SSVEP based Brain-Computer Interfaces for 2-D Analog-like control: is it possible?

Raffaele Ferrante, Luigi Bianchi

Abstract**—**In this study, we propose a new SSVEP-based BCI approach for 2D cursor control. Our goal is to allow a subject to gaze at a point on a PC screen and move a cursor on it, not fixing a flickering LED but gazing between 4 LEDs. The result is a dependent BCI which provides a mean ITR of 21 bit/min (SD: 3 bit/min). Data were collected using a wireless electroencephalograph with just two dry electrodes (O1, O2) and analyses were performed offline.

Keywords**—** Analog-Like Control, BCI, Harmonics, SSVEP, EEG, Dry Electrodes.

I. Introduction

A Brain-Computer Interface (BCI) is a communication or interaction system in which messages or commands that an individual sends to the external world do not pass through the normal brain's output pathways of peripheral nerves and muscles: some well-defined brain activity is extracted directly from the brain and translated into the desired action. Actually, several different brain signals have been successfully used, such as EEG, fNIRS, fMRI, MEG and ECoG and several different strategies to process them have been adopted (e.g., P300, SSVEP, mu, SCP)[1].

We can divide BCIs into two main categories: dependent and independent. A dependent BCI needs a peripheral pathway activation (i.e. the ability to gaze) to generate a useful signal, whereas an independent BCI does not.

SSVEP systems, compared with the other BCI systems, have recently gained a lot of interest because they can be used after a very short training time providing good performances as compared to other systems. They are based on the fact that when a user watches a light flickering at a fixed frequency *f*, the EEG power spectrum of occipital region channels shows a peak localized at the same *f* frequency and its relative harmonics. Thus, it can be possible for a user to activate a command or a specific function by gazing at a flickering light, usually a LED, which acts as a digital switch, by analyzing EEG signals and look for the presence of the spectral peak. Moreover, if several LEDs flicker at different frequencies, each of them can be bound to a different action that then can be executed. In other words, the system guesses the action by analyzing the EEG signal at the occipital region.

Due to SSVEP signals stationarity, time domain analyses are not always the best option to process them and frequency domain analyses are often considered a better option [2].

In Fig. 1 (left panel) a typical power spectrum relative to the O1 electrode position, while a user is looking at a 9Hz flashing LED, is shown: peaks at 9Hz and other harmonics can be easily observed. Similarly, when the same user looks at a 7Hz flashing LED, peaks at 7Hz and harmonic frequencies can be also easily identified (Fig 1, right panel).

It has been also found [3] that, in the spectrum of EEG signals acquired during a stimulation with two lights flickering at two different frequencies f_1 and f_2, and close to each other, it is sometimes observed the presence of peaks at the average frequency $(f_1+f_2)/2$ or their sum (f_1+f_2).

Other important features to take into account describing the quality of a BCI system are the level of user-friendliness, the level of comfort and, as already mentioned, a short training time to be able to operate it. Classical SSVEP based BCIs, however, fail to provide a comfortable solution because requiring fixating a flashing LED causes quickly fatigue. For this reason, in a previous study [4] we have demonstrated that it is possible to obtain a 1-D analog-like control asking subjects to gaze between two flickering LEDs, thus avoiding this problem. This is possible because the amplitude of the spectral peaks decreases as the gaze of the user moves away from the flickering LED so that it is possible to estimate the distance of a fixed target with respect to the flickering light in a workspace of 30 cm and with a mean error of 2cm [4].

Another important issue is that with our approach performances can be boosted thus providing another important advantage with respect to classical implementations.

At state of the art, BCI protocols focusing on two-dimensional control are often hybrid processing of different type of brain signals. Protocols are mainly based on a digital approach (e.g. using frequency as a tag to select a command instead of another one) and few works proposed continuous control protocols [4] [5] so that they actually are two BCI systems that work in series.

In this study, we propose a new SSVEP-based BCI approach for 2D cursor control, thus improving our previous 1D work. Our goal is to allow a subject to gaze at a point on a PC screen and move a cursor on it, not fixing a flickering light but gazing between 4 lights thus avoiding lack of comfort issues while boosting performances.

R. Ferrante is with the Department of Civil Engineering and Computer Science of the "Tor Vergata" University of Rome, Italy. e-mail: raffaele.ferrante@ uniroma2.it).

L. Bianchi., is with the Department of Civil Engineering and Computer Science of the "Tor Vergata" University of Rome, Italy. e-mail: luigi.bianchi@ uniroma2.it).

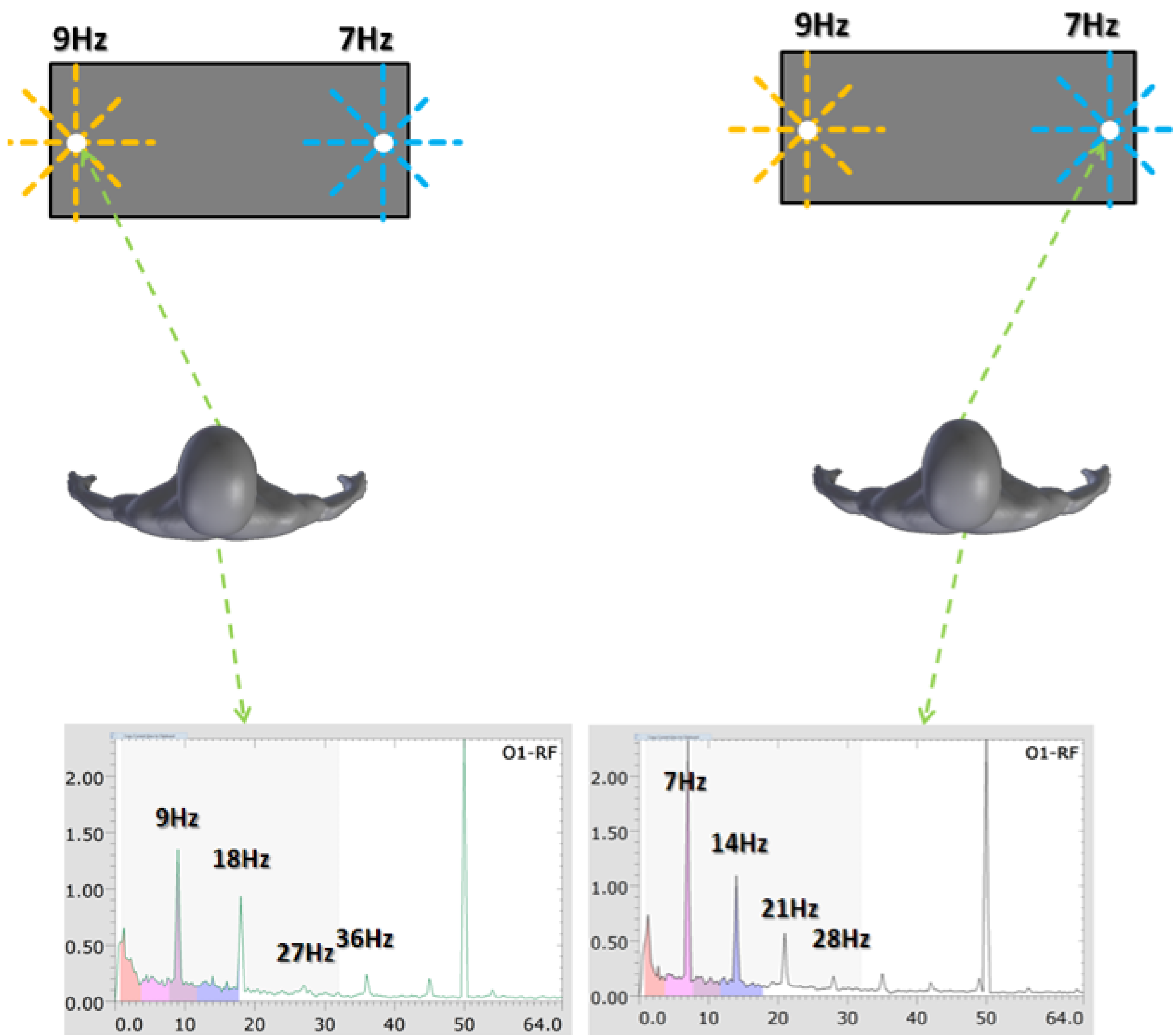

Fig. 1: Power spectra relative to O1 while gazing at a 9Hz (left) and 7Hz (right) flickering LED.

II. Materials And Methods

A. The Experimental Protocol

Twelve volunteers participated to the study, 7 males and 5 females, with an average age of 30y (SD: 7y).

Four white LEDs are used to elicit the SSVEP potentials, driven by an Arduino UNO board, to allow a full control on the stimulation frequency and of the light intensity. The white color is chosen because it is the one that was reported in previous studies to provide the higher responsiveness [6]. In this protocol we choose the four stimulation frequencies in order to avoid harmonics overlaps at the lower frequencies (<50Hz) and to avoid overlaps with the monitor refresh rate (60 Hz).

The four LEDs are set on a squared frame of 21.7cm (i.e. 800 pixels) (Fig. 2) whose diagonals are parallel and perpendicular with the direction of the gravity force.

To maximize the responsiveness [7], frequencies are also chosen within the α band and are settled as 8.5 Hz (bottom), 9.5 Hz (right), 10.5 Hz (top), 11.5 Hz (left).

The frame is placed on a 24 inches PC monitor, this last used to indicate the target positions to fixate.

Every subject is positioned at 80 cm from the screen with his/her eyes centered with the center of the frame. An eye tracker (The Eye Tribe) was used to collect gaze data to verify that users performed correctly the task.

We ask each subject to gaze at one among 64 different targets, positioned on an 8 by 8 matrix. Each target (e.g. fixation point) is defined by a point on the screen that is turned on one time per trial while the others are off. In Fig. 2 all possible target positions are shown. Targets are distributed uniformly between the four LEDs whose flickering frequencies are illustrated in Fig. 3.

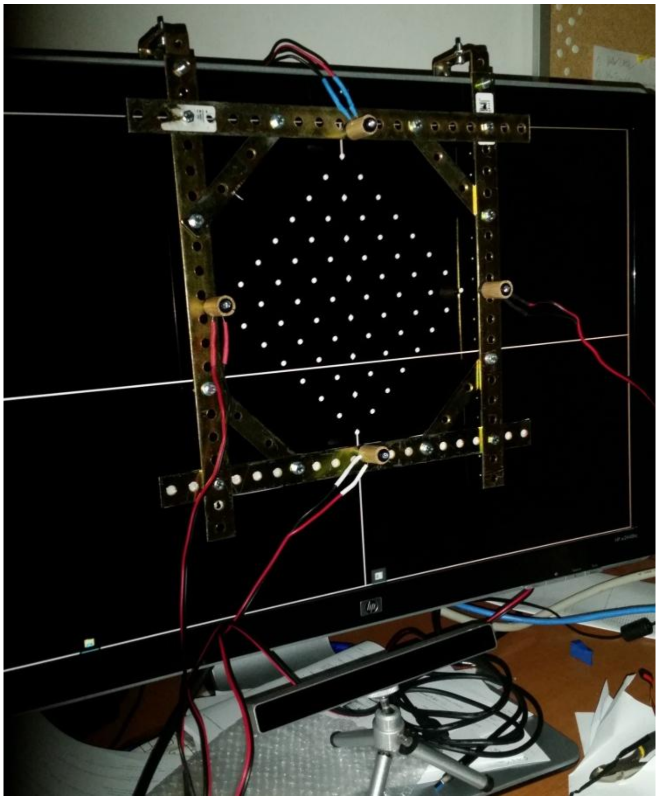

Fig. 2: the custom frame used in the study and the 64 targets all turned on to calibrate the system. Arrows indicate LED positions.

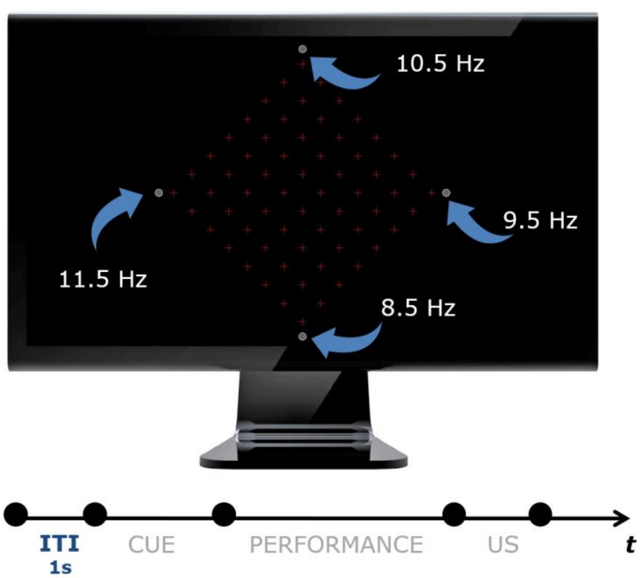

Fig. 3: spatial distribution of the targets and LEDs

A. Data acquisition

The acquisition is done using a wireless, 8-channel, Neuroelectrics StarStim electroencephalograph with 500Hz sampling rate and a 125Hz low-pass filter. A standard headset based on 10-10 EEG system is used but only two dry-electrodes are used and positioned at the O1, O2 locations of the 10-20 international system.

In this protocol, we want to use only two dry electrodes to have the simplest set-up, in order to let the system be utilizable in a wide range of different situations.

B. Data analysis

The off-line processing of the collected data allows us to build, through various phases, a subject-specific model that can calculate the coordinates of the gaze position on the screen and to estimate the error committed in this calculation. The data are firstly processed with the NPX Lab software [8] and then with custom-made Matlab scripts.

BCI's performances are often defined by using the Information Transfer Rate (ITR) which considers either speed, accuracy, number of choices and frequency of transferred bits. For a generic BCI system, with N commands available to the user and p probability to be chosen and with s commands selected every minute, the ITR is described as follow:

$$ITR = s*[\log2(N)+p*\log2(p)+(1-p)*\log2(1-p/N-1)]$$

Twelve tracks, one for each subject, were exported in EDF+ format and processed with NPXLab [8].

For each subject, the Fast Fourier Transform is computed for each 4 seconds Performance epoch and exported to obtain a new output file. This file (in ASCII format) contains a matrix of 64 rows and n+2 columns. Each row is associated with a single trial of one single subject, the first two columns reporting the coordinates, in terms of pixels, of each target. The remaining n columns describe the whole dataset: each column reports the values of the spectral amplitudes of each single frequency for both O1 and O2 electrodes (all frequencies from 0 Hz to 249 Hz with a resolution of 0.25 Hz). The datasets are then loaded into the Matlab environment, where the rest of the processing is executed.

As the number of features is greater than the number of observations (2000 vs. 64) we need to drastically reduce them.

A first selection is made by selecting only the features in the 5-99 Hz band (380 features per sensor).

At this point, we decided to face the problem of the correspondence between features and spatial coordinates of the targets by breaking it down into four polar coordinates sub-problems, one for each LED representing the origin of the polar systems. For each target the radius (ρ) and phase (ϕ) (Fig. 4), relative to the 4 coordinate systems, are computed, thus obtaining eight values (4 radii and 4 phases). Eight linear regressions were computed to correlate each spectral feature with each of the 8 coordinates. A total of 6080 linear regressions (380 * 2 * 8) were then performed.

It has been observed, in a previous study [4], that the ρ and ϕ can be related to the angular distance of the gaze position from the LED. Therefore, the idea was to construct eight different linear models capable of estimating ρ and ϕ from the spectral features. A unique algorithm capable of predicting the coordinates of the target on the screen was then developed starting from the spectral characteristics of the EEG signal.

Because of the limited number of observations made, the dataset to compute the model was further reduced: we selected the 48 spectral features with the best correlations among the 6080. This number (48) is used to limit the phenomenon of overfitting by selecting 75% of the maximum number of free parameters possible (63, equal to the number of observations minus one).

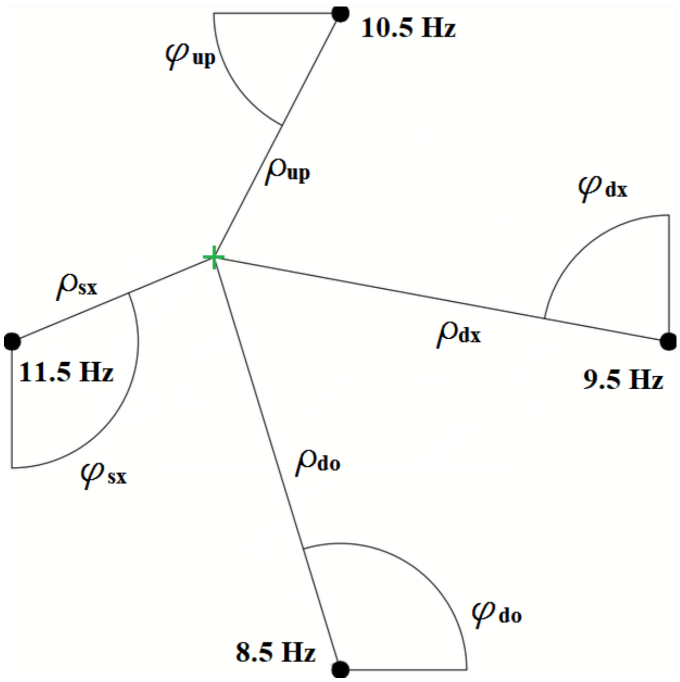

Fig. 4: definition of the coordinate systems Green cross indicates target position.

Then, a multiple linear regression is performed on the set of 48 features, obtaining the 49-parameters of the linear model. The "corrected Akaike information criterion" (AICc) is also calculated. AICc is a coefficient that considers both the goodness of the model's adaptation to the observed data and its complexity in terms of quantity of parameters that constitute it. At this point a new regression is performed, excluding the feature with the highest (worst) *p*-value from the input data. The AICc is also calculated for this new model. This operation is iterated 47 times excluding the less statistically relevant feature each time and calculating the AICc again.

At the end of the process, the model with the best AICc among the computed 48 is finally chosen, thus the features set to be used is determined.

For each of the 4 coordinate systems, then, the mean error of its predictive ability is computed by using a leave-one-out method. This technique consists in recalculating the model coefficients excluding one observation at a time, applying the model to the observation previously excluded and defining the error between the real value of ρ or ϕ and the predicted one. Since this protocol included 64 observations, the procedure can be repeated 64 times. For each coordinate system, the mean error was computed to provide an index of the quality of the model.

Once the features to be used are defined we need to get a reliable estimation of the coordinates of the target by merging the information obtained from the 4 different coordinate systems.

For each target an 800*800 matrix M is defined where each cell will hold a score relative to one pixel of the targets working space.

For each of the 4 coordinate systems, a normal Gaussian function is constructed with zero mean and with the SD equals to the previously computed mean error, in order to obtain a function directly related with the quality of the calculated model. At this point, for each of the 4 coordinate systems, we define a ring function with the radius estimated by the model centered on the origin of the coordinate system, and whose section orthogonal to the circumference is the previously computed Gaussian. By summing the values of the 4 rings, into the cells of the M matrix, we obtain a representation such as the one of fig 5.

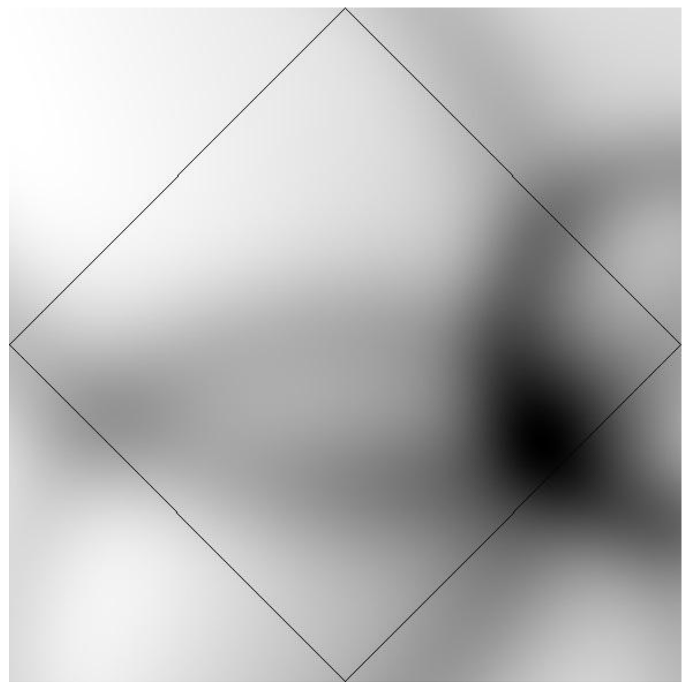

Fig. 5: visual representation of matrix M for one target prediction.

The cell with the highest value corresponds to the point of the space which represents the best prediction of the target.

We decide to bring to the edge of the domain any predictions that hypothesize the target outside the workspace, obtaining an improvement in the estimation without affecting the validity of the protocol.

Finally, the distance between the predicted and the real target is calculated and the average error on all 64 targets is evaluated.

Again, the mean error of the predictive ability is computed by using a leave-one-out approach.

If a predicted value falls outside the target's workspace, it is moved on the nearest workspace boundary. In this way, the error is reduced by using information that is in any case known a priori (a boundary condition of the prediction domain) without altering the statistical validity of the results.

III. RESULTS

On Table I the results for predictions in the 2D workspace in terms of mean error of the 64 targets are reported. The data are presented individually for each of the 12 subjects and then an average between them is done. The subject that presents the best results was S10, which provides a mean error of 2.0 cm, whereas S1, the worst performing one shows a mean error of 2.8cm.

The average error committed in the 2D predictions, calculated on all subjects is 2.4 cm (SD: 0.2 cm) which is about one order of magnitude less than the length of the diagonal of the workspace.

TABLE I

Subject	Error [cm]	Error [px]
S1	2.8	104
S2	2.6	95
S3	2.3	83
S4	2.5	93
S5	2.7	100
S6	2.3	84
S7	2.4	87
S8	2.6	96
S9	2.3	86
S10	2.0	75
S11	2.7	99
S12	2.1	79
Avg	2.4	90
SD	0.2	9

Table 1: errors in 2D models

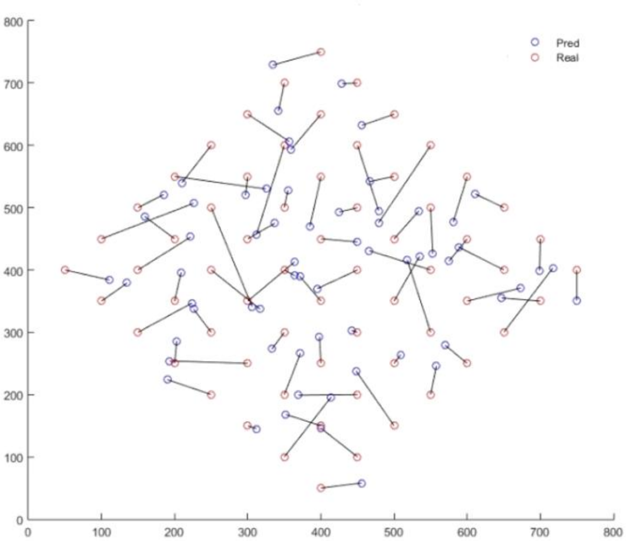

Fig. 6: Real (red) and estimated (blue) positions of the target relative to S10.

In Fig. 6 are reported the actual (red) and estimated (blue) gaze position relative to subject 10. Each segment represents a trial so that one can have an idea of the distance among the real and estimated target position.

Finally, the theoretical ITR indices are calculated for each subject hypothesizing an online BCI with a 6s trial duration and reported in Table II.

TABLE II

Subject	ITR
S1	17
S2	19
S3	23
S4	20
S5	18
S6	21
S7	24
S8	23
S9	23
S10	27
S11	18
S12	23

Table 2: Theoretical ITR [bit/min]

IV. CONCLUSIONS

Preliminary studies have shown that the amplitude of the spectrum of SSVEP signals is modulated by the distance of the gaze from the stimulus that has elicited them [4].

Linear models have been built to approximate this trend. The models committed errors, on average, lower at 15% of the maximum distance measured and, in the best case, less than 10%.

The algorithm that was implemented for the construction of the models has selected relatively high frequencies compared to the expectations and compared to the classic frequencies of the SSVEPs [9]. The reason could be the use of dry electrodes, which guarantee good acquisition in a wider band compared to gel electrodes. Especially in the subjects who presented the better results, in addition to the fundamental stimulation frequencies, superior harmonics and combinations of these same harmonics were automatically selected. That denotes a non-linearity in the transmission of the visual signal from the retina to the visual cortex or in the genesis of the bioelectric signal in the cortex itself.

The results achieved in the linear models made it possible to obtain good performance even in the 2D prediction of the target position. The space within which the targets were visualized was 13.5 cm × 13.5 cm and the average error committed was 2.3 cm.

The training phase has been reduced as short as possible, consisting of only 8.5 min. The whole protocol was easy and intuitive. The system, thanks to the dry electrodes (no assembly stuff and no gel in the hair) and the wireless electroencephalograph, was comfortable and practical, simplifying any use for any subject or patient. Subjects reported that visual stimulation was neither fatiguing nor bothersome.

Future work will include online implementation and testing on a BCI and NeuroFeedback platform such as [10, 11].

REFERENCES

[1] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain-computer interfaces for communication and control. Clinical Neurophysiology, 113(6), 767–791.

[2] Vialatte, F. B., Maurice, M., Dauwels, J., & Cichocki, A. (2010). Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives. Progress in Neurobiology, 90(4), 418–438.

[3] Regan, M. P., & Regan, D. (1988). A frequency domain technique for characterizing nonlinearities in biological systems. Journal of theoretical Biology, 133(3), 293-317.

[4] Bianchi, L., Ferrante, R., & Ouitadamo, L. R. (2018, October). Analog-Like Control is Possible in SSVEP Based Brain-Computer Interfaces. In 2018 IEEE Life Sciences Conference (LSC) (pp. 235-238).

[5] Allison, B. Z., Brunner, C., Altstätter, C., Wagner, I. C., Grissmann, S., & Neuper, C. (2012). A hybrid ERD/SSVEP BCI for continuous simultaneous two dimensional cursor control. Journal of Neuroscience Methods, 209(2), 299–307.

[6] Cao, T., Wan, F., Mak, P. U., Mak, P., Vai, M. I., & Hu, Y. (2012). Engineering in Medicine and Biology Society Conference Flashing Color on the Performance of SSVEP-based Brain- Computer Interfaces, 1819–1822.

[7] Birca, A., Carmant, L., Lortie, A., & Lassonde, M. (2006). Interaction between the flash evoked SSVEPs and the spontaneous EEG activity in children and adults. Clinical Neurophysiology, 117(2), 279–288.

[8] Bianchi, L. The NPXLab suite 2018: A free features rich set of tools for the analysis of neuro-electric signals. WSEAS Transactions on Systems and Control. Vol 13, 2018, Pages 145-152.

[9] Zhu, D., Bieger, J., Garcia Molina, G., & Aarts, R. M. (2010). A Survey of Stimulation Methods Used in SSVEP-Based BCIs. Computational Intelligence and Neuroscience, 2010, 1–12.

[10] Bianchi, L. Speedy'O'Brain: A neuro-feedback videogame driven by electroencephalographic signals International Journal of Biology and Biomedical Engineering Volume 12, 2018, Pages 229-234.

[11] Bianchi L. The Software Model of the "Speedy'O'Brain" Neurofeedback Videogame, International Journal of Circuits, Systems and Signal Processing, in press.