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Automated characterization of multiple alpha peaks in multi-site electroencephalograms

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Abstract

The identification of alpha rhythm in the human electroencephalogram (EEG) is generally a laborious task involving visual inspection of the spectrum. Moreover the occurrence of multiple alpha rhythms is often overlooked. This paper seeks to automate the process of identifying alpha peaks and quantifying their frequency, amplitude and width as a function of position on the scalp. Experimental EEG was fitted with parameterized spectra spanning the alpha range, with results categorized by multi-site criteria into three distinct classes: no distinguishable alpha peak, a single alpha peak, and two alpha peaks. The technique avoids visual bias, integrates spatial information, and is automated. We show that multiple alpha peaks are a common feature of many spectra.

Keywords: EEG; Alpha rhythm; Automatic detection

1. Introduction

Correlations of the electroencephalogram (EEG) with brain functions are widely used diagnostically, and are inferred to be closely connected to brain dynamics, information processing, cognition, and states of arousal (Niedermeyer, 1999). The alpha rhythm was first identified in humans by Berger (1929) as the most prominent feature in the EEG. The normal alpha rhythm varies in amplitude, frequency, morphology, and spatial distribution from one individual to the other. It also varies with time, and some individuals with a normally functioning brain never show an alpha rhythm (Niedermeyer, 1999). Development and verification of an improved automated method for quantification of alpha activities is the core aim of this paper.

In the literature there are descriptions of several rhythms within the conventional adult alpha frequency range of 7–13 Hz (Niedermeyer, 1997). Generally the alpha rhythm is present in the relaxed awake state, with the conventional alpha rhythm more prominent in the eyes-closed state than with eyes open. The conventional alpha rhythm is associated with the visual cortex, "central alpha" or rolandic mu rhythm with the sensorimotor cortex, and the so-called tau rhythm with the auditory cortex (Niedermeyer, 1999). As with the conventional alpha, which is blocked by visual stimuli, the mu rhythm is blocked by movements (Niedermeyer, 1997), and the tau rhythm is blocked by auditory stimuli. Thus in the traditional alpha rhythm range there could exist a number of peaks, each differently modulated by experimental conditions and associated with a particular region of the brain (Samson-Dollfus et al., 1997). It is possible for more than one alpha rhythm to be present in a single recording. Splitting of the alpha peak into two sub-peaks, separated by up to 1–2 Hz, has been found to occur in the normal population(Nunez and Srinivasan, 2006; Robinson et al., 2001).

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Alpha band activity in the EEG varies with cognitive and memory performance (Berger, 1929). Increases in alpha band activity at frontal and temporal sites are observed in short-term memory tasks (Klimesch, 1999). A relaxed waking state is the optimal condition for the posterior alpha rhythm, so EEG can serve as a tool for the assessment of arousal (Niedermeyer, 1999). A reduction of the alpha frequency can indicate exogenous intoxication (e.g., alcohol) or occur in demented patients (Samson-Dollfus et al., 1997). Alpha frequency also systematically changes with age, as has been well documented since Smith (1941), which suggests that alpha frequency is an indicator of neural maturation or myelination. Thus alpha frequency can serve as a diagnostic tool for onset of dementia (Samson-Dollfus et al., 1997), neural maturation (Klimesch et al., 1993), and potentially intelligence (Posthuma et al., 2001), cognitive states (Klimesch et al., 2007), and memory performance (Clark et al., 2004).

The identification of the alpha rhythm is generally done visually: a trained scorer inspects the EEGs (either in time series or power spectra), identifies, and quantifies the alpha peak based on personal or laboratory-specific operational criteria for which there are incomplete standardization. This is a time-consuming and subjective process, further complicated by factors such as noise, the presence or absence of certain peaks at some of the sites, and broad-band background signals. This paper thus seeks to find an objective automated algorithm for the identification and characterization of peaks.

There have been numerous attempts to automate information extraction from EEGs, including use of time domain analysis (Hjorth, 1970), applications of fractal dimensions (Arle and Simon, 1990; Pritchard, 1992), statistical measures (Nakamura et al., 1992), wavelet transforms (Schiff et al., 1994), and adaptive neural networks (Herrmann et al., 2001; Huupponen et al., 2001). Time domain analysis describes the characteristics of an EEG trace with descriptive parameters based on time series data using a statistical approach. This technique does not attempt to compete with human identification, but rather provides parameters that may be useful in quantifying subtle changes in the EEG, and which may be correlated with physiological variables (Hjorth, 1970). Arle and Simon (1990) applied fractal dimension to EEG analysis for the detection of transients and showed that the quasi-random background EEG has a different fractal dimension to transient deterministic data, which is useful in isolating transient signals. The wavelet transform provides an alternative to the Fourier transform in EEG analysis. Statistical measures have been used to extract similar information to the traditional visual analysis using periodograms from the EEG data (Nakamura et al., 1992), but only a single alpha peak was considered and the channels were treated separately. The frequency and the amplitude of the alpha peak were found using adaptive neural networks (Herrmann et al., 2001), but work to date only considered the possibility of a single alpha peak.

In contrast to the above techniques, the method developed in this paper extracts detailed measures for the background spectrum as well as for each alpha peak: its frequency, amplitude, and peak width. These parameters have direct link to the physiology of the generation mechanism and potentially help to distinguish the various proposed generation mechanisms, which are still in controversy. The possibility of multiple alpha peaks raises the problem of distinguishing a single alpha peak, whose frequency changes spatially, from the case of multiple spatially separate sources. The method developed in this paper is capable of resolving such smooth spatial variations in frequency as well as multiple peaks, thus aiding identification. The method is based on codification of visual inspection, and analysis spanning all the electrodes to help eliminate artifacts.

The structure of this paper is as follows: In Section 2 we outline subject demographics, EEG collection criteria, and our alpha quantification and classification algorithms. In Section 3 we present the parameters extracted from the spectrum from the categorization of a 100 normal subjects. In Section 4 we summarize the main results.

2. Method

2.1. Subjects and EEG

EEG data used in this paper were selected from a database previously collected by the Brain Dynamics Center, Westmead Hospital, Australia. In compiling the data, EEG recordings of healthy adult subjects from the general community were obtained with the appropriate ethical clearances and informed consent (Bahramali et al., 1999). The data selected for this study include 100 subjects (49 females and 51 males) with mean ages of 44 years (S.D. = 16 years) and 45 years (S.D. = 15 years), respectively. The EEGs were acquired as part of a wider battery of electrophysiological tests. Only the EEG measures from the eyes-closed state were used in this study. The subjects were asked to rest quietly with their eyes closed for the 2-min duration of the task and were awake and non-drowsy throughout the recordings. An electrode cap using the International 10-20 system of scalp sites with 19 electrodes was used to acquire the EEG data. EEGs were recorded at a 250 Hz sampling rate through a SynAmps amplifier using a linked earlobe reference and a low-pass third-order Butterworth filter with −6 dB point at 50 Hz. Ocular artifacts were corrected offline according to the method of Gratton et al. (1983). For further details see Bahramali et al. (1999).

The electroencephalogram was first divided into successive 8.192 s segments, which were windowed, Fourier transformed, modulus squared, and averaged to produced one power spectrum per recording site. Deviations of $> 100\,\mu V$ from the mean caused the segment to be rejected prior to transformation.

2.2. Alpha quantification method

The alpha rhythm is characterized by state dependence and complex topography that is inconsistent across individuals, posing significant challenges to automatic quantification. Our method addresses the need for unbiased and robust quantification of alpha power, frequency, and topography. The general approach described here is to fit parametric functions to the spectra from each recording site, then combine the parameters from all sites to produce a simple topographically informative sum-