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A Speller Mechanism for Alternative Communication Using Brain-Computer Interface: A Scoping Review

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***Abstract*— Brain-computer interface (BCI) spelling software aids the disabled in their ability to communicate. The BCI speller allows patients to communicate without using their bodies by translating brain waves into computer commands. EEG signals are used by BCI spellers to create letters. You can pick from a variety of BCI spellers that use electroencephalogram readings. The three main parts of a BCI speller system are the paradigm, the data collection mechanism, and the signal processing algorithms. Feature extraction, feature optimization, and classification algorithms are explored alongside BCI speller paradigms in this research. Both the benefits and drawbacks of the speller paradigm and the machine learning approach are discussed in this article. Future BCI speller research may be free of certain limitations.**

Keywords*— Brain-computer interface; Motor imagery; steady-state visually evoked potential (SSVEP); P300; Machine learning

I. Introduction

Neurological disorder, ALS, and elderly patients use brain-computer interface (BCI) systems to communicate [1]. Brain signals from participants express their ideas without physical activity. EEG, ECoG, NIRS, MEG, fMRI, and EEG may assess brain activity [2]. EEG has good temporal resolution, but poor spatial resolution compared to fMRI. EEG signal, obtained non-invasively, is employed more in clinical and research applications. EEG data gathering systems are cheaper and more portable, making them more practical. Preprocessing, feature extraction, classification, and control interface are typical BCI system steps.

BCI applications have used many GUI and signal processing methods in recent decades. Visual speller paradigm, feature extraction, and classification methods classify them.

II. Brain Computer Interface Speller Paradigms

Patients with disabilities are the primary users of BCI spellers. The system of letters, numbers, and symbols used to spell words is complex. The brain-computer interface (BCI) speller system interprets the subject's EEG signal to select the appropriate character from the speller paradigm and generate the user's control command. EEG signals are used in a variety of applications, including motor imaging (MI), steady-state visually evoked potential (SSVEP), P300, and hybrid speller systems [3]. While [3] focuses solely on BCI speller paradigms, this study examines the entire BCI system. The concepts of the BCI speller paradigm and EEG signal processing are explored in this work.

A. Motor Imagery Speller

MI is a mental expression of motor behavior. Patients with motor impairments can use MI-based BCI systems for non-muscular communication. A spellchecker based on MI doesn't need any outside input to do its job. Characters in [4] can be hexed with Hex-O-Spell. In Fig.1, a circle is surrounded by six hexagons, each of which has an arrow pointing in its direction. The arrow is guided by your right foot and your imagination. There are a total of 30 objectives on this spellchecker (26 letters + 4 punctuation), split among six hexagons at a rate of five each hexagon. With Hex-O-Spell, you can cast a spell in two simple steps. The first step is for the subject to select the appropriate hexagon. The five characters can now be arranged into a hexagon. Step two involves the participant selecting the role. The repetition of a letter or sound forms a word. MI is a mental expression of motor behaviour. Patients with motor impairments can use MI-based BCI systems for non-muscular communication. A spellchecker based on MI doesn't need any outside input to do its job. Characters in [4] can be hexed with Hex-O-Spell.

In Fig.1, a circle is surrounded by six hexagons, each of which has an arrow pointing in its direction. The arrow is guided by your right foot and your imagination. There are a total of 30 objectives on this spellchecker (26 letters + 4 punctuation), split among six hexagons at a rate of five each hexagon. With Hex-O-Spell, you can cast a spell in two simple steps. The first step is for the subject to select the appropriate hexagon. The five characters can now be arranged into a hexagon. Step two involves the participant selecting the role. The repetition of a letter or sound forms a word.

Initial Selection Stage two screening

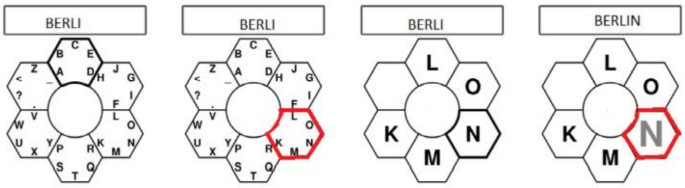


Fig.1. Motor imagery speller Hex-O-Spell paradigm [4]

B. SSVEP (Steady-state visual evoked potential) speller

When the subject stares at stimuli with a constant frequency, SSVEP appears in the EEG signal. Correspondence between stimulus frequencies and EEG waves. Character recognition using the SSVEP-based speller paradigm is depicted in Fig. 2. The BCI speller makes use of an SSVEP-based hierarchical structure [6]. The individual has a one-stage spelling process for frequently used characters and a two-stage process for other characters. The user can immediately start reaping the benefits of the BCI speller's SSVEP-based technology. The SSVEP speller tyres and stresses the subject by using a wide range of stimulation frequencies. Reduced accuracy in user classifications [7]. Brightness and duty cycle of visual stimuli are critical to character recognition [8]. The SSVEP speller does poorly in situations where the stimulus frequencies are harmonics.

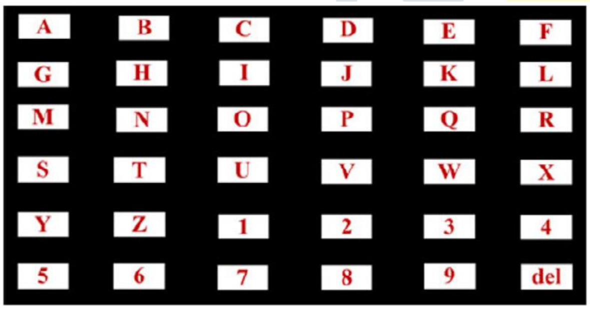


Fig.2.SSVEP speller row-column paradigm [5].

C. Event-related potential (P300 speller)

Farwell and Donchin presented a P300-based character recognition speller in 1988 [9]. P300 target emerges in EEG wave when subject concentrates on random stimuli. The SSVEP-based speller fatigues more than the P300-based speller. Like MI-based spellers, the P300 speller does not require calibration or subject training. P300 speller paradigms involve row-column (RC), single character (SC), region-based (RB), and text on 9 keys (T9) [10–14].

Because of its user-friendly interface, the RC paradigm has become the standard for BCI spellers [10]. 66 and 88 steller paradigms are both possible. A 6x6 speller paradigm is depicted in Fig.3a. Spelling letters, numbers, and symbols are randomly amplified in rows and columns of the speller matrix. Pay attention to the individual. P300 in the EEG wave happens when the targeted character row or column becomes more prominent. That's why the P300 might tell you where in the row or column a character is located. In the end, we pick the necessary letter from a grid made up of letters from every row and every column.

The SC paradigm also makes use of a character matrix, like the RC one (Fig.3b). In the SC paradigm, a single trait becomes more pronounced [11]. As the SC paradigm has a lower flashing probability of the desired character, P300 is improved by enhancing a single character randomly with a delay between flashes. The SC paradigm has a more gradual flash than the RC one. To complete a round or epoch, a 6 6RC speller needs only 12 intensifications, while a 6 6SC speller needs 36.

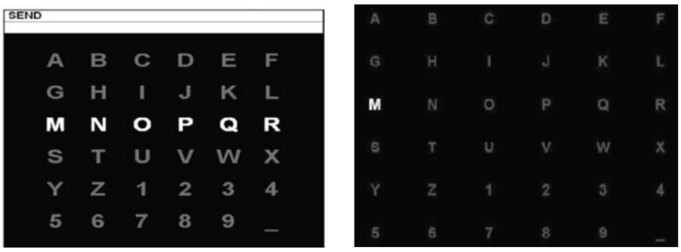
Fazel-Rezai et al. presented a region-based (RB) P300 speller in 2009 [12]. Fig.4 shows a seven-region RB speller. Regions contain characters in this speller. RB spellers identify characters twice. First, the character-containing area is chosen. Step 2 enlarges the specified region and recognises the required character. Compared to the RC paradigm, the GUI architecture is sophisticated. In [13], a simple RB speller divides thirty characters into five areas in the initial step. The second step enlarges the zone and selects a character from six.

P300-based character recognition uses a T9 speller paradigm [14]. Here, the speller matrix dimension is 3 ×3and each location comprises a group of characters. Spellers include word dictionaries. The subject spells a few starting characters of the word until the list of proposed words falls below the threshold. In Fig.5, the screen number selects the word. GeoSpell optimises covert visual attention character recognition [15,16].

D. Hybrid spellers

Multiple features or signals are used in a hybrid spelling procedure. The hybrid speller combines multiple BCI methods either in a sequential fashion or simultaneously. [17] defines a sequential hybrid system using P300 and SSVEP for vehicle destination attributes. Both the P300 and SSVEV spellers agree on the final destination. It takes a little more time to determine the destination using the sequential approach. In [18], a quick speller system is depicted in Fig. 6 that uses P300 and SSVEP. Spelling the character requires looking at both the P300 and SSVEP at the same time. System computational load is increased due to dual-signal processing. Classification accuracy is enhanced when SSVEP is combined with RSSP [19]. In [20], a P300 speller based on audio-visual regions is shown to enhance character recognition. Human facial expressions are a powerful visual stimulator [21]. The efficiency of the system is enhanced by this P300/SSVEP hybrid BCI speller. In [22], a hybrid chip-on-board (COB) BCI paradigm is designed specifically for the collection of P300 and SSVEP signals. LEGO robots are easily controlled by this fusion of paradigms.

P300 and SSVEP-based spellers require external visual cues, whereas MI-based spellers do not. However, a typical motor imagery-based approach takes training, spells slowly, and tires the patient. Frequencies in SSVEP-based spellers exhaust users. SSVEP speller performs badly when stimulus frequencies are near to harmonics, while P300-based speller paradigm uses a single frequency. SS-MVEP-based BCI systems reduce user mental fatigue [23]. Hybrid BCI spellers employ various BCI paradigms, which fatigues the subject and raises computational and system costs.



(a) P300 speller row-column paradigm [10]

(b) P300 speller's single-character paradigm [ll]

Fig.3. Various paradigms for P300-based spellers

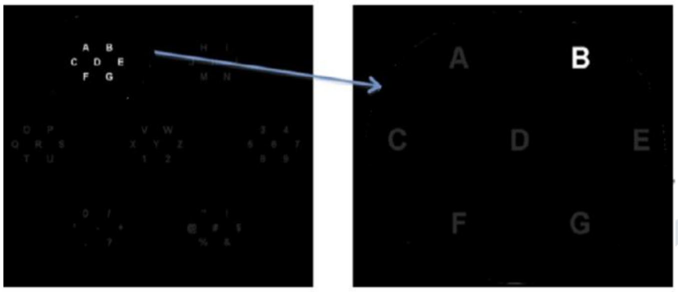


Fig.4. Aregional-based paradigm employed by the P300 speller [12]

Fig. 5. A T9 paradigm applied to P300 speller [14].

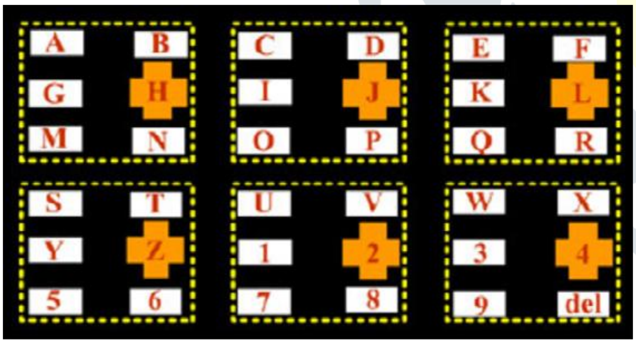


Fig. 6. P300 and SSVEP signal-based hybrid paradigm [18].

III. Feature-extraction approaches

Extraction of EEG features is essential for the BCI system to define the subject's cognitive state. Use just a handful of features that stand in for the signal's most important aspects for the best results. Better P300-based character recognition requires feature extraction. The original data is collected or created to provide comparable and distinguishing details for various categories. Machine learning suggests that even the best classifier could fail to recognise a BCI system with insufficient features, so feature extraction is essential for BCI applications. The methods of extracting features from BCI systems are discussed in [24,25]. Features are extracted using a variety of methods, including those based on time, frequency, time-frequency, and deep learning.

A. Temporal features

Temporal variations in the EEG signal are used for feature extraction. The amplitude of an EEG signal in the time domain is the most fundamental temporal parameter. In BCI applications requiring P300 categorization, EEG data from multiple channels is combined to form a feature vector. This time-domain characteristic [26] is widely used for P300-based character recognition. Temporal dynamics of EEG signals can also be used for classification [27]. Amax, Ap, An, and pp are temporal representations of EEG signals [27]. Temporal characteristics are a straightforward representation of the temporal variation present in an EEG signal. Signal frequency variation cannot be portrayed.

B. Frequency domain features

The frequency band or patterns of the EEG signal change depending on the subject's task. Mental tasks, such as MI or cognitive tasks, used in conjunction with a BCI, affect rhythm amplitude [28]. The frequency of stimuli affects the SSVEP signals. Narrowband frequency feature [5], power spectral density (PSD) feature [29], and band power feature [29, 30] are the most fundamental feature extraction techniques in the frequency domain. Band-pass filters can be applied to EEG signals to extract band power information. The power of a signal can be calculated by squaring the filtered signal and averaging it over some period of time [29]. These features are commonly used in motor imagery detection [31]. PSD illustrates the relationship between power and frequency. There are two ways to determine signal PSD. Transform the signal by either squaring its Fourier transform or finding its autocorrelation function [32]. CCA demonstrates a relationship between stimulus frequency and EEG signal [5]. It is possible to get an accurate reading of the SSVEP response with CCA. The frequency domain only shows changes in the signal's frequency, not its amplitude, over time..

C. TFD (Time-frequency domain) features

In the past, BCI systems have mostly gleaned information from the time or frequency domains. The time and frequency domain information of the EEG is necessary for BCI applications. In order to extract time-frequency information from EEG signals, BCI applications use STFT [33] and WT [34]. The short-time Fourier transform (STFT) multiplies the input signal by a small non-zero window and then calculates the Fourier transform over that signal. The signal was Fourier transformed while this window slid across it. Therefore, signal time-frequency information is extracted from the frequency domain over a short time period. STFT has better temporal resolution than Fourier transform because it decomposes the signal with a constant window size. The main drawback of STFT is that all frequency bands have the same frequency and temporal resolution due to the fixed size of the analysis window. However, if the time resolution is high, then it will be more interesting. This problem is addressed by wavelet analysis.

In order to handle frequencies in a variety of ways, WT uses multi-resolution analysis. This technique is effective at pinpointing the source of both low- and high-frequency signals with pinpoint accuracy. WT works well for a wide variety of signal and image processing tasks. The use of wavelets such as the Daubechies, Coiflet, Morlet, bi-scale, and Mexican hat in BCI applications has shown encouraging results. Although more computationally intensive than time or frequency domain features, time-frequency domain features provide information in both time and frequency domains for the EEG signal.

IV. Feature Optimization Techniques

Data mining and machine learning suffer from the "curse of dimensionality" [55]. The high dimensionality of EEG features causes the classifier model to overfit. A classifier's efficiency is diminished when it uses redundant or superfluous features. The features of multiple EEG channels are combined into a single feature vector. Expanding the feature vector. Poor performance of the classification algorithm is observed [55] when the size of the training sample is small in comparison to the feature dimension. In order to address this issue, researchers have turned to various feature optimization and feature selection techniques, such as principal component analysis (PCA) [56-58], Fisher discriminant analysis (FDA) [59], higher order spectral regression discriminant analysis (HOSRDA) [60], and independent component analysis (ICA) [61]. There are a number of other methods used for effective channel selection, including sequential floating forward selection (SFFS), recursive channel elimination (RCE), binary differential evolution (DE), and sparse common spatial pattern (SCSP).

V. Feature Classifiers

A BCI system's final stage is class identifying characteristics [24]. [25,69] provide classification techniques for this phase. Unsupervised, supervised, and semi-supervised classification techniques exist. Unsupervised classifier is used to classify unidentified feature sets. Semi-supervised classifiers combine supervised and unsupervised classification, where feature sets are coupled with different classifiers.

A. *Semi-supervised*

Semi-supervised classifiers are investigated [74] when the data set is insufficient. Unsupervised learning [2] is used to improve a classifier model that was trained with the training set data. Online semi-supervised LS-SVMs [74] are used by P300-based spellers. An example of an adaptive semi-supervised classifier is spectral regression kernel discriminant analysis (SRKDA) [75], which is used for multi-class MI classification. Asynchronous and self-calibrated BCI classifier systems are developed for online character recognition in [16,76]..

B. *Supervised*

Due to the lack of label information in the training data, unsupervised and semi-supervised classifiers perform poorly. Lack of labelled data makes the classifier's decision boundary imperfect, resulting in poor performance. Most BCI research uses supervised classifiers. The training data is used to build the decision boundary in supervised classification [48]. In BCI applications, LDA, MLP-BP-NN, and SVM are the most used supervised classifiers.

To classify information, Fisher's LDA makes use of a hyperplane. LDA presumes that classes have similar means and variances [77]. LDA classifiers address problems with two-class data. The OVR method, where one class is positive and the others are negative, is used in conjunction with a large number of hyperplanes to solve multi-class problems. By maximising the distance between the means of the two classes and minimising the interclass variance, LDA uses a hyperplane to separate the data [77]. The LDA classifier is commonly used in online BCI systems because of its low processing cost. LDA has been used in motor imaging and P300-based BCIs [17,34,77]. LDA is most effective with easily separable data [78]. When the number of features exceeds the number of trials, it also struggles.

MLP-BP-NN is a nonlinear classifier with input, hidden, and output neurons [51]. The buried layer processes MLP-BP-NN input data. Output neurons classify incoming data. Back-propagation updates MLP-BP-NN layer weights during training. MLP-BP-NN is a versatile multi-class classifier with enough neurons and layers. MLP-BP-NN classifies two, three, and five BCI tasks [79–82].

The MLP-BP-NN classifier is susceptible to the local-minimum problem, which degrades its performance. The selection of hidden layer nodes and the number of hidden layers also have a significant impact on classification performance, which is another drawback of this classifier. SVM is widely used in BCI applications because it provides a global and unique solution without getting stuck in local minima points, and it can function as a linear or nonlinear classifier depending on the kernel function [78,83]. As a result of reducing structural risk, SVM is able to generalise better than traditional classification methods [84]. Similar to LDA, SVM creates hyperplanes out of the feature vector. If two hyperplanes have different distances from the nearest training sample, then SVM will pick the one with the larger margin [58]. Classification of EEG data is accomplished with SVM and its variants, such as LS-SVM [83] and GSVM [77]. The efficacy of BCI speller systems is determined by ITR. ITR in a BCI speller system may be improved with the help of 1D-CNN or 3D-CNN [45,46,85-87]. For SSVEP and SSMVEP signal classifications, [23] develops a limited penetrable visibility graph (LPVG) using a broad learning system (BLS) that outperforms previous methods.

Signal averaging, a traditional method for improving signal-to-noise ratio, can diminish bio-signal-induced EEG signal variance (SNR). Ensemble of classifiers minimizes classifier variability and improves classification performance. Ensemble classifiers increase classifier performance [26,45,48,49,51].

C. *Unsupervised*

Data can be categorised without human oversight using features like distance. Instead of using user IDs, the computer groups the training data based on its inherent patterns [70]. Unsupervised learning cannot provide feature classification, even for a small dataset. The iterative technique (EM) is used in P300-based character recognition [71]. For unsupervised classification of MI signals [72], the Gaussian mixture model (GMM) is used. The method of BCI used in [73] is unsupervised adaptive sequential EM with GMM.

VI. Database Available

BCI study requires datasets. In-house datasets predominate. Table1 highlights a few publicly available datasets.

TABLE I. Popular BCI speller datasets

Sr. No.	Name of the Database	Subjects
1	Dataset IIb of BCI competition II [10]	01
2	Dataset II of the BCI competition III [88]	02
3	EPFL dataset [89]	09
4	LINI dataset [90]	030
	BNCI dataset [11]	010

VII. Conclusion

The BCI speller system for character recognition is examined in detail in this article. The MI, SSVEP, P300, and hybrid BCI speller paradigms are analysed to determine their efficacy in character recognition. Several feature extractions, feature optimization, and classification methods are described for use with the BCI speller system. In this article, we look at the benefits and drawbacks of several distinct machine learning algorithms and system architectures. The article goes on to detail the challenges currently faced by the BCI industry.

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