Chapter 14

Topography Estimation of Visual Evoked Potentials Using a Combination of Mathematical Models

Takenao Sugi
Saga University, Japan

Kazuhiko Goto
Saga University, Japan

Satoru Goto
Saga University, Japan

Yoshinobu Goto
International University of Health and Welfare, Japan

Takao Yamasaki
Kyushu University, Japan

Shozo Tobimatsu
Kyushu University, Japan

ABSTRACT

This study proposes a method for estimating the topographical distribution of Visual Evoked Potentials (VEPs) from separated power spectrum components by a combination of models. VEPs with various temporal frequencies were recorded from nine healthy adults. The original power spectrum consisted of the VEP; background activities, artifacts, and other components were then obtained. To extract the VEP components from the original power spectrum, models corresponding to background activities, especially for posterior alpha rhythm, the low-frequency component and the high-frequency component, caused due to the EMG artifact, were constructed, and the relevant parameters were estimated. Finally, VEP components were calculated by subtracting them from the original power spectrum. The topographical distribution of the first harmonic (1F) and second harmonic (2F) components of the VEP were obtained by the proposed method. The estimation of the other components, aside from the VEPs, was also investigated. The merits and usefulness of the proposed method were analyzed with a comparison to the conventional stimulus-locked averaging method. The proposed method has several advantageous points compared to the conventional averaging method. Specifically, the posterior alpha rhythm and the EMG artifact were accounted for directly in the estimation of the VEP components. Therefore, an accurate estimation of the VEP components can be performed even the measurement of the components are prone to the error.

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INTRODUCTION

An electroencephalogram (EEG) is a summation of neuronal electrical activities that are recorded from the human scalp; this recorded activity provides a significant amount of information about the brain. Electrical responses are generated in the optic area of the cerebral cortex according to the visual stimuli received by the eyes and are called visual evoked potentials (VEPs) (Tobimatsu & Celesia, 2006). VEPs reflect the information processing of the visual system in the brain and are widely utilized in the clinical diagnosis of defects in visual conduction and other vision-related problems.

Flash stimuli by a strobe scope and/or pattern-reversal (flicker) stimuli by a display unit are usually used as VEP recordings (F-VEP and P-VEP). VEPs are divided into two groups, according to a difference in temporal frequency. Transient VEPs (TR-VEPs) can be observed with a temporal frequency of less than 1 Hz, and steady-state VEPs (SS-VEPs) are generated by a temporal frequency of over 3.5 Hz (Regan, 1977; Celesia, 1985). Time domain analysis is mainly used for the characterization of TR-VEP parameters such as amplitude, duration and waveform patterns (Tibimatsu, Celesia, & Cone, 1988), and SS-VEP is mostly characterized by frequency domain analysis utilizing Fourier transforms (Tobimatsu, & Celesia, 2006). In the analysis of the SS-VEP, the first harmonic (1F) component is the same as the temporal frequency and the second harmonic (2F) component is twice the temporal frequency; these are the principal characteristics.

Many studies on the relationship between VEP components and temporal frequencies for SS-VEPs by flicker stimuli have been performed previously (Regan, 1968, 1988; Yamasaki, Goto, Kinukawa, & Tobimatsu, 2008; Pieh, McCulloch, Shahani, Mactier, & Bach, 2009). Amplitude changes of 1F and 2F components from temporal frequencies have been investigated. Analysis of VEPs through topographical information has also been performed (Muller, & Hillyard, 2000; Pastor, Artieda, Arbizu, Valencia, & Masdeu, 2003; Tommaso, et al., 2003). Pastor et al. (2003) analyzed the SS-VEP with a topographical distribution. Tommaso et al. (2003) investigated SS-VEP for habituation and variability phenomena. Muller et al. (2000) reported on a visual-spatial selective attention task.

This study proposes a method for extracting the VEP components from the power spectra of raw EEG data. To separate the power spectrum components, which consist of VEPs, background EEG activities, physiological and technical artifacts, models that corresponded to each activity were constructed and were combined. Specifically, posterior dominant alpha rhythms, low-frequency noise components and high-frequency components from electromyographic (EMG) artifacts were taken into consideration in the modeling. An appropriate mathematical model was constructed for each phenomenon, and the model parameters were then obtained by a nonlinear optimization method. The proposed method was applied to data that were recorded from nine healthy adults, and the results were verified by comparing the calculations of the conventional averaging method in the time domain.

METHOD

Data Acquisition

EEGs were recorded at the International University of Welfare, and the subjects used in this study were nine healthy young adults who ranged in age from 21-25 years. Each subject was seated in a dark room and gazed at a point that was displayed at the center of the monitor. The distance between the subject and the monitor was 0.57 m. Black and white flicker stimuli were displayed to the subject and were presented continuously for 50 s at temporal frequencies that ranged from 6 to 12 Hz. EEGs were recorded with a sampling frequency of 200 Hz and with a filter setting of 0.53-60 Hz.

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