9 Overview of Time-Domain EEG Analyses

9.1 Event-Related Potentials

The logic underlying the computation of an ERP is straightforward: each trial contains signal and noise; the signal is similar on each trial, whereas the noise fluctuates across trials. Because the noise fluctuations are randomly distributed around zero, noise cancels out when many trials are averaged, thus leaving the signal (the ERP). To create an ERP, simply align the time-domain EEG to the time = 0 event (this was probably already done during preprocessing) and average across trials at each time point.

Figure 9.1A shows a few randomly selected trials from one electrode. Figure 9.1B shows all trials from this electrode and the average of all trials superimposed. The average is considerably smaller in magnitude than the individual trials. This is because all non-phase-locked activity, which tends to have larger amplitude, is subtracted out during averaging (see also figures 2.1 and 5.2). Figure 9.1C shows only the ERP with a tighter *y*-axis limit, which accentuates the smaller fluctuations in the ERP.

Thus, the mathematical basis of an ERP is simple: sum the voltage at each time point over trials and then divide by the number of trials. If you will use ERPs mainly as a data quality inspection tool, that is about all you need to know. If you plan on using ERPs to make inferences about cognitive processes, you should familiarize yourself with issues related to component overlap, component quantification, appropriate interpretation, and statistical procedures. See the books by Luck and Handy (Handy 2004; Luck 2005) for more discussions of these issues.

9.2 Filtering ERPs

Keep in mind that time-domain signal averaging over trials is itself a low-pass filter. This is because non-phase-locked activity does not survive time-domain averaging, and frequencies

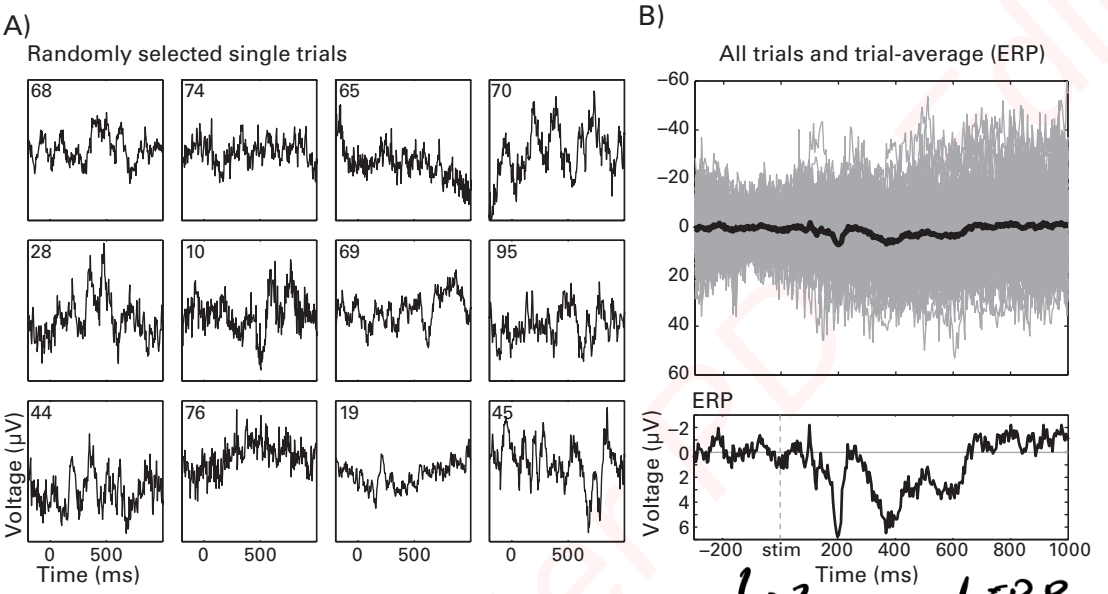
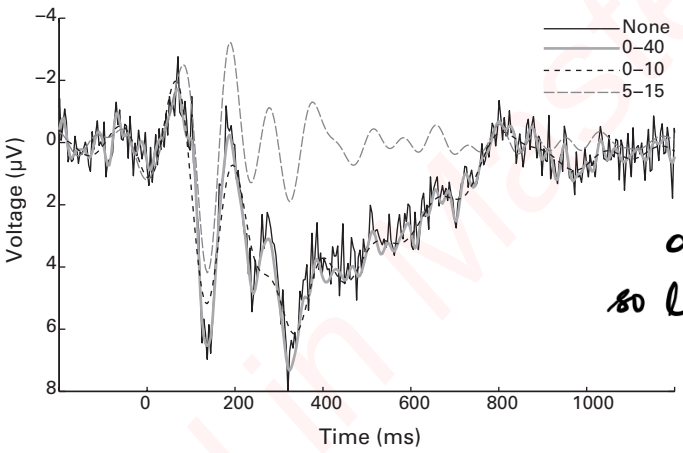


Figure 9.1
Panel A shows single-trial EEG traces from 12 randomly selected trials (number inside plot indicates trial number). Data are from electrode FCz. Panel B shows 99 single trials in gray and their average—the ERP—in black. Panel C shows the same ERP with focused *y*-axis scaling.

above around 15 Hz tend to be non-phase-locked. Averaging ERPs across multiple subjects provides further low-pass filtering because brief neural events are likely to have some temporal jitter across subjects, and thus the average will be smoothed in time. Nonetheless, it is common to apply additional low-pass filters when computing ERPs. Filtering the ERP minimizes residual high-frequency fluctuations, makes the ERPs look smoother, and facilitates peak-based component quantification by reducing the possibility that the peak is a noise spike or an otherwise nonrepresentative outlier. Filtering ERPs is not always necessary, particularly if there are many trials or if you are focusing on later ERP components that tend to be extended in time.

Filtering ERPs is a topic of some debate. Despite the advantages listed in the previous paragraph, poorly designed filters can introduce ripples in the time domain. These ripples (also called ringing artifacts) result from having poorly designed filters, such as filters with very narrow transition zones. The reason these artifacts occur is similar to the reason that edge artifacts occur (figure 7.2). You will learn more about this in chapter 14. The danger of these artifacts when interpreting ERPs is that large ripples in the time domain can appear to

be oscillations. Thus, if you have a poorly constructed filter, you might interpret your results to indicate that there are brain oscillations during your task, when in fact you are interpreting an artifact of the filter. In practice, this situation is easily avoided by constructing filters with gentle transition zones. Ripple artifacts are not the only concern, however. Some filter settings (again, settings that are generally associated with poor filter construction) may introduce systematic biases in ERP components, such as the use of forward-only or causal filters (Acunzo, Mackenzie, and van Rossum 2012; Rousselet 2012). Again, chapter 14 discusses proper filter construction and also provides qualitative and quantitative measures of whether a filter is properly constructed. A final concern of filtering ERPs is that applying the low-pass filter reduces temporal precision because the voltage value at each time point becomes a weighted average of voltage values from previous and subsequent time points. Thus, one of the main advantages of ERPs (its high temporal precision) is reduced. The lower the cutoff frequency of the filter, the more temporal precision is lost. Because of these considerations, you should carefully consider whether a filter is necessary for your ERPs. Figure 9.2 illustrates the effect of different filters on a single-subject trial-averaged ERP.



what is forward-only and causal filter?? what do they do?? Zero phase filtering (forward-backward) latency is not shifted

cutoff means the freq at which the filter starts blocking, lowercutoff means keeping only low frequencies and blocking more of signal so lowercutoff freq = strong filtering but causes smearing in time, making events look shifted / less sharp

Figure 9.2

An ERP from electrode P7 with no filtering (black line) and with different filter settings (numbers in the legend indicate lower and upper frequency bounds in hertz). Note that some filter settings can have dramatic effects on the interpretation of specific ERP features. For example, the 5–15 Hz filter seems to have accentuated the first negative-going peak at around 100 ms and removed the later P3-type component, and the 0–10 Hz filter removed the negative-going peak at around 280 ms. The wide-band 0–40 Hz filter had the least effect on the larger ERP fluctuations while removing the high-frequency fluctuations. This plot is an illustration of why you should carefully consider the frequency range of the filter used for interpreting ERPs, particularly if you use a narrow frequency range.

ERPs are often filtered using a frequency cutoff of around 20 or 30 Hz, and occasionally the frequency cutoffs are as low as 5 or 10 Hz. Note that applying a filter to single trials and then computing the ERP is identical to computing the ERP and then applying a filter (demonstrated in chapter 14). Filtering the data before trial averaging is thus not necessary, although it can be useful for data inspection or independent components analysis.

9.3 Butterfly Plots and Global Field Power/Topographical Variance Plots

A butterfly plot shows the ERP from all electrodes overlaid in the same figure (figure 9.3A). If the data are referenced to the global average, the butterfly plot will show ERPs symmetric about the zero horizontal line. Butterfly plots are useful for detecting bad or noisy electrodes.

The global field power is the standard deviation of activity over all electrodes. Global field power can be obtained simply by computing the standard deviation over all electrodes at each point in time, and is best interpreted when using the average reference (Murray, Brunet, and Michel 2008). Thus, during periods of cortical quiescence, the global field power will

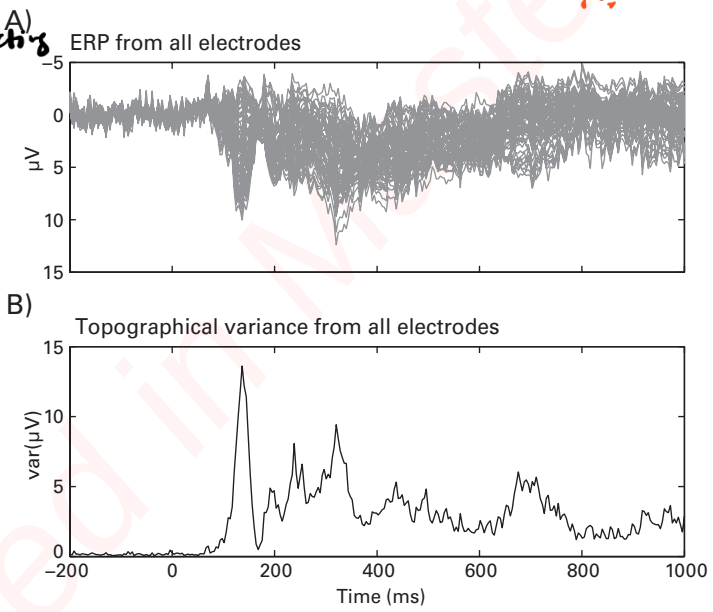


Figure 9.3
An example butterfly plot (panel A) and a topographical variance plot (panel B). Although they lack spatial information, these plots are useful for data inspection and provide an overview of the time periods with cortically diverse events, including approximately 180 ms, 220 ms, 320 ms, and 700 ms.

be small. In contrast, as different brain regions become active, global field power increases. Note that global field power is not redundant with average amplitude—a large-amplitude, spatially broad component such as a P3 may have relatively low global field power if most electrodes have the same activity levels.

Topographical variance accentuates the global field power and thus facilitates visual inspection (figure 9.3B). Butterfly plots and topographical variance plots are useful as data quality indices and to confirm the timing of the representations of task events in the data.

9.4 The Flicker Effect

The flicker effect in EEG research refers to entrainment of brain activity to a rhythmic extrinsic driving factor (Regan 1977; Vialatte et al. 2010). For example, if you look at a strobe light that flickers at 20 Hz, there will be rhythmic activity in your visual cortex at 20 Hz, phase-locked to each light flash from the strobe light. This can be measured as a narrowband increase in power or phase alignment at the frequency of the visual flicker, or it can be measured in the ERP. This effect is also referred to as steady-state evoked potential, frequency tagging, SSVEP (steady-state visual evoked potential), SSAEP (auditory evoked potential), or something similar.

The flicker effect is arguably an underutilized tool in cognitive electrophysiology. The main benefit of the flicker effect is that it allows you to "tag" the processing of a specific stimulus. For example, by having multiple stimuli that flicker at different frequencies on the screen at the same time, you can independently track processing of each tagged stimulus, measured by changes in the EEG power at the stimulus frequency. This is a powerful technique because the spatial precision and accuracy of EEG are normally much too low to examine the representations of specific stimuli. The flicker effect allows you to "fake" a very high spatial resolution, as if you could isolate populations of neurons that respond to one stimulus. One limitation of the flicker effect is its poor temporal precision: it takes several hundred milliseconds for the flicker effect to stabilize, and longer periods of time provide an increased signal-to-noise ratio. Thus, this approach is ideal for stimuli that can remain on screen for several seconds.

One may wonder in which brain regions the flicker will entrain neural network activity. Evidence suggests that stimulus flicker can entrain brain activity beyond the stimulated sensory area (e.g., early visual cortex in the case of visual flicker). For example, theta-band visual flicker increases hemodynamic activity in medial prefrontal regions (Srinivasan et al. 2007a). EEG and MEG studies suggest that spatially widespread networks, including frontal and parietal areas, can exhibit a flicker effect that, in some cases, appears to [illegible]

frequency (Ding, Sperling, and Srinivasan 2006; Srinivasan, Bibi, and Nunez 2006). If neural entrainment to a rhythmic exogenous stimulus extends beyond primary sensory areas, it is possible that the flicker may facilitate cognitive processes that utilize those frequencies. Indeed, there is some evidence that performance on cognitive tasks can be modulated by stimulus flicker frequency (Thut, Schyns, and Gross 2011; Williams, Ramaswamy, and Oulhaj 2006) and that entrainment can modulate processing of stimuli that are presented in phase compared to stimuli presented out of phase with the entrainment stream (Mathewson et al. 2012). Furthermore, the brain may retain a memory trace of the frequency at which items were tagged (Wimber et al. 2012).

Stimulus flicker frequencies up to 100 Hz can evoke a flicker effect (Herrmann 2001), although lower frequencies generally elicit a stronger flicker effect (that is, larger in magnitude). Other stimulus factors such as size, luminance, and contrast will impact the signal-to-noise ratio of the flicker effect.

It remains debated whether the stimulus flicker effect reflects a neural oscillation or repeated ERPs to each stimulus presentation (Capilla et al. 2011; Moratti et al. 2007; Thut, Schyns, and Gross 2011). This debate has implications for the interpretation of the flicker effect in terms of neurophysiological mechanisms of oscillations but does not impact its usefulness as a tool for isolating the processing of specific stimuli.

There are no special analysis techniques for studying the flicker effect; you can examine the ERP or perform frequency decomposition or time-frequency decomposition as described throughout this book. In general, a peak in the frequency domain at the flicker frequency should be readily observed in a spectral plot, and the magnitude of this frequency peak can be compared to the same frequency before the flickering stimulus began, or it can be compared to the power of neighboring frequencies for which there was no flicker.

9.5 Topographical Maps

Topographical maps are an excellent and nearly ubiquitously used method for showing the spatial distribution of EEG results. Topographical maps are fairly straightforward to construct. It is useful to understand how they are made, although in practice it is easier to use plotting routines that come with a data analysis package rather than to write your own topographical map routines. Creating a topographical map is conceptually similar to interpolating an electrode (see figure 7.5), except that instead of estimating the activity at one point in space corresponding to a missing electrode, activity is estimated at many points in space between electrodes. Figure 9.4 illustrates why it is useful to interpolate activity in the space between electrodes.

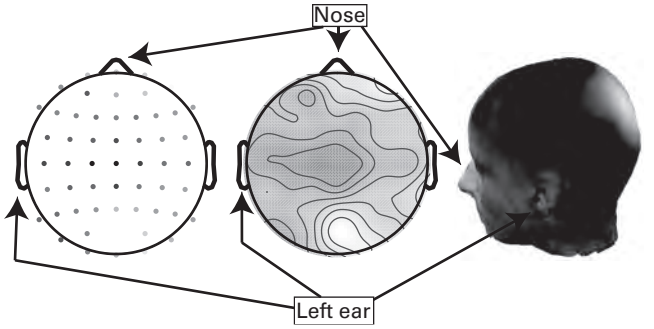


Figure 9.4
The same data shown by coloring dots on a topographical map (left) or interpolating those values over a surface (middle and right). Clearly, the interpolated maps are easier to interpret. Two-dimensional plots show data from all or most electrodes; 3-D plots (right) look more realistic but obscure data from part of the scalp. Locations of the nose and left ear are indicated to facilitate orientation and comparison.

In Matlab, creating a topographical map can be done by defining a set of grid points on a surface on which to interpolate data, based on the data from known topographical positions. The more grid points (that is, the finer the surface lattice), the smoother the topographical plot will be. However, increased smoothness comes at the expense of increased computation time, and smoother topographical plots do not contain any more information than less smooth topographical plots. The online Matlab code goes through, step-by-step, how topographical maps are created. In practice, however, it is easiest to use the topographical plotting routines that come with eeglab, fieldtrip, or other EEG analysis programs. For the remainder of this book, topographical maps are created using the eeglab function `topoplot`.

Most topographical plots are two-dimensional (2-D). To interpret 2-D topographical plots, look at the plot as if you are looking down on the top of someone's head, with the nose on the top of the plot and the left and right ears on the left and right sides, respectively (fortunately, topographical plots are always shown in neurological convention).

Sometimes 3-D topographical plots are shown. There are advantages and disadvantages of 2-D and 3-D topographical plots. Two-dimensional plots are a bit less intuitive to interpret in an anatomical sense but show activity simultaneously from all or most electrodes (if you have many electrodes, those electrodes on or close to the face and neck may be excluded from the plots). Three-dimensional plots are easier to interpret and look nicer in figures, but they show activity from only a third of the head; multiple views would be required to show the full topographical distribution.

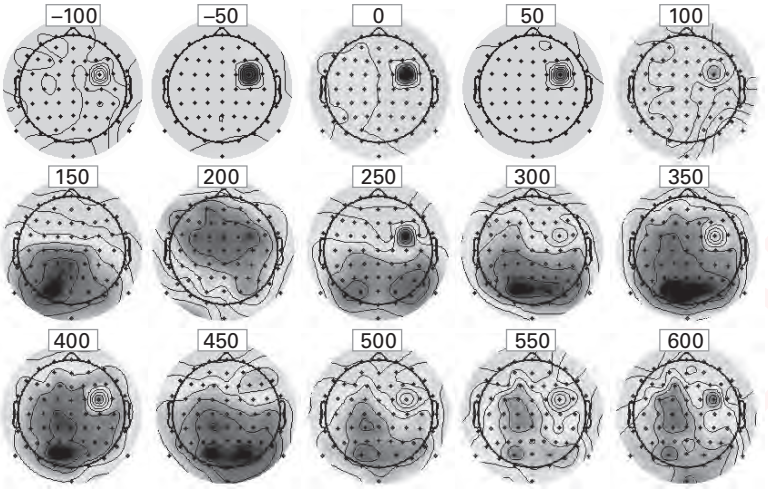


Figure 9.5 (plate 1)
Plotting topographical maps over time facilitates rapid data quality inspection. The numbers in white boxes indicate the latency at which the topographical data are plotted (in milliseconds) with respect to trial onset. These plots show, among other things, that there is one bad electrode. In this case the bad electrode was generated by replacing the true EEG activity at electrode FC4 with randomly generated numbers.

Inspecting topographical maps of ERPs for each subject is a good idea, even if you have no hypotheses that can be tested with ERPs. Topographical maps of ERPs provide excellent and rapid data inspection possibilities. Topographical maps allow you to confirm the timing of task events, and they allow to you detect bad or noisy electrodes. An example is shown in figure 9.5 (plate 1).

9.6 Microstates

A good description of microstates is available on Scholarpedia (scholarpedia.org/article/EEG_microstates; accessed in late 2012), so it is copied here: "In EEG as well as ERP map series, for brief, subsecond time periods, map landscapes typically remain quasi-stable, then change very quickly into different landscapes" (Lehmann 1971). The durations of these "landscapes," as well as their topographical characteristics, vary over time and as a function of task demands. Durations tend to be around the alpha range (70–130 ms), and topographical distributions tend to fit into four or five distinct patterns. Microstates have been linked to

cognitive processes from perception to memory to language (Britz and Michel 2010; Lehmann et al. 2005; Muller et al. 2005; Pitts and Britz 2011), including microstates during the prestimulus interval that predicts upcoming stimulus processing (Britz and Michel 2011; Lehmann et al. 1994).

The following is a brief description of how microstates are identified; more details and algorithms can be found in publications by Brunet, Murray, and Michel (2011) and Murray, Brunet, and Michel (2008). To identify microstates, consider that when there are temporally stable topographical distributions, the difference between the topographical maps at times t and $t + 1$ is small. For example, in the case that the voltage does not change over two successive time points, the temporal difference is zero. In contrast, rapid changes in the topographical distribution of activity (the cortical landscape of electrophysiological activity) from one time point to the next would result in a large temporal difference. Thus, when the temporal difference (also called global map dissimilarity) remains low for a period of tens to hundreds of milliseconds and then suddenly becomes relatively large, this sharp increase is considered to be a transition from one state to another. The stable maps are then used in a hierarchical clustering analysis in order to identify a small number of topographical distributions that best characterize the topographical maps during periods of stability. These are called cluster maps. Finally, the topography at each time point is labeled according to the cluster map to which it is most similar. This produces a time course of map topographies and can be used in task-related and statistical analyses. The software package cartool is designed for studying microstates (sites.google.com/site/fbmlab/cartool).

9.7 ERP Images

An ERP image is a 2-D representation of the EEG data from a single electrode. Rather than all trials averaged together to form an ERP, the single-trial EEG traces are stacked vertically and then color coded to show changes in amplitude as changes in color. They are also useful as single-subject data inspection tools because trials with large-amplitude data (which likely contain artifacts) can easily be seen. ERP images can also be used to link trial-varying task parameters or behaviors to the time-domain EEG signal. This is done by sorting the EEG trials according to values of the aligning event, such as the reaction time or the phase of a frequency-band-specific signal at a certain time point. Thus, the trial sequence no longer corresponds to chronological order but rather to the values of the aligning event.

Two examples of ERP images are shown in figure 9.6. Figure 9.6A shows an ERP image from electrode FCz aligned to the reaction time on each trial. The reaction times are plotted

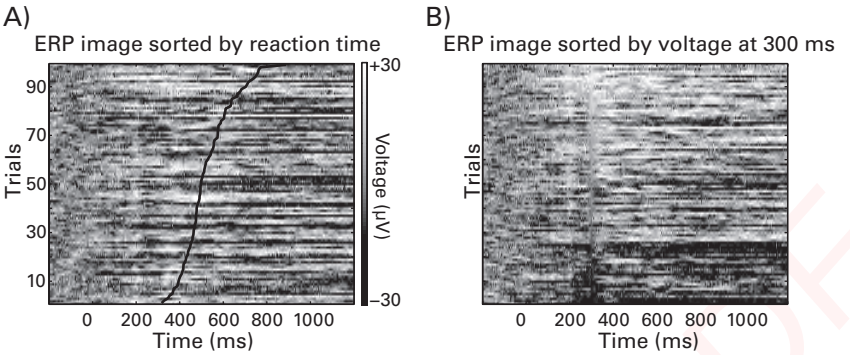


Figure 9.6
Example ERP images, both using data from electrode FCz. Time is on the *x*-axis, trials are on the *y*-axis, and the grayscale intensity (or color if you create this figure on your computer) corresponds to the EEG voltage values over time and trials. In panel A the trials are re-sorted according to the reaction time on each trial, and in panel B the trials are re-sorted according to the voltage value at 300 ms. The black line in panel A corresponds to the reaction time on each trial.

on top of the EEG data as a black line. You can see that the reaction time line goes monotonically to the right. This shows that the trials were re-sorted from their initial chronological configuration to one that follows the reaction time distribution. In this example there is no clear visual relationship between the single-trial EEG and reaction time. Figure 9.6B shows an ERP image that is aligned to the voltage value at 300 ms poststimulus.

ERP images are often smoothed, for example by convolving the image with a 2-D Gaussian, to facilitate interpretation and to minimize the influence of noise or other nonrepresentative single-trial fluctuations. The program eeglab has easy-to-use options for creating and smoothing ERP images.

Despite their name, ERP images are not limited to time-domain EEG data; they could also be made from frequency-band-specific activity, such as the filtered signal, power, or phase. ERP images may sometimes look like time-frequency plots because time is on the *x*-axis and the data are colored. However, the *y*-axis of ERP images contains no frequency information.

9.8 Exercises

1. Compute the ERP at each electrode. Select five time points at which to show topographical plots (e.g., 0 to 400 ms in 100-ms steps). In one figure, make a series of topographical plots at these time points. To increase the signal-to-noise ratio, make each plot show the average of

activity from 20 ms before until 20 ms after each time point. For example, the topographical plot from 200 ms should show average activity from 180 ms until 220 ms. Indicate the center time point in a title on each subplot.

2. Loop through each electrode and find the peak time of the ERP between 100 and 400 ms. Store these peak times in a separate variable and then make a topographical plot of the peak times (that is, the topographical map will illustrate times in milliseconds, not activity at peak times). Include a color bar in the figure and make sure to show times in milliseconds from time 0 (not, for example, time in milliseconds since 100 ms or indices instead of milliseconds). What areas of the scalp show the earliest and the latest peak responses to the stimulus within this window?