Thought Recognition through EEG signals

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***Abstract*—In this work we propose a new method for classifying yes/no thoughts based only on the electroencephalography (EEG) signal. The results show very good generalization performances with few training points, thus making it suitable for a real-application scenario with patients unable to communicate due to ASL disease.**

I. Introduction

Amyotrophic Lateral Sclerosis (ASL) is a neurological degenerative disease that mainly involves the nerve cells. Both the upper motor neurons and the lower motor neurons degenerate or die, and stop sending messages to the muscles. In this condition, muscles gradually weaken, start to twitch, and waste away until the brain loses its ability to initiate and control voluntary movements. People affected by neurodegenerative disease such as ALS end up in a completed locked in state (CLIS) in which movements and communication become impossible. Nonetheless, cognitive abilities are intact and different studies prove that quality of life in these people can be good and is strongly positively correlated with the possibility of communicating.

Previous works, such as Chaudhary U et al (2017), showed the possibility of designing a Brain-Computer Interface that allow basic communication, distinguishing yes and no thoughts of the patient. This kind of systems can use both non-invasive or invasive data acquisition instrumentation.

In our case, only non-invasive techniques were used: electroencephalography (EEG), electrooculography (EOG), electromyography (EMG) and functional near-infrared spectroscopy (fNIRS).
In a session, the patient answer 20 questions (10 yes + 10 no answer in a random sequence). The questions allow only a yes or no response and the answers are assumed to be known. The questions are sampled from a set built with the help of the patient family. Each session is approximately 10 minutes long and 28 signals are simultaneous acquire using different techniques, in particular:

- 15 fNIRS signals
- 5 EEG signals
- 4 EOG signals
- 4 EMG signals

In our work, we analyze the data acquired during three sessions, for a total of 30 yes signal and 30 no signals.

The state of the art results of such a system uses a support vector machine (SVM) on the fNIRS dataset while using EEG just for asserting a vigilant state. The average performances of SVM+fNIRS achieved a 70% of classification accuracy. The non-excellent efficiency of this system allows to ask the patient only general question, mainly about his daily routine preferences but is still inappropriate for sensitive issues, such as decisions on the end of life, a significant topic for people in this situation.

In our work, we decided to use only EEG signals. EMG and EOG signals were discarded for the short-term results they can ensure. Indeed, due to the quick degeneration of the disease, the patient is destined to lose the use of the jaw muscles and the eyes movement, activities which were recorded with these techniques. Consequently, classifiers built using these signals would lose accuracy with the evolution of the disease. No techniques have been implemented to integrate the information coming from the EEG and fNIRS signals, therefore the fNIRS signal was not used because alone it results less informative than the other.
Starting from the extraction and selection of features, we set a SVM classifier to discriminate between yes and no signals.

II. Methods

A. Dataset

The data were acquired during three consecutive sessions. The EEG electrodes were placed in the position C5, C6, FC5, FC6 and Cz of the international 10-20 system for electroencephalography electrode placement. The sampling frequency is 500Hz.
For further information about the data acquisition see Chaudhary U et al (2017)

B. Signal Filtering

First of all the drift of the signal was removed using the Matlab function `detrend` which removes a linear trend from a vector. The signal was processed using a passband Chebyshev Type II filter. In particular, after the visual inspection of the power spectrum and according to the physiological characteristics of EEG signals, the bandpass was set from 0.1 Hz to 30 Hz with 150 dB attenuation in the stop-bands. The filter was initially designed using the Matlab function `cheb2ord`, which set the filter order, and `cheby2`. Finally, with the function `zp2sos`, the zero-pole model of the filter was converted into a second-section form to improve the stability.

The filtering procedure was applied to the entire signals which were then segmented and labeled into yes/no instances using a trigger signal.

C. Feature Extraction Approach

The purpose of this phase is to calculate a number of features able to well characterize the signals under examination. For this goal, we used a MATLAB library developed for the analysis of EEG in neonatal intensive care, described in Toole J and Boylan G (2017). Despite the different application area, it resulted suitable for the extraction of useful features to describe our signals. The features extracted can be divided into four main categories: range, amplitude, spectral and connectivity.

- *Amplitude features:* characterization of the signals in the time domain. Amplitude is quantified by signal power and signal envelope. Also the gaussianity of the process is evaluated with skewness and kurtosis.
- *Range features:* range EEG (rEEG) is an alternative representation of EEG signals in the time domain. In particular, rEEG estimates a peak-to-peak measure of voltage. Range features, extracted from rEEG, summarizes their trends with different measures.
- *Spectral features:* quantification of the spectral characteristic of the signals starting from the Power Spectral Density (PSD).
- *Connectivity features:* measures of the connectivity and symmetry between the two hemispheres. This features are estimated using the symmetric channels C5, C6 and FC5, FC6.

All the features, apart from the spectral difference and the spectral edge frequency, are estimated within four different frequency bands of the EEG: [0.5-4; 4-7; 7-13; 13-30] Hz.
It is also fair to mention that in the three first categories (Range, Amplitude, Spectral) there are Single-Channel-Features which are calculated independently for each of the five acquisition channels. Conversely, the connectivity features are Multiple-Channel-Features since they are calculated considering the signals of the channels C5, C5, FC5 and FC6 jointly. This determined the structure of the features matrix.

D. Feature Selection

As described in the introduction our dataset is composed of 60 binary question with known answer (which we call instances). For each instance we have a total of 386 of different features all concatenated in a single row, thus our dataset is represented by a 60×386 matrix which we call *full features dataset*. Not all the features carry useful information for our classification goal thus it is important to develop a computationally feasible automatic algorithm able to understand what is the subset that yields the best performances. A brute force approach is indeed impractical because it would require to test $\sum_{k=1}^{386} \binom{386}{k} \approx 1.57 * 10^{116}$ different combinations.

In order to reduce this number, a score was given to each feature using ANOVA F-test. Using this, only the top *k* features with the highest score were selected. It was then defined a new *k-reduced dataset* of size $60 \times k$.

For assessing the best value of k it is necessary to better define what we mean for "best performances". Given our specific problem, it is important to maximize the generalization accuracy of our classifier with the least number of train instances. Thus we choose to keep the smallest k that, given a particular classifier, would yield the highest validation accuracy on the test set while training on few instances (train set 20% test set 80% of the whole dataset). In order to have a stable estimate of the result (given the few instances available), 2000 randomly sampled partition of the dataset were used keeping fixed the train/test fraction.

The algorithm for choosing the best k features can be summarized as follows:

1) Get the k-reduced dataset using ANOVA F-test score statistics
2) Randomly split the instances in train/test partition with train 20% and test 80% of the dimension of the whole dataset.
3) Fit the classifier on the train set and estimate the performances on the test set
4) Repeat the steps 2-3 for 2000 times and average the results. Call α_k the performances on the k-reduced dataset and save it in a vector called α

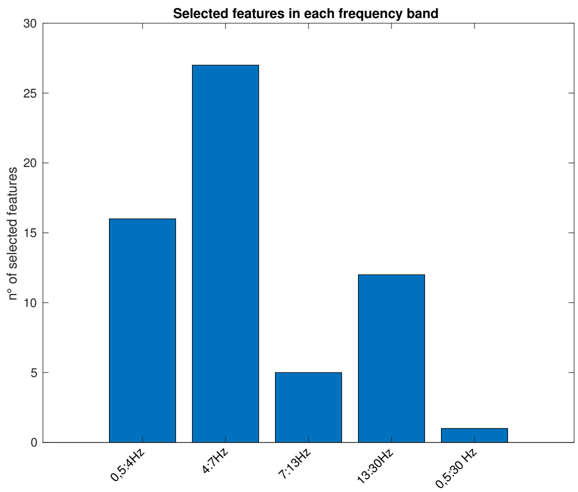

Fig. 1: Histogram of the selected features belonging to each sub-band

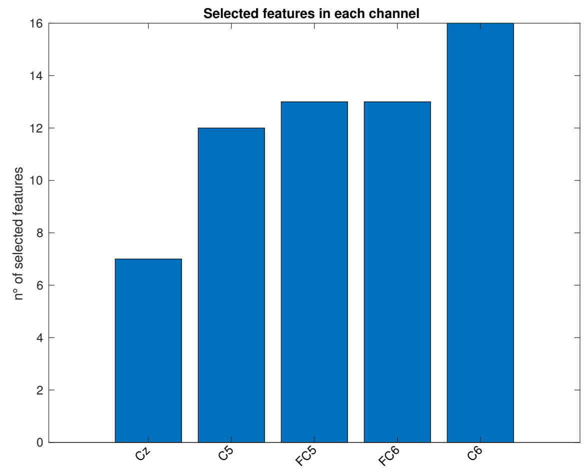

Fig. 2: Histogram of the selected features belonging to each channel

5) Iterate for k going from 1 to 386 and return $k_{best} = \min(\arg\max_k \alpha)$

E. Classifier

We used a Support Vector Machine (SVM) with linear kernel and penalty term C=1 as classifier. For numerical and technical reasons, before using the SVM, we standardized the data centering each feature to have null mean and unit variance. The parameters for the standardization were computed on the training set and propagated to the test set.

III. RESULTS

In this section the results are presented

A. Feature selected

The optimal number of feature for our dataset resulted in $k = 61$; in particular, the features selected are reported in the Table I in appendix A.

As we can deduce from histogram reported in Figure 1, most of the feature selected (43 of 61) are calculated in the two lower frequencies bands ([0.5-4; 4-7]Hz). Regarding the contribution of the different channels to representative features, as shown in Figure 2, channel C5, C6, FC5, and FC6 contribute quite equally while Cz seems to be the least informative channels with 7 of 61 features brought.

None of the connectivity features was selected for the classification.

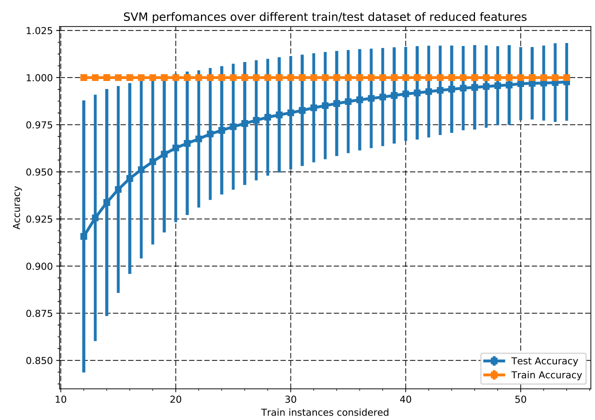

Fig. 3: Performances of the SVM with $k = 61$ with different train/test size. Each point represent the mean of the results on 10'000 random partition and the error bar represent its standard deviation

B. Classifier performances

In Figure 3 are presented the accuracy results for different train/test partition size. For each train/test fraction, the accuracy of 10'000 randomly sampled datasets were computed: each point is the mean and each error bar represent the standard deviation of the distribution.

Even though the SVM is always in overfitting, it does indeed present very good generalization performances on our dataset with few training samples. This is a very desirable property in a real-application scenario.

Moreover the SVM is extremely fast in both training and computing predictions and is memory efficient as it only require a subset of the training points in the decision function (also called support vectors), so the hardware requirement for the classification are minimal.

IV. Conclusions

Our proposed method perform better than state of the art, giving more than 90% of accuracy even with few training points.

V. Future works

It would be of interest to extend the study to other patients in similar conditions so to understand if the features selected in this study can generalize the answers of all the patients. Moreover, try to use the same procedure on a group of healthy subjects could help highlight possible differences in the relevant features for the classification.

Appendix A
Features selected

Appendix B
Features List

FB: features generated for each frequency band (FB)

Feature index	*Feature Name*	*Band Frequency*	*Channel*
10	Range Lower Margin	7:13Hz	FC5
13	Range Upper Margin	4:7Hz	FC5
17	Range Width	4:7Hz	FC5
21	Range SD	4:7Hz	FC5
38	Amplitude SD	7:13Hz	FC5
44	Kurtosis	0,5:4Hz	FC5
45	Kurtosis	4:7Hz	FC5
57	Power	4:7Hz	FC5
65	Flatness	4:7Hz	FC5
66	Flatness	7:13Hz	FC5
69	Entropy	4:7Hz	FC5
70	Entropy	7:13Hz	FC5
73	Edge Frequency	0,5:30 Hz	FC5
81	Range Median	13:30Hz	FC6
92	Range Width	7:13Hz	FC6
105	Range Assimetry	13:30Hz	FC6
109	Amplitude Power	13:30Hz	FC6
114	Skew	0,5:4Hz	FC6
117	Skew	13:30Hz	FC6
118	Kurtosis	0,5:4Hz	FC6
119	Kurtosis	4:7Hz	FC6
121	Kurtosis	13:30Hz	FC6
127	Envelope SD	4:7Hz	FC6
135	Relative power	4:7Hz	FC6
138	Flatness	0,5:4Hz	FC6
142	Entropy	0,5:4Hz	FC6
157	Range Lower Margin	4:7Hz	C5
160	Range Upper Margin	0,5:4Hz	C5
164	Range Width	0,5:4Hz	C5
168	Range SD	0,5:4Hz	C5
172	Range CV	0,5:4Hz	C5
191	Skew	13:30Hz	C5
192	Kurtosis	0,5:4Hz	C5
200	Envelope SD	0,5:4Hz	C5
212	Flatness	0,5:4Hz	C5
213	Flatness	4:7Hz	C5
216	Entropy	0,5:4Hz	C5
217	Entropy	4:7Hz	C5
227	Range Median	4:7Hz	C6
235	Range Upper Margin	4:7Hz	C6
239	Range Width	4:7Hz	C6
243	Range SD	4:7Hz	C6
247	Range CV	4:7Hz	C6
255	Amplitude Power	4:7Hz	C6
259	Amplitude SD	4:7Hz	C6
261	Amplitude SD	13:30Hz	C6
262	Skew	0,5:4Hz	C6
271	Envelope Mean	4:7Hz	C6
275	Envelope SD	4:7Hz	C6
283	Relative power	4:7Hz	C6
286	Flatness	0,5:4Hz	C6
287	Flatness	4:7Hz	C6
290	Entropy	0,5:4Hz	C6
291	Entropy	4:7Hz	C6
303	Range Median	13:30Hz	Cz
311	Range Upper Margin	13:30Hz	Cz
315	Range Width	13:30Hz	Cz
319	Range SD	13:30Hz	Cz
339	Skew	13:30Hz	Cz
353	Power	4:7Hz	Cz
357	Relative power	4:7Hz	Cz

TABLE I: 61 Features selected as most representative for the classification using ANOVA

Feature Name	***Description***	***FB***
Amplitude Total Power	time-domain signal: total power	yes
Amplitude SD	time-domain signal: standard deviation	yes
Skew	time-domain signal: skewness	yes
Kurtosis	time-domain signal: kurtosis	yes
Envelope Mean	envelope: mean value	yes
Envelope SD	envelope: standard deviation (SD)	yes

TABLE II: Amplitude features

Feature Name	***Description***	***FB***
Mean	range EEG: mean	yes
Median	range EEG: median	yes
Lower Margin	range EEG: lower margin (5th percentile)	yes
Upper Margin	range EEG: upper margin (95th percentile)	yes
Width	range EEG: upper margin - lower margin	yes
SD	range EEG: standard deviation	yes
CV	range EEG: coefficient of variation	yes
Asymmetry	range EEG: measure of skew about median	yes

TABLE III: Range features

Feature Name	***Description***	***FB***
Spectral Power	spectral power: absolute	yes
Spectral Relative Power	spectral power: relative (normalised to total spectral power)	yes
Flatness	spectral entropy: Wiener (measure of spectral flatness)	yes
Entropy	spectral entropy: Shannon	yes
Difference	difference between consecutive short-time spectral estimates	no
Edge Frequency	cut-off frequency (fc): 95% of spectral power contained between 0.5 and fc Hz	no
FD	fractal dimension	yes

TABLE IV: Spectral features

Feature Name	***Description***	***FB***
BSI	brain symmetry index (see Van Putten 2007)	yes
Correlation	correlation (Spearman) between envelopes of hemisphere-paired channels	yes
Coherence Mean	coherence: mean value	yes
Coherence Max	coherence: maximum value	yes

TABLE V: Connectivity features