A Different Statistical Approach Aiming at EEG Parameter Investigation for Brain Machine Interface Use

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Abstract: A lot of effort has been made to investigate EEG features that could better represent signal characteristics. The results are usually based on the best mean recognition rates and statistical analysis is done only when different methods are compared. In this work, we propose a new approach that applies multiple rate inter-comparisons based on large samples aiming at detecting differences among treatments in order to recognize their importance for the classification rates. Ten frequency band compositions expressed by power spectral density averages were extracted from 8 EEG channels during 4 motor imageries, and spatial feature selections were also considered during the recognition process. Classification rate in large samples can be represented by a normal distribution and, for multiple rate inter-comparisons, the level of significance was corrected based on the Bonferroni Method. The variables were considered to be independents and the test was performed as non paired samples in a very conservative approach. The results showed that there are significant differences among cases of spatial feature selection and thus the considered electrodes are important parameters. On the other hand, considering or not the Delta and Theta bands along with different arrangements for Gamma band resulted in no significant difference.

1 INTRODUCTION

Brain Machine Interfaces (BMI) studies have been focused on the development of rehabilitation systems and, more recently, on the application to games and automation systems. One of the ways to implement these systems is to use motor imageries recorded through Electroencefalogram (EEG) from the cortex, using some kind of processing technique to identify specific patterns related to the intended movement. After that, these patterns can be translated into control commands to external devices (Al-Ani and Trad, 2010; Millan et al., 2010).

Many authors declare that motor imageries can modify the neuronal activities in the primary sensorimotor areas in a very similar way as observed when the movements are really executed. This implies the predominance in the acquisition of the EEG from the motor area (C3, C4, Cz) (Hema et al., 2010; Herman et al., 2008). Other studies are based on multichannel acquisition (Liu et al., 2005; Higashi et al., 2009).

In addition to the position of the acquired signals, it is important to extract features from original EEG signals, which are able to distinguish among mental states. The EEG signal has a frequency spectrum ranging from 0.1 Hz to 100 Hz which is classified into five frequency bands. There is no consensus about the exact band limits. Small differences exist depending on the author. However, in general, the frequency bands can be considered as Delta (0.1 - 4 Hz) , Theta (4 - 8 Hz), Alpha (8 12 Hz) , Beta (12- 28 Hz) and Gamma (28 - 100 Hz). The task of EEG spectral quantification is particularly challenging considering the complexity of the dynamics of non stationary EEG. It is required to take into account the time variation of the relevant frequency components (Liu et al., 2005; Herman et al., 2008; Al-Ani and Trad, 2010; Hema et al., 2010).

Another part of the success of a BMI is dependent on subject's training and motivation, making them able to learn to control the intensities of specific frequency bands, which can be used for the communication feature (Herman et al., 2008; Al-Ani and Trad, 2010; Hema et al., 2010).

Herman et al. (2008) presented an extensive comparative study involving different approaches to

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spectral signal representation such as power spectral density techniques, atomic decompositions, time-frequency energy distributions, continuous and discrete wavelet approaches, and also various classifiers aiming at distinguishing between right and left hand motor imageries. They used EEG data from 2 different datasets, from a total of eleven subjects. The EEG signal was acquired during 8 seconds trials, with bipolar electrodes over C3 and C4 locations based on international standard 10/20 system, and band-pass filtered in the range of 0.5 - 30 Hz. The statistical analysis was based on five-fold cross validation for comparisons amongst classifiers. Classification accuracy with Tukeys Honestly Significant Difference criterion defined the best methods to extract spectral features, and ANOVA was used to evaluate the variability among subjects. Using these criterions, the power spectral density approaches demonstrated the most consistent robustness and effectiveness in extracting the discriminant characteristics. With regard to classification methods, the study has shown the superiority of Support Vector Machines with Gaussian kernel. Furthermore, it was concluded by Herman et al. (2008) that the combination of different EEG datasets undertaken by subjects, with varying levels of prior experience and in motor imagery, enables a higher inter-subject variance.

Hema et al. (2010) investigated the effect of the power spectrum feature of each of ten sub-bands of 10 Hz width using motor imagery signals of 10 seconds (s) period recorded from C3 and C4 channels and a neural classifier aiming at distinguishing among four tasks. The data signal was segmented into 0.5 s segments with an overlap of 0.25 s, and each segment was filtered using a Chebyshev band pass filter with a bandwidth of 10 Hz. The sum of the power spectrum values was calculated and then a logarithmic transform was applied. For each subject, ten neural network models, for each of the ten sub bands of 10 Hz bandwidth, were developed. Classification rates between 89.23% and 94.47% were achieved for sub-band frequencies from 21 - 40 Hz.

Fitzgibbon et al. (2004) demonstrated that gamma band power spectrum corresponding to complex mental tasks had great increase relative to a Control condition, and the spatial distribution of such increase was task-related. These studies suggested that higher frequency bands (30 - 100 Hz) may contain useful information for classification between different mental states and encouraged Liu et al. (2005) to also investigate the effect of 10 Hz width sub-bands into the classification of different mental tasks. Differently, Liu et al. (2005) used EEG signals from C3, C4, P3, P4, O1 and O2. Seven subjects participated in the experiment and five mental tasks were analyzed, including no specific mental task, mental multiplication, mental letter composing, geometric figure rotation and visual counting. Again, a period of 10 s constituted a trial, and the sum of weighted power spectrum was used as feature extracted from ten 10 Hz wide sub-bands, segmented into 1 s segments with an overlap of 0.9 s. A Fisher's Linear Discriminant based classifier was used to distinguish between the mental tasks. In this case, frequencies ranging from 30 to 100 Hz resulted in greater classification accuracy, over 85%.

2 METHODOLOGY

Based on the previously discussed studies, and in order to validate the proposed approach, EEG signals were systematically recorded at 1000 Hz using a Bioamplifier plus PowerLab 16/30 configuration from AdInstruments, according to the approved protocol (COEP - USJT - No.088/2011). Three able body subjects were requested to sit comfortably during the experiment in which they had to perform 4 motor imageries (right or left hand close, right or left arm flex). EEG signals were acquired transversally from F, C, P and O areas (from Fz, Cz, Pz and, Oz to F3, F4, C3, C4, P3, P4, O1 and O2 respectively). The commands were randomly given through the computer monitor summing 45 repetitions for each movement imagination. After eliminating those corrupted with unusually excessive noise, or with simultaneous movement, only 39 samples were used for each motor imagery for each subject.

A segment of 2.5 s of each trial was selected and the Power Spectral Density Averages in ten different frequency band configurations were computed as features. The common part among those arrangements was: (A) Alpha (8 - 12 Hz), (B1) Beta1 (12 - 16 Hz), (B2) Beta2 (16 - 20 Hz), (B3) Beta3 (20 - 28 Hz). The investigation was based on the influence of considering or not the (D) Delta (0 - 4 Hz) and (T) Theta (4 - 8 Hz) bands, and five configurations of Gamma band : (G1) 28 - 32 Hz; (G2) 28 - 64 Hz; (G3) 28 - 100 Hz; (G4) Gamma1 (28 - 32 Hz), and Gamma2 (32 - 64 Hz); (G5) Gamma1 (28 - 32 Hz), Gamma2 (32 - 64 Hz), and Gamma3 (64 - 100 Hz). The ten treatments are defined in Table 1. A spatial feature selection, applying different electrode combinations and aims to finding the most useful and discriminatory information, was also carried out to improve classification performance.

Fisher's Linear Discriminant Analysis (Thomaz and Gillies, 2005) was used as classifier, implementing a few experiments aiming at discriminating be-

Table 1: Band Configurations Treatments.

Treatment	Considered Bands
T1	A, B1, B2, B3, G1
T2	A, B1, B2, B3, G2
T3	A, B1, B2, B3, G3
T4	A, B1, B2, B3, G4
T5	A, B1, B2, B3, G5
T6	D, T, A, B1, B2, B3, G1
T7	D, T, A, B1, B2, B3, G2
T8	D, T, A, B1, B2, B3, G3
T9	D, T, A, B1, B2, B3, G4
T10	D, T, A, B1, B2, B3, G5

tween right and left hands, right and left arms, right and left limbs, right arm and right hand, left arm and left hand, and hands and arms (Castro et al., 2013). Subject's training and feedback that usually contribute to increase the classification rates were absent in this work. The EEG were acquired just after volunteers received instructions and there was no feedback and the classification process was done offline.

To determine the importance and the significance of the different frequency band configurations and also the spatial feature selection in the classification process, multiple inter-comparisons, two by two, of the mean classification rates were made, for each parameter. This is a well established statistical procedure, however, to the best of our knowledge, it has not previously been applied in this context.

The result of a classification has a binomial distribution (it is right or wrong). This distribution, with large samples, according to the central limit theorem, follows a normal distribution with

$$p : N(\hat{p}; \frac{\hat{p}(1-\hat{p})}{n}) \tag{1}$$

where p is the population classification rate under study, $\hat{p}$ is the sample classification rate and n is the sample size.

The sample size is defined as the number of repetitions (always 39), multiplied by the number of treatments (10 for the frequency band configurations and 15 for the spatial feature selection) multiplied by the number of possibilities during classification (2 classes). This originates the sample sizes shown in Table 2, confirming the previous assumption of large samples.

For multiple comparisons, two by two, with a 5% level of significance, a correction was made by the Bonferroni Method (Bland and Altman, 1995), assuming a very concervative approach. The new level of significance is given by:

Table 2: Sample sizes.

Parameter	2 classes
Frequency Bands	1170
Spatial Feature Selection	780

$$\alpha' = \frac{\alpha}{\binom{k}{2}} \tag{2}$$

where k is the number of treatments. Therefore, $\frac{\alpha'}{2}$ is the focus when performing a bilateral test.

For example, using $k = 15$ for spatial feature selection results in $\frac{\alpha'}{2} = 0.00023809$ and $Z_{\frac{\alpha'}{2}} = 3.4938$. While, using using $k = 10$ as for frequency band configurations, $\frac{\alpha'}{2} = 0.0006$ and $Z_{\frac{\alpha'}{2}} = 3.2389$.

Based on the normal approximation, as mentioned before, comparing between two classification rates the Z score is given by:

$$Z_{res} = \frac{\hat{p}_1 - \hat{p}_2}{\hat{\sigma}_{p_1;p_2}} \tag{3}$$

where

$$\hat{\sigma}_{p_1;p_2} = \sqrt{p^*(1-p^*)(\frac{1}{n_1} + \frac{1}{n_2})} \tag{4}$$

and

$$p^* = \frac{n_1\hat{p}_1 + n_2\hat{p}_2}{n_1 + n_2} \tag{5}$$

Thus, if $|Z_{res}| > Z_{\frac{\alpha'}{2}}$ there is a significant difference between both rates.

3 RESULTS

The best mean classification rate for each experiment and each subject is presented in Figure 1. Inside each bar, there is the indication of the best electrode combination followed by the specific treatment resulted from the best classification value. Sometimes more than one combination is shown as in the case of Right versus left Hand Classification for Subjects 2 and 3. It is clear that the results are subject dependent and that the training and feedback could contribute to reduce classification rates close to aleatory values. Results from subject 1 outperformed those obtained by the others, probably due to some abilities to imagine. The figure also shows a lack of a standard pattern related

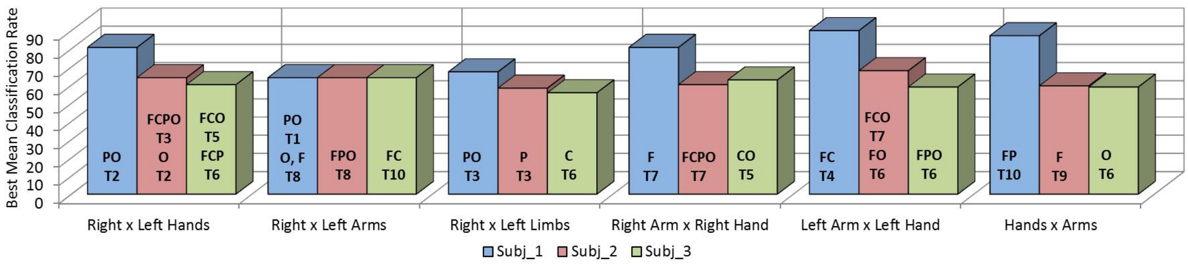

Figure 1: Best Mean Classification Rates for each experiment based on the investigated parameter influence.

to the studied parameters. For each classification experiment the best parameter combination was different. However, there was a predominance in the use of the F, P and O areas related to cognition and vision, respectively, over the C area, related to movement. This area appeared more in combination with others and for subject 2 and 3. A great variation related to the treatments can also be noticed, with a small advantage in the treatments that included Delta and Theta bands (from T6 to T10) over their absence.

Applying the statistical methods for subject 1 data, obtained from the experiment Right versus Left Hands Classification Rates, the Z_{res} scores for each inter-comparison based on Frequency Bands Configuration and Spatial Feature Selection, can be seen in Figures 2 (a) and (b), respectively. To facilitate the analysis, the numbers were arranged in a decrescent order from the top left corner to the bottom right one. The cells marked in light orange are those with $|Z_{res}| > Z_{\frac{\alpha'}{2}}$, indicating a significant difference between both rates. The cells in white indicate that there are no significant differences among them during the comparison process. Thus, when analyzing both figures, one can observe that, when aiming at discriminating between Right and Left Hands, the results based on different frequency band arrangements (2 (a)) had significant different classification rates only if the treatment T10 was used in comparison with the results obtained when treatment T1, T2 and T3 were used (see Table 1). On the other hand, the results based on the different electrode combinations (2 (b)) had significant different classification rates when P and PO electrodes were used in respect to FC, F, FCO, C, FCPO, O, CO, FO, and FPO electrode combinations. A subset was formed by the results when CP was used, showing a significant difference from those obtained by using FC, F, FCO, and C options. Following the sequence, the use of FP resulted in classification rates different from those reached by using FC, F, and FCO, while CPO results differentiated only from those when FC was used.

In general, the feature frequency band, configured into ten treatments did not show to make great differences during classification processes. For subject 1, treatments T1 and T6, that differ by the absence or not of the bands Delta and Theta, showed classification rates significantly different when compared to the other treatments, being the worst ones in experiments Left Arm versus Left Hand and Arms versus Hands. Regarding subject 2, for the experiment aiming at discriminating between Right and Left Hands, the treatment T6 achieved significantly different results when compared to T2, T3 and T4, while the treatment T9 also produced results different from T3. In other words, the highest classification rates (those obtained with T2 and T3) were significantly different from the lowest ones (obtained by using T6 and T9). The intermediate cases did not present significant differences. The same situation was verified for subject 3 to distinguish between Right and Left Arm. The treatment T1 obtained classification rates significantly higher than those obtained when used T2 and T8.

On the other hand, in all experiments involving spatial feature selection, the use of a different combination of electrodes always presented situations where there were significant differences, as shown in Figure 2 (b). Even for subjects 2 and 3, in experiments where the classification rates were close to aleatory values, as to differentiate between Arms and Hands (Figure 3) or Right and Left Limbs (Figure 4), it was possible to detect significant differences. The higher differences were always between the electrode combination that produced the best mean classification rates against those combinations that produced the worst results. However, it can be noticed that intermediate groups also showed significant differences.

4 DISCUSSION

This work applied a well established statistical method over multiple inter-comparisons of the mean classification rates based on different arrangements of the frequency bands and spatial feature selection aiming at investigating the significance of the variation of

	T10	T9	T6	T5	T7	T8	T4	T3	T2	T1
T10		-1.386	-1.47	-1.513	-1.682	-1.936	-3.215	-3.387	-4.034	-4.208
T9			-0.084	-0.127	-0.296	-0.55	-1.831	-2.004	-2.652	-2.826
T6				-0.042	-0.211	-0.466	-1.747	-1.919	-2.568	-2.741
T5					-0.169	-0.424	-1.705	-1.877	-2.526	-2.699
T7						-0.254	-1.536	-1.708	-2.357	-2.53
T8							-1.281	-1.454	-2.103	-2.276
T4								-0.172	-0.822	-0.996
T3									-0.649	-0.823
T2										-0.174
T1										

(a)

	FC	F	FCO	C	FCPO	O	CO	FO	FPO	FCP	CPO	FP	CP	P	PO
FC		-0.6617	-1.2235	-1.7360	-2.1990	-2.1990	-2.4570	-2.5603	-2.8192	-3.3388	-3.6520	-5.1824	-5.3960	-6.5284	-6.8010
F			-0.5619	-1.0747	-1.5380	-1.5380	-1.7963	-1.8997	-2.1588	-2.6792	-2.9928	-4.5262	-4.7403	-5.8759	-6.1494
FCO				-0.5129	-0.9764	-0.9764	-1.2348	-1.3383	-1.5976	-2.1184	-2.4323	-3.9679	-4.1824	-5.3204	-5.5947
C					-0.4636	-0.4636	-0.7220	-0.8256	-1.0850	-1.6061	-1.9203	-3.4576	-3.6724	-4.8125	-5.0873
FCPO						0.0000	-0.2585	-0.3621	-0.6215	-1.1428	-1.4572	-2.9959	-3.2109	-4.3527	-4.6280
O							-0.2585	-0.3621	-0.6215	-1.1428	-1.4572	-2.9959	-3.2109	-4.3527	-4.6280
CO								-0.1036	-0.3631	-0.8844	-1.1989	-2.7382	-2.9534	-4.0961	-4.3716
FO									-0.2595	-0.7809	-1.0953	-2.6349	-2.8501	-3.9932	-4.2688
FPO										-0.5214	-0.8359	-2.3760	-2.5914	-3.7352	-4.0111
FCP											-0.3146	-1.8555	-2.0711	-3.2164	-3.4927
CPO												-1.5413	-1.7570	-2.9031	-3.1797
FP													-0.2159	-1.3644	-1.6419
CP														-0.7871	-0.9722
P															-0.2778
PO															

(b)

Figure 2: Z_{res} scores for each inter-comparison using subject 1 data, for the experiment Right versus Left Hands, based on (a) Frequency Bands Configurations (b) Spatial Features Selection.

each parameter for the classification process.

At first, following some statistical analysis features, the assumption that both variables are independent (treatments based on frequency band arrangements and spatial feature selection based on different electrode combinations) is a conservative approach, due to the possibility of non definition of differences for the same significant level. In other words, a higher difference between the compared situations is necessary when considering the hypothesis of dependency between such variables.

The Bonferroni Method was used to correct the level of significance for multiple inter-comparisons. Again, it is a conservative approach because it is the most restrictive treatment in respect to the statistically significant differences.

The sample sizes used in this work were large enough to make the approximation by the normal distribution useful and the continuity correction not necessary.

The methodology adopted following this approach was able to indicate the significant differences in classification results when various arrangements of the same variable were applied, identifying and justifying its importance and the need for further investigation.

The results showed that the principal frequency bands are the Alpha and Beta and sometimes the lower part of the Gamma Bands, which are the same ones usually used in other works. The use or not of the other bands, and the way that they are used do not produce significant classification rate differences. In other words, they do not present useful information related to motor imageries. This is in accordance with Hema et al. (2010) that found the range from 21 - 40 Hz as the principal frequency band for motor imagery, while the higher frequencies, as showed by Liu et al. (2005) are related to complex cognitive activities.

On the other hand, different electrode combinations based on the spatial features selection made significant difference. This feature is related to the cerebral area and thus with the brain function. In almost all the performed experiments, the principal areas which contributed to the best results were those related to cognitive processes, sensation, and vision (F, P and O). The motor area (C) had a very restricted contribution for motor imagery based on the protocol used in this work. This area showed significance only

	C	CPO	CO	CP	FCP	FCPO	P	FPO	PO	FP	O	FCO	FO	FC	F
C		-0.937	-1.116	-1.188	-1.476	-1.691	-2.944	-3.195	-3.302	-3.802	-3.873	-4.052	-4.623	-5.231	-6.839
CPO			-0.18	-0.252	-0.539	-0.754	-2.008	-2.259	-2.366	-2.867	-2.939	-3.117	-3.689	-4.297	-5.9084
CO				-0.072	-0.359	-0.575	-1.829	-2.079	-2.187	-2.687	-2.759	-2.938	-3.51	-4.118	-5.7296
CP					-0.287	-0.503	-1.757	-2.008	-2.115	-2.616	-2.687	-2.866	-3.438	-4.046	-5.6581
FCP						-0.215	-1.47	-1.72	-1.828	-2.329	-2.4	-2.579	-3.151	-3.76	-5.3721
FCPO							-1.254	-1.505	-1.612	-2.113	-2.185	-2.364	-2.936	-3.545	-5.1577
P								-0.251	-0.358	-0.859	-0.931	-1.11	-1.683	-2.292	-3.9073
FPO									-0.107	-0.609	-0.68	-0.859	-1.432	-2.042	-3.6572
PO										-0.501	-0.573	-0.752	-1.325	-1.934	-3.55
FP											-0.072	-0.251	-0.824	-1.433	-3.0496
O												-0.179	-0.752	-1.361	-2.9781
FCO													-0.573	-1.182	-2.7993
FO														-0.609	-2.2268
FC															-1.6177
F															

Figure 3: Z_{res} scores for each inter-comparison using subject 2 data, for the experiment Arms versus Hands using different electrode combinations.

	PO	FPO	FO	O	FP	CPO	P	FCPO	CO	F	FCO	CP	FCP	FC	C
PO		-0.2961	-1.9841	-2.3480	-4.2979	-4.4415	-4.7283	-5.0504	-5.0862	-5.3364	-6.0142	-7.3297	-8.1453	-8.3579	-8.6413
FPO			-1.6881	-2.0521	-4.0027	-4.1463	-4.4332	-4.7555	-4.7913	-5.0416	-5.7198	-7.0362	-7.8524	-8.0652	-8.3488
FO				-0.3642	-2.3173	-2.4612	-2.7487	-3.0717	-3.1076	-3.3585	-4.0384	-5.3589	-6.1781	-6.3917	-6.6765
O					-1.9534	-2.0973	-2.3849	-2.7080	-2.7439	-2.9949	-3.6751	-4.9963	-5.8161	-6.0298	-6.3148
FP						-0.1440	-0.4318	-0.7553	-0.7912	-1.0425	-1.7238	-3.0478	-3.8699	-4.0843	-4.3702
CPO							-0.2878	-0.6113	-0.6472	-0.8985	-1.5798	-2.9040	-3.7262	-3.9407	-4.2266
P								-0.3235	-0.3594	-0.6107	-1.2921	-2.6165	-3.4390	-3.6535	-3.9396
FCPO									-0.0359	-0.2873	-0.9687	-2.2934	-3.1161	-3.3307	-3.6168
CO										-0.2513	-0.9328	-2.2575	-3.0802	-3.2948	-3.5810
F											-0.6815	-2.0063	-2.8292	-3.0439	-3.3301
FCO												-1.3251	-2.1484	-2.3632	-2.6496
CP													-0.8236	-1.0386	-1.3252
FCP														-0.2150	-0.5017
FC															-0.2867
C															

Figure 4: Z_{res} scores for each inter-comparison using subject 3 data, for the experiment Right versus Left Limbs using different electrode combinations.

for subjects 2 and 3 to distinguish between Right and Left Limbs. These results showed that the imagination may be more a cognitive and sensorial activity than a motor one. However, these findings were in disagreement with other authors who used only the motor area saying that motor imagination cause similar changes in the motor cortex as movement execution (Hema et al., 2010; Herman et al., 2008).

It is important to mention here that the direction of the used signal was transversally acquired from the scalp and the power spectral density was extracted over the 2.5 s period entirely. Hema et al. (2010) and Liu et al. (2005) used a segmented data, and both of them, as well as Herman et al. (2008) used a total period of time at least more than 3 times longer than the 2.5 s used in this work. A longer period of time increases the resolution of the feature and provides more information. These differences may be responsible for the inconsistencies and for the lower values noticed in some classification rates. Thus, this point needs further investigation.

The differences in the results of different subjects, specially those close to aleatory values presented by subjects 2 and 3 (Figure 1), indicate that more investigation is needed and that a training process, together with some feedback to the subject, could contribute to the improvement of classification results. This is due to the possibility of active participation of the subject to modulate the signal and adapt to the system criterion. The results showed here were acquired without this process. Nevertheless, the methodology proposed was able to identify significant differences. The inter subject variability is described by Herman et al. (2008) and others as a regular behavior. Thus, an adaptive system could be more appropriated for online use.

5 CONCLUSIONS

The numerical analysis, by itself, sometimes can lead us to wrong conclusions, without any meaning. A higher or lower classification rate might be important but requires further investigation about their significance. This work applied a standard statistical approach, useful for situations of multiple intercomparisons of classification rates, but not previously applied in the context of EEG feature analysis for a BCI system. Six motor imaginaries were implemented: Right versus Left Hands, Right versus Left Arms, Right versus Left Limbs, Right Arm versus Right Hand, Left Arm versus Left Hand, and Arms versus Hands. A total of 8 EEG potential difference was used, and the data was transversally acquired. The method was able to highlight the cases where there were significant differences between the compared arrangements. The method also indicated that the use of Delta, Theta and Gamma Bands (above 32 Hz) did not produce significant differences in the classification rates. On the other hand, the location of the signal, represented by the several combinations of the electrodes, achieved significant different results, and the principal areas were F, P and O excluding the commonly used motor area (C). Thus, this variable needs further investigation as part of a BCI system.

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