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Brain–computer interfaces based on code-modulated visual evoked potentials (c-VEP): a literature review

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Abstract. *Objective.* Code-modulated visual evoked potentials (c-VEP) have been consolidated in recent years as robust control signals capable of providing non-invasive brain–computer interfaces (BCIs) for reliable, high-speed communication. Their usefulness for communication and control purposes has been reflected in an exponential increase of related articles in the last decade. The aim of this review is to provide a comprehensive overview of the literature to gain understanding of the existing research on c-VEP-based BCIs, since its inception (1984) until today (2021), as well as to identify promising future research lines. *Approach.* The literature review was conducted according to the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) guidelines. After assessing the eligibility of journal manuscripts, conferences, book chapters and non-indexed documents, a total of 70 studies were included. A comprehensive analysis of the main characteristics and design choices of c-VEP-based BCIs was discussed, including stimulation paradigms, signal processing, modeling responses, applications, etc. *Main results.* The literature review showed that state-of-the-art c-VEP-based BCIs are able to provide an accurate control of the system with a large number of commands, high selection speeds and even without calibration. In general, a lack of validation in real setups was observed, especially regarding the validation with disabled populations. Future work should be focused toward developing self-paced c-VEP-based portable BCIs applied in real-world environments that could exploit the unique benefits of c-VEP paradigms. Some aspects such as asynchrony, unsupervised training, or code optimization still require further research and development. *Significance.* Despite the growing popularity of c-VEP-based BCIs, to the best of our knowledge, this is the first literature review on the topic. In addition to providing a joint discussion of the advances in the field, some future lines of research are suggested to contribute to the development of reliable plug-and-play c-VEP-based BCIs.

Keywords: visual evoked potential (VEP), code-modulated VEP (c-VEP), brain–computer interface (BCI), electroencephalogram (EEG), literature review.

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1. Introduction

For decades, mankind has fantasized about the possibility of controlling devices with brain signals. Despite that there is still a long way to achieve this goal, recent progress in computational neuroscience took a step forward and contributed to the development of the first non-invasive brain–computer interface (BCI) systems. Through a real-time monitoring of the electroencephalographic (EEG) signals, BCIs are able to translate users' intentions into application commands [1]. Traditionally, BCIs have been aimed at improving the quality of life of motor-disabled people by replacing their central nervous system outputs. Recent studies have also been focused on applying BCIs for neurorehabilitation [2], cognitive training [3], mental state monitoring [4] and even leisure activities [5]. Unfortunately, despite the efforts within the research community, BCIs are still considered an *orphan technology*; i.e., the BCIs have been tested in the laboratory but do not provide sufficient incentives to be commercially interesting in their current form [1]. Rarely is the technological readiness level (TRL) high enough for commercial applications, as the methods are often not validated with either the target group of users or in their own environment [1].

A major limitation of current BCIs is their inconsistent performance, which tends to vary substantially during and between sessions and individuals [1]. Due to the inherent limitations of the EEG (e.g., low spatial resolution, poor signal-to-noise ratio, volume conduction), users' intentions are not directly reflected in their raw EEG signals, even in the rare cases where neural representation of cognitive processes is well-known [1, 6]. Thus, decoding users' intentions in real-time is a challenge that the researcher should face. In practice, BCI paradigms rely on the detection of measurable changes in the EEG related to different tasks, known as control signals [1, 7].

The selection of a control signal usually depends on the purpose of the system. For instance, in therapeutic applications where an accurate and explicit control of the BCI may not be required, but the reinforcement of neural pathways through neurofeedback training (e.g., neurorehabilitation, cognitive training), self-regulated control signals such as sensorimotor rhythms (SMR) or slow-cortical potentials (SCP) are more common [1, 6, 7]. On the other hand, BCIs for control and communication purposes often rely on event-related potentials (ERP), i.e., time-locked responses to certain events [1, 7], usually as visual evoked potentials (VEP). Their modulation through the user's volitional attention to one of the possible targets allows the BCI to detect the ERP and emit the corresponding command. Unlike SMR or SCP, these control signals allow the discrimination of a great amount of classes, while requiring less training and achieving a higher decoding accuracy and information transfer rate (ITR) [1]. For ERP-based BCIs, *oddball* paradigms that elicit P300 responses have demonstrated their feasibility for healthy users (HU, approx. accuracy >90%, ITR of 10–25 bpm) [8–10] and motor-disabled users (MDU, approx. >80%, 10–25 bpm) [8, 9, 11, 12]. For VEP-based BCIs, steady-state VEPs (SSVEP) have traditionally stood out due to their simplicity and speed. The classical SSVEP system flickers each command at a particular frequency, generating an oscillatory response in the EEG that matches the frequency of the command the user is looking at [1]. This methodology has been mainly tested with HU (approx. >90%, 40-50 bpm) [13, 14], and seldom with MDU (approx. >80%, 10-40 bpm) [15, 16]. For a comprehensive review on SSVEPs, see Vialatte et al. [17].

Whilst P300 and SSVEP-based BCIs are able to provide a suitable level of system control, performances do not approximate to a muscle-based control, nor to the required level of reliability for a practical use [1]. During the last decades, the research community has proposed novel approaches toward the development of plug-and-play, non-invasive BCIs; such as reduced calibration, asynchronous systems, adaptive systems, or variations of known paradigms. Among these proposals, a growing interest in a novel control signal arose due to its ability to reach excellent performances and reduced calibration times: the code-modulated VEPs (c-VEP). In this paradigm, commands flash following pseudo-random noise codes, generating EEG responses that are more correlated with the command the user is paying attention to than with the rest [13].

The basis of c-VEP systems was proposed by Sutter in 1984 [18] and tested with an amyotrophic lateral sclerosis (ALS) patient in 1992 [19], reaching communication rates of 10-12 words per minute using an invasive electrocorticographic (ECoG) system. These studies were ignored by the research community until 2009, when Bin and colleagues [13] demonstrated the feasibility of Sutter's idea in an EEG-based BCI, showing that the c-VEP approach (91%, 92.8 bpm) outperformed the classical SSVEP paradigm (85%, 39.7 bpm) in HU using only one EEG channel (i.e., Oz) [13]. These results caused an exponential outburst of c-VEP-based studies in the literature, which reasserted the efficacy of this control signal to achieve state-of-the-art high-speed non-invasive BCIs. Notwithstanding its popularity, to the best of our knowledge, there is no literature review on c-VEP-based BCI systems.

Therefore, this literature review aims to gain a comprehensive understanding of the existing research about EEG-based BCIs that apply c-VEP as control signal. In total, 70 studies have been included in this review, which allowed us to draw joint conclusions

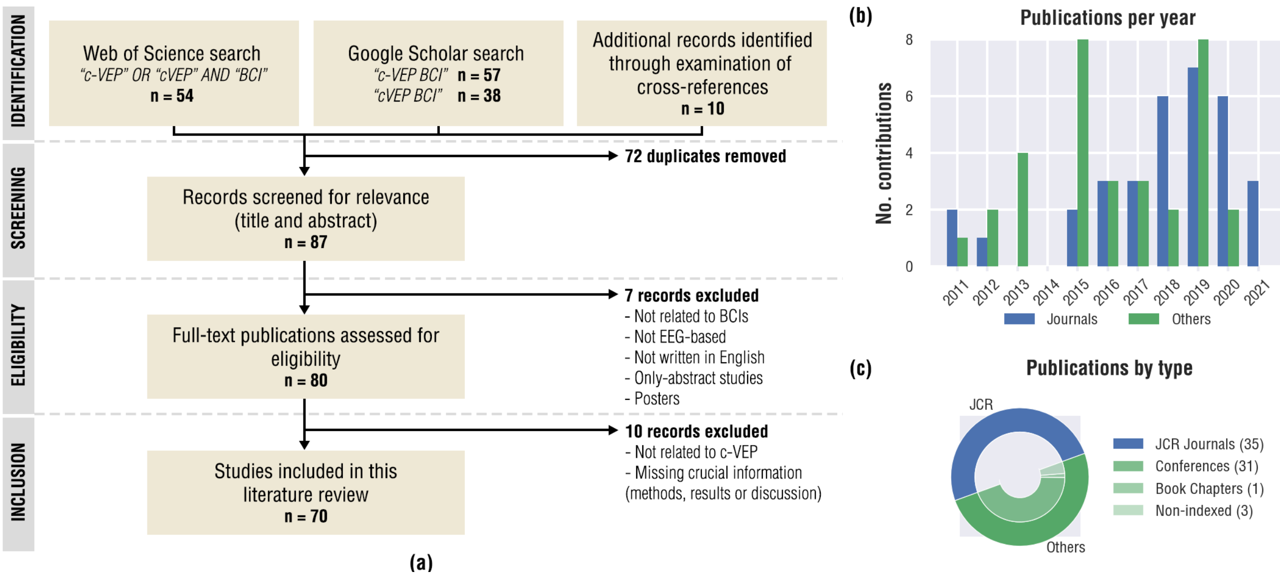

Figure 1. (a) Flowchart of the study selection process as carried out in accordance with the PRISMA guidelines. (b) Distribution of c-VEP-related publications per year during the last decade. (c) Number of c-VEP-related JCR-indexed journals, conferences, book chapters and non-indexed records included in the literature review.

about past and current approaches, as well as to identify current challenges and future research lines in this exciting field.

The manuscript is organized as follows. Section 2 details the study selection process and the basis of c-VEP systems. In section 3, an analysis of the main aspects of c-VEP-based BCIs is shown: comparison with other solutions, paradigms, signal processing, sensor robustness, public databases, applications, etc. State-of-the-art c-VEP BCIs, open questions, current challenges and future research lines are discussed in section 4. Finally, section 5 draws a joint conclusion considering all the reviewed studies.

2. Methods

2.1. Study selection process

This literature review was conducted according to the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA) guidelines [20]. A systematic search within Web of Science (WOS) and Google Scholar (GS) databases was performed to identify BCI studies based on c-VEP. For WOS, the advanced search query was 'c-VEP' OR 'cVEP' AND 'BCI', including all years and databases. For GS, two separate searches were conducted using the terms 'c-VEP BCI' (GS1) and 'cVEP BCI' (GS2). In order to provide a comprehensive review of the literature, all types of records were screened, including journal publications indexed in Journal Citation Reports (JCR), conferences, book chapters and non-indexed studies. Figure 1 details the study selection process according to the PRISMA statement. As shown, a total of 159 records were identified through the aforementioned searches (WOS: 54, GS1: 57, GS2: 38). Ten additional records were identified through other articles references. After duplication removal, 87 studies were screened for relevance via title and abstract examination. Seven records were excluded in this step, that were either unrelated to BCIs or EEG, were not written in English or were only composed by an abstract/poster. Thus, 80 publications were assessed for eligibility by carefully reading the entire manuscript. At this point, studies that were not related to c-VEP or that lacked crucial information (e.g., methods, results, discussion) were excluded. After the selection process, a total of 70 studies were included in this literature review. A table that summarizes the main aspects of all the included studies is available in the supplementary material.

2.2. The basis of c-VEPs

Interestingly, stimulus modulations of VEP-based BCIs share many similarities with the channel access methods used in telecommunications, which allow more than two terminals to share bandwidth without causing interference to their transmissions. Considering a terminal as a selection command, SSVEP-based BCIs work like frequency-division multiple access (FDMA), assigning each command to a different stimulation frequency. For that reason, SSVEP are also known as frequency-modulated VEP (f-VEP). Similarly, c-VEP-based BCIs use pseudorandom sequences to encode each command, as code-division multiple access

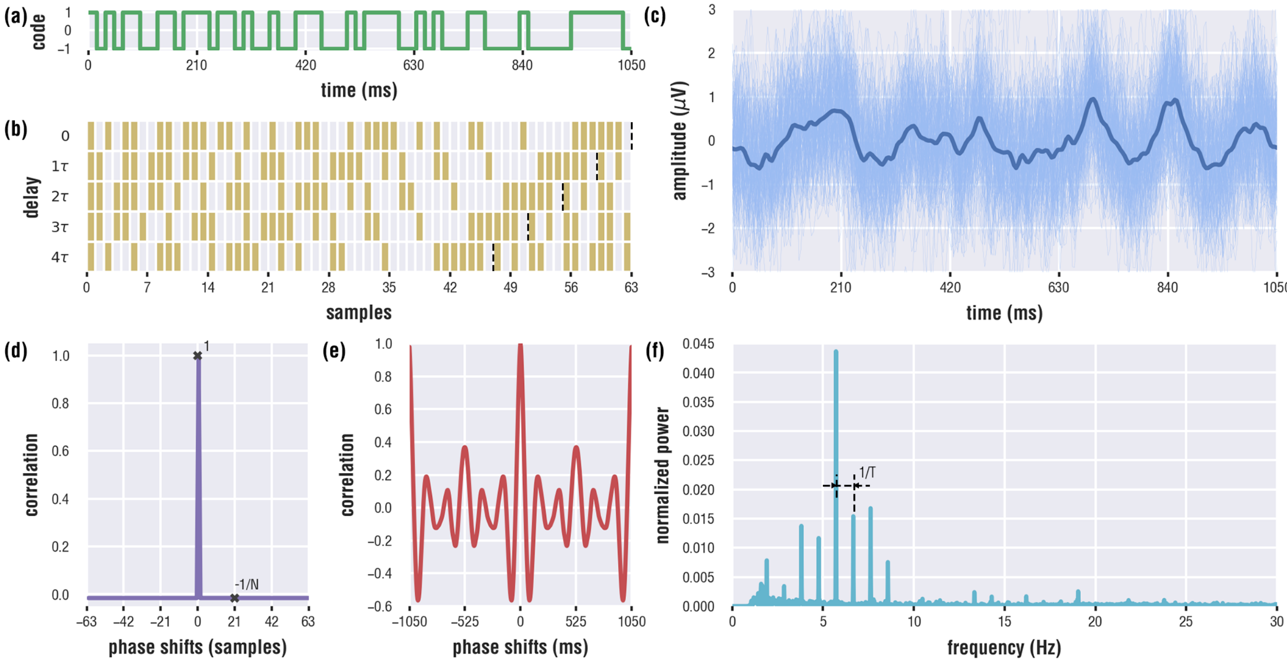

Figure 2. Codes and evoked responses of a c-VEP system with a monitor rate of 60 Hz. (a) Main code derived from a binary m-sequence of 63 bits. (b) Delayed versions of the m-sequence using shifts of $\tau = 4$ samples, which would be assigned to different commands. (c) Main template, computed as the averaged EEG responses to 150 calibration cycles. (d) Periodic autocorrelation function of the m-sequence. (e) Periodic autocorrelation function of the template. (f) Normalized power spectral density of the template.

(CDMA) does [21]. As a result, the broadband stimulation in c-VEP causes broadband responses that can be decoded robustly even in the presence of narrow-band interference (e.g., salient unrelated brain oscillations, such as α waves). On the other hand, SSVEP are based on narrow-band stimuli, so they can be decoded in the presence of broadband noise [22].

Although each command could be modulated by a different code, finding a family of codes with suitable cross-correlation properties is not trivial [22]. Thus, the classical approach relies on finding a pseudorandom binary sequence that presents low auto-correlation values for non-zero circular shifts, then encoding each command with time-delayed versions of the original sequence [13, 19]. Maximal length sequences (i.e., m-sequences), easily generated by linear feedback shift registers (LFSR), are often employed in c-VEP-based BCIs due to their excellent autocorrelation properties; i.e., 1 for a null shift, and $-1/N$ otherwise, where N is the length of the m-sequence [21].

Figure 2 summarizes the rationale behind a c-VEP-based BCI system. A binary 63-bit m-sequence (generated using a LFSR of length $m = 6$ with taps 110000 and polynomial $x^6 + x^5 + 1$) is shown in figure 2(a). A LFSR of length $m = 6$ generates an m-sequence of length $2^m - 1 = 63$ bits. In this case, the monitor rate was 60 Hz, so a complete cycle lasted $T = 1.05$ s (i.e., 63/60). Figure 2(b) shows the encoding of 5 possible commands, which would flicker using time-delayed versions of the m-sequence, whose lags increase with a step of $\tau = 4$. Whenever the screen is refreshed, each command lightens if its current code sample is 1, and dims otherwise. After recording, pre-processing and averaging all EEG responses to complete calibration cycles of the original m-sequence, a main template is computed, as shown in figure 2(c). Several signal processing methods to create this template will be discussed in the following sections. The periodic autocorrelation of the m-sequence is depicted in figure 2(d). Although the stimuli of different commands will be uncorrelated, it cannot be claimed that the EEG responses will be uncorrelated as well. This effect can happen when brain is modeled as a linear system, and even more when a nonlinear dynamic system is assumed [23]. Figure 2(e) plots the auto-correlation function of the EEG template. For the case of time-shifted stimuli, despite responses not being completely uncorrelated for certain lags like in the underlying bit-sequence, usually there is enough distinction to identify the time-shift of the EEG responses. This is achieved by creating templates for each command, circularly shifting the main template according to their lags. In online sessions, whenever an EEG response to several test cycles arrives, it is pre-processed and compared with all the templates. Hence, the selected command is identified as the one

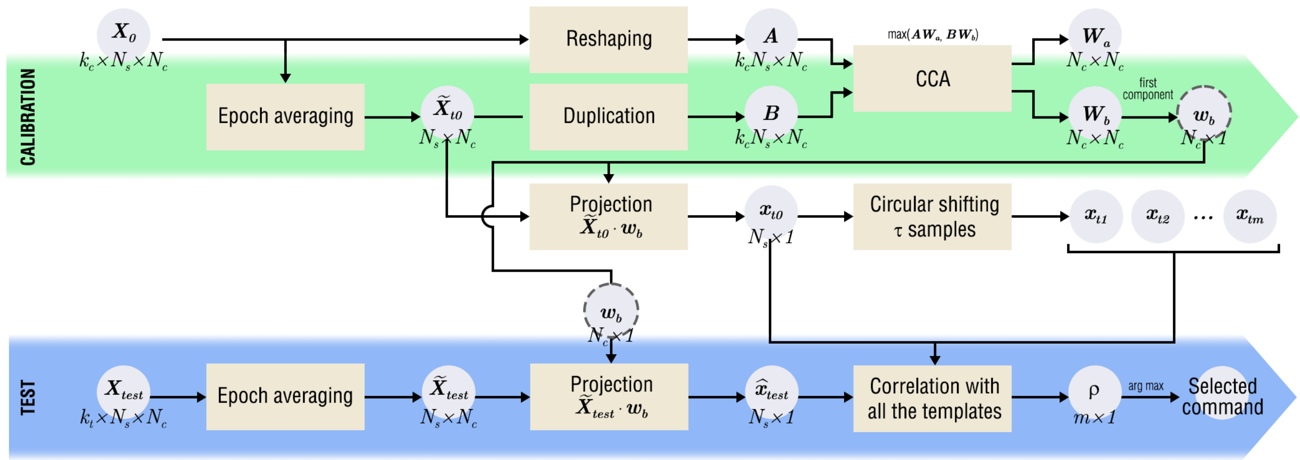

Figure 3. The reference processing pipeline for c-VEP-based BCIs. Calibration stage aims at computing the templates for each command, according to their lags. In online sessions, the test stage projects the trial epochs and determines the selected command through a correlation analysis. Variables N_s, N_c, k_c and k_t refer to the number of samples, channels, calibration cycles and test cycles, respectively; while τ indicates the lag step.

whose template reaches the maximal correlation with the processed EEG response [13]. Finally, figure 2(f) shows the power spectral density of the EEG responses used to build the template. Since the maximum frequency component for a 60 Hz monitor is 30 Hz (i.e., equivalent to the code 10101010...), the gamma band (i.e., $\gamma \in 30 - 100$ Hz) will be least affected by the stimulation. Note that the peaks of the spectrum correspond to the harmonics of the m-sequence period (i.e., $1/T = 0.952$ Hz), which are more pronounced over the 1-10 Hz band.

3. Results

3.1. Equivalent terms

The term "c-VEP", which either stands for *code-modulated* or *codebook* VEP, has been used consistently in 91.30% of the studies included in the review (i.e., 63/70), consolidating as the main term over the years. However, there are several subsidiary terms that should be known to identify further research in the field. For instance, Thielen et al. [24, 25] referred to them as *broad-band VEPs* (BBVEPs), according to their spectral properties. On the other hand, Nagel et al. [26] initially used the term *random VEPs* (rVEPs) to describe c-VEPs produced as responses to completely random codes. Since c-VEPs do not refer specifically to VEPs caused by m-sequences, but to pseudorandom codes in general, rVEPs can be also considered a synonym for c-VEPs. Of note, some authors used the term 'noise-tagging' to refer to the general approach of employing pseudorandom codes to modulate stimuli in different paradigms [27].

3.2. A reference processing pipeline

Throughout the years, a great amount of methodologies have been proposed to improve the performance of c-VEP-based BCIs. These approaches have targeted all system stages, such as paradigm variations, stimulus presentation, feature extraction and classification, asynchrony, etc. Although all of these ideas will be discussed in the following subsections, we have identified a reference signal processing pipeline that is exactly the same in 24 out of 70 studies. We expect it to be improved by other state-of-the-art methods, and to evolve into a best practice or 'gold standard'. However, we encourage its as-is implementation as reference pipeline and as a first approximation to c-VEP-based BCIs.

The reference approach, depicted in figure 3, uses a multi-channel EEG system (55/70), where commands are encoded by delayed versions of a 63-bit m-sequence (35/70). The lag step may be $\tau = 2$ (20/70) or $\tau = 4$ (61/70) depending on the number of possible commands, usually 32 or 16, respectively. During training, the user is asked to focus on a reference target (which can be any command, although it is usually the one without lag for simplicity) for k_c calibration cycles. Then, EEG epochs are reshaped with dimensions $\boldsymbol{X}_0 \in \mathbb{R}^{k_c, N_s, N_c}$, where N_s are the number of samples of a complete cycle, and N_c the number of EEG channels. A multi-channel response is computed by averaging over the k_c cycles, obtaining $\tilde{\boldsymbol{X}}_{t0} \in \mathbb{R}^{N_s, N_c}$. Afterward, canonical correlation analysis (CCA) is applied to maximize the correlation between individual epochs and the averaged EEG response (44/70). CCA finds linear projections of two signals $\boldsymbol{A}$ and $\boldsymbol{B}$ that maximize the correlation between them [28]. In this case, $\boldsymbol{A} \in \mathbb{R}^{k_c \cdot N_s, N_c}$ would be the concatenated $\boldsymbol{x}_0$ epochs; and $\boldsymbol{B} \in \mathbb{R}^{k_c \cdot N_s, N_c}$ the $\tilde{\boldsymbol{x}}_{t0}$ replicated k_c times to match the dimensions. After optimizing:

$$\max_{\boldsymbol{W}_a,\boldsymbol{W}_b} \frac{\boldsymbol{W}_a^T\boldsymbol{A}^T\boldsymbol{B}\boldsymbol{W}_b}{\sqrt{\boldsymbol{W}_a^T\boldsymbol{A}^T\boldsymbol{A}\boldsymbol{W}_a \cdot \boldsymbol{W}_b^T\boldsymbol{B}^T\boldsymbol{B}\boldsymbol{W}_b}}, \tag{1}$$

spatial filters $\boldsymbol{W}_a \in \mathbb{R}^{N_c,N_c}$ and $\boldsymbol{W}_b \in \mathbb{R}^{N_c,N_c}$ are obtained. For c-VEP-based BCIs, only the filters $\boldsymbol{w}_a$ and $\boldsymbol{w}_b$ that maximize the correlation coefficient between the projected epochs (i.e., $\boldsymbol{A}\boldsymbol{w}_a$) and template (i.e., $\boldsymbol{B}\boldsymbol{w}_b$) are required; i.e., the first components (columns) of $\boldsymbol{W}_a$ and $\boldsymbol{W}_b$, respectively [29]. Then, the multi-channel response is projected to obtain the reference template $\boldsymbol{x}_{t0} = \tilde{\boldsymbol{X}}_{t0} \cdot \boldsymbol{w}_b$, where $\boldsymbol{x}_{t0} \in \mathbb{R}^{N_s,1}$. Templates for the rest of the commands $(\boldsymbol{x}_{t1}, \boldsymbol{x}_{t2}, \ldots, \boldsymbol{x}_{tm})$ are computed by circularly-shifting $\boldsymbol{x}_{t0}$ according to their lags. In the test (i.e., online) mode, EEG epochs are averaged and projected with $\boldsymbol{w}_b$ to obtain a spatially-filtered epoch; i.e., $\hat{\boldsymbol{x}}_{test} = \tilde{\boldsymbol{X}}_{test} \cdot \boldsymbol{w}_b$ with $\hat{\boldsymbol{x}}_{test} \in \mathbb{R}^{N_s,1}$. Subsequently, the Pearson's correlation coefficients $\boldsymbol{\rho}$ between the resulting vector and all the templates are calculated, identifying the selected command as the one that reaches the maximal correlation value; i.e., $y = \arg\max_i \rho(\hat{\boldsymbol{x}}_{test}, \boldsymbol{x}_{ti})$.

Another equivalent possibility to avoid online averaging would be to concatenate the k_t test EEG epochs and use $\boldsymbol{w}_a$ to obtain a spatially-filtered vector; i.e., $\hat{\boldsymbol{x}}'_{test} = \tilde{\boldsymbol{X}}'_{test} \cdot \boldsymbol{w}_b$, where $\tilde{\boldsymbol{X}}'_{test} \in \mathbb{R}^{k_t \cdot N_s, N_c}$ and $\hat{\boldsymbol{x}}'_{test} \in \mathbb{R}^{k_t \cdot N_s,1}$. Then, the correlation would be computed between this resulting vector and the replicated version of each template k_t times (i.e., $\boldsymbol{x}_{ti} \in \mathbb{R}^{k_t \cdot N_s,1}$).

3.3. Comparison with SSVEP systems

One of the questions that arose when c-VEP-based BCIs were proposed was whether they would outperform SSVEP systems. Bin et al. [13] were the first researchers to attempt to answer this by comparing a system (12 HU, Oz) controlled by SSVEP with one controlled with c-VEP. Results showed that c-VEP (95.0%, 92.8 bpm) outperformed SSVEP (88.0%, 39.7 bpm) both in terms of accuracy speed. However, care must be taken when interpreting these ITR results, as the SSVEP system had 6 targets, while the c-VEP included 16 commands. Since ITR depends on the total number of possible selections, speed is biased toward the c-VEP system. Years later, Kapeller et al. [30] obtained similar performance results (c-VEP: 98.2%, SSVEP: 91.4%) when controlling a 4-command robot (11 HU, 8 channels). In 2019, Gembler et al. [14] indirectly compared an 8-command system (20 HU, 10 channels) using both quantitative (c-VEP: 94.0%, 92.7 bpm; SSVEP: 96.3%, 75.1 bpm) and qualitative (i.e., questionnaire) measures. Although the c-VEP system reached a higher speed, the SSVEP system achieved a higher accuracy. In terms of user-experience, some users slightly preferred the SSVEP system. However, differences between both paradigms in terms of performance and user-friendliness were not significant. They concluded that, since performances were similar, the optimal paradigm depends on users' preferences. Recently, Volosyak et al. [31] compared a 4-target system by performing an analysis of BCI illiteracy (86 HU, 16 channels). All participants were able to control the c-VEP (97.8%, 40.23 bpm) system, while 3 users were not able to control the SSVEP (95.3%, 37.87 bpm) one. They stated that c-VEP performances (both accuracy and ITR) were significantly higher than SSVEP ones. Users' questionnaires did not show any difference in terms of comfort between both systems.

In conclusion, c-VEP systems seem to be able to achieve similar or even higher selection speeds [13, 14, 30, 31] and accuracies [13, 30, 31] than SSVEP-based BCIs. As mentioned above, Volosyak et al. [31] reported statistical differences to support the superiority of c-VEP, while Gembler et al. [14] did not find significant differences between both paradigms and the other studies did not perform any statistical analysis [13, 30]. Even though a meta-analysis would be beneficial to give insight into these results, unfolded ITR and accuracy values for each user were not available for most studies.

The particular aspects of SSVEP and c-VEP paradigms may make a difference when designing a BCI system. Although recommended, an SSVEP-based BCI does not necessarily require a mandatory calibration, while in general a c-VEP does [13]. On the other hand, c-VEP is less sensitive to non-related basal EEG activity than SSVEP, which presents a narrow-band response [13, 22]. As SSVEP systems usually encode each command with different carrier frequencies, the number of targets is somewhat limited by the monitor's refresh rate [32]. Furthermore, carrier frequencies over beta band are thought to be more difficult to discriminate [33], making SSVEP-based BCIs more suitable for applications that need fewer commands. Of note, some state-of-the-art SSVEP-based BCIs employs phase modulation as well. Even though the number of commands of a circular shifting-based c-VEP system is limited by the lag step τ and the sequence length, it is usually less restrictive [13].

3.4. Comparison with eye tracking devices

Another interesting question is whether c-VEP BCIs could compete against eye trackers. Nezamfar et al. [34] asked 10 HU to solve maze tasks using a 4-command system controlled by a single-channel (i.e., Oz) c-VEP-based BCI and an eye tracker (ET). Although mean accuracies were similar between both modalities (92.6% c-VEP, 91.4% ET), c-VEP results were more consistent over participants. Furthermore,

Table 1. Bit-sequences employed in the reviewed studies.

Sequence type	#	References
M-sequences	58	[13, 14, 18, 19, 25, 29–31, 34, 35, 43–90]
Gold	9	[22, 24, 43, 44, 87, 88, 91–93]
Kasami	2	[88, 89]
Barker	2	[43, 44]
Golay	5	[23, 88, 90, 94, 95]
APA	4	[23, 88, 94, 95]
De Bruijn	1	[88]
Hand-crafted	5	[45, 82, 96–98]
Random	4	[26, 97–99]

#: number of studies, APA: almost perfect autocorrelation.

questionnaires showed that most users preferred c-VEP over ET because the control was significantly faster and required less total calibration time (ET needed a re-calibration after each task). They also observed difficulties of ET calibration for users that wore eyeglasses [34]. Even though further research should be conducted to validate these findings, it is worth highlighting that c-VEP and ET systems seem to be comparable in terms of accuracy and speed. Therefore, c-VEP-based BCIs might be appropriate when ET calibration is hindered (e.g., eyeglasses, contact lenses, low ambient lighting, blepharoptosis). For the sake of fairness, it should be mentioned that BCIs also present some technical disadvantages, such as the EEG cap setup (i.e., gel electrodes, impedance measurement) and the fragility of the wired channels. It was also suggested that ET information could supplement the BCI system, improving the c-VEP decoding [35].

3.5. Bit-sequences

Generating bit-sequences, or codes, with appropriate autocorrelation properties is not trivial. For that reason, most of the studies (58/70) relied on binary m-sequences [36], binary codes generated through a LFSR using primitive polynomials over the Galois Field of base 2; i.e., GF(2) [21]. As shown in figure 2, m-sequences have overall minimum autocorrelation values for non-zero circular shifts, which makes them optimal for classic c-VEP-based BCIs. However, some studies used alternatives such as Gold [37] (9/70), Kasami [38] (2/70), Barker [39] (2/70), Golay [40] (5/70), almost perfect autocorrelation (APA) [41] (4/70), de Bruijn [42] (1/70), hand-crafted (5/70), or random sequences (4/70). Table 1 enumerates the studies that used these variations. In general, some studies suggested that the performance of BCIs based on time-delayed versions of a single bit-sequence does not vary significantly when using different code types [43–45].

As shown, a 63-bit m-sequence is usually sufficient for modulating up to 32 commands. Applications that require more commands, however, must rely on longer m-sequences [73], increasing the selection time; or on multi-sequence paradigms, in which (1) different bit-sequences modulate subgroups of commands [23, 89, 94, 95], or where (2) each command is modulated by a different bit-sequence [22, 24, 26, 34, 35, 46, 48, 49, 55, 62, 64, 92, 93, 97–99]. In the latter case, it is recommended to prevent cross-talk between neighboring commands by distributing each bit-sequence in function of their cross-correlation properties [24].

For multi-sequence systems, using sets of m-sequences is not convenient because they do not guarantee low cross-correlations between them [21]. By contrast, Gold [22, 24, 43, 44, 87, 91–93] and Kasami [89] sequence sets are easy to generate and present acceptable auto-correlation and periodic cross-correlation properties, making them especially suitable for this purpose [21]. In a nutshell, both sets are derived from combinations of preferred pairs of m-sequences. For a preferred pair of m-sequences generated with a polynomial of order m, there are 2^m+1 Gold codes and $2^{m/2}(2^m+1)$ Kasami sequences (e.g., 65 Gold and 520 Kasami sequences for a preferred pair of 63-bit m-sequences). Note that the large set of Kasami sequences contains both the Gold codes and the so-called small set of Kasami sequences [21].

There are some single-sequence alternatives to m-sequences. For instance, Barker and Golay sequences, which obey a more restrictive rule: to present low aperiodic correlation values (i.e., correlation over incomplete periods of codes). Barker codes [43, 44] guarantee a minimum aperiodic correlation, however, only Barker codes of length ≤ 13 exist [21]. Golay sequences [23, 90, 94, 95] are pairs of complementary codes with low aperiodic correlations without length restrictions, hence they are used in digital applications for which Barker sequences are not available [21]. De Bruijn sequences also exist as a special class of nonlinear shift register codes with maximal length, whose cardinality behaves as a double exponential growth (there are $2^{(2^{m-1})-m}$ de Bruijn sequences of length 2^m) [88, 100]. However, auto- and cross-correlation properties vary among different codes [100]. APA sequences, defined as complex periodic sequences such that all out-of-phase correlation coefficients are zero except one, are also popular [23, 88, 94, 95].

Some studies claim that the use of different sequence types does not appear to significantly affect overall performances as long as low values of auto- and/or cross-correlation are guaranteed [43–45]. By contrast, Torres & Daly [88] recently reported significantly higher performances for de Bruijn, APA and Golay sequences in comparison with m-sequences, Gold and Kasami codes using simulated data. Further analysis with real EEG data would be recommended to validate these findings. Finally, several authors recently opted to use fully random codes (see section 3.13) [26, 97–99], or to create custom codes [45, 82, 96] or modulations of known families [24] to confine spectral density to high-frequency bands (e.g., by xor-ing the bit-sequence with a bit-clock at a doubled rate), reducing visual fatigue.

3.6. Stimuli variations and p-ary sequences

Binary sequences encoded as white/black (WB) flashes are the most common stimulus presentation across the reviewed studies (60/70)). However, some authors opted to use different color combinations to display the stimuli [29, 35, 57, 58, 62, 64, 68]. The rationale behind these variations are user safety, visual comfort or performance purposes. For instance, Aminaka et al. [58, 68] used green/blue (GB) flashes because it is known to be the combination with the lowest risk of triggering photoparoxysmal responses in users suffering from photosensitive epilepsy [101], although the combination has demonstrated to perform significantly worse (74%) than WB (79%) in c-VEP-based BCIs [58]. Others based their studies [35, 57, 62, 64] on the opponent process theory of color vision, which claims that neural channels for color processing are composed of pairs of opponent colors: yellow/blue (YB), red/green (RG) and WB [102]. Nezamfar et al. [62] compared the three combinations, finding that RG elicited the strongest c-VEP responses for rates of 60 Hz (YB: 94.5%, RG: 98.5%, WB: 89.2%) and 110 Hz (YB: 88.5%, RG: 89.5%, WB: 83.4%); as well as being less tiring for users due to its equiluminance. Riechmann et al. [57] reinforced those results by comparing RG (68.0%) versus WB (66.0%), although performance differences were not significant. Finally, Wei et al. [29] compared different color/black combinations, finding that WB (99.0%) and yellow/black (96.0%) achieved a significantly higher accuracy than green/black (93.0%), red/black (88.0%) or blue/black (84.0%); probably due to its greater contrast and the joint stimulation of the cones and rods of the retina.

Of note, some authors (5/70) employed alternating checkerboard patterns to encode each command, rather than simple flashes [34, 35, 44, 62, 64]. In SSVEP-based BCIs, these complex stimuli are believed to elicit more pronounced responses than simple ones, although inducing weaker high-frequency components [17]. Whether this phenomenon is also present in c-VEP-based BCIs remains as an open question, as no study has compared performances using both types of stimuli. Other stimuli variations, such as size and proximity, were also studied by Wei et al. [29], concluding that the larger and further apart the stimuli are, the higher the accuracy. They recommended using stimuli sizes greater than or equal to 3.8° visual angle, and separations of at least 4.8° (measured from center to center between consecutive targets) [29].

A recent approach that leads to display stimuli with different color tones or intensities is the use of p-ary sequences. Specifically, m-sequences are not limited to the binary domain, but can be generated using primitive polynomials of GF(p), where p must be prime [103]. Gembler et al. [84] compared binary (i.e., $p = 2$) and quintary (i.e., $p = 5$) m-sequences with 60, 120 and 240 Hz refresh rates. To encode the quintary sequence, they used white, black and three additional shades of grey. Even though both achieved similar results (binary vs. quintary: 99.4%, 98.5% at 60 Hz; 97.6%, 97.5% at 120 Hz; 97.9%, 97.6% at 240 Hz), quintary patterns were significantly less annoying for users, especially for the 60 Hz condition [84]. The extra dimensions provided by p-ary sequences not only allows to exploit color variations, but also other characteristics such as stimuli sizes, changing images, apparent motions, tactile textures, etc. However, to the best of our knowledge, no study have explored these kind of modulations yet.

3.7. Circular shifting vs. ensemble

Concerning signal processing topics, a widespread approach to generate the template $\boldsymbol{x}_{ti}$ of the i-th command is to circularly shift $\boldsymbol{x}_{t0}$, the reference template, $i\tau$ samples apart (section 3.2). Even though the c-VEP response does not necessarily share the auto-correlation properties of the stimulation sequence [23, 24, 62, 73], this method has repeatedly shown its usefulness in c-VEP paradigms.

However, some studies (7/70) have trained all templates separately, averaging c-VEP responses to each of the bit-sequences individually, instead of using the circular shifting method [14, 45, 51, 56, 66, 74, 76]. Gembler & Volosyak [74] showed that this ensemble method achieved a significantly higher grand average accuracy than the circular shifting one for window decoding lengths of 150-450 ms (e.g., for 450 ms, circular: 85.0%, ensemble: 93.0%). This may be due to the additional response expected at the beginning of each flashing, which is not modeled in the circular approach but is captured using the ensemble method. Despite the improvement in performance, the ensemble method entails a significantly longer calibration (i.e., CT, where C is the number of commands and T is the duration of the circular shifting calibration), which might be counter-productive in practical applications.

3.8. Presentation rates

In order to maximize the speed of command selection, the presentation rate (i.e., sampling rate of the code) generally matches the screen refresh rate. Therefore, most of the studies display the bit-sequences at 60 Hz (47/70). Over the years, some researchers compared the performance of the system when using different sequence rates (see table 2).

The studies of Aminaka et al. [58, 60, 61] consistently showed higher performances of 60 Hz (mean: 88.2%) over 80 Hz (mean: 83.1%) rates for 31-bit m-sequences in a BCI that used light emitting diodes (LED) for stimulus presentation. Nezamfar et al. [48, 49] compared 15 Hz and 30 Hz rates using m-sequences of 31 bits, reporting higher accuracies for the 30 Hz condition. Then, they also compared 30 Hz, 60 Hz and 110 Hz rates for m-sequences of 31, 63 and 127 bits [62]. They achieved a higher grand average accuracy in the 60 Hz condition, although the 110 Hz rate was perceived as less fatiguing by the participants. On the contrary, Wittevrongel et al. [66] compared 60 Hz (up to 5 cycles) and 120 Hz (up to 10 cycles) rates for a 63-bit m-sequence, stating that the faster the presentation rate, the higher the accuracy for equal-length stimulation duration. Gembler et al. [69] observed the same behavior when comparing 60 Hz (77.7%, 3 cycles), 120 Hz (78.6%, 6 cycles) and 200 Hz (75.9%, 12 cycles) for a 63-bit m-sequence. As shown, the accuracy was comparable when the same stimulation duration was used, which implied more test cycles for the higher presentation rates. Similarly, Başaklar et al. [73] tested a 127-bit m-sequence using 60 Hz (1 cycle, 92.0%), 120 Hz (2 cycles, 97.0%) and 240 Hz (4 cycles, 87.0%). The accuracy at 120 Hz was significantly higher than at other presentation rates. Additionally, they observed a decrease in the number of distinguishable patterns in the 240 Hz condition, where the c-VEP template approximated to a sinusoid, presumably due to the nonlinearity of the visual system. Finally, Gembler et al. [76] studied the performance of 30 Hz, 60 Hz and 120 Hz for different age groups (young: 20-28 years, elderly: 62-83 years). Interestingly, the presentation rate did not affect the elderly, who obtained similar results (30 Hz: 96.5%, 60 Hz: 98.6%, 120 Hz: 99.7%); but 60 Hz achieved significantly higher results for the young subgroup (30 Hz: 96.4%, 60 Hz: 97.9%, 120 Hz: 96.6%). Nevertheless, the authors suggested the use of 120 Hz, which also achieved appropriate performances and was preferred by the users in terms of user-experience.

Table 2. Presentation rates employed in the reviewed studies

Rate	#	References
15 Hz	3	[48, 49, 75]
20 Hz	1	[75]
30 Hz	7	[48, 49, 57, 62, 66, 75, 80]
40 Hz	1	[19]
60 Hz	47	[13, 14, 22, 23, 26, 29, 31, 35, 43, 44, 47, 50, 51, 53, 54, 56, 62, 66–76, 78–80, 82–94, 97–99]
62.5 Hz	1	[96]
70 Hz	1	[19]
80 Hz	5	[58–61, 68]
90 Hz	1	[45]
100 Hz	1	[46]
110 Hz	3	[34, 62, 64]
120 Hz	6	[24, 69, 71, 73, 80, 84]
200 Hz	1	[69]
240 Hz	2	[73, 84]

As shown, there is no consensus on which presentation rate is most suitable for c-VEP-based BCIs. The accuracy seems to depend on many variables, such as the number of calibration and test cycles, bit-sequence length, number of commands and codes, etc. Presentation rates of 120 Hz may be appropriate for some users, since they present twice as many cycles as the 60 Hz rate [66, 69, 73], which can lead to shorter calibration and selection times. However, care must be taken when increasing the presentation rate, since c-VEP templates may become less orthogonal to each other [73]. Note that EEG responses maintain the same spectral distribution even if presentation rate increases, presumably due to (i) the nonlinearity of the visual system [23, 24, 73] and (ii) the fact that cones are less responsive to high frequency stimuli [62]. Of note, there is a clear consensus that the higher the sequence rate, the less fatiguing the stimulation is for the user [48, 62, 69, 73, 76].

3.9. Equivalent neighbors

In 1992, Sutter [19] claimed that the flash patterns of adjacent commands are also perceived by the visual system and contributes to the joint EEG response. Under this assumption, it was hypothesized that EEG responses to the commands that are located at the outer edges of a speller grid are different than the other templates, potentially decreasing the accuracy. According to this hypothesis, commonly known as the principle of equivalent neighbors, many studies opted to surround the boundary commands of the speller matrix with non-selectable commands [13, 19, 23, 26, 47, 50, 52, 53, 65, 67, 69, 70, 88–90, 94, 97]. Targets are placed in such a way that the relation among the perceived delays (i.e., the target cell and the leak from its contiguous neighbors) is homogeneous throughout the matrix, at the expense of including additional rows and columns. In 17 out of the 70 studies included in this review this principle is followed. Despite its widespread use throughout the literature, so far no study has demonstrated whether using it improves the general performance of a c-VEP system. Further research is necessary to determine if using equivalent neighbors benefits the system or, on the contrary, it causes an unnecessary waste of space including extra rows and columns.

3.10. Raster latencies

The update of a frame is not performed simultaneously for all pixels in the screen on standard monitors, but use rasterization to update each line sequentially from top to bottom (i.e., vertical blanking). This process causes a raster latency that increases systematically (e.g. from the upper left pixel to the lower right pixel), generally resulting in latency variations among c-VEP commands, as they are placed in different positions across the screen. In 2018, Nagel et al. [70] demonstrated that these variations affect to the point of significantly improving the performance of the system if they are corrected (92.0% vs. 95.4%). Some of the studies (5/70) included in this review employed this correction [22, 70, 97–99]. Although maximal raster latency seems consistent at about 95% of the refresh cycle for cathode ray tube and liquid-crystal display monitors (i.e, 15.55 ms for 60 Hz) [70], it is recommended to measure the delay between top and bottom lines using an optical sensor of some kind. The measured delays can be used to shift back the estimated templates to improve overall system accuracy.

3.11. Single-channel versus multi-channel approaches

Unlike other BCIs such as those relying on SMR or the P300, c-VEP systems may achieve suitable performances using only one EEG electrode [13, 34, 43, 44, 48, 49, 62, 64, 87, 96]. Some of the studies in this review obtained an average accuracy over 90% using only the Oz channel [13, 34, 48, 49, 62, 64, 87]. Several studies determined, via brute force searches, that the most discriminative channel was Oz [13, 48, 49], presumably because it was the one that reflected more information about the primary visual cortex, placed in the occipital lobe [1]. However, several studies demonstrated that using multi-channel recordings benefits the overall c-VEP system [47, 52], outperforming the single-channel approach significantly (98.0% vs. 95.0% [47]; 96.3% vs. 92.3% [52]). Of note, the signal-to-noise-ratio (SNR) of a localized relevant signal source can be strengthened by mixing distant electrodes with negative weights to reject common noise, under the assumption that those electrodes may carry similar noise patterns, but without the relevant signal (e.g., Laplacian spatial filtering) [1]. Therefore, most of the studies (58/70) included in this review follow a multi-channel approach. These multi-channel studies typically used spatial filtering approaches discussed in section 3.12. A method for finding a minimum number of suitable channels and optimal montages (including sensor pairing) was proposed by Ahmadi et al. [91].

3.12. Alternative spatial filters

As shown in section 3.2, CCA is the most popular (42/70) algorithm to generate spatial filters for multi-channel c-VEP-based BCIs [14, 23, 24, 26, 29–31, 45, 47, 52–54, 56–58, 60, 67, 69, 70, 72–75, 80, 82–84, 88–91, 94, 95, 97, 98]. However, some authors proposed other algorithms to (1) supplement CCA (e.g., filter banks, multiple weighted components), or to (2) replace it with alternative spatio-temporal filters or encoding models (section 3.13).

Filter banks (4/70) are arrays of bandpass filters that separate the input signal into multiple components, each one carrying a sub-band of the original signal. Gembler et al. [83, 83, 86, 92] proposed a 3-length filter bank over 8-60 Hz, 12-60 Hz, and 30-60 Hz. The EEG signal is filtered with the bank, and the traditional processing pipeline (detailed in section 3.2) is then applied for each sub-band; i.e., computing its own CCA spatial filter. In the end, a total of 3 correlation vectors ρ_1, ρ_2, and ρ_3 are obtained. A weighted [83, 86] or simple [84] average can be used to obtain a unique ρ vector and proceed to determine the selected command as usual. The addition of filter banks reached a higher accuracy (97%) than standard CCA (92%), possibly because the 10 Hz visual α band was less dominant in classification [83]. Another promising approach is to use a combination of canonical variables, instead of only one. As explained in section 3.2, the first column of $\boldsymbol{W}_b$ is used as spatial filter. However, Mondini et al. [104] recently hypothesized that relevant information might be spread over more than one coefficient. For that reason, several studies opted to concatenate the projected responses of n filters $\boldsymbol{w}_{b1}, \boldsymbol{w}_{b2}, \ldots, \boldsymbol{w}_{bn}$ before computing the correlation coefficient with the template [83, 86].

In recent years, some alternative spatio-temporal filters have been proposed as substitute of CCA. For instance, spatio-temporal beamformers (stBF) (3/70) [45, 66, 71], which add temporal information by averaging epoch segments. Shirzhiyan et al. [45] reported a significantly higher accuracy using stBF (94.0%) than CCA (91.1%). Dimitriadis et al. [71] proposed the use of δ-α phase-amplitude coupling (PAC) estimates after stBF, reaching significant improvements in accuracy and speed in comparison with Wittevrongel et al. [66]. Some authors also performed regression with neural networks

(NN) (2/70) [65, 88] and least mean square error (LMSE) with lasso regularization (1/70) [65] to create alternative spatio-temporal filters that outperformed CCA in several studies (lasso: 94.1%, NN: 93.5% CCA: 92.1 % [65]; NN: 96.0%, CCA: 95.0% [88]). Over the years, other methods such as principal component analysis (PCA) or independent component analysis (ICA) have been tested, but results could not compete against the gold standard (PCA: 24.0%, ICA: 62.0%, CCA: 95.0%) [88].

3.13. Modeling c-VEP responses

Recently, some studies (8/70) took the regression approaches to another level by inferring EEG responses to simple events (e.g., flashes) with the aim to predict the c-VEP responses to different bit-sequences [22, 24, 26, 82, 93, 97–99].

Thielen et al. [24] proposed *reconvolution*, a linear generative model composed by two stages: (1) decomposition, in which the EEG response to a training bit-sequence is decomposed into one or several flash VEPs (e.g., one for each possible flash duration); and (2) composition, where the response to a potentially unknown bit-sequence is predicted by combining these VEP responses. The combination of this method and CCA (trained with 36 Gold codes) achieved a mean online accuracy of 86.0% in a speller encoded by a different set of 36 Gold codes [24]. An important aspect of this encoding model is that the averaging, which is normally done at the level of full bit-sequences (i.e., cycles), is done at the level of individual events (e.g., flashes). Specifically, bit-sequences are sequences of non-periodically placed flashes. Assuming the linear superposition hypothesis it is possible to model the response to a sequence of events as the linear addition of the responses to the individual events. Recently, *reconvolution* was embedded in a CCA so that it simultaneously optimizes a spatial filter as well as a temporal filter (i.e., the transient responses to individual events) [25, 93]. Furthermore, it was hypothesized that such encoding model can limit the calibration data to less than a minute up to none at all [22]. In fact, an adaptive version of *reconvolution* was proposed to investigate whether a zero-calibration c-VEP system is feasible [22]. Results showed that the proposed approach reached the same speed and accuracy as a supervised calibrated version, with the benefit of already selecting selected several commands while the traditional approach was still calibrating [22].

Nagel et al. [26, 97, 98] employed linear ridge regression models based on sliding windows to develop: (1) *EEG2Code*, which takes the EEG response and predicts the code used to generate it; and (2) *Code2EEG*, which takes a sequence and predicts the associated EEG response. Responses to commands encoded with random sequences were used to calibrate both models. Results of *EEG2Code* combined with CCA reached performances around 90% when predicting 1,000 different random stimuli. In online experiments, their approach achieved mean accuracies of 97.8% [97] and 99.3% [98] when discriminating among 32 classes.

Yasinzai & Ider [82] studied single-edge VEP responses (i.e., 1-0 and 0-1 transitions) and the possibility to predict the complete c-VEP response to bit-sequences using the superposition of these individual events. Correlations between predicted and real EEG responses to some bit-sequences were not sufficient to ensure an adequate control of the BCI (e.g., m-sequence ρ: 0.46). However, they found a series of constraints that, provided they are met, allow generating handcrafted superposition optimized pulse (SOP) sequences that achieve high correlations between the real and predicted c-VEP responses (e.g., ρ: 0.79). They tested the performance of a proposed 120-bit SOP sequence in a 35-target c-VEP-based speller, achieving an average of 95.9% online accuracy and 57.19 bpm. They concluded that, although there are nonlinear interactions in the way the response to a bit-sequence is generated, a linear superposition of individual events could lead to acceptable predictions for previously optimized bit-sequences.

Note that all these methods used linear models (i.e., linear in their parameters) to predict unknown c-VEP templates. Although assuming linearity in the composition of single events into c-VEP templates has proven to be sufficient for modeling these visual responses, it is well-known that the brain behaves as a nonlinear dynamic system [23, 82]. In fact, the actual recognition of a specific event pattern in the stimulus (which triggers the response) is a nonlinear aspect of these approaches [24]. In this context, Nagel & Spüler [99] combined *EEG2Code* with deep learning, allowing the integration of nonlinear relationships between events and c-VEP responses. The architecture, based on a convolutional neural network (CNN) and trained with 384 s of data, achieved an offline mean accuracy of 84% when discriminating between 500,000 different simulated random codes. In an offline analysis, the model achieved an accuracy of 98.5% using a speller composed of 32 targets. Although results are promising, an additional online analysis with more users is suggested to validate these preliminary findings.

3.14. Alternative classification

As shown in section 3.2, finding the maximum correlation coefficient between the spatially filtered EEG responses and the c-VEP templates is the most common "classification" approach (54/70) to identify the selected command in real-time. However, some authors employed alternative classification methods for this purpose, such as direct correlation of the EEG responses with the bit-sequences [46], support vector machines (SVM, 5/70) [59–61, 68, 85], one-class SVM (OCSVM, 5/70) [50, 52, 53, 57, 70], linear discriminant analysis (LDA, 4/70) [30, 78, 79, 85], or naïve Bayesian classifiers [48] (1/70).

Even though there are some studies that used multi-class linear SVMs [59–61, 85] or LDAs [30, 78, 79, 85] to discriminate between c-VEP targets, performances typically decrease when the number of commands increase. For that reason, the recommended approach is to apply OCSVM and use distancies between margins as a direct substitute for a correlation comparison [50, 52, 53, 57, 70]. Once CCA is trained, individual calibration epochs are averaged and projected using $\boldsymbol{w}_b$ (see section 3.2). Subsequently, the projected epochs are processed by the OCSVM, which creates a hyper-sphere that encloses a given percentage of data, which makes it less sensitive to outliers than the simple averaging method of the reference pipeline (section 3.2). The center of the sphere is used as a template, creating templates for the rest of commands by shifting it. When an online epoch arrives, Euclidean distances between the returned OCSVM score and the centers of each target are calculated, selecting the command that yields the minimum distance. Spüler et al [52] obtained a significant improvement in decoding accuracy using the OCSVM and Euclidean distance (92.32%) compared to the standard averaging and correlations (89.90%).

3.15. Calibration

In comparison with other BCIs, except SSVEP-based, c-VEP-based systems do not require an excessive amount of training trials to calibrate the signal processing pipeline. As stated in section 3.3, SSVEP-based systems do not require a mandatory calibration, although recommended. P300-based BCIs, on the other hand, require a copy-spelling stage of several words, which usually lasts between 15-20 min [8, 9]. Even though many of the reviewed studies recorded a large number of cycles to train their models to perform offline analyses, it is well-known that c-VEP based BCIs can yield a high accuracy with reduced calibration times. For instance, Mohebbi et al. [87], who achieved an average accuracy of 95.1% with 12.5 s of calibration; Spüler et al. [50], reaching 95.0% with 1:08 min; or Gembler et al. [72], that achieved 91.7% with 1:24 in, among others.

Despite that the duration of the calibration is drastically reduced in comparison with other types of BCIs, some authors proposed algorithms to eliminate it completely [22, 53, 54]; i.e., unsupervised calibration algorithms toward plug-and-play devices. Spüler et al. [53, 54] proposed to use only two targets with a great delay between them. After applying k-means over the scores of OCSVM, two different clusters are expected to be found. A cross-validation procedure is continuously applied to detect the cluster that belongs to each command, contributing to train the OCSVM classifier without knowing the labels a priori. However, only two targets are available until enough training trials are recorded to create representative templates. Although the achieved accuracy (85.1%) was lower than using the typical supervised calibration (94.43%), authors claimed the method might be useful for completely locked-in patients [53, 54]. More recently, Thielen et al. [22, 25] proposed an adaptive version of *reconvolution* to investigate whether it is feasible in zero-calibration contexts. Using the structure matrices of each class, the label of an online epoch is determined by maximizing the explained variance among all models. They also used an early stopping algorithm to vary the duration of each trial, which decreases as the unsupervised calibration goes by. Results showed that users achieved an online accuracy of 99.6% with an average selection time of 4.2 s (using 12 s in the first trial), demonstrating that a zero-calibration scenario is possible [22].

Although not calibration in a strict sense, Spüler et al. [50] also proposed an unsupervised adaptation of the classifier using error potentials (ErrP); i.e., a predicted label is considered correct unless an ErrP is detected. Using these unlabeled data to update the templates proved beneficial for the system, as long as the previous supervised calibration is appropriate.

Another interesting research line is the use of transfer learning, which involves using models trained in one setting and applying them in another setting (e.g., inter-user, within users, etc). One of the most common approaches involves training a model with a set of users and testing it to unseen users. Then, a refining of the model is applied to each user for optimizing user-specific performances [12]. In spite of the popularity of this technique nowadays, only two studies tried to apply transfer learning using LDA and SVM models. However, reported results were not adequate to achieve a suitable generalization [79, 85]. Whether deep learning based approaches such as *EEG2Code* [99] are able to make transfer learning feasible for c-VEP-based BCIs is still an open question.

3.16. Early stopping and asynchrony

Many of the reviewed studies (18/70) applied adaptive early stopping techniques to dynamically choose in real-time the time required to perform a selection in online mode [14, 22, 24, 25, 50, 57, 67, 72, 74, 75, 80, 83, 84, 86, 89, 93, 98, 99]. All of these studies based their approaches on threshold comparisons, delivering the selected command when an optimized measure surpassed a predefined value.

These measures are usually derived from the correlation coefficients ρ between the online trials and the templates, such as direct comparison with ρ_{max} [14, 43, 44, 67, 72, 74, 80, 83, 84, 86, 87], cumulative correlation [75], logistic regression models [89], comparisons between ρ_{max} and a Beta distribution fitted to the rest of coefficients [22, 25], or transformations into p-values [98, 99]. Others used a margin criterion: difference between the first and second highest correlation [24, 93] or class margins in OCSVM hyperplanes [57]. Generally, a properly calibrated early stopping technique is beneficial for the overall system performance to the point of yielding an adequate accuracy without a drastic extension of the selection time [67] (e.g., accuracies over 90% have been achieved using a mean of 3.17 s [14], 3.26 s [74], or 5.17 s [72] per trial).

Interestingly, some of these studies (11/70) [14, 22, 24, 72, 74, 83, 84, 86, 93, 98, 99] applied their algorithms under a sliding window strategy. The great advantage of this approach is that it is not necessary to wait to the end of a cycle to perform a selection, but the system constantly makes decisions whenever a buffer of EEG data is received. This could even lead to correct classifications before completing a sequence cycle [14]. Furthermore, two of these algorithms were improved toward an automatic threshold calibration, making them completely unnoticeable to the user [14, 22].

Early stopping techniques could also be applied to provide a self-paced control of the system. BCIs are inherently synchronous systems; i.e., they are constantly translating EEG activity into commands, even without a voluntary intention from users. This mode is unpractical in real contexts, as it requires an expert to setup and control the application flow. An asynchronous (i.e., self-paced, *brain switch*) system would give the user the control of when trials should start. This may be achieved by a non-control state detection stage to monitor user's attention and detect whether the user wants to deliver a selection or not [8, 9]. In this context, some of the studies adapted their algorithms to provide an asynchronous stage, avoiding command selections if threshold is not surpassed [14, 30, 43, 44, 57, 72, 74, 83, 86, 87, 98, 99]. However, more efforts should be devoted to develop filter methods (i.e., independent of the classification stage) to guarantee robustness against the inter-session variability due to the non-stationarity of the EEG [10, 105]. Note that static thresholds are wrapper methods that are prone to be invalid whenever slightly different data from training arrives, and must be also re-trained when the decoding classifier is updated.

3.17. Dry electrodes

During the last years, several companies have attempted to reduce hardware limitations that prevent BCIs from being adopted commercially. A typical limitation is the need of gel to improve the contact between the scalp and the EEG sensors; i.e., to reduce the electrode impedance [1]. Although necessary, gels are not ideal for long-term recording because they eventually dry out; nor are they practical, because users rely on experts to set up the system. As an alternative to wet electrodes, several materials have been proposed to achieve dry (e.g., metal pins, spring-loaded) or semi-dry (e.g., polymer wick-based) non-invasive recordings, at the cost of normally exhibiting worse SNRs [106]. In principle, the inherent robustness of c-VEP stimulation would allow the use of these types of electrodes (eventually at the expense of trial duration). Of note, the non-stationarity of the electrode-skin impedance would still need to addressed, e.g., by recalculating the spatial filtering [1]. In this context, active electrodes where pre-amplification is performed locally at each electrode can perform well in environments with noise and/or high electrode-skin impedance [1].

In this context, Spüler [67] studied whether dry electrodes are adequate for c-VEP-based BCIs. He achieved an average accuracy of 75.9% (13.63 s per trial) using a 15-channel dry system, observing a large inter-user variability in performance. The accuracy, however, was substantially lower than those reported in previous studies with wet electrodes. Although a direct comparison using the same user pool is necessary to quantify this decrease in performance, the author claimed that dry electrodes might be acceptable for c-VEP-based BCIs.

3.18. Applications and portability

During the literature review, we have identified c-VEP-based BCIs with different applications, such as control of robots [30, 43, 44, 87], virtual agents [57], virtual keyboard and mouse to control any Microsoft Windows program [63], or even performing of psychological experiments [78, 79]. However, most of the studies have been devoted to provide spellers for alternative communication purposes (for a comprehensive review of speller BCIs, see [107]). Some of these implemented virtual keyboards with word suggestions using n-gram language models, favoring the communication speed for final users [64, 72, 74, 83]. Of note, most of these applications required a computer to display the stimuli or process the EEG signal. Among the reviewed studies, only two opted to implement a solution in a completely portable system such as an iPad Pro (Apple Inc.) [22, 93].

3.19. Long-term use

An important but frequently ignored research line in BCIs is the analysis of long-term viability of classifiers. Owing to the high inter-session variability and non-stationarity of the EEG, BCI classifiers should be re-calibrated frequently in P300 or SMR-based BCIs [12]. Gembler et al. [86] studied whether c-VEP templates are still useful two weeks after the calibration. They found that 8 out of 10 participants could control the system with an average accuracy of 97.1%. They observed a slight non-significant decrease in accuracy (first session: 98.5%), claiming that c-VEP re-calibration from session to session might not be needed for most users. Similarly, Yasinzai & Ider [82] demonstrated that VEP responses to single flashes do not show a significant inter-session variability two weeks apart. Interestingly, no studies have focused on analyzing the influence of user-learning on the decoding performance.

3.20. Covert visual, auditory and tactile

Although systems based on P300, SSVEP and c-VEP have been traditionally considered dependent BCIs (i.e., depending on user's muscle-based control of gaze direction), some studies showed that this statement is not entirely true [1]. Recently, researchers have developed paradigm variations for controlling P300 and SSVEP-based BCIs using covert attention; i.e., attending to a target stimulus, while not gazing directly at it [1]. Even though performances are generally higher when using a typical overt control, covert attention might be appropriate for users who lack reliable gaze control [1].

For c-VEP-based BCIs, to date only one study by Waytowich & Krusienski [56] designed an alternative paradigm to explore non-foveal gaze fixation. They proposed a ring-based distribution of 4 stimuli encoded with an m-sequence ($\tau = 15$), where commands were slightly displaced from the stimulus locations (2–5° of visual angle from foveal center). Although direct foveal fixation reached a higher accuracy (99.4%) than parafoveal fixation (89.7%), it is claimed that covert control is feasible. Nevertheless, further research should be conducted to validate these findings and study how the distance between stimuli and targets affects system performance, as well as to give insight into how many targets can be decoded.

Furthermore, so far only one study explored another sensory modality other than vision. Farquhar et al. [27] explored the use of noise-tagging, the stimulus paradigm behind code-modulated evoked potentials, within the auditory domain. Participants were simultaneously presented with two stimuli, one to each ear, and had to attend to either one of them. For a total of three HU, they found an accuracy higher than chance (about 56.3%), which was lower than using frequency-tagging (about 64.3%); i.e., the stimulus protocol underlying SSVEP. To our knowledge, the tactile sensory modality has not been explored yet with noise-tagging. The exploration of these auditory, tactile and covert visual attention may be an important future research direction to make code-modulated BCIs generally accessible.

3.21. Motor-disabled users

Despite BCIs are generally developed with the aim of improving the quality of life of motor-disabled users, studies often fail to test their systems with target users. In fact, among the 70 studies included in this review, only two studies tested their c-VEP-based BCIs with people with disabilities [19, 93]. In 1992, Sutter tested an invasive ECoG system with an ALS patient, reaching speeds of 10-12 words per minute [19]. Recently, a study from Verbaarschot et al. [93] tested an EEG-based speller based on c-VEP composed by 29 commands with a population of 20 HU (12 young, <35 years; 10 old, ≥ 35 years) and 10 ALS patients. Copy-spelling results showed that the ALS patients were able to control the system (79.3%, 20.3bpm), although achieving lower overall performances than the HU (young: 94.3%, 24.8bpm; old: 88.3%, 21bpm). Of note, ALS results were more heterogeneous, since 2 of them could not control the full keyboard. In general, the use of c-VEP-based systems by ALS patients seems feasible and promising to provide an alternative device for communication in the early and middle stages of the disease [93].

The rest of the studies (68/70) validated their BCIs with healthy users, making it impossible to infer their viability in a real-world context. Although the c-VEP responses for ALS patients have been shown to be very similar to those of HU [93], it has been widely documented that people with disabilities tend to reach lower BCI performances than control users. This issue may be due to problems inherent to the disease [93], and/or indirect such as mental disabilities, essential tremors, nystagmus, etc [8, 9, 11]. Thus, c-VEP systems have been shown to provide an excellent level of control for healthy participants; however, more efforts should be devoted to validate these systems with target populations and to study its feasibility outside the laboratory.

3.22. Public databases

Five of the included studies (5/70) have made available their datasets to the public [22, 24, 66, 91, 98]. Details of these databases are summarized in table 3. Note that two of them offer raw data [22, 24], while the other two provide pre-processed data [66, 91, 98]. To the best of our knowledge, these are the only open datasets available for c-VEP-based BCIs, helpful for other researchers to develop and benchmark novel methodologies to improve the performance of these systems. Additionally, we encourage researchers to open up their analysis scripts alongside their data to improve open science.

4. Discussion

Throughout the manuscript, a comprehensive literature review on c-VEP-based systems since its inception (1984) until today (2021) has been performed. In section 3, the main aspects of 70 related studies have been analyzed in 22 subsections. In the following, all of these are taken into account to discuss the level of development of current state-of-the-art c-VEP BCIs, the immediate challenges and promising research lines.

4.1. State-of-the-art c-VEP systems

Over the years, c-VEPs have been consolidated as a robust control method to achieve reliable and high-speed BCIs. In the early studies, c-VEPs were validated as a suitable alternative to P300 and SSVEP-based BCIs [13, 19], even to eye tracking devices [56]. Soon, multi-channel single circularly shifted m-sequence CCA-based approaches became established as the preferred signal processing pipeline [47]. Although other classification alternatives such as OCSVM were proposed [50], traditional template matching correlation-based methods prevailed. Frame rate (often limited by the display hardware) was also identified as a trade-off between performance and speed, finding that presentation rates in the range of 60-120 Hz maintain a suitable balance between both variables [73, 76]. Regarding sequence generators, system performances did not vary significantly in real EEG data as long as adequate auto-correlation properties were guaranteed [44, 45]. Of note, filter banks [83] and stBF [66, 71] also arose as promising supplements and alternatives to CCA, respectively.

Even though c-VEP-based BCIs were able to reach high performances when using a single-sequence, its length restricts the number of commands that can be decoded (e.g., using a 63-bit sequence: 16 for $\tau = 4$, 32 for $\tau = 2$). Thus, multi-sequence systems emerged to increment the maximum number of discriminative classes [23, 95]. Due to the need to consider not only appropriate auto-correlation properties, but also minimal cross-correlation between sequences, BCI performances were prone to decrease [23]. In order to encode more commands, some authors opted to implement nested selection matrices [72], or control a "virtual mouse" over the keyboard layout [64]. Recently, modeling c-VEP responses using linear regression [22, 98] and deep learning [99] has made it possible to discriminate random flashing codes. The possibility to decode more than 500,000 different simulated classes has also suggested a change in the paradigm and a possible solution to decode a large number of commands [99].

Once performances in terms of accuracy and speed are guaranteed even for systems that encompass a great amount of different classes, efforts might be focused to improve other practical aspects such as adaptation, asynchrony or user-friendliness. For instance, plug-and-play c-VEP-based BCIs are becoming a reality due to the development of cutting-edge zero-calibration algorithms [22]. Early stopping techniques based on sliding windows have also been shown to be beneficial to adapt the selection time [14, 22, 99], as well as to provide an asynchronous control of the system [14, 99]. Informing the user about the adaptive confidence of the classifier in real-time via colored frames [24] or progress bars [74] makes the experience more immersive and may favor the user to attend to the stimuli. Another simple but effective recent proposal is to correct for raster latencies, which can degrade the overall system performance if not corrected [70].

Reducing user-fatigue has also been a priority in recent years. Under the assumption that traditional c-VEP-based systems do not depend significantly on the type of sequence provided a low auto-correlation is guaranteed, some authors proposed hand-crafted sequences with tuned spectral components that are more pleasant to the user [45, 96]. Higher presentation rates have also been repeatedly shown to be less fatiguing for users, although the aforementioned trade-off concerning accuracy should be taken into account [62, 69, 73, 76]. In this context, non-binary sequences emerged as a promising approach to reduce user-fatigue, since encoding different labels with shades of greys would substantially reduce subjective discomfort caused by flicker patterns [84]. In addition to the intensity levels, the use of colors instead of a simple black and white contrast is promising, although results are not conclusive.

Owing to the increase of wireless EEG equipment, the possibility of developing completely portable c-VEP-based systems lays on the table. Most smartphones and tablets work on 60 Hz rates, although there are some on the market that are able to reach 120 Hz. Favoring portability is a key aspect for

Table 3. Available public databases of c-VEP-based BCI studies

Article	Ref.	Data type	Users	N_c	Sampling rate[a]	Sequence rate	Bit-sequence(s)
Thielen et al. (2015)	[24]	Raw	12 HU	64	2048 Hz	120 Hz	65 Gold codes (126 bits)[b]
Wittevrongel et al. (2017)	[66]	Pre-processed	17 HU	32	100 Hz	60 Hz	M-sequence (63 bits)
					200 Hz	120 Hz	M-sequence (63 bits)
Nagel & Spüler (2019)	[98]	Pre-processed	10 HU	32	600 Hz	60 Hz	150 random codes (15 bits)[b]
Ahmadi et al.	[91]	Pre-processed	5 HU	256	360 Hz	60 Hz	65 Gold codes (126 bits)[b,1]
			10 HU	8	360 Hz	60 Hz	65 Gold codes (126 bits)[b,2]
Thielen et al. (2021)	[22]	Raw	41 HU	8	512 Hz	60 Hz	65 Gold codes (126 bits)[b]

[a] EEG sampling rate; [b] The full set of codes was not used, only the required subset to encode each command with a unique sequence. N_c: number of recorded channels, HU: healthy users. Direct links: Thielen et al. (2015) [doi.org/10.34973/1ecz-1232], Wittevrongel et al. (2017) [kuleuven.app.box.com/v/CVEP], Nagel & Spüler (2019) [doi.org/10.6084/m9.figshare.7611275.v1], Ahmadi et al. (2019) [[1]: doi.org/10.34973/psaf-mq72, [2]: doi.org/10.34973/ehq6-b836] Thielen et al. (2021) [doi.org/10.34973/9txv-z787].

practical BCIs, however, only one study implemented the system on a tablet [22]. Note that because of the ubiquity of the Internet nowadays, a client/server architecture would solve any computational cost issue that might arise with regards to signal processing [108].

As shown, the exponential increase in c-VEP-based studies in the last decade has led to a substantial advance in the field. Nowadays, the implementation of the aforementioned ideas and algorithms would guarantee a high control accuracy and speed. Therefore, it is suggested that research in the next few years could be more focused toward practical use of these systems in real word scenarios.

4.2. Current challenges and future directions

4.2.1. Bit-sequences. Arguably, one of the most important aspects of a c-VEP-based BCI is the choice of stimulation sequence(s) used to evoke the c-VEP. As demonstrated throughout this review, the original studies as well as many studies after have used a single m-sequence that exhibits a favorable autocorrelation function [13]. By circularly shifting the m-sequence, the stimulation sequences of the other commands are created. As discussed in section 3.5, this circular shifting approach is also used with other bit-sequences such as APA, Barker, de Bruijn, Golay, Gold, and Kasami sequences. Alternatively, several studies utilized Gold and Kasami sets, which present low cross-correlation properties. In general, the reason for using these types of bit-sequences is to exploit the low correlation between them, which is assumed to lead to low cross-talk between the evoked c-VEP responses, which in turn should optimize decoding accuracy [22]. Note that the circular-shifting approach requires a reliable timing signal between stimulus presentation and EEG acquisition; whereas the use of code families (e.g., Gold, Kasami) does not require such an exact synchronization, since they can be detected regardless of time shifts.

Despite all of them having good correlation properties, several studies have investigated whether the choice of bit-sequences and code families can substantially affect the decoding accuracy. Although some studies found that most of them yield a similar accuracy [43–45], Torres & Daly [88] claimed that de Bruijn, Golay, and APA sequences outperformed m-sequences, Gold codes, and Kasami sequences in simulated EEG data. Additionally, other studies have investigated custom made bit-sequences [45, 82, 96]. For example, random bit-sequences showed a similar performance as m-sequences [26]. In a subsequent study, a non-significant increase was observed for slightly optimized bit-sequences taking into account a specific number of bit-changes versus the random bit-sequences [97]. Furthermore, chaotic codes were shown to yield a similar accuracy as compared to m-sequences while reducing user-fatigue [45]. Similarly, codes that were optimized by taking into account some aspects of the visual system physiology increased the accuracy as compared to m-sequences [82, 96]. In general, further research is needed to study which predefined or manually optimized bit-sequences yield the best performance, and what are the properties that make one bit-sequence favorable over another.

Apart from reaching higher decoding performance, care should be taken to make the stimulation patterns as convenient for the user as possible. Throughout the literature, we have identified several attempts to make the flash patterns less irritating and fatiguing. For instance, modulating any bit-sequence to limit low-frequency content [24], using alternative colors than the high-contrast black-white [58, 62], or using higher presentation rates [58, 66, 69]. Additionally, care must be taken on the size and proximity of the different commands in the speller grid [29]. Furthermore, within other paradigms than c-VEP, the appearance of the stimuli has been shown to substantially affect ERP components and the decoding performance, such as the use of checkerboards [17], specific overlays such as famous faces [109], or motion-onset [110], among others. Again, additional research is required to make the external stimulation that is necessary to evoke c-VEP responses more practical and optimal for robust and long-term adoption of these BCIs.

Finally, in section 3.9, we showed that many studies apply the principle of equivalent neighbors [19], assuming that c-VEP responses to the outer commands are sufficiently different to entail a decrease in accuracy with respect to the inner commands. However, this assumption has never empirically tested to be true or not, despite its widespread use in the literature. The use of equivalent neighbors severely limits the choice of stimulus parameters and might increase confusion, but may potentially increase overall decoding performance. Additionally, this setup is a opportunity that arises when using the circular shifting method to homogenize time-shifts throughout the matrix, which is argued to require a better time synchronization than paradigms that do not rely on circular shifting.

4.2.2. Signal processing pipeline. Another important ingredient in the design of a c-VEP-based BCI is the decoding stage. As discussed in this review, many of the studies rely on a type of template-matching algorithm in which, by some similarity (e.g., Pearson's correlation) or distance metric (e.g., Euclidean), the current EEG is compared to certain learned templates (i.e., the c-VEP responses to each candidate bit-sequence underlying each potential command). These templates are either built by some standard pooling approach (e.g., an average), or by means of a modeling approach (e.g., *reconvolution*, *EEG2Code*). Additionally, most studies used CCA to optimize spatial filters to combine the information obtained from multiple EEG channels. But still, several exciting future directions to improve the signal processing pipeline are identified below.

Firstly, deep learning has shown its potential in common domains like image classification and language processing, and is starting to be adopted in the BCI community as well (see e.g., [12, 111, 112]). Within c-VEP-based BCIs, the typical convolutional neural network architecture that performs both spatial and temporal convolutions has been explored as well, with positive results over standard regression approaches [99]. Aside its nonlinear characteristic, applying deep learning in this context has the benefit of integrating all components that are otherwise optimized sequentially. Specifically, these networks are designed to optimize both a spatial filter as well as a cascade of temporal filters and a hierarchical classification in an end-to-end fashion.

Since deep learning is a rapidly progressing field, many of its novel developments are ready to be adopted in the BCI field to improve performances. One concrete future direction would be to explore the temporal characteristics of the c-VEP response. Specifically, currently models predict whether an on-state (or a flash) happened or not. Given the highly nonlinear nature of the brain (i.e., neuronal adaptation, habituation, neural entrainment), incorporating temporal structure might benefit the decoding, e.g. by adopting recurrent neural networks. A second concrete example concerns transfer-learning. Despite that c-VEP templates show a low inter-session variability [82, 86] and calibration is not as tedious as for other types of BCIs, it would be interesting to study whether applying cross-subject transfer learning (e.g., using deep learning) is feasible, providing enough data is available. In that case, a pre-trained network might serve any new user, employing an unsupervised adaptive strategy to refine the classifier as more trials are recorded. Furthermore, it would be also interesting to evaluate the influence of user-learning on the overall decoding performance of the system.

Another important aspect in the classification pipeline, related to the aforementioned, is the adoption of adaptive methods. First and foremost, EEG is a non-stationary signal, reflected in changing data distribution over time that may be caused by many factors such as loss of electrode connectivity, user-learning, as well as user-fatigue. Additionally, considering a pre-trained cross-subject classifier, adaptation and fine-tuning to the current user might be an important aspect to take into account.

In spite of their excellent decoding performances, some of the modeling approaches introduced in section 3.13 also allow to give insight about the underlying generation of c-VEPs [22, 82, 99]. The sliding window mechanism of *EEG2Code* [99] and *reconvolution* [22] try to mimic the actual behavior of our brains in response to noise-like bit-sequences. In particular, *reconvolution* learns responses to individual events that constitute the bit-sequence, instead of learning responses to the full time series. Apart from the benefit of reducing the amount of training data toward a zero-calibration system [22], the framework also poses a fundamental neuroscientific question: what is the basic element (i.e., event) that the brain responds to? Several open questions around the assumption of linearity still remain. Specifically, is it possible to model the c-VEP response by the convolution of one basic flash VEP, or should the duration of the flash be considered to take into account neural adaptation? In particular, Yasinzai & Ider [82] have exploited the influence of basic VEP linear superpositions in generating full c-VEP responses to bit-sequences, although they stated that nonlinear interactions appear to play an important role in this process. Giving answers to these questions would be of importance to those models which typically predict flash versus no-flash, as they could predict the length of a flash as well. The application of explainable deep learning on models such as *EEG2Code* [99] could be also an interesting future research line to give insight into the presumably nonlinear generation of the c-VEP response.

Finally, several aspects along the signal processing pipeline tend to remain on the background. For instance, CCA is a linear subspace method that finds linear projections of the data to achieve maximal correlation between two variables. Like any other subspace method, CCA returns multiple components, which in CCA are orthogonal. Typically, in a c-VEP classification pipeline, only the first component is used as spatial filter, while the other components might contain relevant information [83, 86]. Analyzing the relevance of these components could also pose an interesting research line.

4.2.3. Toward practical plug-and-play BCIs. Apart from the limitations of non-invasive recordings, which c-VEPs try to bypass as control signals to reach suitable performances, EEG equipment should ideally not require gel, be comfortable, cheap, easy to setup, portable, robust to movements and perform well in real-world environments. Even though some studies focused on developing c-VEP-based BCIs without calibration [22], with reduced user-fatigue [84], fully portable and using water-based [22] or dry electrodes [67], more efforts should be made to propose final self-paced systems that can be applied in a real context without intervention of an expert. Although out of the scope of this manuscript, EEG hardware improvements should play an essential role in making BCIs commercially interesting. Further endeavors could also be directed to develop practical applications with low-cost hardware. Due to the robustness of c-VEPs against inter-session variability [82, 86] and poor signal quality [67], as well as the possibility to accurately decode them using a single EEG channel [13]; the use of wireless EEG equipment with reduced channel sets [91] appears to be feasible.

Furthermore, to make c-VEP-based BCIs practical, a considerable effort should be made to make the exogenous stimulation more user-friendly. As discussed above and owing to the fact that increasing the presentation rate (>120 Hz) seems to affect to the system performance negatively [73], non-binary sequences have emerged as promising alternatives to reduce visual fatigue [84]. Another interesting research line to improve users comfort could be focused on testing systems with different p-ary sequences, such as non-binary Golay pairs, or m-sequences over GF(p).

Additionally, a fully practical BCI setup should include an asynchronous stage (e.g., non-control detection) so that the user can use the system when needed, avoiding false selections to be made whenever the user gazes away from the application [44, 86, 98]. Ideally, the asynchronous detection method should rely on filter-based approaches (i.e., independent of the classification stage) to favor the robustness of the BCI against the inter-session variability of the EEG.

Finally, current c-VEP-based BCIs are mostly gaze-dependent, implying some form of muscle control (i.e., directing one's gaze) is required. Developing alternative covert paradigms, e.g., by using covert visual attention or other sensory modalities such as auditory or tactile BCIs; might be required to make c-VEP-based BCIs accessible to late-stage ALS patients or any disease that impair gaze control. We identified only two studies that attempted to use c-VEP with covert visual attention [56] or auditory responses [27]. Typically, decoding accuracy suffers substantially when these types of interaction are used, which emphasizes the need for further research.

4.2.4. Applications. From the onset of the research field, most BCI applications were focused on improving the quality of life of severely disabled people, e.g., locked-in patients, ALS, multiple sclerosis, cerebral palsy, stroke, etc. However, although the majority of the reviewed studies emphasizes this objective to justify the relevance of their proposals, only two studies validated the system with disabled users [19, 93]. As it is well-known that performances tend to decline in motor-disabled populations [8, 9, 93], ensuring the robustness of these systems with target users is currently essential to take the leap from laboratories to real applications. Particularly, the study of Verbaarschot et al. [93] demonstrated that the use of non-invasive c-VEP-based spellers by ALS patients is feasible. We would like to encourage new research applied in target populations to analyze the viability of c-VEP decoding in other diseases, as well as to reaffirm these findings.

Of note, noise-like sequences are not only used in the BCI field to effectively encode commands. Many of these sequences are used in telecommunication domains because of their error correcting characteristics. Additionally, they have shown their value in measuring stimulus responses in complex nonlinear dynamical systems. For instance, narrow-band and broadband noise have been used to characterize hearing abilities or to select appropriate parameters of hearing-aids [113]. Furthermore, the use of noise-like patterns have greatly improved the assessment of the eye and the optic tract with multifocal VEP [114]. The estimation of specific evoked responses has been shown to benefit a randomization based on m-sequences [115], and to estimate impulse responses in general [116]. Finally, a general framework that allows the characterization of VEPs with continuous signals was devised (unlike the discrete ones in this review) in the visual domain, known as visually evoked spread spectrum response potential (VESPA) [117]; and in the auditory domain, the auditory evoked spread spectrum response potential (AESPA) [118]. In general, these noise-like methods facilitate the estimation of evoked potentials, which can be exploited for various applications.

Finally, we would like to encourage new researchers to open up their data and analysis pipelines, as well as to use the currently available open datasets [22, 24, 66, 91, 98] to serve as benchmark for offline analyses. In such a way, new research can easily be compared quantitatively to favor improvements in existing algorithms and the development of novel proposals. In addition, proper results reports would allow for further meta-analyses to combine the results of different studies and draw joint conclusions about the state-of-the-art in c-VEP-based BCIs.

5. Conclusion

The ability of c-VEPs to achieve reliable high-speed control is well-known in the non-invasive BCI community. In this manuscript, a comprehensive literature review of 70 studies since its inception (1984) until today (2021) has been performed, including journal publications, conferences, book chapters and non-indexed documents. As a result, multi-channel circularly shifted m-sequence CCA-based systems were identified as the preferred approach in most studies. However, this reference pipeline might be improved by implementing c-VEP response modeling, raster latency correction, adaptive calibration, or early stopping approaches. Recently, some studies have also devoted efforts to make c-VEP-based BCIs more user-friendly, e.g. reducing visual fatigue using high-frequency stimulation, hand-crafted codes or non-binary sequences. A detailed table of all the included studies is available in the supplementary material.

Nowadays, most of the initial challenges of c-VEP-based BCIs have been overcome. The implementation of some of the discussed cutting-edge algorithms allows to provide a reliable control of a BCI with a large number of commands, high selection speeds and even without calibration. Although this technology is beginning to make the leap to its commercialization, a general lack of validation with motor-disabled populations was observed. Therefore, future research should focus on developing c-VEP-based BCIs toward real applications, emphasizing their portability, asynchrony, and validation with target users.

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6. References

[1] Jonathan Wolpaw and Elizabeth Winter Wolpaw. *Brain-computer interfaces: principles and practice*. OUP USA, 2012.

[2] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday. Brain-machine interfaces for rehabilitation in stroke: A review. *NeuroRehabilitation*, 43(1):77–97, 2018.

[3] Javier Gomez-Pilar, Rebeca Corralejo, Luis F. Nicolas-Alonso, Daniel Álvarez, and Roberto Hornero. Neurofeedback training with a motor imagery-based BCI: neurocognitive improvements and EEG changes in the elderly. *Medical and Biological Engineering and Computing*, pages 1–12, 2016.

[4] P. Arico, G. Borghini, G. Di Flumeri, N. Sciaraffa, and F. Babiloni. Passive BCI beyond the lab: Current trends and future directions. *Physiological Measurement*, 39(8), 2018.

[5] Gabriel Alves Mendes Vasiljevic and Leonardo Cunha de Miranda. Brain–Computer Interface Games Based on Consumer-Grade EEG Devices: A Systematic Literature Review. *International Journal of Human-Computer Interaction*, 36(2):105–142, 2020.

[6] Gert Pfurtscheller and Fernando H. Lopes da Silva. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology*, 110(11):1842–1857, 1999.

[7] Luis Fernando Nicolas-Alonso and Jaime Gomez-Gil. Brain computer interfaces, a review. *Sensors*, 12(2):1211–1279, 2012.

[8] Víctor Martínez-Cagigal, Javier Gomez-Pilar, Daniel Álvarez, and Roberto Hornero. An asynchronous P300-based Brain–Computer Interface web browser for severely disabled people. *IEEE Transactions*

on Neural Systems and Rehabilitation Engineering, 25(8):1332–1342, 2017.

[9] Víctor Martínez-Cagigal, Eduardo Santamaría-Vázquez, Javier Gomez-Pilar, and Roberto Hornero. Towards an accessible use of smartphone-based social networks through brain-computer interfaces. *Expert Systems with Applications*, 120:155–166, 2019.

[10] Eduardo Santamaría-Vázquez, Víctor Martínez-Cagigal, Javier Gomez-Pilar, and Roberto Hornero. Asynchronous Control of ERP-Based BCI Spellers Using Steady-State Visual Evoked Potentials Elicited by Peripheral Stimuli. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(9):1883–1892, 2019.

[11] Lynn M. McCane, Susan M. Heckman, Dennis J. McFarland, George Townsend, Joseph N. Mak, et al. P300-based brain-computer interface (BCI) event-related potentials (ERPs): People with amyotrophic lateral sclerosis (ALS) vs. age-matched controls. *Clinical Neurophysiology*, 126(11):2124–2131, 2015.

[12] Eduardo Santamaría-Vázquez, Víctor Martínez-Cagigal, Fernando Vaquerizo-Villar, and Roberto Hornero. EEG-Inception: A Novel Deep Convolutional Neural Network for Assistive ERP-Based Brain-Computer Interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(12):2773–2782, 2020.

[13] Guangyu Bin, Xiaorong Gao, Yijun Wang, Bo Hong, and Shangkai Gao. VEP-based brain-computer interfaces: Time, frequency, and code modulations. *IEEE Computational Intelligence Magazine*, 4(4):22–26, 2009.

[14] Felix Gembler, Piotr Stawicki, Abdul Saboor, and Ivan Volosyak. Dynamic time window mechanism for time synchronous VEP-based BCIs-Performance evaluation with a dictionary-supported BCI speller employing SSVEP and c-VEP. *PLoS ONE*, 14(6):1–18, 2019.

[15] Adrien Combaz, Camille Chatelle, Arne Robben, Gertie Vanhoof, Ann Goeleven, et al. A Comparison of Two Spelling Brain-Computer Interfaces Based on Visual P3 and SSVEP in Locked-In Syndrome. *PLoS ONE*, 8(9), 2013.

[16] Betts Peters, Steven Bedrick, Shiran Dudy, Brandon Eddy, Matt Higger, et al. SSVEP BCI and Eye Tracking Use by Individuals With Late-Stage ALS and Visual Impairments. *Frontiers in Human Neuroscience*, 14(November):1–15, 2020.

[17] François-Benoît Vialatte, Monique Maurice, Justin Dauwels, and Andrzej Cichocki. Steady-state visually evoked potentials: focus on essential paradigms and future perspectives. *Progress in Neurobiology*, 90(4):418–438, 2010.

[18] Erich E Sutter. The visual evoked response as a communication channel. In *Proceedings of the IEEE Symposium on Biosensors*, pages 95–100, 1984.

[19] Erich E. Sutter. The brain response interface: communication through visually-induced electrical brain responses. *Journal of Microcomputer Applications*, 15(1):31–45, 1992.

[20] David Moher, Alessandro Liberati, Jennifer Tetzlaff, Douglas G. Altman, Doug Altman, et al. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, 6(7), 2009.

[21] Jack K. Holmes. *Spread Spectrum Systems for GNSS and Wireless Communications*. 2007.

[22] Jordy Thielen, Pieter Marsman, Jason Farquhar, and Peter Desain. From full calibration to zero training for a code-modulated visual evoked potentials brain computer interface. *Journal of Neural Engineering*, 2021.

[23] Qingguo Wei, Yonghui Liu, Xiaorong Gao, Yijun Wang, Chen Yang, et al. A Novel c-VEP BCI Paradigm for Increasing the Number of Stimulus Targets Based on Grouping Modulation with Different Codes. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(6):1178–1187, 2018.

[24] Jordy Thielen, Philip Van Den Broek, Jason Farquhar, and Peter Desain. Broad-band visually evoked potentials: Re(con)volution in brain-computer interfacing. *PLoS ONE*, 10(7):1–22, 2015.

[25] Jordy Thielen, P Marsman, Jason Farquhar, and Peter Desain. Re(con)volution: accurate response prediction for broad-band evoked potentials-based brain computer interfaces. In *Brain-Computer Interface Research*, pages 35–42. Springer, 2017.

[26] S Nagel, W Rosenstiel, and M Spüler. Random Visual Evoked Potentials (rVEP) for Brain-Computer Interface (BCI) Control. *7th Graz Brain-Computer Interface Conference*, (September):1–7, 2017.

[27] J Farquhar, J Blankespoor, R Vlek, and P Desain. Towards a noise-tagging auditory bci-paradigm. In *Proceedings of the 4th International BCI Workshop and Training Course*, pages 50–55, Graz, Austria, 2008.

[28] Wolfgang Härdle and Léopold Simar. Canonical Correlation Analysis. In *Applied Multivariate Statistical Analysis*, pages 321–331. Berlin, 2 edition, 2007.

[29] Qingguo Wei, Siwei Feng, and Zongwu Lu. Stimulus specificity of brain-computer interfaces based on code modulation visual evoked potentials. *PLoS ONE*, 11(5):1–17, 2016.

[30] C. Kapeller, C. Hintermuller, M. Abu-Alqumsan, R. Pruckl, A. Peer, and C. Guger. A BCI using VEP for continuous control of a mobile robot. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 5254–5257, 2013.

[31] Ivan Volosyak, Aya Rezeika, Mihaly Benda, Felix Gembler, and Piotr Stawicki. Towards solving of the Illiteracy phenomenon for VEP-based brain-computer interfaces. *Biomedical Physics and Engineering Express*, 6(3), 2020.

[32] Ivan Volosyak, Hubert Cecotti, and Axel Gräser. Optimal visual stimuli on LCD screens for SSVEP based brain-computer interfaces. *2009 4th International IEEE/EMBS Conference on Neural Engineering, NER '09*, pages 447–450, 2009.

[33] Ivan Volosyak, Diana Valbuena, Thorsten Lüth, Tatsiana Malechka, and Axel Gräser. BCI demographics II: How many (and What Kinds of) people can use a high-frequency SSVEP BCI? *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(3):232–239, 2011.

[34] Hooman Nezamfar, Seyed Sadegh Mohseni Salehi, Matt Higger, and Deniz Erdogmus. Code-VEP vs. eye tracking: A comparison study. *Brain Sciences*, 8(7), 2018.

[35] Berkan Kadioglu, Ilkay Yildiz, Pau Closas, Melanie B. Fried-Oken, and Deniz Erdogmus. Robust Fusion of c-VEP and Gaze. *IEEE Sensors Letters*, 3(1):2019–2022, 2019.

[36] Solomon W Golomb. *Shift register sequences: secure and limited-access code generators, efficiency code generators, prescribed property generators, mathematical models.* World Scientific, 2017.

[37] Robert Gold. Optimal binary sequences for spread spectrum multiplexing (corresp.). *IEEE Transactions on Information Theory*, 13(4):619–621, 1967.

[38] Tadao Kasami. Weight distribution formula for some class of cyclic codes. *Coordinated Science Laboratory Report no. R-285*, 1966.

[39] RH Barker. Group sysnchronizing of binary digital systems. *Communication Theory*, pages 273–287, 1953.

[40] Marcel Golay. Complementary series. *IRE Transactions on Information Theory*, 7(2):82–87, 1961.

[41] Jacques Wolfmann. Almost perfect autocorrelation sequences. *IEEE Transactions on Information Theory*, 38(4):1412–1418, 1992.

[42] Nicolaas Govert De Bruijn. A combinatorial problem. In *Proc. Koninklijke Nederlandse Academie van Wetenschappen*, volume 49, pages 758–764, 1946.

[43] Jonas Isaksen, Ali Mohebbi, and Sadasivan Puthusserypady. A comparative study of pseudorandom sequences used in a c-VEP based BCI for online wheelchair control. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, volume 2016-Octob, pages 1512–1515. IEEE, 2016.

[44] Jonas L. Isaksen, Ali Mohebbi, and Sadasivan Puthusserypady. Optimal pseudorandom sequence selection for online c-VEP based BCI control applications. *PLoS ONE*, 12(9):1–13, 2017.

[45] Zahra Shirzhiyan, Ahmadreza Keihani, Morteza Farahi, Elham Shamsi, Mina GolMohammadi, et al. Introducing chaotic codes for the modulation of code modulated visual evoked potentials (c-VEP) in normal adults for visual fatigue reduction. *PLoS ONE*, 14(3):1–29, 2019.

[46] K. Momose. Evaluation of an eye gaze point detection method using VEP elicited by multi-pseudorandom stimulation for brain computer interface. *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 3:5063–5066, 2007.

[47] Guangyu Bin, Xiaorong Gao, Yijun Wang, Yun Li, Bo Hong, and Shangkai Gao. A high-speed BCI based on code modulation VEP. *Journal of Neural Engineering*, 8(2), 2011.

[48] Hooman Nezamfar, Umut Orhan, Shalini Purwar, Kenneth Hild, Barry Oken, and Deniz Erdogmus. Decoding of Multichannel EEG Activity from the Visual Cortex in Response to Pseudorandom Binary Sequences of Visual Stimuli. *International Journal of Imaging Systems and Technology*, 21(2):139–147, 2011.

[49] H. Nezamfar, U. Orhan, D. Erdogmus, K. E. Hild, S. Purwar, et al. On visually evoked potentials in EEG induced by multiple pseudorandom binary sequences for brain computer interface design. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 2044–2047. IEEE, 2011.

[50] Martin Spüler, Wolfgang Rosenstiel, and Martin Bogdan. Online Adaptation of a c-VEP Brain-Computer Interface(BCI) Based on Error-Related Potentials and Unsupervised Learning. *PLoS ONE*, 7(12), 2012.

[51] Masaki Nakanishi and Yasue Mitsukura. Periodicity detection for BCI based on periodic code modulation visual evoked potentials. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, pages 665–668. IEEE, 2012.

[52] Martin Spüler, Wolfgang Rosenstiel, and Martin Bogdan. One class SVM and canonical correlation analysis increase performance in a c-VEP based brain-computer interface (BCI). In *ESANN 2012 proceedings, 20th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, number April, pages 103–108, 2012.

[53] Martin Spüler, Wolfgang Rosenstiel, and Martin Bogdan. Unsupervised online calibration of a c-VEP Brain-Computer Interface (BCI). In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 8131 LNCS, pages 224–231, 2013.

[54] Martin Spüler, Martin; Rosenstiel, Wolfgang; Bogdan. Unsupervised BCI Calibration as Possibility for Communication in CLIS Patients? In *Proceedings of the Fifth International Brain-Computer Interface Meeting 2013*, number June, pages 10–12, 2013.

[55] Hannes Riechmann, Andrea Finke, and Helge Ritter. Hierarchical Codebook Visually Evoked Potentials for fast and flexible BCIs. *Proceedings of the Annual International Conference of the IEEE Engineering in*

Medicine and Biology Society, EMBS, pages 2776–2779, 2013.

[56] Nicholas R. Waytowich and Dean J. Krusienski. Spatial decoupling of targets and flashing stimuli for visual brain-computer interfaces. *Journal of Neural Engineering*, 12(3), 2015.

[57] Hannes Riechmann, Andrea Finke, and Helge Ritter. Using a cVEP-Based Brain-Computer Interface to Control a Virtual Agent. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(6):692–699, 2016.

[58] Daiki Aminaka, Shoji Makino, and Tomasz M Rutkowski. Chromatic and High – frequency cVEP – based BCI Paradigm. In *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2015)*, pages 1906–1909. IEEE, 2015.

[59] Daiki Aminaka, Shoji Makino, and Tomasz M Rutkowski. EEG Filtering Optimization for Code–Modulated Chromatic Visual Evoked Potential–Based Brain–Computer Interface. In *International Workshop on Symbiotic Interaction*, pages 1–6, 2015.

[60] Daiki Aminaka, Shoji Makino, and Tomasz M. Rutkowski. SVM classification study of code-modulated visual evoked potentials. In *2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2015*, number December, pages 1065–1070. Asia-Pacific Signal and Information Processing Association, 2015.

[61] Daiki Aminaka, Shoji Makino, and Tomasz M. Rutkowski. Classification Accuracy Improvement of Chromatic and High–Frequency Code–Modulated Visual Evoked Potential–Based BCI. In *International Conference on Brain Informatics and Health*, pages 275–284, 2015.

[62] Hooman Nezamfar, Seyed Sadegh Mohseni Salehi, and Deniz Erdogmus. Stimuli with opponent colors and higher bit rate enable higher accuracy for c-VEP BCI. In *2015 IEEE Signal Processing in Medicine and Biology Symposium*. IEEE, 2015.

[63] Martin Spüler. A Brain-Computer Interface (BCI) system to use arbitrary Windows applications by directly controlling mouse and keyboard. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2015-Novem:1087–1090, 2015.

[64] Hooman Nezamfar, Seyed Sadegh Mohseni Salehi, Mohammad Moghadamfalahi, and Deniz Erdogmus. FlashTypeTM: A Context-Aware c-VEP-Based BCI Typing Interface Using EEG Signals. *IEEE Journal on Selected Topics in Signal Processing*, 10(5):932–941, 2016.

[65] Jun Ichi Sato and Yoshikazu Washizawa. Neural decoding of code modulated visual evoked potentials by spatio-temporal inverse filtering for brain computer interfaces. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2016-Octob(1):1484–1487, 2016.

[66] Benjamin Wittevrongel, Elia Van Wolputte, and Marc M. Van Hulle. Code-modulated visual evoked potentials using fast stimulus presentation and spatiotemporal beamformer decoding. *Scientific Reports*, 7(1):1–10, 2017.

[67] Martin Spüler. A high-speed brain-computer interface (BCI) using dry EEG electrodes. *PLoS ONE*, 12(2):1–12, 2017.

[68] Daiki Aminaka and Tomasz M. Rutkowski. A Sixteen-Command and 40 Hz Carrier Frequency Code-Modulated Visual Evoked Potential BCI. In *Brain-Computer Interface Research: A State-of-the-Art Summary 6*, pages 97–104. 2017.

[69] Felix Gembler, Piotr Stawicki, Aya Rezeika, Abdul Saboor, Mihaly Benda, and Ivan Volosyak. Effects of Monitor Refresh Rates on c-VEP BCIs. In *International Workshop on Symbiotic Interaction*, pages 53–62. Springer International Publishing, 2018.

[70] Sebastian Nagel, Werner Dreher, Wolfgang Rosenstiel, and Martin Spüler. The effect of monitor raster latency on VEPs, ERPs and Brain–Computer Interface performance. *Journal of Neuroscience Methods*, 295:45–50, 2018.

[71] Stavros I. Dimitriadis and Avraam D. Marimpis. Enhancing performance and bit rates in a brain–computer interface system with phase-to-amplitude cross-frequency coupling: Evidences from traditional c-VEP, fast c-VEP, and SSVEP designs. *Frontiers in Neuroinformatics*, 12(May), 2018.

[72] Felix Gembler, Piotr Stawicki, Abdul Saboor, Mihaly Benda, Roland Grichnik, et al. A Dictionary Driven Mental Typewriter Based on Code-Modulated Visual Evoked Potentials (cVEP). In *Proceedings - 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018*, pages 619–624. IEEE, 2018.

[73] Toygun Başaklar, Yiğit Tuncel, and Yusuf Ziya Ider. Effects of high stimulus presentation rate on EEG template characteristics and performance of c-VEP based BCIs. *Biomedical Physics and Engineering Express*, 5(3), 2019.

[74] Felix Gembler and Ivan Volosyak. A novel dictionary-driven mental spelling application based on code-modulated visual evoked potentials. *Computers*, 8(2), 2019.

[75] Federica Turi and Maureen Clerc. Adaptive parameter setting in a code modulated visual evoked potentials. In *8th Graz Brain-Computer Interface Conference 2019*, 2019.

[76] Felix Gembler, Piotr Stawicki, Aya Rezeika, and Ivan Volosyak. A Comparison of cVEP-Based BCI-Performance Between Different Age Groups. In *Proceedings of the International Work-Conference on Artificial Neural Networks (IWANN 2019)*, volume

11506 LNCS, pages 394–405. Springer International Publishing, 2019.

[77] Felix Gembler, Mihaly Benda, Abdul Saboor, and Ivan Volosyak. A multi-target c-VEP-based BCI speller utilizing n-gram word prediction and filter bank classification. In *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, volume 2019-Octob, pages 2719–2724. IEEE, 2019.

[78] Faqiang Peng and Zhihua Huang. A c-VEP BCI System for Psychological Experiments. In *Proceedings of the 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI 2019*, pages 6–10, 2019.

[79] Dewei Luo and Zhihua Huang. A Subject-Transfer Study on Detecting c-VEP. *Proceedings - 2019 Chinese Automation Congress, CAC 2019*, pages 2956–2959, 2019.

[80] R. K. Grigoryan, D. B. Filatov, and A. Y. Kaplan. High-speed brain-computer communication interface based on code-modulated visual evoked potentials. *Bulletin of Russian State Medical University*, 8(2):26–31, 2019.

[81] Federica Turi, Nathalie Gayraud, and Maureen Clerc. Auto-calibration of c-VEP BCI by word prediction. *Preprint HAL*, 2020.

[82] Muhammad Nabi Yasinzai and Yusuf Ziya Ider. New approach for designing cVEP BCI stimuli based on superposition of edge responses. *Biomedical Physics and Engineering Express*, 6(4), 2020.

[83] Felix W. Gembler, Mihaly Benda, Aya Rezeika, Piotr R. Stawicki, and Ivan Volosyak. Asynchronous c-VEP communication tools—efficiency comparison of low-target, multi-target and dictionary-assisted BCI spellers. *Scientific Reports*, 10(1):1–13, 2020.

[84] Felix W. Gembler, Aya Rezeika, Mihaly Benda, and Ivan Volosyak. Five Shades of Grey: Exploring Quintary m -Sequences for More User-Friendly c-VEP-Based BCIs. *Computational Intelligence and Neuroscience*, 2020, 2020.

[85] Zhihua Huang, Wenming Zheng, Yingjie Wu, and Yiwen Wang. Ensemble or pool: A comprehensive study on transfer learning for c-VEP BCI during interpersonal interaction. *Journal of Neuroscience Methods*, 343(February):108855, 2020.

[86] Felix Gembler, Piotr Stawicki, Aya Rezeika, Mihaly Benda, and Ivan Volosyak. Exploring Session-to-Session Transfer for Brain-Computer Interfaces based on Code-Modulated Visual Evoked Potentials. In *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, volume 2020-Octob, pages 1505–1510, 2020.

[87] Ali Mohebbi, Signe K.D. Engelsholm, Sadasivan Puthusserypady, Troels W. Kjaer, Carsten E. Thomsen, and Helge B.D. Sorensen. A brain computer interface for robust wheelchair control application based on pseudorandom code modulated Visual Evoked Potential. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, volume 2015-Novem, pages 602–605. IEEE, 2015.

[88] Juan Antonio Ramirez Torres and Ian Daly. How to build a fast and accurate code-modulated brain-computer interface. *Journal of Neural Engineering*, 2021.

[89] Jun Ichi Sato and Yoshikazu Washizawa. Reliability-based automatic repeat request for short code modulation visual evoked potentials in brain computer interfaces. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, volume 2015-Novem, pages 562–565. IEEE, 2015.

[90] Qingguo Wei, Yin Huang, Maoquan Li, and Zongwu Lu. VEP-based brain-computer interfaces modulated by Golay complementary series for improving performance. In *ICBEB2015*, volume 24, pages S541–S549, 2016.

[91] S. Ahmadi, M. Borhanazad, D. Tump, J. Farquhar, and P. Desain. Low channel count montages using sensor tying for VEP-based BCI. *Journal of Neural Engineering*, 16(6), 2019.

[92] Li Zheng, Yijun Wang, Weihua Pei, and Hongda Chen. A Fast Brain Switch Based on Multi-Class Code-Modulated VEPs. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pages 3058–3061. IEEE, 2019.

[93] Ceci Verbaarschot, Daniëlle Tump, Andreea Lutu, Marzieh Borhanazad, Jordy Thielen, et al. A visual brain-computer interface as communication aid for patients with amyotrophic lateral sclerosis. *Clin. Neurophysiol.*, 2021.

[94] Qingguo Wei, Huayun Gong, and Zongwu Lu. Grouping modulation with different codes for improving performance in cVEP-based brain-computer interfaces. *Electronics Letters*, 53(4):214–216, 2017.

[95] Yonghui Liu, Qingguo Wei, and Zongwu Lu. A multi-target brain-computer interface based on code modulated visual evoked potentials. *PLoS ONE*, 13(8):1–17, 2018.

[96] Mohammadreza Behboodi, Amin Mahnam, Hamidreza Marateb, and Hossein Rabbani. Optimization of Visual Stimulus Sequence in a Brain-Computer Interface Based on Code Modulated Visual Evoked Potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2(c), 2020.

[97] Sebastian Nagel and Martin Spüler. Modelling the brain response to arbitrary visual stimulation patterns for a flexible high-speed BCI. *PLoS ONE*, pages 1–16, 2018.

[98] Sebastian Nagel and Martin Spüler. Asynchronous non-invasive high-speed BCI speller with robust non-control state detection. *Scientific Reports*, 9(1):1–9, 2019.

[99] Sebastian Nagel and Martin Spüler. World's fastest brain-computer interface: Combining EEG2Code with deep learning. *PLoS ONE*, 14(9):1–15, 2019.

[100] Susanna Spinsante, Stefano Andrenacci, and Ennio Gambi. Binary De Bruijn sequences for DS-CDMA systems: analysis and results. *Eurasip Journal on Wireless Communications and Networking*, 2011(1):4, 2011.

[101] Jaime Parra, Fernando H. Lopes Da Silva, Hans Stroink, and Stiliyan Kalitzin. Is colour modulation an independent factor in human visual photosensitivity? *Brain*, 130(6):1679–1689, 2007.

[102] Leo M Hurvich and Dorothea Jameson. An opponent-process theory of color vision. *Psychological Review*, 64(6p1):384, 1957.

[103] Giedrius T. Buračas and Geoffrey M. Boynton. Efficient design of event-related fMRI experiments using m-sequences. *NeuroImage*, 16(3 I):801–813, 2002.

[104] Valeria Mondini, Anna Lisa Mangia, Luca Talevi, and Angelo Cappello. Sinc-windowing and multiple correlation coefficients improve SSVEP recognition based on canonical correlation analysis. *Computational Intelligence and Neuroscience*, 2018, 2018.

[105] Víctor Martínez-Cagigal, Eduardo Santamaría-Vázquez, and Roberto Hornero. Asynchronous Control of P300-Based Brain–Computer Interfaces Using Sample Entropy. *Entropy*, 21(3):230, 2019.

[106] Guang Li Li, Jing Tao Wu, Yong Hui Xia, Quan Guo He, and Hong Guang Jin. Review of semi-dry electrodes for EEG recording. *Journal of Neural Engineering*, 17(5), 2020.

[107] Aya Rezeika, Mihaly Benda, Piotr Stawicki, Felix Gembler, Abdul Saboor, and Ivan Volosyak. Brain–computer interface spellers: A review. *Brain Sciences*, 8(4):57, 2018.

[108] Víctor Martínez-Cagigal, Eduardo Santamaría-Vázquez, and Roberto Hornero. A Portable P300-based Brain-Computer Interface as an Alternative Communication Device. In Diego Torricelli, Metin Akay, and Jose L. Pons, editors, *Proceedings of the 5th International Conference on Neurorehabilitation (ICNR2020)*. Springer International Publishing, 2020.

[109] Tobias Kaufmann, Stefan M Schulz, Claudia Grünzinger, and Andrea Kübler. Flashing characters with famous faces improves erp-based brain–computer interface performance. *Journal of Neural Engineering*, 8(5):056016, 2011.

[110] Bo Hong, Fei Guo, Tao Liu, Xiaorong Gao, and Shangkai Gao. N200-speller using motion-onset visual response. *Clinical Neurophysiology*, 120(9):1658–1666, 2009.

[111] Robin Tibor Schirrmeister, Jost Tobias Springenberg, Lukas Dominique Josef Fiederer, Martin Glasstetter, Katharina Eggensperger, et al. Deep learning with convolutional neural networks for EEG decoding and visualization. *Human Brain Mapping*, 38(11):5391–5420, 2017.

[112] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of Neural Engineering*, 15(5):056013, 2018.

[113] Alexander Ya Supin. Spectrum resolving power of hearing: measurements, baselines, and influence of maskers. *Audiology Research*, 1(2):1–8, 2011.

[114] J Vernon Odom, Michael Bach, Mitchell Brigell, Graham E Holder, Daphne L McCulloch, et al. ISCEV standard for clinical visual evoked potentials:(2016 update). *Documenta Ophthalmologica*, 133(1):1–9, 2016.

[115] Giedrius T Buračas and Geoffrey M Boynton. Efficient design of event-related fMRI experiments using M-sequences. *Neuroimage*, 16(3):801–813, 2002.

[116] Aage R Møller and Hae Dong Jho. Responses from the exposed human auditory nerve to pseudorandom noise. *Hearing Research*, 42(2-3):237–252, 1989.

[117] Edmund C Lalor, Barak A Pearlmutter, Richard B Reilly, Gary McDarby, and John J Foxe. The VESPA: a method for the rapid estimation of a visual evoked potential. *NeuroImage*, 32(4):1549–1561, 2006.

[118] Edmund C Lalor, Alan J Power, Richard B Reilly, and John J Foxe. Resolving precise temporal processing properties of the auditory system using continuous stimuli. *Journal of Neurophysiology*, 102(1):349–359, 2009.