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SELECTION OF SUBJECT-SPECIFIC EEG CHANNELS AND FEATURES FOR ONLINE PERFORMANCE WITH A BCI

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Abstract: *A person with limited or complete absence of voluntary muscle control may find in a brain-computer interface (BCI) an alternative way to communicate with other people and interact with the environment. A non-invasive electroencephalogram (EEG) based BCI translates brain signals measured over the scalp into commands to a computer. One of the major problems in developing efficient BCI algorithms is the inter-subject variability of scalp recorded potentials. Spatial characteristics of brain mapping and spectral and temporal particularities of each person's brain signals contribute to this issue. In this paper, a method for improving the accuracy on classification by choosing subject-specific features and channels in an EEG based BCI is proposed and compared with a publicly available dataset. The methods are later tested with a BCI system consisting of a commercial EEG headset and a microcontroller for simulating real time applications. The EEG signals considered in this paper are related to motor-imagery (MI), as it is in many publications in the field when aiming the actuation of robotic devices.*

Keywords: *Brain-Computer Interface (BCI), Electroencephalography (EEG), Motor-Imagery.*

1. INTRODUCTION

Many disorders can affect a person's ability to communicate with other people and control external environment. In these cases, a brain-computer interface (BCI) can be an important alternative to restore function[1]. Because of its relatively low cost, portability, and easiness to use, electroencephalography (EEG) is the most popular brain recording modality in the BCI field[2,3].

One of the major challenges in BCI research is the inter-subject variability with respect to spatial patterns and spectrotemporal characteristics of brain signals[4]. To outcome the spectrotemporal specificity, many researchers use subject-specific features in their BCI algorithms[5-7]. For the spatial patterns issue, many channel selection methods have been proposed with different approaches[8-13]. Subject-specific features and channel selection is useful to improve classification accuracy, and understanding how these procedures affect BCI performance is important for developing more efficient methods.

In this paper, a method is proposed for choosing subject-specific features and channels in an EEG based BCI. The main purpose is to improve the accuracy rate of the BCI algorithm aiming the control of robotic devices, and provide means to understand how channel selection affects BCI performance.

2. METHODOLOGY

2.1. Computational Procedures

The proposed method is divided into three steps. A publicly available dataset[14] was used for validating the method. The dataset consists of data from seven subjects, named as A through G. EEG signals were recorded from 59 electrodes placed accordingly to the extended 10-20 system. Each subject alternated between two out of three possible motor-imagery signals: left hand, right hand, and foot. Classification was done for every 1s interval of EEG signals.

Step 1 is performed as it follows: seven channels that are most likely aligned with the motor cortex are selected to provide features. In spatial preprocessing, three possibilities are considered: no spatial filter, Common Spatial Patterns (CSP), and Surface Laplacian (SL). For feature extraction, the groups of information considered are: Fast Fourier Transform (FFT) spectrum, Discrete Wavelet Transform (DWT) coefficients and time domain points. In the preliminary stage, combinations of spatial preprocessing and quantity of features per channel with each group of information alone are tested and evaluated by the accuracy achieved in classification. In the final stage, the best quantities of features per channel and preprocessing obtained in each case are combined and once again tested and evaluated. By the end of this step, the spatial filter and the features to be extracted for each channel in step 2 is determined.

Step 2 is performed as it follows: 39 channels, including the ones used in step 1, are selected as a starting group. Step 2 starts out extracting features from these 39 channels and then eliminates one-by-one the less important ones. By the end of this process, the method finds a locally optimal sub-group of channels for every sub-group quantity varying from 39 to one.

Step 3 is performed as it follows: given a set of channels used for feature extraction, all the others (used exclusively for spatial filtering) are eliminated one-by-one. The criterion for elimination is the distance of the electrode to an average position between feature channels, with the more distant one being the first to be eliminated. By the end of this process, classification accuracy with the desired group of feature channels is tested with every possible quantity of electrodes.

Figure 1 shows a schematic of electrodes positions used in the dataset. The seven electrodes in the middle of the green line are the ones used in step 1, the colored channels are the 39 used as a starting group in step 2, and the others not filled with any color are used exclusively for spatial filtering.

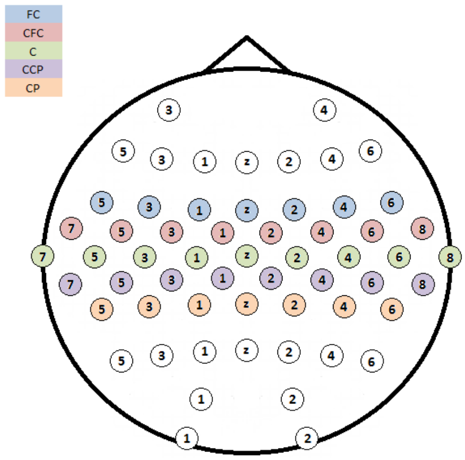

Figure 1. Channels used for generating the public dataset.

2.2. Experimental Procedures

The pieces of equipment used are: Emotiv Epoc Headset for EEG signal acquisition[15], notebook Toshiba Satellite M645, 2.53GHz processor, and 4GB RAM for applying the computational methods, Raspberry Pi microcontroller, 1.2GHz processor, and 1GB RAM for online signal analysis[16], and a simple circuit as the output of the system. Emotiv power source is a small embedded battery, and signal is sent to the processing unit by Bluetooth, so it is a wireless EEG equipment. Raspberry Pi can use many different power sources, including cell phone batteries. Figure 2 shows the Emotiv Epoc Headset with the dongle that receives the signal by Bluetooth (on the left) and Raspberry Pi with the electronic circuit with red and green LEDs as the output. These pieces of equipment were selected aiming future work with embedded systems.

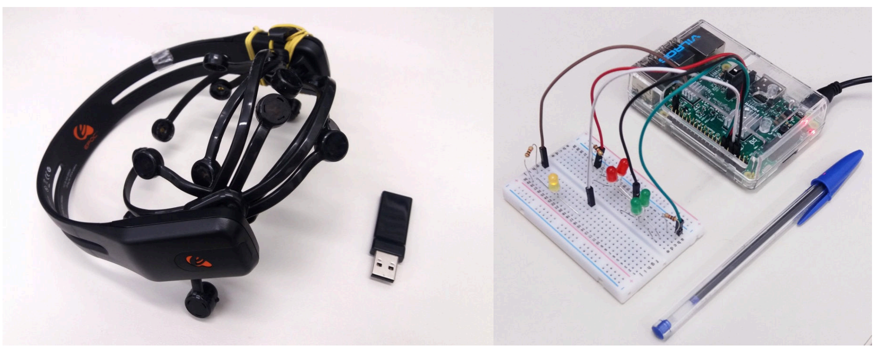

Figure 2. Emotiv Epoc Headset, the EEG equipment, and the Bluetooth dongle (left), and Raspberry Pi connected to the output circuit (right).

Firstly, EEG data is acquired for applying the proposed method using the notebook. For signal acquisition, the subject was oriented to remain in a relaxed position and execute imaginary movements of left and right hands. Then, the best features and electrode configuration is selected, and the optimized algorithm is uploaded to the Raspberry Pi microcontroller, with the best identified configuration. Finally, the subject is requested to execute an online task.

3. RESULTS AND DISCUSSION

3.1. Computational Results

Step 1 of the proposed method is evaluated with the public dataset. The best accuracy result achieved with each feature extraction method alone (preliminary stage of step 1) is represented for each subject, see Fig. 3. DWT stands for Discrete Wavelet Transform, numbers 2 and 3 after DWT refers to the level of decomposition, while letter 'a' indicates that it was the approximation level, FFT is Fast Fourier Transform, TDA and TDV are Time Domain Areas and Variance, respectively.

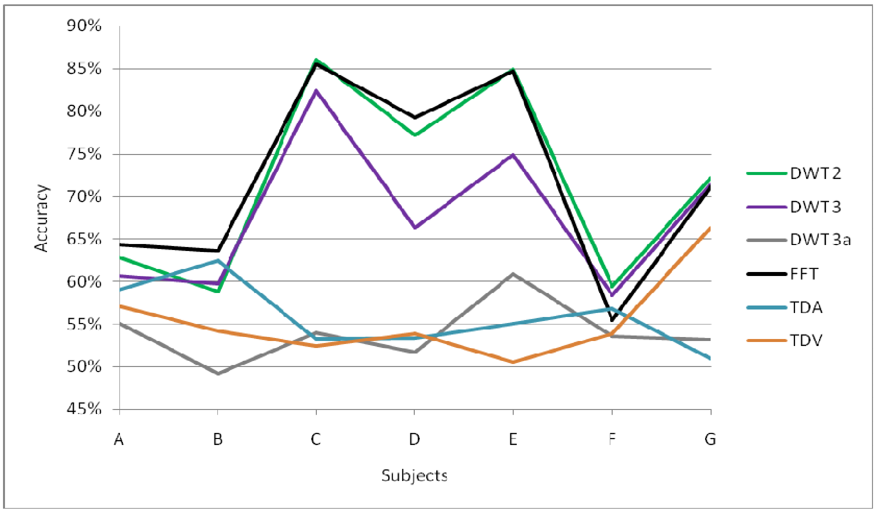

Figure 3. Results for the preliminary stage of Step 1 using the public dataset.

When analyzing each technique alone, it can be seen that FFT and DWT 2 were superior to the rest (72.01 and 71.62% average), followed by DWT 3 (67.69% average). Time domain features and DWT 3a had a poor performance. FFT, DWT 2, and DWT 3 use features from 0 to 30Hz, 12.5 to 25Hz, and 6.25 to 12.5Hz, respectively. DWT 3a uses features from 0 to 6.25Hz. These results seem reasonable, since motor-imagery is usually related to changes in the alpha (8-12Hz) and beta (12-30Hz) bands over the sensorimotor cortex[17]. In the final stage of step 1, the best configuration for each technique were combined and tested in every possible way. The winning configuration of this step is represented for every subject A through G, see Table 1.

Table 1. Final results for Step 1 using the public dataset.

Subject	Spatial Filter	Feature extraction method	Features per channel	Accuracy
A	No filter	FFT	5	64.36%
B	SL	TDA	1	63.86%
		FFT	3	
C	SL	DWT 2	1	86.05%
D	SL	DWT 2	1	84.88%
		FFT	1	
E	SL	DWT 2	1	88.62%
		FFT	5	
F	SL	DWT 2	1	59.47%
G	SL	FFT	2	71.15%

Subject A did not use any spatial filter, while the six other subjects used SL. Since no artifact removal technique was applied in the preprocessing and the CSP algorithm is highly sensitive to outliers[18], this may be the cause for SL superiority. FFT appeared in the best configuration of step 1 for five subjects and DWT 2 appeared for four subjects. Besides FFT and DWT 2, only TDA features appeared in the final results (subject B). Accuracy varied from 59.47 to 88.62%, and no winner configuration was the same for more than one subject, showing the well-known inter-subject variability of EEG signals. It is interesting to notice that for subjects B, D, and E the combination of two techniques improved the accuracy.

Step 2 of the proposed method is then evaluated with the public dataset, with results shown in Fig. 4. The horizontal axis represents the quantity of feature channels, while the vertical axis represents the highest accuracy with the corresponding quantity of electrodes.

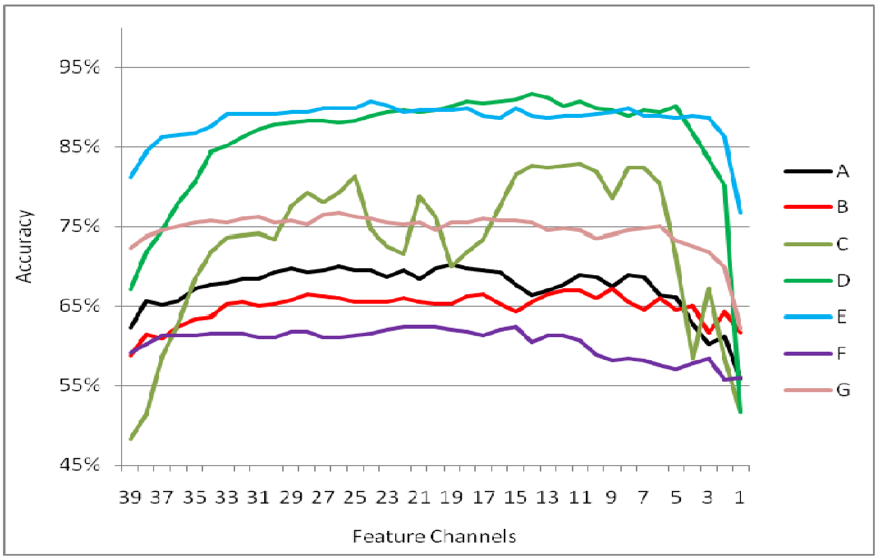

Figure 4. Results for Step 2 using the public dataset.

The behavior of the lines shown in Fig. 4 suggests that with the features selected from step 1, the 39 channels contains information that compromise classification, while groups with less than seven electrodes loses valuable information, also compromising the classification. The optimal group within the 39 channels lies on quantities from nine to 26 according to the proposed method, and was never the same for two or more subjects. The best accuracy values for each subject from A through G are: 70.26, 67.23, 82.95, 91.78, 62.40, and 76.68%. Notice that only for subject C the method was not able to achieve better result than with seven channels in step 1. Still analyzing subject C, it can be seen that its line in Fig. 4 has the most different behavior among the others, with large variance in accuracy when analyzing results for quantities near to each other.

Step 3 is finally executed, with results shown in Fig. 5. There are no results for subject A, as it did not use any spatial filter, so only features channels were used in step 2. For the sake of clarity, Fig. 5 is divided in half, so to avoid the lines from superimposing excessively.

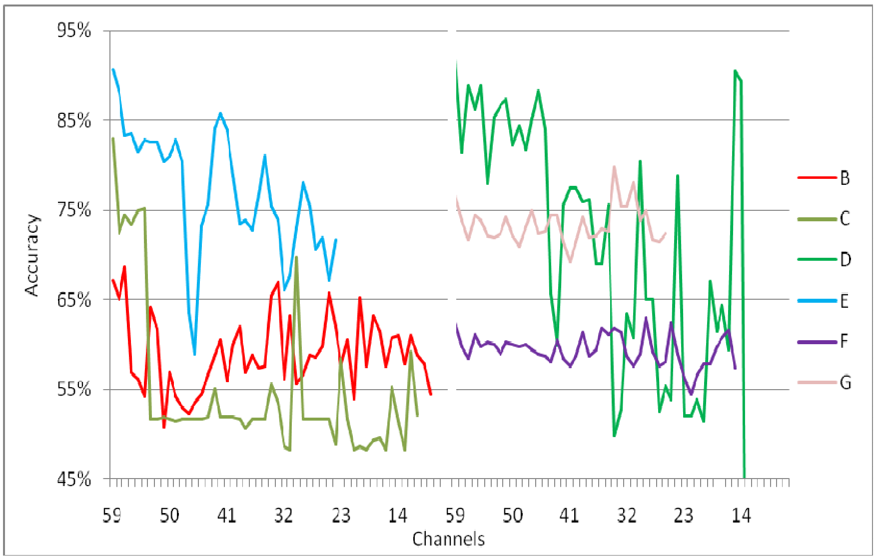

Figure 5. Results for Step 3 using the public dataset.

Results shown in Fig. 5 demonstrate an unpredictable behavior for every subject. The expectation was that the elimination of electrodes would gradually decrease accuracy, because SL increases spatial resolution as a function of electrodes density[19]. Since SL is calculated in this paper as a smoothing function on a spherical surface, it is not trivial to understand how each electrode position affects the potential distribution after smoothing. Thereby, the criterion for elimination can be one of the causes for such results. For subjects B, F, and G, step 3 predicted improvement in accuracy with specific quantities of electrodes: 68.67 (57 channels), 62.93 (29 channels), and 79.81% (34 channels), respectively.

Previous results were carried out with a portion of the public dataset. The unused portion of the same dataset is now used for validating the proposed methodology. Table 2 shows the accuracy when using this different portion of data for testing step 1 winners with seven and 39 channels. In other words, these results were obtained with feature selection, but no channel selection procedure, as only step 1 was executed in this case and channels were defined taking into consideration literature information, rather than computational methods. As expected, accuracy values are inferior to the ones obtained when executing the method. Subject B presented the larger difference between values during execution of the method and values with the unused data. Subjects B and F did not reach 60% of accuracy, while C and D obtained values above 80%.

Table 2. Validation of feature selection from step 1.

	A	B	C	D	E	F	G
7 channels (step 1)	61.54%	52.57%	83.98%	81.70%	79.63%	59.20%	73.21%
39 channels	61.78%	54.70%	52.32%	68.44%	77.78%	59.13%	73.68%

Still considering the new portion of the dataset, Tab. 3 shows the accuracy obtained with the best configurations after channel selection performed in steps 2 and 3. Also, the best configurations with only seven feature channels are tested to check if the proposed method improved the accuracy when compared to the seven channels used in step 1. In this case, step 3 was not applied.

Analyzing Tab. 3 it can be seen that channel selection was effective for all subjects, except for subject C, as already predicted when executing step 2 previously. For subjects C, D, and, E, results with the seven best channels were higher than results with the best selected group of electrodes. This is not very surprising, as the differences predicted previously between the best group and the best seven were not bigger then differences that occurred between accuracy values when executing the method and when using the new potion of data to validate it. Subjects D, E, and G achieved accuracy values above 80%, and only subject B remained with accuracy inferior to 60%.

Table 3. Validation of channel selection from steps 2 and 3.

	A	B	C	D	E	F	G
Best	64.62%	59.52%	79.07%	85.15%	84.92%	62.40%	80.86%
Best seven	64.62%	58.31%	79.59%	86.21%	86.77%	56.00%	76.79%

3.2. Experimental Results

Emotiv has 14 electrodes, most of them near the frontal area (Fig. 6), which represents a challenging scenario for motor-imagery classification. This is reinforced by the fact that Emotiv does not provide good quality signals when compared to other EEG equipments[20].

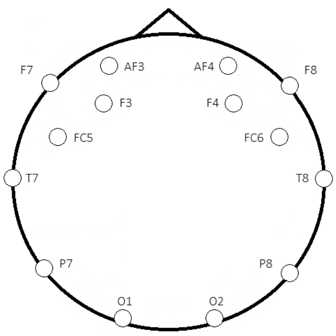

Figure 6. Electrodes positioning in Emotiv, according to the 10-20 extended system.

In order to adapt the methodology to the current situation, as data is now acquired from different EEG equipment, steps 2 and 3 were ignored. Also, one more change to the methodology is made as a consequence from previous analyses: only FFT is used in step 1 as a feature extraction technique. In this case, besides the spatial filter, the quantities of features per channel and the size of a hamming window that multiplies the time interval before Fourier transformation could vary. These modifications intend to minimize the time needed for applying the methods without compromising the efficiency of step 1.

Before applying the proposed method for finding the best configuration, two offline analyses were performed to check if the subject would achieve a reasonable accuracy when step 1 is applied.

Data to perform these analyses were acquired in different days. The first signal acquisition was done as described: the subject was asked to sit comfortably and not to make any voluntary movements. Then, 1 min of left hand MI was recorded followed by 1 min of right hand MI, and 1 min of mental relaxation. This was repeated seven times, totalizing 7 min for each MI. During this procedure, subject could not focus sight in his body parts. The second signal acquisition differs from the first by allowing the subject to look at the body part that was imagined to be moving, and by the fact that it was recorded 7 min straight of left hand MI followed by 7 min straight of right hand MI. Two time intervals are tested as the interval in which all the preprocessing, feature extraction and classification are done: 1s and 2s.

Results for the two offline analysis are shown in Tab. 4. In both analyses the performance was better with 2s being processed at a time. The most interesting fact, although, is the increase observed in the second analysis. The ability to execute the imaginary movements varies for different people and can be improved with time. The subject in this experiment had no previous experience with any activity related to executing imaginary movements, but with only two sessions it was possible to achieve 85% in accuracy with 1s being processed at a time, and 90% with 2s. This is probably also related to the differences in signal acquisition. According to the subject, the second signal acquisition was more comfortable then the first, but he could not say if it was a consequence of these differences in the procedure or consequence of his familiarization with the activity. Nevertheless, these values are obtained from a feature selection procedure and require other analyses with different data to check if the configuration that obtained these results can actually perform in the same way. In the second analysis with 1s as the time interval processed at a time, the spatial filter was SL, and for every other no spatial filter was used. This may be caused by the small quantity of electrodes available in Emotiv and the spacing between them, which makes it harder to generate a smooth spherical potential distribution to represent EEG signals measured along the scalp.

Table 4. Offline analyses before online operation.

Analysis	Time Interval for classification	Accuracy
1	1s	64.03%
	2s	75.00%
2	1s	85.55%
	2s	90.00%

Finally, the online experiment took place. Since results from the two offline analyses showed higher precision when processing 2s intervals at a time, step 1 was executed in this condition. Signal was acquired only once and followed the same procedures described in the second offline analysis. With this dataset, step 1 was executed using the notebook. The best configuration selected by step 1 obtained 99.51% of correct commands, which is surprisingly good when compared to previous results and considering the known limitations of the hardware. No spatial filter was used once again. It took near 4 min to update the algorithms to Raspberry Pi with the desired configuration.

The first session was performed so the subject could familiarize with the experiment. After that, one online session with 2s intervals processed at a time and one with 1s intervals processed at a time were performed. The subject was oriented to verbally indicate the MI that was being executed and could freely decide when to alternate them.

In order to evaluate online performance, the control of horizontal position of an up moving particle was simulated with the results obtained in real time activity. To do so, one LED was used for indicating the movement towards left and the other for indicating the movement towards right. Figure 7 shows the results for the familiarization session and the other two. On top of each graphic is indicated the time interval processed to classify the signal. The red line refers to the LEDs that were turned on, while the blue line refers to the MI that was executed by the subject. The horizontal dashed lines indicate when the subject switched the MI being executed.

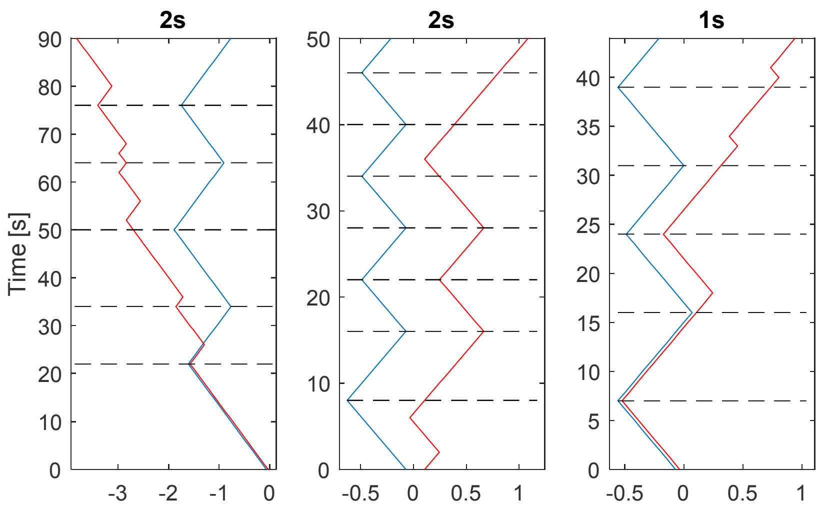

Figure 7. Results for the online performance.

Analyzing Fig. 7, one can see that the worst online performance happened in the familiarization session. In this case, a strong tendency to choose the left command was noticed from the classifier. When the right hand MI was executed, accuracy was 35%, while the accuracy for the left hand MI was 92%. The entire session accuracy was 67.67%, which is a reasonable value when compared to the first offline analysis, but not a good result when the right hand MI tendency is considered.

The middle graphic presents two wrong commands in the first moment, a small delay to recognize the right hand MI further in the activity, and after 40s the left hand MI was not recognized. Accuracy was 76%, which is a good performance, especially because no tendency in the classifier was noticed. This result is better than the first offline analysis, and worse than the second.

The third graphic shows online performance when only 1s was classified at a time. A small delay to recognize left hand MI near 15s, one wrong command near 40s, and an entire left movement that was almost completely ignored around 35s represents all the incorrect commands in this session. The accuracy was 75%, which can be considered a better performance than the previous session, as this time only 1s intervals was used for classification and the feature selection was performed for 2s intervals, so it would not necessary fit to this situation.

Although step 1 selected the best configuration by achieving 99.51% of correct commands, it is expected that online performance presents a big decrease in accuracy. When measuring data in the calibration session, subject can concentrate in the MI being executed, as it goes on for 7 min. Also, there are no expectations concerning results in this stage, but when performing online there is, as described by the subject. Subject also drew attention to the alternation of MIs in a short period of time, differing from what was practiced in calibration and offline analyses sessions, increasing the level of difficulty while executing the activity. Finally, Emotiv equipment may have an important role in decreasing performance when in online activities. Electrodes can easily change their positions during use because of the flexible arms that hold the electrodes with nothing to avoid sliding over the hair. The saline solution used for providing a better electric contact between electrode and scalp is another negative point, since it is lost over time, decreasing signal quality. All these points should be taken into consideration to provide fair analyses on real time performance with Emotiv.

Raspberry Pi performed adequately classifying 1s intervals of EEG signals in real time, substituting a regular computer that is commonly used in this kind of experiment. Thereby, it can be seen that a BCI system using Raspberry Pi can be implemented with no need for greater modifications on the existing hardware originally not driven by brain signals. The major concern is related to EEG equipment. Emotiv has many advantages when embedded systems are considered, such as portability, friendly design, wireless, low cost, and easiness to use, but there is still a gap of quality between Emotiv signals and other clinical EEG devices. Besides, it is desired different options concerning electrodes quantities and positions for suiting many BCI applications, such as the one in this paper.

4. CONCLUSIONS

In the first part of this paper a method for selecting subject-specific features and channels is proposed and evaluated with a publicly available dataset. When analyzing results for seven subjects, the method proved itself efficient in most cases, and suggested that features extracted with FFT and spatially filtered with SL is probably the best option among others considered in the method.

In the second part of the paper, an online experiment was prepared. The pieces of equipment used were chosen in order to provide means for applying the algorithms and methods to an embedded system in future works. Considering the known limitations of EEG equipment used and the lack of experience of the subject, results were good enough to encourage further research aiming more challenging applications.

5. ACKNOWLEDGMENTS

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6. REFERENCES

Wolpaw, J. R., Birbaumer, N., Mcfarland, D. J., Pfurtscheller, G., and Vaughan, T. M., “Brain-computer interfaces for communication and control,” Clinical Neurophysiology, vol. 113, no. 6, pp. 767–91, 2002.

Ramadan, R. A., and Vasilakos, A. V., “Brain computer interface: control signals review,” Neurocomputing, vol. 223, pp. 26–44, 2017.

Yuan, H., and He, B., “Brain-Computer Interfaces Using Sensorimotor Rhythms: Current State and Future Perspectives,” IEEE Transactions on Biomedical Engineering, vol. 61, no. 5, pp. 1425–1435, 2014.

Blankertz, B., Dornheg, E G., Krauledat, M., Müller, K. R., and Curio, G., “The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects,” NeuroImage, vol. 37, no. 2, pp. 539–550, 2007.

Galán, F., Nuttin, M., Lew, E., Ferrez, P. W., Vanacker, G., Philips, J., and Millán, J. del R., “A brain-actuated wheelchair: Asynchronous and non-invasive Brain-computer interfaces for continuous control of robots,” Clinical Neurophysiology, vol. 119, no. 9, pp. 2159–2169, 2008.

Rodríguez-Bermúdez, G., García-Laencina, P. J., Roca-González, J., and Roca-Dorda, J., “Efficient feature selection and linear discrimination of EEG signals,” Neurocomputing, vol. 115, pp. 161–165, 2013.

Ricardo, R. A., Aurélie, D., Yvan, M., Véronique, L. N., and Marc, A. J., “Brain computer interface: comparison of two control modes to drive a virtual robot.” European Scientific Journal, 2015.

Lal, T. N., Schröder, M., Hinterberger, T., Weston, J., Bogdan, M., Birbaumer N., and Schölkopf, B., “Support Vector Channel Selection in BCI,” IEEE Transactions on Biomedical Engineering, vol. 51, no. 6, pp. 1003–1010, 2004.

Wang, Y., Gao, S., and Gao, X., “Common Spatial Pattern Method for Channel Selection in Motor Imagery Based Brain-computer Interface,” Engineering in Medicine and Biology, vol. 5, pp. 5392–5395, 2005.

Arvaneh, M., Guan, C., Ang, K. K., and Quek, C., “Optimizing the Channel Selection and Classification Accuracy in EEG-Based BCI,” IEEE Transactions on Biomedical Engineering, vol. 58, no. 6, pp. 1865–1873, 2011.

Kee, C., Ponnambalam, S. G., and Loo, C., “Multi-objective genetic algorithm as channel selection method for P300 and motor imagery data set,” Neurocomputing, vol. 161, pp. 120–131, 2015.

He, L., He, Y., Le, Y., and Li, D., “Channel selection by Rayleigh coefficient maximization based genetic algorithm for classifying single-trial motor imagery EEG,” Neurocomputing, vol. 121, pp. 423–433, 2013.

Qiu, Z., Jin, J., Lam, H., Zhang, Y., and Wang, X., “Improved SFFS method for channel selection in motor imagery based BCI,” Neurocomputing, vol. 207, pp. 519–527, 2016.

Müller, K. R., Blankertz, B., Vidaurre, C., Nolte, G., and Curio, G., “BCI Competition IV - dataset 1,” 2008. Available: <http://www.bbci.de/competition/iv/>. Access in: January 2017.

Emotiv EPOC Headset. Available: <https://www.emotiv.com/>

Raspberry Pi. Available: <https://www.raspberrypi.org/>

Nicolas-Alonso, L. F., and Gomez-Gil, J., “Brain computer interfaces, a review,” Sensors, vol. 12, no. 2, pp. 1211–1279, 2012.

Yong, X., Ward, R. K., and Birch, G. E., “Robust Common Spatial Patterns for EEG signal preprocessing.,” Conf. Proc. IEEE Eng. Med. Biol. Soc., pp. 2087–2090, 2008.

Babiloni, F., Cincotti, F., Carducci, F., Rossini, P. M., and Babiloni, C., “Spatial enhancement of EEG data by surface Laplacian estimation: The use of magnetic resonance imaging-based head models,” Clin. Neurophysiol., vol. 112, no. 5, pp. 724–727, 2001.

Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., and Dutoit, T., “Performance of the Emotiv Epoc headset for P300-based applications,” Biomedical Engineering Online, vol. 12, no. 1, p. 56, 2013.

7. RESPONSIBILITY NOTICE

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