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Technical Report

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Dataset of an EEG-based BCI experiment in Virtual Reality and on a Personal Computer

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Abstract – We describe the experimental procedures for a dataset that we have made publicly available at <https://doi.org/10.5281/zenodo.2605204> in mat (Mathworks, Natick, USA) and csv formats. This dataset contains electroencephalographic recordings on 21 subjects doing a visual P300 experiment on PC (personal computer) and VR (virtual reality). The visual P300 is an event-related potential elicited by a visual stimulation, peaking 240–600 ms after stimulus onset. The experiment was designed in order to compare the use of a P300-based brain-computer interface on a PC and with a virtual reality headset, concerning the physiological, subjective and performance aspects. The brain-computer interface is based on electroencephalography (EEG). EEG data were recorded thanks to 16 electrodes. The virtual reality headset consisted of a passive head-mounted display, that is, a head-mounted display which does not include any electronics with the exception of a smartphone. This experiment was carried out at GIPSA-lab (University of Grenoble Alpes, CNRS, Grenoble-INP) in 2018, and promoted by the IHMTEK Company (Interaction Homme-Machine Technologie). The study was approved by the Ethical Committee of the University of Grenoble Alpes (Comité d’Ethique pour la Recherche NonInterventionnelle). Python code for manipulating the data is available at <https://github.com/plcrodrigues/py.VR.EEG.2018-GIPSA>. The ID of this dataset is *VR.EEG.2018-GIPSA*.

Résumé - Dans ce document, nous décrivons une expérimentation dont les données ont été publiées sur <https://doi.org/10.5281/zenodo.2605204> aux formats mat (Mathworks, Natick, USA) et csv. Ce jeu de donnée contient les enregistrements électroencéphalographiques (EEG) de 21 sujets durant une expérience de type 'P300 visuel' sur PC (personal computer) et en VR (virtual reality). Le P300 visuel est une perturbation du signal EEG apparaissant 240-600 ms après le début d'une stimulation visuelle. Le but de cette expérience était de comparer l'utilisation d'une interface cerveau-machine (ICM) basée sur le P300, sous PC et avec un casque de VR. Cette comparaison portait sur les aspects physiologiques, subjectifs et la performance de l'ICM entre PC et VR. L'ICM était basée sur l'EEG. L'EEG de chaque sujet a été enregistré grâce à 16 électrodes réparties sur la surface du scalp. Le casque de VR était 'passif', c'est-à-dire qu'il ne comportait aucune électronique à l'exception d'un smartphone utilisé pour la virtualisation. L'expérience a été menée au GIPSA-lab (Université de Grenoble-Alpes, CNRS, Grenoble-INP) en 2018 dans le cadre d'une thèse d'entreprise avec la société IHMTEK (Interaction Homme-Machine technologie). L'étude a été approuvée par le comité d'éthique de l'université Grenoble-Alpes (Comité d'Ethique pour la Recherche Non-Interventionnelle). Nous fournissons également une implémentation python pour manipuler les données à <https://github.com/plcrodrigues/py.VR.EEG.2018-GIPSA>. L'identifiant de cette base de données est *VR.EEG.2018-GIPSA*.

Introduction

In this work, we focus on the so-called P300 Brain-Computer Interface (BCI), a stable and accurate BCI paradigm relying on the recognition of a positive potential occurring in the EEG peaking 240 to 600 ms after stimulation onset. We implemented such a BCI on an ordinary and affordable smartphone-based head-mounted VR device and compared the user experience and the performance of the BCI on VR with a traditional BCI running on a Personal Computer (PC). An example of application of this dataset can be seen in (1).

Participant

A total of 21 volunteers participated in the experiment (7 females), with mean (sd) age 26.38 (5.78) and median age 26. 18 subjects were between 19 and 28 years old. Three subjects at age 33, 38 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. The study was approved by the Ethical Committee of the University of Grenoble Alpes (Comité d’Ethique pour la Recherche Non-Interventionnelle).

Material

VR

We have chosen the usage of a passive HMD, consisting of a mask with no electronics and a regular smartphone. Among these masks, the VRElegant headset (Elegant, Austin, the US) is affordable, comfortable and adapts to a wide range of smartphones (**Figure 1b**). The VRElegant was coupled with a Huawei Ascend mate 7 (Huawei, Seoul, South Korea). The mate 7 (**Figure 1a**) was a middle-range smartphone, affordable for the general public. It also has a large screen (1920 x 1080), which makes it very interesting to improve the immersion feeling in VR.



Figure 1. (a) Huawei Mate 7 (Huawei, Shenzhen, China) and (b) VRElegant (Elegant, Austin, the US). From: www.flickr.com and <https://photomania.net>.

EEG

EEG signals were acquired by means of a standard 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 (**Figure 2**). 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 (2,3). Data were acquired with no digital filter applied and a sampling frequency of 512 samples per second. For ensuing analyses, the application tagged the EEG using USB. The tags were sent by the application to the amplifier through the USB port of the PC or smartphone. It was then recorded along with the EEG signal as a supplementary channel. The tagging process was different under PC and VR because 1) a mini-USB to USB adaptor was necessary for the smartphone (VR), 2) two different serial port communication libraries were used on VR and PC (4,5) and 3) the smartphone screen was turned 90° in VR. This results in a different mean tagging latency as explained in (6). The mean tagging latency was around 38 ms in PC and 117 ms in VR. These mean latencies (in PC and VR) should be used to correct ERPs by shifting them respectively in PC and VR condition (7).

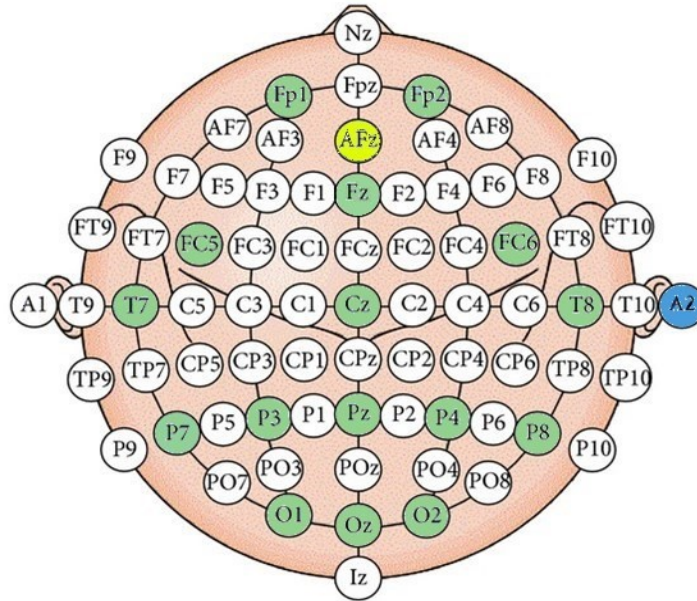


Figure 2. In green, the 16 electrodes placed according to the 10-10 international system. We used AFZ (in yellow) as ground and A2 (in blue) as a reference.

Procedure

In order to compare the use of BCI with HMD (VR) and without HMD (PC), we developed a simple P300 interface consisting of a six by six matrix of white flashing crosses. The task of the subject was to focus on a red-squared target (**Figure 3**). The user interface was identical for the PC and VR conditions. It was implemented within the Unity engine (Unity, San Francisco, US) before being exported to the PC and VR platforms thanks to the engine. In this way, we ensure that the visual stimulation is the same in the two experimental conditions.

The experiment was composed of two sessions. One session ran under the PC condition and the other under the VR condition. The order of the session was randomized for all subjects. Each session comprised 12 blocks of five repetitions. All the repetitions within a block have the same target. A repetition consisted of 12 flashes of groups of six symbols chosen in such a way that after each repetition each symbol has flashed exactly two times (8,9). Thus, in each repetition the target symbol flashes twice, whereas the remaining ten flashes do not concern the target (non-target). The EEG signal was tagged corresponding to each flash.

After each repetition a random feedback was given to the subject in the form of the BCI item selection. The feedback was ‘correct’ if the selected symbol was the target, ‘incorrect’ otherwise. The probability of the feedback to be correct was drawn randomly from a uniform

distribution with expectation 70%. The use of a random feedback ensures that the performance of a participant does not depend on the feedback, avoiding confounding effects due to intersubject variability, for instance, the perceived confidence or frustration in operating the BCI, which may affect the actual performance and concentration of the participants.

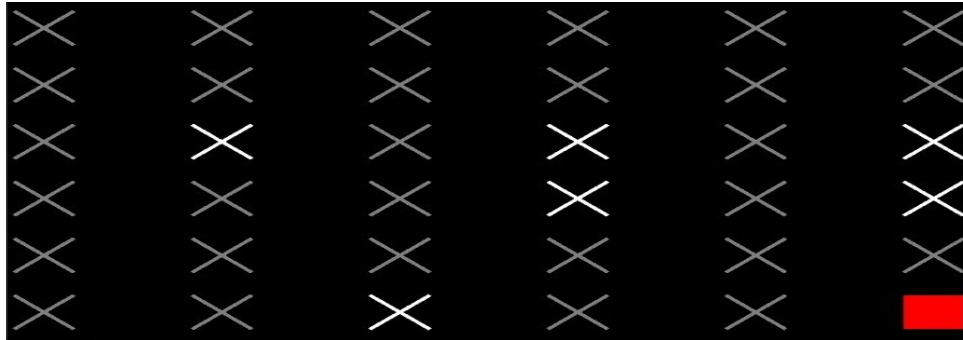


Figure 3. User interface at the moment when a group of six symbols is flashing. The red-square symbol is the target. The cross signs the non-target.

A pilot experiment showed that the Inertial Measurement Unit (IMU) of the smartphone sometimes accumulated an unexpected amount of drift, causing the virtual world slowly moving around the subject. Therefore, in the experiment the IMU was deactivated, thus the application was always fixed in front of the subject's eyes.

Questionnaire

At the end of the experiment, each subject filled in a questionnaire. This questionnaire was composed of ten questions presented in **Table 1** with their corresponding variable name. **Table 2** presents three other variables we computed on the basis of the value of these ten first variables. When the question was open such as 'How many hours did you play First Player Shooter a week?' the authors associated a categorical variable to this question and created the levels.

<i>Number</i>	<i>Question</i>	<i>Variable name in dataset</i>
1	Evaluate your tiredness before the experiment on a scale from 0 to 10 where 0 is 'no fatigue'	FatigueBefore
2	Evaluate your tiredness after the experiment on a scale from 0 to 10 where 0 is 'no fatigue'	FatigueAfter
3	Did you feel a sensation of discomfort?	DoesParticipantFeelDiscomfort (1 for a positive answer to question 3, 0 elsewhere)
4	Did you prefer the PC or VR session (answer: PC, VR, SAME)	DoesParticipantPreferVR
5	Evaluate your sensation of control under PC on a scale from 0 to 10 (0 = 'no control')	SensationOfControlInPC
6	Evaluate your sensation of control under VR on a scale from 0 to 10 (0 = 'no control')	SensationOfControlInVR
7	How many hours a week do you play video games?	XP_VG (1 for none; 2 for occasional; 3 for regular)
8	How many hours a week do you play First Player Shooter?	XP_FPS (1 for none; 2 for occasional; 3 for regular)
9	Have you ever experienced Virtual Reality? If yes, how many times?	XP_VR (1 for none; 2 for occasional and 3 for repetitive experience in VR)
10	Please circle your gender: Male – Female.	IsMan (0 for female; 1 for male)
11	How old are you?	Age

Table 1. Questionnaire

<i>Variable name in dataset</i>	<i>Description</i>
FatigueDiff	FatigueAfter – FatigueBefore
SensationOfControlPreference	1 if the sensation of control under PC was greater than the sensation of control under VR, 3 if vice versa.
IsVRSessionFirst	1 if VR session was presented first and 0 otherwise.

Table 2. Description of factors and their levels

Organization of the Dataset

For each subject we provide two *mat* (and *csv*) files (Mathworks, Natick, USA) containing the complete recording of the sessions in the two experimental conditions (VR and PC). Each 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 contains the experimental events. The rows in column 18 (Event) are filled with zeros, except at the timestamp corresponding to the beginning of an event, when the row gets one of the following values:

- 102 for the end of a repetition.
- 100 for the onset of a new block.
- 20–25 and 40–45 when a group which does not contain the target flashes. The twelve groups are separated in six rows and six columns, in such a way that a symbol is included in exactly one row and one column (9). Note that the naming of rows and columns do not refer to the physical rows and columns in the matrix, although it was the case in the first implementation of the protocol (10). The first digit of the values indicates whether the group is a ‘row’ (digit 2) or a ‘column’ (digit 4). The second digit indicates the number of the flashed row or column in the range [0, 5]. Note that the groups are randomized between the repetitions thus a physical symbol in the matrix does not correspond to the same row or column.
- 60–65 and 80–85 when a group containing the target flashes. The first digit of the values indicates whether the group is a row (digit 6) or a column (digit 8). The second digit indicates the number of the flashed row or column in the range [0, 5].

For ease of use, we provide columns 19 to 22, which are filled with zeros, except at the timestamp corresponding to the following events:

- Column 19 (IsTarget) contains one when a group containing the target flashes.
- Column 20 (IsNonTarget) contains one when a group which do not contain a target flash.
- Column 21 (IsStartOfNewBlock) contains a positive integer in the range [1, 12]. Values correspond to the number of the started block.
- Column 22 (EndOfRepetitionNumber) contains a positive integer in the range [1, 5]. Values corresponds to the number of achieved repetition for a same target.

The *Header.mat* (or *Header.csv*) file contains the column names, sorted by the ascending column number, including the name of the EEG channels we used. We also provide a *Questionnaire.mat* (and *Questionnaire.csv*) file which contains, for each subject, the value of the 14 variables presented in **Table 1** and **Table 2**. Note that the questionnaire also includes the demographic variables, that is, the genre and age of the subjects. The names of the variable within the *Questionnaire.mat* (and *Questionnaire.csv*) file are reported in the *Questionnaire_header.mat* (and *Questionnaire_header.csv*) file.

We also supply an open-source Python code example (1) using the analysis framework MNE (11,12) and MOABB (13,14), a comprehensive benchmark framework for testing popular BCI classification algorithms. This python code is a classification example of the P300 using epochs of signals with duration one second. The performance of the classifier is evaluated in PC and VR. A complete analysis of this dataset is available in (7).

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