

# Screen text character selection for people with oral communication problems using EEG signal processing

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**Abstract:** This paper presents research work related to EEG signal processing in the field of linear feature extraction for people with severe oral communication problems. A battery of characters is shown on a PC screen, one of which is highlighted at 5.7 Hz. When the user is focusing on the target character, his brain generates the P3b component of the P300 Event Related Potentials (ERP). Fisher's Linear Discriminant Analysis (FLDA) is used as the classification algorithm after a pre-processing stage consisting of filtering, down sampling and channel selection. The database is the "Data Set II" of the BCI Competition III. Using 4 iterations, 80.65% of accuracy is obtained. 90.3225807% of accuracy is achieved using 14 iterations. These results are very useful because we just use a 4 channel system instead of the traditional 8 to 32 channels system where the best results only reach 85%. Future work will combine the presented work with the neural networks classification technique.

**Keywords:** EEG signal processing, P300, Fisher's Linear Discriminant Analysis, Brain Computer Interface

## I. INTRODUCTION

The main aim of this project is to improve the quality of life for people with severe physical disabilities, such as congenital double athetosis, by providing a tool for an augmentative communication system.

In this way, a non-speaking person will be provided with an effective communication system, so that he/she can become an active communicator. For this purpose, the technology called BCI (Brain Computer Interface) is used.

BCI technology is a communication system that translates brain activity into commands for computers and other devices [1]. Taking into account that BCI technology is a very wide discipline, this project is focused on the so-called P300 components of Event Related Potentials.

The P300 waves are used for recognizing the visual cognitive function in a stimulus presentation task called "oddball paradigm". The Event Related brain Potentials (ERPs) are a non-invasive method used to measure brain activity during cognitive processing [1-2]. ERP components are transient electric potential fields and appear in a certain period of time once there has been a stimulus, for instance, an image. Each component reflects the activation of the brain associated with one or more mental operations [2-3].

The project consists of developing an application that will be useful for the detection of characters by illuminating them and studying the brain response to these stimuli.

This work is intended for use by people with a disability that prevents or limits brain communication skills considerably. This could be either owing to the difficulty or impossibility to speak, or by the lack of hand movement control.

In order to solve this initial problem, firstly different alternatives were looked at. Once they had all been considered, it was decided to make the prototype based on BCI technology.

Below are listed the benefits of the technology that has been used compared with the other alternatives:

- Videoculography based systems.  
The first reason for discarding this type of technology is the price at which products of this kind are sold, because it is a fairly high price for this type of communication system.
- Synthesized and Digitalized Voice based communicators.  
Such devices were ruled out because the market aimed at is one of people with very limited mobility. This collective have difficulty in using these devices due to the lack of control of their upper extremities.
- Physical communicators based on boards.  
This method was discarded because it is a rudimentary method. This was the method traditionally used before the support of new technologies.

## II. OBJECTIVE/HYPOTHESIS

The main objective of this project is to provide people who are not able to communicate with certain autonomy so as to

establish a conversation.

To perform this task, the chosen technology not only has to be comfortable for the user, but also effective. It has to follow the following points:

- Detect the P300 wave  
The system must be able to detect the brain response to a photo-stimulus.
- Differentiate the characters.  
The main objective of this project is the interpretation of the message that the user wants to transmit, showing the desired word on the screen.
- Time consumption.  
This has to be done as quickly as possible so that the conversation is as fluid as possible. Therefore, the T9 technology (described in the next section) has been introduced.
- Simplicity.  
The user interface should be easily understandable and manageable by the user.
- Non-invasive system  
The system has to be a non-invasive one, preventing the user from having to undergo medical procedures to place the electrodes.
- Robustness.  
The success rate of the applied algorithms must be greater than 80%.

### III. METHODS

This section is going to present the different methods used for this application.

#### A. Event Related Potentials

An Event Related Potential (ERP) is an electrical potential registered in the nervous system when a visual or auditive stimulus is presented [1-6].

#### P300 wave

The P300 wave is an ERP registered as a positive voltage deflection that occurs 300 milliseconds after the presentation of the stimulus. The P300 response is the result of the overlapping of slow rhythms that can be decomposed in different frequency bands. The predominant component of the P300 wave is the delta frequency band. The other component is the theta component.

The P300 wave has two secondary signals: the P3a and the P3b (see Figure 1). The P3a wave is generated after every stimulus presentation and the P3b is generated when a different stimulus is displayed from a known stimulus. In this case, the P3a wave will be generated with every row and column display and the P3b will be generated when a row or column that the subject is looking at is displayed.

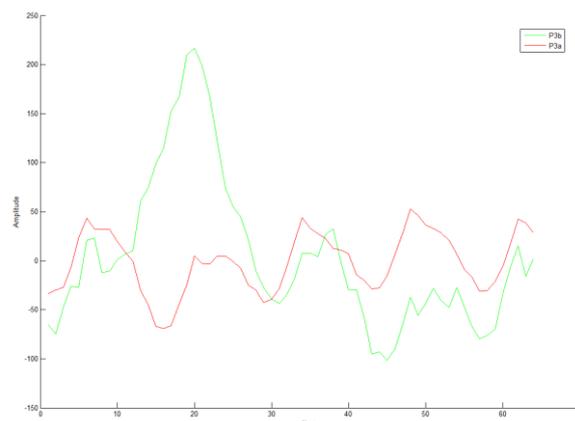


Fig. 1. P3a y P3b waves

**B. Paradigm**

The selected paradigm is a modification of a widely used Standard Paradigm.

The Standard Paradigm

In the Standard Paradigm, first described in [4], a user focuses on one out of 36 different characters. The objective is to predict the correct character in each of the provided character selection epochs.



Fig. 2. Character Matrix Display

The user is presented with a 6 by 6 matrix of characters (see Figure 2). The user’s task is to concentrate on the characters in a word that was prescribed by the researcher (i.e., one character at a time). All rows and columns of this matrix were successively and randomly intensified at a rate of 5.7Hz. Two out of 12 intensifications of rows or columns contained the desired character (i.e., one particular row and one particular column). The responses evoked by these infrequent stimuli (i.e., the 2 out of 12 stimuli that did contain the desired character) are different from those evoked by the stimuli that did not contain the desired character and they are similar to the P300 responses previously reported.

Proposed Modification

The test lasts the time shown in Figure 3 (in red) for each character (with intensifications of 100 milliseconds every 175 milliseconds).

With the Standard Test, which has been carried out in several studies [8-12], when 15 intensifications are performed, the elapsed time is approximately 31.5 seconds, because the time between consecutive intensifications is 2.1 seconds. However, with the proposed modification, instead of 12 rows and columns, there are 6 rows and columns, so the elapsed time is half that of the Standard Test. This means that between two consecutive intensifications the time consumption is 1.05 seconds, and the overall time is 15.75 seconds.

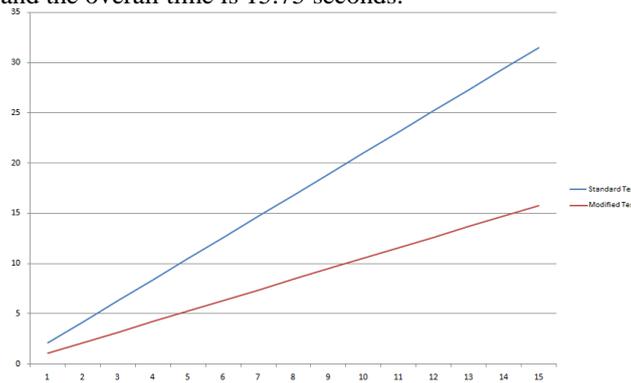


Fig. 3. Standard and Modified Paradigm time length

The proposed modification is based on the predictive text [13]. The predictive text is an input technology used where one key or button represents many letters, such as on mobile phones and in accessibility technologies [14]. Each key pressed results in a prediction rather than repeatedly sequencing through the same group of letters it represents, in the same, invariable order. Predictive text makes efficient use of fewer device keys. In this case, the proposed predictive key will consist of a 6-row and 6-column character matrix, like on a mobile phone, and, with pre-stored words and an efficient algorithm, the prediction time will decrease.

Data Base

The chosen data base is the BCI Competition III, available at [15]. Inside this competition, there were several different

tasks and one of them was the “P300 speller paradigm”. The corresponding data is the “Data Set II”. This data set was provided to the competition by the Health Department of the Wadworth Center, University of Albany, USA [16].

C. Signal Processing Techniques

The main signal processing technique is Fisher’s Linear Discriminant Analysis, but other techniques have been also used. All these techniques are described below.

Fisher’s Linear Discriminant Analysis (FLDA)

To establish the Fisher’s Linear Discriminant Analysis as the classifier for this research work, several features of different classifiers were discussed [17-19]. These features are shown in Table 1. These features are briefly described below:

Generative vs. Discriminant

The Generative Classifiers “learn” the two classes. So, in order to classify a feature vector, these classifiers compute the resemblance to the classes and the most similar ones are chosen.

The Discriminant Classifiers only “learn” how to classify the classes in order to classify the feature vector directly.

Static vs. Dynamic

The Static Classifiers cannot take temporary information into account during the Classification Stage since they only classify a single feature vector.

The Dynamic Classifiers can classify a sequence of feature vectors and catch the temporary dynamic.

Stable vs. Unstable

In Stable Classifiers, small variations in the Training Stage do not affect the Testing Stage. But in Unstable classifiers, little variations cause large undesirable variations.

Regularized

Regularization consists of controlling the complexity of the classifier in order to avoid overtraining. A Regularized Classifier has better overall results and is more robust.

Of all these features, some are more consistent than others. The stability is the main feature taken into account to choose the FLDA as our classifier. This feature means that tiny variations in the Training Stage do not affect the overall performance of the classifier. One of the reasons for making the classifier have this feature is that as the electrodes are going to be placed several times, it might happen that the placement varies slightly.

Taking this feature into account, the only two classifiers that remain are the FLDA and the Support Vector Machine (SVM). Viewing the whole table, it might seem that the SVM is more robust and it is also a regularized method. But in the SVM method, a few parameters of its hyperplane have to be defined manually. This is not a problem if the classifier is going to classify data from the same person (with the same P300a and P300b values).

TABLE I  
CLASSIFIERS’ FEATURES

	Linear	No Linear	Generative	Discriminant	Dynamic	Static	Regularized	Stable	Unstable	Robust
Fisher’s Linear Discriminant Analysis	✓			✓		✓		✓		
Support Vector Machine	✓			✓		✓	✓	✓		✓
Multilayer Perceptron		✓		✓		✓			✓	
Finite Impulse Response Neural Network		✓		✓	✓				✓	
Temporal Delay Neural Network		✓		✓	✓				✓	
Adaptive Logic Network		✓		✓		✓			✓	
Bayes Quadratic Classifier		✓	✓			✓			✓	
Input Output Hidden Markov Models		✓		✓	✓				✓	
k “Nearest Neighbour”		✓		✓		✓			✓	
Mahalanobis Distance		✓		✓		✓			✓	

But the P300a and the P300b values vary depending on the person that is trained. This is way the definitions of the parameters of the hyperplane vary with each person. So, eventually, Fisher’s Linear Discriminant Analysis (FLDA) was chosen.

FLDA is a Static Classifier so it might seem that no temporary features could be evaluated, but the data compression carried out to classify the two classes allows the special feature extraction (see “Data Extraction” section).

FLDA is a modification of LDA (Linear Discriminant Analysis). The main differences are that LDA assumes that the distributions are Normal Distributions and that they have the same covariance [20-23].

Having two different classes (P300a and P300b), the FLDA displays the data in a projection (1) and then a threshold is set two classify the data into two classes (2), (3).

$$y = w^T x \tag{1}$$

$$y \geq -w_0 \text{ as the } C_1 \text{ class} \tag{2}$$

$$y < -w_0 \text{ as the } C_2 \text{ class} \tag{3}$$

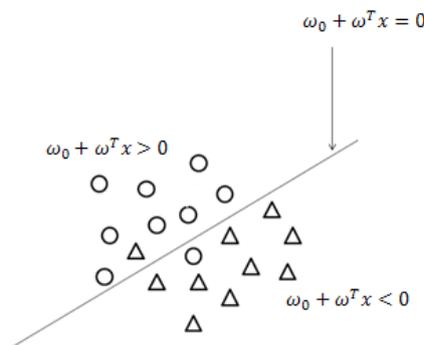


Fig. 4. Fisher’s Linear Discriminat Analysis

Having two classes with  $N_1$  points of the  $C_1$  class and  $N_2$  points of the  $C_2$  class, the mean value of the vectors is defined as:

$$m_1 = \frac{1}{N_1} \sum_{n \in C_1} x_n \tag{4}$$

$$m_2 = \frac{1}{N_2} \sum_{n \in C_2} x_n \tag{5}$$

Using the expression (1), the points of the two classes are projected in a 1-D space called  $y$ . The variance of the two projected classes is defined as:

$$s^2_1 = \sum_{n \in C_1} (y_n - m_1) \tag{6}$$

$$s^2_2 = \sum_{n \in C_2} (y_n - m_2) \tag{7}$$

with:

$$m_1 = w^T m_1 \tag{8}$$

$$m_2 = w^T m_2 \tag{9}$$

and:

$$y_n = w^T x_n \tag{10}$$

The criterion of FLDA to classify the two classes is minimizing the following function:

$$J(w) = \frac{w^T S_B w}{w^T S_W w} \tag{11}$$

where:

$$S_B = (m_2 - m_1)(m_2 - m_1)^T \tag{12}$$

and:

$$S_W = \sum_{n \in C_1} (x_n - m_1)(x_n - m_1)^T + \sum_{n \in C_2} (x_n - m_2)(x_n - m_2)^T \tag{13}$$

So, the classification criterion is:

$$w \propto S_w^{-1}(m_2 - m_1) \tag{14}$$

The basis of the algorithm consists of building a feature vector to project the data over and extracting the features so as to be able to correctly classify the two classes. Once the hyperplane is built, the following steps have to be modified. It is supposed that a P300 evoked potential is caused by two intensifications (one row and one column) and it is also known that the P300 response is invariant to the row/column stimulus. To perform the final classification, the maximum value of the rows and the columns have to be taken and combined:

$$predicted\_row = \max_{rows} \left[ \sum_{i_{row}} \omega \cdot f(x_{i_{row}}) \right] \tag{15}$$

$$predicted\_column = \max_{columns} \left[ \sum_{i_{columns}} \omega \cdot f(x_{i_{columns}}) \right] \tag{16}$$

Filtering & Data Extraction

The Filtering Stage is a very important stage since the acquired signals can have undesirable artifacts that may disturb our classification. The Filtering Stage has been performed with a 6 order Butterworth filter. After each stimulus, even though it is a non-objective one, there are sequences of 800 milliseconds. It has to be said that these sequences are overlapped by previous sequences. This is because the sequences are extracted every 800 milliseconds and the intensifications are presented every 175 milliseconds. 800 milliseconds were chosen because the P300 event-related potentials appear 300 milliseconds after the stimulus and have a frequency of 5.7 Hz [24-25]. So, by choosing 800 milliseconds, the whole wave is captured.

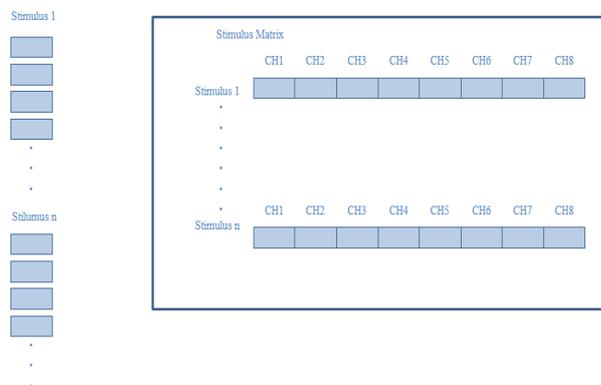


Fig.5. Stimulus Matrix

In order to make Fisher’s Linear Discriminant Analysis a Dynamic Classifier, the feature vector is technically no longer a feature vector, but a feature matrix. This matrix is a concatenation of the sequences previously extracted in the Training or Testing Stage. In the Training Stage two matrixes are built. But in the Testing Stage, the dimension of the matrix is the same as the number of different stimuli. The objective and non-objective matrixes are built firstly by putting all the channels in a one-dimensional vector and by making a matrix using the vectors of the whole stimulus. Figure 5 is an example of how the objective-stimulus array is built.

Downsampling

The sample frequency of the electroencephalogram (EEG) machine is of 240 Hz [16]. Having this frequency, the data Processing Stage lasts approximately 4.5 seconds and the CPU consumption is unreasonable. That is why a Downsampling Stage is required, to make the computer waste less time and resources by reducing the data resolution. The different results of choosing several downsampling values can be seen in the “Results” section.

Channels Choice

The authors have chosen 4 electrodes with the following placement along the scalp (according to the 10-20 international electrode location [26]): PZ, PO7, PO8, OZ. This choice is analyzed in the “Results” section.

*D. System Design*

To have a general overview of the system, the general diagram is shown in Figure 6.

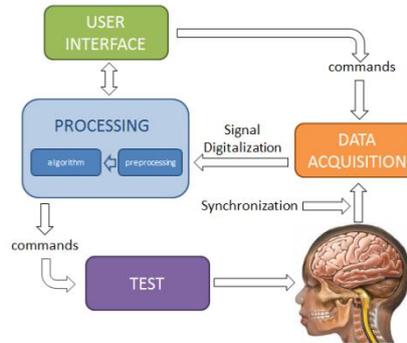


Fig. 6. High-Level Diagram

As can be observed, there are different types of modules or phases inside the diagram. The data acquisition is performed by the C written code compiled with Matlab MEX utility and all other duties are performed using Matlab.

Data acquisition

There has to be a device able to obtain the brain activity of the subject who is performing the task (paradigm) in order to apply the algorithm. This task is carried out by the Brainclinics PET 4.0 commercial EEG [27]. The acquired data (programmed in C language) have to go through the module responsible for the data-processing (programmed with Matlab). There has to be synchronization between these two tasks because the programming language used is different for each stage.

Data Processing

The data Processing Stage is responsible for firstly training the classifier, and secondly, reporting the results of Fisher’s Linear Discriminant Analysis.

User Interface

The User Interface shows the data acquisition to the researcher and the task (paradigm) to the user. It is also in charge of starting of the Processing Stage.

User Task/Test/Paradigm

The test was programmed using the C language and the OpenCV library. Therefore, there has to be a way to synchronize the command from the Data Acquisition Stage to get the test started. The Test also has to synchronize the stimulus presentation with the data acquisition, so that the acquired data has a specific synchronization field in which the stimulus presentation synchronization is reported. In the Training Stage another field appears in which the objective and non-objective stimuli are targeted.

Synchronization

The synchronization between all the modules is done using mailslots. Mailslots are a procedure for unidirectional communication that allows the sending, receiving and saving messages [36]. The process that creates the mailslot is the server process, and it defines the maximum length of the message. Another process can be a client process to send messages to the server process. A client process can write messages in a process that is its own computer, as has been done for this project, but can also send messages to processes located in a remote computer.

IV. RESULTS

To ensure that the algorithm works correctly, several modifications were performed over the initially proposed algorithm to improve it. The first application of the algorithm was performed with the following values in the Preprocessing Stage:

- Sample frequency: 240 Hz
- Sample frequency after the downsampling: 20 Hz
- Channels: C<sub>Z</sub>, F<sub>Z</sub>, P<sub>3</sub>, P<sub>4</sub>, PO<sub>7</sub>, PO<sub>8</sub>, O<sub>Z</sub> of the international 10-20 electrode location system.

TABLE II.  
 FIRST RESULTS

Repetitions	Accuracy (%)
1	32,25806
2	51,6129
3	54,83871
4	70,96774
5	70,96774
6	74,19355
7	74,19355
8	77,41935
9	77,41935
10	74,19355
11	77,41935
12	77,41935
13	80,64516
14	83,87097
15	87,09677



Fig.7. First results

There are 15 intensifications of each row and column for each character. So the results vary depending on the number of intensifications: the more iterations shown, the better results you achieve. These results can be analyzed in Table 2 and in Figure 7.

It can be seen that the accuracy rate increases and, when the 15 iterations are shown, 87.09677% accuracy is achieved. Once the first approximation is done, several changes were performed to try and improve the efficacy of the algorithm. The first modification was the downsampling of raw data.

It has been proved that to classify the raw data without doing any downsampling, the elapsed time is of 4.5 seconds. So, to reduce this time, several downsampling modifications were done:

- Frequency after downsampling: 40 Hz. Estimated elapsed classification time: 2.1 seconds.
- Frequency after downsampling: 80 Hz. Estimated elapsed classification time: 2.8 seconds.
- Frequency after downsampling: 120 Hz. Estimated elapsed classification time: 3.6 seconds.

TABLE III.  
 FIRST MODIFICATION

#	Frequency			
	20 Hz	40 Hz	80 Hz	120 Hz
1	32,26	38,71	41,94	38,71
2	51,61	45,16	48,39	67,742
3	54,84	67,74	70,97	70,968
4	70,97	83,87	77,42	74,194
5	70,97	74,19	87,1	77,419
6	74,19	80,65	87,1	83,871
7	74,19	80,65	87,1	87,097
8	77,42	80,65	90,32	90,323
9	77,42	80,65	90,32	87,097
10	74,19	83,87	90,32	90,323
11	77,42	83,87	90,32	90,323
12	77,42	87,1	90,32	90,323
13	80,65	87,1	90,32	90,323
14	83,87	87,1	90,32	90,323
15	87,1	87,1	90,32	90,323

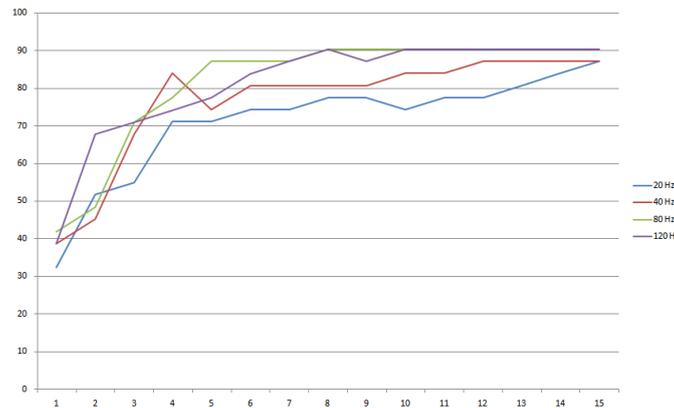


Fig. 8. First modification

The accuracy of the algorithm after downsampling is given in Table 3 and Figure 8.

After analyzing these results, both 120 Hz and 80 Hz have the same accuracy at the final intensification. On one hand, if 120 Hz is chosen, the final accuracy is reached after 8 intensifications. On the other hand, if 80 Hz is chosen, the final accuracy is reached after 10 intensifications.

Even though the results of the 80 Hz frequency are slightly worse, if 120 Hz is chosen, the amount of data rises by 30%. Taking into account all this information, the data have been downsampled to 80 Hz.

TABLE IV.  
 SECOND MODIFICATION

#	Filtering			
	Repetitions	[0.5 50]	[1.0 35]	[1.5 20]
1		41,94	38,71	35,48
2		48,39	45,16	45,16
3		70,97	74,19	64,52
4		77,42	80,65	80,65
5		87,1	83,87	87,1
6		87,1	80,65	87,1
7		87,1	87,1	83,87
8		90,32	90,32	87,1
9		90,32	90,32	87,1
10		90,32	90,32	90,32
11		90,32	90,32	90,32
12		90,32	90,32	90,32
13		90,32	90,32	90,32
14		90,32	90,32	90,32
15		90,32	90,32	90,32

The second modification performed was the filtering cutoff frequencies of the band-pass Butterworth filter. This modification has been applied to the downsampled data (sample frequency=80Hz). The different frequencies are the following:

- Butterworth 6 order band-pass filter 0.5 Hz – 50 Hz.
- Butterworth 6 order band-pass filter 1.0 Hz – 35 Hz.
- Butterworth 6 order band-pass filter 1.5 Hz – 20 Hz.

The results are shown in able 4 and Figure 9.

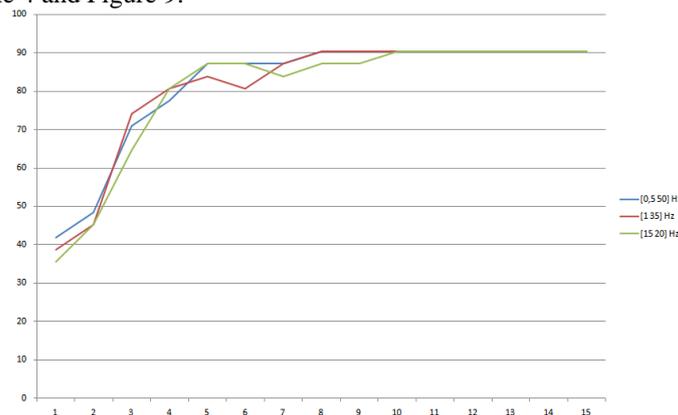


Fig. 9. Second modification

As can be seen, the results are quite similar. However, the results using 0.5 and 50 Hz as cutoff frequencies seem to be better, so these filterings were chosen.

To sum up, the Preprocessing Stage maintains these parameters:

- Sampling frequency: 240 Hz
- Sampling frequency after the downsampling: 80 Hz
- Butterworth 6 order band-pass filter: 0.5 Hz – 50 Hz
- Channels: C<sub>Z</sub>, F<sub>Z</sub>, P<sub>3</sub>, P<sub>4</sub>, PO<sub>7</sub>, PO<sub>8</sub>, O<sub>Z</sub>.

Having optimized the preprocessing step, the obtained results (see Table 5) can be compared with the results obtained in the competition from which the raw data was taken [20].

TABLE V.  
 COMPETITION RESULTS

Participants	Accuracy after 15 repetitions	Accuracy after 5 repetitions	Mean accuracy
Alain Rakotomamonjy	96.5%	73.5%	<b>85%</b>
Zhou Zongtan	90.0%	59.5%	<b>74.75%</b>
Li Yandong	90.5%	55.0%	<b>72.75%</b>
Li Zhonglin	87.5%	57.5%	<b>72.5%</b>
Ulrich Hoffmann	89.5%	53.0%	<b>71.25</b>
Renzhi Lu	83.0%	54.5%	<b>68.75%</b>
Gerardo Gentiletti	78.5%	46.0%	<b>62.25%</b>
Gautam Kunapuli	75.0%	34.0%	<b>54.5%</b>
Qi Hongzhi	33.5%	27.5%	<b>30.5%</b>
Kiyong Yang	7.5%	7.0%	<b>7.25%</b>

As can be seen, the measured parameters are the accuracy after 15 repetitions and after 5 repetitions. The winner has achieved 85% in total accuracy. In this research, the resulting accuracy after 5 repetitions is 87.1% and after 15 90.3% (Figure 19), so the mean accuracy is 88.7% (Figure 19), which is higher than the winner of the competition. The last modification consists of choosing 4 channels from the first selected 8 channels. To perform this task, several electrode locations of the scalp were selected (see Figure 10).

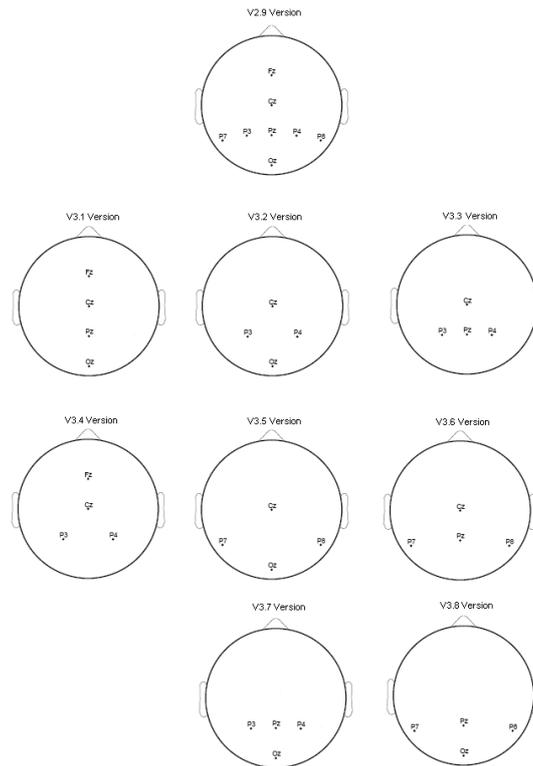


Fig.10. Electrode placement

The results of each location are shown in Table 6, Table 7 and Figure 11.

TABLE VI.  
 THIRD MODIFICATION I

ElectrodeLocation I				
Repetitions	v3.1	v3.2	v3.3	v3.4
1	12,9	12,9	22,58	16,13
2	29,03	32,26	22,58	29,03
3	32,26	45,16	32,26	45,16
4	41,94	58,06	48,39	51,61
5	45,16	48,39	54,84	48,39
6	45,16	48,39	48,39	51,61
7	48,39	58,06	58,06	54,84
8	38,71	61,29	61,29	58,06
9	41,94	64,52	61,29	58,06
10	45,16	61,29	54,84	61,29
11	45,16	61,29	67,74	64,52
12	48,39	61,29	67,74	67,74
13	45,16	64,52	67,74	67,74
14	41,94	70,97	58,06	67,74
15	51,61	67,74	70,97	64,52

TABLE VII.  
 THIRD MODIFICATION II

ElectrodeLocation II				
Repetitions	v3.5	v3.6	v3.7	v3.8
1	32,26	32,26	16,13	35,48
2	51,61	51,61	32,26	54,84
3	58,06	54,84	22,58	54,84
4	64,52	77,42	41,94	80,65
5	74,19	77,42	35,48	80,65
6	74,19	77,42	38,71	77,42
7	77,42	80,65	45,16	83,87
8	80,65	80,65	48,39	87,1
9	80,65	83,87	54,84	87,1
10	77,42	80,65	54,84	87,1
11	77,42	80,65	54,84	87,1
12	77,42	80,65	51,61	87,1
13	80,65	83,87	51,61	87,1
14	83,87	83,87	51,61	90,32
15	83,87	83,87	61,29	90,32

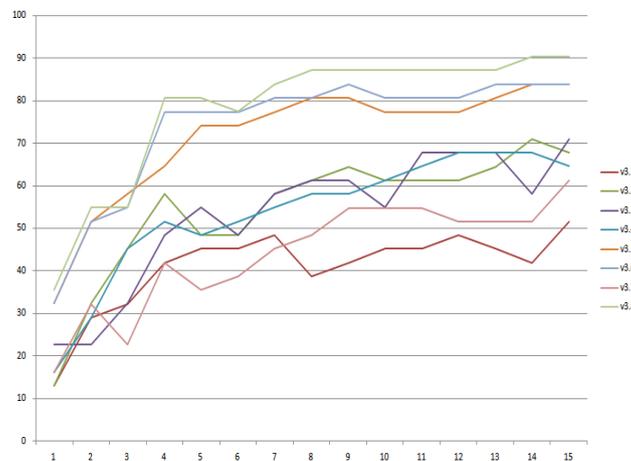


Fig. 11. Third modification

It can be observed that best electrode placements are those of the v3.8 version. The placements are: P<sub>Z</sub>, PO<sub>7</sub>, PO<sub>8</sub> and O<sub>Z</sub>. Therefore, the electrodes are placed in the parietal lobe (one of whose main function is visual attention) and in the occipital lobe (which is closely connected to visual tasks). Therefore, with this electrode location, the accuracy achieved is 90.3225807%, the same accuracy as that achieved with the 8 electrode placement. But as can be appreciated in Figure 12, the final percentage is achieved with 14 iterations, instead of with 8 iterations, as in the 8 electrode placements version.

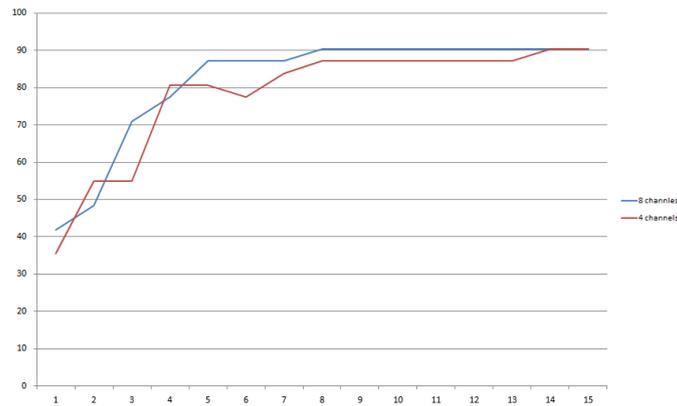


Fig.12. Second modification vs Third modification



Fig. 13. User testing the final electrode location

### V. CONCLUSIONS

The aim of the study was to provide a reliable way of communication for people with disabilities. A success rate of 90% was achieved in accuracy (see “Results” section for a more exhaustive overview). Furthermore, the time needed to present the whole stimulus paradigm to the subject has been reduced by a half, without losing any precision.

However, there is some information that needs to be analyzed to try and achieve better results. According to the modifications of the initial results, there is something more to say about them than just choosing the best results and going straight to the Processing Stage.

Three modifications have been made to the initial parameters in the Preprocessing Stage: the downsampling (to add less data to the process), the filtering (to minimize the effects of the artifacts) and the electrode location (to choose 4 channels from the initial 8 electrodes).

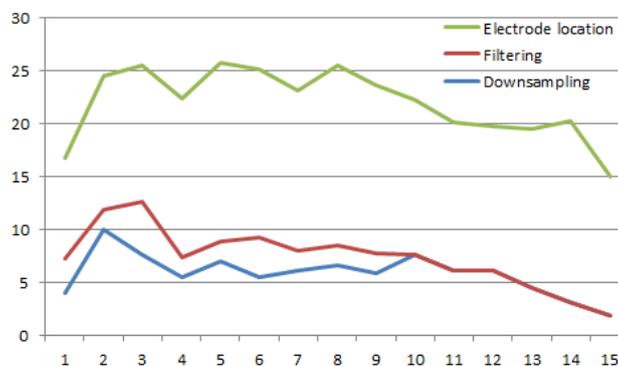


Fig. 14. Standard Deviation of the modifications

In Figure 14, the Standard Deviation of the three modifications is shown.

The blue curve is the deviation of the Downsampling Stage. It can be seen that the standard deviation of this Stage is very small. In fact, that was the objective of this modification: to have the same results with the downsampled data as with the initial amount of data.

The red curve refers to the Filtering Stage. Even if the Standard Deviation is bigger than the downsampling modification with few iterations, it goes down with more iterations. The interpretation of this is that the modification of the cutoff frequencies of the ban-pass filter is not very significant for achieving better results.

The green curve shows that the Standard Deviation of the electrode location modification is quite big. This means that the proposed method is very sensitive to the electrode placement in the scalp. The placements have been chosen taking into account the electrode placements of the 10-20 system [19].

The Standard Deviation values of the modification of the electrode locations mean that the placements should not be those. It would be better to establish our own electrode location without following the standard to avoid variability in the results of the chosen eight placements.

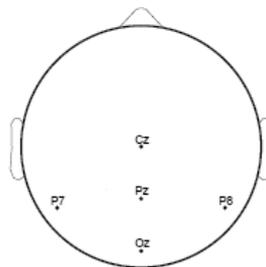


Fig. 15. Best electrode placements

The best results were achieved with the electrode location shown in Figure 15, so the proposed placements should be located somewhere between these locations.

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