

# The Impact of Passive Head-Mounted Virtual Reality Devices on the Quality of EEG Signals

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## Abstract

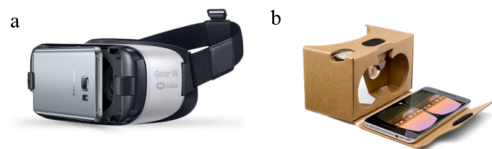
Thanks to the low price, the use of a head-mounted device (HMD) equipped with a smartphone is currently a common set-up for virtual reality (VR). Brain-computer interface (BCI) based on electroencephalography (EEG) is a promising technology to enrich the VR experience. However, the effect of using HMDs on the acquisition of EEG signals remains still unknown. In fact, the smartphone is placed close to the head where EEG sensors are located, thus the smartphone's electronics may perturb the acquisition of the EEG signal. In the present study, we compare the spectral properties of the EEG signal acquired on 12 subjects wearing a SamsungGear HMD equipped with a Samsung S6 smartphone turned on and off. Our study shows that there is no significant difference in the spectral properties of the EEG in these two experimental conditions. We conclude that a smartphone-based HMD is compatible with EEG technology. Some technical problems related to the concurrent use of a HMD and an EEG-based BCI are also discussed.

## CCS Concepts

•Human-centered computing → Virtual Reality; Laboratory experiments; Interaction devices;

## 1. Introduction

Since the first Oculus device (Facebook, California, US), several other head-mounted-devices (HMD) for virtual reality (VR) have been commercialized, such as the SamsungGear (Samsung, Seoul, South Korea) and the HTC Vive (HTC, Taoyuan, Taiwan). These devices contain on-board electronics, thus we will refer to them as "active". Other devices such as the Google CardBoard (Google, Mountain View, US) consists of just a mask with lens in which we insert a smartphone. These devices do not contain on-board electronics, thus we will refer to them as "passive" (Figure 1.).



**Figure 1:** SamsungGear (a) can be used in passive (inserting a smartphone) or active (with on-board electronic supplied) mode. The Google Cardboard (b) is a very simple passive HMD.

As compared to a personal computer (PC), a HMD liberates the hands and in some conditions allows the user to move freely in a restricted area. A disadvantage is that it can be uncom-

fortable due to its weight and the fact that the user may experience motion-sickness [ANW\*03, DL92, HR92, MS92]. Among other well-known virtualization devices we may mention the CAVE (Cave Automatic Virtual Environment) [CNSD\*92], which is a projection of a 3D environment on the walls of a cube-sized room or alternatively displayed on large LCD screens. In contrast to HMDs, with this system the user does not need to wear any equipment. However, there is no difference in motion sickness using a CAVE in comparison to an HMD [CKG16]. Moreover, the CAVE is much less transportable and much more expensive, thus so far CAVE systems have mainly concerned universities and corporations, whereas the enthusiasm of the general public has been tepid.

Electroencephalography (EEG) is a natural candidate to improve VR immersion as it can replace and/or enhance the classical mechanical input channels by means of Brain-Computer Interface (BCI) technology [BB00, Bay03, CLK\*02, LLR\*08, LRL08, Lot12, RADE09]. A BCI introduces a direct communication channel between the brain and an external device, that is, the user can send commands without resorting to the usual muscular pathways. It can also provide physiological information about the mental state of the user (concentration, fatigue and cognitive load, for example). In this work, we focused on EEG-based BCIs because they are portable, non-invasive, non-expensive and easy to set up in comparison to other BCI technologies such as those based on magnetoencephalography or magnetic resonance imaging. Tradition-

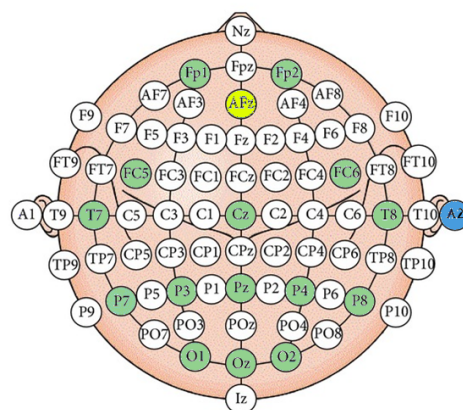
ally, BCIs have been conceived to control prosthesis or to provide communication for people suffering from severe motor disabilities [WW12]. More recently these interfaces have been proposed in the context of gaming or simulation with the purpose of providing an original way of interacting with the game and/or physiological information about the mental state of the player [Lot12]. Previous works suggest that the performance of BCI systems in VR is comparable to the performance of BCI looking at a normal computer screen [BB00, Bay03, CLK\*02, LLR\*08, LRL08, Lot12, RADE09]. In [LLR\*08, Lot12] the authors made a review of existing games coupling VR and BCI, concluding that BCI-based VR games are feasible. In particular: study [BB00] has shown that the use of HMD is possible with a BCI based on visual stimulation; study [Bay03] made a comparison of a visual BCI in a virtual environment and a computer monitor, showing that there is no significant difference in the two environments; finally, study [CLK\*02] suggested that VR immersion helps concentration and proposed a framework based on VR and BCI to treat people suffering from hyperactivity. All the studies above suggest that virtual reality can yield better result, or shorter training time. Training time refers to the calibration phase needed by machine learning algorithms in BCI systems. Calibration engages time and cognitive resources of the user. Depending on the BCI paradigm the training phase may take minutes to weeks. In [RADE09], the authors compared the performance of a training in a VR environment to a standard feedback (e.g., the position of a bar on the screen varying with the user's performance). After a 3-weeks training, the authors demonstrated that the training with VR led to a better performance: the authors do not say in which extent the training can be shortened, but the error rate decreased faster using VR feedback as compared to standard feedback. Nonetheless, as pointed out in [Lot12], most BCI studies have been carried out in laboratory conditions. The same authors describe a game, already presented in [LRL08], tested "out of the lab", with promising but unsatisfactory results - only 25% of the participants were able to control the interface. Thus, there is still no evidence that a BCI-enriched VR system is practically possible in real-world situations.

Although the literature suggests that the BCI performance in VR environment is satisfactory, a natural question is whether the VR device induces perturbations onto the EEG signal. In fact, as per today, there is no way to know if the difference in performance observed between the VR and non-VR conditions are due to the different interaction modes or by instrumental differences. To answer this question in this study we test whether the electromagnetic noise produced by a smartphone inserted in a passive HMD affects the EEG signal. To the best of our knowledge, no study has tried to answer this basic, yet fundamental, question before. For the test we have employed the SamsungGear in passive mode. This amounts to just a mask with lenses, in which we insert a smartphone (Figure 1). We have chosen this device because it is a very common set-up that has gained the acceptance of the general public. We have recorded EEG signals with 16 electrodes covering the whole scalp using the same EEG device while wearing or not a passive HDM. We have then compared the absolute amplitude spectrum of the signal for frequencies between 0.5 and 36Hz, which is the frequency band-pass of interest for all current EEG-based BCI applications. Our results show that the amplitude spectrum is not impacted by the use of a passive head-mounted-device.

## 2. Exposition

12 volunteers participated to the experiment (3 females), with mean (SD) age 26.25 (2.63). Subjects were recruited at the University of Grenoble-Alpes. Before the experiment, the subjects were informed that they will be exposed to electromagnetic contamination due to the proximity of a smartphone put in proximity of their eyes. The experiment was conducted after the subject signed an informed consent form.

EEG signals were acquired by means of an amplifier g.USBamp (g.tec, Graz, Austria) and an EC20 cap with 16 electrodes (Easy-Cap, Herrsching am Ammersee, Germany) placed according to the 10-10 international system (Figure 2). The electrical reference was placed on the right earlobe and the ground was the AFz electrode. The amplifier was linked by USB connection to a PC where the data were recorded by means of the software OpenVibe [RLG\*10]. Data were digitized at a sampling frequency of 512Hz with no digital filter applied. We used two identical smartphones in order to quickly switch between the two experimental conditions. In both conditions the subject wore the SamsungGear device. In one condition the smartphone was switched-off and in the other it was switched-on. Anything else in the two conditions was identical. Smartphones used as VR devices were Samsung S6 running under Android OS Nougat. The Specific Absorption Rate (SAR) of the smartphone was 0.382 Watt/Kg (Head) and 0.499 Watt/Kg (Body).



**Figure 2:** In green, the 16 electrodes placed according to the 10-10 international system [CLN85]. We used AFz (in yellow) as reference and A2 (in blue) as the ground.

The experiment took place in a small experimental room (around 2m square). Subjects were asked to sit on a desk in front of screen at a distance of about 50 cm. In order to mimic real-world usage we did not employ any instrumental noise-reduction device such as a Faraday cage. The EEG cap and the Samsung Gear were then placed on the subject. We continuously swapped the smartphones into the Samsung Gear. In both condition the screen of the smartphone was black and a purple marker was stuck on the left part of the screen in both devices (Figure 3). Having one marker might seem unnatural as one eye is looking at something that the other cannot. However, in a pilot study it was established that it was difficult for the subjects to reproduce stereoscopic vision with two

markers because small differences in shape and position between the two markers were unavoidable. Additionally, there was a tiny white line on the center of the switched-on smartphone to mark separation between left and right part of the screen on the running smartphone. This line was hidden by the Samsung Gear when the smartphone was put into it. The luminosity of the screen was comparable in the two conditions. Subjects were asked to focus on the marker and to listen to the music that was diffused during the experiment (Bach Invention from 1 to 10 on harpsichord). The music was presented via the speakers of a personal computer. The marker and the music were introduced to homogenize the mental activity of the subjects during EEG recording. In addition, fixating the purple marker aimed at minimizing eye movement artifacts.

The experiment comprised 10 blocks. There were five blocks in the condition switched-on and five blocks in the condition switched-off. Each block consisted of one minute of EEG data recording with the eyes opened. Hence, a total of 10 minutes were recorded for each subject. The sequence of the 10 blocks were randomized prior to the experiment for each subject using a random number generator featuring no autocorrelation. This experimental design allows the use of an exact randomization test for testing hypotheses [EO07].

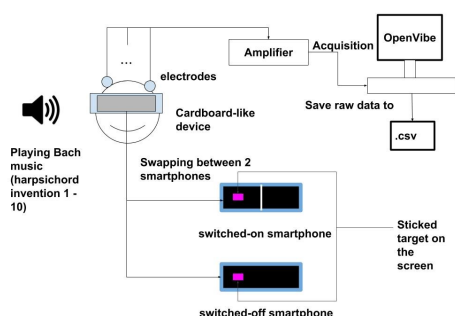


Figure 3: Experimental setup.

Data analysis was implemented in MATLAB (Mathworks, Natick, MA, USA). As pre-processing, we applied a 4th order forward-backward IIR<sup>1</sup> Butterworth filter in the bandpass region 0.5-36Hz. Then we used a forward-backward IIR notch filter at 50Hz with a Q factor equal to 35. Butterworth and notch filtering are both common standard pre-processing for EEG analysis. The range of 0.5-36Hz was chosen because it includes the overwhelming majority of EEG energy and all frequencies of interest for traditional BCI, while the notch filter removes the power line noise from the signal. The central 40 seconds of each block were used for ensuing data analysis and to avoid instabilities of the signal due to switching smartphone in the HMD. Artifacts were removed from the signal. We inspected the signal visually using Icon Software<sup>2</sup> to make sure that all channels recorded proper signal. We then cut each block in adjacent segments of 2s and we applied an automatic artifact rejection procedure with Fieldtrip [OFMS10] to reject segments with artifact. An automatic procedure was preferred in order not to introduce a systematic bias.

Artifact rejection with Fieldtrip consists in a z-transform of the

filtered data, averaging it over channels (here electrodes) and a threshold for the accumulated z-score set to 4.0. As an exclusion criterion for the analysis, we rejected a block if it presented less than four 2s valid segments, that is, if more than 60% of this block was corrupted by artifact. However, this criterion was never fulfilled. For each block, the average (SD) number of 2s segment retained for all subjects was 8.2 (1.97) for condition smartphone switched-on, and 8.47 (1.6) for condition smartphone switched-off. We assessed by mean of a within subject one-way ANOVA that the number of artifacted segments did not differ in the two experimental condition ( $p > 0.05$ , Figure 4). The test ANOVA is used here to determine whether there is a significant statistical difference between the mean of the number of artifacted segments in the switched-off and switched-on condition.

For each block, the average amplitude spectrum was computed by Fast Fourier Transform (FFT), averaging for each block the absolute amplitude spectrum across the retained segments. Figure 5 shows the amplitude spectra averaged over all subjects, for electrode Fp1, CZ and Oz.

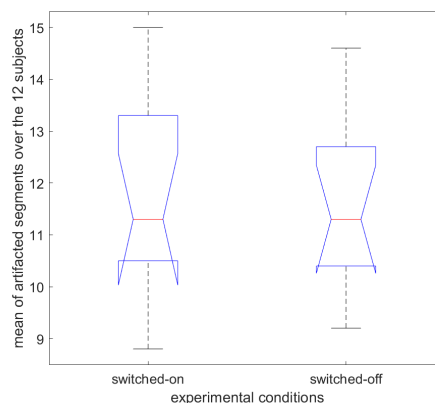
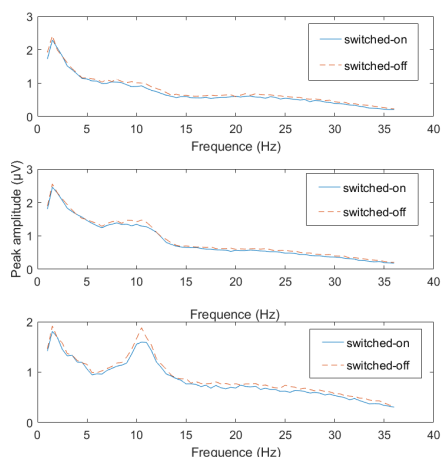


Figure 4: Box-plots of the number of artifacted segments in the two experimental conditions.

The spectra in Figure 5 are very similar in the two conditions, presenting the same spectral profile. The only noticeable difference is the peak at 11Hz, which is more pronounced in the switched-off condition as compared to the switched-on condition at the Oz electrode. To test the null hypothesis that the amplitude spectra do not differ in the two experimental conditions we performed two-tailed univariate randomization tests [EO07], t-max multiple-comparison randomization tests [NH02] and cluster-based randomization tests [MO07]. The latter two tests are commonly used in EEG neuroimaging because they allow to correct for multiple comparisons, i.e., they ensure that the probability to commit even one type I error is below the predefined alpha level, which as usual in this study we set to 0.05. Furthermore, they adapt to any degree and form of correlation among the hypotheses, which is desirable since EEG data is highly correlated across adjacent frequencies and adjacent electrodes, thus other ways to account for the multiple comparison problem may result in unduly conservative tests. All tests were within subjects. In total, there were 16 electrodes and 71 frequencies going from 0.5 to 36 Hz in steps of 0.5Hz. Thus,



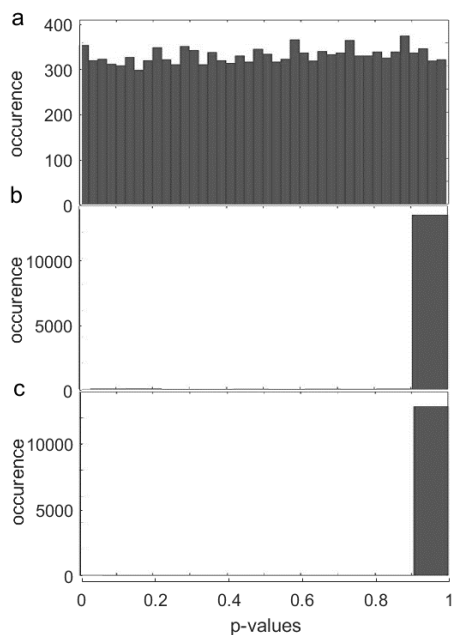
**Figure 5:** Amplitude spectrum of the Fp1 (up), CZ (center) and Oz (bottom) electrodes in the two experimental conditions.

the number of tests is 1136 ( $16 * 71$ ). We used the implementation of Ehinger for randomization tests<sup>3</sup>, Groppé for t-max test<sup>4</sup>, and fieldtrip ("ft\_freqstatistics" function in the MATLAB toolbox) for cluster-based test [OFMS10]. Results are shown in Figure 6. Figure 6-a shows that the non-corrected p-values for all subjects are uniformly distributed between 0 and 1, as expected under the omnibus null hypothesis. Figure 6-b and 6-c show that the corrected p-values are concentrated between 0.9 and 1. Taking together, the results demonstrate that there is no significant difference between the two experimental conditions.

### 3. Discussion

In this study we found that the amplitude spectrum of the EEG is not impacted by the concurrent use of a passive HMD equipped with a commercial smartphone. This finding is consistent with behavioral results reported in the introduction showing that when using this kind of device, the performance of a BCI is equal or better compared to using a PC [BB00, Bay03, CLK\*02, RADE09]. Our study, however, has a number of limitations. First, the subjects were asked not to move during the entire experiment, so as to avoid all instrumental and biological EEG artifacts related to movement. This is not representative for a normal use scenario. Indeed, sometimes in the Virtual Reality context users may move freely and even walk around a room. In our experiment the subject was sitting on a chair. Previous studies suggest that EEG is not analyzable without appropriate signal filtering in locomotion context [LGMF12, GGBS\*10, GGMF10].

Also, in VR, gyroscopic imprecision may make the virtual scene slightly move around [BC03, SN15] because the gyroscope of the virtual device is imprecise and has an amount of drift. This effect can force the user to move the head/body to follow the virtual scene. Thus, we expect that this gyroscopic imprecision may introduce movement artifacts in the EEG due to head movement, which are not related to electromagnetic noise. We did not observe this in



**Figure 6:** Histogram of p-values for the randomization tests (a, non-corrected), t-max test (b, corrected), cluster-based test (c, corrected).

the present study though. In the case where the BCI application is based on visual stimulation (such as P300 and Steady-State Visual Evoked Potential - SSVEP), the target stimulus also moves with the virtual scene because of the gyroscopic imprecision. We wonder if the fact that this target is moving produces higher or lower target detection. On a 2D-screen application, [SGK11, GSK13] suggest that Event Related Potential (ERP) detection based on P300 is also efficient when the target is moving. Concerning SSVEP stimulation, reference [LAL11] suggests that ERP detection on a moving target is possible in a virtual world. Consequently, we expect that a gyroscopic drift will not affect the performance of BCI application based on visual stimulation, if this drift does not force the user to compensate virtual world rotation by moving the head.

The drift problem is part of the positional tracking that does not use sensors placed in the environment. Indeed, the gyroscope and the accelerometers used in commercial smartphones are not in general sufficiently accurate to establish the position and orientation in a 3D space. A solution to this problem is to use the smartphone's camera and combine image analysis with gyroscope and accelerometers data. Sensor Fusion for positional tracking is an active field of research [CMPC06, DDVPR14, LBFS14, SSHP15] tightly linked to VR applications, since the exact user position and orientation are needed to reproduce as accurately as possible user movements in virtual world. Considering the present popularity of VR devices, the industry has considered the problem and already announced new products in this domain such as the Google Tango (Google, Mountain View, US), the Zed Stereo Camera (Stereo-Lab, San Francisco, US) and the Bridge Headset (Apple, Cupertino, US).



BCI paradigms that use visual stimulation could introduce significant differences between the right and the left camera. In Virtual Reality, the stereoscopic vision is simulated by using two different cameras, one for the left eye and the other for the right eye, that render the virtual world from a different perspective. Then, left and right cameras are rendered on the left and right part of the physical screen - the smartphone's screen is split in two. We have found that there is a delay in the range of 10 to 100 ms between the stimuli on left and right part of the screen. The delay was measured by placing a photodiode in the middle of the two parts of the screen and lightening at the same time a group of pixels placed in front of these two photodiodes. We were able to determine the moment when a group of pixel light-on and compute the delay by measuring the absolute difference in time of these moments. The delay was 13 milliseconds for a Huawei MT7-L09 (Huawei, Shenzhen, China), a mid-range smartphone that is not specialized for VR, and 74 milliseconds for the Samsung S6. The 13 milliseconds delay for the Huawei smartphone could be caused by the time required to update the pixels on the screen when updating the texture<sup>1</sup>. For the Samsung S6 additional factors seems to play a role. The difference between the two smartphones we have observed show that there is large variability between the display of commercial smartphones and that not all of them can render in a fast and precise manner. Besides hardware concerns, the internal low-level implementation of the graphical engine of the Android OS should be investigated in more details to understand the reasons of these delays. The question is important, because a very large delay could lead to the perception of two stimuli instead of one. So, the ERP could change as a function of this delay leading to higher or lower accuracy as compared to the use of a computer screen.

Another relevant question is whether stereoscopic vision may influence ERP. This is supported by [ABM\*17] and [Frm\*16] who have shown that ERP shape may vary with the perception of depth. This is also well assessed in [MHK17], where the authors have built a classifier based on ERP capable of recognizing stimuli that occur at a different depth. However, this experiment employed an Oculus Rift (Facebook, CA, US), which is very different from the device we have used in the present study. To our knowledge, the impact on the ERP due to the delay between textures drawing for right and left camera in a stereoscopic vision has not been sufficiently studied, thus it needs further attention, in particular if the VR is emulated by a smartphone.

Considering all these aspects, we wonder if target recognition on visual-stimulation-based BCI systems coupled with a SamsungGear is as accurate as suggested by previous studies. Indeed, as reported in the introduction, the use of the lab's usage has not been sufficiently studied. Yet, such real-world usage is the natural one for a low-cost device such the SamsungGear. Finally, in order to compare the classification accuracy of BCI systems with and without VR, as done in the aforementioned studies, it would be appropriate to employ modern classifiers such as neural networks [CG11, LCL\*07], random forest [SSFMP15] and Riemannian geometry [Con13, CBB17].

#### 4. Conclusion

We have tested the effect of the SamsungGear head-mounted-device equipped with a smartphone on the quality of the EEG sig-

nal. We answered this question by comparing the EEG amplitude spectrum when the device is switched-on and when it is switched-off. After applying the appropriate filtering and artifact rejection, we performed the analysis using three kinds of statistical tests. The analysis shows that there is no influence of the virtual reality device on the EEG amplitude spectrum.

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\*Notes

## Section 2

1. Infinite Impulse Response
2. <https://sites.google.com/site/marcocongedo/software/icon>
3. <https://github.com/behinger/permtest>
4. <http://fr.mathworks.com/matlabcentral/fileexchange/29782-mult-comp-perm-t1-data-n-perm-tail-alpha-level-mu-reports-seed-state->

## Section 3

1. An example of LCD screen refreshing in slow motion : <https://www.youtube.com/watch?v=wts8f1bNnbo>