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

Timofei I. Voznenko[1]*, Alexander A. Dyumin[1,2]†, Evgeniya V. Aksenova[3], Alexander A. Gridnev[1]‡ and Vladislav A. Delov[1]

[1] National Research Nuclear University MEPhI (Moscow Engineering Physics Institute)
Moscow, Russia
[2] Moscow Institute of Physics and Technology
Dolgoprudny, Russia
[3] Mental Health Research Center
Moscow, Russia

Abstract

Nowadays, the alternative methods of human-computer interactions are in development. These methods can drastically improve usability of cyber-physical systems and devices, as mobile robots, especially for disabled people. Brain-computer interfaces (BCI) are among them. Unfortunately, BCIs 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 noise pollution influence in the form of unwanted music on the quality of control through BCI. In general, the obtained results showed the negative impact on the accuracy of control for the most of participants.

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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

*Corresponding author. E-mail address: snaipervti@gmail.com
†Corresponding author. E-mail address: a.a.dyumin@ieee.org
‡Corresponding author. E-mail address: aleksgridnev@gmail.com

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technology can be used to translate brain activity into a command, for example to execute some 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 studies to improve the BCI. In particular, some studies are related to various methods of EEG data processing, for example described by Shishkin et al. [4] or Trofimov et al. [5].

The external factors play 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 styles 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 to 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 styles were chosen: classical music, electronic music, jazz, pop music, rap and rock. These styles were chosen as the most known, and they represent 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 style was chosen to simulate a noise in the form of background conversations.

3 Methods

3.1 Participants

The research was conducted on 32 healthy participants (aged 20 to 25, with mean in 23, six women, all are Russian students) in accordance with the Helsinki Declaration. All participants gave the 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 paper. 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.

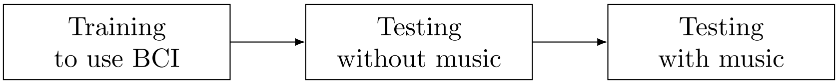

Figure 1: The scheme of the experiment

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 issue the command for forward movement

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 has been being shown a random picture. Inanimate objects or animals can be shown in the pictures during the test. If the inanimate object is shown on the picture (for example, a crockery or a cabinet) it must lead to the forward motion command execution using BCI. Accordingly, if the animal is shown on the picture it must not lead to any actions. 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 style) is five minutes. With such test length, the participants didn't tire of concentrating on the command execution.

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

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

The arguments are the numbers of cases where:

- TN (true negative) – the participant didn't execute 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 execute the command when it was needed.

The accuracy value shows the participant's correct actions percentage for the whole test.

4 Results

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

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

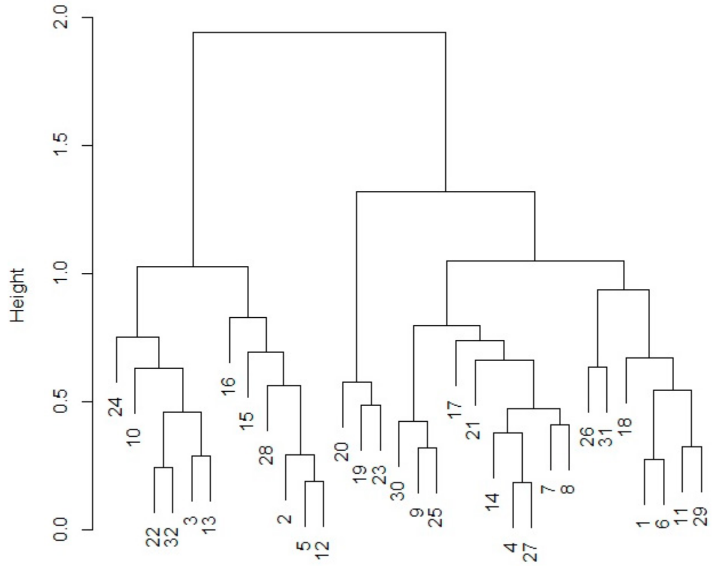

Figure 3: The representation of participants clustering based on music styles' response

Thus, five 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 fifth group. The result of the criterion application showed that the data satisfy the normal distribution. Next, the paired Student's t-test was applied to the test result pairs with and without music of certain style. The result of applying the criterion (Table 2) shows the significance level of the p differences.

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

5 Conclusion

The impact of music listening on control performance through BCI was investigated in this work. The main finding is that different music styles can influence differently based on operator's profile – the five potential groups of operators are singled out through our experiments based on response to music styles. On some of them any music presence do not cause statistically significant changes in control accuracy, others showed decrease in control accuracy for different music styles. After the experiments with music presence, the most of participants said that if they like music of a certain style, they were distracted by its listening, and it was harder to concentrate. If they didn't like the music, most of participants tried to ignore it.

Some participants showed improvement of accuracy when listening to music of certain style (i.e., fourth group for pop music), but in general, music presence did not help increase the correct actions during the testing, and therefore it didn't have a statistically significant positive effect on the quality of BCI usage. But, we plan further experiments to investigate these effects.

Thus, it was shown that the most of participants have negative 'unwanted music' impact on the control accuracy. Therefore, in current state of research, we can recommend sound suppressing equipment utilization during BCI usage in critical environments.

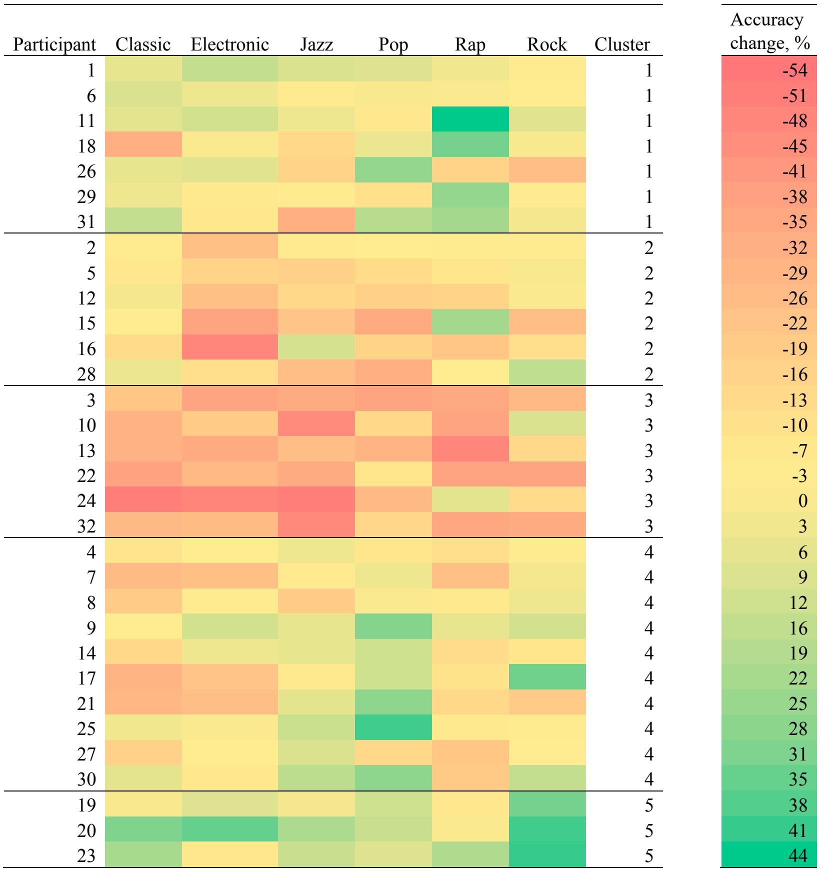

Table 1: The thermal table for the test results splitting by changing the accuracy value

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 accuracy 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 accuracy values with its statistically significant changes

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