COBEM 2017-2456
CLASSIFICATION OF RIGHT AND LEFT ELBOW MOVEMENT WITH LOWER GAMMA ACTIVITY

E.Y. Veslin
M.S. Dutra
Department of Mechanical Engineering, Federal University of Rio de Janeiro, Rio de Janeiro / RJ, Brazil.
elkinveslin@ufrj.br, max@mecanica.coppe.ufrj.br

L. Bevilacqua
Department of Civil Engineering, Federal University of Rio de Janeiro, Rio de Janeiro / RJ, Brazil.
bevilacqua@coc.ufrj.br

L.S.C. Raptopoulos
W.S. Andrade
Federal Center of Technological Education Celso Suckow da Fonseca – CEFET/RJ Campus of Nova Iguaçu, Nova Iguaçu / RJ, Brazil.
luciano.raptopoulos@cefet-rj.br, waltencir.andrade@cefet-rj.br

A.S. Pereira
M. Fiorani
J.G.M. Soares
Laboratory of Physology of Cognition, Biophysics Institute Carlos Chagas Filho, Federal University of Rio de Janeiro, Rio de Janeiro / RJ, Brazil.
mfiorani@biof.ufrj.br, jmsoares@biof.ufrj.br

Abstract. *This paper describes the use of lower gamma band for classification of the right versus left elbow rotation in two different cognitive states: planning and movement execution. We made a discrimination analysis for each interval in 14 channels around the motor cortex, and founded common regions of high separability around the cue presentation and after the movement onset and use it to build the feature vector.The dimensionality of the features were reduced with LDA and posteriorly tested with eight classification algorithms in a 10-fold cross validation. The bests results showed that both classes could be identified with a mean of accuracy of 78% in both intervals with a difference of 2%. This results shows that the lower gamma band can be used for the classification of elbow movement in BCI systems in specific time intervals using a unique selected band frequency in all subjects.*

Keywords: *Electroencephalography, Machine Learning, Activity recognition, Brain-computer interfaces, Rehabilitation robotics*

1. INTRODUCTION

The interpretation and use of brain patterns related to cognitive tasks is the basis of the Brain Computer Interfaces (*BCI*) systems. Some *BCI* systems use the processed brain activity through electroencephalogram (*EEG*), to control external devices Wolpaw *et al.* (2002) or artificial mechanisms Frolov *et al.* (2013a) destined to assisting movement in handicapped persons, with partial or total restriction on their limbs movement. Examples of such devices are: exoskeletons Soekadar *et al.* (2015), Lalitharatne *et al.* (2012), prosthetic apparatus Hochberg *et al.* (2006), wheel chairs Sim *et al.* (2016), Zhang *et al.* (2016) or robotic manipulators Roy *et al.* (2016).

One of the most prominent signal of the motor cortex related to body movement and used in *BCI* systems is the Mu activity Frolov *et al.* (2013b), which is a differentiation of the alpha activity (8-15 Hz) produced in the primary motor cortex (*M1*). Decreases of Mu have been reported during voluntary movement: Cassim *et al.* (2000),Robinson *et al.* (2013), imaginary movement (IM) Pfurtscheller *et al.* (2006) and even, visualized movement Pineda (2005), Lana *et al.* (2015), in relation to an alteration in the frequency oscillation Pfurtscheller and da Silva (1999).

Alongside to alpha (or Mu) have been reported electrical fluctuations in other bands as beta (16-35 Hz), during limb movement and preparation Jeon *et al.* (2011) which present similar behaviors to the Mu band, and also in the gamma band (35 Hz and higher) related to their influence during the imaginary and real movement performance Ahn *et al.* (2013), Mirnaziri *et al.* (2013), Aoki *et al.* (1999). The gamma band presents induced oscillations in the *EEG* signal around the 40 Hz frequency produced by visual stimulation and movement task Pfurtscheller and da Silva (1999), related to an information processing that may occur with alpha and beta desynchronization (reduction of the oscillatory activity). On the other hand, it is theorized that high amplitudes of the gamma oscillations could enhance the cortical excitability in the sensory and motor areas of the cortex facilitating the motor processing Seeber *et al.* (2015).

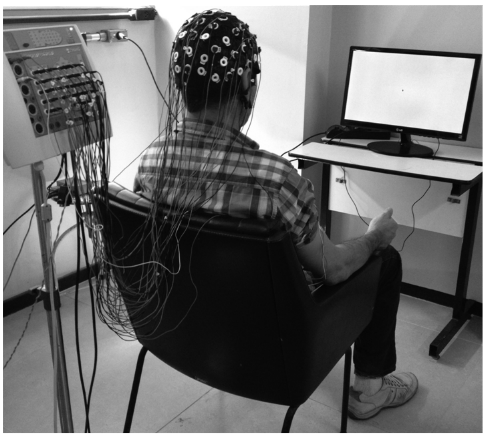
Gamma oscillations occur in different and separated areas, showing a parallel activity in both phase and time locking event related oscillationsBaşar *et al.* (2001). Pfurstcheller et al. Pfurtscheller *et al.* (1993) theorized that this behavior is related to movement interaction between the brain sensorimotor areas during the motor preparation, generating a 40 Hz *ERS* related to motor programming rather than a stimulus processing. Similar conclusions were established by Ginter et al. Ginter Jr *et al.* (2005) and Szurhaj et al. Szurhaj *et al.* (2005). The latter, found a 40-60 Hz oscillation related to movement execution in *M1* and somatosensory area, hypothesizing that gamma works as an integrator during the movement with sensory data. Aoki et al. Aoki *et al.* (1999) added a possible connection of gamma band synchronization with intense concentration, tying the generation of a specific task that is made carefully with a synchronism between different brain areas. This cortical communication may be reflected as an increase of the attention that happens when the gamma band augmented its energy.

Gamma band has been used for detection and classification of *EEG* signals for cognitive response in addition to the lower frequency bands to obtain greater classification accuracy Mensh *et al.* (2004),Mirnaziri *et al.* (2013). Adding gamma to the feature vector enhanced the classification rates, Palaniappan (2006). Mirnaziri et al, Mirnaziri *et al.* (2013) showed a complementary amelioration of gamma when is used in combination with Mu and beta bands. In this case as a unique feature vector including a signal with a large band set (8-50 Hz). The addition of gamma band seems to expand the information that contains the feature vector, achieving a better performance in the classification of imagery of foot, tongue and bilateral hand movement than using only Mu and beta.

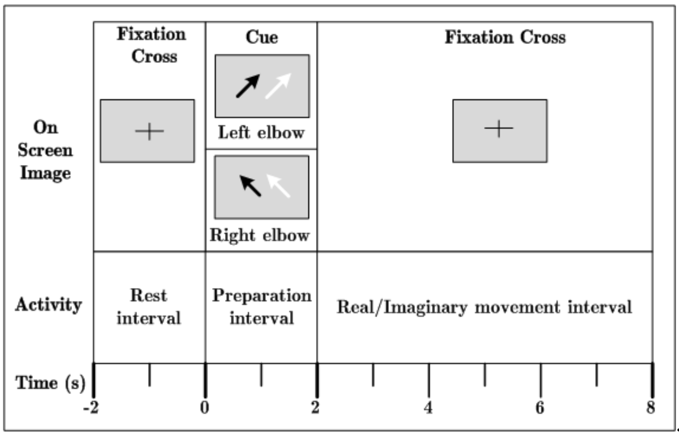
Other experiments involving gamma and their role in movement using electrocorticography (*ECoG*) Scherer *et al.* (2009),Ryun *et al.* (2017), Pfurtscheller *et al.* (2003) or stereoelectroencephalography (*sEEG*) Szurhaj *et al.* (2005) reported successful in movement classification but those systems implement readings extracted of invasive procedures.

Although previous studies reported strong relationship between lower gamma band and real and imaginary movement, its use in *BCI* systems is related mostly with enhancement properties, as a signal that improves the classification tasks. Meanwhile in solely applications the band has not been enough explored due to interferences caused by external artifacts as the eye movement. Nevertheless successfully applications in wrist movement classification have been reported Khan and Sepulveda (2010) for example.

Based in the electrophysiological evidence and the lack of information about the lower gamma role in non invasive *BCI* applications for elbow movement in real tasks, this paper evaluates the capability of the lower gamma band in classification in single trial conditions during two cognitive states: the preparation and movement execution. In order to do that, this band was studied in twelve volunteers, and we verified that in specific time intervals, it had similar high discrimination patterns among the selected channels in all the voluntaries, allowing to identify the kind of task (during the execution) and also to predict it (during the preparation). A 10-fold cross validation was run for both intervals in order to test the data in eight classification algorithms and was founded that the movement could be classified and predicted with a mean of successful of 78%.

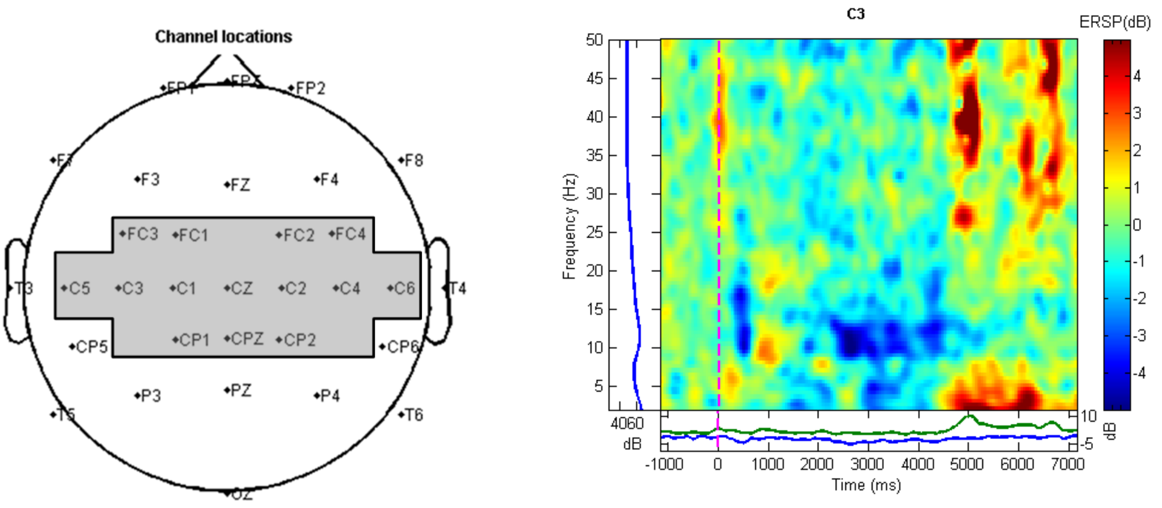


(a) Task paradigm.



(b) Timing of the task.

Figure 1: Volunteer disposition in front of the command screen (a). Description of the trial, referencing the on screen image during the time interval and the activity developed by the volunteer (b). The cue arrow color commands the task: black for execute a movement and white for not, the arrow's inclination indicates which arm the volunteer have to move.



(a) Task paradigm.

(b) Timing of the task.

Figure 2: (a) 32 Channel locations around the scalp, the electrodes where distributed according to a 10-10 System with modifications. The gray area indicates the channels selected for the study. (b) Spectral map from C_3 channel from one volunteer during left arm movement. A μ *ERD* is presented around the 2.5 s until 4.5 when the movement ends. Low gamma presents a high *ERS* at the end of the movement. Source *EEGLAB*.

2. MATERIALS AND METHODS

This study was conducted in accordance with the protocol approved by the Ethics Committee of *Universidade Federal do Rio de Janeiro* (Approbation number: 851.521).

Twelve healthy right-handed volunteers (8 females and 4 males), without previous training in similar procedures were studied in this experiment after giving their informed consent. During the test the volunteer is comfortably seated on a chair, with his arms in the rest position (Fig. 1).

A screen was used to present the cue for the elbow movement or imagination, the instruction was randomly generated in order to avoid any anticipation on the action. The experiment consisted of three tests (left or right arm rotation and no movement) each one consisting of 60 trials of 10 seconds of duration.

The trial started with the presentation of a fixation cross at the center of the screen (Fig. 1b). After 2 seconds (rest interval) the cross was replaced by the instructive arrow which was presented for 2 seconds (preparation interval). Then the arrow was replaced by the fixation cross and the subject executed the instruction within a 6 seconds movement interval. The duration of this interval was configured so that it was as long as the action was executed and the brain activity returns to a rest state Pfurtscheller and da Silva (1999).

The movement consisted on the elbow flexion and its return for the rest position (a movement interval of 90° to 150°, approximately), it was executed when the arrow on screen appears in black color, the left/right command therefore, was given by the arrow's direction.

2.1 EEG recording and signal processing

The *EEG* was recorded continuously from scalp electrodes using the *Neuron-Spectrum* system and software (Neurosoft Ltd,Ivanovo, Russia). A total of 32 passive *Ag-AgCl* electrodes were distributed around the scalp using a *MCScap* (Medical Computer Systems Ltd, Moscow, Russia) with removable electrodes according to a 10-10 modified system (Fig. 2a), The impedance for all electrodes was kept below 10K Ω and the system was referenced to two interlinked ear reference (A1-A2). Two additional *EMG* electrodes monitored the muscular activity in both biceps.

The signals were amplified, digitalized with a sampling rate of 1000 Hz and band-pass filtered in the 0.5-100 Hz frequency band. EEG data were preprocessed using EEGLAB Matlab toolbox. Artifacts as eye blinking and head movements presented as components with homogeneous contributions, were removed using the *ICA* algorithm implemented in the *EEGLAB* toolbox using *runica* as decomposition method through the 10 seconds signals in all the recorded trials. Segments with high signal interference or disturb were also removed. Finally a fourth order pass-band filter in the band of 1 to 55 Hz was applied in order to remove another non interest signals.

2.2 Feature Extraction

We selected a set of 14 channels (FC_3, FC_1, FC_2, FC_4, C_5, C_3, C_1, C_Z, C_2, C_4, C_6, CP_1, CP_Z and CP_2) from the current *32-array* according to this proximity to the sensorimotor cortex. A spectral map of the recorded experiment is presented in the 2b for the channel C_3, the illustration presents the activity in the two studied time intervals: preparation (0 to 2 s) and movement execution (2 to 8 s), the movement is executed around the 2.4 to 4.5 s, an *ERD* in μ band appears during the task, low gamma band maintaining a high activity during the preparation time, whit a *ERS* just before the beginning of the movement (2 s) and a relative low activity during the movement, then a *ERS* was presented at the end of the movement.

Posteriorly, the signal was filtered in the 35-45 Hz band with a 4th order Butterworth pass-band filter, then the mean lower gamma activity of all the trials for each volunteer was determined according to Pfurtscheller and da Silva (1999) as:

$$\mathbf{X} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}_i \tag{1}$$

The activity was obtained through N trials, where $\mathbf{x}_i$ is the channel information for the i trial of L number of points, $\mathbf{X}$ is matrix $\in \Re^{14xL}$ being $j = 1, ..., 14$ the number of channels. Later, the signal was squared in order to get their band-power.

A comparison of the brain activity related to the preparation and movement of the arms was made through a discrimination map Glassman (2005), this method allows to find differences in the distributions of the classes among all the subjects, measuring the overlapping of the signals on time t. The discrimination is performed using a wavelet transform, selecting a subset of coefficients that provides a compact representation that shows the energy distribution of the *EEG* signal in time. According to Glassman (2005) the discrimination between the coefficients of two classes is determined as:

$$D = \frac{|\mu_2 - \mu_1|}{\sqrt{\sigma_2^2 + \sigma_1^2}} \tag{2}$$

Where *D* is the discrimination measure, μ_n and σ_n^2 are the distribution mean and variance of the coefficients for the compared classes $n = [1, 2]$ (right or left movement) at time t. The expression penalizes higher variance values in the distributions when their means are close to each other. In case of the distribution being less spread, the discrimination magnitude is higher.

The channels were ranked in descending order according to their discrimination magnitude, then the feature vector was built using the mean and the standard deviation of the wavelet coefficients in the intervals of high discrimination, this statistics represents the time-frequency distribution on each channel and reduce the dimensionality of the feature vector Subasi and Gursoy (2010).

2.3 Classification and Cross Validation

A Linear Discriminant Analysis (*LDA*) was implemented for data reduction. *LDA* creates a set of *w* vectors that discriminate the classes through a projection of the data in a new low dimensional space. *LDA* has a wide use on *BCI* systems Banville and Falk (2016) due to its reduced computational cost, and its good relationship between complexity and answer quality. Also *LDA* is robust notwithstanding the input classes have no normal distribution and different covariances Blankertz *et al.* (2011).

Once the data was dimensionally reduced, the feature vector was tested with eight different classification algorithms: Euclidean, Mahalanobis, Bayesian, k Nearest Neighbor (*k-NN*), and Supported Vector Machines (*SVM*) with linear, quadratic, polynomial and Gaussian kernel.

In order to determine a optimal number of channels j, and the *C* and σ value for the *SVM*, a 10-fold cross validation for each volunteer was made. In a *k-fold* test, the data is segmented in groups of trials (folds) and then, divided into two sets: training and validation. In this work, a 10-fold (each fold contains 10 trials) is made, where on each run 1 fold is left as the validation fold, while the remaining acts as training folds. The advantage of the *k-fold* cross validation is that all data is used as training and validation, changing its role for each run until all the folds are used for both tasks.

Finally 10 trials of both classes were left to run a test step with the optimal parameters (number of channels, C and σ) founded in the cross validation, the error distribution and the F-Score gave the classification accuracy. The θ values for each *SVM* model were determined using the *svmtrain* library in *Matlab*. The optimal parameters were those who minimizes the error of classification.

3. RESULTS

A total of 600 trials divided in twelve volunteers were used to study the gamma band activity during preparation and development of the arm movement in the elbow joint. After the construction of the band power time course, the differences

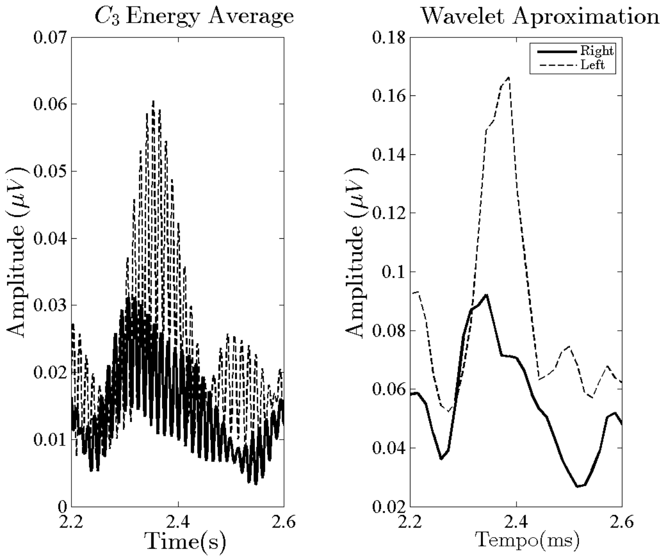
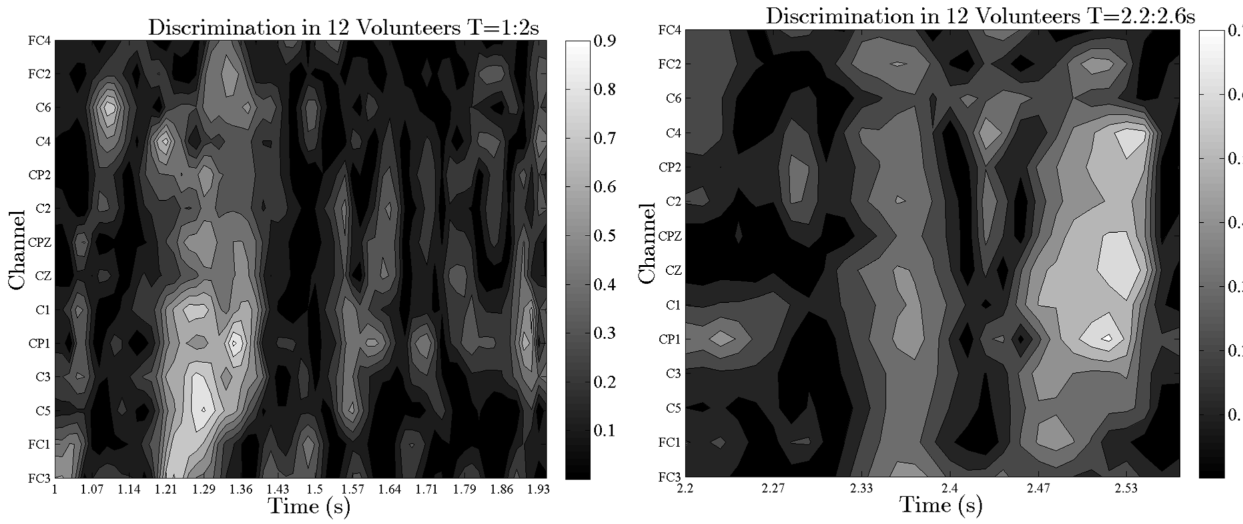


Figure 3: Wavelet approximation and original signal of the C_2 channel for real movement around the 2.2 to 2.6 seconds. The signal was build using the *Coif1* wavelet family on the 4th level. This figure shows the related gamma *ERS* prior to movement for the right and left actions, describing a difference in their amplitudes.



(a) Preparation Inteval Discrimination

(b) Movement Interval Discrimination

Figure 4: Discrimination of the activity in the gamma band for 12 volunteers in preparation and movement intervals. The darker zones represents time intervals where discrimination drops, while the clear ones represents an increase of its value. In the first interval a visible discrimination area is presented around the 1.14 and 1.36 seconds for both tasks, while a large band around the 2.33 to 2.53 seconds describes the gamma activity at the beginning of the movement.

for left and right movements in the signal response are found through the discrimination maps. Fig. 3 illustrates the wavelet transformation for left and right movements in the C_2 channel at the beginning of the movement interval. The coefficients were estimated with a 4th level *Coif1* wavelet family, being the most suitable for *EEG* signals Gandhi *et al.* (2011). As a result, a minor resolution signal is generated, with coefficients that represent their magnitude for both classes.

In the Fig. 4 are presented the discrimination map of the channels in the preparation (Fig. 4a) and movement intervals (Fig. 4b). Were founded high discrimination values between the 2.33 and 2.53 seconds, being minor around the FC_n channels and higher in the C_1, C_Z and C_2 channels. One interval of lower discrimination around the 2.4 s divide the region in two zones. The discrimination zone around 2.33 and 2.4 seconds, responds to the gamma *ERS* in the beginning of the movement, and it is presented with higher values around the central channels and reducing as it propagates. While in the preparation interval a region of high discrimination was presented approximately between the 1.14 and 1.36 seconds.

Two feature vector was built with the mean and the standard deviation of the wavelet coefficients, one extracted of the

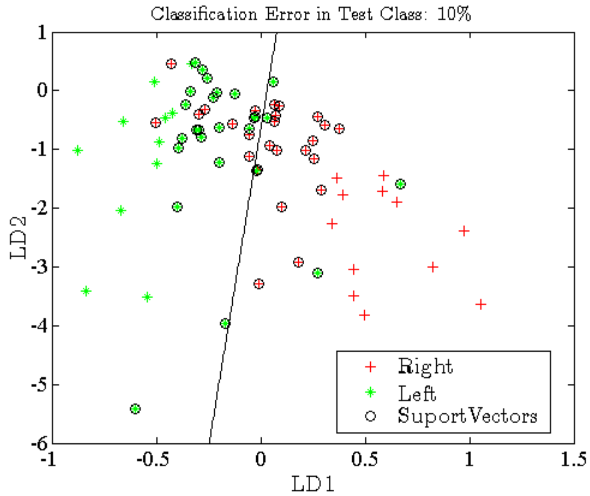
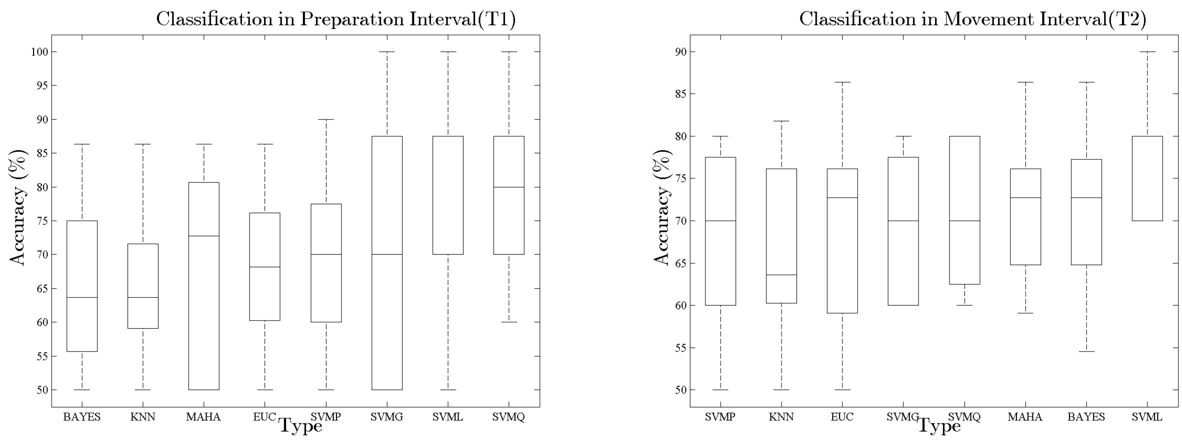


Figure 5: Classification response for one volunteer using the feature vectors of the time interval T2 (2,45 to 2,53 s). The *LDA* separate the left and right trials identifying two classes. The classification algorithm used was a *SVM* with linear kernels, which error of classification is presented on the title of the graph.



(a) Classification Response in T1

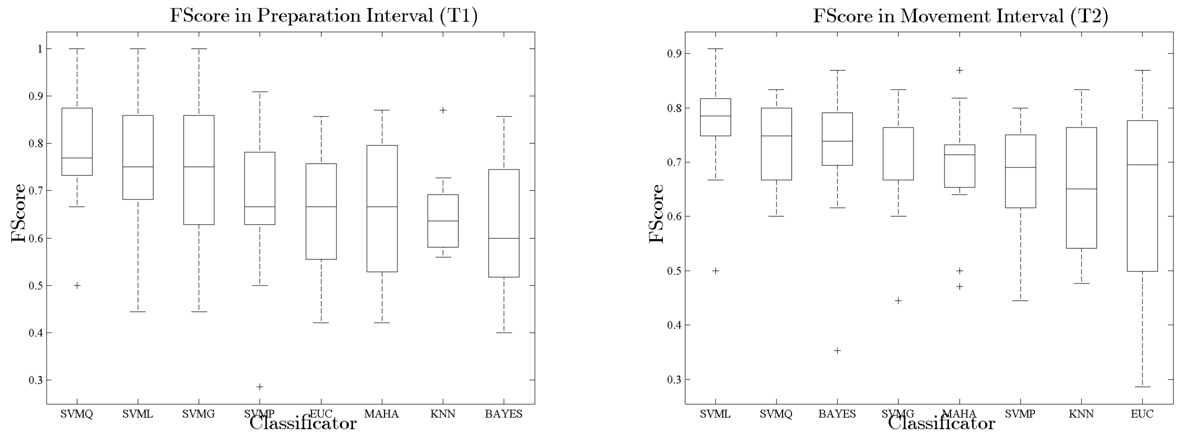
(b) Classification Response in T2

Figure 6: Box plot that describes the classification accuracy on each algorithm for the time intervals T1 (1.21 to 1.36 s) and T2 (2.45 to 2.53 s). The response was sorted in ascending order. *SVM* with quadratic kernels had the best accuracy for the preparation interval, whereas that in the movement interval was best the *SVM* with linear kernels.

interval 1.21 to 1.36 seconds (named T1) and the other of the interval 2.45 to 2.53 seconds (named T2). The selection of the time interval was made heuristically in accordance with the regions of higher discrimination for each map.

The number of channels, the C values and σ constants for the *SVM* classifiers where founded with a greedy algorithm, evaluating all the possibilities for each volunteer. For instance, Fig. 5 exhibits a classification result for one volunteer using the feature vector T2 after they where dimensionally decreased. The used algorithm was a *SVM* with linear kernels, which result gave a classification error of 10%. Both classes presented some overlap after de separation done by the w vectors of the *LDA*. The classes distribution in the new space depends of the number of channels, whereas that, the hyperplane configuration is depending of the parameters C and σ.

The accuracy distribution on each algorithm in ascending order for the selected time ranges T1 (6a) and T2 (6b) are presented in the Fig. 6. For the preparation interval was found that the *SVM* with linear (*SVML*) and quadratic (*SVMQ*) kernels have the best accuracy response (with a mean accuracy of 79.1% and 75.4% respectively) , meanwhile the *SVM* with linear kernels have the best response for the movement interval (77.3%). The F-score 6 shows that the algorithms whit major accuracy (*SVMQ* and *SVML* in each interval) have the best trade-off between Precision and Recall for all the volunteers. On the other hand, the F-score distribution was more compacted in the movement interval, suggesting that the classification performance is better in that cognitive state.



(a) F-Score for T1 interval

(b) F-Score for T2 interval

Figure 7: Box plot that describes the F-Score of each algorithm response for the time intervals T1 (1.21 to 1.36 s) and T2 (2.45 to 2.53 s) sorted in descending order. The distribution of the values are more compact for the movement interval, inferring that it has better classification performance.

4. DISCUSSION

In this paper we report a feasible use of feature vectors build with lower gamma band wavelet coefficients, for the classification of right/left elbow movement. Previous works Scherer *et al.* (2009) and Ryun *et al.* (2017) have already proposed that gamma band could be used to classify movements. Being these results obtained through invasive procedures, they have a good reading and discriminative information about the role of the gamma band in movement, nevertheless our purpose is an alternatively path using non-invasive *EEG* reading for *BCI* systems.

Cited articles as Palaniappan (2006), Mirnaziri *et al.* (2013) and Mensh *et al.* (2004) used gamma as a complementary signal in combination with other bands giving an important contribution on the build of feasible feature vectors. In Palaniappan (2006) was identified five mental with a combination of filtered *EEG* signal in the delta, theta alpha and beta bands as feature vector. The addition of the gamma band in the frequency of 24 to 37 Hz to the feature vector enhanced the classification rates (using an Elman neural network as classifier). Similar results were reported by Mensh *et al.* (2004) working in the motor cortex area using the same band frequency and by Mirnaziri *et al.* (2013) using a unique feature vector build with a large band signal (8-50 Hz) set in an electrode array of 22 positions. The addition of gamma, seems to expand the information that contain the feature vector, achieving a better performance in the classification of imagery of foot, tongue and bilateral hand movements than using only μ and beta or gamma, being the latter who presents the worst classification rate according to the researcher. The effectiveness of the use of gamma band due to his complementary information role in *BCI* applications were also reported by Salari and Rose (2013), Akrami *et al.* (2005) and Ravi and Palaniappan (2006).

On the other hand, few studies introduce non-invasive *BCI* feature vectors with gamma band oscillations: Ahn *et al.* (2013) with a validation of the performance across subjects in*MI* using *MEG* with *EEG*; Miller *et al.* (2008) in tongue movement detection; and Khan and Sepulveda (2010) with classification of wrist imagery movement.

One question that arises is how to take advantage of the reported gamma enhancement properties and use it to elbow *BCI* implementations. Thus, the employment of the discrimination maps, not only helped in the improvement of the *LDA* response, but also gives to us a heuristically tool that facilitates the exploration of the signal and allows to find time intervals where the signals have high separability. This extracted sections build the feature vectors used to identify the cognitive states.

We found two different segments where the gamma band presents high discrimination between left and right elbow movement. The first segment is presented in the preparation interval (T1) during the *1.21* to *1.36* seconds approximately. The second segment is presented in the movement interval (T2). Discrimination allowed to us to built feature vectors of high separability between the classes, optimizing the LDA response when reduces their dimensionality. Fig. 8 is an example of the application of a feature vector built from a region of low discrimination, the classes where classified using a *SVM* whit linear kernels, the mean response drops from the 75.4% obtained previously to 70%. As the discrimination allows to observe similarities between the brain activity of the volunteers, the regions of high or low separability were common among them. Thus, gamma band seems to present a less inter-individual variability than other bands, what could propitiate the construction of *BCI* systems using a unique selected band frequency and the same time interval for all subjects.

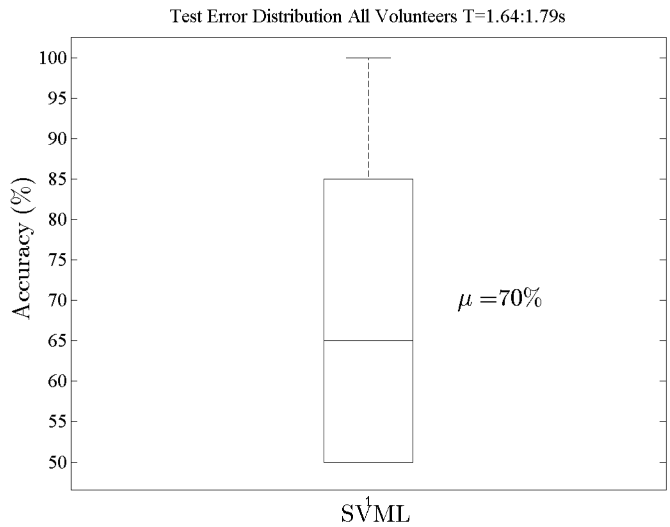


Figure 8: Classification response for one volunteer using the feature vectors of the time interval T1 (1.64 to 1.79 s). The classification algorithm used was a *SVM* with linear kernels, the classification accuracy drops compared with the previous response.

The *SVM* with linear kernels presents the best responses for the preparation and the movement interval, although that, in T1 was slightly surpass by the SVM with quadratic kernels. The discrimination made by the *LDA* in the feature vector linearly separate both classes, therefore, is reasonable to think that a algorithm that optimizes that linear hyperplane could fix their inclination based on the proximity of the responses. Non linear hyperplanes arrange unique frontiers that could lead to over-fitting when the classifier was evaluated with the test folds. Whereas that, algorithms based in Bayes decision theories, fails in the determination of a trial class as is indeterminate it relation with the distribution of the classes due to their superposition, thus their performance was surpassed by the linear algorithms.

The results obtained in this study are encouraging as the accuracy of the *SVM* classifier was greater than 70% , without any training or feedback on the volunteers, that can make *BCI* system more reliable for all individuals. Due to the classification success during the preparation of the movement, it is possible to anticipate to it.

We estimate that the response in the classification rate, could be improved with a increasing of the training and the number of volunteers. The increment of the accuracy with training was shown, for example, in a *BCI* set-up procedure using mu and beta frequency, where the subjects performed several sessions until their classification accuracy reached a level of about 70% Mueller-Putz *et al.* (2010).

5. CONCLUSION

The experimental results presented in this works show that it is possible to achieve a good response in classification of the elbow movement using solely feature vectors composed of gamma band signals. The use of Discrimination maps on the selection of the feature vectors improved the classification rate success. The experiment allowed to us to find common behaviors on the event response in all the subjects during the preparation and the movement execution.

The elbow movement reflected through the gamma band activity presents a high discrimination at the beginning of the movement, and previously one second after the volunteer receives the order. In both cases, it is possible to distinguish both movements with a mean classification success of 78% around the subject.

Whereas, the result obtained could be improved adding other bands information into the feature vector, our interest was focused on the possibility of classification using only the lower gamma activity giving a cognitive response for a task. Future works will include in the study imaginary movements.

6. ACKNOWLEDGEMENTS

The authors would like to thank to FINEP, CNPq, FAPERJ, Fundação COPPETEC and DIPPG/CEFET-RJ for supporting our works. As well as to the students Edwiges Beatriz Coimbra de Souza e Aline Macedo Rocha Rodriguez for helping in the EEG data acquisition, and Marco Vinicio Chiorri for technical assistance.

7. REFERENCES

Ahn, M., Ahn, S., Hong, J.H., Cho, H., Kim, K., Kim, B.S., Chang, J.W. and Jun, S.C., 2013. "Gamma band activity associated with bci performance: simultaneous meg/eeg study". *Frontiers in human neuroscience*, Vol. 7, p. 848.

Akrami, A., Solhjoo, S., Motie-Nasrabadi, A. and Hashemi-Golpayegani, M.R., 2005. "Eeg-based mental task classification: linear and nonlinear classification of movement imagery". *proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual*, pp. 1–4.

Aoki, F., Fetz, E., Shupe, L., Lettich, E. and Ojemann, G., 1999. "Increased gamma-range activity in human sensorimotor cortex during performance of visuomotor tasks". *Clinical Neurophysiology*, Vol. 110, No. 3, pp. 524–537.

Banville, H. and Falk, T., 2016. "Recent advances and open challenges in hybrid brain-computer interfacing: a technological review of non-invasive human research". *Brain-Computer Interfaces*, Vol. 3, No. 1, pp. 9–46.

Başar, E., Başar-Eroglu, C., Karakaş, S. and Schürmann, M., 2001. "Gamma, alpha, delta, and theta oscillations govern cognitive processes". *International journal of psychophysiology*, Vol. 39, No. 2, pp. 241–248.

Blankertz, B., Lemm, S., Treder, M., Haufe, S. and Müller, K.R., 2011. "Single-trial analysis and classification of erp components—a tutorial". *NeuroImage*, Vol. 56, No. 2, pp. 814–825.

Cassim, F., Szurhaj, W., Sediri, H., Devos, D., Bourriez, J.L., Poirot, I., Derambure, P., Defebvre, L. and Guieu, J.D., 2000. "Brief and sustained movements: differences in event-related (de) synchronization (erd/ers) patterns". *Clinical neurophysiology*, Vol. 111, No. 11, pp. 2032–2039.

Frolov, A., Biryukova, E., Bobrov, P., Mokienko, O., Platonov, A., Pryanichnikov, V. and Chernikova, L., 2013a. "Principles of neurorehabilitation based on the brain-computer interface and biologically adequate control of the exoskeleton". *Human Physiology*, Vol. 39, No. 2, pp. 196–208.

Frolov, A., Húsek, D., Bobrov, P., Mokienko, O. and Tintera, J., 2013b. "Sources of electrical brain activity most relevant to performance of brain-computer interface based on motor imagery". *Brain-Computer Interface Systems-Recent Progress and Future Prospects*, pp. 175–193.

Gandhi, T., Panigrahi, B.K. and Anand, S., 2011. "A comparative study of wavelet families for eeg signal classification". *Neurocomputing*, Vol. 74, No. 17, pp. 3051–3057.

Ginter Jr, J., Blinowska, K., Kamin, M., Durka, P., Pfurtscheller, G., Neuper, C. *et al.*, 2005. "Propagation of eeg activity in the beta and gamma band during movement imagery in humans". *Methods Archive*, Vol. 44, No. 1, pp. 106–113.

Glassman, E.L., 2005. "A wavelet-like filter based on neuron action potentials for analysis of human scalp electroencephalographs". *IEEE Transactions on Biomedical Engineering*, Vol. 52, No. 11, pp. 1851–1862.

Hochberg, L.R., Serruya, M.D., Friehs, G.M., Mukand, J.A., Saleh, M., Caplan, A.H., Branner, A., Chen, D., Penn, R.D. and Donoghue, J.P., 2006. "Neuronal ensemble control of prosthetic devices by a human with tetraplegia". *Nature*, Vol. 442, No. 7099, pp. 164–171.

Jeon, Y., Namb, C.S., Kim, Y.J. and Whang, M.C., 2011. "Event-related (de)synchronization (erd/ers) during motor imagery tasks: Implications for brainecomputer interfaces". *Int. J. Ind. Ergon.*, Vol. 41, pp. 428–436.

Khan, Y.U. and Sepulveda, F., 2010. "Brain-computer interface for single-trial eeg classification for wrist movement imagery using spatial filtering in the gamma band". *IET signal processing*, Vol. 4, No. 5, pp. 510–517.

Lalitharatne, T.D., Yoshino, A., Hayashi, Y., Teramoto, K. and Kiguchi, K., 2012. "Toward eeg control of upper limb power-assist exoskeletons: A preliminary study of decoding elbow joint velocities using eeg signals". In *Micro-NanoMechatronics and Human Science (MHS), 2012 International Symposium on*. IEEE, pp. 421–424.

Lana, E.P., Adorno, B.V. and Tierra-Criollo, C.J., 2015. "Detection of movement intention using eeg in a human-robot interaction environment". *Research on Biomedical Engineering*, Vol. 31, No. 4, pp. 285–294.

Mensh, B.D., Werfel, J. and Seung, H.S., 2004. "Bci competition 2003-data set ia: combining gamma-band power with slow cortical potentials to improve single-trial classification of electroencephalographic signals". *IEEE Transactions on Biomedical Engineering*, Vol. 51, No. 6, pp. 1052–1056.

Miller, K.J., Shenoy, P., Den Nijs, M., Sorensen, L.B., Rao, R.P. and Ojemann, J.G., 2008. "Beyond the gamma band: the role of high-frequency features in movement classification." *IEEE Trans. Biomed. Engineering*, Vol. 55, No. 5, pp. 1634–1637.

Mirnaziri, M., Rahimi, M., Alavikakhaki, S. and Ebrahimpour, R., 2013. "Using combination of μ, β and γ bands in classification of eeg signals". *Basic and clinical neuroscience*, Vol. 4, No. 1, p. 76.

Mueller-Putz, G., Scherer, R., Pfurtscheller, G. and Neuper, C., 2010. "Temporal coding of brain patterns for direct limb control in humans". *Frontiers in neuroscience*, Vol. 4, p. 34.

Palaniappan, R., 2006. "Utilizing gamma band to improve mental task based brain-computer interface design". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 14, No. 3, pp. 299–303.

Pfurtscheller, G., Brunner, C., Schlo, A. and da Silva, F.L., 2006. "Mu rhythm (de)synchronization and eeg single-trial classification of different motor imagery tasks". *NeuroImage*, Vol. 31, p. 153 – 159.

Pfurtscheller, G. and da Silva, F.L., 1999. "Event-related eeg/meg synchronization and desynchronization: basic principles". *Clin. Neurophysiol.*, Vol. 110, pp. 1842 – 1857.

Pfurtscheller, G., Graimann, B., Huggins, J.E., Levine, S.P. and Schuh, L.A., 2003. "Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement". *Clinical neurophysiology*, Vol. 114, No. 7, pp. 1226–1236.

Pfurtscheller, G., Neuper, C. and Kalcher, J., 1993. "40-hz oscillations during motor behavior in man". *Neuroscience letters*, Vol. 164, No. 1, pp. 179–182.

Pineda, J.A., 2005. "The functional significance of mu rhythms: translating "seeing" and "hearing" into "doing"". *Brain Research Reviews*, Vol. 50, No. 1, pp. 57–68.

Ravi, K. and Palaniappan, R., 2006. "Neural network classification of late gamma band electroencephalogram features". *Soft Computing*, Vol. 10, No. 2, pp. 163–169.

Robinson, N., Vinod, A.P., Ang, K.K., Tee, K.P. and Guan, C.T., 2013. "Eeg-based classification of fast and slow hand movements using wavelet-csp algorithm". *IEEE Transactions on Biomedical Engineering*, Vol. 60, No. 8, pp. 2123–2132.

Roy, R., Mahadevappa, M. and Kumar, C., 2016. "Trajectory path planning of eeg controlled robotic arm using ga". *Procedia Computer Science*, Vol. 84, pp. 147–151.

Ryun, S., Kim, J.S., Jeon, E. and Chung, C.K., 2017. "Movement classification using ecog high-gamma powers from human sensorimotor area during active movement". In *Brain-Computer Interface (BCI), 2017 5th International Winter Conference on*. IEEE, pp. 96–98.

Salari, N. and Rose, M., 2013. "A brain-computer-interface for the detection and modulation of gamma band activity". *Brain sciences*, Vol. 3, No. 4, pp. 1569–1587.

Scherer, R., Zanos, S.P., Miller, K.J., Rao, R.P. and Ojemann, J.G., 2009. "Classification of contralateral and ipsilateral finger movements for electrocorticographic brain-computer interfaces". *Neurosurgical Focus*, Vol. 27, No. 1, p. E12.

Seeber, M., Scherer, R., Wagner, J., Solis-Escalante, T. and Müller-Putz, G.R., 2015. "High and low gamma eeg oscillations in central sensorimotor areas are conversely modulated during the human gait cycle". *Neuroimage*, Vol. 112, pp. 318–326.

Sim, K.S., Kiang, K.D.T. and You, L.Z., 2016. "Eeg controlled wheelchair". In *MATEC Web of Conferences*. EDP Sciences, Vol. 51.

Soekadar, S.R., Witkowski, M., Vitiello, N. and Birbaumer, N., 2015. "An eeg/eog-based hybrid brain-neural computer interaction (bnci) system to control an exoskeleton for the paralyzed hand". *Biomedical Engineering/Biomedizinische Technik*, Vol. 60, No. 3, pp. 199–205.

Subasi, A. and Gursoy, M.I., 2010. "Eeg signal classification using pca, ica, lda and support vector machines". *Expert Systems with Applications*, Vol. 37, No. 12, pp. 8659–8666.

Szurhaj, W., Bourriez, J.L., Kahane, P., Chauvel, P., Mauguière, F. and Derambure, P., 2005. "Intracerebral study of gamma rhythm reactivity in the sensorimotor cortex". *European Journal of Neuroscience*, Vol. 21, No. 5, pp. 1223–1235.

Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G. and Vaughan, T.M., 2002. "Brain–computer interfaces for communication and control". *Clinical neurophysiology*, Vol. 113, No. 6, pp. 767–791.

Zhang, R., Li, Y., Yan, Y., Zhang, H., Wu, S., Yu, T. and Gu, Z., 2016. "Control of a wheelchair in an indoor environment based on a brain–computer interface and automated navigation". *IEEE transactions on neural systems and rehabilitation engineering*, Vol. 24, No. 1, pp. 128–139.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.