Recording and Analyzing High-Density Event-Related Potentials With Infants Using the Geodesic Sensor Net

Mark H. Johnson

Center for Brain and Cognitive Development
School of Psychology
Birkbeck College, London

Michelle de Haan

Center for Brain and Cognitive Development
School of Psychology
Birkbeck College, London
Institute of Child Health
University College, London

Andrew Oliver

Center for Brain and Cognitive Development
School of Psychology
Birkbeck College, London

Warwick Smith

Center for Brain and Cognitive Development
School of Psychology
Birkbeck College, London
Department of Phonetics
University College, London

Haralambos Hatzakis, Leslie A. Tucker, and Gergely Csibra

Center for Brain and Cognitive Development
School of Psychology
Birkbeck College, London

This article provides an overview of the use of the Geodesic sensor net system for high-density event-related potential (ERP) recording in infants. Some advantages and
disadvantages of the system, as applied to infants, are discussed. First, we illustrate that high-density data can be recorded from infants at comparable quality to that observed with conventional (low density) ERP methods. Second, we discuss ways to utilize the greater spatial information available by applying source separation and localization procedures. In particular, we focus on the application of one recent source separation method, Independent Component Analysis (ICA). Finally, we show that source localization can be applied to infant high-density data, although this entails adopting a number of assumptions that remain to be verified. In the future, with improved source separation algorithms, we suggest that single-trial or single-subject analyses may become feasible.

In recent years, there has been burgeoning interest in the relationship between postnatal brain development and cognitive function (e.g. Johnson, 1997; Nelson & Bloom, 1997). Unfortunately, however, the methods available for studying the relationship in human infants remain relatively poor. Most functional brain imaging methods available for studying adults cannot be applied to healthy infants for a variety of reasons (e.g., excessive noise, sensitivity to movement, and unknown risk factors for the developing brain). ERPs have been used for several decades to study neural correlates of infant perception and cognition, but they offer relatively poor scalp-spatial localization. This poor sampling of voltage change at the scalp surface compounds well-known difficulties in determining the underlying brain sources and can cause problems of spatial aliasing that lead to distortions in measurement of the spatial distribution of ERPs (e.g., see Srinivasan, Tucker, & Murias, 1998). Recently, a new method, the Geodesic Sensor Net (GSN), has been developed that allows a large number of electrodes to be applied relatively quickly to the scalp surface (Tucker, 1993). The GSN consists of an array of sensors (currently 64 for infant nets and 128 for adult nets, plus an additional vertex reference electrode in each net) arranged in an elastic tension structure, which can be relatively quickly and easily slipped on and off the participant’s head. The arrangement of the electrodes in relation to the more commonly used international 10–20 system is shown in Figure 1 for adults and in Figure 2 for infants.

To provide good localization of potential underlying dipoles, the ERP recording system needs to meet two requirements: a large number of electrodes on the scalp and an even distribution of electrodes over the head surface. With regard to the first requirement, recent studies suggest that the optimal number of electrodes on an adult head is about 256, providing less then 2-cm resolution (Junghöfer, Elbert, Leiderer, Berg, & Rockstroh, 1997). On the head of a 6-month-old infant, similar resolution can be achieved with 128 sensors, and even the 64-sensor system described in this article can yield a sampling density of less than 3 cm. With regard to the second requirement, the GSN system was specifically designed to provide evenly distributed sensors over a wide variety of head shapes (Tucker 1993). Without even sampling, and without electrodes below the canthomeatal
FIGURE 1  This figure shows the arrangement of electrodes in the adult GSN. The hexagons represent the 128 electrodes; the gray circles represent the electrodes used in the international 10–20 system. Cz is the vertex reference electrode (electrode 129).

FIGURE 2  This figure shows the arrangement of the GSN for the infant net in a similar format to that of Figure 1.
line, the subsequent estimation of brain electric sources can be distorted (Junghöfer, Elbert, Tucker, & Braun, 1999).

The GSN involves a geodesic tension structure made from elasticated webbing in which Ag/AgCl sensors are encased in a saline electrolyte (Tucker, 1993). The geodesic tension conforms the geometry of a sphere to the head shapes of individual participants. The GSN is made in different sizes and designs to fit the head sizes of different age groups (for further information see http://www.egi.com). Due to its high-operating impedance level, the GSN is only recommended for use with amplifiers that allow high-input impedance, such as the purpose-built EGI Net Amps EEG amplifier (see http://www.egi.com). The high-operating impedance of the EGI system merits further comment. Although lower electrode impedances can be achieved through scalp abrasion, EGI recommends that this is both unnecessary and unsafe. It is unsafe because, even with regular use of disinfectants and sterilization, some risk of infection resulting from scalp abrasion remains (Ferree et al., 2001; Putnam, Johnson, & Roth, 1992). It is unnecessary because, with the 200 megohm input impedance of EGI amplifiers, the variation in electrode impedance between 5 kΩ and 50 kΩ is negligible. Picton et al. (2000) recommend that for an amplifier to record accurately, the electrode impedance should be less than the input impedance of the amplifier by a factor of at least 100, a criterion that is easily met by the EGI system.

It is readily apparent that the GSN offers a number of advantages over conventional EEG technology for use with infants. First, the net takes only a few minutes to apply (see below). Second, because the application is quick and no abrasion of the scalp is required, most infants under 1 year readily accept the net without distress, especially when one experimenter attracts the infant’s attention while another applies the net. Specifically, in our experience, less than 10% of young infants are distressed when the net is installed. Third, the ease of application and comfort means that infants can often tolerate longer test sessions than with conventional methods, thus allowing more trials to be conducted. Finally, because the net is merely soaked in the electrolyte solution beforehand, there are no gels or pastes left to wash from the infant’s head afterwards, which encourages parents to make repeat visits.

In our experience, using the GSN with infants also presents challenges. Due to its high impedance design, and the fact that the electrodes are not fixed rigidly to the scalp, movement artifacts are as common as in the Electrocap or other cap electrode methods. (Note that collodin electrodes, such as those used clinically, are more resistant to movement artifacts). Due to increased mobility, this can make testing children over the age of 12 months more difficult. At present, there is no way to restrain movement of the head without disturbing the electrodes and/or distressing infants. Second, in our experience, older infants (above 12 months) commonly attempt to grasp the GSN, which causes displacement of electrodes, as well as possible damage.

Despite these challenges, there is currently no other feasible method to allow high-density recording in young infants, and several studies have already been
conducted successfully with this method (e.g., Dehaene-Lambertz & Dehaene, 1994; Csibra, Tucker, & Johnson, 1998, in press; de Haan, Oliver, & Johnson, 1998, submitted; Carver et al., 1999). In this article, we aim to (a) provide an overview of the use of the GSN system for high-density ERP recording in infants, (b) identify advantages and disadvantages of the system as applied to infants, (c) illustrate that high-density data can be recorded from infants at comparable quality to that observed with conventional (low-density) ERP methods, (4) discuss ways to utilize the greater spatial information available by applying source separation and localization procedures, (5) show that source localization can be applied to infant high-density data, and (6) suggest that single-trial or single-subject analyses may become feasible in the near future. Although we focus specifically on infants, many of the issues discussed are also relevant to high-density ERP recording in older children, clinical populations, and adults.

INSTALLING THE GSN WITH INFANTS

In our experience, the net is most easily and quickly applied if the infant sits on the parent’s lap and there are three experimenters present. One experimenter sits in front of the infant and entertains him or her by talking, playing with toys that make noise (e.g., toy phones that ring or books with buttons playing recorded noises), or blowing bubbles to distract the infant’s attention from the procedure of applying the net. A second experimenter measures the infant’s head circumference at the level of the brow ridge to determine the appropriate size of net to use. This experimenter also locates the vertex position by measuring the distance midway between the nasion and inion and between preauricular points; this position is marked with a grease pencil to provide a marker for correct placement of the net. These measurements are taken from behind the infant as unobtrusively as possible to avoid possible distress. The net is then soaked in warm electrolyte (salt water) for 1 min and placed on a towel to soak up any excess electrolyte solution. It is important to blot excess solution from the net in this way so that it does not accidentally drip into the infant’s face and eyes when the net is applied. Current EGI infant nets have electrodes that extend below the eyes. However, these electrodes are sometimes removed so that there is no danger of the sponge electrodes coming into contact with the eyes during installation. If vertical EOG is required, two additional separate electrodes can be applied below the eyes. In our laboratory, it is standard practice to videotape the infant’s eye throughout the experiment and to subsequently analyze the tape frame-by-frame for eye movements. This can be used as an initial step for excluding trials.

The third experimenter holds the net-to-amplifier connector leads so that the net hangs freely for the second experimenter to place his or her fingers into the outside edges of the lowest band of elastic (in an even and outstretched manner) at the sides of the net. The net is then flipped over so that it hangs from the fingers with the inside facing the experimenter, who then checks for any inverted electrodes or
tangles and adjusts the hold on the net as needed. The net is then flipped back over so that the sponges are facing down again. Only when the net is ready to place on the infant’s head, does the experimenter move in front of the infant. The net is placed on the infant’s head with a gentle rocking motion, while the third experimenter guides the positioning of the net by leading the vertex electrode to the marked vertex location and by ensuring that the ear electrodes are aligned with the preauricular points. The chinstrap is then adjusted under the infant’s chin to keep the net in position. As most young infants do not have much hair, the contact of electrodes is generally good on application. If the infant does have hair, the electrodes are gently wiggled to make better contact with the scalp. The whole process of preparing and applying the net takes about 5 min (not including time to check impedances), with the actual placing of the net taking approximately 30 s.

During the experimental session, it is possible that some slippage of the net can occur due to infant movement, particularly on the forehead. For this reason, we recommend videotaping the infant’s head throughout the session so that trials containing any such slippage or other sources of noise (e.g., sneezing and yawning) can be identified later. Slippage can be minimized by having a variety of sizes of infant net available and ensuring that the correct size is installed.

COMPARATIVE DATA

For the purpose of comparison, we present illustrative data collected under similar conditions from a conventional EEG/ERP system and from the GSN system. The experiment with the conventional ERP system was conducted at the University of Minnesota, as part of a doctoral dissertation (de Haan, 1996; see also Nelson, 1994, on the application of conventional ERP recording to human infants). The experiment conducted with the GSN system was carried out at the MRC Cognitive Development Unit in London and has been reported elsewhere (de Haan et al., in press).

For the GSN system, the participants were seventeen 6-month-old infants \((M = 187 \pm 3\) days, 8 boys) and 11 adults \((M = 32\) years \(\pm 10\) years, 6 men) with normal or corrected-to-normal vision. The testing session consisted of 194 trials. During each trial, 97 different female faces were shown, once upright and once inverted (i.e., 50/50 probability of upright/inverted). The order of presentation was random (with the constraint that the same orientation was not presented more than three times in a row), and each of the 97 faces was shown once before any was shown a second time in the other orientation. All adults viewed all 194 trials, whereas infants continued until they became too fussy/bored to continue. For the purpose of comparison, we present the grand average recordings from selected sensors in Figures 3a and 3b.

For the conventional ERP system, the participants were 22 six-month-old infants \((M = 185\) days, \(SD = 5\), 14 boys) and 8 adult females \((M = 31\) years, range = 21–45 years). The ERP test consisted of 90 trials, during which each of 15 different images
FIGURE 3a  Data from 6-month-old infants

FIGURE 3b  Data from adults
(5 different upright women’s faces, 5 different inverted women’s faces, and 5 different infant toys without faces) were shown six times each. There were two different sets of 15 stimuli; half of the participants (4 adults and 11 infants) saw each stimulus set. The order of presentation was random, with the constraint that each stimulus appeared equally often in each block of 30 trials. The ERPs recorded in response to the upright and inverted faces are shown in Figures 3a and 3b.

A detailed technical comparison between the two recording setups is provided in Table 1. In figures 3a and 3b, we present grand averages from the two age groups with the two recording methods. Considering that these results were obtained in different laboratories, with different detailed methods (such as the exact size and luminance of the stimuli), there are no apparent major differences between the recordings for adults. The GSN recording is of slightly higher amplitude and appears to contain more high-frequency detail. This latter difference could be due to the lower sampling rate and low pass filter setting (30 vs. 45 Hz) in the conventional recording and/or to the differing time constant of the amplifier.\(^1\) Another possibility is that the quality of data is improved due to infant state resulting from the quicker installation time with the GSN. Whatever the cause, it counteracts fears that high-electrode impedance will result in lower amplitude ERPs (see also our earlier discussion of impedance to see reasons for why this is unlikely to be an issue). Clearly, any such comparison between the two different recording systems has limitations. However, we are further encouraged that another comparison between the EGI system and conventional recording with 18-month-olds reported nearly identical results from the two methods (Carver et al., 1999).

**SOURCE SEPARATION**

High-density ERP recording raises challenges with regard to analyzing the complex spatiotemporal data that is produced. Conventional ERP analysis typically focuses on a small number of channels and identifies differences between trial types in certain time windows. Although this method can be used with high-density data, it does not take full advantage of spatial information present in the data. Informal inspection of spatial information can be achieved through viewing scalp-surface voltage maps and animations of these maps showing changes over time. Animations, in particular, can be useful for capturing large scale spatiotemporal events (see Curran, Tucker, Kutas, & Posner, 1993). More formal methods of analyses of spatiotemporal data usually involve source separation.

Electrical recordings made at the scalp may be interpreted as a mixture of the activity of a number of underlying generators in the brain. By analogy, if you used three microphones (instead of electrodes) in different places in a room in which two peo-

---

\(^1\) Although both recordings were made with the same hi-pass setting, amplifiers may differ in the hi-pass filter circuit, such that the attenuation of slow waves may differ between them.
ple were speaking simultaneously (instead of using neural generators), the problem
would be how to statistically separate out the voices of the two speakers from audio
tape, given that they are both recorded on all three microphones. Source separation
consists of identifying different generators in the brain on a statistical basis, where
each “source” is described in terms of a varying course of activity and a consistent
distribution across the scalp. In other words, a statistically independent source can be
represented as both a time-invariant scalp-surface map and a time course of the

<table>
<thead>
<tr>
<th>TABLE 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical Specifications of Event-Related Potential Recording</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>EGI System</th>
<th>Grass System</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Electrodes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metal</td>
<td>Silver–silver chloride</td>
<td>Silver–silver chloride</td>
</tr>
<tr>
<td>Array density</td>
<td>62 including 2 mastoids, 4 EOG</td>
<td>14 including 2 earlobes, 2 EOG</td>
</tr>
<tr>
<td>Application</td>
<td>Geodesic Sensor Net</td>
<td>Foam pads, EC2 cream, cloth headbands, earclips, adhesive EOG collars</td>
</tr>
<tr>
<td>Impedances</td>
<td>Operating impedance, 10–40 k</td>
<td>Average ~ 5 k measured before and after recordings</td>
</tr>
<tr>
<td><strong>Amplifiers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td>EGI net amps</td>
<td>Grass model 12A5</td>
</tr>
<tr>
<td>Gain</td>
<td>25,000 times for all</td>
<td>10,000 times for scalp, 5,000 times for EOG</td>
</tr>
<tr>
<td>Low-pass filter</td>
<td>45 Hz Bessel</td>
<td>30 Hz</td>
</tr>
<tr>
<td>High-pass filter</td>
<td>0.1 Hz Bessel</td>
<td>0.1 Hz</td>
</tr>
<tr>
<td>Notch filter</td>
<td>Not engaged</td>
<td>60 Hz</td>
</tr>
<tr>
<td><strong>Recordings</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sampling rate</td>
<td>250 Hz (every 4 msec)</td>
<td>100 Hz (every 10 msec)</td>
</tr>
<tr>
<td>Reference</td>
<td>Vertex</td>
<td>Vertex</td>
</tr>
<tr>
<td>Length</td>
<td>2,000 msec</td>
<td>1,600 msec</td>
</tr>
<tr>
<td></td>
<td>336 msec pre-event</td>
<td>100 msec pre-event</td>
</tr>
<tr>
<td></td>
<td>1,664 msec post-event</td>
<td>1,500 msec post-event</td>
</tr>
<tr>
<td><strong>Data reduction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rereferencing</td>
<td>Average mastoids</td>
<td>Average earlobes</td>
</tr>
<tr>
<td>EOG artifact rejection</td>
<td>Trials excluded if visual inspection revealed presence of blinks or eye movements</td>
<td>Trials excluded if EOG signal exceeded 200 v</td>
</tr>
<tr>
<td>EEG artifact rejection</td>
<td>Channels excluded if any sample exceeded A–D values, if any sensor was not making contact, or if there were any sharp, high-amplitude deflections</td>
<td>Channels excluded if EEG signal went beyond ± 100 v</td>
</tr>
<tr>
<td><strong>Trials in average</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upright</td>
<td>Infants: 27</td>
<td>Infants: 25</td>
</tr>
<tr>
<td></td>
<td>Adults: 68</td>
<td>Adults: 29</td>
</tr>
<tr>
<td>Inverted</td>
<td>Infants: 25</td>
<td>Infants: 25</td>
</tr>
<tr>
<td></td>
<td>Adults: 71</td>
<td>Adults: 29</td>
</tr>
</tbody>
</table>
“strength of expression” of that spatial map in accounting for the overall ERP at that point in time. It is important to note that source separation is potentially a different problem from that of localizing the individual generators of electrical activity within the brain (which will be discussed in the next section of the article). This is because a statistical source can produce a scalp map indicative of several temporally coactive neural generators (i.e., one or more regions showing exactly the same time course of activation during the trials under analysis).

One recently devised method of source separation is ICA (Bell & Sejnowski, 1995; Lee, Girolami, Bell, & Sejnowski, 2000). As with other such methods, when applied to ERP data, each component produced by ICA consists of a time series and a weight vector such that the “projection” of the time series through the weight vector reconstructs the activity of the source at the scalp. The sum of all projected components reconstructs the entire original signal. Thus, ICA “unmixes” the ERP data into a set of components that are assumed to reflect the activity of a collection of different brain sources. The extent to which ICA components validly represent the activity of different brain areas activated in a task or trial depends crucially on the assumptions underlying the method. As the assumptions made by ICA are important to the validity of the analysis method as a tool for decomposing the ERP, it is useful to briefly discuss them here (see also Makeig, Jung, Bell, Ghahremani, & Sejnowski, 1997).

• Linear summation — ICA, like spatial Principal Component Analysis (PCA), assumes that the ERP is a linear combination of the activity of the underlying sources.
• Spatial stability — ICA (again, like spatial PCA) assumes a constant mixing matrix, which is a valid assumption as long as the brain generators are spatially fixed and activation is not dynamically migrating. However, active brain regions can be distributed across the brain and need not necessarily be spatially localized to a small area.
• Temporal independence — ICA tries to find sources that are statistically independent in the time domain. This may be considered an extension of the more commonly applied method, PCA. However, PCA imposes the condition that the time courses of the components are not correlated in their second-order statistics, whereas ICA requires the absence of higher order, as well as second-order, correlations. In other words, PCA yields statistically independent components only if they are normally distributed, whereas ICA seeks independent components of any distribution.

Although the aforementioned assumptions are general to ICA, the following additional assumptions are often necessary for particular implementations of ICA, including those that we consider in this article.

• Sparse activity — It is assumed that the sources are active for short periods of time or that they have bursts of activity; PCA does not assume this.
• Identical distributions — It is assumed that the distribution functions of all the time series of the underlying sources are identical.

There are good reasons to believe that these assumptions approximate the properties of real brain potentials (see Makeig, et al., 1997, for a detailed discussion). To summarize, the assumptions underlying ICA entail the rapid and brief activation of spatially fixed brain regions. The method is likely to be less effective in situations where brain processing involves dynamic “waves” of activity and/or prolonged sustained periods of activation. In such cases, the dynamic wave of activity is likely to be chopped into a number of separate sources with different time profiles and scalp maps.

Applying ICA to high-density recordings introduces some extra challenges that relate mainly to the greater quantity of data involved. Specifically, it produces the same number of independent components as recording sensors, making it challenging to decide which of these components is of interest and which of them represent noise or artifacts. Another problem is ensuring appropriate ratios between the number of electrodes and the number of time points in the data used for analysis. ICA is a relatively new method and is being improved by the introduction of new algorithms, so some of the difficulties discussed here may be overcome in the near future. However, as we have shown, it is feasible to use ICA on high-density recordings from infants and adults, even with currently available algorithms.

An important potential benefit of ICA is that it could provide a method for examining both intersubject and intertrial variability. Specifically, we could potentially examine whether variability of brain electrical activity is primarily due to spatial or temporal factors. For individual differences, this could be important for comparing small numbers of participants with developmental disorders to controls, whereas analyzing intertrial variability could provide basic information about mechanisms of cortical specialization for cognitive functions (Johnson, 1999). ICA may be used to analyze either time-locked averaged data or nonaveraged “raw” EEG data. If conventional averaging procedures are performed first, then the initial averaging filters out components of the EEG that are not time locked to the stimulus. This allows ICA to focus on the neural activity that is time locked. If ICA is applied to raw EEG data, then some of the components it identifies will not be time locked to the stimulus and, indeed, may only occur in single trials. ICA applied to averaged data can potentially provide information about intersubject variability in brain function, whereas ICA applied to raw EEG data is useful because it can potentially detect occasional nontime-locked neural events and identify artifacts in the raw EEG data.

ICA on Averaged ERPs

Averaged ERPs, in response to upright faces, were calculated within each participant after applying standard artifact rejection methods (for details, see Table 1). ICA
was performed using the procedures developed by Makeig, Bell, Jung, & Sejnowski (1996) and Makeig et al. (1997) because this implementation of ICA has been investigated, in detail, for the analysis of EEG and ERP data using a smaller number of electrodes. This ICA algorithm requires that datasets consist of several times more time points than electrodes; if this is not the case, the solution will be “overfitted” in the sense that components (whose time series consist of single spikes at each time point) will tend to be generated. Thus, to increase the ratio of inputs (electrodes) to time points, we preprocessed our data using PCA to reduce the spatial variables to eight principal components before applying ICA. These eight principal components accounted for a large amount of the variance of the original signal in each case (greater than 94%); therefore, little information was lost and the time point-to-“electrode” ratio was improved. The validity of the use of PCA as a preprocessing technique prior to ICA is discussed further in Attias and Schreiner (1998).

When ICA was performed on the ERP data discussed earlier, it resulted in eight components for each participant, each of which consisted of a spatially constant temporal activation pattern (time course of activation) and a temporally constant spatial-weight vector (scalp-surface map). Standard statistical tests performed on the averaged ERP data for the individual participants indicated that between condition (upright vs. inverted faces) differences were evident in adult recordings at about 150 msec poststimulus onset and at about 400 msec in infant recordings. Accordingly, when the ICA procedure had been performed on the data from the individual participants, the resulting temporal activation patterns for each component were examined for each individual, and we studied components that expressed activity around the latencies given above.³

³The evidence for the importance of between-condition differences at these latencies was derived from performing t tests on the amplitude of averaged ERPs, under different conditions, at certain electrode locations (electrodes 58, 76, and 97, for adults; and 31, 37, and 47, for infants; see Figures 1 and 2). These were the first points on the time series that revealed a significant difference between the two trial types (for details, see de Haan et al., 1998).

³For adult participants, components were selected in which a deflection occurred in the temporal activation pattern in the range between 120 and 200 msec poststimulus; the deflection was a negativity, as assessed by projecting the temporal activation pattern through the scalp weight matrix and examining the direction of the deflection at electrodes 58, 76, and 97. A similar procedure was performed for infant participants. In this case, we located components with deflections in the range between 305 and 465 msec poststimulus; the deflections were positive, as assessed by examining the projection at electrodes 31, 37, and 47. If more than one source passed these criteria, the source with the largest activation when projected at channels 31, 37, and 47 (by inspection) was chosen. The criteria were applied separately to the portions of the temporal activation patterns corresponding to each condition, so it was possible that the components that passed the above criteria could be different for the two experimental conditions. Thus, it was logically possible that (a) no components passed the criteria for either condition, (b) a component that passed the criteria for one condition, but no component passed the criteria for the other condition, or (c) components passed the criteria for both conditions. In the latter case, either two different components were selected (one for each condition) or one single component (which passed the criteria for both conditions) was selected. This procedure resulted in selection of none, one, or two components for each participant.
Figure 4 shows the results of ICA performed on averaged data in the upright face condition for a single adult participant. The upper panel shows the actual average ERP recorded at a central occipital electrode location. The lower two panels show two ICA components. For each component, the scalp weight vector is shown in the form of a scalp map on the left and the temporal activity pattern is shown as a curve on the right. Figure 5 is a comparable display for an infant participant. The ERP recording is shown from the middle occipital electrode, and, in this case, five ICA components are presented. To informally compare the results of ICA with those of PCA, Figure 6 shows (in the same format as the preceding figure) the actual ERP and the first two unrotated principal components (as opposed to independent components) for the same infant participant.

Figures 4 and 5 show how ICA is able to decompose the averaged ERP into a set of independent components that may overlap in time. In the case of the adult participant, the ERP activity around 150 msec is decomposed into two main components—one with a prominent negativity and one with a double positivity. Similarly, Figure 5 shows how the ERP for an infant is decomposed into a set of temporally overlapping components. Of particular interest here is the fact that ICA decomposes the positivity, with maximum around 400 msec, into three components. Comparison with the ERP traces suggests that some features of the ERP may indeed be captured in the ICA components. In contrast to the ability of ICA to decompose the ERP into independent temporally overlapping components, the results of PCA applied to the same data, as shown in Figure 6, suggest that PCA may not always be able to do this. Specifically, the first principal component for the infant looks very similar to the original ERP, and there is no evidence that PCA is able to decompose the complex positivity. Thus, performing ICA on data that has been reduced in dimensionality by PCA first, can produce more components than does using PCA alone.

ICA and raw EEG Analysis

We now turn to the second method of application of ICA in which it is applied to raw EEG data. In contrast to the analyses of averaged data described above, no artifact removal was performed nor were the data low-pass filtered. For this analysis, we focused on narrower time ranges due to the large size of the data to be processed. ICA was performed directly on the EEG data without preprocessing.

---

4 The results given apply to unrotated principal components. However, we know of no principled way to assess which rotation is most appropriate.

5 For adults, we used 600 msec of data from each trial (36 msec prestimulus to 564 msec poststimulus) and, for infants, 900 msec (36 msec prestimulus to 864 msec poststimulus). For adults, each condition consisted of 97 trials; the number of trials performed by the infant participants varied. The total number of time points was thus 29,100 for adults (2 conditions x 97 trials x 600 msec x 250 Hz) and a similar order of magnitude for infants.
FIGURE 4  In this figure, we show two ICA components produced from the analysis of the averaged ERP from adult A. For simplicity, only data relating to the upright face presentation condition is shown. The topmost time series plot shows the actual ERP recorded at a single electrode (electrode 76) for the purpose of comparison to the ICA components. Below this, the ICA components’ scalp intensity vectors are shown on the left; the time activation patterns are shown on the right. The components’ activation patterns are shown normalized on a scale between \([-1, +1]\). The shading of the vectors is indicated in the grayscale bar. Light gray represents the most negative values; dark gray represents the most positive values. For each ICA component, the temporal activation pattern (shown on the right hand side of the figure for the two components) is expressed at each scalp location. However, it is scaled according to the value of the vector (i.e., for any component, the temporal activation pattern is identical at each scalp location—apart from its magnitude, which is scaled according to the value of the vector at that location and reversed at scalp locations where the vector has negative values). The shading pattern for the vectors is defined to be in the range between \(-4s\) and \(+4s\), where \(s\) is the standard deviation of the distribution of the values in the vector. The scalp weight vectors were converted into scalp maps using spherical interpolation between the values of the vectors at each electrode location.
FIGURE 5  In this figure, we show five ICA components produced from the analysis of the averaged ERP from infant B. The form of the figure is similar to that described in the legend for Figure 4.
through PCA. Apart from these differences, the ICA procedure itself was identical to that used for analyzing averaged data.

There are various methods for selecting components of interest when the analyses are performed on raw data. For example, one may consider the total amount of variance in the EEG that is accounted for by the component, how time locked the temporal activation pattern is, or how kurtotic the temporal activation pattern is. The most relevant components (from the large number generated by ICA with a large number of electrodes) may often be identified by inspection of the form of

FIGURE 6 PCA of averaged ERP recordings for infant B. In this figure, we show the first two PCA components produced from the analysis of the averaged ERP from infant B. The form of this figure is similar to previous ones, except principal components (rather than independent components) are presented.
the weight vector, the time average of the temporal activation pattern, and the projection of the activation through the weight vector.

Two components were selected for investigation from the ICA on the EEG of the same adult reported earlier. These included one component that showed strong activity at posterior electrode sites (component a) and a second component that showed activity at anterior electrode sites (component b). In Figure 7, the time series of component (a) is shown in comparison to the raw EEG.

FIGURE 7 The upper panel shows all 97 trials of the upright condition for adult A, showing the ICA component selected. The lower panel shows the actual raw EEG for adult A, recorded at electrode 76.
The temporal activation pattern of a component produced by analysis of raw EEG data consists of activity in many trials for both conditions and it may be averaged across trials to show its average activation pattern in both conditions. This is demonstrated in Figure 8, which shows the averaged temporal activation pattern and scalp vector for components (a) and (b).

As previously described, an ICA component’s temporal activation pattern may be projected through the weight vector to reconstruct the activity of the component at the same scalp locations and in the same units as the EEG recording. Figure 9 shows the results of performing this procedure for an adult participant, summing the reconstructed activity of component (a) and four other components that were selected because they also expressed activity at posterior electrode sites, and then averaging the resulting reconstructed “ERP” that was produced using these five components across trials.

Although, for clarity, we have presented analyses from adult participants, there is a potential benefit of the ICA approach for infant data: a reduction in intertrial variability of the ICA component as compared to the conventional ERP components. This is evident by inspection of Figure 7, where it is clear that the latency of the minimum deflection of component (a) is considerably less variable than that of the equivalent component in the EEG. Statistical analysis of the

![Figure 8](image.png)

**FIGURE 8** This Figure shows the ICA components (a) (top) and (b) (bottom) produced by analysis of raw data. The components’ time series have been averaged across trials.
variability of latency in the ICA component, as compared to the raw EEG, confirms that the ICA component has much lower intertrial variability than measurement of the raw ERP itself. Thus, ICA may be useful in reducing intertrial variability in analysis of infant ERP data. A preliminary analysis of infant data in this way is presented in Figure 10.

Figure 8 shows the results of components (a) and (b) averaged across trials. Comparing component (a) with the corresponding component produced...
by the analysis of averaged data for adult A (see Figure 4, middle panel) indicates that these components are quite similar both in time series and weight vectors. However, component (a) was produced by analysis of raw EEG data that had not corrected for artifacts prior to ICA being performed. Thus, Figure 8 suggests that ICA can extract components from such noisy data that are similar to those extracted from a data set that has been previously corrected for artifacts.

In Figure 7, one can see that component (b) has strong activity at anterior electrode sites. We believe that this reflected activity that was due to quasi time-locked eye movements that occurred in some adult participants in the face-processing experiment. Figure 9 shows the reconstruction of the ERP using component (a) and four other components. Reconstructing the ERP using selected ICA components can clean ERP in the sense that artifacts, or suspected artifacts, such as those expressed by component (b), may be removed.

Finally, we intend to analyze the nature of the increased variability in infant ERP responses by applying ICA to raw EEG data. A preliminary analysis (performed in this way) of one 6-month-old showed that selecting sources for the time course revealed several independent sources with different scalp-surface maps. Although all of these sources were in posterior regions of the scalp, the results indicated that spatial variability may be as significant as temporal variability in infants’ ERPs.

**SOURCE LOCALIZATION**

The goal of source localization is to find the location, orientation, and magnitude of dipoles in the brain that may be responsible for the ERP observed at particular lat-
tencies (Nunez, 1990). A particular advantage of high-density recordings, in general, and the GSN, in particular, is that it may allow more accurate source localization (Tucker, 1993). If neural activity occurs in a small region of tissue in which neurons are aligned in parallel orientation, then the source may be represented as a single electrical dipole (i.e., a localized, oriented electrical source). Several methods for localization using ERP data involve prior structural magnetic resonance imaging (MRI; see, e.g., Gevins, Le, Brickett, Reutter, & Desmond, 1991; Gevins, et al., 1994), an approach that is not usually feasible for studies on groups of healthy infants. However, programs such as the Brain Electromagnetic Source Analysis (BESA; see, e.g., Berg & Scherg, 1991; Scherg and Berg, 1996) are designed to identify likely candidate locations and orientations of dipoles in the brain purely by analyzing the distribution of electrical activity recorded at the scalp electrodes and applying it to simplified models of the head and brain. The variables that can be manipulated in BESA include the number, orientation, location, and relations among sources; the head model and its physical and electrical parameters; the time range for the solution; and the criteria (energy, variance, and separation) for convergence to solution.

We illustrated the source localization technique on the conventional ERPs that were collected in the face perception study and also on the ICA components identified above. For the localization performed on the ERP, dipoles were fitted to the data at 128 msec poststimulus latency because this was the latency at which the posterior electrodes had their minimum values following presentation of the upright face. With regard to the ICA components, localization was performed directly on the scalp weight vectors because, as mentioned above, these are temporally invariant. In each case, the localization proceeded as follows. Two dipoles were placed at randomly chosen locations and with randomly chosen orientations, with the constraint that they were symmetric in both location and orientation. Source fitting was performed, the constraint of dipole symmetry was relaxed, and localization was performed again using this dipole locations and orientations as the starting location. The entire procedure was repeated five times to ensure consistency of fitting.6

The results of source localization are shown in Figures 11, 12, and 13. Figure 11 shows the results of conventional ERP at 128 msec. Figure 12 shows the results of localization for ICA component (a). Figure 13 shows the results of localization for

6The following parameters were specified for the BESA package source localization procedure. The residual variance was used as the criterion for minimization, with the stopping criterion equal to 0.00001% change in residual variance. A three-shell head model was used with sphere radius of 85 mm, scalp thickness of 6 mm, bone thickness of 7 mm, CSF thickness of 1 mm, scalp conductivity of 0.33 mho/m, bone conductivity of 0.0042 mho/m, CSF conductivity of 1 mho/m. Dipole fitting was performed using instantaneous dipole fitting.
FIGURE 11  BESA source localization for the artifact corrected averaged ERP for adult A.

FIGURE 12  BESA source localization for the ICA component (a) for the raw data analysis of adult A.
FIGURE 13  BESA source localization for the ICA component (b) for the raw data analysis of adult A.

FIGURE 14  BESA source localization for infant upright face data.
ICA component (b). These results are from one of the five repetitions of the localization procedure, but the results were very consistent across the five repetitions.

Comparison of Figures 11 and 12 shows that the results of localization performed on the artifact-corrected ERP are very similar in terms of location and orientation to those performed on component (a). The residual variance of the fitted dipoles is of a similar order of magnitude in both cases. This demonstrates the power of ICA to extract clean, localizable sources from raw EEG data. As was previously mentioned, we suspected that component (b) was due to an eye movement source; this is supported by the localization of this component to the eyes, which provides further evidence that ICA can be used to identify and remove artifacts.

We have also attempted source localization on infants. Although, in general, dipole fitting results in solutions that account for less variance in infants than in adults, reasonable solutions (< 10% residual variance) can be obtained in about half of the participants (see Figure 14). There are a number of specific issues with regard to source localization in infants. First, skull thickness and density are different in infants than in adults, and, in infants under 3 months of age, fontanels are not yet completely closed. Second, the spherical head model may be less appropriate for infants than for adults in that skull thickness is probably more variable. To our knowledge, there are, as yet, no recommended changes to the standard settings of BESA for infant data. Further research is clearly required in this area to determine the most appropriate settings and models for use in infant source localization.

GENERAL DISCUSSION

In this article, we have discussed the recording and analysis of high-density ERP data in infants using the GSN. We conclude that it is now feasible to record high-density data from infants and that the results obtained are comparable to those obtained with conventional systems. Currently, however, we believe that there are some limitations to the use of the system with infants outside the age range of 3 to 12 months. Under 3 months of age, the challenge is to overcome poor neck support of the head in a way that does not interfere with electrode placement. With toddlers, movement artifacts and manual grasping of the net are obstacles to overcome. However, studies with these age groups are ongoing in other laboratories, so the difficulties may not be insurmountable.

We illustrated some strategies for analyzing high-density data and focused on one source separation method, ICA. Generally, whether applied to infant or adult recordings, in single trial or averaged form, ICA reduces complex spatio-temporal datasets to a much smaller number of components. These components may provide information about the activity of real brain sources that underlie the overall ERP. We suggested that a further advantage of ICA is that it could produce components that would be more easily localizable using dipole localization methods.
This was supported by the fact that a source generated from ICA performed on raw EEG (that had not been corrected for artifacts) was localizable and that a result consistent with that from localization of manually corrected averaged ERP was produced.

In the medium-term future, we see the potential that ICA, or related methods, could allow the extraction of a small number of trial events from a longer period of unsegmented ongoing EEG. This could radically change the design of infant ERP experiments, because an infant would only have to perform a response, or process a stimulus, a small number of times during a laboratory session. This may allow the study of cortical activity preceding internally generated “spontaneous” actions (e.g., reaching for objects) or the investigation of cortical activity resulting from surprising displays, such as impossible events involving objects. Of course, a variety of other approaches to high-density data analysis can also be taken, such as EEG coherence analysis and time-frequency analysis.

With regard to dipole localization, current methods are usually designed with head models based on adults. Further research is needed to establish the appropriate values for variables, such as those for the electrical parameters of the head. One likely effect of the postnatal growth of cortex within the skull is the increased deepening of major and minor sulci. During such developmental changes, some banks of neurons may change their angle and/or position relative to the nearest skull landmarks. We believe that such changes could be modeled using similar approaches to those used to visualize the properties of cells within sulci (Dale & Sereno, 1993).

How can data collected with high-density ERPs constrain or inform hypotheses about postnatal functional brain development in infants? Johnson (1999, 2000) provides a framework for considering some of the changes that might be observed and identifies two specific processes, specialization and localization. In this context, specialization refers to changes in how finely “tuned” the response properties of a cortical region are. For example, a region of cortex may begin postnatal life being responsive to a wide variety of visual stimuli; however, with development, it might narrow its response to a subset of the original (e.g., only faces). Changes in localization are defined as changes in the overall extent of cortical tissue activated in a given task context. Some evidence indicates that there is more widespread activation of cortical areas following stimulus presentation in infants than in adults and that, with further development, the areas activated become restricted to a subset of those originally activated. Johnson (2000) outlines how changes in specialization and localization may reflect the same underlying process. Briefly, as cortical regions become more specialized for processing certain kinds of stimuli, they become less responsive to other stimulus and task contexts, thus reducing the overall extent of cortical activation (increased localization). These and other changes in cortical processing during postnatal development may be traced through the use of high-density ERPs in the following ways. First, using conven-
tional single-channel ERP analysis methods, we can assess whether, at a given electrode, infants show a less-selective response to a range of stimuli than adults or older children. This entails comparisons between stimuli within an age group. Second, by examining high-density scalp maps, we can ascertain whether such selective responses are widespread over many recording sites (e.g., over right and left hemispheres), or whether they are confined to a smaller region. Of course, caution is required in not overinterpreting scalp-surface maps in terms of the underlying neural activation. The next level of analysis is source separation. By isolating independent underlying sources of scalp-surface profiles, we can potentially examine whether developmental changes are due to (a) a decrease (or increase) in the number of different sources (or the extent to which they are temporally coincident), (b) changes in the scalp-surface area of one or more sources, or (c) decreases (or increases) in the intersubject variability of scalp-surface maps. The latter possibility will be important to rule out, because previous work that shows an apparent increase in spatial localization during development has depended on grand averages composed from several volunteers. Possibilities (a) and (b) are consistent with changes in the number of cortical areas activated. Turning to the specialization of cortical activation, we can compare the independent sources observed in one condition to those generated by a closely related condition (e.g., presentation of upright versus inverted faces). If there is increasing specialization with age, we would predict that, although at a younger age both conditions generate the same independent source (same cortical circuits), with development one or more sources active in the key condition will not be in the other. Thus, this source(s) has become activated by a narrower range of stimuli. Finally, the third level of analysis concerns identifying brain dipoles (which may map onto independent sources) in different stimulus conditions at different ages.

Picton et al. (2000) have produced a number of useful guidelines for recording and publishing human ERPs, regardless of the details of the system used to collect data. We recommend complete adherence to these guidelines when recording high-density ERPs, with a few exceptions specific to testing infants. First, passive viewing paradigms are often useful with infants because it is difficult to elicit a consistent manual response, with the exception of saccades (Csibra et al. 1998, 2001). Further, passive-viewing paradigms allow the same “task” to be administered to age groups from infancy to adults, whereas most other paradigms are restricted to certain age groups only. The second recommendation of Picton et al. (2000) that requires further comment concerns the use of a pacifier for young infants. Although a pacifier can lead an otherwise fussy infant to complete more experimental trials, we do not recommend its use unless necessary, given the likelihood of jaw muscle artifacts. A third area discussed by these authors that requires further comment is their recommendation that, when making comparisons between groups, some homology between the components being measured needs to be demonstrated. This is a tricky issue when, for example, comparing infant and
adult waveforms. One way to approach this problem is to conduct experiments on the properties of ERP components of infants. However, it is possible that the same underlying neural generators have different response properties at different ages. Another approach we are pursuing is to analyze the shape and timing of waveforms at different ages and then describe the functions that can transform one to the other. Such functions can then form a basis for making comparisons between components at different ages.

The exploration of functional brain development during postnatal life has only just begun. The new technology we have discussed in this article provides but one tool that can be used to illuminate the brain basis of infant behavior. In the future, we hope that other noninvasive technologies, such as Near Infrared Spectroscopy: optical imaging (Hebden, Arridge, & Delpy, 1997), will add to our armory and help bring about major advances in our knowledge of the developing brain.

**ACKNOWLEDGMENTS**

This research was financially supported by Medical Research Council Programme Grant G97 15587 and European Commission Biomed Grant BMH4–CT97–2032.

We thank Don Tucker and everyone at Electrical Geodesics for technical assistance and advice.

**REFERENCES**


tentials to study cognition: Recording standards and publication criteria. *Psychophysiology, 37*, 127–152.


