Brain and Language **66,** 61–88 (1999)
Article ID brln.1998.2025, available online at http://www.idealibrary.com on IDEAL®

A Wavelet Packet Model of Evoked Potentials

Jonathan Raz

Department of Biostatistics, University of Michigan

Linda Dickerson

Department of Pharmacology, Georgetown University

and

Bruce Turetsky

Department of Psychiatry, University of Pennsylvania

The standard methods for decomposition and analysis of evoked potentials are bandpass filtering, identification of peak amplitudes and latencies, and principal component analysis (PCA). We discuss the limitations of these and other approaches and introduce wavelet packet analysis. Then we propose the ''single-channel wavelet packet model,'' a new approach in which a unique decomposition is achieved using prior time–frequency information and differences in the responses of the components to changes in experimental conditions. Orthogonal sets of wavelet packets allow a parsimonious time–frequency representation of the components. The method allows energy in some wavelet packets to be shared among two or more components, so the components are not necessarily orthogonal. The single-channel wavelet packet model and PCA both require constraints to achieve a unique decomposition. In PCA, however, the constraints are defined by mathematical convenience and may be unrealistic. In the single-channel wavelet packet model, the constraints are based on prior scientific knowledge. We give an application of the method to auditory evoked potentials recorded from cats. The good frequency resolution of wavelet packets allows us to separate superimposed components in these data. Our present approach yields estimates of component waveforms and the effects of experiment conditions on the amplitude of the components. We discuss future extensions that will provide confidence intervals and *p* values, allow for latency changes, and represent multichannel data.

The work of Drs. Raz and Turetsky was funded by NIH Grant R29 MH51310. We thank Jennifer Buchwald for providing the cat data and for many helpful discussions. Bin Zhang prepared Fig. 3, and we gratefully acknowledge his help.

Address reprint requests to Jonathan Raz, Department of Biostatistics, University of Michigan, 109 South Observatory, Ann Arbor, MI 48109-2029.

0093-934X/99 $30.00

1. INTRODUCTION

Many approaches to analysis of evoked potentials (EPs) are designed to identify features of the recorded waveforms that represent functionally or anatomically distinct brain processes. The most common approach is peak analysis (Donchin & Heffley, 1976), which involves computation of peak amplitudes and latencies (possibly after bandpass filtering the data), and application of standard statistical methods, particularly analysis of variance, to these derived measures. An important limitation of peak analysis is that estimates of the effects of experimental conditions can be biased when the EP components are superimposed in both time and frequency. This is because a change in amplitude of one component can create an apparent change in peak amplitude or latency of a second component, even when there is no real change in the second component. A further disadvantage of peak analysis is that the reduction of the data to amplitudes and latencies at isolated time points is inefficient when an entire waveform is available (Donchin & Heffley, 1976). Peak amplitude and latency are particularly difficult to measure in a broad wave and when the signal-to-noise ratio is low.

A widely used alternative approach is principal components analysis (PCA), which represents the data as a linear combination of component waveforms (Donchin, 1966). Typically, the EP components are estimated by applying varimax rotation to the eigenvectors (Wood & McCarthy, 1984). The limitations of this approach have been discussed in detail by many authors, including Donchin and Heffley (1976), Wood and McCarthy (1984), Möcks and Verleger (1986), and Turetsky, Raz, and Fein (1990). Most important, the principal components or factor scores are uncorrelated (Johnson & Wichern, 1992), which is an unrealistic mathematical constraint. A further limitation is that the eigenvectors are orthogonal before rotation, so that they may be a poor representation of real brain processes (Möcks & Verleger, 1986). Even if there exists a rotation of the eigenvectors that yields the true EP components, we typically do not have the information necessary to choose this rotation (Möcks & Verleger, 1986). Still another disadvantage is that latency changes complicate the interpretation of the results (Möcks, 1986).

Several authors have proposed statistical models of the Fourier coefficients, rather than of original EP time series or the principal components (Brillinger, 1981; Woestenburg, Verbaten, Van Hees, & Slangen, 1983; Möcks, Köhler, Gasser, & Pham, 1988; Raz, Cardenas, & Fletcher, 1995). The advantages of the frequency domain representation are that: (1) parsimony can be achieved by excluding frequencies that are not of interest; (2) stationary correlated noise due to background brain activity and other sources is represented by uncorrelated errors in the frequency domain; and (3) latency changes are represented as phase changes, which may be easier to estimate. An important drawback of frequency domain models is that EP components