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Evaluating OpenBCI Spiderclaw V1 Headwear's Electrodes Placements for Brain-Computer Interface (BCI) Motor Imagery Application

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Abstract

Motor imagery can be defined in terms of imagined movement from the first person perspective. It has been getting many researchers' attention since it could be implemented in many important applications such as neurological rehabilitation, sports training, prosthesis movement control, and so on. This research evaluates OpenBCI for Motor Imagery application, especially whether the OpenBCI Spiderclaw V1 headwear electrodes placements are sufficient for motor imagery application. OpenBCI 32 bit board with daisy chain (16 channels) was used in this research. OpenVibe's motor imagery CSP scenarios were adopted. After subjects had finished working with the OpenVibe motor imagery scenarios, they were asked to fill Movement Imagery Questionnaire-3 (MIQ-3). MIQ-3 results were used to validate whether subject suffer from "BCI illiteracy". It could be concluded that the OpenBCI Spiderclaw V1 electrodes placements are not optimum for motor imagery application. The average of accuracy measurements which was around 60% for all subjects shows poor motor imagery performance. Furthermore, 16 channel electrodes configuration with a wide temporal filter range [8-30 Hz] showed better performance compared to other settings in this research. However, further study is needed to improve the statistical significance of these findings. On the MIQ-3 results, kinesthetic imagery score reflects the most correlated with the accuracy measurement, supporting the suggestion that questionnaire could be used to predict user's motor imagery performance.

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Keywords: *Brain-Computer Interface, BCI, Motor Imagery, OpenBCI, OpenVibe, MIQ-3*

1. Introduction

1.1. Motor Imagery and OpenBCI

Motor imagery means simulating an action/movements in individual's mind. It can be defined in terms of imagined movement from the first person perspective [18][9]. Motor imagery has been getting many

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researchers' attention since it could be implemented in many important applications such as neurological rehabilitation, sports training, prosthesis movement control, and so on.

Motor imagery research and applications have been developed using various electroencephalogram (EEG) devices: expensive medical EEG device, Commercial off-the-shelf EEG devices such as Emotiv or NeuroSky, and so on. However, recently many researchers have been giving attention to the OpenBCI, the open-source brain-computer interface (BCI) device (not to be confused with OpenBCI software - http://openbci.pl). OpenBCI has its roots as a crowdfunding project. The OpenBCI Board is a versatile and affordable bio-sensing microcontroller that can be used to sample electrical brain activity (EEG), muscle activity (EMG), heart rate (EKG), and more. It is compatible with almost any type of electrode and is supported by an ever-growing, open-source framework for signal processing applications (http://openbci.com) [23]. This device open opportunities for researchers to develop innovative BCI research and applications because of its open source nature, which means its software and hardware might be modified and developed as needed.

So far, only limited OpenBCI research reports have been published. For instances, Azokar [3] used OpenBCI to control a Quadrotor. Bondre and Kapgate [4] develop a framework for Steady State Visually Evoked Potentials (SSVEP) in Brain Computer Interface (BCI). Firtina et al. [6] develop Emotion Engine using OpenBCI, which acts as a hub between the computer and the user. It takes the user's physiological data through body sensors and continuously estimate the user's emotional state based on previously collected data from the user. The contribution of this research is that it might be one among the first which evaluating OpenBCI for Motor Imagery application.

1.2. OpenVibe and OpenBCI Spiderclaw V1 Headwear

OpenVibe (http://openvibe.inria.fr) is a novel open-source software platform to design, test and use brain-computer interfaces in real and virtual environments [17][15]. OpenVibe is meant to be a set of software modules for the acquisition, pre-processing, processing and visualization of cerebral data, as well as for the interaction with virtual reality displays [16]. OpenVibe has been implemented in many Brain-Computer Interface research, such as P-300 [5][11][12][10], as well as motor imagery [1]. This research adopted the OpenVibe's motor imagery scenarios.

Many researchers suggested the optimum electrodes placements for motor imagery application are around the C3 and C4 locations [14]. However, this research questioned the accuracy of motor imagery when the electrodes placements utilize the OpenBCI Spiderclaw V1 Headwear's scheme. According to the 10-20 systems, they were located at Fp1, Fp2, C3, C4, T5, T6, O1, O2, F7, F8, F3, F4, T3, T4, P3, and P4. Therefore, another contribution of this research is that a conclusion whether the Spiderclaw V1 electrodes placements sufficient for motor imagery application would be drawn.

2. Methods

2.1. OpenBCI

The first step of this research was to construct OpenBCI EEG device and its headwear. The Spiderclaw v1 headwear design (available on OpenBCI website) was 3d printed (Figure 1.a). However, the size of its design seemed to be too large for most of the users in this research (Figure 1.b and Figure 1.c). Therefore, it was decided that in this experiment, the EEG electrodes were placed manually on users' head, based on 10-20 systems (see Figure 2.a and Figure 2.b). OpenBCI 32 bit board with daisy chain (16 channels) was used in this research. OpenBCI GUI software was used to check whether the electrode placement had been working correctly (Figure 2.c).

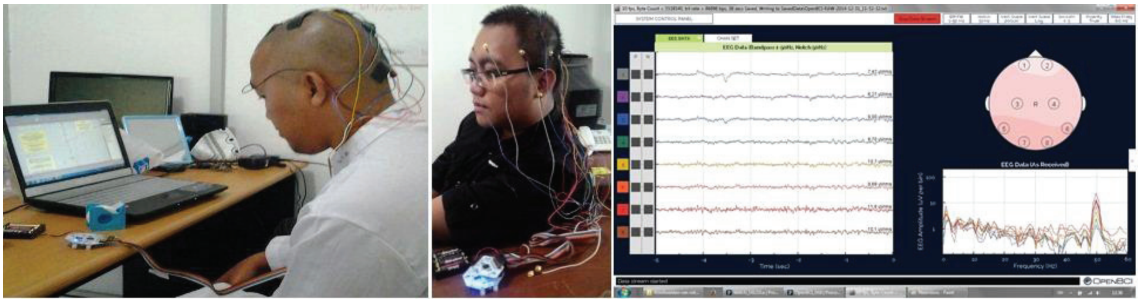

Figure 1. (a) OpenBCI electrodes placed on user's scalp. (b) Direct placement without headwear. (c) OpenBCI GUI software

Figure 2. (a) 3d printed OpenBCI headwear. (b) Prototype used by respondent (c) The size is too large for some users

2.2. OpenVibe Motor Imagery

This research adopted OpenVibe’s motor imagery CSP scenarios. It consists of several steps: signal monitoring, acquisition, CSP training, classifier training, online testing, and replay (see Figure 3).

According to [24], the signal monitoring scenario (Figure 3.a) was used to check the quality of the signals before starting an experiment. One should check the quality of the signals and ensure that: eye blinks are visible; jaw clenching is visible; alpha waves are visible when closing eyes. Temporal filter (Butterworth band pass) was used.

The acquisition scenario (Figure 3.b) was used as a first step to collect some training data. Those data will later be used to train a classifier for online testing. After 40 seconds running this scenario, it starts the instruction sequence. Left/right arrows will be presented to let users imagine left/right-hand movements. There will be 20 arrows of each side (see Figure 4.a). The stimulator configuration was written in Lua script (www.lua.org).

The CSP training scenario (Figure 3.c) trains the Common Spatial Pattern spatial filter that will be used in the further steps. Then the Stimulation based epoching boxes provide examples for the CSP Spatial Filter Trainer: class 1 for LEFT trials; class 2 for RIGHT trials. Spatial filter coefficients computed according to the Common Spatial Pattern algorithm. The CSP algorithm increases the signal variance for one condition while minimizing the variance for the other condition. The goal of the algorithm is to improve the discrimination of two types of signals. The spatial filters are constructed in a way they maximize the variance for signals of the first condition while at the same time they minimize it

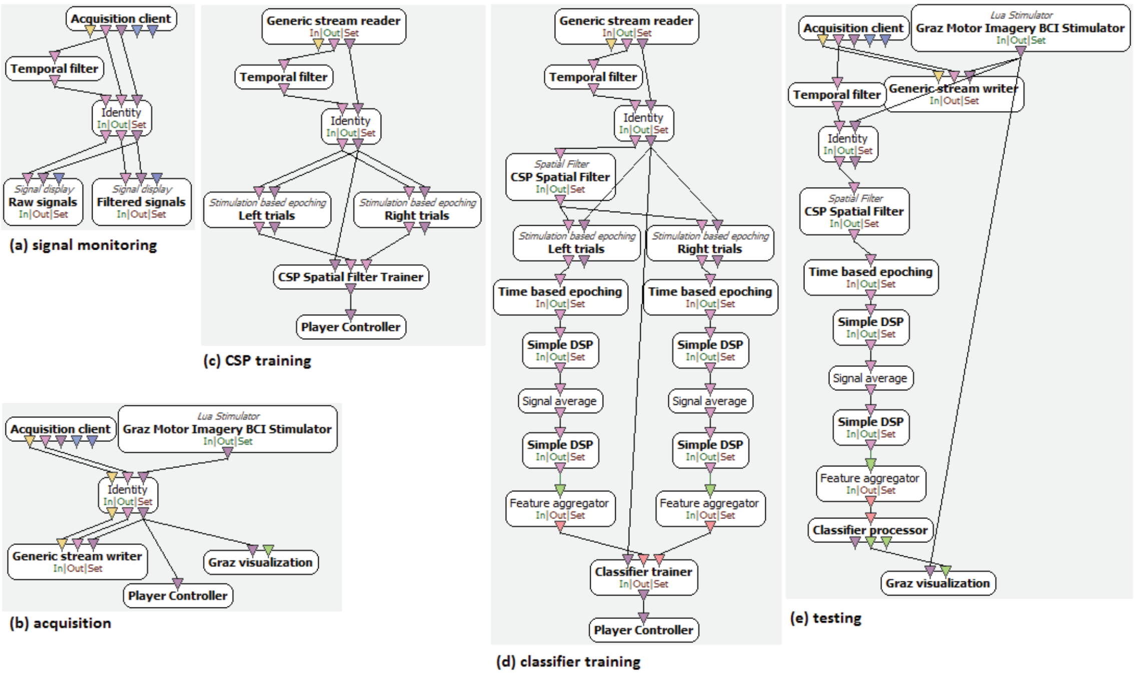

Figure 3. Motor imagery scenario in OpenVibe

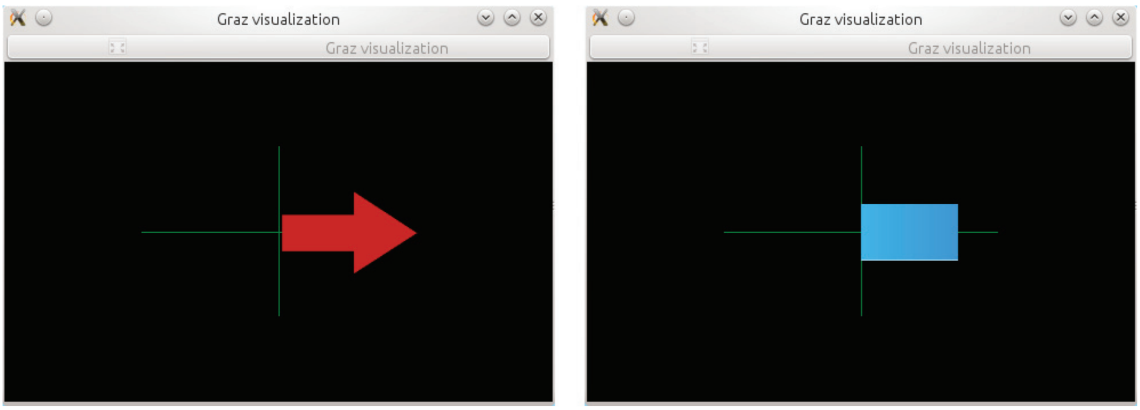

Figure 4. (a) Motor Imagery Instruction. (b) Classification result shown to user during testing

for the second condition. This can be used for discriminating the signals of two commonly used motor imagery tasks (e.g. left versus right-hand movement).

In the classifier trainer scenario (Figure 3.d), the CSP spatial filter configuration produced in the previous scenario is used prior to the feature extraction, followed by the feature extraction part. Then stimulation based epoching is used to select four seconds of signal half a second after the instruction was shown to the user. The signal is then splitted in blocks of 1 second every 16th second and the logarithmic band power is computed. The matrices can then be converted into feature vectors. This scenario produces a classifier configuration file at the end of the experiment that will be used during online sessions.

Finally, the online testing scenario can be seen at Figure 3.e. This scenario can be used online once the CSP spatial filter and the classifier are trained. The CSP spatial filter produced in the earlier scenario is used prior to the feature extraction, followed by the feature extraction part similar with at the previous scenario. The spatial filter maps M inputs to N outputs by multiplying each input vector with a matrix. Finally, the feature vectors are classified with an LDA classifier. Note that the state vector of the classifier (which in the case of the LDA is the distance to the separation plane) is sent to the Graz Visualization box for feedback (see Figure 4). In order to display correct feedback, the Graz Visualization box expects a negative value for one class and a positive value for the other class.

2.3. Data collection

This research involved 10 participants, all healthy male between 22 to 30 years old. OpenVibe's motor imagery scenario with CSP algorithm was modified. EEG recording was done in two phases. The first stage was conducted using eight-channel configurations, which electrodes were placed at Fp1, Fp2, C3, C4, T5, T6, O1 and O2 according to the 10-20 systems. Next, additional eight more channels (16 channel in total) placed at F7, F8, F3, F4, T3, T4, P3, and P4 were added. The recorded EEG data would be studied under two temporal filters setting. First, configuration with low cut frequency at 1 Hz and high cut frequency at 30 Hz. Second, filter in a smaller frequency band [8-12 Hz]. Therefore, for each participant, eight motor imagery accuracy measurements would be collected. The accuracy is computed given the results from classifiers, compared to the targets received. As a result, 80 accuracy measurements would be gathered from all participants in total.

After the participant had finished working with the OpenVibe motor imagery scenarios, they were asked to fill a questionnaire. The questionnaire used in this research was the Movement Imagery Questionnaire-3 (MIQ-3), which is the most recent version of the Movement Imagery Questionnaire [8].

2.4. Precautions towards BCI Illiteracy using Movement Imagery Questionnaire-3 (MIQ-3)

Since the cognitive function of each might slightly differ during practicing motor imagery, measurement of motor imagery ability is an important issue. According to the recent literature review conducted by Laura et al. [13], explicit motor imagery ability can be measured by questionnaire and mental chronometry. Moreover, implicit motor imagery ability can be measured through prospective action judgment and motorically driven perceptual decision paradigms.

The Movement Imagery Questionnaire-3 (MIQ-3) is the most recent version of the Movement Imagery Questionnaire [8] and the Movement Imagery Questionnaire-Revised [7]. It is a 12-item questionnaire to assess individual's ability to image four movements using internal visual imagery, external visual imagery, and kinesthetic imagery [22]. MIQ-3 requires the respondent to image four movements; a knee lift, jump, arm movement, and waist bend. Participants are asked to perform physically, and afterwards image the movement. Each movement is imaged three times, once from an external visual perspective, once from an internal visual perspective, and once kinesthetically, resulting in a total of 12 movements physically performed and then imaged. Following each image, participants rate the ease they can produce the image on a 7-point Likert-type scale. It is ranging from 1 (very hard to see/feel) to 7 (very easy to see/feel). A higher score, therefore, represents a higher ability to perform visual or kinesthetic imagery [21]. Williams et al. [22] identified the MIQ-3 to be a valid and reliable questionnaire.

The phenomenon of "BCI illiteracy" means that not everybody could use BCI application effectively, about 20% of subjects are not proficient with a typical BCI system [2]. In this research, MIQ-3 results were used to validate whether a subject suffers from “BCI illiteracy”. Any subject with this phenomenon would be excluded from further data analysis.

3. Results and Discussion

The MIQ-3 results from all participants are presented in Table 1. As suggested by previous research [19][20], motor imagery questionnaire could be used as a method to detect BCI illiteracy. From the Table 1, it could be seen that all participants were able to do the imagery task quite well. In average, most subjects report that “somewhat it was easy to see or to feel” when completing the task given in the questionnaires. Because of “BCI illiteracy” phenomenon did not emerge in this research. Therefore, the motor imagery accuracy data from all respondents would be used for further data analysis.

Table 2 shows the accuracy measurements from motor imagery application when the user run the experiment. The number shown in bold and highlighted means the peak of user’s performance, compared to the user’s performance in other configurations. After repeating the experiment, almost all subjects’ accuracy were increasing and reaching top performance under 16 channel electrodes configuration with a wide temporal filter range [8-30 Hz]. However, based on the ANOVA analysis that resulted in F= 0.21 lower than F crit= 2.72 means that the null hypothesis was accepted. It might need larger data size, to be able to conclude the statistical significance of this finding.

Furthermore, to compare the accuracy of 8 channels with 16 channel configuration and 8-30Hz with 8-12Hz temporal filter setting, F-Test and t-Test were conducted. Both F-Test concluded that the variances of the two populations are equal (accept the null hypothesis). Similarly, the t-Test result suggested not rejecting the null hypothesis. The observed differences between the sample means were not convincing enough to say that the average number of study hours between 8-30Hz and 8-12Hz, 8 channels and 16 channel as well, differ significantly.

The average of accuracy measurements was around 60% for all subjects. It shows that the motor imagery performances using OpenBCI Spiderclaw v1 configurations were still inferior to experiments with electrodes positioned around C3 and C4 for optimum setting [14]. This finding suggests that those who want to develop motor imagery application should place electrodes around C3 and C4, instead of insist on the Spiderclaw v1 design.

Table 1. MIQ-3 results

Subject	Internal Visual Imagery	External Visual Imagery	Kinesthetic Imagery	average
subj1	6	6	3.75	5.25
subj2	6.25	5.75	5.75	5.92
subj3	6.25	4.5	5.75	5.50
subj4	6.5	5.75	6.5	6.25
subj5	6.75	6.5	5	6.08
subj6	6.25	7	4.75	6.00
subj7	4.5	6	3.75	4.75
subj8	5.75	7	6	6.25
subj9	6.75	6	3.75	5.50
subj10	5.75	5.25	4.5	5.17

Table 2. Users' accuracy when running the Motor Imagery scenario

Subject	Motor Imagery CSP Scenario's Accuracy							
	8-30 Hz filter				8-12 Hz filter			
	8 channel		16 channel		8 channel		16 channel	
	1st trial	2nd trial	1st trial	2nd trial	1st trial	2nd trial	1st trial	2nd trial
subj1	50.78%	64.56%	47.15%	**69.75%**	60.23%	63.53%	46.02%	63.53%
subj2	52.78%	66.27%	54.46%	**70.29%**	49.90%	60.93%	49.59%	60.93%
subj3	52.38%	70.65%	55.43%	**71.26%**	49.65%	70.35%	51.01%	70.35%
subj4	65.34%	67.71%	52.81%	**68.56%**	58.32%	66.62%	57.54%	66.62%
subj5	49.65%	**65.45%**	47.78%	62.36%	44.26%	62.14%	54.11%	62.14%
subj6	53.08%	63.67%	45.33%	**73.86%**	44.76%	63.47%	52.23%	63.47%
subj7	71.64%	66.52%	49.23%	**73.19%**	65.46%	64.78%	63.90%	64.78%
subj8	50.30%	82.85%	59.81%	**82.83%**	56.05%	74.32%	69.83%	74.32%
subj9	46.97%	62.10%	43.91%	**66.12%**	49.90%	60.38%	44.62%	60.38%
subj10	48.91%	65.74%	51.28%	**68.50%**	45.28%	64.55%	54.60%	64.55%

Table 3. Correlation between MI-CSP accuracy and MIQ-3

	MI-CSP accuracy	*Internal Visual*	*Kinesthetic*	*External Visual*	*MIQ-3 average*
MI-CSP accuracy	1				
Internal Visual	-0.595360519	1			
Kinesthetic	**0.434405169**	0.317475218	1		
External Visual	0.114363829	0.004181174	-0.08261231	1	
MIQ-3 average	0.090546213	0.641609096	0.761381681	0.441080048	1

As can be seen in Table 3, considering the correlation between the performance of motor imagery experiment and the MIQ-3 result, kinesthetic imagery score reflects the most correlated with the accuracy measurement. However, the external visual imagery was removed from regression analysis because of its P-values below 0.05. The R Square values from regression analysis show good value, as much as 0.79. It means that 79% of the variation in MI-CSP accuracy was explained by the independent variables Internal Visual Imagery and Kinesthetic Imagery. This finding supports the Vuckovic's [20] suggestion that questionnaire could be used to predict user's performance while running BCI applications, especially motor imagery applications.

4. Conclusion

It could be concluded that the OpenBCI Spiderclaw V1 electrodes placements is not optimum for motor imagery application. It was located at Fp1, Fp2, C3, C4, T5, T6, O1, O2, F7, F8, F3, F4, T3, T4, P3, and P4. The average of accuracy measurements which was around 60% for all subjects shows poor motor imagery performance. Electrodes might be better concentrated at around C3 and C4 for motor imagery application, imagining right hand and left-hand movement. Additionally, 16 channel electrodes configuration with a wide temporal filter range [8-30 Hz] showed better performance compared to other settings in this research. However, further study is needed to improve the statistical significance of these findings. Utilizing MIQ-3 self-report questionnaire, “BCI illiteracy” phenomenon were not observed from experiment subjects. Interestingly, kinesthetic imagery score reflects the most correlated with the accuracy measurement, supporting the suggestion that questionnaire could be used to predict user’s motor imagery performance.

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