Impact of age, VR, immersion, and spatial resolution on classifier performance for a MI-based BCI

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ARTICLE

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ABSTRACT
There are many factors outlined in the signal processing pipeline that impact brain–computer interface (BCI) performance, but some methodological factors do not depend on signal processing. Nevertheless, there is a lack of research assessing the effect of such factors. Here, we investigate the impact of VR, immersiveness, age, and spatial resolution on the classifier performance of a Motor Imagery (MI) electroencephalography (EEG)-based BCI in naïve participants. We found significantly better performance for VR compared to non-VR (15 electrodes: VR 77.48 ± 6.09%, non-VR 73.5 ± 5.89%, p = 0.0096; 12 electrodes: VR 73.26 ± 5.2%, non-VR 70.87 ± 4.96%, p = 0.0129; 7 electrodes: VR 66.74 ± 5.92%, non-VR 63.09 ± 8.16%, p = 0.0362) and better performance for higher electrode quantity, but no significant differences were found between immersive and non-immersive VR. Finally, there was not a statistically significant correlation found between age and classifier performance, but there was a direct relation found between spatial resolution (electrode quantity) and classifier performance (r = 1, p = 0.0129, VR; r = 0.99, p = 0.0859, non-VR).

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() motor imagery; brain–computer interfaces; virtual reality; classifier performance; EEG

1. Introduction

The evolution of brain–computer interfaces (BCIs) has largely advanced in recent years, projecting a promising future for BCIs in rehabilitative applications. Typically, neurorehabilitative strategies that use BCIs employ Motor Imagery (MI) or the imagining of physical movement as a helpful tool for rehabilitating people suffering from motor impairment [1]. However, only 65% of people are able to control MI-BCIs, according to [2]. This is an important concern when looking for strategies that can improve and generalize BCI performance for all users. For the scope of this paper, BCI classifier performance will be referred to as BCI performance and is considered to be the percentage of correct classification of movement intent during training trials.

There are many methodological factors that can impact BCI performance, some of which are outlined in the signal processing pipeline used in [3]. Many other factors do not depend on signal processing but can impact on the performance of such BCI systems. Psychological factors such as mood and depression and stimulation intake such as caffeine, before an electroencephalography (EEG) session, affect EEG signals [4–6]. Another factor to consider is the number of electrodes used during data acquisition. Using a higher quantity of electrodes provides a higher spatial resolution [7], meaning better precision for identifying the source origin of the signals, and more accurate decoding with better classifier performance, as reported in magnetoencephalography studies [8]. Other factors related to the delivery of the BCI feedback, such as the use of Virtual Reality (VR) or immersive systems like Head Mounted Displays (HMD). These can increase the immersiveness and engagement of a user [9] while introducing potential benefits, such as enhanced system learnability and mental state classification performance [10]. The use of VR has been important to the field of neurorehabilitation, offering an entertaining and alternative means of interactive rehabilitation via serious games [11]. Upon further inspection, VR, with and without the use of games, had a positive impact on not only stroke patients [12–15] but also the elderly population [16–19]. When combined with VR games, immersive BCI techniques have had a positive impact on motor function recovery, particularly in stroke patients [20]. Prior research has shown age-related differences in terms of the hemispheric asymmetry [21], effect in the sense of touch [22], and changes in the sensation of the human hand [23]. In terms of EEG, it has been shown that mainly Gamma rhythms are more closely related to

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age differences [24,25]. However, literature concerning the impact of age on sensorimotor rhythms and specifically on MI-BCI performance is very scarce. However, there seems to be a gap in the literature concerning the impact of age on MI-BCI performance. This type of research is especially important if research advancements are to be made for the rehabilitation of stroke patients and other impaired elderly.

Hence, there is a lack of research providing information about the impact between BCI performance for a MI-based task and each of the four previously mentioned factors: age, VR, immersiveness, and EEG spatial resolution. Therefore, the goal of this study is to evaluate the impact of these four factors on a standard processing BCI pipeline on both younger and older naïve BCI populations. This information will aid in identifying the factors that contribute to MI-BCI performance and in quantifying them such that those factors can be systematically exploited to achieve the maximum performance for all users.

2. Materials and methods

To evaluate the impact of age, VR, immersiveness, and EEG spatial resolution, a set of data was acquired from healthy volunteers of different ages during BCI-based MI. Using various setups allowed for the comparison of effects that the aforementioned factors had on classifier performance. The two MI methodologies that were used in this study include NeuRow and Graz. NeuRow, developed for upper limb motor rehabilitation, is a three-dimensional VR environment for MI-BCI. It consists of a first-person perspective rowing game whose goal is to capture as many flags as possible in a fixed time [26]. The Graz paradigm is considered to be the standard method of instructional MI via commanding directional arrows. The next sections detail each of the factors of interest and part of the employed methodology utilized in this work.

2.1. Experiment

The experiment was divided into two sessions: VR (NeuRow in both immersive and non-immersive modalities) and non-VR (Graz in non-immersive modality). In the VR session, the participant mentally performed a rowing action as the MI goal while observing an avatar row a boat using NeuRow. For the non-VR session, the participant performed the same rowing MI when a cue is displayed on a screen, following the Graz paradigm [27] as shown in Figure 1.

2.2. Population

All participants were healthy volunteers with no known neurological clinical history. The participants were recruited based on their motivation to participate in the study, and they were asked to avoid caffeine or energy drink consumption the day of data acquisition. The complete sample under study was composed of 18 participants, 10 males and 8 females, with 33.41 ± 12.39 years of age (N = 18, 10 males and 8 females, 33.41 ± 12.39 y.o.). All were right-handed except for one, according to the Edinburgh inventory [28]. The sample was divided into two groups: the adult-immersive sample (N = 5, 5 females, 50.4 ± 6.02 y.o.) and the young sample. The young sample was split into two subgroups: young-immersive (n = 7, 5 males and 2 females, 27.29 ± 4.31 y.o.) and young-non-immersive (N = 6, 5 males and 1 female, 25 ± 5.33 y.o.). The

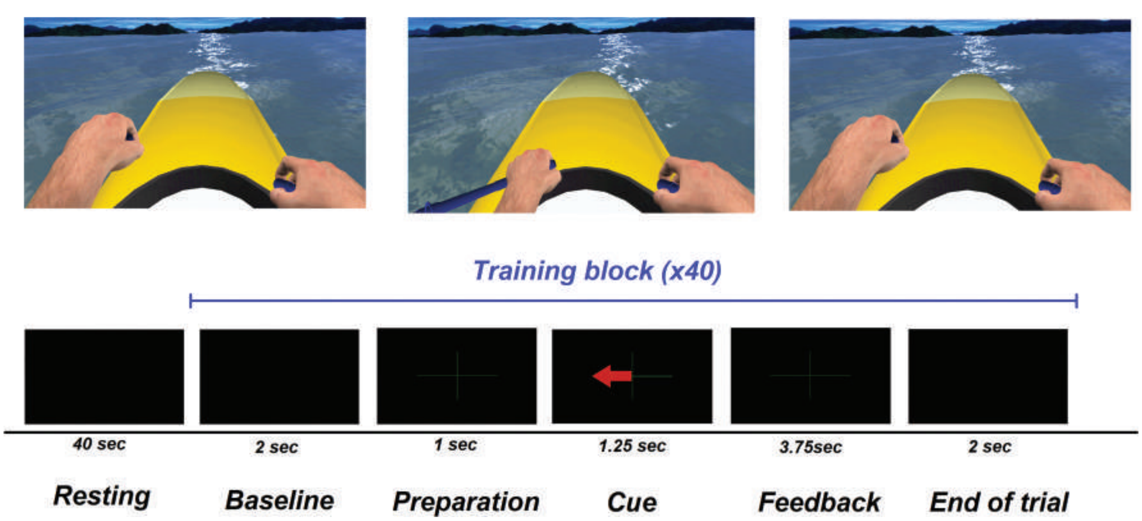

Figure 1. Training block paradigm.

immersive groups used an HMD for the VR sessions (young participants YA01, YA02, YA03, YA04, YA05, YA06, YA07; and older participants OA01, OA02, OA03, OA04, and OA05). The young-non-immersive group (participants YA08, YA09, YA10, YA11, YA12, and YA13) used a screen for the VR session. All participants used a screen for the non-VR session.

2.3. Data acquisition

EEG data were acquired in two different geographical locations using two EEG systems equipped with 32 active electrodes, configured to the 10–20 System of Electrode Placement, and a sampling frequency of 500 Hz, down-sampled to 250 Hz. The real-time EEG processing pipeline was implemented in OpenVibe [29] in both locations. The young non-immersive dataset was acquired at the first location, using a wireless Liveamp 32 EEG amplifier (Brain Products GmbH, Munich, Germany). At the second location, the remaining datasets were acquired using a wireless g.Nautilus (g.tec, Graz, Austria). All participants underwent 40 trials of BCI training (20 left-hand and 20 right-hand MI tasks), for both VR and non-VR sessions. Peripheral electrodes were excluded from data processing to reduce the presence of artifacts. To quantify the impact of using different electrode setups for the MI-BCI performance, the acquired data were processed using three montages: 15, 12, and 7 channels, shown in Figure 2. The electrode positions and montages were selected due to their coverage of the major part of the motor, premotor, and posterior parietal areas across the available 10–20 electrode positions shared by both EEG devices employed to acquire the data.

2.4. Protocol

The session began with an explanation of the experiment to the potential participant, followed by gathering written informed consent. Next, the participant was guided through MI training and was instructed to physically and mentally (MI) practice the rowing motion. The first session always consisted of the VR condition (either immersive or non-immersive conditions) and the second session of the non-VR condition. The participant was comfortably seated at the setup shown in Figure 3. After receiving confirmation from the participant that the instructions were understood, the EEG cap with mounted electrodes was placed on the participant's head, the gel was applied, and the electrodes' impedance was verified to be satisfactory (<30 kΩ). Non-immersive conditions were presented on a 25-in. Samsung screen. For the immersive conditions, an Oculus Rift CV1 HMD (Facebook Technologies, Irvine, California) was placed over the EEG headset, and impedance quality was checked again.

For each session, the training lasted about 8 minutes and included the acquisition of EEG data, training a spatial filter, and training a linear classifier. Once the first session was finished, participants were asked about his/her fatigue, and consent was obtained to start the second session. Impedance quality was checked again before proceeding. The second session followed the same instructions for motor imagery and settings described above. Additionally, the timeline is described in Figure 4.

2.5. Data processing

EEG data processing was based on the pipeline described in [3] and included the use of temporal and spatial filtering for training a linear classifier in the OpenVibe platform [29]. Specifically, raw EEG

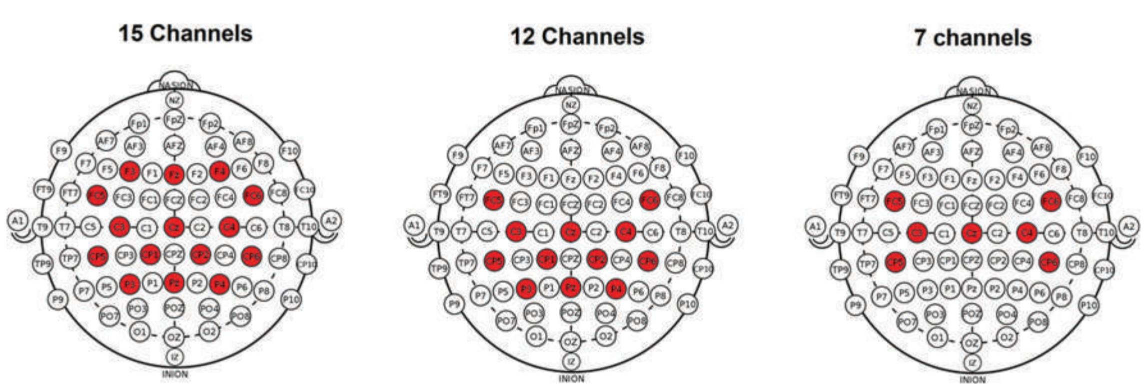

Figure 2. The 3 EEG montages selected to test impact of spatial resolution in MI-BCI performance.

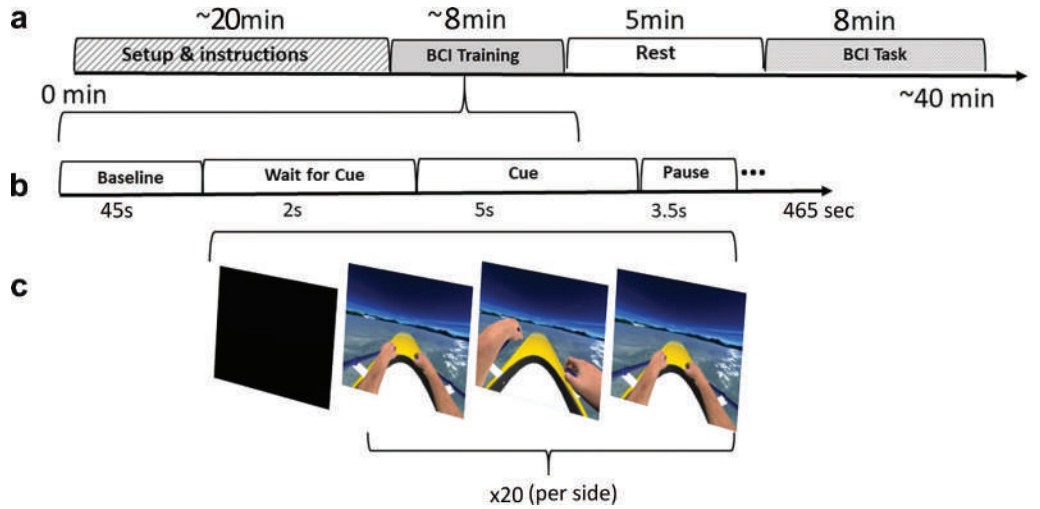

Figure 3. VR setup: A) Desktop computer running the acquisition software and NeuRow.

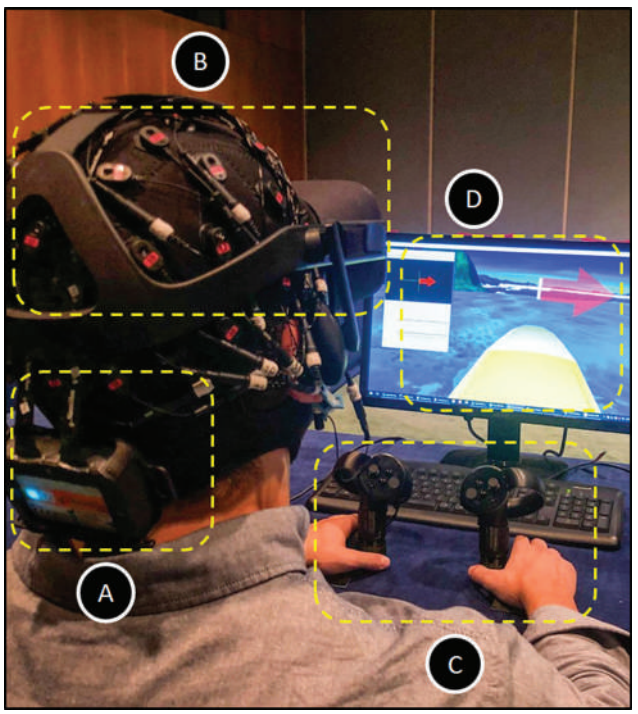

Figure 4. Experiment timeline.

signals were filtered from 8 to 30 Hz (within the Alpha and Beta band range), limiting the signal content to frequencies of interest; denoising the desired signal; and eliminating the potential constant offset, linear trending, and noise caused by the power line (50/60 Hz) present in the signal. Next, signals were spatially filtered using a Common Spatial Pattern filter (CSP), which works by reducing the input, obtained from a specific number of EEG channels, into four surrogate channels [30]. Each EEG channel's signal was expressed as a linear combination of the representative outputs. The variance contribution was extracted from each channel, such as in [31], and used to train a Linear Discriminant Analysis (LDA) classifier. Equation 1 shows how the variance is extracted. Sub-index p represents each output signal.

$$Hamming_{features} = Log\left(\frac{Var_p}{\sum_{p=1}^{4} Var_p}\right) \quad (1)$$

2.6. Data metrics

The main outcome variable was the LDA classification performance (as a percentage) during the MI-BCI sessions. It was obtained using 5-fold cross-validation during training sessions. The Anderson–Darling test was used for testing normality [32]. Signed-rank tests [33] were used to test statistical differences between paired samples. Spearman's correlation [34] was utilized to test the correlation between variables, and repeated measures ANOVA tests were used for detecting differences between related means of participant groups.

3. Results

In this section, the results show the effect of age, VR, immersiveness, and EEG spatial resolution on MI-BCI performance. For all statistical comparisons, the significance level was set to 5% ($p < 0.05$).

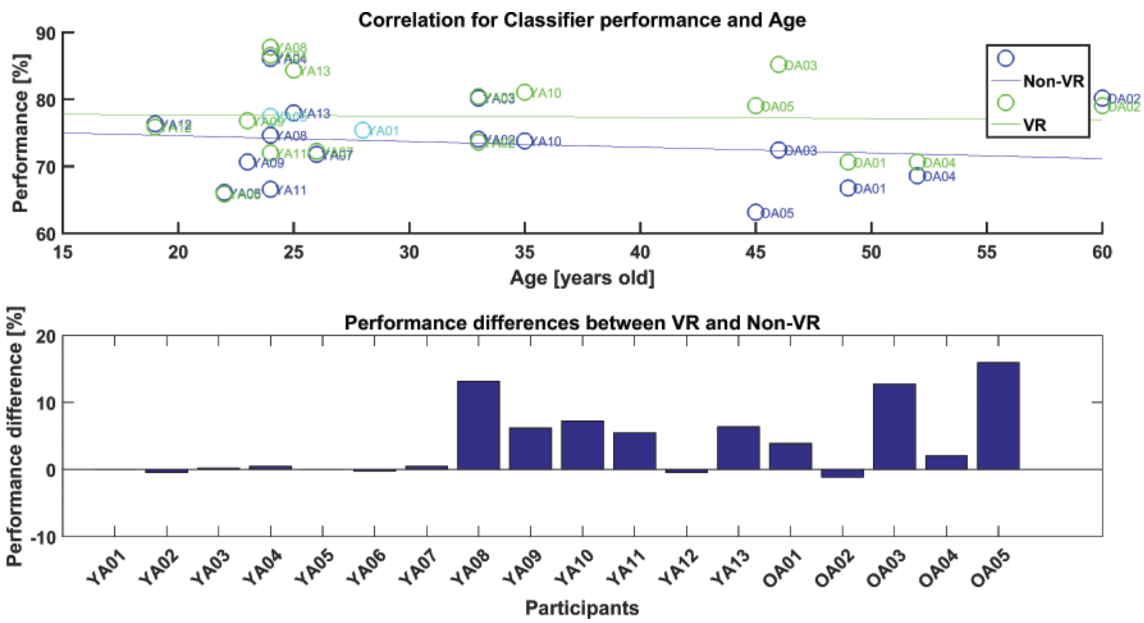

Figure 5. Top: Correlations between MI-BCI performance and age for the 15-electrode montage.

Table 1. ANOVA results for testing in between-group differences for MI-BCI performance for each electrode montage.

Condition	Montage	F-value (F(2,15))	p-value
VR	15 electrodes	0.597	0.563
	12 electrodes	0.768	0.481
	7 electrodes	0.276	0.763
Non-VR	15 electrodes	1.402	0.277
	12 electrodes	0.131	0.879
	7 electrodes	1.474	0.26

3.1. *Impact of age*

The impact of age on MI-BCI performance was measured, and a correlation was tested between age and the MI classifier performance obtained from the participants, as shown in Figure 5. Results showed a non-significant correlation between age and MI classifier

performance for all montages, meaning that age is not a factor that affects performance quality in BCI.

In addition, we tested for performance differences between the participant groups using ANOVA analyses. The performance was normally distributed for the three groups according to the following results of the normality Anderson–Darling test for the 15-channel montage: young-immersive (VR $p = 0.96$, non-VR $p = 0.98$), young-non-immersive (VR $p = 0.93$, non-VR $p = 0.74$), and adult-immersive (VR $p = 0.28$, non-VR $p = 0.76$). The results were consistent for the remaining electrode montages. There were no significant differences between groups for either the VR or non-VR sessions for any of the three-electrode montages, as summarized in Table 1. Based on these results, in the following analyses we merged the three groups with the resulting sample of VR-immersive (N = 12), VR-non-immersive (N = 6), and non-VR (N = 18) in the following analyses.

3.2. *Performance comparison by spatial resolution*

The same electrode montages were tested for all participants. Performance differences were tested in an offline analysis for three-electrode montages (15, 12, and 7 electrodes) for data acquired during VR and non-VR sessions. Comparisons were done using signed-rank tests, and the results are shown in Table 2.

Significant differences were found across all montages, regardless of the MI methodology employed. The 15-electrode montage was the best performing one, followed by the 12 – and 7-electrode montages. Performance from both the VR and non-VR conditions was higher for the 15-electrode montage than the 12-electrode montage (VR: 77.48% vs. 73.26%, $p = 0.0016$; non-VR: 73.5% vs. 70.87%, $p = 0.0156$), and the 12-electrode montage was higher than the 7-electrode montage (VR: 73.26% vs. 66.74%, $p = 0.0003$; non-VR: 70.87% vs. 63.09%, $p = 0.0004$).

Table 2. P values and Cohen's d effect size of comparison results for testing between-group differences for MI-BCI performance.

		VR			Non-VR		
p-values/Cohen's D value		15-chan	12-chan	7-chan	15-chan	12-chan	7-chan
VR	**15-chan**	N/A	0.0016/0.91	0.0002/2.37	0.0096/0.75	N/A	N/A
	12-chan	0.0016/0.91	N/A	0.0003 /1.58	N/A	0.0129/0.6	N/A
	7-chan	0.0002/2.37	0.0003/1.58	N/A	N/A	N/A	0.0362/0.55
Non-VR	**15-chan**	0.0096/0.75	N/A	N/A	N/A	0.0156/0.65	0.0002/1.54
	12-chan	N/A	0.0129/0.6	N/A	0.0156/0.65	N/A	0.0004/1.19
	7-chan	N/A	N/A	0.0362/0.55	0.0002/1.54	0.0004	N/A

N/A = Not Applicable

3.3. Comparison between mi methodologies

3.3.1. VR vs NON-VR

The role that VR plays has been tested comparing the NeuRow paradigm with the Graz paradigm, which is known to be the classical MI methodology. Boxplots of the comparisons are shown in Figure 6 and their results in Table 2.

Significant differences were found between VR and non-VR MI methodologies for all electrode montages, with consistently significantly higher MI-BCI performance for the VR condition (15 electrodes: VR 77.48 ± 6.09% vs. non-VR 73.5 ± 5.89%, p = 0.0096; 12 electrodes: VR 73.26 ± 5.2% vs. non-VR 70.87 ± 4.96%, p = 0.0129; 7 electrodes: VR 66.74 ± 5.92% vs. non-VR 63.09 ± 8.16%, p = 0.0362).

From Figure 5 (bottom), it is possible to check that VR immersive methodology has an increment of BCI performance for older participants (6,68 ± 7,29%) (participants OA01, OA02, OA03, OA04, and OA05) similar to the young group that used a screen during the VR session (Participants YA08, YA09, YA10, YA11, YA12, and YA13) (6,32 ± 4,34%). Meanwhile the BCI performances among the young participants, who used an HMD in the immersive scenario (participants YA01, YA02, YA03, YA04, YA05, YA06, and YA07), remained similar (0.063 ± 0.34%).

3.3.2. Immersive vs non-immersive

MI-BCI performance comparisons for the immersive and non-immersive groups were done using an independent sample t-test. The results are as follows: for the 15-electrode montage: 76.38% Immersive vs 79.68% Non-immersive with p = 0.292, a 95% confidence interval, and a difference of [−9.88, 3.28]; for the 12-electrode montage: 72.5% Immersive vs 74.78% Non-immersive with p = 0.4 and a 95% confidence interval, and a difference of [−7.83, 3.26]; and for the 7-electrode montage: 66.1% Immersive vs 68.03% Non-immersive with p = 0.53 and a 95% confidence interval, and a difference of [−8.32, 4.46]. In conclusion, the level of immersion for VR – either delivered through an HMD or through a screen – had no effect on performance.

All results comparisons are summed-up in Table 2.

4. Discussion

The objective of this work was to bring to light how to improve BCI performance in naïve participants through a cross-sectional study while trying to diminish the learning effect as a confounding factor. The LDA classifier was selected for our processing pipeline because of the trade-off between processing load and speed, and it is highly known in the literature as being the most common classifier used for motor imagery data. We recognize that benchmarking with different classifier types is an important step, but there would be a permanent limitation of results for the entire universe for the different types of classifiers.

4.1. Impact of age

Neuronal interaction between areas changes with aging, leaving the appearance of compensation [35]. This compensation can affect the neuronal recruiting of additional areas during MI [36,37]. In [38], the average left vs. right BCI performance accuracy of older subjects (72.0 ± 8.07 years old) was 66.4 ± 5.70%, 15.9% lower than that of the younger subjects (82.3 ± 12.4%) and significantly different (t(10) = −3.57, p = 0.005)). Nevertheless, our results have shown that for the studied sample (<50 years old) and the electrode montages used, age is not a direct factor affecting MI-BCI performance, given our correlation analysis. Discrepancies in the results obtained by [38] can be related to the important differences of age between their groups of study or our limited sample size. Therefore, it is possible to speculate, based on our results and other studies, that the BCI performance drop can be found at the intermediate

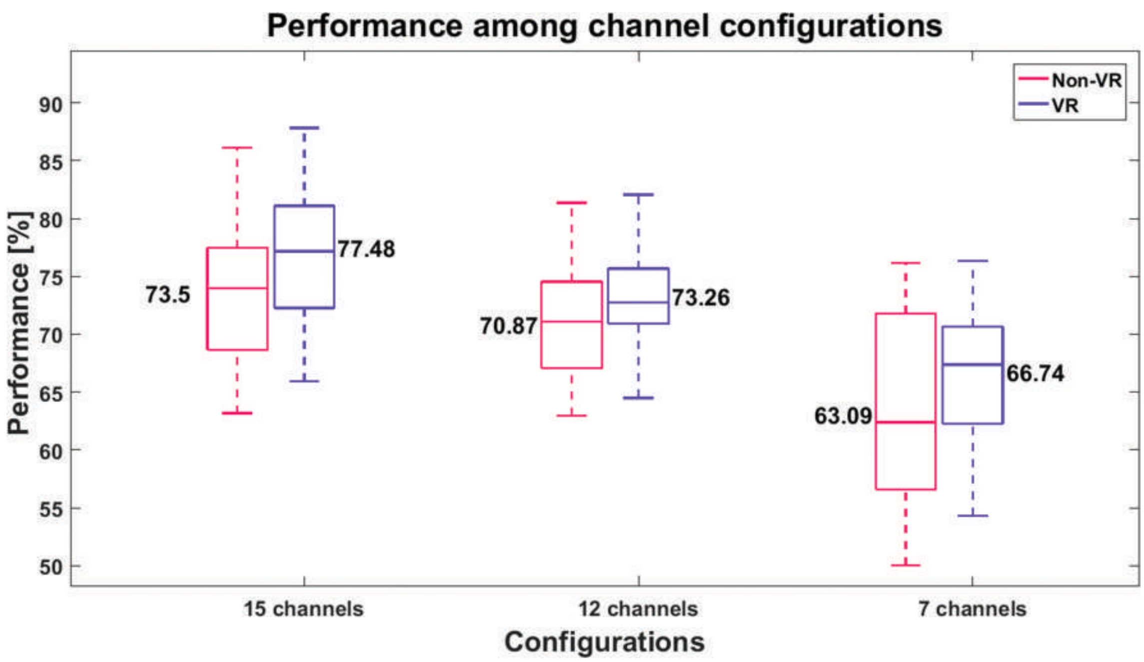

Figure 6. Performance among channel configurations.

age of 50 years old. Nevertheless, a new study with a more appropriate age-related population should be performed to investigate further.

4.2. Performance comparison by spatial resolution

The MI signature is a distinct and localized EEG pattern and there are several studies claiming high MI performance using only two channels per hemisphere [39,40]. The former asseveration is true in theory. Nonetheless, MI patterns are clear in highly trained participants after many sessions and by averaging many trials. Furthermore, naïve subjects do not generate a clear time-frequency EEG pattern [41,42]. Therefore, we have tested whether the spatial resolution could be a performance relieving factor for these non-clear naïve EEG patterns. Our results have illustrated that the number of electrodes used directly affects MI-BCI performance. There is an important performance drop of 10% between the 15-channel montage and the 7-channel montage that is independent of the methodology used (VR or non-VR). Concerning the 15-electrode montage, classifier performance was 77.48 ± 6.09% for VR sessions and 73.5 ± 5.89% for non-VR sessions. For the 7-electrode montage, the classifier performance was 66.74 ± 5.92% for the VR sessions and 63.08 ± 8.16% for the non-VR sessions. The relation between increased MI-BCI performance and electrode quantity can be interpreted as the effect of a higher spatial resolution from using more electrodes covering the supplementary and pre-motor cortex, which are involved in MI [42], and the posterior parietal cortex, which is activated simultaneously for visuomotor coordination and proprioception [43].

4.3. VR vs non-VR

Gamification has opened the doors to new captivating strategies, giving participants instantaneous outputs as rewards. When games are combined with VR, the immersion of the participant increases [9], and for stroke patients, the paretic limb movement is amplified [44]. The results in this work showed significant differences between the VR and non-VR conditions for all of the electrode montages that were tested. They exposed that using VR strategies can favor MI-BCI performance.

4.4. Immersive vs non-immersive

Previous studies have shown that the inclusion of HMDs influences participants' immersion and engagement for the desired task [45]. However, our data did not reveal any difference between the immersive and non-immersive conditions. This suggests that the effect of the level of immersion was reduced and that the main driver for improved MI-BCI was the VR component. However, we need to be cautious due to the low number of participants in each subgroup (12 immersive participants and 6 non-immersive participants).

Table 3. Conclusion Sum-up.

Factor	Conclusion	Observation
Age	There were not significant differences in BCI performance between the age groups.	Participants representing the older adult group (<50 years old) in this study are younger than other studies (>70 years old) that reported significant differences between age groups.
VR	Significant differences were found between classifier performance for VR and non-VR modalities for all the electrode montages. Using VR modalities can enhance BCI performance.	VR sessions were carried out first and that can have a confounding effect on performance comparison.
Immersion	Our data did not reveal any difference between the immersive and non-immersive conditions. This suggests that the effect of the level of immersion is reduced and that the main driver for improved MI-BCI is the VR component.	There is a low number of participants in each subgroup, 12 participants in immersive and 6 participants in non-immersive.
Spatial Resolution	Our results have illustrated that the number of electrodes used, directly affects MI-BCI performance. There is an important performance drop of 10% between the 15-channel montage and the 7-channel montage.	Covering major pre-motor and parietal areas with a higher number of electrodes improves MI-BCI performance in naïve subjects, independent of the methodology used (VR or non-VR).

Here, we have analyzed different factors that can affect BCI performance. Moreover, other methodological strategies such as targeting broader brain area activation from different MI approaches can improve BCI performance. Neuromodulation is a promising coadjuvant in neurorehabilitation and has encouraging pilot results using rTMS [46]. In [47] a correlation between BCI performance and sense of agency was found and that the act of imagining making a fist was more effective than raising arms in imagination. Recent studies have started to use multiplayer modalities [20,48], which offer a competitive effect that can strengthen a participant's commitment. These different strategies can advantageously be used together and boost the effects found in this work.

5. Conclusion

Covering major premotor and parietal areas with a higher number of electrodes improves the MI-BCI performance by roughly 10% when using the 15-electrode montage compared to a 7-electrode montage. Our results confirmed that VR, in favor of HMDs, has a significant impact on MI-BCI performance, although the effect of immersion level was not significant. We did not identify a direct correlation between MI-BCI performance and participant age. The most remarkable findings for each factor investigated in this work are summed up in Table 3.

6. Limitations

This work has a set of limitations that should be considered, such as high heterogeneity of participants and EEG setup differences between data collection sites. The heterogeneity of participants was tested for normality distribution and differences across groups without any significant differences. Nonetheless, it is possible that the differences between groups could be more revealed using a higher number of participants in each group. Consistency between the EEG systems used was ensured by using the same number of electrodes, electrode placements, type of electrodes, data acquisition protocol, processing pipelines, and by verifying impedance quality. However, we cannot completely rule out the potential effect of the equipment on the collected data. Since both the VR and non-VR conditions were collected for each participant using the same equipment, a potential effect should not affect the presented comparative analyses. Psychological factors such as mood or depression were not controlled, but none of the participants showcased a noncooperative mood or depressive symptoms. Consistently having the VR session first for the young and older adult group can have an impact on performance. The fact that all the data presented here are of naïve participants is considered to be a strength of the study because prior experience can be ruled out as a confounding variable. The significance of the results was not corrected for multiple comparisons due to the reduced sample size. Even so, the results showed a clear tendency for differences of the analyzed groups.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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