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A Systematic Review of Computational Intelligence Techniques for Channel Selection in P300-Based Brain Computer Interface Speller

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Abstract: Electroencephalography (EEG)-based P300 speller aids in restoring the communication and control capabilities in patients suffering from motor disabilities. However, the quality and quantity of the data collected from EEG recordings have a substantial influence on the P300 speller's performance. Hence, selecting the optimum number of recording electrodes, i.e., channels for each user, is a significant difficulty for the P300 speller. There are two fundamental objectives of the channel selection process: (1) to extract the most crucial information from the relevant channels, hence reducing the computing complexity of P300/non-P300 signal processing operation, and (2) to lessen the potential overfitting that could result from using unwanted channels to boost performance. For obtaining the best channel subsets, different channel selection techniques, including manual, filtering, wrapper, and embedded approaches, have been applied by past researchers. This research provides an in-depth examination of recent advancements, status, challenges, and potential solutions related to channel selection strategies in P300 speller systems. Each channel selection technique is thoroughly explored, including detailed comparisons between them. The notable advantages and drawbacks of each method are emphasized along with the discussion on the future direction and scope of work in the field of channel selection in P300 speller. The review underscores that channel selection methods enable the use of a reduced number of channels without compromising classification performance. By eliminating noisy or irrelevant channels, these approaches contribute to enhanced system performance.

Keywords: electroencephalography, P300 speller, channel selection

1. Introduction

Brain computer interface (BCI) schemes are utilized in various applications, including communication, rehabilitation, neuro-prosthetics, neurofeedback, etc., for people with neuromuscular disabilities [1]. Electroencephalography (EEG) signals are highly utilized inputs for a conventional BCI system because of their portability, cost-effectiveness, and non-invasive EEG electrodes [2]. Furthermore, the positive deflection in recorded EEG at about 300 ms post-stimulus gives rise to the attention-based event-related potential (ERP) known as the P300. Visual, auditory, or somatosensory stimuli can be used in the P300 paradigm to elicit the P300 response [3].

Among P300 BCI protocols, the Farwell and Donchin style row-column (RC) speller [4] is famous and often used. The RC P300 speller protocol exposes the user to a symbol matrix where each row and column of the matrix intensifies separately within a set time interval and in an arbitrary sequence. Only the row and column intensifications with the targeted symbol are paid attention to and counted by the subject. A P300 response is produced in the patient's EEG when they pay attention to and silently count the infrequently occurring target stimuli in a series of target and non-target stimuli. The targeted row and column may be determined, and the intended symbol can be inferred by analyzing the P300 response.

The real-time implementation of the P300 speller is affected by several factors, such as high equipment costs, high processing costs, and low classification accuracy. Investigators have adopted different approaches to handle these issues effectively. Two key variables that might affect how effectively the P300 speller operates are the recording electrode/channel locations and the number of electrodes whose data are used for feature engineering and classification [5]. The EEG signals are usually acquired using multiple channels. For the further operation of ERP classification and character detection, one can either use data from all the channels used for recording or select a subset of channels. Even though multiple-channel EEG recordings enable extensive options for application, specialized channel selection is more effective for better results. For clinical implementation, the P300 speller system needs to employ an ideal number of electrodes to reduce cost and complexity, improve user convenience and information transfer

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rate, and prevent redundant data that result from using irrelevant electrodes. In this respect, channel selection techniques like manual, filter-based, wrapper, embedded, and hybrid approaches have been employed recently. The channel selection algorithms use the most appropriate channels to increase P300 speller performance.

Considering the importance of channel selection, the authors got motivated to review the progress made in this field. Therefore, a survey of major developments to channel selection in the P300 speller is presented in this work. Furthermore, a summary of various methods adopted by past researchers is presented under different heads like P300 detection or character detection performance, the number of selected channels, the dataset, and the classifier to compare the channel selection strategies. This review may help researchers working in the field of P300 spelling to choose suitable algorithms. Additionally, this study should also aid in identifying the drawbacks of the current channel selection techniques and lead the way for the creation of novel ones.

To the author's best information, the presented study is the first survey on channel selection techniques for P300 spellers. The remaining parts of the article are structured as follows: Section 2 contains the importance of channel selection and motivation behind writing the review, Section 3 covers the process of selecting the research article for this survey, and different channel selection strategies are covered in Section 4. Challenges associated with state-of-the-art channel selection techniques and viable solutions are presented in Section 5. Lastly, the authors conclude the study in Section 6.

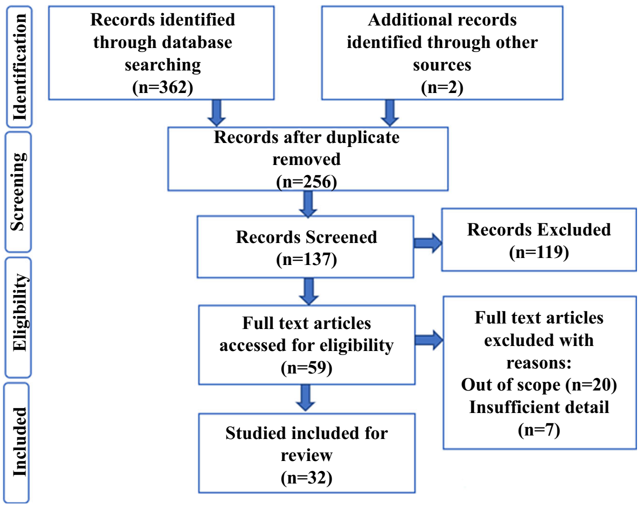
2. Motivation

Channel selection techniques involve choosing the most reliable and relevant brain signal channels or electrodes for detecting the P300 ERP, which occurs when a user focuses on a character in a grid. The selection of EEG channels directly impacts the signal-to-noise ratio, classification performance, and user experience. Thus, the effective channel selection enhances signal quality, user comfort, and spatial resolution, leading to accurate character selection and reduced cognitive load. It also aids in calibration, adapting to individual differences, and optimizing the overall usability of the system, making it an essential step for achieving efficient and reliable communication for users of the P300 speller. By comprehensively analyzing the current state of channel selection methods within the context of P300 spellers, this article aims to shed light on their strengths, limitations, and impact on system performance. Through guiding future research, this review article strives to advance the field, optimize communication capabilities for those in need, and contribute to the broader understanding of BCIs.

3. Inclusion/Exclusion Criterion

With the help of search terms like "P300 Speller," "EEG Speller," and "Channel Selection in P300 Speller," a thorough search of the published literature was conducted for this study. Based on the results volume, the following databases, ScienceDirect, Google Scholar, IEEE Explore, and Web of Science, were selected for the literature search. The search considered all journal articles and conference proceedings published since 1988. Additionally, other publications were included from the references of research articles found through electronic search. Several papers on channel selection in EEG-based BCIs were obtained during the preliminary screening. An exclusion condition was incorporated in the search thread to extract only those studies focused on channel selection in P300 speller. The search turned up 362 papers in total from the chosen databases. After importing the data into Mendeley, the duplicate records were then deleted. The lasting 256 research articles were evaluated manually for relevancy based on the title and abstract. Publications that only addressed the P300 speller's channel selection were permitted, while works based on other P300 BCIs were not. Based on the screening, 32 research articles were deemed pertinent to this study. Figure 1 depicts the whole database screening process through a flow diagram.

Figure 1
Flowchart depicting the process of literature selection



4. Channel Selection Techniques

Since the inception of the P300 speller, several strategies have been employed by researchers for channel selection. As depicted in Figure 2, the channel selection strategies may be grouped into four main categories: (1) manual, (2) wrapper, (3) filter-based, and (4) embedded method. In the manual approach, researchers have chosen the channels based on the previous literature or their own expertise [6]. In wrapper approaches, the candidate channel subsets produced by the search algorithm are evaluated by a classification algorithm. On the other hand, filtering approaches assess the candidate channel subsets using self-determining assessment standards such as a Fisher distance measurement, mutual information measurement, consistency measurement, or dependency measurement. In embedded approaches, channel selection is part of the classifier development; the channels

Figure 2
Types of channel selection techniques

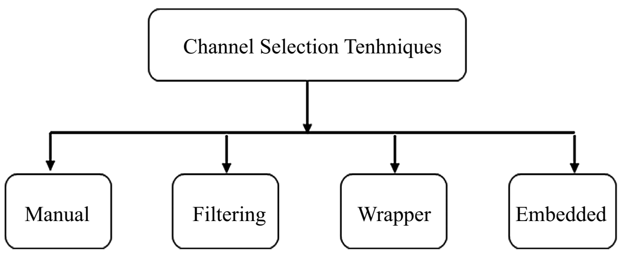
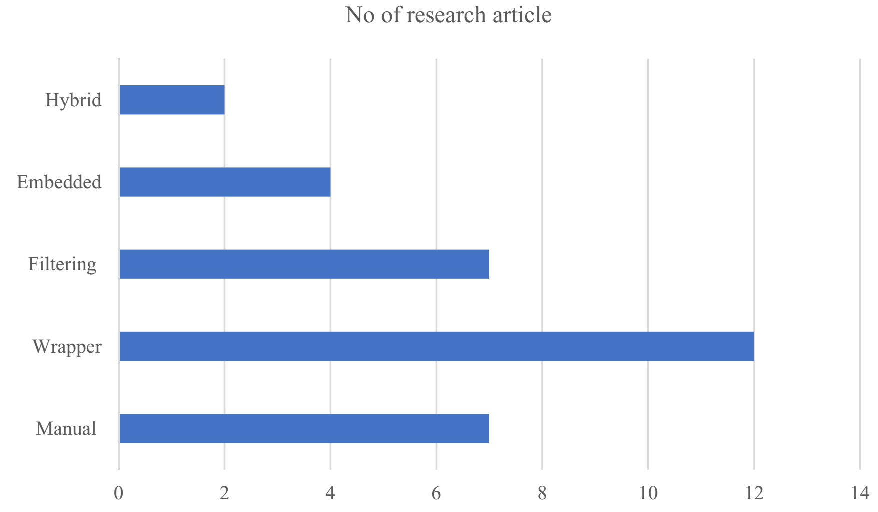


Figure 3
Distribution of channel selection modalities used in literature for P300 speller



are chosen according to criteria developed all through the learning procedure of a particular classifier [6]. The channel selection and the classification are brought together using embedded approaches. They are less prone to overfitting and computationally costly. They are built on the principle of recursive channel elimination, which keeps only channels of valued magnitude. Few studies have used a hybrid strategy that combines any of the four basic approaches covered above. Figure 3 depicts the channel selection technique-wise distribution of research articles reviewed in this study. The following subsections discuss each channel selection strategy mentioned above in detail.

4.1. Manual technique

Manual channel selection in a P300 speller involves the deliberate and strategic choice of specific EEG channels or electrodes to capture and detect the P300 ERP. This method requires human expertise to identify the most relevant and reliable channels for recording brain signals associated with the P300 response. In the earlier years of P300 speller BCI research, most works concentrated on data collected from typical midline scalp locations (i.e., Cz, Pz, Fz). Lately, Krusienski et al. [7] investigated the utility of incorporating data from the electrode at posterior locations (namely Oz, PO7, PO8). They concluded that combining the posterior and central channel sets considerably improves performance. Following the conclusions made in Krusienski et al. [7], Nijboer et al. [8] manually chose electrodes at locations P3, Pz, P4, Fz, Cz, Oz, PO7, and PO8 for the online copy spelling task. El Dabbagh and Fakhr [9] employed a recursive algorithm that, by removing a single channel at a time, analyzes the effectiveness of the support vector machine (SVM) classifier following its training process. The channel whose removal improves the performance of the classifier is deleted. Until all channels are removed once, they follow the same process again to find the optimum set of electrodes.

In another study, to avoid the complicated calculation of 64 electrodes recorded data, Zahra et al. [10] selected Fz, C3, Cz, C4, PO7, PO8, and Pz for their study on BCI-competition II dataset using linear discriminant analysis (LDA) classifier. The choice of channels was inspired by the first runner-up of the BCI competition [11]. Nashed et al. [12] selected two parietal and two occipital lobe electrodes as P7 and P8 are involved in processing cognitive tasks, whereas O1 and O2 are involved in human vision. The experimental results led them to conclude that their autoencoder (AE)-based classification model improves single-trial classification performance when choosing the combination of cognitive and visual channels. Ramirez-Quintana et al. [13] opted for data from three electrodes (O1, O2, and Oz) for convolutional neural network (CNN)-based P300 classification in their BCI. Since the occipital lobe contains significant cortical layers of the visual cortex that compose the visual perception capabilities, they concluded that the occipital lobe alone could produce a distinctive P300 signal. Won et al. [14] chose Fz, Cz, Pz, CP1, and CP2 electrodes from the frontal and parietal regions for the classification using stepwise LDA (SWLDA). So, from the above literature, we can conclude that in the manual approach of channel selection, researchers have majorly chosen the electrodes that cover the central, parietal, and occipital regions of the brain. Table 1 summarizes the various researches adopting manual channel selection in terms of the dataset, number of participants, channel selection techniques, number of the selected channel, number of available channels, and classification performance.

4.2. Wrapper technique

The wrapper approach essentially treats the channel selection as part of the classification process itself. It evaluates the quality of the selected channels based on how well the classification algorithm performs with those channels. The iterative nature of the wrapper approach allows for dynamic refinement of the channel subset to enhance the accuracy and effectiveness of the P300 speller system. Figure 4 shows the generalized workflow of the wrapper approach.

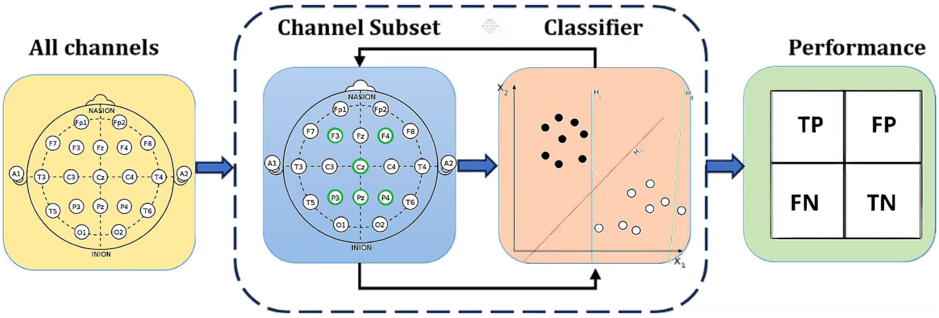
Optimization techniques that draw their inspiration from natural selection, for example, genetic and other population-based algorithms, form a particular type of wrapper method [6]. An optimization approach is a potent tool for obtaining the ideal combination of operating circumstances and the required design parameters [15]. A group of P300 speller researchers considered the selection of channels as an optimization issue, and they employed a variety of methodologies to identify the best possible channel combination. Among numerous evolutionary optimization

Table 1
Summary of manual channel selection for P300 speller

Reference	Language	Subject	Technique	TC	SC	Classifier	Dataset	Classification performance
Krusienski et al. [7]	English	7	Manual	64	6	SWLDA	Self-recorded	MCA: 92.5%
Nijboer et al. [8]	English	4	Manual	16	8	SWLDA	Self-recorded	MCA: 78.8%
El Dabbagh and Fakhr [9]	English	2	Manual	64	1	SVM	BCI comp.-III dataset II	MCA: 97%
Zahra et al. [10]	English	1	Manual	64	7	LDA	BCI comp.-III dataset II	MCA: 97.4%
Nashed et al. [12]	English	2	Manual	14	4	AE with SoftMax	Self-recorded	MCDA: 54.68% (single trial)
Ramirez-Quintana et al. [13]	English	8	Manual	–	5	CNN	Self-recorded	MCA: 96%
Won et al. [14]	English	55	Manual	32	5	SWLDA	Self-recorded	—

Note: TC = total channel, SC = selected channel, MCA = mean classification accuracy, MCDA = mean character detection accuracy

Figure 4
Workflow of wrapper technique for channel selection



approaches, particle swarm optimization (PSO) is popular due to its more straightforward implementation, higher computing speed, and more effective global optimizer quality. Jin et al. [16] used PSO to find the ideal electrode configuration. They also used Bayesian LDA (BLDA) to identify words in the P300 speller based on the Chinese language. In a P300 speller for English, Arican and Polat [17] framed the channel count reduction and classification accuracy improvement as a binary optimization problem and employed binary PSO (BPSO). PSO and BPSO were designed to accomplish a single objective function. However, maximizing classification accuracy while reducing the channel count is a multi-objective optimization issue. In this regard, Chaurasiya et al. [18] adopted an approach based on multi-objective binary PSO (MOBPSO). For choosing the ideal channel sets in BCI applications, a unique multi-objective hybrid algorithm was suggested by Martínez-Cagigal et al. [19]. Their approach combines the salient features of multi-objective PSO and forward selection. By performing the local search for each channel, they improved the classification and reduced the necessary number of channels. Recently, Martínez-Cagigal et al. [20] compared 8 different single and multi-objective algorithms like binary multi-objective PSO (BMOPSO) and pareto evolutionary algorithm for incremental learning (PEAIL) for channel selection process. They concluded that high inter-subject variability in optimal channel sets necessitates optimization for each individual rather than employing a single set for all of them.

Apart from optimization techniques, genetic algorithms (GAs) have been adopted by few researchers for channel selection. GA provides a significant deal of promise for studying inter-channel relations and the combined outcome of different channel combinations, given that the fitness value is unaffected by any one channel. For a P300-based BCI, Kee et al. [21] developed an automatic channel selection method utilizing GA and BLDA. Atum et al. [22] used GA in a wrapper approach for channel selection in subject-independent and subject-dependent settings for single-trial classification. They used Fisher's LDA (FLDA) as a classifier in their experiments. The primary finding from their research is that rather than customizing the channel subset for individual subjects, a subject-independent subset of the channels could be used without compromising the speller's performance. The parieto-occipital zone housed the most often chosen channels in their study (Oz, Pz, PO8 and PO7). The results show that for BCIs utilizing visual stimulus processing like the P300 speller, information from the parietal and occipital area is crucial.

Differential evolution (DE) is an evolutionary computing technology that is straightforward and only needs two control parameters to be tuned. It has been shown to be superior to conventional evolutionary optimization techniques such as GA and PSO for several real-world issues. For example, for Devanagari script-based P300 speller, Chaurasiya et al. [23] and Chaurasiya et al. [24] adopted a binary DE-based channel selection technique to identify and use the finest channel subset in a weighted ensemble of SVM (WESVM)-based classification. The same authors presented a multi-objective binary DE (MOBDE) technique in a subsequent

Table 2
Summary of wrapper channel selection methods for P300 speller

Reference	Language	Subject	Technique	TC	SC	Classifier	Dataset	Classification performance
Jin et al. [16]	Chinese	11	PSO	36	8	BLDA	Self-recorded	MCA: 89.33%
Arican and Polat [17]	English	2	BPSO	64	8	Boosted Tree	BCI comp.-III dataset II	MCA: 89.9%
Chaurasiya et al. [18]	English	2	MOBPSO	64	30	SVM	BCI comp.-III dataset II	MCA: 90.75%
Martínez-Cagigal et al. [19]	English	4	HMO	16	8	LDA	Self-recorded	MCA: 97%
Kee et al. [21]	English	18	GA	64	4	BLDA	Self-recorded	MCDA: 90%
Atum et al. [22]	English	2	GA	64	8	FLDA	BCI comp.-III dataset II	MCDA: 91.15%
Chaurasiya et al. [23]	Devanagari	10	Binary DE	64	28	WESVM	Self-recorded	MCA: 87.2%, MCDA: 92.2%
Chaurasiya et al. [24]	Devanagari	9	MOBDE	64	26	SVM	Self-recorded	MCA: 92.6%
Chaurasiya et al. [25]	Devanagari	10	Binary DE	64	26	SVM	Self-recorded	MCDA: 99%
Salvaris and Sepulveda [26]	English	2\1	SFS	64	10	E-FLD	BCI comp.-II and III	MCDA: 95% (BCI-III) 100% (BCI-II)
Martínez-Cagigal et al. [20]	English	2	LDA	64	20 14	BMOPSO PEAIL	BCI comp.-III dataset II	MCDA: 92.5% MCDA: 94%
Zhao et al. [27]	English	2/1	BLDA	64	AT	RSBSBL	BCI comp.-II and III	MCDA: 97.5% (BCI-III) 100% (BCI-II)

Note: TC = total channel, SC = selected channel, MCA = mean classification accuracy, MCDA = mean character detection accuracy, AT = automatic

study [25] to address the trade-off between channel count and classification performance.

In another wrapper approach, Salvaris and Sepulveda [26] performed a sequential floating forward search (SFFS) strategy to select an optimum number of channels for an ensemble of Fisher linear discrimination (E-FLD)-based classification. The SFFS's most frequently chosen channels agree with the channels chosen using the technique used by Rakotomamonjy and Guigue [11]. For both the datasets used in their study, electrodes from the central and parietal regions, including POz, CPz, and Pz, were selected. Additionally, in the BCI comp. III dataset, PO7 and PO8 were in the top four channels chosen for both subjects. Zhao et al. [27] evaluated the effectiveness of regional smoothing block sparse Bayesian learning (RSBSBL) for channel selection and created a model for an automatic selection iteration technique to save time. The experimental findings show that RSBSBL is capable of choosing optimal channels, which results in good recognition accuracy.

Table 2 summarizes the various research adopting wrapper channel selection in terms of the dataset, number of participants, channel selection techniques, number of the selected channel, number of available channels, and classification performance.

4.3. Filtering technique

A filter-based approach for channel selection in the context of a P300 speller involves evaluating the relevance of different EEG channels or electrodes based on specific criteria before the classification process. Figure 5 shows the generalized workflow of the filter approach. Filter-based approaches for channel selection rely on univariate statistics, mutual information, correlation, etc. Scalability, higher speed, and independence from the classifier are a few advantages of the filter technique. Among different researchers employing filter-based approach for channel selection, Shahriari and Erfanian [28] used mutual information as a channel selection tool. They selected channels with maximal dependence on the targeted class and minimal reliance on themselves. Utilizing the joint distribution of the participants' EEG data and the labels, Speier et al. [29] found sets of electrodes using Gibbs sampling. The association between the number of channels and speller performance was demonstrated by offline evaluation using a naive bayes classifier. The best four-electrode configuration (PO7, PO8, POZ, CPZ) was prospectively assessed. Yang et al. [30] used the Fisher distance between the target P300 ERP and non-target NP300 ERP to select the dominant channels. Their

Figure 5
Workflow of filter technique for channel selection

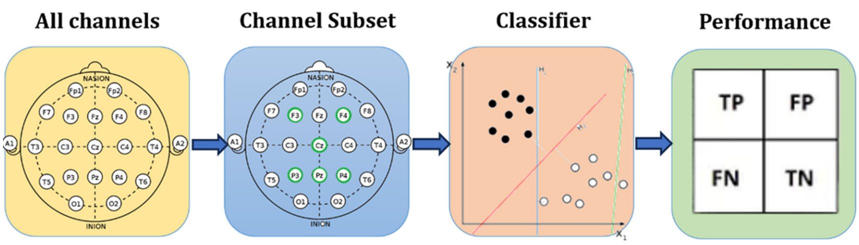


Table 3
Summary of filtering-based channel selection methods for P300 speller reviewed in this study

Reference	Language	Subject	Technique	TC	SC	Classifier	Dataset	Classification performance
Shahriari and Erfanian [28]	English	2	Mutual information	64	8	SVM	BCI comp.-III dataset II	MCA: 96.7%
Speier et al. [29]	English	15	Gibbs sampling	32	4	Naïve Bayes	Self-recorded	ITR: 20.83 BPM
Yang et al. [30]	English	1	F score	64	55	SVM	BCI comp.-II	MCDA: 100%
Xu et al. [31]	English	9	PM	32	8	FLDA	Self-recorded	–
Xiao et al. [32]	English	25	XDAWN	64	16	DPCM	Self-recorded	AUC: 86.5%
Colwell et al. [33]	English	18	Jump-wise regression	32	8	SWLDA	Self-recorded	MCA: 79.1%
Ryan et al. [34]	English	36	Jump-wise selection	32	8	SWLDA	Self-recorded	MCA: 85.97%

Note: TC = total channel, SC = selected channel, MCA = mean classification accuracy, MCDA = mean character detection accuracy, ITR = information transfer rate, BPM: bits per minute

study uses the Fisher score-based channel selection method to remove irrelevant EEG channels and improve the P300 detection performance. Xu et al. [31] adopted a phase measurement (PM) approach to demonstrate its efficacy in channel selection. Their proposed approach splits EEG channels into clusters by analyzing their phase connections. It then ranks the channels to ensure that the first n channels accurately reflect the most significant sources. Xiao et al. [32] applied the concept of xDAWN for channel selection. They used multi-window discriminative canonical pattern matching to choose the channel with high SNR for each subject to increase the character detection accuracy with small training examples. The xDAWN-based spatial filter used in their pre-processing significantly aids in choosing the best channels. Colwell et al. [33] and Ryan et al. [34] employed jump-wise channel selection approach in a filter-based technique to obtain the best-performing channels. Table 3 summarizes the various researches adopting filtering-based channel selection in terms of the dataset, number of participants, channel selection techniques, number of the selected channel, number of available channels, and classification performance.

4.4. Embedded technique

Embedded techniques for channel selection involve incorporating the channel selection process directly into the training of the classification algorithm itself. This approach aims to simultaneously optimize the selection of relevant channels and the performance of the classification model within a unified framework. In the embedded technique, channels are chosen using criteria developed during the learning process of a particular classifier. Figure 6 shows the generalized workflow of the embedded approach for channel selection.

The channel selection module is aggregated within the architecture in a few deep-learning classifiers. For example, a P300 speller with channel selection aggregated within CNNs was recently utilized by Cecotti and Gräser [35]. Using eight chosen channels, they claimed a mean classification score of 87% for BCI competition III dataset II. In another embedded approach, Kshirsagar and Londhe [2] used channel-wise convolution to identify healthy and noisy channels and then pooled the 8 high-rank channels for further processing in their Devanagari script-based speller system.

Kabbara et al. [36] calculated classification performance-based S score for each channel separately, and then channels exceeding the threshold were chosen for final classification. Shojaedini and Adeli [37] performed CNN-based recursive channel elimination for their P300 speller. Table 4 summarizes the various researches adopting embedded channel selection in terms of the dataset, number of participants, channel selection techniques, number of the selected channel, number of available channels, and classification performance.

Figure 6
Workflow of embedded technique for channel selection

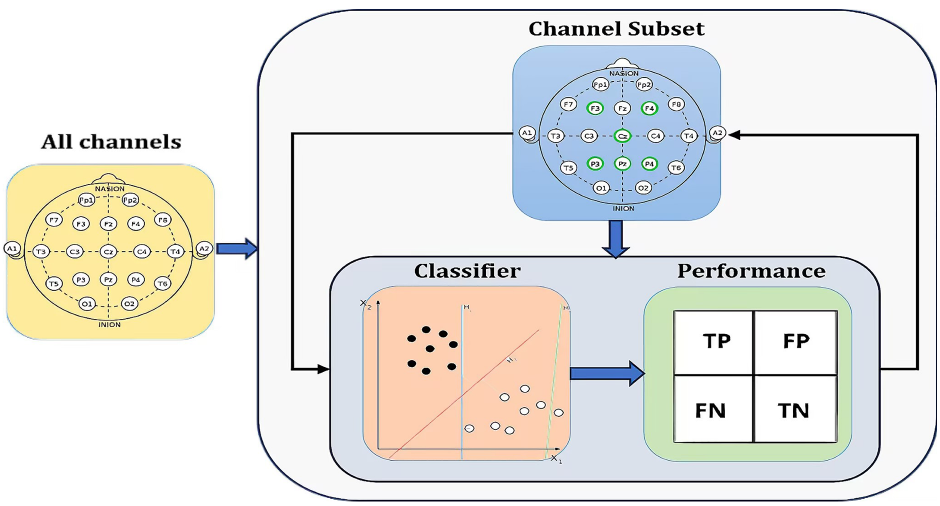


Table 4
Summary of embedded channel selection methods for P300 speller

Reference	Language	Subject	Technique	TC	SC	Classifier	Dataset	Classification performance
Cecotti and Gräser [35]	English	2	CNN	64	8	CNN	BCI comp.-III dataset II	MCA: 87%
Kshirsagar and Londhe [2]	Devanagari	10	CNN	16	8	CNN	Self-recorded	MCA: 95%
Kabbara et al. [36]	English	10	CNN	64	24	CNN	Self-recorded	MCDA: 97.34%
Shojaedini and Adeli [37]	Arabic	11	S score	19	–	SVM	Self-recorded	MCA: 95%

Note: TC = total channel, SC = selected channel, MCA = mean classification accuracy, MCDA = mean character detection accuracy

Table 5
Summary of hybrid channel selection methods for P300 speller

Reference	Language	Subject	Technique	TC	SC	Classifier	Dataset	Classification performance
Perseh and Sharafat [38]	English	2	IBPSO	64	22	BLDA	BCI comp.-III dataset II	MCA: 97.5%
Thulasidas and Guan [39]	English	9	F score	64	10	SVM	Self-recorded	MCA: 99%

Note: TC = total channel, SC = selected channel, MCA = mean classification accuracy

4.5. Hybrid technique

Apart from the approaches mentioned earlier, few studies have incorporated a combination of any two approaches. Perseh and Sharafat [38] adopted a two-stage strategy to locate the dominant channels. They started by sorting channels utilizing the Bhattacharyya distance and cutting off 50% with smaller distances. Next, they determined which channels are more relevant, utilizing the improved BPSO (IBPSO) algorithm on the remaining channels. Thulasidas and Guan [39] first manually selected 25 out of 64 channels and then each channel's Fisher channel score (FCS) was calculated. Once they get the FCS, the channels were arranged in order of increasing FCS. The channels with lower FCS and negative impact on classification performance were then eliminated. Embedded techniques offer the advantage of optimizing both channel selection and classification simultaneously, potentially leading to a more efficient and accurate P300 speller system. Table 5 summarizes the various researches adopting hybrid channel selection in terms of the dataset, number of participants, channel selection techniques, number of the selected channel, number of available channels, and classification performance.

5. Current Challenges and Proposed Solution

5.1. Current challenges

The recent developments and present status of channel selection techniques in the P300 speller are described in Section 4. The extensive analysis in this work has shown that it is feasible to employ a limited number of EEG channels between 1 and 80% of the available channels while still performing the classification/detection tasks with little to no performance loss. In turn, shorter setup time and fewer electrodes will retain the subject's convenience while reducing processing complexity. However, despite the intensive studies for more than two decades, we still lack a system that can accurately select the channels in EEG-based P300 speller for real-world applications. Even though numerous research has been conducted, the results of many studies [9, 10, 17, 18, 22, 26, 28, 35, 38] are somewhat limited by size of the dataset. In addition, studies with fewer participants may not adequately address the subject variability brought on by more participants. In the case of the manual approach [7–10, 12–14], selecting channels based on an understanding of neurophysiology does not always produce the best results.

Moreover, the wrapper approaches [16–19, 22–25, 28] have proved effective in improving the efficiency of the speller, but due to its time-consuming nature, it performs poorly in clinical applications. The wrapping methods frequently over-fit and become trapped in local optimums. Additionally, wrapper and, to a smaller extent, embedding techniques [2, 35–37] have a high computational overhead, adding significant limits when handling many channels. The filter-based methods [28–34] disregard the relationship between channels and thus suffer from poor classification performance. Filter-based methods do not work with the combination of multiple channels. Finally, the strategies adopted in the studies reviewed for this article are not user-friendly because the methodologies involve a complete set of EEG channels for every subject prior to picking an optimal channel subset.

A comparative summary of different channel attention techniques comprising their methodology, merits, and demerits is presented in Table 6.

5.2. Proposed solution and future direction

1) EEG signals collected from different people vary significantly from one another and there is significant inter-subject variability, robust approaches can be designed by large-scale analysis using data from a sufficiently large number of subjects.
2) Most of the recent research uses healthy participants as their foundation. More research is needed to learn how well these approaches work on people with brain injuries.
3) A fully automated embedded channel selection-like approach is desirable for handling the high variability in practical BCI systems. More focus should be on designing embedded channel selection techniques that could give acceptable performance with optimum computational overhead.
4) Developing algorithms that, in response to the changing properties of the EEG signals, dynamically modify the channel weights during a P300 speller session is highly required to adapt to the

Table 6
Comparative summary of channel selection methods for P300 speller

Method	Approach	Merit	Demerit
Manual	Expert knowledge	No algorithm overhead [7–10, 12]	Subjective and vary across experts, potentially introducing bias [13] Might not be practical for large-scale applications [14] Might not scale well for large datasets or real-time applications [12]
Wrapper	Iterative	Consider the interaction between channels and the classification algorithm [17] Potentially optimal channel subsets [21, 22]	Computationally intensive [23] Prone to overfitting [23, 26]
Filter	Independent	Computationally efficient [28] Less likely to overfit the classifier [30]	Do not capture interactions between channels and the specific classification algorithm [31, 33] Might not adapt well to specific datasets or classification tasks [33]
Embedded	Model based	Optimize channel selection and classification simultaneously [2] Less prone to overfitting	Proper tuning of hyperparameters is crucial to achieve optimal results [35, 36]
Hybrid	Combination	Leverage the strengths of multiple techniques, potentially leading to a more robust solution [38]	Most complex to implement Require careful design and validation [39]

user's cognitive state change and improvement in performance over time. BCI applications have recently used channel attention mechanisms to give relevant and healthy channels more importance. Authors suggest using a channel-wise attention-based channel selection approach in P300 speller as a possible future direction. Attention-based channel selection can select the relevant channels with higher weight instead of working with all the channels. Such approaches can be easily aggregated with the classifier model plus would not create a computation burden.

5) Techniques that consider user preferences, user-specific patterns, and aspects of brain anatomy to customize channel selection for each user. Personalized strategies can considerably improve accuracy and user satisfaction.
6) Examining the strategies that would let the P300 speller system adjust gradually as the user's EEG data changed over time. For instances involving long-term usage, this is especially important.

6. Conclusion

Effective channel selection strategies are essential for finding an optimum channel subset for the intended BCI application because EEG data are acquired from diverse brain regions. After thoroughly reviewing the available research on channel selection in P300 speller, the authors conclude that channel selection methods allow for using fewer channels without negotiating classification performance. By removing noisy or irrelevant channels, channel selection approaches improve system performance. The clinical viability of P300 speller systems may be improved by optimizing the count of recording electrodes to lower cost, setup time, and processing needs. Despite the several efforts made by past researchers, designing of an efficient and fast channel selection strategy that could be embedded with the classifier model is still an open research area. Lastly, this comprehensive review will overview the channel selection techniques incorporated by previous researchers in the P300 speller and help promising researchers interested in P300 speller BCI.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Narendra D. Londhe is an Editorial Board Member for *Artificial Intelligence and Applications,* and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

References

[1] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology*, *113*(6), 767–791. https://doi.org/10.1016/s1388-2457(02)00057-3

[2] Kshirsagar, G. B., & Londhe, N. D. (2022). DS-P3SNet: An efficient classification approach for Devanagari script-based P300 speller using compact channelwise convolution and knowledge distillation. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(12), 7431–7443. https://doi.org/10.1109/TSMC.2022.3156861

[3] Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI2000: A general-purpose brain-computer interface (BCI) system. *IEEE Transactions on Biomedical Engineering*, *51*(6), 1034–1043. https://doi.org/10.1109/TBME.2004.827072

[4] Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical*

Neurophysiology, *70*(6), 510–523. https://doi.org/10.1016/0013-4694(88)90149-6

[5] Alotaiby, T., El-Samie, F. E. A., Alshebeili, S. A., & Ahmad, I. (2015). A review of channel selection algorithms for EEG signal processing. *EURASIP Journal on Advances in Signal Processing*, *2015*(1), 66. https://doi.org/10.1186/s13634-015-0251-9

[6] Baig, M. Z., Aslam, N., & Shum, H. P. H. (2020). Filtering techniques for channel selection in motor imagery EEG applications: A survey. *Artificial Intelligence Review*, *53*(2), 1207–1232. https://doi.org/10.1007/s10462-019-09694-8

[7] Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2008). Toward enhanced P300 speller performance. *Journal of Neuroscience Methods*, *167*(1), 15–21. https://doi.org/10.1016/j.jneumeth.2007.07.017

[8] Nijboer, F., Sellers, E. W., Mellinger, J., Jordan, M. A., Matuz, T., Furdea, A., . . . , & Kübler, A. (2008). A P300-based brain–computer interface for people with amyotrophic lateral sclerosis. *Clinical Neurophysiology*, *119*(8), 1909–1916. https://doi.org/10.1016/j.clinph.2008.03.034

[9] El Dabbagh, H., & Fakhr, W. (2011). Multiple classification algorithms for the BCI P300 speller diagram using ensemble of SVMs. In *IEEE GCC Conference and Exhibition,* 393–396. https://doi.org/10.1109/IEEEGCC.2011.5752542

[10] Zahra, A., Vahid, A., & Sadeghi, M. T. (2013). Comparison of performance of different feature extraction methods in detection of P300. *Biocybernetics and Biomedical Engineering*, *33*(1), 3–20. https://doi.org/10.1016/S0208-5216(13)70052-4

[11] Rakotomamonjy, A., & Guigue, V. (2008). BCI competition III: Dataset II-Ensemble of SVMs for BCI P300 speller. *IEEE Transactions on Biomedical Engineering*, *55*(3), 1147–1154. https://doi.org/10.1109/TBME.2008.915728

[12] Nashed, N. N., Eldawlatly, S., & Aly, G. M. (2018). A deep learning approach to single-trial classification for P300 spellers. In *4th Middle East Conference on Biomedical Engineering,* 11–16. https://doi.org/10.1109/MECBME.2018.8402397

[13] Ramirez-Quintana, J. A., Madrid-Herrera, L., Chacon-Murguia, M. I., & Corral-Martinez, L. F. (2021). Brain–computer interface system based on P300 processing with convolutional neural network, novel speller, and low number of electrodes. *Cognitive Computation*, *13*(1), 108–124. https://doi.org/10.1007/s12559-020-09744-2

[14] Won, K., Kwon, M., Jang, S., Ahn, M., & Jun, S. C. (2019). P300 speller performance predictor based on RSVP multi-feature. *Frontiers in Human Neuroscience*, *13*, 261. https://doi.org/10.3389/fnhum.2019.00261

[15] Arvaneh, M., Guan, C., Ang, K. K., & Quek, C. (2011). Optimizing the channel selection and classification accuracy in EEG-based BCI. *IEEE Transactions on Biomedical Engineering*, *58*(6), 1865–1873. https://doi.org/10.1109/TBME.2011.2131142

[16] Jin, J., Allison, B. Z., Brunner, C., Wang, B., Wang, X., Zhang, J., . . . , & Pfurtscheller, G. (2010). P300 Chinese input system based on Bayesian LDA. *Biomedical Engineering*, *55*(1), 5–18. https://doi.org/10.1515/BMT.2010.003

[17] Arican, M., & Polat, K. (2020). Binary particle swarm optimization (BPSO) based channel selection in the EEG signals and its application to speller systems. *Journal of Artificial Intelligence and Systems*, *2*, 27–37. https://doi.org/10.33969/AIS.2020.21003

[18] Chaurasiya, R. K., Saraf, A., Sarala, D., Kanikdaley, T., & Jogi, S. (2018). Multi-objective binary-PSO for improving the performance of P300 speller. In *3rd International Conference on Internet of Things: Smart Innovation and Usages*, 1–7. https://doi.org/10.1109/IoT-SIU.2018.8519891

[19] Martínez-Cagigal, V., Santamaría-Vázquez, E., & Hornero, R. (2019). A novel hybrid swarm algorithm for P300-based BCI channel selection. In *World Congress on Medical Physics and Biomedical Engineering 2018*, 41–45.

[20] Martínez-Cagigal, V., Santamaría-Vázquez, E., & Hornero, R. (2022). Brain–computer interface channel selection optimization using meta-heuristics and evolutionary algorithms. *Applied Soft Computing*, *115*, 108176. https://doi.org/10.1016/j.asoc.2021.108176

[21] Kee, C. Y., Kuppan Chetty, R. M., Khoo, B. H., & Ponnambalam, S. G. (2012). Genetic algorithm and Bayesian linear discriminant analysis based channel selection method for P300 BCI. In *International Conference on Intelligent Robotics, Automation, and Manufacturing,* 226–235. https://doi.org/10.1007/978-3-642-35197-6_25

[22] Atum, Y., Pacheco, M., Acevedo, R., Tabernig, C., & Biurrun Manresa, J. (2019). A comparison of subject-dependent and subject-independent channel selection strategies for single-trial P300 brain computer interfaces. *Medical & Biological Engineering & Computing*, *57*(12), 2705–2715. https://doi.org/10.1007/s11517-019-02065-z

[23] Chaurasiya, R. K., Londhe, N. D., & Ghosh, S. (2016). Binary de-based channel selection and weighted ensemble of SVM classification for novel brain–computer interface using Devanagari script-based P300 speller paradigm. *International Journal of Human-Computer Interaction*, *32*(11), 861–877. https://doi.org/10.1080/10447318.2016.1203047

[24] Chaurasiya, R. K., Londhe, N. D., & Ghosh, S. (2016). A novel weighted edit distance-based spelling correction approach for improving the reliability of Devanagari script-based P300 speller system. *IEEE Access*, *4*, 8184–8198. https://doi.org/10.1109/ACCESS.2016.2614494

[25] Chaurasiya, R. K., Londhe, N. D., & Ghosh, S. (2017). Multi-objective binary DE algorithm for optimizing the performance of Devanagari script-based P300 speller. *Biocybernetics and Biomedical Engineering*, *37*(3), 422–431. https://doi.org/10.1016/j.bbe.2017.04.006

[26] Salvaris, M., & Sepulveda, F. (2009). Wavelets and ensemble of FLDs for P300 classification. In *4th International IEEE/EMBS Conference on Neural Engineering*, 339–342. https://doi.org/10.1109/NER.2009.5109302

[27] Zhao, X., Jin, J., Xu, R., Li, S., Sun, H., Wang, X., & Cichocki, A. (2022). A regional smoothing block sparse Bayesian learning method with temporal correlation for channel selection in P300 speller. *Frontiers in Human Neuroscience*, *16*, 875851. https://doi.org/10.3389/fnhum.2022.875851

[28] Shahriari, Y., & Erfanian, A. (2011). A mutual information based channel selection scheme for P300-based brain computer interface. In *5th International Conference on Neural Engineering*, 434–437. https://doi.org/10.1109/NER.2011.5910579

[29] Speier, W., Deshpande, A., & Pouratian, N. (2015). A method for optimizing EEG electrode number and configuration for signal acquisition in P300 speller systems. *Clinical Neurophysiology*, *126*(6), 1171–1177. https://doi.org/10.1016/j.clinph.2014.09.021

[30] Yang, L., Li, J., Yao, Y., & Li, G. (2007). An algorithm to detect P300 potentials based on F-score channel selection and support vector machines. In *Third International Conference on Natural Computation*, *2*, 280–284. https://doi.org/10.1109/ICNC.2007.172

[31] Xu, M., Qi, H., Ma, L., Sun, C., Zhang, L., Wan, B., . . . , & Ming, D. (2013). Channel selection based on phase measurement in P300-based brain-computer interface. *PLOS ONE*, *8*(4), e60608. https://doi.org/10.1371/journal.pone.0060608

[32] Xiao, X., Xu, M., Han, J., Yin, E., Liu, S., Zhang, X., Jung, T. P., & Ming, D. (2021). Enhancement for P300-speller classification using multi-window discriminative canonical pattern matching. *Journal of Neural Engineering*, *18*(4), 046079. https://doi.org/10.1088/1741-2552/ac028b

[33] Colwell, K. A., Ryan, D. B., Throckmorton, C. S., Sellers, E. W., & Collins, L. M. (2014). Channel selection methods for the P300 speller. *Journal of Neuroscience Methods*, *232*, 6–15. https://doi.org/10.1016/j.jneumeth.2014.04.009

[34] Ryan, D. B., Townsend, G., Gates, N. A., Colwell, K., & Sellers, E. W. (2017). Evaluating brain–computer interface performance using color in the P300 checkerboard speller. *Clinical Neurophysiology*, *128*(10), 2050–2057. https://doi.org/10.1016/j.clinph.2017.07.397

[35] Cecotti, H., & Gräser, A. (2011). Convolutional neural networks for P300 detection with application to brain–computer interfaces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *33*(3), 433–445. https://doi.org/10.1109/TPAMI.2010.125

[36] Kabbara, A., Hassan, M., Khalil, M., Eid, H., & El-Falou, W. (2015). An efficient P300-speller for Arabic letters. In *International Conference on Advances in Biomedical Engineering*, 142–145. https://doi.org/10.1109/ICABME.2015.7323272

[37] Shojaedini, S. V., & Adeli, M. (2020). A new method for improvement of the accuracy of character recognition in P300 speller system: Optimization of channel selection by using recursive channel elimination algorithm based on deep learning. *Journal of Health Management & Informatics*, *7*(1), 42–51.

[38] Perseh, B., & Sharafat, A. R. (2012). An efficient P300-based BCI using wavelet features and IBPSO-based channel selection. *Journal of Medical Signals & Sensors*, *2*(3), 128–143. https://doi.org/10.4103/2228-7477.111994

[39] Thulasidas, M., & Guan, C. (2005). Optimization of BCI speller based on P300 potential. In *IEEE Engineering in Medicine and Biology 27th Annual Conference*, 5396–5399. https://doi.org/10.1109/IEMBS.2005.1615702

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