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SUPPORT VECTOR MACHINE TO CLASSIFY FEATURES OF MOTION IMAGINARY EEG

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ABSTRACT

Nowadays, encephalograms (EEG) have many applications in marketing, psychology, neuroscience, psychiatric studies and brain computer interfaces. The last one is being motivated by the advance of technology that now allows known details of brain's areas related with cognitive, motion and sensorial activities, using these information to operate mechanical devices with the brain. This paper has as objective make an experiment for acquiring brain signals associated with the thoughts of a movement to left or right from a person with motion disability, these signals will pass by a band pass filter, a common spatial pattern analysis (CSP) and lately are classify through support vector machines (SVM). Obtaining as a result, recognition of 70% from the imaginary movement signals to left and 80% of recognition from the signals related to the imaginary movement to right.

Keywords: electroencephalogram, common spatial patterns, support vector machines, emotiv.

1. INTRODUCTION

A brain computer interface (BCI) is a system which is able to detect cognitive, sensorial and motion activities from a user and use this information as inputs for controlling a mechanical or electric system [1].Nowadays, devices for detecting these brain activities are noninvasive, due to use of superficial electrodes located specifically according with the international standard 10:20 [2].

The main problem with this type of electrodes is that the captured signal can have noise or detected wrong signals. Due to this, the captured signals need a stronger treatment that allow an appropriate identification and classification[3][4].

Depend of the application for the BCI, is possible use different data processing methodologies, in the specific case of motion imagination the method more popular for the identification of encephalogram (EEG) captured by superficial sensors is the common spatial pattern (CSP) analysis [5].

The CSP analysis seeks determine the features spatially filtered that allow maximize the variance of one class and at the same time minimize the variance with the other class, reason why are obtained the same features number for both class allowing classify two tasks of imaginary movement [6].

A common complement in the identification and classification of imaginary movement signals beside of the CSP for the features extraction is the support vector machine (SVM). The SVM is a machine learning algorithm for a general classification of at least two tasks, based on the construction of a hyperplane that divide spatially all samples per class [7].

Example of the combination of these algorithms is the thesis developed by Quang le, which used CSP and SVM to recognize two imaginary movements of patients with Amyotrophic Lateral Sclerosis, where was recognized 83% of the recollected samples [8]. Similarly, the work made in [9] used the SVM algorithm to classify two motion task of a specific user, reaching a recognizing of 91.64%.

Taking account the previous information, this work has as objective the development of a data processing methodology for recognize two tasks of imaginary movement from a user with physical disability. This methodology consist in a relevant channels selection, a sequential filtered with ranges of 4Hz, after is extracted the features with CSP of each band filtered and the SVM classify the features of the two imaginary movements. Obtaining as a result a recognizing of 90% for the imaginary movement to right and 80% for the imaginary movement to left.

2. METHODOLOGY

The classification of signals belong of an imaginary movement to right or left, use signals obtained from the Brodmann areas processed by filtered technics, CSP and classify using SVM, as shown the methodology in Figure-1.

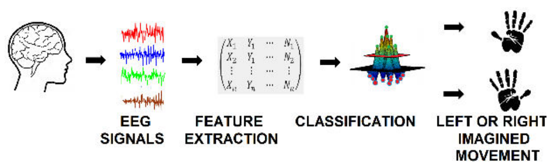

Figure-1. Methodology used.

In this work the Emotiv® sensor was used to acquire the electric signals of the brain according with the acquisition paradigm shown in Figure-2. This paradigm was designed with an initial period of 7 seconds for configuration, time in which the software of visual stimuli is synchronized with the software of capture brain signals through Emotiv®. After this period, the paradigm has 3 seconds where is shown a Cartesian axis, which refer to the waiting time and continue other 3 seconds where is shown the visual stimulus for help the user to imagine the movement to left or right.

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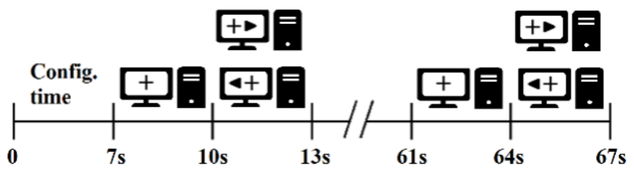

Figure-2. Data acquisition paradigm.

The visual stimulus consist in an arrow moving from the center of the Cartesian axis to left or right during 3 seconds, the movement of the arrow corresponds to the movement of the user need to imagine.

Each paradigm's session takes 67 seconds in which the user imagine 10 times the movement to left or right, due to that the experiment consist in 10 sessions, 200 samples for training the SVM were obtained.

Once the samples were obtained, the methodology shown in Figure-3 was used, in which starts with a selection of channels that give relevant information about the imaginary movement to left or right.

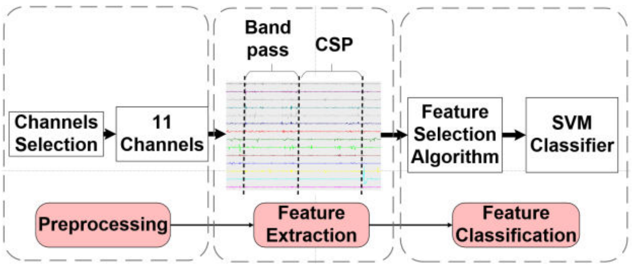

Figure-3. Dara processing methodology.

For the channels selection, the toolbox EEGLAB of MATLAB® was used, which allowed determine the Event Related Potentials (ERP) of each sample. With the ERP is possible observe the answer from the brain to an imaginary movement in each channel of the Emotiv®, allowing a comparison among channels and determining which ones are the most relevant channels [10], [11].

Once selected the relevant channels during the motion imagination is necessary proceed with the feature extraction. For that the captured signals from each relevant channel are filtered in the frequencies related to the motion imagination.

Previous studies have demonstrated that the brain waves alpha (8-12 Hz) and beta (13-30 Hz) have a major activation during the imagination of a movement both left as right[12],[13]. Due to this information, for this work a sequential filter with range of 4Hz from 8Hz to 30Hz was used.

For the filtering process two types of bandpass filter were used, a FIR equiripple filter and IIR elliptic filter. With the filtered signals, the CSP analysis was used in order to extract the main features of each signal.

In the CSP analysis each signal is represented by a matrix compoused by n x m, where n is the number of channels and m is the number of samples per channel. With this information the spatial covariance of the matrix (δ) was calculated with the equation 1.

$$\delta = \frac{\alpha\alpha^T}{\mathrm{tr}(\alpha\alpha^T)} \tag{1}$$

Where $(\alpha^T)$is the transposed matrix, *tr* refers to the diagonal sum of the elements of$(\alpha\alpha^T)$. Consequently, the spatial covariance is define for both the imaginary movement to left as the imaginary movement to right.

The CSP seeks define a matrix X that with δdefine the diagonal of the matrixA_a for the imaginary movement to left andA_b for the imaginary movement to right[15]. This information is represented by the equation 2 where$A_a + A_b = I$(identity matrix).

$$X^T\delta_a X = A_a, X^T\delta_b X = A_b \tag{2}$$

With the equation 2, the composed spatial covariance was define in the equation 3[16].

$$\delta_c = \delta_a + \delta_b \tag{3}$$

Knowing thatδ_c factorized is equal to$\delta_c = \mathrm{U}_c\mathrm{A}_c U_c^T$ where $\mathrm{U}_c$is the eigenvectors matrix andA_c is the diagonal of the eigenvalues matrix. In this way, the whitening transform was calculated through the equation 4 for equalize the variances in the space covered by U_c[17].

$$P = \sqrt{\mathrm{A}_c{}^{-1} U_c^T} \tag{4}$$

Once equalized the variances is possible define that the eigenvalues of$\mathrm{U}_c\mathrm{A}_c U_c^T$ are equal both the imaginary movement to left$(S_a = P\delta_a P^T)$ as the imaginary movement to right $(S_b = P\delta_b P^T)$. That means that both imaginary movements have the same eigenvector matrix (Y) [18].

Once established the previous parameters is possible filter spatially using equation 2 and redefine it as$X^T = Y^T P$, in this way extract the main features of the signal using equation 4.

$$CSP = X^T\alpha \tag{5}$$

The CSP is an analysis to discriminate the two imaginary movements through the number of used channels; the CSP obtains the same number of features. This mean that the CSP gives a square matrix where the first half are the features related with the imaginary movement to left and the second half are the features related with the imaginary movement to right.

With the extracted features for both imaginary movements, they was used for training the SVM labeling the imaginary movement to left with 1 and the imaginary movement to right with -1.

The SVM seeks create a surface or hyperplane that separate the 2 labeled classes (1,-1), but due to the signals are not lineal is necessary use the Kernel function to classify the two imaginary movements, in this case the SVM is represented by equation 5.

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$$f(x) = sign(\vec{w} \cdot \Phi(\vec{x}) + b) \quad (6)$$

Where$\Phi(\vec{x})$ is the dimensional space of the data, where is added the Gaussian function of Kernel represented by$K(\vec{x}_i, \vec{x}_j) = \exp(-\gamma||\vec{x}_i - \vec{x}_j||^2$, which seeks separate spatially the two classes. This mean that one class is spatially projected to up and the other class is spatially projected to down, allowing an appropriate separation between the two classes, as is shown in figure 4.

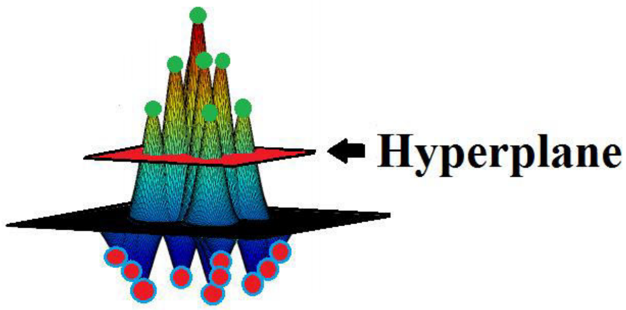

Figure-4. Hiperplane of the Gaussian function of Kernel.

Taking into account that the perpendicular vector of the hyperplane has a dual formulation, it is equal to $\vec{w} = \sum_{i=1}^{N} \alpha_i \gamma_i \Phi(\vec{x})$which represents the SVM as is shown in equation 6.

$$f(x) = sign(\sum_{i=0}^{N} \alpha_i \gamma_i K(\vec{x}_i, \vec{x} + b) \quad (7)$$

With the SVM established, the 200 samples were taken to train 11 support vector machines, one for each relevant channel selected. From all the samples, the 80% was used for training the SVMs and the 20% remained was used for validating the training of each SVM.

3. RESULTS

The Emotiv® sensor has 14 sensor (AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1 and O2) distributed according with the international standard 10:20. Using the MATLAB's toolbox the signals capture by the Emotiv® were processed to identify the ER, as is shown in Figure-5.

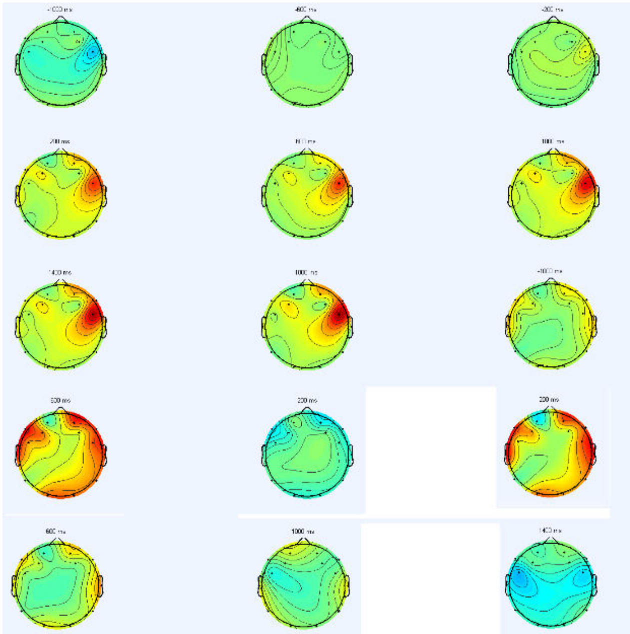

Figure-5. ERP for the imaginary movement to left and to right.

From this spatial selection, the channels AF3, F4 and P7 were discarded due to that their information were not relevant during neither of the imaginary movements.
After selected the 11 channels, each one was filtered with a bandpass filter FIR and IIR. Taking into account that the Emotiv's sample frequency is 128 Hz, the samples presented frequencies between 0 Hz and 64Hz.

In order to filter between 8Hz and 30Hz, two types of bandpass filter were used. In figure 6 is shown that the filter IIR allowed the pass of near frequencies of the desired cutting frequencies. On the other hand, the filter FIR presented a faster response that did not allow the pass of additional frequencies.

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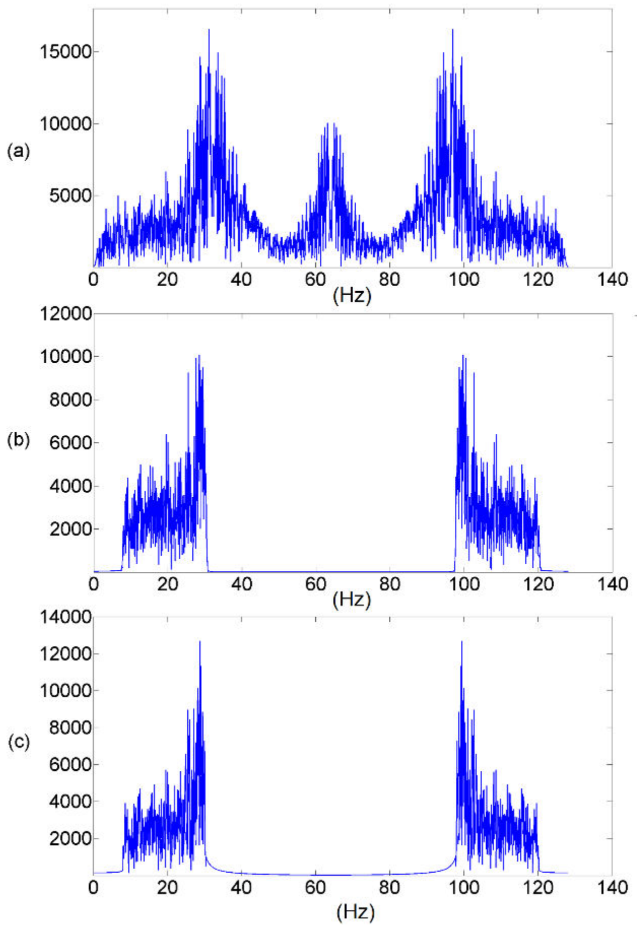

Figure-6. Response of the fast fourier transform of a sample (a), Response of FIR filter (b) and response of IIR filter (c).

With the filtered samples was possible extract the main features trough CSP, obtained as a result 7 features that describe the imaginary movement to left and 7 features that describe the imaginary movement to right.

These features are shown in Figure-7, where 7 of 10 samples of the imaginary movement to right had a downward trend in the fourth feature. On the other hand, 8 of 10 samples of the imaginary movement to left presented a fluctuate behavior in the fourth and fifth feature.

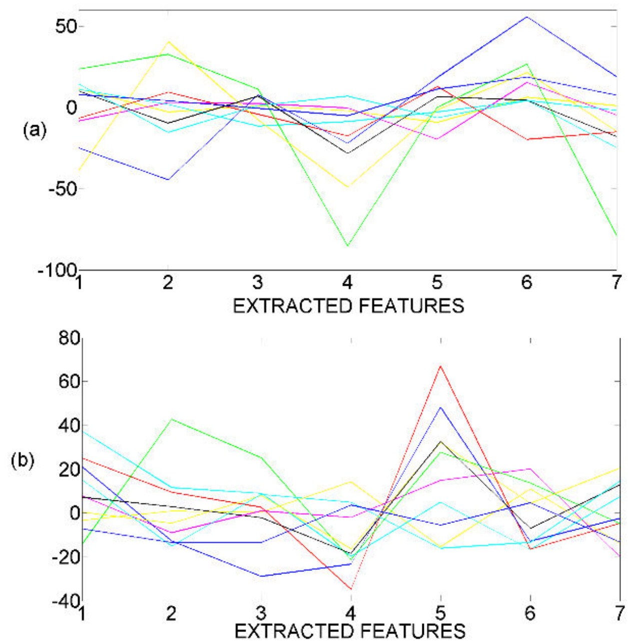

Figure-7. Extracted features from O_2 channel for the imaginary movement to right (a) and for the imaginary movement to left (b).

With the extracted features of the brain signals, the 80% of these features were used to train 11 support vector machines, one for each selected channel. Taking into account that the imaginary movement to left was labeled with (1) and the imaginary movement to right was labeled with (-1), then the 20% of the remained features were used to validate the SVMs, this process was made both for features filtered by FIR and IIR filter.

Table-1. Data filtered with IIR filter.

Number of SVM	Test Left 1	Test Right 1	Test Left 2	Test Right 2
1	1	-1	1	-1
2	-1	-1	1	-1
3	-1	-1	1	-1
4	-1	-1	1	-1
5	-1	-1	1	-1
6	1	-1	1	-1
7	-1	-1	1	1
8	1	-1	1	-1
9	1	-1	1	1
10	1	-1	1	1
11	1	-1	1	1
Mode	1	-1	1	-1

Four random samples was taken, where 4/4 of the samples filtered with IIR filter were recognized by the SVM both for the imaginary movement to right and the

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imaginary movement to left. The recognition was given by the mode of the result of all 11 SVM, where for the first example the 11 SVMs recognized correctly while in the other example just 7 SVMs were correct.

Table-2. Data filtered with FIR filter.

Number of SVM	Test Left 1	Test Right 1	Test Left 2	Test Right 2
1	-1	-1	-1	-1
2	-1	-1	-1	-1
3	-1	-1	1	1
4	-1	-1	-1	-1
5	-1	-1	-1	-1
6	-1	-1	1	-1
7	1	1	1	1
8	-1	-1	-1	-1
9	1	1	1	1
10	1	1	1	1
11	1	-1	1	-1
Mode	-1	-1	1	-1

On the other hand, the SVMs recognized 4/4 samples filtered with FIR filter for the imaginary movement to right and recognized 2/4 samples of the imaginary movement to left. In each random example the recognition was given by about 7 SVM but neither samples presented a correct recognition on the part of the 11 SVMs.

4. CONCLUSIONS

Make the filtering of brain signals with an IIR filter allowed the pass of additional frequencies to the desired ones, making more flexible the identification of an imaginary movement of the user with physical disability. Prove of the previous is that the 90% of the filtered samples with IIR filter were recognized both for imaginary movement to right and left.

On the other hand, the use of FIR filter for filtering brain signals related with an imaginary movement of a person with physical disability blocks additional frequencies, this mean if the user is not concentrated imagining the movement the SVM cannot recognize the brain signal. Prove of this trend is the recognition of just 50% and 80% for the samples of an imaginary movement to left and right respectively.

The using of multiple support vector machines with different bandpass filter of 4Hz range, allowed a statistic appreciation in the recognizing of a brain signal even if the user with physical disability is not concentrated in imagine a movement or if the brain signal has noise in . This prove that for recognize an imaginary movement through the general combination of CSP and SVM algorithm can have good results and even it can improve the results applying a different or stronger data processing methodology .

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