equations (Hillyard and Galambos, 1970). The calculation of propagation factors is illustrated in Figs. 50 and 51. Because the fields spread differently across the scalp, separate propagation factors should be calculated for eye movements and for blinks. Blinks can be identified by the rate of change in the potential recorded on a vertical EOG channel (Gratton, Coles and Donchin, 1983). They are more easily identified using a three-dimensional EOG montage (Elbert et al., 1985). Propagation factors can be calculated from calibration trials obtained prior to the experiment or from the actual eye movements recorded during the experiment.

The use of the EOG as an estimate of ocular activity is problematic. What is really recorded at the EOG channels is a combination of ocular potentials and EEG activity (generated mainly in the frontal regions of the brain). This leads to at least two problems. First, the linear regression procedures may give rise to incorrect propagation factors since the brain activity has a different scalp distribution from ocular activity. This problem can be reduced by using averaged blinks or averaged eye movements to calculate the regression factors and by filtering the data to attenuate the EEG activity (Lins, Picton, Berg et al., 1993a). A second and more difficult problem, however, occurs during the subsequent subtraction procedures. This will partially subtract out the frontal EEG activity as well as the EOG (Berg and Scherg, 1991a,b). There is no way to prevent this.

In addition, the EOG can often be a complex mixture of different activities. For example, during an upward eye movement there is a 'rider artifact' at the beginning of the movement. This is probably caused by the eye moving somewhat more rapidly than the eyelid and thereby slipping under the eyelid at the initial part of the movement. Because of this blink-like process, the scalp distribution of the potentials associated with the initial part of the eye movement differs from the scalp distribution of those associated with the later part of the eye movement (Lins et al., 1993a,b).
Source analysis might help to overcome these problems since it can postulate separate sources for both the EEG and the EOG and since it can distinguish between different overlapping generators for the EOG artifact. The EOG activity can be analyzed using source dipoles to model the different ocular potentials (Berg and Scherg, 1991b). Frontal EEG generators or other generators causing potentials recorded over the frontal scalp can be modelled simultaneously. Figure 52 shows the source analysis of the potentials recorded during blinks and eye movements. Some sources are associated with the rotation of the eyeballs and others with the blinks and blink-like rider artifacts at the beginning of eye movements.

However, the use of dipoles to model the EOG activity also poses problems. The geometry of the skull around the eyes is quite different from the normal spherical head model used to evaluate the intracerebral sources and the ocular dipoles are located outside rather than within the skull. These problems can lead to inaccuracies in the location of the dipoles and can make it impossible to predict accurately how much they contribute to the different electrode locations.

Berg and Scherg (1991a, 1994a) have recently proposed a technique for removing ocular artifacts which overcomes the head model problem. This technique uses ‘ocular source components’ defined by principal components analysis or linear regression within a multiple source analysis of EOG and EEG. First, one records the potentials from the electrode montage that will be used in the experiment while the subject performs standard eye movements and blinks. A PCA of the variance in these ‘calibration signals’ (Fig. 52) will give components that represent blinks, horizontal eye movements and vertical eye movements (or some linear combination thereof). The spatial distribution of these source components, the ‘source vectors’ or propagation factors, can then be used in parallel with the forward weighting coefficients of the EEG source

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**Fig. 52.** Source dipoles and source components for ocular potentials. The left side of this figure shows the source analysis of a set of ocular calibration waveforms. These calibration waveforms spliced together the average waveforms (from eight different subjects) for blinks, up-saccades, down-saccades, right-saccades and left-saccades. Source dipoles were then set up to model the recorded data. Source dipoles 1 and 2 were used to explain the upward eye movements. Source dipoles 3 and 4 were used to explain the lateral eye movements. Source dipoles 5 and 6 were determined by fitting to the blink portion of the calibration waveforms. When all six dipoles are used together these blink dipoles pick up some of the activity in the upward and lateral eye movements. On the right of the figure are shown the source components. These were determined by principal component analysis (PCA) of the calibration waveforms. Three separate PCAs were performed. The first one evaluated the vertical eye movements and yielded components 1 and 4. The second was based on the lateral eye movements and yielded components 2 and 5. The final PCA was based upon the blinks and yielded component 3. Since these components have been specifically selected to represent different kinds of eye movements, one can evaluate simultaneous activities in the different source components. During a blink, for example, there is a small downward deflection in the first component representing vertical eye movements. At the beginning of upward, left and right saccades there are small deflections on the blink component (3) representing ‘rider-artifact’. Data derived from Lins et al. (1993b).
dipoles in a multiple source model for the scalp recorded electrical activity (Lins et al., 1993b).

Evaluating EOG artifacts using the 'source components' approach has three major advantages over the use of a dipole model for the EOG. First, it is more accurate since the calibration procedure implicitly performs an experimental measurement of the real head model with respect to the EOG sources. Hence, it does not force the EOG patterns into idealized dipolar topographies and model misspecification errors are substantially reduced. Second, a much better suppression of the EOG artifacts is achieved in the corrected EEG scalp waveforms, particularly if large EOG artifacts are being removed (Fig. 53). Third, fewer components can be used to represent a comparable amount of the EOG activity.

We therefore recommend that source components be used for removing the EOG artifacts from ERP recordings. Although these components can be calculated from the eye movements during an experiment, we suggest a separate ocular calibration recording. At this time recordings are made using the same montage as will be used in the experiment. The head position and the direction of resting gaze should be the same as in the experiment. The optimum number of electrodes near the eyes is not known. The recording montage should probably include at least seven electrodes near the eyes. Four of these electrodes could be at routine EEG locations: Fp1, Fp2, F7, F8. Electrodes on both cheeks below the eyes and an electrode at the nasion would make up the minimum complement.

During the ocular calibration, the subject is asked to blink for a brief period and then to make saccades separately in the up, down, left and right directions. The size of the saccades should be between 15 and 20° to ensure that the ocular potentials contribute to the recordings a greater part of the variance than the EEG. If the up-down and left-right saccades are combined, the size of the saccades should be approximately 30° (±15°). If possible, multiple recordings from the blinks and from each of the saccades should be averaged together to give average waveforms. The recordings should then be combined in some way to form an ocular data set.
Source components are calculated on this ocular data set. The optimum number of components is not known. We have found that five components is sufficient for excellent compensation and that three components provide adequate compensation. One should probably choose those components showing waveforms related to the eye movements and located near the eyes. The source components can be separately calculated for each of the movements or types of movements (and combined later into a set of weighting functions), or calculated together from a combined data set. Ultimately, the set of weighting functions is stored for use in analyzing or correcting the experimental data.

Concluding comments

General principles

We have tried to suggest in this chapter the power that is presently available for ERP research. It is certainly possible to use ERPs to discover something about how the human brain works when it perceives stimuli, makes decisions and controls behavior. ERP techniques can provide information about the different regions of the brain that are active during these processes, can monitor the time course of these activities, and may even suggest what might be going on in these regions. We can observe the what, when and where of human brain function, albeit the picture is somewhat fuzzy.

The techniques of recording ERPs are complex. Complex techniques can easily lead to errors if they are used without understanding. We have tried to present in this chapter the general principles of the techniques and to outline the cautions that must be obeyed in using them.

One major general principle of ERP recording is to monitor the recordings at all levels of the analysis. Do not simply plug the electrodes into the subject and read the measurements from the computer. You will feel much more comfortable about interpreting the averaged ERP if you have looked at the unaveraged EEG recordings. Many of the artifacts that can subtly alter the average recording are quite obvious in the EEG recordings. Similarly, you will feel much more confident about the source analysis if you have evaluated the spatiotemporal maps of the recorded activity prior to analysis.

A second major principle is never to consider the ERP findings in isolation. The human brain can only be understood through the converging viewpoints of many different sciences. Other brain imaging techniques can provide constraints for ERP interpretation. Basic neuroscience research in animals can demonstrate the connectivity and the processing patterns of the neural tissues that generate ERPs. Psychological theory can provide ERP research with both paradigms for evaluation and models for testing.

Any final interpretation of ERP data must be submitted to the test of 'making sense'. Does the interpretation fit with data recorded independently by other techniques? Can its predictions be confirmed by further experimentation? Does it explain something that we did not previously understand? These are the three questions that determine whether the findings make sense or not.

Future of ERP technology

What will happen to ERP technology over the next few years? In recent years digital signal processing has moved into 'real time'. More and more processing is being performed as data are being recorded rather than after the fact. The power of digital signal processing will continue to increase. Filtering will become more sophisticated. Adaptive filtering (Aunon and Keirn, 1991) that alters the filtering algorithms on the basis of characteristics of the incoming data will become more and more widely used.

Digital signal processing should allow single-trial analysis to become both possible and powerful. The trial-to-trial variation of an ERP waveform will probably tell us a great deal about human brain function. Single-trial analysis will benefit from the use of spatial as well as temporal data. One suggestion that we have made in this chapter is to use source filtering to monitor the activity of different brain regions.

Brain electric source analysis will become more and more closely linked to other methods of brain
imaging. MRI images can be used to localize where exactly in the brain source-dipoles are located after source analysis (Hillyard, 1993). These anatomical images may also be used to adjust the source analysis parameters to allow for more accurate localization (Buchner, Fuchs, Wischmann et al., 1994). Functional MRI or PET images can show regions of the brain that are active during certain tasks and these regions can then be used to constrain the locations of sources in the electrical source analysis. The electrical analysis might then demonstrate the time course of activity in each cerebral region. This combined analysis will have to proceed cautiously since there may be metabolically active regions of the brain which do not show ERP activity, either because the active cells do not generate open fields or because the activity is not time-locked to the stimulus or other event used to synchronize the ERP analysis. Similarly, sources of ERP activity may not show up on the PET analysis, perhaps because they are only active very briefly in relation to each event and this does not show up as a significant change in the overall metabolic activity.

At present, source analysis is based upon rather simplistic models of the human head. More sophisticated models (Meijs, Bosch, Peters et al., 1987; Peters and de Munck, 1990) and finite-element models (Yan, Nunez and Hart, 1991) derived from magnetic resonance images of the head will become available. The calculations for source analysis using finite-element models are very time-consuming. Techniques will be developed, however, to improve the efficiency of such calculations, and we suggest that MRI will be used not only to provide a map upon which to place the sources once they are determined, but also as a means to set up the head model whereby the source are calculated.

Further improvements might be possible if the source analysis were based on the covariance matrices of single sweeps in the frequency domain (Valdés, Bosch, Grave et al., 1993). This might overcome the problem of time jitter in the ERP which can lead to severe cancellation of the signal in the average. At the same time, it might provide a better separation and definition of the background EEG and a statistical basis for assessing the reliability of the source parameters using (for example) a maximum likelihood test.

Our present view of the component structure of the ERP waveforms has two distinct aspects. On the one hand we have looked at the components defined on the basis of the experimental manipulations, with each component representing 'a source of controlled, observable variability' (Donchin et al., 1978). Principal component analysis appears to be a reasonable approach to these components. On the other hand, we have looked at components defined on the basis of their generators within the brain. Source analysis is the way to evaluate these components. We need to combine these two approaches. A simple technique that considers both the experimental variance and the scalp distribution of the recordings is a source analysis of difference waveforms (Scherg et al., 1989). Another approach would be to perform source analysis on the recomposed waveforms for PCA components. Optimally, we should evolve a more formal model to combine the techniques.

An important extension of the techniques of source analysis would therefore be to incorporate experimental and subject variance within the model. Möcks (1988) has suggested using a model of identical source components for all subjects apart from an individual amplitude factor, which may be different for each component and subject. Turetsky, Raz and Fein (1990) have extended the spatiotemporal dipole model to include subjects and experimental conditions by assuming identical source parameters across subjects, while allowing their source components to be different in overall amplitude, latency and time course. However, neither the restriction to exponentially decaying sinusoidal source waveforms (Turetsky) nor the invariance in latency (Möcks) are compatible with experimental evidence on the interindividual variability (in both amplitude and latency) of cortical macroscopic activities (Scherg and von Cramon, 1986, 1990). Therefore, parameters describing the changes of the source waveforms among the different subjects and among the different experimental conditions ought to be included in the spatiotemporal model along with parameters accounting for the individual variability of
source locations and orientations (Scherg and Picton, 1991).

Ultimately we would like to define an ERP component as the electrical representation of a particular type of information processing within a particular region of the brain. The goal of monitoring the activity of the human brain as it performs a task by means of a particular set of such components should be within our reach within the next few years.

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