EEG Alpha Waves Dataset

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Technical Report

17 December 2018

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Keywords: Electroencephalography (EEG), occipital dominant rhythm, alpha waves, experimentation.

Abstract - We describe the experimental procedures for a dataset that we have made publicly available at https://doi.org/10.5281/zenodo.2348891 in both *mat* (Mathworks, Natick, USA) and *csv* formats. This dataset contains electroencephalographic recordings of 20 subjects in a simple resting-state eyes open/closed experimental protocol. The electroencephalographic headset consisted of 16 electrodes. Data were recorded during a pilot experiment taking place in the GIPSA-lab, Grenoble, France, in 2017 (1). Python code for manipulating the data is available at https://github.com/plcrodrigues/Alpha-Waves-Dataset . The ID of this dataset is *ALPHA.EEG.2017a-GIPSA*.

Résumé - Dans ce document, nous décrivons une expérience dont les données ont été publiées sur https://doi.org/10.5281/zenodo.2348891 aux formats mat (Mathworks, Natick, USA) and csv. Cette base de données contient les enregistrements électroencéphalographiques de 20 sujets au repos avec les yeux ouverts ou fermés. Le casque d'électroencéphalographie comportait 16 électrodes. Les données ont été enregistrées durant une expérience pilote, qui s'est déroulée au GIPSA-lab, Grenoble, France en 2017 (1). Nous fournissons également une implémentation en Python pour manipuler les données sous https://github.com/plcrodrigues/Alpha-Waves-Dataset. L'identifiant de cette base de donnée est ALPHA.EEG.2017-GIPSA.

Introduction

The occipital dominant rhythm (commonly referred to as occipital ‘Alpha’) is prominent in occipital and parietal regions when a subject is exempt of visual stimulations, for instance when keeping the eyes closed (2). In normal subjects its peak frequency is in the range 8-12Hz. The detection of alpha waves on the ongoing electroencephalography (EEG) is a useful indicator of the subject’s level of stress, concentration, relaxation or mental load (3,4) and an easy marker to detect because of its high signal-to-noise-ratio. This experiment was conducted to provide a simple set of EEG signals carrying very distinct signatures on each experimental condition. It can be useful for researchers and students looking for an EEG dataset to perform tests with signal processing and machine learning algorithms. An example of application of this dataset can be seen in (5).

Participants

Data were recorded during a pilot experiment taking place in the GIPSA-lab, Grenoble, France, in 2017 (1). A total of 20 volunteers participated in the experiment (7 females), with mean (sd) age 25.8 (5.27) and median 25.5. 18 subjects were between 19 and 28 years old. Two participants with age 33 and 44 were outside this range. All participants provided written informed consent confirming the notification of the experimental process, the data management procedures and the right to withdraw from the experiment at any moment.

Material and Procedures

EEG signals were acquired using a research grade amplifier (g.USBamp, g.tec, Schiedlberg, Austria) and the EC20 cap equipped with 16 wet electrodes (EasyCap, Herrsching am Ammersee, Germany), placed according to the 10-10 international system. The locations of the electrodes were FP1, FP2, FC5, FC6, FZ, T7, CZ, T8, P7, P3, PZ, P4, P8, O1, Oz, and O2. The reference was placed on the right earlobe and the ground at the AFZ scalp location. The amplifier was linked by USB connection to the PC where the data were acquired by means of the software OpenVibe (6,7). We acquired the data with no digital filter and a sampling frequency of 512 samples per second. For ensuing analyses, the experimenter was able to tag the EEG signal using an in-house application based on a C/C++ library (8). The tag were sent by the application to the amplifier through the USB port of the PC. It was then recorded along with the EEG signal as a supplementary channel.

For each recording we provide the age, genre and fatigue of each participant. Fatigue was evaluated by the subjects thanks to a scale ranging from 0 to 10, where 10 represents exhaustion. Each participant underwent one session consisting of ten blocks of ten seconds of EEG data recording. Five blocks were recorded while a subject was keeping his eyes closed (condition 1) and the others while his eyes were open (condition 2). The two conditions were alternated. Before the onset of each block, the subject was asked to close or open his eyes according to the experimental condition. The experimenter then tagged the EEG signal using the in-house application and started a 10-second countdown of a block.

Organization of the dataset

For each subject we provide a single *mat* (and *csv*) file (Mathworks, Natick, USA) containing the complete recording of the session. The file is a 2D-matrix where the rows contain the observations at each time sample. Columns 2 to 17 contain the recordings on each of the 16 EEG electrodes. The first column of the matrix represents the timestamp of each observation and column 18 and 19 contain the triggers for the experimental condition 1 and 2. The rows in column 18 (resp. 19) are filled with zeros, except at the timestamp corresponding to the beginning of the block for condition 1 (resp. 2), when the row gets a value of one. The attribute names of the matrix are provided in the *Header.mat* (or *Header.csv*) file. We also provide a *demographic.mat* (and *demographic.csv*) file which is a 2D-matrix informing the age, gender and fatigue for each subject. The *demographic_header.mat* (and *demographic_header.csv*) contains the column names of the matrix.

We supply an open-source Python code example (9) using the framework MNE (10,11). This example shows how to download the data using Python. The code shows also how to extract the epochs of given subjects from the dataset and then classify them using machine learning techniques.

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