Detection of steady state visual evoked potential based on autoregressive models

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***Abstract*—The steady-state visual evoked potential is electrical signals associated with an intermittent luminous stimulation that blinks with a certain frequency. The signals that come from the brain can be analyzed and estimated what kind of frequency signal is the one that is stimulated in a time window. Our efforts in this work are guided by the autoregressive methods of estimation using in this case the AR approach.**

***Index Terms*—AR,SSVEP, Forecasting,BCI.**

I. Introduction

Neurosciences and Neuro-technology are continuously advancing and so individuals, society and healthcare professionals have to up date themselves with advancement. Brain computer Interface (BCI) is one such emerging technology in Neurosciences [1].

BCI is a technology that receives, analyzes, and transfer the signals generated from brain into output commands in real world to accomplish a particular task. In doing so, they are unique, as they do not include the normal neuromuscular pathways of peripheral nerves and muscles to perform a function, which is the site of pathology in paralyzed patients [2].

In this interfaces, there is some characteristic signals, in this case, the milestone of the development of this project will be the ones that are called the evoked potentials and in specific the Steady State Evoked Potential (SSVEP).

Evoked potentials, consisting of stereotypical changes of electrical activity evoked by sensory stimuli and measured at the scalp, were first recorded in the middle of the last century. Since then, they have become an important tool for understanding the relationships between physical stimuli, brain activity, and human cognition [3].

These two types of responses comprise event-related potentials (ERPs), which are "the general class of potentials that display stable time relationships to a definable reference event" [4]. In their most common form, ERPs are recorded in response to an isolated, discrete stimulus event. This two responses are the transient and the exogenous ERPs, the exogenous ones can be generated in response to a train of stimuli presented at a fixed rate. Because the responses to such periodic stimuli can be very stable in amplitude and phase over time, those responses have been referred to as the steady-state visually evoked potential [3].

II. SSVEP

The steady-state visually evoked potential (SSVEP) is a stimulus-locked oscillatory response to periodic visual stimulation commonly recorded in electroencephalogram (EEG) studies in humans. Due to its high signal-to-noise ratio, relative immunity to artifacts, non-invasiveness and ease of recording, the SSVEP has become a popular modality in visual cognitive neuroscience research.

SSVEP based BCIs are made up of different light sources which blink at different frequencies, so when the subject directs the look at some of these sources, at the cortical level, and most primarily in the primary visual cortex, evokes this potential.

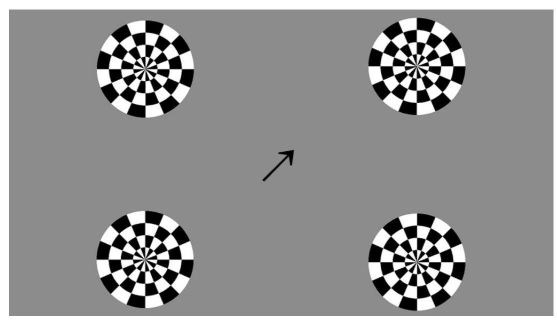

Fig. 1. Luminous Stimulation in different frequency's

Because the SSVEP response is periodic, it is confined to a specific set of frequencies, and it is thus natural to analyze it in the frequency domain instead of the time domain. The stimulus frequency determines the response frequency content: The response spectrum has narrowband peaks at frequencies that are directly related to the stimulus frequency.

The detection of this frequencies should be seen as a opportunity, this because each frequency stimulation is related to certain brain activity, activity that is being monitor by the BCI. If we can predict what frequency is associated with an specific frequency stimulation on SSVEP signal, can be used as tool to improve paralyzed mobility or communication.

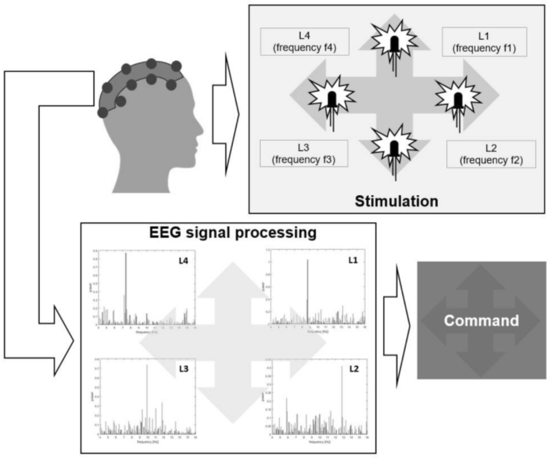

Fig. 2. Detection diagram of SSVEP

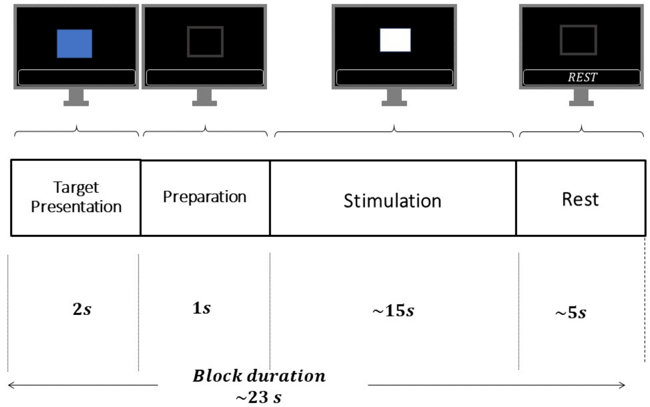

Fig. 4. Experimental process

III. Data Extraction

The data set of these cerebral responses is subtracted from an investigation group part of the Tecnologico de Monterrey. The data collected consists of almost 100 signals that are associated with different frequency stimulus. Each data frame contained 8 time series that correspond to every channel in the BCI ("Fig. 3"). To simplify our estimation work, we collect only one signal from an arbitrary channel.

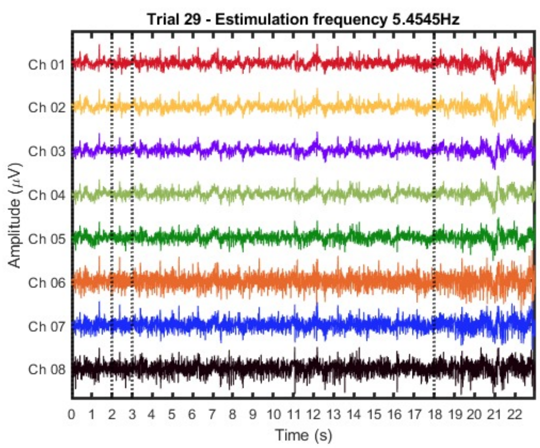

Fig. 3. Data from BCI, in eight channels.

As we said before, the stimulation frequency of the data is known, this parameter will be helpful in this way, thus because we can test our estimation and compare our results with another data frame that shares the same frequency stimulation parameter.

With the selection of one signal, we must analyze if all the data correspond to the stimulation, the experiment stages are represented in the "Fig. 4", which is classified into time intervals for all these stages.

We could see this clearly in the "Fig. 5", where every stage is colored to distinguish and select only the stimulation data.

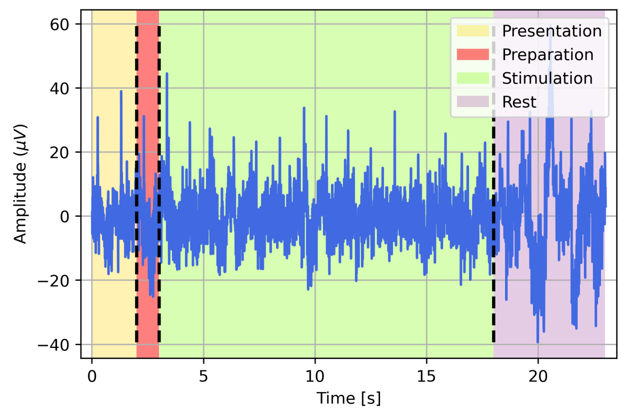

Fig. 5. Data analysis

Then with the stimulation signal we can start to implement the regression model that we would use to estimate these frequencies that are associated with the luminosity stimulus.

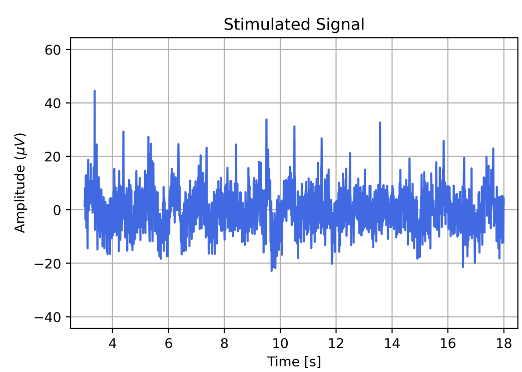

Fig. 6. Data Wrangling

IV. FORECASTING METHODS

A forecasting method is a procedure for computing forecast from present and past. s such it may simply be an algorithmic rule and need not depend an an underlying probability model. Alternatively it may arise from identifying a particular model.

In this work we will concentrate in the Univariate methods, this is when only the forecast depends only in present and past values of the time series that is estimated or predicted.

A. Modelling Approach

Around the several models used in forecasting, we are going to use the Box-Jenkins approach, this method use ARIMA models to estimate the parameters in a time series:

- **Stationary**:
  To address this model approach is important to determinate that the time series is stationary, this means that there are not trend or seasonal characteristics in the data, if there would be the case, need to be differentiated until have a $P - value < 0.05$ that ensure that is stationary (This could be proved by a Augmented Dick-Fuller test).
- **Parameter Estimation:**
  To determinate the parameters used in the ARIMA model, need to check the autocorrelation and partial autocorrelation lags of the time series.
- **Coefficients Estimation:**
  With the model selected and with the orders of the parameters, we can build or model and get the coefficients used, this coefficients are estimated by the MLE (Maximum Likelihood Estimation).

Considering all this aspects we can select an ARIMA model to the estimation of our time series, for this work we will use an $ARIMA(p, 0, 0)$ that represent an Autoregressive Model $(AR(p))$.

B. Autoreggresive Model

A procces $\{X_t\}$ is said to be an autoregressive procces of order p if

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + Z_t \tag{1}$$

where $\{Z_t\}$ denotes a purely random process $(Z_t \sim N(0, \sigma^2_{Z_t}))$

A useful property of an AR(p) process is that it can be shown that the partial ac.f (autocorrelation function) is zero at all lags greater than p. This means that the sample partial ac.f can be used to hel to determinate the order of an AR process (assuming the order is unknown as is usually the case) by looking for the lag value at which the sample "cuts off"(meaning that it should be approximately zero, or at least not significantly different from zero, for higher lags) [5].

C. Estimation of the frequency using PSD

The estimation of the power spectrum using AR(P) models follows:

$$S(f) = \frac{\sigma^2_{Z_t}}{|\sum_{j=1}^{p} \phi_j \exp^{-i2\pi jf}|} \tag{2}$$

The spectrum of the signal estimation are going to allowed to determinate the frequency stimulation registered by the BCI, and goes like:

$$f_{estim} \sim argmax(S(f)) \tag{3}$$

The rationale behind this scoring is to provide more importance to stimulus that produce peaks in its flickering frequency and/or its harmonics, and to reward sharp and narrow peaks since this indicates a strong SSVEP [5].

V. AUTOREGRESIVE MODEL IMPLEMENTATION

Using the data associated with the luminous stimulus we would check the stationarity of time series using a adfuller test:

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P-value: 0.0009672424556578054
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Then we select an order of lags to determinate the order of the AR model.

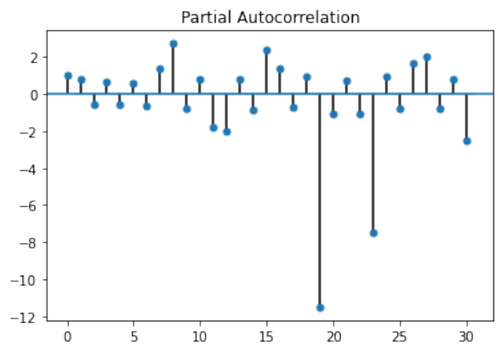

Fig. 7. Partial Autocorrelation Function Graph

We can check that the dispersion of the function doesn't give a confident signal, then we make a list of AR(p) models that change p in a progressive way, and only using the $P - value$ parameters to choose the significance of the coefficient used, taking $p = 9$ as the best parameter taken.

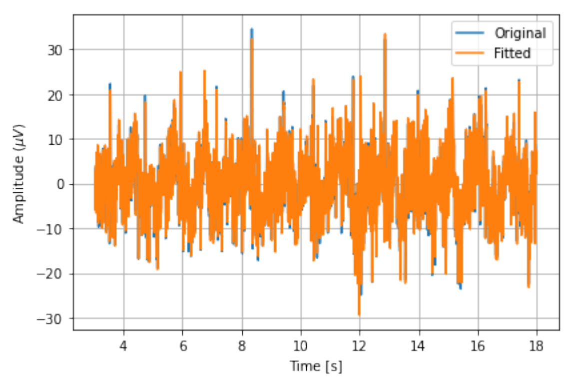

Fig. 8. Fitted AR(9) Model

Then for visual porpuses we plot our fitted model, as we declare earlier, the goal of this work is to estimate the frequency not the next values of the signal, therefore all the variables used in Eq. (2) need to be fulfilled. To construct the sumatory of the Eq. (2) we should use the Euler's formula to compute the correct values, hence, we will have that:

$$|\sum_{j=1}^{p} \phi_j \exp^{-i2\pi jf}| = |\sum_{j=1}^{p} \phi_j cos(2\pi jf)| \qquad (4)$$

And with the residuals of the time series we can calculate the variance of this errors ($\sigma^2_{Z_t}$). Then can be computed the power spectrum of the signal.

The computation of the power spectrum of a single signal can be showed in Fig. 9, where we can find that the peak of the spectrum is between $4 - 6Hz$, this showed that the estimated frequency signal must be in this range.

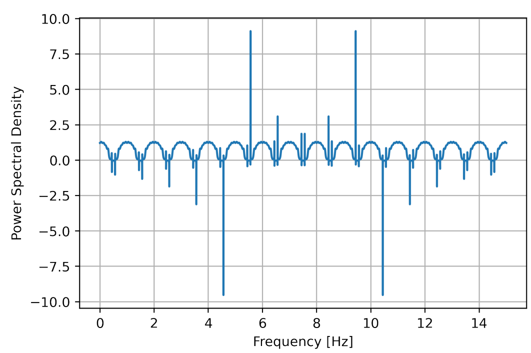

Fig. 9. Power Spectral Density

VI. Results

With the results achieved, we would propose to use the signals of the 8 channels of the data, these multichannel signals have the same frequency stimulus and accordingly, with the results in standalone mode, we will evaluate the accuracy of the constructed model. Therefore using the data collected from the $sample\,80$ of the $patient\,1$ that was put through a luminous stimulation with an associated frequency of $7.5Hz$.

Computing the power spectrum in Fig.10, the maximum argument of the function is between $6 - 8Hz$, being a good estimation but not how is the percentage of error between the estimated frequency and the original data.

Therefore we present the results of the estimations in the Table.I, the calculated error between those signals show that the had a 12% for the majority of the signals, and having only for three almost the current value of the original data.

Using the sample 8 from the same patient, that is triggered by a stimulus frequency of $5Hz$, we repeat the previous process and it's computed the power spectrum of the signal in the Fig.11, and having a the maximum argument in the range of $4 - 6Hz$.

Then we calculate the error from the original data and the estimation using auto-regressive models, observing that from the majority of the signal the error is of the 10%, and with others of 30%.

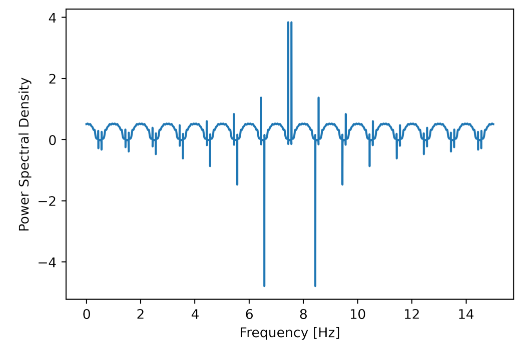

Fig. 10. Power Spectral Density in Sample 80

TABLE I
Results

Signal Used	Frequencies		
	Stimulation Frequency	***Frequency Estimation***	***Error***
$T1\_80\_1$	7.5	6.56	0.93969784
$T1\_80\_2$	7.5	6.56	0.93969784
$T1\_80\_3$	7.5	6.56	0.93969784
$T1\_80\_4$	7.5	6.56	0.93969784
$T1\_80\_5$	7.5	7.44	0.06056265
$T1\_80\_6$	7.5	6.56	0.93969784
$T1\_80\_7$	7.5	7.44	0.06056265
$T1\_80\_8$	7.5	7.44	0.06056265

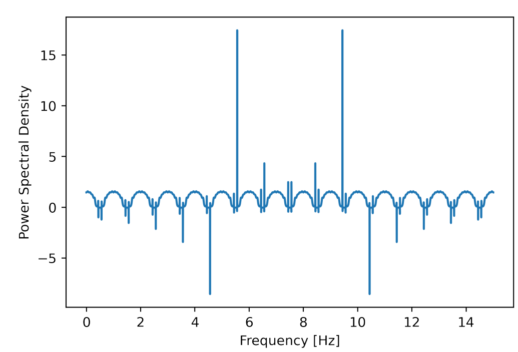

Fig. 11. Power Spectral Density in Sample 8

TABLE II
Results

Signal Used	Frequencies		
	Stimulation Frequency	***Frequency Estimation***	***Error***
$T1\_8\_1$	5.0	5.56	0.56
$T1\_8\_2$	5.0	5.56	0.56
$T1\_8\_3$	5.0	6.56	1.56
$T1\_8\_4$	5.0	5.56	0.56
$T1\_8\_5$	5.0	5.56	0.56
$T1\_8\_6$	5.0	5.56	0.56
$T1\_8\_7$	5.0	6.56	1.56
$T1\_8\_8$	5.0	5.56	0.56

VII. Discussion

In comparison with [5], our approach used in this work is only a simplistic one. The estimation of this frequency not only relay on the calculation of the spectrum, they find an optimal p to get the best value and they score and select the best data that corresponds to the signal and also implement specialized detection methods of SSVEP that triggered confident estimations of 98%. In the case of our work, the estimation of the values was optimal in a $p = 9$ where the estimated values of the frequency were in the nearest range of the original data, having in some results of the signals errors of 2% but in the other channels almost 30%. We can also relate that the values of p are not the best for every sample, in the sample 8 the best was a value of $p = 10$, where the error was minor in comparison with the estimation with $p = 9$. Will be interesting if we can use different autoregressive methods and check if they are a viable option to address this problem.

VIII. Conclusion

One of the greatest challenges that we would face in the future will be the correct selection of the order in the AR models, the approach committed in this work shows the potential that these estimations to get the frequency evoked for this stimulus and contribute to the design of technologies to address the movement problems that had the paraplegic patients. A comparison of these estimations with the ones that can be calculated from the signal processing using FFTs will be an interesting next topic to consider and check the quality and performance in the detection of these expected frequencies as future work.

Acknowledgment

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