Comparing a template approach and complex bandpass filtering for single-trial analysis of auditory evoked M100

Alfred Link¹*, Martin Burghoff¹, Anna Salajegheh³, David Poeppel¹, Lutz Trahms¹ and Clemens Elster¹

¹ Physikalisch-Technische Bundesanstalt, Berlin, Germany
² University of Maryland, College Park, MD, USA

Abstract

Two methods for single-trial analysis were compared, an established parametric template approach and a recently proposed non-parametric method based on complex bandpass filtering. The comparison was carried out by means of pseudo-real simulations based on magnetoencephalography measurements of cortical responses to auditory signals. The comparison focused on amplitude and latency estimation of the M100 response. The results show that both methods are well suited for single-trial analysis of the auditory evoked M100. While both methods performed similarly with respect to latency estimation, the non-parametric approach was observed to be more robust for amplitude estimation. The non-parametric approach can thus be recommended as an additional valuable tool for single-trial analysis.

Keywords: bandpass filtering; evoked signals; Hilbert transform; maximum likelihood; single-trial analysis.

Introduction

Analysis of evoked potentials (EPs) or evoked fields (EFs) in electroencephalography (EEG) or magnetoencephalography (MEG) is a frequently applied tool in neuroscience and psycho-physiological research. A basic problem is that single evoked signals (ESs) are typically small in amplitude when compared to the background activity. To improve the signal/noise ratio (SNR), measurements for many single trials are typically averaged prior to analysis. However, trial-to-trial variations may occur, and this information is then lost subsequent to averaging.

For this reason, single-trial analysis has attracted interest for over 20 years and many different methods have been proposed [1–11]. Frequently, parametric signal (and noise) models are utilized [3–5, 7–11]. Most of these [3–5, 8–10] rely on the assumption that the ES and background EEG/MEG are independent.

In this paper, two different approaches for single-trial analysis are compared, a well-established parametric template approach [10] and a recently introduced non-parametric procedure based on complex bandpass filtering [13, 14]. The latter approach is derived from a procedure originally developed for characterizing single-beat variations in electro- and magnetocardiograms [15]. Both the parametric and the non-parametric approach aim at characterizing single trials in terms of amplitude and latency with respect to stimulus onset. While the established parametric approach assumes that all ESs contain a constant time signal (template), the only assumption of the non-parametric approach is that single ESs are well-pronounced deflections with known spectral contents.

Method comparison was carried out by analyzing pseudo-real data synthesized from real MEG measurements.

Materials and methods

The two methods for single-trial analysis are briefly described. While the template-based maximum likelihood estimation exploits a parametric signal model, the non-parametric approach characterizes single-trial behavior in terms of the envelope and phase of a derived bandpass signal. In contrast to the complex bandpass filter method, the template-based maximum likelihood estimation works iteratively. Nevertheless, the calculation times for both methods are not critical for the application considered.

Template-based maximum likelihood estimation (ML)

For the template approach, single trials \(x(n), i=1,2,\ldots,K\), with \(n=0,1,\ldots,N-1\) time samples are modeled according to:

\[ x(n)=a_s(n-\tau)+w(n), \quad n=0,1,\ldots,N-1, \]

where \(s(n)\) denotes the common template of the set of \(K\) single trials, and \(a_s\) and \(\tau\) denote the amplitude and latency of the \(i\)th single trial. The noise processes \(w_i\), \(i=1,2,\ldots,K\), containing background activities are modeled as realizations of a common zero-mean stationary Gaussian process. According to Jasikowski and Verleger [10], the parameters \(a_s\) and \(\tau\) are estimated using a maximum likelihood approach based on Fourier transformation of the time domain model (1):

\[ X(k) = a \cdot S(k) \cdot \exp(-j \omega_s \cdot \tau) + W(k), \]

where \(k=0,1,\ldots,N-1\), capital letters indicate the Fourier transforms of the time domain quantities, and \(\omega_s=2\pi k/N\).
The estimates $a_{s,t}$ to $\tau_{s,t}$, $S_a(\omega_s)$ and $f_{s,t}(\omega_s)$, are given by the sample sequence of the modulated Gaussian magnitude response function. Such a filter has an optimum linear bandpass filter is used with a Gaussian content of the evoked response. For this, a complex bandpass filtering (BF) procedure can be terminated after five iterations, with no improvement for further iterations. In agreement with these findings, the maximum-likelihood estimates of the gain in pass-band. The width of the bandpass $\omega_{t-1}$ and $\omega_{t}$, given in this paper are based on five iterations for iteratively maximizing Eq. (3).

Complex bandpass filtering (BF)

The complex bandpass filtering method [13, 14] filters a single trial to reduce its spectrum to a relevant frequency content of the evoked response. For this, a complex linear bandpass filter is used with a Gaussian magnitude response function. Such a filter has an optimal time-bandwidth product suitable for time frequency analysis. The set of filter impulse response coefficients is determined at the same time the center frequency of the bandpass. The normalization factor $h_{\text{norm}}$ determines the gain in pass-band. The width of the bandpass [0.02, $L$] can be approximately determined from $\Delta f = 0.13 \beta^{-1}$. For the input $x(n)$, $n = 0, \ldots, N-1$, the filter output is the convolution sum:

$$z(n) = x(n) \ast \text{Re}[h(n)] + j x(n) \ast \text{Im}[h(n)],$$

where $\nu(n) = x(n) \ast \text{Im}[h(n)]$ is the Hilbert transform of $u(n) = x(n) \ast \text{Re}[h(n)]$. Then, the envelope and phase of the output signal $z(n)$ are given by:

$$E(n) = [u^2(n) + \nu^2(n)]^{1/2},$$

and

$$\psi(n) = \text{Arctan}[\nu(n)/u(n)],$$

where the multi-branch character of the arctangent function is indicated by the capital A. The envelope and phase can be calculated at each sample point $n$. In the subsequent analysis, the envelope and phase were calculated for all single trials at the sample point $n_v$ where the absolute of the average for the $K$ single trials considered was maximum. For the single trials $x(n)$, the corresponding complex bandpass filter output signals $z(n)$ are given around $n_v$ by the approximation:

$$z(n) = E(n_v) \exp[j \omega_c (n + n_v + \psi(n_v)/\omega_s)] .$$

Hence, the single-trial amplitudes were determined by

$$a_{sv} = E(n_v)$$

and the single trial latencies by

$$\tau_{sv} = n_v + \psi(n_v)/\omega_c$$

where $\nu \cdot \pi < \psi(n_v) \leq \pi + \nu \cdot \pi$; i.e., the phases were computed modulo $2\pi$, with $\psi$ denoting the mean direction of the unit vectors $r_i = [\cos \psi_i, \sin \psi_i]$.

For ease of method comparison, the estimates $a_{sv}$ and $\tau_{sv}$ were subsequently scaled and shifted such that their means equal 1 and 0, respectively.

For the M100 data of the auditory stimulus experiment, we found that the main spectral content was around 10 Hz. Hence, for the sampling frequency $F_s = 500$ Hz the filter was designed with $f_c = 0.02$, $L = 40$ and $\beta = 20$, leading to the center frequency $F_c = F_s f_c = 10$ Hz; the resulting magnitude response has a bandwidth of approximately 3.5 Hz (0.13 $\beta^{-1} F_s$) and a bandstop attenuation of approximately 32 dB at the zero frequency. No fine-tuning of the parameters was carried out.

Method assessment

The single-trial methods were assessed by analyzing pseudo-real test data constructed from single-trial M100 response data. The test data were generated such that: (i) the simulated ESs emerge as shifted and scaled templates according to the model used by the template approach; and (ii) the simulated background activities closely resemble the measured ones.

Pseudo-real test data

Generation of test data was based on MEG measurements of auditory evoked M100 responses to three different tone stimuli (125, 250 and 1000 Hz) recorded at a sampling rate of 2 kHz. Preprocessing was carried out by low-pass filtering and subsequent down-sampling by a factor of 4. Filtering was carried out in both the forward and reverse directions by an eighth-order low-pass Chebyshev type I filter (equiripple in the pass-band) with a cutoff frequency of 200 Hz. The single trials were further baseline-corrected by subtracting offsets determined for the individual pre-stimulus intervals of 200 ms in duration. A detailed description of the experimental settings is given elsewhere [13]. From each MEG, two channels were chosen, each reflecting one field extremum on either hemisphere. Each channel supplied a data set of $K = 210$ single trials of 600 ms in duration (200 ms pre-stimulus to 400 ms post-stimulus onset). Thus, for three different tone stimuli, six different data sets were obtained from the MEG measurements for one subject. Since MEGs were recorded for nine subjects, 54 different data sets were used for construction of the test data.
From each single data set, a corresponding set of test data consisting of the same number of single trials was generated by choosing a signal model for the ES for each simulated single trial. As a basis for the modeled ES, the signal average for a duration of 200 ms after stimulus onset of the measured single data set was selected. The ES of the simulated $i$th single trial was then constructed as the signal average shifted and scaled by the chosen latency and amplitude, $\tau_{SIM,i}$ and $a_{SIM,i}$, according to the ES model of the template approach outlined above. To this ES an AR process of seventh order and 600 ms in duration was added to account for the single-trial background activity and noise. The model parameters of the AR process were chosen as those obtained by the Burg algorithm [16] applied to the $i$th measured single trial over the pre-stimulus epoch. By choosing the variance of the AR process, the SNR of the constructed test signals was controlled. The SNR was determined as the ratio of the maximum of the absolute of the average and the estimate of the standard deviation of the background activities calculated from the background signals of the pre-stimulus epoch for the set of $K$ single trials. For the underlying 54 different sets of measurements, the SNR values span a range from 0.3 to 1.4, with a mean value of approximately 1.

**Simulation parameter** The $K$ amplitudes $a_{SIM,i}$, $i=1,2,\ldots,K$, of a single test set were drawn randomly from a normal distribution with mean 1 and variance $\sigma^2_a$, where negative amplitudes were rejected to avoid unrealistic features; latencies $\tau_{SIM,i}$ were drawn randomly from a uniform distribution within $[-\Delta \tau,\Delta \tau]$. For given latency spread $\Delta \tau$, variance $\sigma^2_a$, and a chosen SNR, the construction of test data based on the 54 different scenarios was repeated 60 times using randomly drawn $a_{SIM,i}$, $\tau_{SIM,i}$, and AR background processes to provide a statistically meaningful representation of the test situation.

Figure 1 illustrates the “pseudo-real” behavior of the test data generated, which were composed of a scaled and time-shifted average (middle Figure) and modeled individual background activities of measured single trials. For the chosen value of $\text{SNR} = 1$, the test data (bottom Figure) remarkably resemble the measured single trials (top Figure).

Data for each test situation were analyzed by the template approach using maximum likelihood estimation (ML) and complex bandpass filtering (BF) methods. Prior to comparison, the simulated amplitudes $a_{SIM,i}$ and latencies $\tau_{SIM,i}$ were scaled to yield means of 1 and 0 ms, respectively. Recall that the same holds for the corresponding estimates. For each single data set, the root mean squared errors (RMSEs) were calculated, as well as the correlation coefficients between estimated and true parameters. The resulting RMSEs and the correlation coefficients were averaged over the $54 \times 60$ different scenarios and repetitions.

**Results**

To assess the performance of the ML and BF estimates, two different latency spreads, $\Delta \tau = 8$ ms and $\Delta \tau = 24$ ms, were considered, while the variance $\sigma^2_a$ of single-trial amplitudes was chosen as 0.3. The values chosen for $\Delta \tau$ and $\sigma^2_a$ are expected to cover typical ranges of latency and amplitude variations. Figures 2 and 3 show the resulting RMSEs and correlation coefficients, $\text{RMSE}_{\tau,a}$ and $\rho_{\tau,a}$, as a function of the SNR.

![Figure 1](image-url)
For large SNR the two methods performed well and with similar quality. RMSEs tend to zero and correlation coefficients approach 1; i.e., both methods work perfectly in the low noise case.

For both methods, the RMSEs of latency and amplitude estimates were slightly worse for larger latency spread than those obtained for smaller spread. On the other hand, correlation between the latencies and their estimates was better for both methods in the case of the larger latency variation (Figure 3 bottom). This is because the latency estimation errors are only slightly larger for the wider latency spread of $\Delta \tau=24$ ms.

The two methods appear to perform similarly with respect to latency estimation in all cases. For reliable detection, the latency differences should exceed the RMSEs of the corresponding estimates. From Figure 2 it is evident that to detect latency differences between single trials of the order of, say, 15 ms, the SNR must exceed 1.

Performance differences are evident for amplitude estimation. While the BF and ML methods perform similarly in terms of the correlation coefficients, the BF amplitude RMSEs are clearly smaller than those obtained for the ML estimates in the range of high noise contamination.
(SNR \leq 1); i.e., the BF method yields more reliable estimates in these cases than ML. Note that a small SNR (SNR \leq 1) is typical for M100 measurements.

**Conclusion**

Two methods for single-trial analysis were compared, an established parametric template approach and a recently proposed non-parametric method based on complex bandpass filtering. The comparison was carried out on pseudo-real test data derived from auditory evoked MEG measurements. The focus of the analysis was amplitude and latency estimation of the M100 response. Data synthesis was based on the signal model employed by the parametric template approach. Method performance was assessed on the basis of the correlation between underlying amplitudes/latencies and their estimates. In addition, RMSE values were considered. The results show that the parametric template approach and the non-parametric method are both well suited for single-trial analysis of the auditory evoked M100. While both methods performed similarly with respect to latency estimation, the complex BF method yielded more reliable amplitude estimates than the template-based ML approach. This was particularly true for the small SNR values relevant for typical M100 measurements. Note that the complex BF method requires fewer assumptions than the template-based ML estimation. It is concluded that the non-parametric approach can be recommended as an additional valuable tool for single-trial analysis.

**References**


