Feature Extraction Process with an Adaptive Filter on Brain Signals Motion Intention Classification

Luis F. Marín-Urías, J. Alejandro Vásquez-Santacruz, Rogelio de J. Portillo-Vélez, Félix O. Rivera-Hernández
Facultad de Ingeniería
Universidad Veracruzana
Boca del Río, Ver. Mexico
e-mail: luismarin@uv.mx

Mario Castelán
Robótica y Manufactura Avanzada
CINVESTAV - IPN
Ramos Arispe, 25900, Mexico
e-mail: mario.mcastelan@cinvestav.mx

***Abstract*—Identifying motor imagery from an electroencephalogram (EEG) has been researched from different perspectives and methods of classification. Translating a brain signal into a language understandable for machines relies on feature extraction techniques, which vary from working on the frequency domain to dealing with raw data. Using statistical information to classify motor imagery has shown encouraging results. In this paper we benefit from statistical approaches and propose a different perspective to boost results obtained through brain signals provided by a low cost EEG. Our motivation is based on the natural separability of classes exhibited by statistical indicators such as the mean and standard deviation. A special emphasis in our method is made on filtering data to subject readings in an adaptive manner, leading to a successful classification rate of 97%, outperforming Hjorth's mobility and complexity measure, a state-of the art technique used in EEG signal classification.**

Keywords: BCI; EEG; Motion Intention Classification; Motor Imagery; KNN.

I. INTRODUCTION

In order to improve self-sufficiency in people with reduced motion capabilities, it is necessary to create assistive technologies that not only are governed by a specific control strategy for a desired task, but that also allow the interpretation of motion intentions.

Giving this self-sufficiency has been partially addressed from different perspectives. For instance, an autonomous service robot may facilitate users with objects they desire [1][2], easing quality of life but lacking in providing a sensation of independency. Another approach has been to provide robots with a tele-operation based control [3] or even using exoskeletons with muscular signal activation [14]. These are significant approaches that offer a greater sensation of self-sufficiency to users. Still, patients that have suffered motion disorder diseases like sclerosis and Parkinson are not able to steadily control robots or exoskeletons, neither by using hands or extremities nor by using signals provided by muscular nervous terminals. Identifying brain motion intentions is therefore an open problem as stated in [4], where a review of motion command identification is developed.

Most of the work done on classifying brain signals uses a fixed band pass filter based on the work in Yuan et al. [4] where fixed frequencies are established for each type of data describing a mental state for a specific activity. Nevertheless, the brain is a labile organ, i.e., neural signals change through time while performing activities, which is known as neuroplasticity.

In order to identify and decode elements of information, non-stationary models are required. For this reason, some signal treatment strategy is needed to identify neural activities, as in the work of Wang et al. [5], where a method to modulate brain signals through a mathematical model was proposed.

From the efforts of Hazarika et al. [11], authors have used the discrete wavelet transform to obtain features and classify epileptic seizures by means of artificial neural networks (ANNs) as in [12] or Support Vector Machines (SVM) as in the work of [10]. Other classification approaches can be found in [9]. As statistical features obtained from wavelets are more susceptible to time-frequency localization than Fourier Transform, which is band limited, the latter assumes a more feasible approach for analysis.

Using statistical data to classify elements from brain signals has been analyzed in [6][18] in order to obtain human emotions from different statistical methods, such as the mean and standard deviation analysis. The results of their work indicated that these two features are not effective enough compared to other approaches. Nevertheless, since their analysis is developed directly from raw data, a lack of pre-processing operations may be a cause for the modest success exhibited by the mean and STD statistical analysis. Another feature extraction method based on statistical data is used in [19], where three features are obtained from the Fisher ratio of the Hjorth's *activity*, *complexity* and *mobility* in order to classify motor imagery. These statistical methods include time rather than only frequency domain as in STFT, increasing the flexibility of data.

Brainwaves of motor imagery classification have also been used to control either virtual [15][16] or real [3] objects that respond to motion commands in two or three dimensions. This has been achieved by using a 64-channel

 ISBN: 978-1-61208-609-5

EEG cap to describe thoughts, supported by a specific control technique.

The main objective of our paper is to gather and classify motion intention commands from brainwaves by using a low cost EEG. Non-invasive EEG brain-computer interface systems have gained interest inside the research community. On one hand, they represent a harmless solution for humans; on the other hand, it is possible to obtain reliable enough information from brain signals after some processing of the data.

This paper is structured as follows: in Section II, the general structure of the motion intention classification is introduced. Additionally, it is explained how pre-processing data through an adaptive filter is useful for achieving feature vector separability. In Section III, results are presented. Finally, in Section IV, we discuss the concluding remarks about the proposed approach.

II. DATA ACQUISITION AND FILTERING

The Motion Intention Classificator (MIC) system is basically done throughout three phases: 1) pre-processing raw information from brainwaves, 2) extraction of dominant features and 3) classification of the resulting features. These phases normally act sequentially and are interdependent. Figure 1 shows the inner work of a general architecture to interpret raw brainwaves into commands for tele-operation.

The output features depend on the extraction methodology, which in this paper is addressed with a statistical mean-STD approach and with the Hjorth's Mobility and Complexity technique.

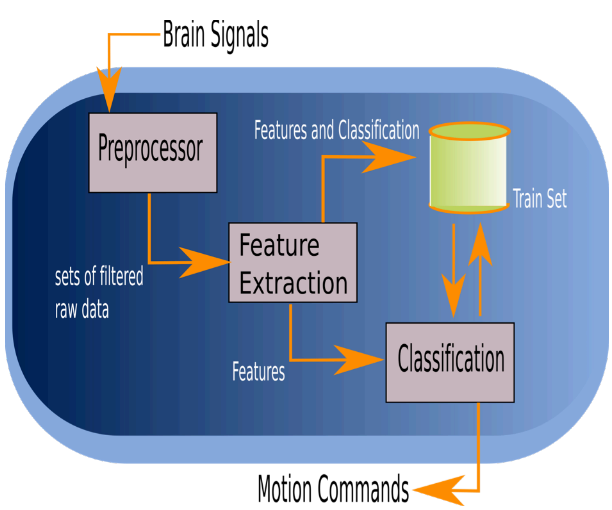

Figure 1. General Architecture of the MIC.

A. Preprocessing data

In order to obtain features from brainwave signals, it is required to set information that will serve as training data to be filtered from the noise induced by sensor readings.

For setting the training data it is necessary to split raw data into sections according to a defined task that a test subject should execute. Once this has been carried out, synchronization with the training system is developed by parsing corresponding sections labeled with the task.

In particular, the test subject is guided by computer images indicating a command of motion intention. The image is basically a geometric form that suggests the subject to concentrate on a particular mental task during 18 seconds with a specific intermittent signal (2 seconds of a displaying task and 2 seconds of a neutral activity). This pattern is periodically repeated with a different command after T seconds for resting between tasks, as depicted in Figure 2. Four different active tasks of motion intention (here referred to as activities) are intended to be extracted: Right (R), Left (L), Up (U) and Down (D), while one more for no intention activity is considered as Neutral (N). The data acquisition process is an important part of this approach and it is illustrated in Figure 2, showing the alternation of the N activity (marked as checkerboard patterns) on each of the tasks. The total process lasted 97s for each test subject. We have set T to 5s between tasks to avoid interference.

We asked 14 naive subjects to sit in front of a monitor giving instructions to them, the subjects must be focused on thinking the action indicated while avoiding body motions during the 97s experiment. After some experiments, we could notice that the neutral activity was correlated with its precedent mental activity, i.e., the N activity had some remaining “inertia" from previous R, L, U and D tasks. In other words, while the training of the N activity was expected to occur during the 2s pause between each trial, in reality there was a presence of neutrality preceded by a non-neutral emotion. This led to different Neutral Activities (NR, NL, NU, ND), which we used for classification.

B. Filtering Data

One key element proposed in our approach is the implementation of an adaptive filter, which is based on statistical information.

Raw data, as used in the work of [6], is usually contaminated with noise that makes it difficult to perform the appropriate classification of different activities. This effect can be seen in Figure 3, where features from each class (represented as geometric figures), which have been obtained from raw data, appear not only close to each other but also mixed, i.e., they are hardly separable and their classification is harder. For this reason, applying a filter becomes necessary to reduce the noise coming from sensor signals.

Copyright (c) IARIA, 2018. ISBN: 978-1-61208-609-5

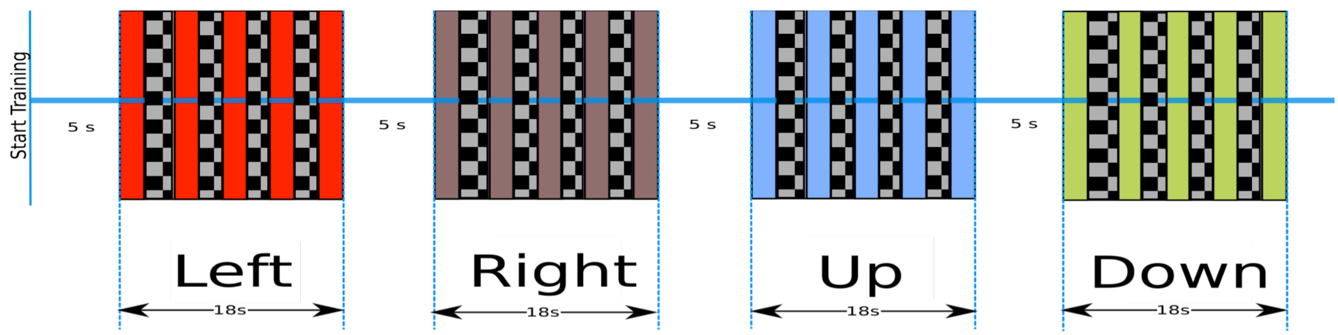

Figure 2. Training session schema, task mental activities are in colors (duration 2s), while neutral activities are in grey between each training task.

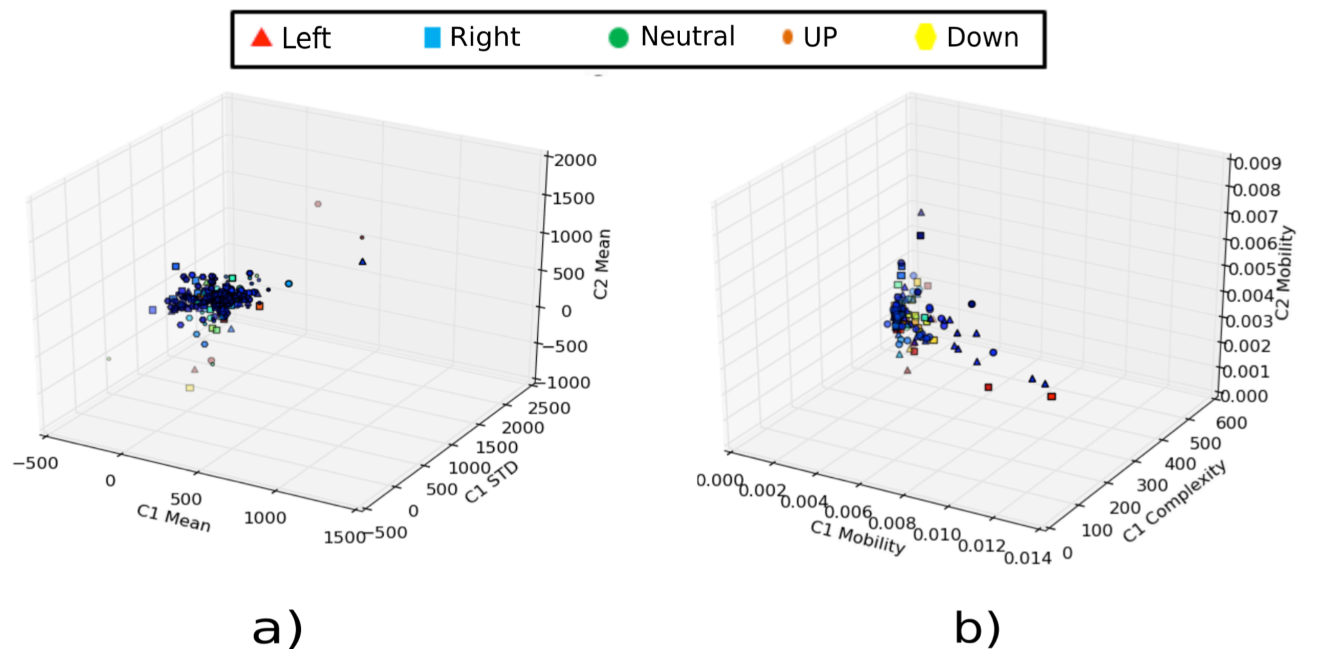

Figure 3. Features extracted without pre-procesing data with two different feature extraction methods. Note how it is difficult to separate features due to their proximity between each activity class..

It is common to use a band pass filter based on fixed frequencies as in [18] for each brain region or for different kinds of mental activities. As mentioned above, the filter used in our approach is based on statistical information from raw data for each sensor, each set and each subject. It is worth noticing that our filter is not based on channels, but in information from activities (L, R, U, D and N).

Let us define the high ($\mu_{\max}$) and low ($\mu_{\min}$) thresholds from data as:

$$\mu_{max}(x_{kj}) = \overline{S}(x_{kj}) + \sigma(x_{kj}) \quad (1)$$

$$\mu_{min}(x_{kj}) = \overline{S}(x_{kj}) - \sigma(x_{kj}) \quad (2)$$

with:

$$\overline{S}(x_{kj}) = \frac{1}{m}\sum_{i=0}^{m} w_{x_{kj}}(t_i) \quad (3)$$

$$\sigma(x_{kj}) = \sqrt{\frac{1}{m}\sum_{i=0}^{m}(w_{x_{kj}}(t_i) - \overline{S}(x_{kj}))^2} \quad (4)$$

where x_{kj} is the training set with the elements of a mental action k from sensor j, and w is the amplitude of the brainwave at the sample time t_i in a total of m discrete readings from sensor.

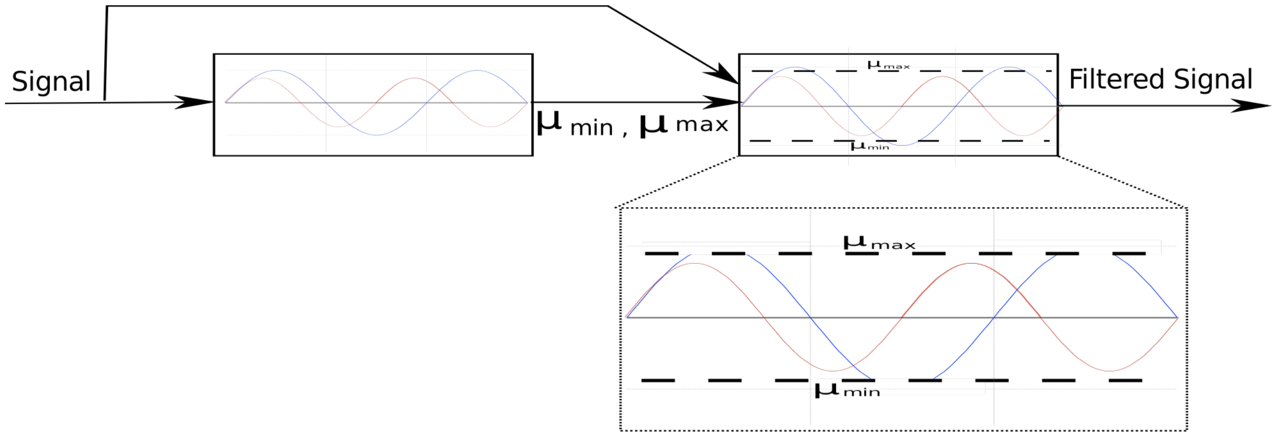

Figure 4. Illustrating thresholds high $\mu_{\max}$ and low $\mu_{\min}$ used on each brain wave. Data above or below these thresholds are dismissed.

Setting thresholds in this way (as depicted in Figure 4) provides flexibility to the filter band so that the filter adapts to each subject and to the wave characteristics. This makes feature vectors belonging to one activity be closer to those from the same activity, and makes them more separated from those belonging to another class. The effects of the filter are more noticeable when comparing Figure 3a with Figure 5 and Figure 3b with Figure 6. Similar filters have been used in [17] to classify frog call sounds (from different frogs), and are also commonly used in data transmission.

C. Feature Extraction.

After separating wave sections corresponding to mental activities and afer having filtered noise, it is necessary to reduce dimensionality by obtaining characteristics from waves, which facilitates classification.

Due to the nature of the Emotiv Epoc device, there are 14 analyzed individual signals (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4). Additionally, a couple of features for each signal are required to extract corresponding activities, which are represented by a classification feature vector in the training set. In total, 28 features for each mental activity, period and subject are acquired and stored as features.

We present two statistical methods for comparison: M1) taking mean and standard deviation as shown in Fig. 5, a close approach to what has been done in [6] and [18], but applied to motor imagery instead of emotions, and compare it with another statistical feature extraction method called M2) the Hjorth's mobility and complexity, a similar approach to what has been developed in [19]. Note that we do not take into account the Fisher ratio because in [19] they use it to find the dominant frequency to adapt in the training phase. This action is solved in our filter phase. Furthermore, we do not take into account Hjorth's Activity as a feature, which is highly correlated with Complexity and Mobility, so as to avoid redundant information. The behavior of M2 can be observed in Figure 6. Note how, while Figure 5 reveals a more noticeable separability between classes, Figure 6 shows how some features are highly separated although classes are still mixing.

III. Classification Results

For experiments, 14 subjects were selected to generate the knowledge base; each subject participated at different times of the day (3 times per day for each subject) and in some subjects different “head/hair conditions” (wet/dry, with/without hair products). The knowledge base is formed leaving one subject out to test the classification results. The sensor used in the experiments is the Emotive Epoc one, which is a non-invasive sensor that provides 14 signals from each user; this is a low cost sensor that naturally induces noise through the wireless communication with the computer (RF). Nevertheless, the approach presented here is a generic approach that can be used with any sensor model, also improving classification rate in the presence of noise.

Even when extracted features are filtered to increase the distance between them in the plot, as depicted in Figures 5 and 6, those features are not linearly separable, so it is necessary to implement a different method to identify each mental activity from brainwaves.

We propose using a *k*NN (*k* Nearest Neighbors) algorithm, where different values of *k* are analyzed (the number of neighbors from all activities) to identify which of them fits the best results. This algorithm has been widely used in many classification problems for its simplicity of training. As we had the hypothesis that features obtained in this way would generate equidistant clusters, *k*NN appeared to fit the best and helped us prove that a good outcome could be achieved.

 ISBN: 978-1-61208-609-5

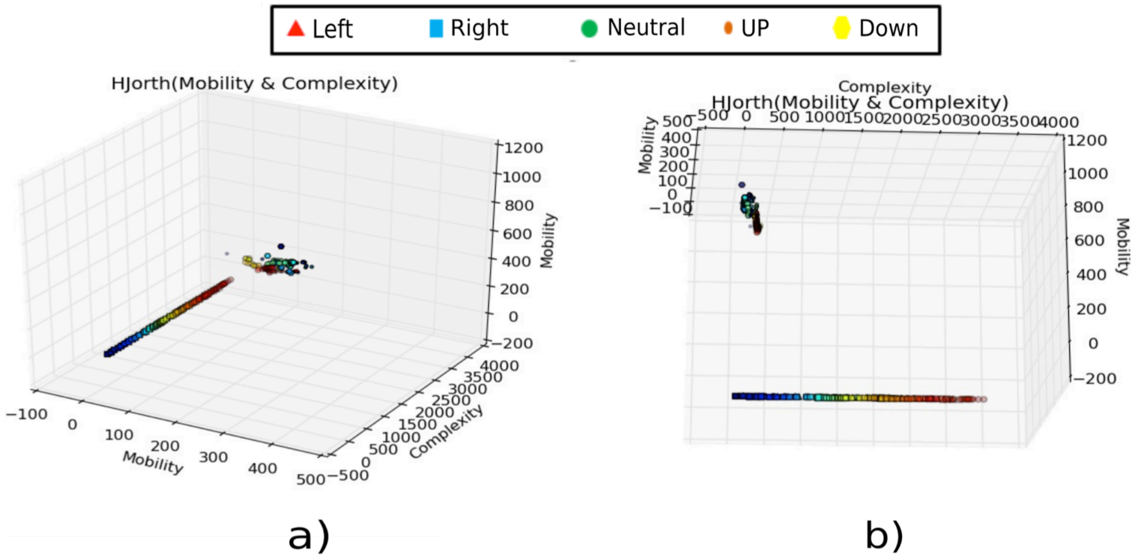

Figure 5. 4D plot showing features after filtering distances on two signals (FC5 and FC6), with Mean FC5 vs Mean FC6 represented by the *X* and *Y* axis, while STD FC5 vs STD FC6 are represented by *Z*. Colors (from blue to red) refer to distances.

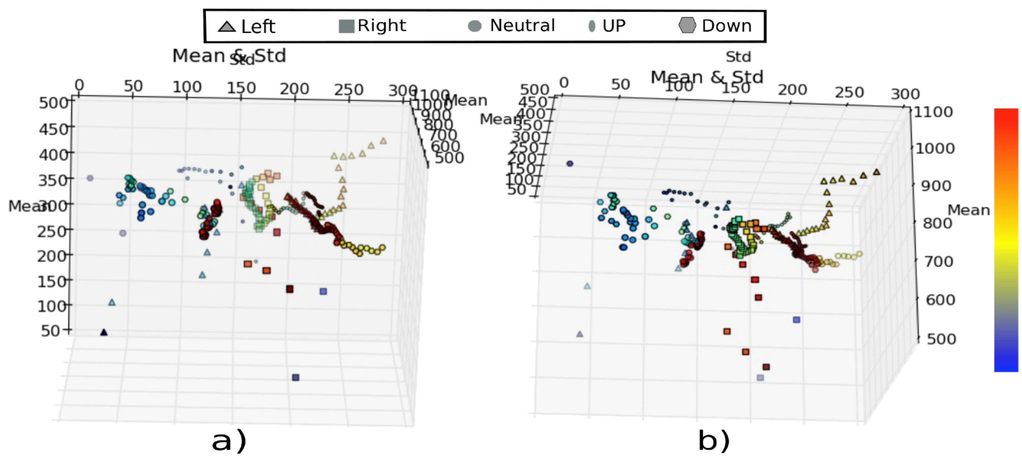

Figure 6. 4D plot showing two perspectives of the distance on two signals (FC5 and FC6) using Hjorth's mobility and complexity features after filtering, axes and colors (from blue to red) refer to distances.

The results from the classification algorithms over Mean and STD are presented in Table I, where it can be noticed that it is best to only consider three neighbors for effectiveness, training and search times. This can be caused by the structure of the class, which seems to be arranged more along lines (as seen in Figures 5 and 6) than along equidistant clusters.

Figure 7 and Table II present the difference between both methods M1 and M2. From the figure, it is noticeable how using an STD-mean strategy provides better results than Hjorth's Mobility and Complexity in all cases of classification, since the overall percentage of effectiveness is higher. Even though the method M2 has a lower accuracy rate than M1, it shows better results in motor imagery classification than in [19] (79.1%) where the same features are used. In Figure 7 and 8, the dashed line represents M1 while the continuous line represents M2; the X-axis refers to neighbor number.

TABLE I. KNN K-VALUES, EFFECTIVENESS, TRAINING TIME AND SEARCH TIME OVER MEAN AND STD

K	Avg. Performance		
	Effectiveness (%)	*Training(s)*	*Search(s)*
3	97.23	0.000641731	0.0006567
5	96.27	0.000661157	0.00066496
9	94.67	0.000644846	0.00068063
13	94.00	0.000644687	0.00068448
17	89.20	0.000647488	0.00070822
25	82.80	0.000638758	0.00073605
30	78.40	0.000653181	0.000760

TABLE II. KNN AVG. OF EFFECTIVENESS COMPARISSON BETWEEN M1 AND M2

K	Avg. Effectivenes (%)	
	M1	*M2*
3	97.23 ± 3.7	94.27 ± 4.39
5	96.27 ± 3.1	91.87 ± 7.2
9	94.67 ± 3.91	83.2 ± 8.37
13	94.00 ± 4.57	79.33 ± 8.24
17	89.20 ± 10.05	78.93 ± 7.95
25	82.80 ± 17.92	75.20 ± 6.66
30	78.40 ± 18.99	74.93 ± 12.15

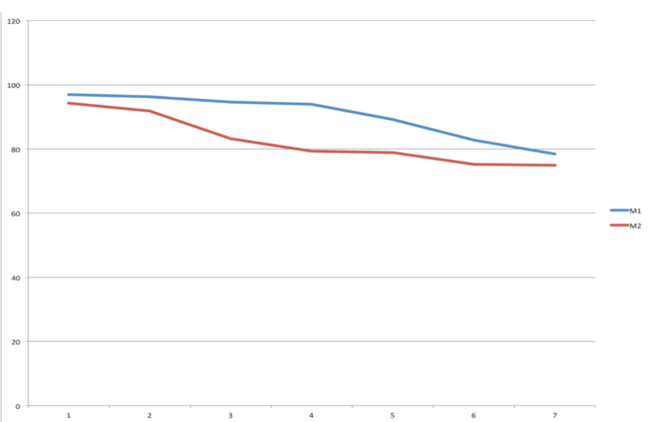

Figure 7. Effectiveness rates of classification between the two feature extraction methods M1 (blue) and M2 (red).

In Table III, we show 250 classification tests done with 50 cases of each class (the same 14 subjects with different conditions in cross-validation) for *k=3* while leaving one subject out and validating with the rest. From the table it can be inferred that the errors in classification are mainly related with the Left activity. This can be related with the structure of the training process, where Left activity is the first in the training set.

TABLE III. CLASSIFICATION

Intention	Confusion Matrix for k=3 using only mean and standard deviation				
	Left	*Right*	*Neutral*	*Front*	*Back*
Left	50	0	0	0	0
Right	3	47	0	0	0
Neutral	1	1	48	0	0
Front	0	0	0	50	0
Back	2	0	0	0	48

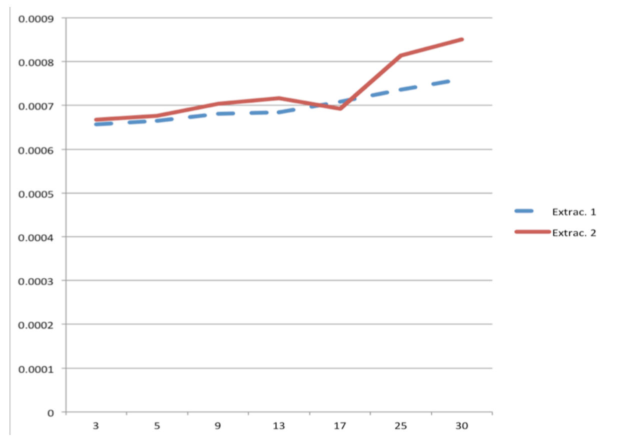

Figure 8. Searching time between methods M1 and M2.

IV. CONCLUSION AND FUTURE WORK

We have presented a statistical-based approach to train, filter and classify motion intentions from brain signals. Our method was motivated by the good separability of classes provided by the mean and standard deviations of the gathered data. Filtering and performing data acquisition in this manner allow us to report satisfactory results, reaching above 97% of accuracy on our test data and with a "lazy" classifier such as *k*NN, allowing the brain signals to become suitable not only for tele-operation purposes, but also for the purposes of emotion recognition. As an additional result, brain inertia could be observed from the experiments. We found that this brain behavior depended on the previous immediate motion intention of the subject, pushing the neutral intention to be closely related with previous brain activities, deeper experiments in this subject will be needed in order to obtain more quantitative results. This inertia helped us re-organize the training process by inserting neutral actions between each activity, thus redefining the usual methodology in literature where "pause" is not taken into account as a part of the knowledge base.

As an extension to this work, we will seek for obtaining a bigger sample of subjects in order to avoid biasing our results. Also, it is recommendable to use some other classification techniques (e.g., Artificial Neural Networks) to obtain more stable results. Furthermore, we plan to implement our methodology on a real-time tele-operation system, which could be used to identify emotions and mental states that are relevant in tele-operation issues. For this, it may be necessary to induce emotions while acquiring at the same time the mental states.

REFERENCES

[1] E. A. Sisbot, L. F. Marin-Urias, R. Alami, and T. Simeon, ”A human Aware Robot Motion Planner”, IEEE Transactions on Robotics, Vol 25. Issue: 5, pp. 874-883 Oct. 2007.

[2] E. A. Sisbot, L. F. Marin-Urias, X. Broker, D. Sidobre, and R. Alami ”Synthesizing robot motions Adapted to human presence”, Intl. J. of Social Robotics, Vol. 2 Issue 3, pp. 329-343, Sep. 2010.

[3] K. LaFleur, ”Quadcopter control in three-dimensional space using a noninvasive motor imagery-based braincomputer interface”. Journal of Neural Engineering, Vol. 10. (2013)

[4] H. Yuan, and B. He, ”Brain-Computer Interfaces Using Sensorimotor Rythms: Current State and Future Perspectives”, IEEE Transactions On Biomedical Engineering, Vol. 61 NO. 5, pp 1425-1435, May, 2014.

[5] Y. Wang et al., ”Tracking Neural Modulation Depth by Dual Sequential Monte Carlo Estimation Point Process for Brain-Machine Interfaces.”, IEEE Transactions On Biomedical Engineering, Vol. 63 NO. 8,p.p 1728- 1741, May, 2016.

[6] T. Y. Chai, S. S. Woo, M Rizon and C.S. Tan, ”Classification of human emotions from EEG signals using statistical features and neural network”, International Journal of Integrated Engineering, 1 (3), 71-79, 2010.

[7] I. Juarez-Moreno, L.F Marin-Urias, J.A. Vasquez-Santacruz, M. Vigueras-Zuñiga “Interface de comunicación remota entre un sistema clasificador de ondas cerebrales y un robot móvil”, Revista de aplicaciones de ingeniera, Volumen 3 No. 9 Pg. 109-116 2016

[8] E. A. Sisbot, L. F. Marin-Urias, X. Broquere, D. Sidobre, R Alami Synthe- sizing robot motions adapted to human presence International Journal of Social Robotics 2 (3), 329-343 2010

[9] A. Subasi, ”EEG Signal Clasification using wavelet feature estraction and a mixture of expert model, Expert Systems with Applications”, vol. 32 , 1084-1093, 2007.

[10] A. Subasi, and M. I. Gursoy, ”EEG Signal Classification using PCA, ICA, LDA and support vector machines”, Expert Systems with Applications, vol. 37, 8659-8666, 2010.

[11] N. Hazarika, J. Z. Chen, A.C. Tsoi, and A. Sergejew, ”Classification of EEG signals Using the wavelet transform”, Journal of Signal Procesing, Vol.59, 61-72. 1997

[12] H. Adeli, Z. Zhou and N. Dadmehr, ”Analysis of EEG records in an epileptic patient using wavelet transform”. Journal of Neuroscience Methods, vol. 123, 69-87. 2003

[13] N. Kwak, N. Muller, and S. Lee, ”A lower limb exoskeleton control system based on visual evoked potentials”. Journal of Neural Engineering, Vol. 12, No. 15, 2015.

[14] K. Kiguchi, T. Tanaka and T. Fukuda, ”Neuro-Fuzzy control of a robotic exoskeleton with EMG signals”. IEEE Transactions on Fuzzy Systems, Vol 12, No. 14. 2004.

[15] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, ”Electroencephalographic (EEG) control of three dimensional movement” Journal of Neural Engineering, vol.7 No. 3 036007, 2010.

[16] A. S. Roye, A. J. Doud, M. L. Rose and B. He, ”EEG control of a virtual helicopter in 3 dimensional space using intelligent control strategies”, IEEE Transactions Neural Systems Rehabilitation Engineering, Vol. 18. No. 6, pp 581-589, Dec. 2010.

[17] J. Xie, M. Towsey, L. Zhang, J. Zhang and P. Roe, ”Feature Extraction Based on Bandpass Filtering for Frog Call Classification”, International Conference on Image and Signal Processing ICISP 2016: Image and Signal Processing pp 231-239, Trois- Rivires, QC, Canada, May 30 - June 1, 2016.

[18] K. Takahashi ”Remarks on SVM-Based Emotion Recognition from Multi-Modal Bio-Potential Signals”, IEEE International Workshop on Robot and Human Interactive Communication Proceedings of the, Kurashiki, Okoyama Japan, September 20-22 2004.

[19] S. Oh, Y. Lee, and H. Kim, ”A Novel EEG Feature Extraction Method Using Hjorth Parameter”, International Jour- nal of Electronics and Electrical Engineering Vol. 2, No. 2, June, 2014