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Analysis of the Information Transfer Rate-ITR in Linear and Non-linear Feature Extraction Methods for SSVEP Signals

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***Abstract*— The most popular paradigm in BCIs is the steady-state visually evoked potential (SSVEP) due to their advantages, such as the high information transfer rate (ITR), the time spent on users in the training phase, and the capacity to discriminate each stimulus. One of the most influential factors in the ITR evaluation is the feature extraction methods since these can increase the accuracy. Here, we compare nine methods for the extraction of features from SSVEP signals to identify those with better performance, according to the time window (TW), its technology (equipment and number of nodes), and the value of ITR. The study identifies two groups: the first one is characterized by presenting variations of correlated component analysis (CCA), which is highly used to increase the ITR due to its efficiency in classification and its capacity of response to reduction (TW), such as MsetCCA, IT-CCA, FBCCA; the second one are the representation special based methods that consider the non-linear nature of the electroencephalogram (EEG) signal such as TRCA, CORRCA, EMD, and VMD. The results show a considerable difference between these groups. The maximum ITR value for FBCCA was 117.75 [bits/min] in a TW of 1.25s, while the VMD method achieved 3120 [bits/min] in a TW of 1s, respectively. The comparison covers signals between 0.55 and 8 seconds, taking into account visual strain, the experimental environment, and other artifacts.**

***Keywords*— Steady-state visually evoked potential; brain-computer interfaces; information transfer rate; canonical correlation analysis; empirical mode decomposition.**

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I. INTRODUCTION

Controlling a device, robot, or another machine using only thoughts has been a fantastic notion that has long captured humanity's imagination and interest. In the last decade, this has become a proven reality by avoiding the conventional communication channels (i.e., muscles or speech) between the brain and a computer. A "Brain-Computer Interface (BCI)" gives the users an alternative communication channel linking their brains and external devices. The BCI allows the control of applications using brain signals without the requirement of using the peripheral nervous system, benefiting access to people with limited motor skills, and developing alternative access methods for healthy users [1].

In a BCI system, the user must generate mental activities to produce voluntary changes in brain signals. These activities can be exogenous or endogenous: the exogenous one depends on the electrophysiological activity evoked by external stimuli (for example, the P300, Visually Evoked Potential (VEP), and the Steady-State Visually Evoked Potentials (SSVEP)); the endogenous one depends on the capacity of the user to control his electrophysiological activity without the need for external stimulation [2].

The paradigm of SSVEP stands out for its minimal training capacity, robustness, high Information Transfer Rate (ITR), and high Signal to Noise Ratio (SNR) [3]. The SSVEP paradigm is a spontaneous response to visual stimuli with specific frequencies through the retina, which emits stimuli to the brain, generating a response with the same spectrum [4]. The stimulus normally appears in the occipital and parietal brain lobes, where it is possible to gather much evidence in a relatively short time [4].

BCI systems based on VEP or SSVEP stimuli have demonstrated successful integration from single or multi-frequency coding. The user transmits different commands by switching their attention to different coded targets [5]. According to Scopus, In the last three years, from 14,016 published works about Brain-Computer Interface, 1,088 corresponds to publications related to the SSVEP in the same period. Among the most common SSVEP signal detection techniques are the Canonical Correlation Analysis (CCA) and its variations and the Empirical Mode Decomposition (EMD).

The SSVEP paradigm generally presents a stable spectrum property, which remains low due to the high probability of interfering with irrelevant noise or artifacts. Therefore, developing a high-performance BCI is important to obtain a high SSVEP frequency accuracy using a short time window (TW) [6]. The development of a BCI-SSVEP with a high ITR would benefit applications such as spelling. A spelling application seeks to reduce both the time it takes to identify a character and the visual fatigue, especially for people with verbal and motor communication disabilities. Besides, tools with high ITR would improve the decision-making mechanisms in the field of interactive entertainment.

Fig. 1 shows a BCI's general structure based on the SSVEP paradigm. It can be divided into four phases: data acquisition, signal processing, classification, and end application. The acquisition of signals from a given piece of equipment corresponds to the first stage. The second and third stages depend on the selected paradigm's characteristics; thus, to better analyze a paradigm's performance, it is necessary to focus on either the second or the third stage. The fourth stage is the interaction with the user environment application or control stage.

This paper presents a comparative analysis between the main feature extraction methods (second stage) considering the ITR metric. Besides, ITR is directly related to several study parameters and comparisons such as accuracy, the time window for target signal recognition, the technology used in BCI-SSVEP signal acquisition, and the number of channels. Section II provides the theoretical background of the state-of-the-art feature extraction methods in the SSVEP paradigm. Section III shows the validation tools of the studied methods, performing comparison according to ITR and accuracy metrics, presenting a summary table with the proposed investigations' values and results. Finally, sections III and IV present the discussion and conclusions on ITR, channel optimization, and the methods studied. Fig. 2 shows a structural flowchart of the research methodology that covers the proposal of this work.

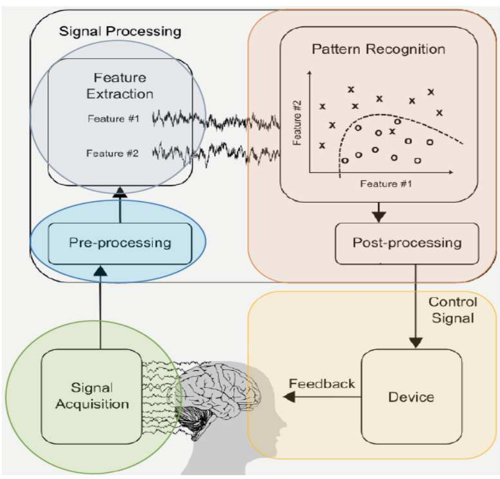

Fig. 1 Structure of a BCI-SSVEP

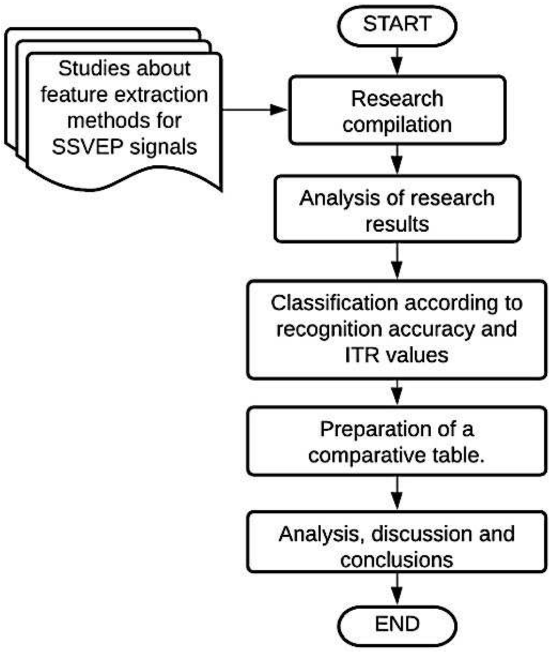

Fig. 2 Flowchart of the research methodology

II. Material and Methods

SSVEP paradigm is a natural response of the brain produced when people keep their eyes fixed on a stimulus that changes at a constant frequency. An EEG equipment is responsible for capturing these stimuli to implement a BCI system [7]. A BCI system based on SSVEP shows many visual stimuli that change at targeted frequencies and are related to a command that needs to be executed. The BCI-SSVEP must detect which stimulus people are observing and execute the command associated with that stimulus.

Many of the SSVEP paradigm feature extraction methods identify the patterns that differentiate one stimulus from another, aiming to respond within a short time window with the highest possible accuracy. Although several feature extraction methods exist, this paper presents two groups: CCA with variations and spatial representation methods.

They have been most relevant in the last years to solve BCI-SSVEP. We also considered aspects such as equipment for acquiring EEG signals, ITR, and TW to compare these methods.

A. Recognition of characteristics on SSVEP paradigm with CCA-based methods

1) Canonical Correlation Analysis (CCA): CCA is a feature extraction technique generally applied in the frequency detection of SSVEP signals, based on statistical methods to determine the correlation of X and Y and their linear combinations. X represents the multichannel SSVEP signals while Y indicates the reference signals, which will be sinusoidal waves with a specific frequency and some harmonics of these [8]. A couple of combinations $x = X^T W_x$, $y = Y^T W_y$, known as canonical variables, are encountered applying CCA in the sets to maximize the correlation. CCA seeks to maximize the correlation of the x and y variables by calculating the weight vectors W_x and W_y. The Y reference signals are based on several harmonic frequencies and a periodic component of the source of the flashing signal displayed with the same frequency. Consequently, the Y signals are adjusted as:

$$Y = \begin{pmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ \vdots \\ \sin(2\pi N_h f_k t) \\ \cos(2\pi N_h f_k t) \end{pmatrix}; \quad t = \frac{1}{S}, \frac{2}{S}, \cdots, \frac{T}{S} \tag{1}$$

being T the number of samples, S the sampling frequency, f_k the stimulus frequency, and N_h the harmonics [9]. The maximization of the correlation of the frequencies of the reference signals will become the target signal, as shown in the following expression:

$$O = \max_k p_k, \quad k = 1,2,\dots,K \tag{2}$$

where K is the maximum number of stimuli and p_k represents the kth CCA coefficient [9].

2) Filter Bank Canonical Correlation Analysis (FBCCA): The FBCCA feature extraction method is a variation of the CCA technique that improves the frequency capture of SSVEP signals [10]. Fig. 3 shows the FBCCA method's scheme and its three main processes, which are described below.

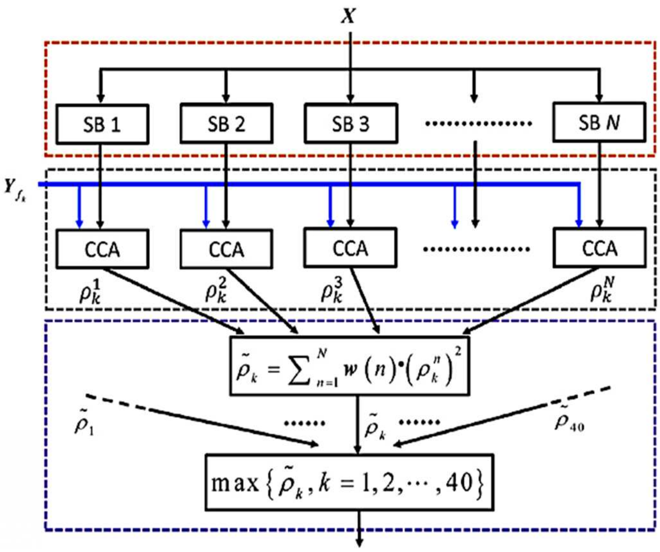

Fig. 3 Schematic diagram of the FBCCA technique for frequency identification of SSVEP signals [10]

The first step is to perform a sub-band decomposition by analyzing a filter bank developed with multiple band-pass filters. The traditional CCA method is then individually utilized by correlating the stimulation frequencies set from reference signals to the sub-band components [10]. Thus, the method obtains a correlation vector ρ, with N values as a function of each signal, as shown in the equation (3):

$$\rho(x, y_k) = [\rho_k^1, \rho_k^2, \dots, \rho_k^N] \tag{3}$$

being $\rho(x, y_k)$ the vector correlation between the variables y_k, $k = 1, 2, \dots, K$(maximum number of stimuli), and each x_n sub-band, $n = 1, 2, \dots, N$. A weighted square sum of correlation values for all components of the sub-band (i.e., $\rho_k^1, \rho_k^2, \dots, \rho_k^N$) and the characteristics are calculated for the identification of the target:

$$\tilde{\rho}_k = \sum_{n=1}^{N} w(n)(\rho_k^n)^2, \tag{4}$$

where n is the sub-band index; thus, the highest correlation will be considered the SSVEP target frequency [11].

3) Individual template based on CCA: Although the standard CCA method has demonstrated its strength in identifying SSVEP signals, the artificial reference signals rarely represent the EEG signals' real behavior. It is due to the absence of training or adjusting procedures based on the subjects. Therefore, CCA does not obtain good accuracy in SSVEP signal recognition, specifically in short-time windowing. The next three approaches show mechanisms to improve the performance through the intervention over the reference signals per stimuli.

The IT-CCA focuses on optimizing the original base signal by extracting characteristics from the EEG data and adding them to the standard target signal [12]. The database of EEG signals consists of training data and test data. Thus, the individual template is obtained using the training data for each subject and stimulus signal. Then, k EEG data tests are recorded for a single stimulus frequency; the kth EEG data is utilized as the training data. The template is generated by averaging the training signals, becoming the user's template for that specific frequency.

The generated individual template is then added to standard reference signals improving the correlation with EEG signals. The optimized signal is shown as:

$$Y = \begin{pmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ \vdots \\ \sin(2\pi N_h f_k t) \\ \cos(2\pi N_h f_k t) \\ Individual\ Template \end{pmatrix} \tag{10}$$

Notice that there will be as many individual templates for each subject as the number of stimulus frequency [12].

4) MsetCCA: The multiset of canonical correlation analysis (MsetCCA) seeks to enhance the reference signals by identifying possible common characteristics of multiple tests at the same stimulus frequency. MsetCCA uses the MAXVAR approach to maximize the highest correlation matrix by providing an extension of the CCA technique applied to multiple sets.

Let $X_i, i = 1,2,\dots,N$ be several sets of random parameters with zero mean and unit variance, the MsetCCA objective function follows [13]:

$$\begin{gathered} \max_{U_1,\dots,U_N} \rho = \sum_{i \neq j}^{N} U_i^T X_i X_j^T U_j \\ s.t. \frac{1}{N} \sum_{i=j}^{N} U_i^T X_i X_j^T U_j = 1 \end{gathered} \tag{5}$$

By using the Lagrange multiplier method, the maximization at (5) can be transformed into the following generalized eigenvalue problem, as a function of equation (6):

$$(R - G)u = \rho G u \tag{6}$$

where:

$$R = \begin{bmatrix} X_1 X_1^T & \cdots & X_1 X_N^T \\ \vdots & \ddots & \vdots \\ X_N X_1^T & \cdots & X_N X_N^T \end{bmatrix},$$

$$G = \begin{bmatrix} X_1 X_1^T & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & X_N X_N^T \end{bmatrix},$$

$$u = \begin{bmatrix} U_1 \\ \vdots \\ U_N \end{bmatrix}$$

The maximum global correlation between the canonical variables can be obtained by applying the given linear transformations as the eigenvector from the highest generalized eigenvalue [13].

5) Multilayer Correlation Maximization (MCM): A multi-layer correlation section (MCM) maximization is an architecture with three-levels developed to optimize the frequency comparisons by maximizing the correlation level by level [14]. MCM reduces common noise and improves performance even more of the MsetCCA for SSVEP signal identification. Each layer is explained below:

- The first layer extracts information related to the frequency of the stimulus from the EEG samples. Thus, $X_{1,m}, \ldots, X_{N,m} \in \Re^{C \times P}$ (C channels and P time points) with N EEG samples recorded for f_m stimulus frequency. The initial level maximizes the correlation of each EEG sample and the sine-cosine reference signal, Y_m, using CCA. The ith sample of the set of linear transformations:

$$W_{i,m} = [\omega_{i,m}^{(1)}, \ldots, \omega_{i,m}^{(L)}] \in R^{C \times L}, \quad (7)$$

being $\omega_{i,m}^{(l)}$ the linear transformation corresponding to the lth eigenvalue. Thus, the eigenvectors take the initial larger L-values, conserved to create the learned linear transformations. It is then used to implement spatial filtering:

$$S_{i,m} = W_{i,m}^T X_{i,m}, \quad (i = 1,2,\ldots,N) \quad (8)$$

The spatial filtering method removes most of the redundant components present in EEG signals. Hence, the data $S_{1,m}, S_{2,m}, \ldots, S_{N,m} \in R^{L \times P}$ identifies only the stimulus related to the target frequency.

- The second layer extracts the common characteristics shared by the spatially filtered data, implemented through $S_{i,m}$ ($i = 1,2, \ldots N$). Based on (5), a set of linear transformations $u_{1,m}, \ldots, u_{N,m} \in R^L$ is resolved to rise to the highest overall correlation between the canonical variants from the spatially filtered data. The optimized reference signal is built as:

$$Z_m = \left[z_{1,m}^T, \ldots, z_{N,m}^T\right]^T \quad (9)$$

where $z_{i,m} = u_{i,m}^T S_{i,m}$ for $i = 1, \ldots, N$ is the canonical variables (common characteristics) obtained through MsetCCA.

- The set of reference signals are reoptimized in the third stage, maximizing the correlation between the optimized reference signal set Z_m and the reference signal sine-cosine Y_m. CCA is implemented between Z_m and Y_m to discover the set of linear transformations $\widetilde{W}_m = [\widetilde{\omega}_m^{(1)}, \ldots, \widetilde{\omega}_m^{(L)}] \in R^{N \times L}$ A linear ponderation of the reference optimized signals is established to extract the target stimuli' frequency with these linear transformations. Therefore, the reoptimized reference signal Q_m given at the target frequency f_m is determined by:

$$Q_m = \widetilde{W}_m^T Z_m \quad (10)$$

B. Recognition of Characteristics on SSVEP Paradigm Based on Spatial Representation

1) Task-related component analysis (TRCA): TRCA is a method where the learning of spatial filters for the extraction of task-related components allows maximizing the reproducibility during each period. Considering that the number of channels N associated with the time signals $x_i(t)$, $i = 1, \ldots, N$ containing k blocks of the same task repeated during the intervals $t \in [t_k, t_k + T]$ with $k = 1, \ldots, K$, where T is the task duration interval. The output $y(t)$ is a linearly weighted sum of the input signals. Fig 4 pictures the TRCA in a task-block. Thus, the method of the task-related component is calculated as:

$$y(t) = \sum_{i=1}^{N} w_i x_i(t) = w^T x(t) \quad (11)$$

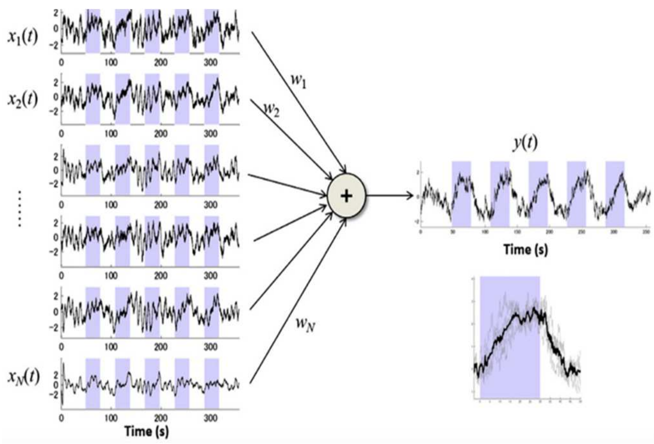

Fig. 4 Diagram of TRCA. Multiple time series (left row) are summed with weights to give a single time course $y(t)$ (right). The shaded area in the time series indicates task blocks of a single task. The weights, or coefficients, are determined to maximize the sum of correlations or covariances of $y(t)$ between task blocks [15].

It is implicitly assumed that the objective signals result from the linearly weighted sum of the components linked to the task and those not linked. Therefore, the task's components can be recovered from the observed signals through the appropriate weighting. The optimized coefficients allow obtaining a task-related element's time profile with the maximum temporal similarity between its intervals [15].

2) Correlated component analysis (CORRCA): This method performs frequency detection using correlated component analysis. This method is used to obtain the highly correlated signal components from multiple EEG signals obtained from various experimental subjects. The CORRCA principle for the analysis between subjects can be applied to the BCI- SSVEP to obtain spatial filters. The linear combinations of the SSVEP data set are robust between trials. They are also highly correlated, i.e., they keep a maximum correlation between subjects.

CORRCA is generally used for learning the spatial filters involving the training data and the stimulus frequencies of each user. In this way, the projection signals are found using a single test and the reference signal, finding the correlation coefficient between them [16].

If $X_1 \in \mathbb{R}^{C\times N}$ and $X_2 \in \mathbb{R}^{C\times N}$ are multidimensional variables, where C represents the number of channels and N is the number of samples, the method tries to solve the weight vector $w \in \mathbb{R}^{C\times 1}$ such that the resulting linear combination $x = w^T X_1$ and $y = w^T X_2$ show the maximum correlation [16].

$$\hat{\rho} = \arg\max_{w} \frac{x^T y}{\|x\|\|y\|} = arg\ max_{w} \frac{x^T R_{12} w}{\sqrt{w^T R_{11} w}\sqrt{w^T R_{22} w}} \quad (12)$$

being $\hat{\rho}$ the correlation coefficient and $R_{ij} = \frac{1}{N}\boldsymbol{X}_i \boldsymbol{X}_{ij}^T$, the covariance matrices of the sample, where $i, j = 1{,}2$. From (12) is differentiated as a function of w, then the expression is equalized to zero and $w^T R_{11} w = w^T R_{22} w$, from here the eigenvectors are found as follows:

$$(R_{12} + R_{21})w = \lambda(R_{11} + R_{22})w \quad (13)$$

The maximum $\hat{\rho}$ corresponds to the leading eigenvector of $(R_{11} + R_{22})^{-1}(R_{12} + R_{21})$ which maximizes the correlation coefficient between x and y. In addition, the second strongest correlation is achieved by projecting the data matrices over the eigenvector corresponding to the second strongest eigenvalue, and so on progressively.

3) Empirical Mode Decomposition (EMD) and Ensemble EMD: EMD is an adaptive method based on non-linear and non-stationary data-driven analysis. EMD could be experimentally decomposed into a residual element and the main forms called Intrinsic Mode Functions (IMFs). Equation (14) presents this approach, in which $\mathrm{e(t)}$ is a temporal sequence, $\mathrm{u_i(t)}$ specifies the IMF from 1 to N, and the residual iteration is $\mathrm{r(t)}$.

$$e(t) = \sum_{i=1}^{N} u_i(t) + r(t) \quad (14)$$

IMFs show full and near-orthogonal oscillation signal variations to be used as baseline functions from the data. This technique has been widely used to analyze non-linear processes and variants in time, such as weather signals, natural phenomena, bio-signals, among others [17].

Also, the Ensemble EMD (EEMD) method was developed to solve the effect of mode mixing. Due to the intermittent signal, the mode blending problem in EMD computing produces strong alias in the IMFs. It could hide individual characteristics in the time-frequency domain. In several tests, the EEMD method includes several sets of white noise in the signal. As the added noise changes in each test, the resulting IMFs show no correlation with the respective IMFs from one test to another. Additional noise can be eliminated by averaging the IMFs collected from the various tests together [18].

The signal $e(t)$ in j^{th} trial can be obtained as follows:

$$e^j(t) = e(t) + a_o w^j(n), \quad \text{for } j = 1, \ldots N \quad (15)$$

being $w^j(n)$ the white noise in j^{th} trial with unit variance and a_o amplitude. The average k^{th} $\overline{u_k(t)}$ is defined as:

$$\overline{u_k(t)} = \frac{1}{N}\sum_j^N u_k^j \quad (16)$$

4) Variational Mode Decomposition (VMD): It is a method that consists of decomposing a multi-component signal into Intrinsically Band Limited Mode Functions (BLIMFs) of the input signal into sub-signals known as:

$$u_k = A_k(t)\cos(\emptyset_k(t)) \quad (17)$$

being $\emptyset'_k(\mathrm{t})$ the phase, $\mathrm{A_k}$ the amplitude and $W_k = \emptyset'_k(\mathrm{t})$ the instantaneous frequency, respectively.

The VMD model's construction is based on three signal processing tools: Hilbert transformation, Wiener filtering, and frequency matching. The VMD consists of decomposing an input signal into K sub-signals (modes) denoted as u_k and each one of these is compact around a central w_k pulse. The restricted variation model built by the VMD [19] is described as:

$$\min_{\{u_k\}.\{w_k\}} \left\{\sum_{k=1}^{k} \left\| \delta_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-jw_k t} \right\|^2\right\} \quad (18)$$

$$s.t. \quad \sum_{k=1}^{k} u_k = f \quad (19)$$

Thus, to build the model, we first use the Hilbert transform to calculate in each mode u_k as an analytical signal and obtain the one-sided frequency spectrum. Later, we multiply by $e^{jw_k t}$ to change the frequency spectrum of the baseband mode. Finally, to estimate the bandwidth, we calculate the mean of the square L^2-gradient rule. To convert the restricted variation problem into an unrestricted variation problem, the increased Lagrangian L is implemented [19]:

$$L(\{u_k\},\{w_k\},\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\sigma(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-jw_k t} \right\|_2^2 + \|f(t) - \sum_k u_k(t)\|_2^2 + \langle \lambda(t), f(t) - \sum_k u_k(t)\rangle \quad (20)$$

The minimization problem is finding the seat of the increased Lagrangian L in a series of iterative sub-signals and central pulsations, as shown in (20).

III. Results and Discussion

A. Parameters

Table I shows some studies about the performance of different SSVEP detection methods. Here $\boldsymbol{Ch}$ is the number of channels from the EEG device, $\boldsymbol{Sub}$ is the number of experimental subjects, and $\boldsymbol{Tr}$ is the number of stimuli (targets). Although the studies considered various metrics to evaluate and compare their performance, the most widely used are ITR and accuracy.

Accuracy is the proportion of correct recognitions to the total number of experiments used. On the other hand, the ITR is shown in equation (21), as recommended by [20]:

$$\mathrm{ITR} = \left[\log_2(N) + P * \log_2(P) + (1-P) * \log_2\left(\frac{1-P}{N-1}\right)\right] * \frac{60}{T} \quad (21)$$

where N is the stimulus frequencies, P is the recognition accuracy, and T represents the duration per trial.

TABLE I
SUMMARY OF STUDIES

No.	Ref.	Description	Ch.	Tr.	Sub.	Feature Extraction Method	ITR [bits/min] (max.)	Average accuracy [%](max.)
1	[9]	Comparative study of PSDA and CCA methods for the detection of the SSVEP paradigm	64	24	7	PSDA CCA	89.54 N/A 112.57 N/A	86.90 N/A 97.62 N/A
2	[21]	SSVEP BCIs developed with the LASSO method for the recognition of stimulus frequency signals	3	4	9	LASSO CCA	60 TW=1s 50.5 TW=1s	100 T=1s 96 T=1s
3	[11]	A Benchmark database for the analysis of BCIs based on SSVEP signals	64	40	35	FBCCA CCA	117.75 TW=1.25s 89.89 TW=1.75s	78 T=1.25s 76 T=1.75s
4	[22]	Comparison of methods based on Canonical Correlation Analysis to detect SSVEP signals	8	12	10	CCA MwayCCA L1-MCCA MsetCCA IT-CCA IT-CCA+CCA	50.40 TW=2s 64.15 TW=1.5s 65.06 TW=1.5s 66.22 TW=1.5s 71.37 TW=1s 91.68 TW=1s	83 T=2s 85 T=1.5s 85 T=1.5s 87 T=1.5s 82 T =1s 93 T=1s
5	[19]	Improvement of the performance of a BCI-SSVEP through the method of Correlated Component Analysis	64	40	35	TRCA CORRCA	155 TW=1s 170 TW=0.8s	82 T=1s 80 T=0.8s
6	[17]	Proposed Variational Mode Decomposition Method for the Development of a High-Performance BCI-SSVEP	8	13	5	EMD EEMD CEEEMD VMD	1900 TW=3s 490 TW=2.5s 200 TW=4s 3120 TW=1s	85 T=3s 84 T=2.5s 90.5 T=4s 75.5 T=1s

The presented works specify the authors' available ITR values and their corresponding accuracy. These values correspond in some cases to the average, and in other cases, to the maximum value. By default, if the papers have both the maximum and average values, we only show the maximum values.

B. *Method comparison for SSVEP paradigm*

The work in [9] presents a comparison of the standard CCA method with the power spectral density analysis (PSDA). The document compares the methods in four aspects: ITR, operating speed, recognition accuracy, and power spectral amplitude. The technology used in this study was the BioSemi ActiveTwo EEG system. The results analyzed in the study related to the four aspects that have been considered show that the CCA method surpassed the PSDA. The CCA method presented a higher value for the fundamental frequency and the second harmonic of the power spectrum. In Table I, the ITR and accuracy data are available, which are higher for the CCA. CCA method also had a better performance in terms of operation speed since it presented an averaged recognition time of 0.32 s and PSDA of 0.42 s.

The research in [21] proposes recognizing SSVEP with a smaller error rate in a shorter time, using the LASSO method. The Nuamps amplifier made data acquisition. The results show that the LASSO method performs better against CCA because it can recognize the BCI stimulus frequency in a smaller time window based on SSVEP. Therefore, the authors concluded that LASSO reduces recognition time without compromising accuracy, which generates a higher ITR value.

Other studies employ methods based on CCA but with some variants to improve their performance. For example, in [11], the authors present a benchmark SSVEP database obtained with a BCI spelling system of 40 targets used to compare the performance between the CCA and FBCCA methods. The results proved a better performance of FBCCA over CCA by obtaining a maximum ITR. The FBCCA method obtained 117.75 [bits/min] over the CCA, which showed an ITR of 89.89 [bits/min].

The authors in [22] compare the CCA method with some other variants such as L1-MCCA, CACC, MsetCCA, ITCCA, MwayCCA, and a method that combines IT-CCA and CCA. The experiment with each user consisted of 15 blocks, with 12 trials for each. A trial had a total duration of 5 seconds (1 second of gaze shifting time and 4 seconds of exposure). According to the results obtained, the traditional CCA and the CACC method had a very similar performance to each other and the lowest among them. On the other hand, the combined method between the IT-CCA and the CCA had the best performance. Here, the mixed method achieved an ITR of 91.68 [bits/min], while the CCA method only obtained 50.40 [bits/min].

In summary, these previous works show that methods based on template modifications get better performance than those based on input data processing.

On the other hand, the spatial representation methods, we checked some relevant studies. In [19], the authors make a comparison between the task-related component analysis (TRCA) and the correlated component analysis (CORRCA). The experiment uses the same dataset of [11]. Analyzing the data obtained, the authors conclude that the TRCA-based method shows less favorable results than the CORRCA-based method. In [17], the authors presented a method using variational mode decomposition (VMD) and EMD, EEMD, and CEEEMD methods. The results show very similar performance in terms of the final accuracy achieved by the four methods. In terms of ITR, the VMD is significantly higher than other methods with 3,120 [bits/min], which allows the authors to conclude that VMD would be the most recommended among them.

In general, comparing the methods based on CCA with any spatial representation methods, we see a very high advantage of the spatial representation methods. The ITR values obtained by the CCA-based methods vary around 100 [bits/min]. In contrast, the spatial representation can obtain values between 155 to 3,120 [bits/min].

C. Discussion

Although various studies have shown that the accuracy achieved with any of them can be high (over 90%), sometimes they spend much time. The goal is to achieve the shortest time possible with high accuracy getting a higher ITR. As a consequence, the subject would be less exposed to stimuli, reducing fatigue. Many methods and algorithms have been developed to point out this goal; here, we only checked two groups: the CCA-based and the spatial representation methods.

The CCA method and its variations are among the most widely used in detecting SSVEP for BCI systems since it is efficient compared to others, with a simple and stable application [17]. However, some other methods, such as spatial representation methods, more recent than CCA, have appeared promising results and showing significantly higher performances than CCA-based methods.

The first four studies (see Table I) show that the performance of the standard CCA can be improved through the use of the traditional method in combination with others, with filters, or with specific alterations to the method. It is worth mentioning that the CCA and the vast majority of commonly used methods are linear. Regarding the spatial representation methods presented, they involve considerations that allow them to be used in non-linear processes. Indeed, the ITR differences between them are not very wide, reaching 117.5 [bits/min]. On the other hand, in the fifth and sixth studies, these values are easily exceeded, especially by the VMD method, which reaches 3,120 [bits/min], showing a critical advance against others.

In [23], the authors mentioned that non-linear methods would give better results than linear methods because the brain naturally emits non-linear signals. Therefore, a significant performance improvement would be expected in future studies to extract SSVEP signal features when considering the use and development of non-linear methods.

Considering all the previous assumptions, we perceive a possible use of the non-linear CCA method [24] for future studies. According to our research, non-linear methods based on CCA have not been presented yet.

This non-linear CCA proposal uses computational intelligence tools such as neural networks to modify the CCA, turning it into a non-linear method. NLCCA has shown good performance in forecasting for meteorological applications; its potential use could considerably detect BCI-SSVEP signals by adding the robust performance of the CCA method and the non-linear nature of brain signals.

IV. CONCLUSION

This article provides evidence about the processing of brain signals that is naturally non-linear. Their processing with methods based on non-linear systems improves the capacity to enhance accuracy, reaching very high information transfer rates. According to the review carried out, it is observed that VMD and FBCCA differ by 96.23% concerning the information transfer rate-ITR.

On the other hand, techniques based on canonical correlation analysis have focused on handling the template and the input EEG-signals as linear approaches. However, there has not been any evidence about the non-linear CCA (NLCCA) method on the BCI-SSVEP paradigm. The NLCCA method could improve performance while processing over the electroencephalogram non-linear nature signals, opening a research field of deep analysis to improve the performance of accuracy and ITR being susceptible parameters for this paradigm.

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