The Experimental Study of 'Unwanted Music' Noise Pollution Influence on Command Recognition by Brain-Computer Interface

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Abstract

Nowadays, the alternative methods of human-computer interactions that can drastically improve usability of cyber-physical systems and devices, as mobile robots, especially for disabled persons are in development. These methods includes usage of brain-computer interfaces (BCI). Unfortunately, BCI's aren't reliable enough to handle critical devices outside lab environments, since the quality of command recognition can be influenced by external conditions, as noise pollution that can distract the user of BCI. In this paper, we are presenting the experimental study results of the influence of noise pollution in form of unwanted music on the quality of control through BCI.

Keywords: brain-computer interface, music influence, command recognition, robotics

1 Introduction

The brain-computer interface (BCI) provides data on brain electrical activity (EEG data) as described by Curran and Stokes [1]. The BCI can be trained to recognize the user's mental images. In order to do this, when the user focuses on the image, his EEG data is fed into the EEG pattern recognition system. Thus, if the user thinks about this mental image again, the EEG pattern recognition system will detect that, as described by Lotte et al. [2]. This technology can be used to translate brain activity into a command, for example to execute some

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command when the user envisions the mental image he or she used to train the BCI. The main drawback of the BCI is the low recognition accuracy in comparison with the medical electroencephalograph (EEG scanner) as considered by Duvinage et al. [3]. Therefore a considerable time is devoted to various researches to improve the BCI. In particular, some researches are related to various methods of EEG data processing, for example described by Shishkin et al. [4] or Trofimov et al. [5].

External factors have an important role in working with BCI, for example sound noise that surrounds the user while she or he is using BCI. In this paper, we present the study of sound noise impact on BCIs' efficiency. The participants had been affected by noise in the form of 'unwanted music'. The influence of different music genres were tested.

2 Related Works

There are several works taking in the consideration influence of external factors on BCI usage, such as environmental noise, visual noise, or music. Some researchers, as Reuderink et al. [6], are considering lost of control as another external factor affecting BCI performance.

Nam et al. [7] examined two environmental noise simulations to simulate the effects of real-world noise. They showed that higher noise levels seem to increase user concentration. According Vidal et al. [8] visual noise leads to decrease of BCI efficiency to control a robotic arm. Zhou et al. [9] explored the influence of background music on BCI usage. They obtained that different performance measures did not reveal any significant performance effect when comparing background music vs. no background. However Lin et al. [10] consider that music could affect users' emotions that could make BCI users feel comfortable during BCI usage.

In order to research the music influence on the BCI usage quality, the following music genres were chosen: classical music, electronic music, jazz, pop music, rap and rock. These genres were chosen as the most known and representing intersection of classifications ISMIR2004 described by Baniya et al. [11] and GTZAN described by Tzanetakis and Cook [12]. However, instead of the hip-hop, the rap musical genre was chosen to simulate a conversational noise.

3 Methods

3.1 Participants

The research was conducted on 32 healthy participants (aged 20 to 25, mean age is 23 years old, six women) in accordance with the Helsinki Declaration and the local institutional rules. All participants gave verbal consent. Eight participants (11, 15, 17, 18, 23, 24, 26, 28) have already participated in several experiments similar to the one described in this research. The other participants didn't have experience of BCI usage.

3.2 The Procedure

The scheme of the experiment is shown in Figure 1.

In the beginning, the participant has passed the training stage for BCI usage. At this stage, the participant has been trained to execute the forward motion command using the BCI. In order to do that, he or she had to think about the mental image she or he wants to execute the command with.

In order to determine the quality of the BCI usage, the participant had to pass tests described by Chepin et al. [13] and Voznenko et al. [14]. The participant have been being shown a random

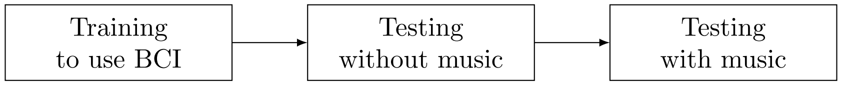

Figure 1: The scheme of the experiment

Figure 2: Two kinds of pictures. (Left) A kitten, the participant must not execute command while he or she sees it. (Right) Dishes, the user must execute the forward movement command

picture. The picture may show an inanimate object or animal. If the picture shows an inanimate object (for example, a crockery or a cabinet) it must lead to the forward motion command execution using BCI. If the picture shows an animal it must not to do that. An example of the pictures used for the tests is shown in Figure 2. In the process of the participants training for BCI usage it was determined that the optimal time for one test (without or with music of a certain genre) is 5 minutes. With such a length of test, the participants didn't tire of concentrating on the forward command execution.

At first, the test was conducted in the silence. Next the tests was conducted while the participant was listening to music of a certain genre. After end of the test, its accuracy percentage (ACC) calculated by the formula 1 was shown.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \tag{1}$$

The arguments are the numbers of following cases:

- TN (true negative) – the participant didn't executed the command when it wasn't needed;
- TP (true positive) – the participant executed the command when it was needed;
- FP (false positive) – the participant executed the command when it wasn't needed;
- FN (false negative) – the participant didn't executed the command when it was needed.

4 Results

After the experiments conducting, and the musical genre influence on the parameters values determining, the percentage change of ACC value between the test results without music and with music for all genres was calculated. The obtained results were applied for hierarchical clustering, that allowed to obtain the participants dendrogram (Figure 3).

Based on the obtained dendrogram, 5 clusters (groups) were selected and the thermal table with colors depending on the increase/decrease of the cell value was constructed (Table 1). The green color is for ACC value increase and the red is for decrease.

Thus, 5 participants groups were selected, for each of which have a common music influence on the test results. The Shapiro-Wilk criterion described by Shapiro and Wilk [15] was applied to the test results for each group, except for group 5. The result of the criterion applying

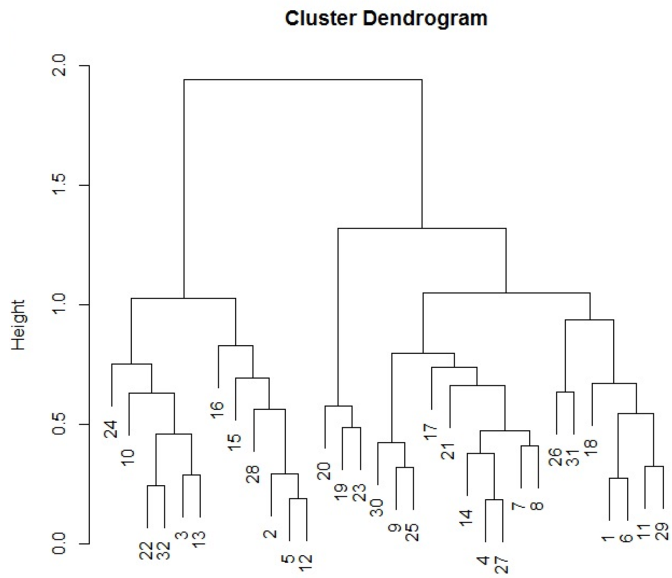

Figure 3: The representation of participants clustering based on music genres' response

showed that the data obeys the normal distribution. Next, the paired t-test of the Student was applied to the test result pairs without music – with the music of certain genre. The result of applying the criterion (Table 2) shows the significance level of the p differences.

The ACC values with its statistically significant changes (with the significance level of the p differences < 0.05) are presented in Table 3.

5 Conclusion

The article examined the influence of listening to music of different genres on the quality of BCI usage. After the hierarchical clusterisation five groups with different music impact were singled out. For the first group, the music did not have a statistically significant influence on the ACC value. The second group have a noticeable ACC decrease when listening to electronic and pop music. For the third group, the music had a negative impact on the test performance, except for rock music (which had no statistically significant effect). The fourth group has an improvement of the ACC value when listening to jazz, and deterioration when listening to classical music and rap. The fifth group was positively influenced by music, but due to the small number of participants in this group, no statistically significant differences were found.

The ACC value deterioration can be explained by the response of the participants to the test. After the test with music, the participants said that if they liked music of a certain genre, they were distracted by listening to it, and it was harder for them to concentrate. If they didn't like the music, they tried to ignore it.

Thus, it was shown that the most of participants have negative 'unwanted music' impact on the accuracy of control. Therefore, it is recommended to use sound suppressing equipment during BCI usage.

No. Participant	Classic	Electronic	Jazz	Pop	Rap	Rock	No. Cluster
1							1
6							1
11							1
18							1
26							1
29							1
31							1
2							2
5							2
12							2
15							2
16							2
28							2
3							3
10							3
13							3
22							3
24							3
32							3
4							4
7							4
8							4
9							4
14							4
17							4
21							4
25							4
27							4
30							4
19							5
20							5
23							5

Color scale, %
-54
-51
-48
-45
-41
-38
-35
-32
-29
-26
-22
-19
-16
-13
-10
-7
-3
0
3
6
9
12
16
19
22
25
28
31
35
38
41
44

Table 1: The thermal table for the test results splitting by changing the ACC value

No music vs		class	electr	jazz	pop	rap	rock
group 1	t-statistics	0.578411	1.466298	-1.255381	1.443887	2.175974	-0.595850
	p-value	0.584028	0.192927	0.256017	0.198883	0.072462	0.573051
group 2	t-statistics	-0.950586	**-4.604521**	-1.918734	**-3.933797**	-0.536770	-0.399902
	p-value	0.385467	**0.005816**	0.113112	**0.011028**	0.614441	0.705741
group 3	t-statistics	**-7.718689**	**-7.496367**	**-9.364111**	**-4.568097**	**-3.809893**	-2.566062
	p-value	**0.000583**	**0.000668**	**0.000234**	**0.006012**	**0.012501**	0.050275
group 4	t-statistics	**-3.176283**	-1.643296	1.430307	**2.543347**	**-3.785360**	0.906273
	p-value	**0.011252**	0.134735	0.186415	**0.031537**	**0.004313**	0.38841

Table 2: The result of the t-test applying to the ACC values

Group	No music	class	electr	jazz	pop	rap	rock
2	64	—	38	—	46	—	—
3	77	45	46	38	56	47	—
4	55	42	—	—	70	44	—

Table 3: The ACC values with its statistically significant changes

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