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SSVEP ("Steady State Visual Evoked Potential) based speller design using EMD on EEG

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The present study is carried out as part of the Neuro-Engineering class provided by the UPV (Universitat Politecnica de Valencia) and has been based on several research papers already conducted by other studies, cited in the bibliography.

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Abstract
EEG-based spellers are Brain-Computer Interfaces (BCIs) which aim to help patients with severe motor and brain injuries regain or at least improve their communication capacities. In particular, the device is able to associate letters visually chosen by the patient to the recorded EEG signal, so as to build words and sentences. Most of these devices correlate frequency and phase of flickering visual stimuli -different for each letter- to the related EEG signals recorded in the occipital area of the brain, such as the Steady State Visual Evoked Potentials (SSVEP). In this study, we have conducted a state-of-the-art analysis of SSVEP-based spellers, underlying the possible limitations and advantages of different methods and approaches. Later, we proposed our solution for the design of a SSVEP speller using the Empirical Mode Decomposition (EMD) as signal processing method and a classifier based on peaks detection for assigning each frequency of the recorded EEG to a character. Finally, we explained each step to carry out for the development and testing of this device, as well as the ethical implication and limitations of SSVEP speller.

I. Introduction

BCIs have been receiving increasing attention in the past decades for their ability to provide an alternative way for interacting with the external world, without using the normal motor output pathways. Particularly, they rely on recording brain activity to allow the communication with the brain in a manner that is compatible with the intentions of humans.
Even though electrocorticography (ECoG) can provide high quality spatial and temporal characteristics of electrical signals by placing electrodes directly on the cortical surface [1], other techniques have become more widespread in human participants for their non-invasiveness. Among all, functional magnetic resonance imaging (fMRI)[2], magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), and electroencephalography (EEG) are the most promising. Although some methods provide higher spatial resolution, EEG is the most up-and-coming, because of its easy measurement of neural activity, inexpensiveness, and portability for clinical use [3]. Particularly, EEG records electrical brain activity caused by the flow of electric currents during synaptic excitations of neurons, thanks to electrodes placed on the scalp.

To develop an EEG-based BCI system for a specific application, a particular paradigm and protocol has to be chosen for all phases of the experiment. Among different paradigms for the implementation of EEG-based speller, the most used ones rely on motor imaginary, external stimulation and error-related potential [4]. In this study we focus on the external stimulation paradigm and how to develop a speller by collecting and decoding the related EEG. At the beginning, the patient performs a particular task (e.g. visual task, imaginary task) for learning how to modulate the brain activity and, in the meanwhile EEG is recorded from the scalp. Later, a neural decoder for the paradigm is generated using the recorded EEG signals as training data. Subsequently, the subject executes the task again and the BCI is controlled by the neural decoder.
The measured brain activity from the BCI is interpreted with the intention of selecting the desired letter shown on a Graphical User Interfaces (GUIs), developed according to the specific BCI paradigm. Particularly, what is recorded is not a spontaneous signal, but an event-related potential (ERP), which is the measured brain response to a specific sensory, cognitive, or motor event. One of the most popular methods in EEG-based speller are visual P300 and SSVEP [5]. P300 wave is an event-related potential which occurs in the human brain as a positive deflection with a time delay of around 300ms after a specific event has occurred. Instead, SSVEP is characterised by positive and negative fluctuations in the EEG signal which are responses to a visual stimulus.

Moreover, the performance of BCI-spellers is evaluated according to the accuracy and the Information Transfer Rate (ITR) of the system. The accuracy is computed by dividing the number of correct commands by the total number of commands, whereas the ITR is expressed as the number of error-free bits per time unit.
In the next paragraph, different types of SSVEP spellers are presented.

II. State-of-the-art

A. SSVEP-based spellers

Many types of BCI speller have been developed over the years, but the SSVEP paradigm has emerged among others because of its efficiency and high performance, as well as it is user-friendly. The main advantages of the SSVEP approach are that it can be relatively low cost, it has low susceptibility to motion artefacts and short/no training time for the patient.
The taxonomy of SSVEP-based spellers includes operation modality (synchronous or asynchronous), gaze dependency, selection modality (direct target selection or moving cursor), stimulus modality (constant flashing or moving/ animation stimuli) and word prediction [5].
With regards to the **type of stimulus** presented, SSVEP systems are based on flickering stimuli with constant frequencies (each stimulus has its unique frequency); in addition, hybrid BCI can also combine flickering stimuli with moving stimuli [6]. The frequencies of stimulation can be varied from low (1–3.5 Hz) to high frequency (75–100 Hz) and the stimulus can be produced using a light-emitting diode (LED) or a cathode ray tube (CRT).
Most of the SSVEP spellers are created as **asynchronous** BCI, which means that the user has the ultimate control over the system whenever he desires. Otherwise, in synchronous systems, BCI will process the measured and analysed brain activity only in limited time intervals. As far as the **gaze dependency** is concerned, EEG-based spellers can involve overt or covert attention. The first one occurs when the user has to pay attention to a specific visual space or region according to his eye movement, whereas in the second one the attention is shifted mentally to the desired focus point when eyes are fixed.
Moreover, SSVEP spellers depend on the **selection modality**. In the "moving cursor" mode, some blocks are present on the screen, and they are used to control the movement of a cursor along the characters to select the desired one. The Bremen-BCI speller [7] shown in Figure 1 is an example of this modality, where each block flickers with a certain frequency to elicit an SSVEP response and move the cursor.

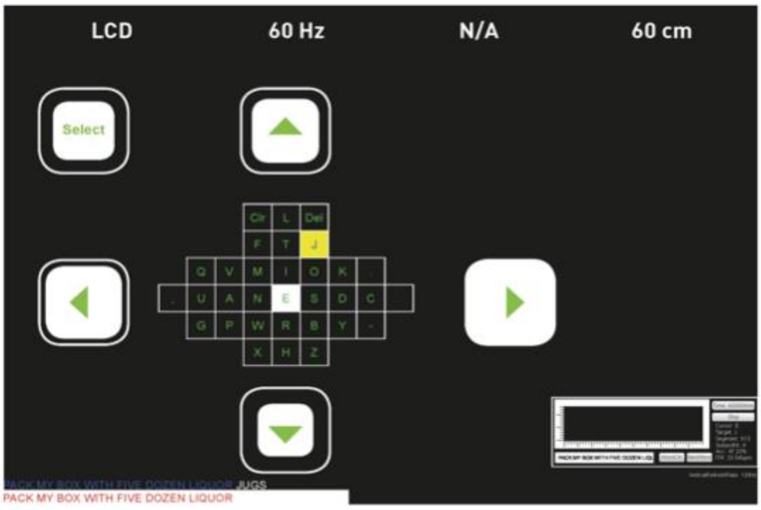

Figure 1. GUI of the Bremen-BCI speller [7]

Instead, in spellers based on direct target selection, each block that is flickered corresponds to a single letter (one-phase SSVEP speller) or to a group of characters (multi-phase SSVEP spellers) [8]. Multi-Phase SSVEP spelling systems typically have a low number of distinct stimuli, which results in high accuracy, but low spelling speed (e.g. 98.49% accuracy with ITR of 27.36 bits/min [9]). Instead, One-Phase modality can achieve higher performance in terms of speed because they allow letter selection in a single step by employing multiple stimuli simultaneously. For instance, Chen et al. used 40 SSVEP targets and they achieved average ITRs of 267 bits/min and accuracy of 89.76% [10].

Moreover, a built-in dictionary can be added for **word predictions** to increase the ITR. In [9], after the selection of at least two characters, six suggested words appear on the GUIs, whereas in [11] the system also keeps track of the most commonly used words to enhance the prediction.
In Table 1 some of the most recent SSVEP spellers are listed according to the taxonomy explained above.

SSVEP BCI speller		
Operation modality	Asynchronous	[8] [10][9][12] [13][14] [15]
	Synchronous	[6][16]
Gaze dependence	Independent	[14]
	Dependent	[6] [8] [9] [10] [12] [13] [15][16]
Selection modality	Direct Target selection	[6] [8] [9] [10] [13][15][16]
	Moving cursor	[12] [14]
Paradigm	Single paradigm (SSVEP)	[8][9][10] [12] [13][14] [15][16]
	Combined Paradigm (SSVEP + Others)	[6]
Word prediction	Yes	[12] [13] [14]
	No	[6] [8] [10] [9] [15][16]

Table 1. BCI speller taxonomy based on operation modality, gaze dependence, selection modality, stimulus modality and word prediction, following the example of [5]

B. EEG analysis and feature extraction methods for SSVEP spellers

As mentioned before, SSVEP spellers correlate frequency and phase of the flickering visual stimuli to the related ERP of the recorded EEG signal using different feature extraction methods. Therefore, it is necessary to select the appropriate technique for attributing each frequency of the recorded signal to a letter.
Since SSVEP is a visual ERP, the signal is extracted from occipital electrodes, and it is possible to use one single channel or multiple channels depending on feature extraction technique. There are methods for selecting first the optimal bipolar electrode with higher SNR and later performing the classification, like the *Power Spectral Density Analysis (PSDA)-SNR* in [17], whereas others are based on PCA, so they combine all the signals from O1, O2 and Oz electrodes. For instance, the *Minimum Energy Combination (MEC)* method finds the optimal combination of electrodes signals for removing strong noise and later determines the target at which the user gazes through a criterion of maxima [18]. Moreover, the *Multivariate Synchronisation Index (MSI)* estimates the synchronisation between signals from the 3 occipital electrodes and the reference signal (created from the stimulus frequencies) for recognizing the corresponding letter. Instead, other methods based on *Power Spectral Density Analysis (PSDA),* such as Discrete Fourier Transform (DFT), detect target frequency from single-channel EEG [16].

The most common techniques to detect and classify target frequency in SSVEP-based BCI are the *Power Spectrum Density Analysis* (PSDA) and the *Canonical Correlation Analysis (CCA)*. Both of them rely on the fact that a periodic pattern with the same frequency of the stimuli can be detected in the EEG signal. The first one is based on the magnitude of the SSVEP periodic pattern that can be easily measured in the frequency domain and the second one on the correlation between the brain signal and the stimulus frequency. However, the CCA method seems to perform the feature extraction better than the PSDA method, mostly in the detection of the harmonic frequency, which are practically not measured by the PSDA technique [19].
Nowadays, some other techniques are also studied in the literature. For example, the spatial filtering approach called *Task-Related Component Analysis (TRCA)*, the *Multiset Canonical Correlation Analysis (MsetCCA)*, in which the reference signal is optimised to increase the accuracy of the CCA method, and the *Likelihood Ratio Test (LRT)* are one of the more up-to-date algorithms [20]. Particularly, this last tests the independence of two sets of multivariate variables in order to increase the accuracy of the frequency recognition in SSVEP [21] [16].
Moreover, one of the simplest techniques used for the feature extraction in SSVEP-based BCI speller is the *Empirical Mode Decomposition (EMD)*. This technique is a data-driven scheme that decomposes the nonlinear and non-stationary EEG signal into a finite and small number of components, which can be described as intrinsic mode functions (IMFs). Each IMF represents the modulation of a certain frequency at a specific time scale. Then, the original signal s[n] can be written as follows:

$$s[n] = \sum_{j=1}^{N} IMF_j[n] + r_N[n]$$

where n is the sample (time), N is the number of IMF functions and r is the residual. From the signal decomposition, those IMFs that correspond to the frequency bands used in the SSVEP will be chosen.
In the next paragraph we are going to explain different methods for feature extraction based on EMD, since it will be used in our SSVEP speller.

C. Different EMD methods for SSVEP- based speller

The most common techniques based on EMD as feature extractors involve other methods previously described for enhancing the accuracy and the SNR of SSVEP, and they are: 1) Traditional EMD (based on PSDA), 2) EMD-Canonical Correlation Analysis (EMD-CCA), 3) EMD- Multivariate Synchronisation Index (EMD-MSI), and 4) EMD- Decision Tree (EMD-DT).

1. Traditional EMD (EMD-PSDA)

The calculation of IMFs can be made for one or multiple EEG channels and the number of IMFs to be used is defined for all the channels. In [22], IMFs are computed for the three occipital electrodes (O1, O2 and Oz) and later the best results were obtained for the second IMF. Then, the Power Spectral Density (PSD) of IMF is calculated, and later a classifier based on rules finds the maximum values and performs a decision by majority vote for the selection of the class. Sometimes the algorithm uses the EMD technique for isolating the useful frequencies in certain IMFs, and then it finds the frequency peaks in the FFT of those IMFs in order to classify each letter.

2. EMD - Canonical Correlation Analysis (EMD-CCA)

The CCA technique is used for multi-channel SSVEP detection, and it measures the linear association between two sets of variables (X and Y) using its autocorrelation and crosscorrelation. The variables are the multichannel EEG signal previously decomposed using EMD (X) and a "Fourier series" of simulated stimulus signals -with different frequencies corresponding to different letters-. The CCA method needs to find the weight vectors, Wx and Wy, that maximise the correlation between x and y, as shown in Figure 2.
In [22], they used the IMF of order 2 for O1, O2 and Oz channels and later the correlation process selected the channel and the class through a criterion of maxima.

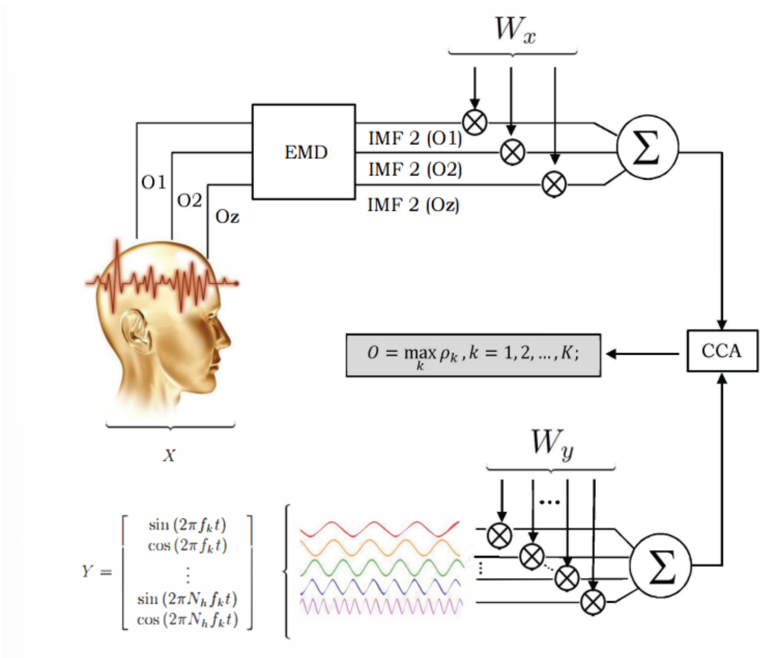

Figure 2. Block diagram for classification using EMD-CCA technique. [11]

The combination of the two techniques allows to avoid the low autocorrelated noise, such as the instrumental noise, and artefacts of the signal of interest [23].

3. EMD - Multivariate Synchronisation Index (EMD - MSI)

As explained above, the Multivariate Synchronisation Index (MSI) aims to recognize the stimulus frequency by measuring the synchronisation between the EEG signals (x) and the reference signal (y), created from the stimulus frequencies in the same way as in CCA. Indeed, a S-estimator based on the entropy of the normalised eigenvalues of the correlation matrix is used to calculate the amount of synchronisation over regions of the cortex, which will be the index for the frequency recognition. In the EMD-MSI method, the input signals are the IMFs obtained from the EEG of the three occipital electrodes. In literature, it is demonstrated that the combination of EMD and MSI methods shows higher performance (accuracy) than traditional EMD and CCA-EMD, using both LED or LCD in the GUI, as we can appreciate in the following Figure 3.

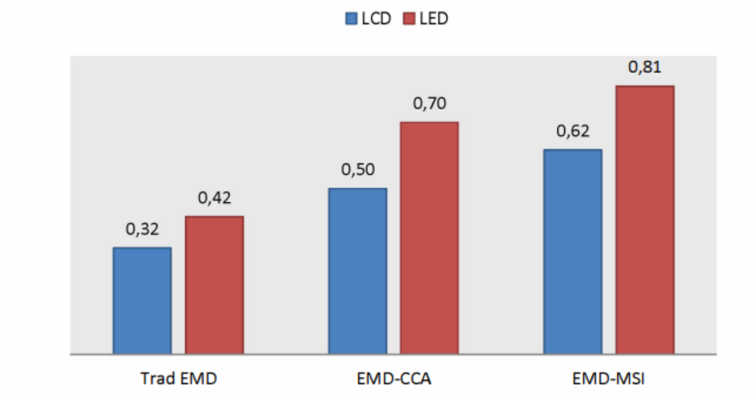

Figure 3. Accuracy for Traditional EMD, EMD-CCA and EMD-MSI, both using LCD and LED in the GUI [22].

4. EMD – Decision Tree (EMD-DT)

In the EMD - Decision Tree method, the classification is performed using an algorithm based on the Decision Tree (DT) [24]. First, EEG signals from the three occipital electrodes are extracted and the first three IMFs are chosen to be the most descriptive ones. Later, some parameters are extracted, like the mean instantaneous frequency of an IMF, the peak of the spectrum or local energy, as input of the Decision Tree classifier. The DT method is composed of different decision nodes connected to each other by branches and it is able to split a complex decision-making process into a collection of simpler decisions, as shown in Figure 4. Thus, the classifier is able to correlate the EEG signal to a letter.

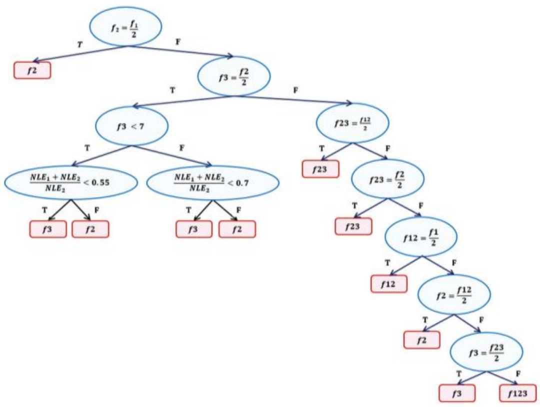

Figure 4. Classification algorithm based on decision tree [24].

In conclusion, it is demonstrated in literature that the use of the combination EMD and decision tree method can improve the recognition rate compared to both the CCA method and the traditional EMD method. [9]

III. Essay development

A. General Scheme

The design of a SSVEP-based speller can be simplified into three stages: benchmark dataset, offline simulation, and online implementation, as schematized in Figure 1 [10]. During the offline system design, it is necessary to define all the parameters for the visual stimulator, as well as training the classifier that allows to attribute the recorded EEG signal to the corresponding specific letter. For this purpose, we need to use a dataset containing SSVEP data from different people and for different frequency of stimulation. At the end, the online system implementation consists of a visual stimulator, a brain pathway and the BCI controller, that uses the classifier to predict the correct letter.

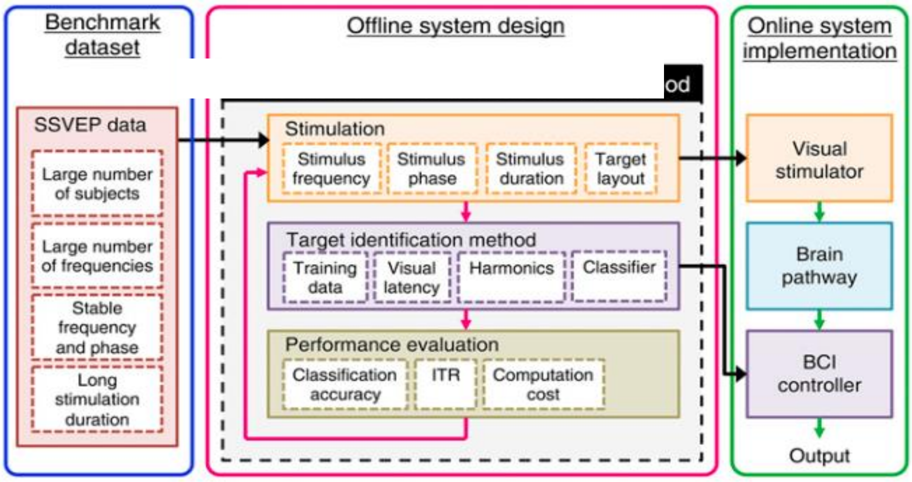

Figure 5. General scheme for the design of a SSVEP-base speller and its subdivision in three different phases: 1) data collection for creating a dataset, 2) offline simulation and 3) online system implementation [10].

B. Offline system implementation

The BCI we wanted to implement is a one-phase SSVEP speller, which involves different stimulus frequencies for each letter or character, because it showed higher spelling speed. For this reason, we selected a benchmark dataset based on 40 different flicking blocks in the GUI, as it will be explained later in detail. Even though asynchronous spellers are more user-friendly because the patient has the ultimate control over the system, here we are going to implement a synchronous BCI. Indeed, after the patient selects a character, the screen will be blank and in that time interval the system will process the EEG signal and perform the classification task. We decided to use the EMD traditional method based on FFT, and we used an algorithm for SSVEP frequency identification that relies on peaks detection in IMFs, since it was the easiest one and it has a low computational cost.

C. Methods

1. Benchmark dataset

The database we used for the offline simulation is the *A Benchmark Dataset for SSVEP-Based Brain–Computer Interfaces* from the Tsinghua BCI lab by Yijun Wang [25]. The data has been acquired with 35 healthy subjects, aged between 17 and 34 years of whom 17 are females and 18 are males.

In our case, we have employed data from 12 different subjects in order to be processed using the Matlab software. Further in this document we explain the conditions of the acquisition as well as the tools used for the experimental setup.

2. Experimental design

During the EEG data acquisition, the patients were seated in a chair distant by 70cm from a 23.6-inch LCD monitor, with a screen resolution of 1920 x 1080 and a refresh rate of 60 Hz. The screen shows a 5 x 8 matrix where each case contains a character: 26 English alphabet, 10 digits and 4 symbols, as shown in Figure 6. The sizes of the characters and stimuli square are 140 x 140 pixel squares, and the whole matrix is 1510 x 1037 pixels square. Each one of the characters is flickering at a precise phase and frequency ranging from 8 to 15.8 Hz with an interval of 0.2 Hz.

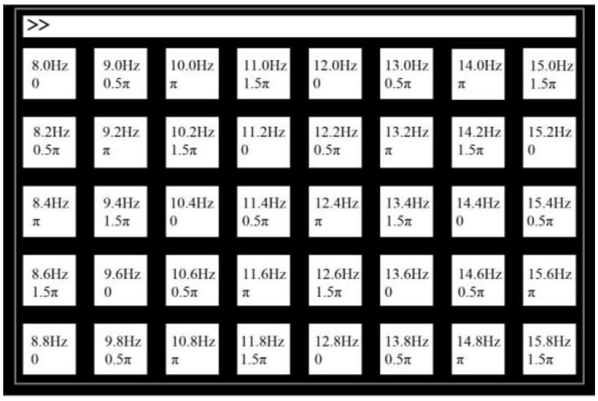

Figure 6. Stimulation interface of the 40-target BCI speller.

The program coordinating all of the stimuli has been developed under MATLAB using the Psychophysics Toolbox V3 [26].

The experiment consisted in a cue-guided target selecting task. Each subject performed 6 blocks of 40 runs (corresponding to the 40 characters, as shown in Figure 7) that were composed of:

- **0.5s of target cue:** a red square was shown at the target location.
- **5s of searching**: the subject had 5s to find the target previously shown among all the flickering stimuli.
- **0.5s of blank screen**

The subjects were instructed to avoid eye blinks during the 5s period and were given several minutes of rest between the 6 blocks.

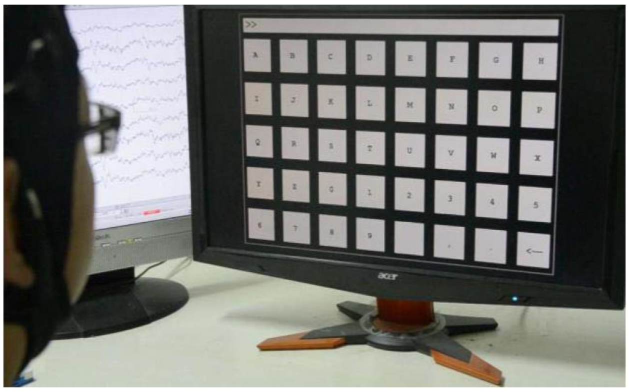

Figure 7. Subject searching for letters

3. Acquisition

The EEG signals have been recorded with 64 channels of the Synamps 2 system from Neurospec, with a sampling frequency of 1000Hz and a bandwidth ranging from 0.15Hz to 200Hz. The setup of the electrodes has been placed according to the international 10-20 system, as shown in Figure 8:

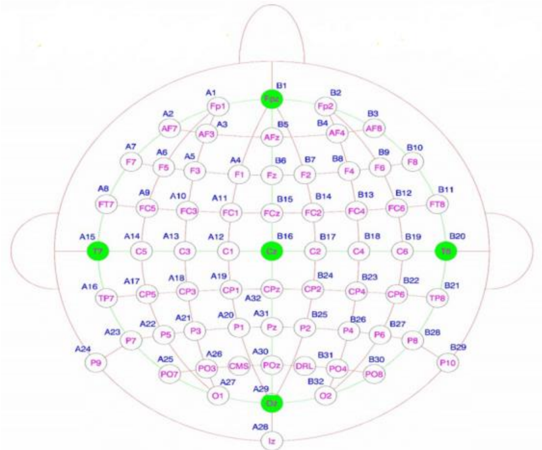

Figure 8. Electrode setup according to the international 10 - 20 system.

The reference electrode has been placed at the Cz vertex. Also, a notch filter at 50Hz has been applied in order to remove the power-line noise. The acquisition process took place during the "5s of searching", so when the patient has to select a letter with the gaze.

4. Processing

The processing and the feature extraction part take place during the "0.5s of blank", so after the letter selection with the gaze. The epochs that are relevant to be analysed correspond to the EEG signal recorded during the 5 seconds stimulation. Since the upper bound frequency of the SSVEP harmonics in this paradigm is around 90Hz [27], all epochs were down-sampled to 250 Hz in order to reduce storage and computational cost. Also, no digital filtering has been applied. Later, the EMD method was applied to the signal.

5. IMFs selection and parametrization

After the EMD algorithm, in order to select which IMFs to consider, the FFT was computed and we identified the second and third IMFs as the most representative ones, since we could appreciate the peak and its harmonics. This is because the combination of these two IMFs has a range of 8-45 Hz approx, comprising the frequencies of the signals used in the experiment. Particularly, for the lower half of the frequencies used in the stimulation, the peaks will appear on the third IMF while the higher ones will remain in the second IMF. Therefore, we decided to add the IMFs together, allowing us to combine information in that frequency range.
The parameters extracted for the classificator will be the peaks in the FFT distribution of these combined IMFs, that will give us the main frequency component of the stimuli along its harmonics, and the normalised local energy in this frequency.
Another possibility explored for further algorithm improvement was the subtraction of IMFs 4-5 to the combination of IMFs 2-3. This subtraction has been performed in order to eliminate noise from lower frequencies, present in IMF 3-5. This has been proven to increase the accuracy of the algorithm.

6. Classification method

To identify the peaks and the harmonics of the combined IMFs signal in the frequency domain, the absolute maximum is found using 70% of its height as a threshold. We selected 70% because it was the optimal value found after testing the algorithm with other percentages. Thus, the main frequency and its harmonics are extracted and the first peak is considered as the main frequency. Later, the frequency associated to this peak is compared to the 40 different stimulation frequency and we assign it to the closest frequency associated to the target letter (cf. figure X with the frequency of each character). This method has the advantage of not having the necessity to perform a calibration/ training test before the patient can use the system.

D. Discussion and results

Various tests have been performed in order to comprehend the behaviour of the system and its needs. Following the procedure for the EEGs and trials used in [25], we averaged the 6 trials corresponding to each letter and we proceeded to the classification. This averaging method for offline processing improves the SNR quite substantially, and so the identification of the peak and the corresponding letter, as we will see with the accuracy values in Table 2. We decided to test the algorithm using the two IMF combinations proposed before.
Later we decided to assess the performance of our algorithm by testing it on a single trial, a condition quite similar to online implementation. The 3 results can be seen in the Table 2 below

IMF Combination	Single run	Averaged
2+3	27.5%	78.12%
(2+3) - (4+5)	34.38%	82.29%

Table 2. Accuracy of the different tests performed

As the accuracy values clearly show, the averaging method leads to a huge improvement of the algorithm, because the results were far higher (82.29%) compared to single trial ones (34.38%). Nevertheless, we cannot use this method for online tests and live cases. Anyway, the results for single run are similar to the ones in [], where they obtained 32% of accuracy using traditional EMD. Moreover, in that article they used only 6 stimulation frequencies for identifying 6 characters, whereas here we have identified 40 letters with the same accuracy value.

E. Conclusion and future perspectives

We have designed a SSVEP-based speller, which is asynchronous and one-phase, and it includes a GUI for the selection of 40 different characters.
The EMD-based method we proposed for feature extraction and character classification showed results comparable in terms of accuracy to others present in the literature based on traditional EMD. Nevertheless, the accuracy is quite low (34.38%) and it should be improved by combining EMD with other techniques, such as the ones analysed in the state-of-the-art.

In this work we did not perform a spelling speed analysis, so in a future study we can compute the ITR and compare it to already existing alternatives. Moreover, we can include a built-in dictionary for word prediction, such that it will improve the spelling speed.

IV. Limitations of SSVEP-based spellers

The main issues for SSVEP-based spellers are related to **ocular fatigue** and to the selection of the optimal **stimulation parameters** (durations and phase interval), which are user-specific and require calibration. So far, the **information transfer rates (ITRs)** are lower compared to electrocorticogram or P300, and they also lack computationally efficient solutions. This results in a speller that is able to identify only a few letters per minute, which leads to a quite **low communication speed** for the patient. In addition, the performance limit of SSVEP speller depends on temporal coding precision in the visual pathway, which is reflected by the **visual latency** in SSVEP, which is difficult to quantify due to the interference from spontaneous EEG activities. Moreover, the **frequency coding** remains challenging, because the discriminability between SSVEPs is not in a very narrow frequency range. Moreover, SSVEP is not applicable for patients with substantial head or **ocular motor impairments**, as well as blind people or patients with loss of gaze control (e.g. totally locked-in patients), because the speller is gaze-dependent.
With regards to the EEG, the limitations of our model will come firstly from the nature of the signal. EEG signals are known for their complexity and the presence of random components along some synchronised activity. This will be a challenge in the feature extraction, because the **signal-to-noise ratio** is quite low and the peaks will coexist along with noise. However, choosing the right IMFs should help solve these issues because it allows us to focus on certain frequency bands, avoiding noise centred in others.
As far as the processing part is concerned, the IMFs components are not the same across different tries when analysing one signal, because of the very nature of EMD. This lack of repetitivity is partially compensated when we choose 3-4 IMFs, because the frequency distribution will vary but it keep close to certain IMF components.

V. Legality and Ethics

The aim of this project is to develop an efficient speller that would be used by people with some motor impairment and are not able to talk normally. Being in that line, the ethics part seems pretty clear, we are not altering or proposing to alter any cognitive function or behaviour but providing an aid for those that have severe difficulties for other types of communication. The misuse of this technology seems unlikely as well as difficult because it relies firstly on a visual stimulus related to a certain frequency provided by a light along with sensing with electrodes on the head. The complexities of the apparatus along its gaze dependency, makes it impossible to use this technology to read or to try to interpret other people's choices without them knowing it.

Anyways, we need to take in consideration some ethical issues about the BCI. One of the most discussed is Humanity and Personhood. In fact, there is a discussion about the possibility of a sense of self changing and the ways BCI can contribute to it. For example, some patients, in some studies [10], felt like they were not themselves anymore and another patient said that the BCI was an "*extension of herself and fused with part of the body*". Other studies argue that BCI technology constitutes a fusion of human and machine, stating that "*the direct implantation of silicon into the brain constitutes an entirely new form of mechanization of the self [...]. The new union of man and* *machine is bound to confront us with entirely new challenges as well*". Another of the main issues about BCI technologies is the fact that it is very important to obtain the informed consent and to be sure that the subjects are aware of all the possible implications of BCI before consenting to use it. As some researchers said, "*The inability to communicate a desire to participate or decline participation in a research trial -when the capacity to form and maintain that desire is otherwise intact- undermines the practice of informed consent. Individuals cannot give informed consent for research if their autonomous choices cannot be understood by others*".

Moreover, some papers discuss about the possibility of a "*right to brain privacy*", which can be similar to the existing privacy legislation, such as General Data Protection Regulation (GDPR) in the European Union or the Health Insurance Portability and Privacy Act (HIPAA) in the United States, to regulate the information gathered in BCI use. Finally, another important topic is privacy, because there is the possibility of extracting private information from people's brains and using it without their knowledge or consent.

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