Clinical EEG and Neuroscience
2020, Vol. 51(1) 19–33

DOI: 10.1177/1550059419842753
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# Visual P300 Mind-Speller Brain-Computer Interfaces: A Walk Through the Recent Developments With Special Focus on Classification Algorithms

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**Abstract**

Brain-computer interfaces are sophisticated signal processing systems, which directly operate on neuronal signals to identify specific human intents. These systems can be applied to overcome certain disabilities or to enhance the natural capabilities of human beings. The visual P300 mind-speller is a prominent one among them, which has opened up tremendous possibilities in movement and communication applications. Today, there exist many state-of-the-art visual P300 mind-speller implementations in the literature as a result of numerous researches in this domain over the past 2 decades. Each of these systems can be evaluated in terms of performance metrics like classification accuracy, information transfer rate, and processing time. Various classification techniques associated with these systems, which include but are not limited to discriminant analysis, support vector machine, neural network, distance-based and ensemble of classifiers, have major roles in determining the overall system performances. The significance of a proper review on the recent developments in visual P300 mind-spellers with proper emphasis on their classification algorithms is the key insight for this work. This article is organized with a brief introduction to P300, concepts of visual P300 mind-spellers, the survey of literature with special focus on classification algorithms, followed by the discussion of various challenges and future directions.

**Keywords**

P300 speller, brain-computer interface (BCI), support vector machine, discriminant analysis, neural network, ensemble classifiers

Received December 1, 2018; revised March 5, 2019; accepted March 14, 2019.

## Introduction

In simple words, brain-computer interfaces (BCIs) are “speech translators” between the human brain and computers. These signal processing systems acquire brain signals through noninvasive electroencephalography (EEG) with the help of scalp electrodes, usually in the 10-20 configuration.[1] By modeling the human brain as an event-response system, the BCIs can be classified as active, reactive, or passive.[2] The active and reactive classes use the brain signals generated in response to manipulated stimuli for applications that target the clinical population (eg, rehabilitation of the movement disabled). On the other hand, passive systems use the involuntary brain signals for work-support applications that target the healthy population[3] (eg, driver safety system).

### *P300 Event-Related Potentials*

Among various EEG signals, the event-related potentials (ERPs) refer to a set of brain signals that are generated in response to some external stimuli (visual, auditory, or somatosensory). Based on the signal characteristics, ERPs may be categorized as transient or sustained.[4] The former type corresponds to short-duration signals that occur after a specific delay from an event onset (eg, P300) while the latter type covers continuous signals that are generated in response to sustained stimuli (eg, steady-state visual-evoked potential). Because of the event-driven nature of ERPs, BCIs based on them fall under the category of reactive systems, which require careful design of the stimuli.[5]

The P300 is a prominent transient ERP component characterized by an endogenous positive deflection in EEG that occurs around 300 ms after a specific stimulus (visual, auditory, or somatosensory).[6] It can be elicited by an “oddball” paradigm in which the subject is exposed to 2 types of repeated

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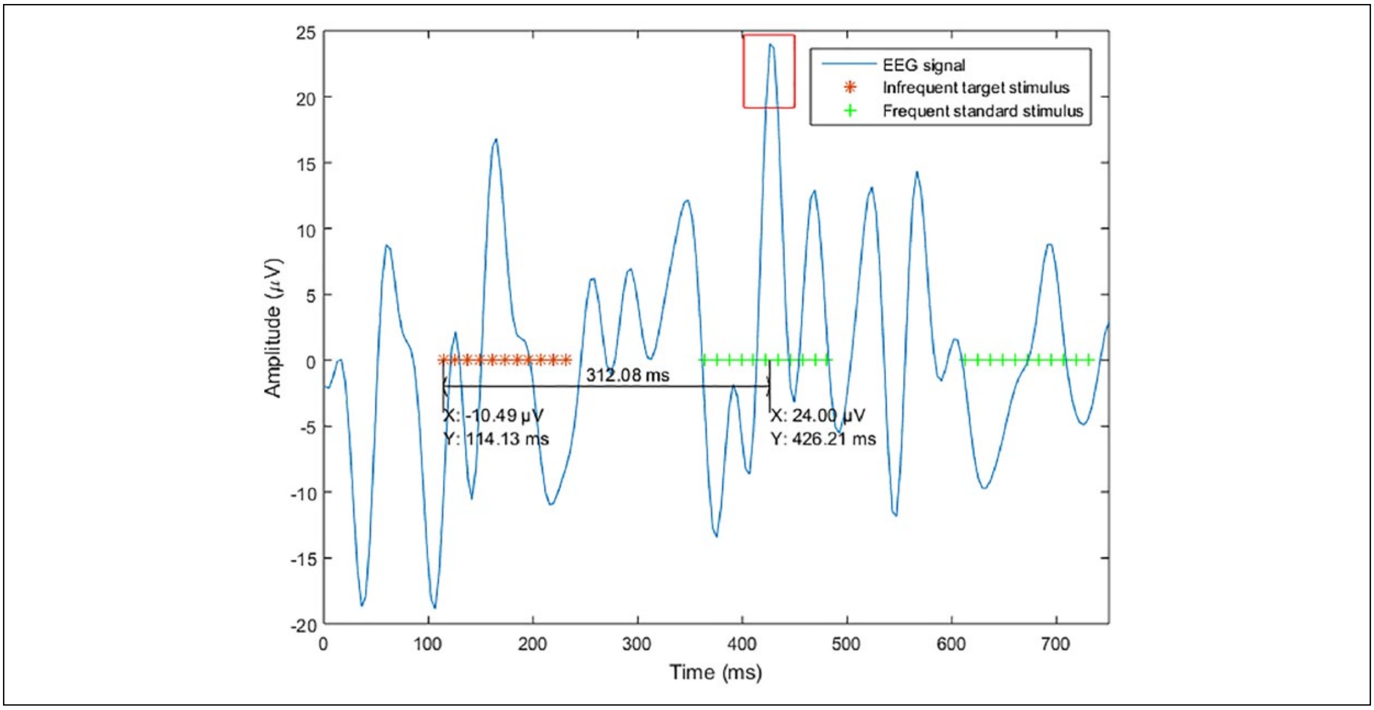


**Figure 1.** Visual P300 component (marked in rectangle), with a delay of approximately 312 ms, generated by an infrequent target stimulus. This signal was recorded from a patient with amyotrophic lateral sclerosis (ALS) using Fz electrode channel, sampled at 256 Hz.[7]

stimuli; one occurring infrequently (known as the target stimulus) and the other occurring frequently (known as the nontarget stimulus). Figure 1 shows the temporal pattern of a P300 wave (marked in rectangle), invoked by an infrequent visual stimulus.[7] As observed in the figure, the P300 wave amplitude is much larger compared with the EEG responses for the frequent standard stimuli. The amplitude and latency of P300 wave are subject dependent. To be more specific, the wave amplitude has a positive association with the uncertainty of occurrence of the target stimuli[8] while its latency depends on the time needed for a subject to cognitively evaluate the target stimuli.[9] Among BCIs based on transient ERPs, P300 systems received greater attention by researchers on account of their comparatively better accuracy and reliability.[10-12]

### P300 Acquisition

EEG signals from scalp electrodes around the central and parietal regions of the brain have the strongest and reliable ERP distribution[13] and thus are commonly used for the detection of P300 component. As recommended by Fabiani et al,[14] most of the conventional P300-based systems employ at least 3 scalp electrodes that are located at Fz, Cz, and Pz locations of the 10-20 international electrode system. Krusienski et al[15] and McCann et al[16] have identified that the electrodes Cz, Pz, Oz, PO7, and PO8 corresponding to the parietal and occipital regions of the brain are relevant for the detection of P300 component in normal subjects. Later, Ijichi and Tanaka[17] found that the electrodes Cz and CP4 are relevant in VP3S for patients with amyotrophic lateral sclerosis (ALS).

## System Description

Mind-speller is a widely researched topic in P300-based BCI literature. Its popularity is aided by its tremendous application possibilities in movement and communication assistance, especially for rehabilitation of the disabled. In the health care sector, it can assist partially paralyzed patients such as those suffering from diseases like ALS and stroke. This section describes the concepts of P300 mind-spellers based on visual stimuli.

Visual P300 mind-speller (VP3S) is a BCI system that facilitates the identification of specific choice in a subject's mind, from among a set of display elements (letters/symbols/images). The system achieves this by executing a group of visual stimulus tests that evoke the P300 signal only for the elements gazed by the subject (ie, target elements). During the experiment, it collects the EEG signals with the help of scalp electrodes (see the P300 Acquisition section) and analyzes it. By detecting and locating P300 components in the EEG, the system can recognize the element gazed by the subject. VP3S can be deployed using simple matrix display to complex virtual reality environments,[18] thereby offering scope for a wide range of applications particularly in medical and gaming-related industries.[19,20]

### Paradigm Designs

Experimental models (commonly known as paradigms) used in most VP3S literature are implemented by means of electronic visual displays (like computer screens). Some of the commonly used VP3S paradigms are discussed in this subsection.

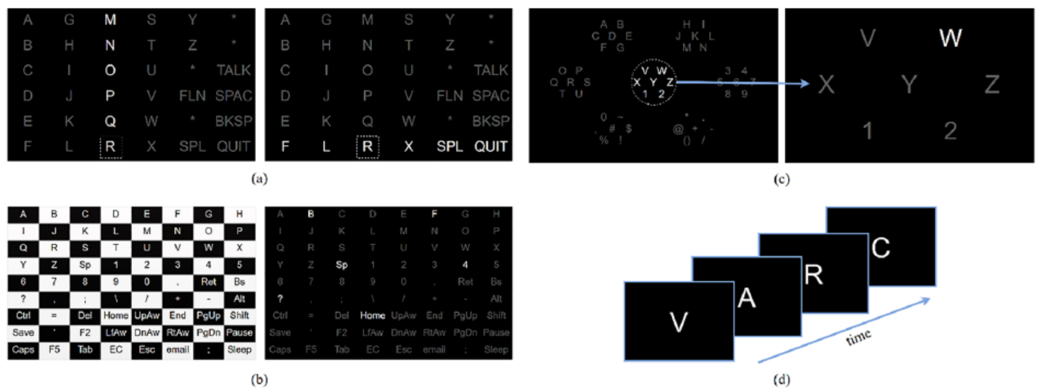


**Figure 2.** Visual P300 mind-speller display paradigms. (a) Row-column flashing based on Farwell and Donchin.[21] (b) Checkerboard-derived flashing based on Townsend et al.[22] (c) Region-based flashing adapted from Fazel-Rezai and Abhari.[23] (d) Rapid serial visual presentation (RSVP) based on Acqualagnav et al.[28]

The original VP3S concept put forth by Farwell and Donchin[21] used a row-column paradigm (RCP) in which the English alphabet along with some word commands (see Figure 2a) were displayed in a matrix format. This system recognized the letter/command focused by a subject through random flashing of different rows and columns. To overcome the adjacency-distraction and double flashes (consecutive flashing of row and column of the target element) in RCP, Townsend et al[22] have developed a checkerboard paradigm (CBP). It ensured that, at any instance, the flashed elements on the display will not be close neighbors, thereby preventing the aforementioned issues (see Figure 2b). For improved VP3S accuracy, Fazel-Rezai and Abhari[23] introduced a region-based paradigm (RBP). It proceeded with the recognition of the group of letters/symbols containing a target element, followed by the identification of the target element (see Figure 2c).

Motor neuron diseases like ALS result in oculomotor dysfunctions.[24] Since the paradigms discussed above are based on overt attention (ie, requires eye movements), they are unreliable for patients with such disabilities.[25] However, paradigms based on covert attention (ie, without eye movements) provides gaze independence and thus pertinent to the aforementioned subjects. Treder and Blankertz[26] confirmed the feasibility of using covert attention in VP3S experiments using a Hex-o-Spell paradigm. However, its efficiency was inferior to that of RCP (overt attention). Later, Liu et al[27] developed a cluster-based paradigm based on covert attention. It demonstrated improved accuracy and communication capabilities compared with that of the Hex-o-Spell.

The rapid serial visual presentation (RSVP), which is another paradigm based on covert attention, uses a series of single letter presentations to identify a target word (see Figure 2d). Acqualagnav et al[28] and Acqualagna and Blankertz[29] have carried out the earliest works in VP3S based on RSVP. They reported that the paradigm provides good speller accuracy while offering gaze-independence. Orhan et al[30] have integrated language models into RSVP for improved word spelling. Chennu et al[31] found that the space-independence in RSVP comes at a price, as it reduces the speller speed. This finding was confirmed by Moghadamfalahi et al[32] in their comparison study of RCP and RSVP. Later, Lin et al[33] developed a triple RSVP paradigm, which achieved improved speller speed by presenting three distinct characters at a time with each character presented thrice. Other successful attempts in utilizing covert attention for VP3Ss are the gaze-independent block speller (GIBS)[34] and Geospell.[35]

All the VP3S paradigms (Table 1) discussed above are synchronous in that the order and timing of element flashes are decided a priori. Consequently, they require continuous user attention to the stimulus presentations and even small distractions could cause misclassification. In practical applications of long durations, this would induce tiredness and loss of interest in the users, which in turn would adversely affect the system performance and its user acceptability. As a solution to this problem, Aloise et al[36] have created an asynchronous speller paradigm (ASP) that was trained with image-based RCP model data (Control trials) and real-life model data (No-Control trials). Unlike synchronous paradigms, which always select an element after fixed number of trials, this model performed element selection only when the corresponding signal score went above specific thresholds.

## *Terminology*

To further improve the clarity of this article, we will define some specific terminologies used in the VP3S literature.

An event refers to the occurrence of a stimulus (ie, flashing of elements/row/column) and a group of events that are used to identify a target character is called a sequence. Most VP3S implementations exhibited very low selection accuracy for single sequence inputs. However, they produced improved accuracy when the input vector was obtained by averaging multiple sequences of the same target character (referred to as trials or repetitions). This performance improvement is the result of trial averaging, which cancels random noise and better highlights P300 signal features. Many articles on VP3S use the

**Table 1.** VP3S Display Paradigms.

| No. | Reference | Type of Display | No. of Characters per Presentation | Stimulus Duration (ms) | ISI (ms) |
|---|---|---|---|---|---|
| 1 | Farwell and Donchin[21] | RCP | 36 | 100 | 500, 125 |
| 2 | Townsend et al[22] | CBP | 36 | 62.5 | 62.5 |
| 3 | Fazel-Rezai and Abhari[23] | RBP | 49 | — | — |
| 4 | Treder and Blankertz[26] | Hex-o-Spell | 30 | 100 | 66 |
| 5 | Liu et al[27] | Cluster based | 6 | 240 | 160 |
| 6 | Acqualagnav et al[28] | RSVP | 1 | 83, 133 | 300 |
| 7 | Lin et al[33] | Triple RSVP | 3 | 250 | 250 |
| 8 | Pires et al[34] | GIBS | 30 | 75 | 75 |
| 9 | Aloise et al[35] | Geospell | 6 | 125 | 125 |

Abbreviations: VP3S, visual P300 mind-speller; ISI, interstimulus interval; RCP, row-column paradigm; CBP, checkerboard paradigm; RBP, region-based paradigm; RSVP, rapid serial visual presentation; GIBS, gaze-independent block speller.

terms *trial* and *sequence* interchangeably, and we will follow this convention. The set of all trials for a target character constitutes a run.

Within a trial, the time period between the onset of a stimulus and that of the following stimulus is termed as the stimulus onset asynchrony (SOA). It comprises 2 subperiods, namely the duration of stimulus ($T_s$) and the blank period from the offset of stimulus to the onset of the next stimulus, known as the interstimulus interval (ISI). For RCP, CBP, and RSVP, the typical duration of stimulus is around 100 ms and that of ISI is between 30 and 200 ms.

## Process Flow

BCI systems can be implemented to operate in offline and/or online analysis mode(s).[37] However, a good BCI system should be able to execute in both the modes. In offline analysis, the system operates on recorded EEG datasets, that is, the operation is non real-time. This simulation mode employs methods such as cross-validation for testing and grading the system performance. Some public datasets available for P300 mind-speller research are the BCI competition II,[38] BCI competition III,[39] and BNCI Horizon 2020.[7,40] All these datasets are derived from VP3Ss based on the RC paradigm. In online analysis, the system operates on real-time EEG data but its classifier may utilize information derived from offline analysis for learning purpose. Also, in online mode the character recognized by the system would be presented to the user as feedback, making it a closed-loop system. Both offline and online analysis modes of a classical VP3S involves preprocessing, feature extraction and classification operations as shown in Figure 3.

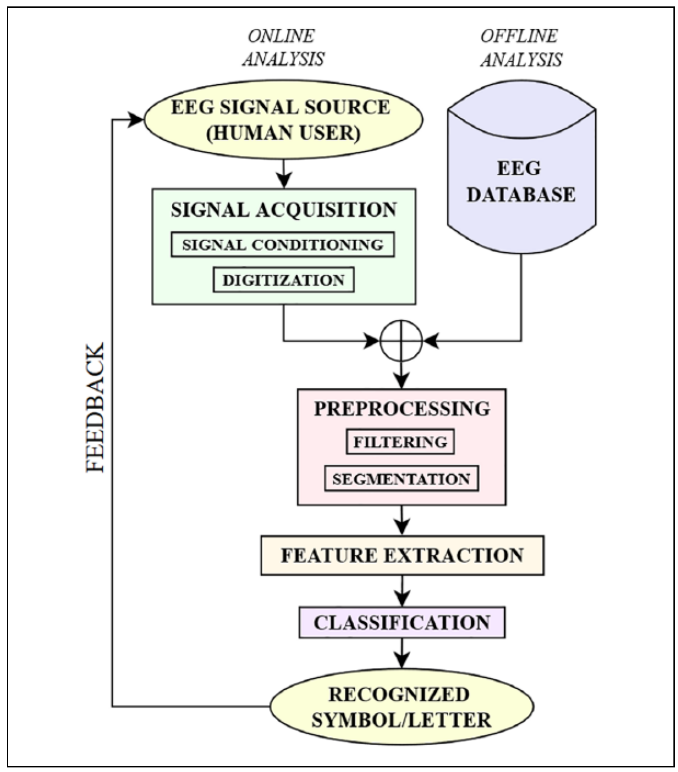


**Figure 3.** Process flowchart of visual P300 mind-speller.

*Preprocessing and Feature Extraction.* The process flow in VP3S begins with preprocessing in which the recorded (or real-time) EEG sequences are cleared of artifacts and noises. Out of band frequency interferences such as baseline variations, line noise, and electromyographic signals can be removed by suitable filtering techniques.[41] However, EEG signal variations caused by eye movements (including blinks, called ocular artifacts) resemble P300 components and thus cannot be removed by simple filtering. Furthermore, it is not an efficient method to reject the affected samples as it would result in information loss and biasing of the dataset. Therefore, the feasible solution is to estimate and correct these artifacts.[42] Generally, eye artifact removal techniques proceed with the simultaneous recording of EEG and electro-oculogram (EOG), followed by the elimination of EOG component from EEG.[43] Some ocular artifact removal methods are regression, information maximization (Infomax), second-order blind identification (SOBI), correlation and principal component analysis (PCA), or independent component analysis (ICA).[44-46]

The artifact-corrected EEG signals are then segmented into "epochs" that usually range from 100 ms before the onset of stimulus presentations (commonly denoted as −100 ms) to between 500 and 1000 ms after the onset.[47-49] Since P300 signals are expected to be present at about 300 ms from the onset of target stimuli, the epoch data after stimuli onset are used for feature extraction while the data points from −100 ms to stimuli onset are used for baseline correction.

The significant features for classification are extracted either by eliminating irrelevant and redundant data points or by identifying and selecting data points containing critical information. In most of the literature we have surveyed, epoch averaging (with or without PCA/ICA) was used for extracting features, while in some works discrete wavelet transform (DWT),[47,49-53] channel correlation analysis (CCA),[54] artificial neural networks (ANNs),[55] and phase synchronization[56] were used.

*Classification.* The classification problem associated with the VP3S is binary since the system needs to decide whether an epoch belongs to the "target" or "nontarget" class. Ideally, an epoch corresponding to a target character on the speller display will contain a P300 component, while that of a nontarget character will be devoid of it. Now, the primary objective is to allocate the epochs to the target or nontarget classes based on whether they contain the P300 component or not, respectively. In the classification process, feature vectors extracted from an epoch are analyzed by a classification algorithm (also called classifier) that decides on "to which class the epoch has to be assigned?" Unsupervised learning algorithms cannot provide reliable classification performance for EEG signals from different subjects due to the subjective distinctions in functional brain maps. However, supervised learning algorithms, after been trained with a previously recorded dataset, can provide better performance while classifying EEG signals and hence are widely used in VP3S applications. Further details of VP3S classifiers are discussed in the Classification Algorithms section.

### Performance Metrics

Accuracy, bitrate or information transfer rate (ITR) and character selection or typing time (TT) are the metrics that are commonly used to evaluate the performance of VP3Ss. For instance, the Farwell and Donchin[21] speller achieved 95% classification accuracy at 12 bits/min ITR with a mean time of 26 seconds for selecting 1 out of 36 elements on the speller display.

Classification accuracy (CA) of a VP3S is defined as the ratio of number of successful target selections to total number of selection attempts by the system. If $N_t$ out of $N$ target character selections are correct for a speller, then its CA is calculated as

$$CA(\text{in percentage}) = \frac{N_t}{N} \times 100 \tag{1}$$

Another uncommon metric similar to CA is the efficiency,[57] which is calculated as the inverse of the expected number of epoch classifications required to correctly recognize a character on the speller display.

ITR quantifies the amount of information transferred from a user to the BCI system. In a VP3S, if the target character selection can be made with probability, $P$ from among $N_C$ equiprobable selections and if each of the nontarget selections have the same probability, $(1-P)/(N_C-1)$, then as per Wolpaw et al,[58] the system ITR or bitrate (in bits/min) can be calculated as

$$ITR = \log_2 N_C + P\log_2 P + (1-P)\log_2\left[\frac{(1-P)}{(N_C-1)}\right] \tag{2}$$

There are 2 variants for the ITR specified in Equation (2), namely theoretical ITR (TITR) and practical ITR (PITR). The former variant is calculated without considering the target character selection time as well as the time elapsed between selections and it is primarily used for benchmarking. The latter variant incorporates both of these time components and helps in analyzing the system speed for real-life applications. Thus, from an analytical perspective, TITR value should be much higher than that of PITR.

In some VP3S literature, a BCI version of the channel capacity called the Nykopp's capacity/ITR[59-61] is used an alternative to the standard ITR. For a speller with classification accuracy CA, while selecting from among $N_C$ possible display characters, the Nykopp's ITR (in bits/symbol) is calculated as

$$ITR_{Nykopp} = \log_2 N_C + C_A\log_2 C_A + (1-C_A)\log_2\left[\frac{(1-C_A)}{(N_C-1)}\right] \tag{3}$$

Typing time of a VP3S specifies the time needed for a subject to input a character (or word) using the speller display. In other words, it quantifies the speed of a speller by considering the time required to select a character on its display and the waiting time between 2 selections. Character and word typing times are usually expressed in seconds/character and min/word, respectively. Shorter typing time indicates a faster system and vice versa.

## Classification Algorithms

We reviewed some VP3S literature (42 articles) published within the past 2 decades and the survey details are explored in the following subsections. For perspicuity, these are organized based on the classification algorithms used in the reviewed literature. Figure 4 shows the year-wise statistics of the surveyed literature and Figure 5 (pie chart) presents the usage statistics of different VP3S classifiers used in these studies. Recent publication related to each of these classifiers along with the analysis type, dataset, speller design, electrodes, preprocessing, feature extraction method, accuracy, and ITR (and/or TT), are arranged in Table 2.

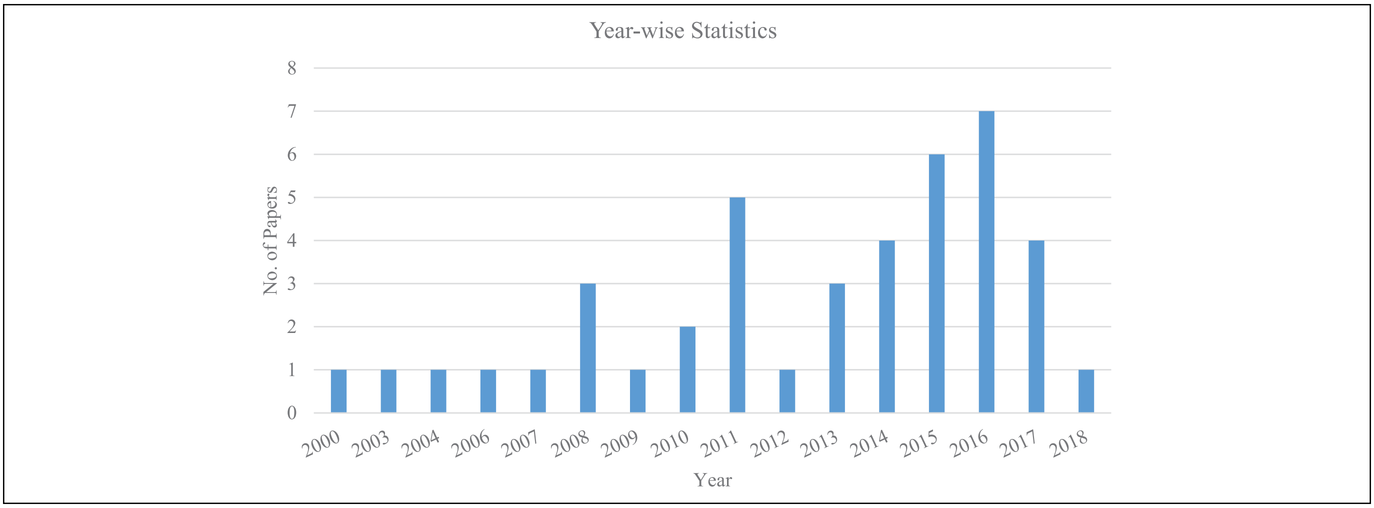


**Figure 4.** Year-wise statistics of the P300 mind-speller literature surveyed.

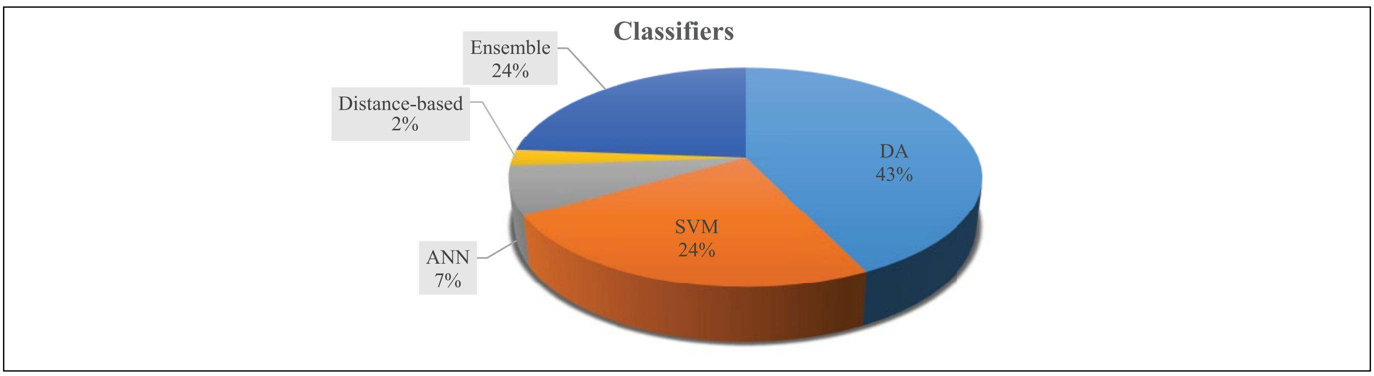


**Figure 5.** Usage distribution of P300 mind-speller classifiers in the literature reviewed (42 articles).

## *Classifiers Based on Discriminant Analysis*

Discriminant analysis (DA) is used for classification of data points with known distribution. Its major objectives of are (1) to draw distinction between classes of data points within data sets and (2) to make decision on "to which class a new data point belongs to?," with minimum error. While the first objective of this supervised learning technique is associated with the training phase, the second objective is applicable during the prediction phase.[62,63] As shown in Figure 5, DA constitutes almost half of the classifiers used in the VP3S literature we surveyed. Various DA classifiers used in VP3S are discussed below.

*Fisher's Linear Discriminant Analysis.* Linear discriminant analysis (LDA), also referred to as the Fisher's linear discriminant analysis (FLDA) is the generalization of the original linear discriminant introduced by Fisher.[64] By assuming equal group variances, it can assign normally distributed data into their corresponding classes, with minimum misclassifications. Technically, the algorithm uses within-class ($S_w$) and between-class ($S_b$) scatter matrices to quantify the compactness of classes and separation between classes respectively. In fact, classification using FLDA can be analyzed as an optimization problem to maximize the between-class to within-class ratio (referred as Fisher's criterion) as given in Equation (4)

$$\hat{w} = \underset{w}{\arg\max} \frac{|w^T S_b w|}{|w^T S_w w|} \tag{4}$$

The projection matrix estimate $\hat{w}$ can be obtained by solving the following Eigen value problem (Equation 5) for an invertible nonsingular matrix $S_w$.

$$S_b^{1/2} S_w^{-1} S_b^{1/2} w = \lambda w \tag{5}$$

The above equation implies that the between-class to within-class ratio of dataset, $D$ is maximized when the projection matrix $w$ is made up of the eigenvectors of $S_w^{-1} S_b$.

In VP3S implementations, FLDA algorithm exhibited good accuracy and fast response while discriminating the "target" and the "nontarget" signals.[53,65] However, it failed in cases where the size of feature set is larger than that of the training set since the resulting within-class scatter matrix is singular. To overcome this problem, Hoffmann et al[66] replaced the inverse

**Table 2.** Survey Table.

| No. | Reference | Analysis Type (and Dataset) | Preprocessing | Feature Extraction | Classifier | Accuracy | ITR/TT |
|---|---|---|---|---|---|---|---|
| 1 | Meshriky et al[53] | Offline (Emotiv H/W custom dataset) | Standardization (Z-score), CAR and Notch filtering, BPF (1-13 Hz), Epoch (−100 to 700 ms) | DWT (Daubechies wavelet) and PCA | FLDA | Mean CA: 91.3% | — |
| 2 | Qu et al[69] | Offline and Online (SynAmps2 H/W custom dataset) | BPF (0.01-20 Hz), Epoch (−100 to 600 ms), Concatenate channels, Decimation (by 6) | Epoch averaging | BLDA | Mean CA Offline (5 trials): 94%, Online: 94% | Offline: 44 bpm, Online (P/T ITR): 29.5 and 57.0 bpm, Online TT: 5.17 s |
| 3 | Ryan et al[79] | Online (g.USBamp H/W custom dataset) | HPF (0.5 Hz), LPF (30 Hz), Epoch (0 to 113-515 ms) | Epoch averaging | SWLDA | Mean CA: 85.97% | Online mean (ITR, TITR): 21.82 and 28.54 bpm |
| 4 | Tahmasebzadeh et al[51] | Offline and Online (Emotiv H/W custom dataset) | BPF (0.5-40 Hz), CAR filtering, Normalization, Epoch (0 to 800 ms) | DWT (weighted t-test selection) | QDA | Mean CA Offline (5 trials): ~71% Online: ~45% | — |
| 5 | Li et al[54] | Offline (BCI comp. III dataset II) | Epoch (0-667 ms), BPF (0.1-10 Hz), Downsampling (20 Hz), Normalization | Channel correlation analysis | Linear SVM | Mean CA (5, 10, 15 epochs): 79.5, 94.5 and 98% | Mean (5, 10, 15 epochs): 15.6, 11.7 and 8.69 bpm |
| 6 | Gao et al[55] | Offline (Biosemi H/W custom dataset) | Eye artifact rejection, LPF (30 Hz), Decimation (512 Hz), Epoch (100-400 ms) | ANN (five ganglion) | Nonlinear SVM (RBF) | Mean CA (2000 iterations): 88.1% | — |
| 7 | Salvaris and Sepulveda[50] | Offline (BCI comp. III dataset II) | LPF (30 Hz), HPF (0.1 Hz), Epoch (0-800 ms) | DWT (Daubechies wavelet) | EFLDA | Mean CA (5, 15 epochs): 71.5, and 95% | — |
| 8 | Kundu and Ari[101] | Offline (BCI comp. III dataset II) | Epoch (0-667 ms), BPF (0.1-20 Hz) | PCA on epochs | ESVM | Mean CA (5, 15 epochs): 72 and 98% | — |
| 9 | Cavrini et al[60] | Offline (EBNeuro H/W custom dataset) | BPF (0.5-30 Hz), Eye artifact removal | Epoch averaging | Fuzzy integral ensemble | Average efficiency: 60.8% | Nykopp's [56] ITR: 16 868 bits/symbol |
| 10 | Zhang et al[102] | Offline (BCI comp. III dataset II) | Epoch (0-1000 ms) | ICA on epochs | Boosting NN (by channel) | Mean CA (5 iterations): ~84% | — |
| 11 | Kshirsagar and Londhe[94] | Offline (actiCAP H/W custom dataset) | BPF (0.1-10 Hz), Epoch (0-600 ms), Normalization | Normalized epochs | CNN | Maximum CA: 94.18% | — |
| 12 | Fira[96] | Offline (BCI comp. III dataset II) | BPF (0.1-10 Hz), Windsorizing (10-90), Epoch (0-1000 ms) | Epoch averaging | Euclidian distance | Mean CA (3 channels, 100 characters): 64.7% | — |
| 13 | Akram et al[106] | Offline and Online (BrainAmp H/W custom dataset) | BPF (0.1-25 Hz), Epoch (0 to 600 ms), Concatenation | Epoch averaging | Random forest | Mean CA (5, 10, 15 epochs): 74%, 90%, and 99% | Mean word typing time: 1.85 min |

Abbreviations: ITR, information transfer rate; TT, typing time; BCI, brain-computer interface; BPF, band-pass filter; LPF, low-pass filter; HPF, high-pass filter; PCA, principal component analysis; ANN, artificial neural network; CNN, convolutional neural network; ESVM, evolutionary support vector machine; CA, classification accuracy; ICA, independent component analysis; RBF, radial basis function; EFLDA, ensemble Fisher's linear discriminant analysis; BLDA, Bayesian linear discriminant analysis; SWLDA, stepwise linear discriminant analysis; QDA, quadratic discriminant analysis.

of within-class scatter matrix in Equation (5) with the Moore-Penrose pseudo-inverse.[67] Though this modification enabled FLDA to operate with increased number of features, its performance got degraded when the number of electrode channels was increased.

*Bayesian Linear Discriminant Analysis.* The Bayesian linear discriminant analysis (BLDA) is a probabilistic approach of FLDA, which avoids overfitting of the discriminating hyperplane. Lei et al[68] have found that, in the presence of strong artifacts, BLDA has the lowest mean relative error and computation time requirement than that of FLDA. Another advantage with BLDA is that its degree of regularization can be estimated from training data, without any cross-validation.

Consider a dataset {X, Y} for a 2-class (class A and class B) problem where X is a set of M dimensional feature vector with $X \in R^{1\times M}$ and Y represents the class labels of each X. By assuming that the dataset is affected by an independent and identically distributed Gaussian noise with zero mean, the posterior probability that a feature vector x belongs to class A is given by

$$p\left(y \geq 0 \mid \vartheta, \sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} \int_{0}^{\infty} e^{-\frac{(y-\vartheta)^2}{2\sigma^2}} dy \tag{6}$$

Hoffmann et al[66] have reported that BLDA provides better accuracy and bitrate compared to FLDA in VP3S applications for severely disabled individuals, especially when the feature set is large. By employing an adaptive version of BLDA in their 3-dimensional (3D) VP3S, Qu et al[69] have achieved 4.9% and 4.0 bits/min increase in the CA and mean PITR respectively, compared with a standard 2D speller. Also, the works by Jin et al[70,71] and Noorzadeh et al[72] have confirmed the feasibility of BLDA as a better alternative to FLDA, for practical VP3S applications.

*Stepwise Linear Discriminant Analysis.* Owing to its good accuracy, simplicity and quick response, the stepwise linear discriminant analysis (SWLDA) has become the most widely deployed discriminant analysis classifier in VP3S applications. FLDA and its other variants demand more training data for stable performance with increased feature vector dimension. Though the operation of SWLDA is similar to that of FLDA, its discriminating features are chosen based on some significance test.[73] By this feature reduction approach, SWLDA can provide stable performance even when the number of available features are large compared with that of the training dataset. Furthermore, the non-exhaustive nature of the algorithm offers comparatively faster convergence than FLDA while avoiding overfits.

SWLDA was first applied in RCP VP3S by Farwell and Donchin[21] to compute the offline classification scores. This study reported SWLDA as the fastest (mean ITR: 2.3 characters/min) method to reach high accuracy (mean CA: 95%) compared with classifications based on peak picking, area and covariance measurements. Later, Donchin et al[74] introduced a bootstrapped approach for this speller using DWT (Daubechies wavelet), which improved its bitrate (mean ITR: 4.3 characters/min at 95% CA). By including posterior electrodes for data acquisition in a standard RCP speller,[21] Krusienski et al[15] were able to improve its online classification accuracy (mean CA: ~80% with 15 sequences). The VP3S systems developed by Frye et al,[75] Halder et al,[76] McFarland et al,[77] Townsend and Platsko,[78] and Ryan et al[79] have adapted feature selection and classification approach specified by Krusienski et al.[15] Guo et al[49] have used features derived from DWT (Daubechies 4 wavelet) with Fisher's criterion (see Equation 4) in their RCP VP3S. This system reported higher performance (mean CA: 80% by averaging 5 trials) for SWLDA compared to support vector machine (SVM) classifier.

The standard CBP VP3S (see Paradigm Designs section) based on SWLDA developed by Townsend et al[22] achieved remarkable improvement in online accuracy (mean CA: 92%) and bitrate (mean ITR: 23 bits/min) compared with an RCP speller based on Farwell and Donchin.[21] Frye et al[75] have added a suppression criterion to this speller, which significantly increased its typing speed (6.46 vs 5.55 characters/min for standard CBP) and consequently its theoretical bitrate was improved (mean TITR: 53.62 bits/min). Also, this system reported an accuracy (mean CA: 87.7%) comparable to that of a standard CBP speller. Ryan et al[79] have used a gray to color (GC) transition instead of the gray to white (GW) flashes in the standard CBP VP3S which enhanced the generated P300 signals thereby improving the system performance (mean CA: 85.97% and TITR: 28.54 bits/min). Townsend and Platsko[78] have developed a VP3S that used some subject derived constraints[80] to achieve the highest reported bitrate (PITR of 120 bits/min) for a free spelling task while maintaining an accuracy (mean CA: 87%) comparable to that of the standard CBP speller.

The ASP VP3S speller[36] discussed in the Paradigm Designs section is based on SWLDA. Compared to a standard CBP speller, it attained good accuracy (mean CA: 95% by averaging ten trials) while allowing small distractions (real-life situation model) by the subjects.

*Quadrature Discriminant Analysis.* Quadratic discriminant analysis (QDA) is a nonlinear version of FLDA that computes separate covariance matrices for each class in the dataset. This independent covariance approach results in more number of parameters and greater chance for overfitting. Tahmasebzadeh et al[51] have developed an RCP VP3S based on wavelet decomposition and QDA. In this system, the rows and columns were classified separately using different mean-covariance pairs. Though the speller demonstrated excellent offline accuracy (mean CA: 100% with 8 repetitions for Emotiv dataset), its online accuracy was unremarkable (mean CA: ~70 with 15 repetitions).

## Support Vector Machine Classifiers

The SVM is a supervised learning model that utilizes a hyperplane (or decision boundary) to distinguish between classes. Although there exists a large number of hyperplanes that discriminate between 2 classes of data, the algorithm selects only the optimal hyperplane, which is at the maximum distance (referred to as "margin") from the closest data point (referred to as "support vectors") in each of the classes. Based on the characteristics of the hyperplane, SVM can be categorized as linear or nonlinear.

*Linear Support Vector Machine.* When an SVM model uses a linear decision boundary to classify data points, it is referred to as linear SVM. Given the weight vector $w$ and bias $b$, the linear boundary through an input vector $x$ may be defined as

$$f(x) = w.x + b \tag{7}$$

Obtaining the best decision boundary is an optimization problem that maximizes the margin $M = 1/w$. In presence of a slack variable (nonlinearity), $\epsilon_i \geq 0$ the optimization problem (known as "soft margin") is mathematically defined by Equation (8), where the regularization parameter $C$ indicates the magnitude of violation penalties.

$$\begin{gathered}\min_{\{w,b\}} \left\{ \frac{1}{2} w^T w \right\} + C \sum_i \epsilon_i \\ \text{subject to } y(w.x + b) \geq 1 - \epsilon_i \end{gathered} \tag{8}$$

A VP3S based on linear SVM for efficient word typing was developed by Akram et al.[81] This system was able to achieve better typing speed (average typing time of 1.19 min/word) compared to a conventional speller (average typing time of 3.36 min/word). A spelling correction method based on weighted edit distance of a misspelled word to its correct entry in an in-built dictionary was introduced by Chaurasiya et al.[48] The work of Meshriky et al[53] reported consistently good performance for their VP3S using DWT and linear SVM classifier in an intermixed color display. Kabbara et al[56] have used phase locking value (PLV), which quantify the phase synchronization between different functional areas of the brain, as the feature in their VP3S. For larger number of trials (ie, >25), the classification performance achieved by this speller (SVM classifier) was comparable to that of the spellers based on xDAWN[82] and SWLDA. However, for fewer trials it demonstrated insignificant performance.

*Nonlinear Support Vector Machine.* In generalized SVM, a kernel function is used to map the data points to a higher dimensional space where they will assume a linearly separable pattern. Typically, a Gaussian kernel given by Equation (9), is used for the mapping.

$$K(x,y) = \exp\left(-\frac{\| x - x_i \|}{2\sigma^2}\right) \tag{9}$$

For some data vectors $x_i$ and their corresponding class labels $y_i$, the decision boundary for efficient classification can be obtained using a nonlinear discriminant function of the type given in Equation (10).

$$S(x) = \sum_{i}^{N_s} y_i \alpha_i K(x, x_i) + b \tag{10}$$

where $N_s$ is the number of support vectors and $0 \le \alpha_i \le C$ and $\sum_i \alpha_i y_i = 0$, where $C$ is the regularization parameter.

Kaper et al[38] have achieved excellent classification accuracy (mean CA: 100% with 5 repetitions) for their VP3S based on nonlinear SVM classifier (Gaussian kernel). A comparable result was obtained by Chaurasiya et al.[83] A similar version of the speller by Kaper et al[38] was reported by Meinicke et al[84] with average and maximum information transfer rates of 50.5 and 84.7 bits/min, respectively. Gu et al[85] have applied least-squares SVM to develop a semisupervised VP3S, which was able to attain 85% online classification accuracy through training and learning process of duration less than 3.5 minutes. Gao et al[55] have combined feature extraction using artificial neural network (5 ganglion) and classification based on SVM with radial basis function (RBF) kernel to obtain a VP3S, which was reported to outperform the traditional SVM with PCA scheme for VP3S.

## Artificial Neural Network

Artificial neural networks (ANNs) or simply neural networks (NNs) are computational models for information processing, which are analogous to biological neural systems in term of structural design and functioning.[86] With their ability to identify and remember patterns in the input data, they can generate classification rules based on the training dataset. Thus, they are well suited for classification of higher dimensional (especially nonlinear) datasets with little or no knowledge of the input-output mapping.[87]

*Multilayer Neural Network.* The simplest of ANNs is the feed forward neural network (or perceptron) that consist of a layer of one or more building blocks called nodes (or neurons). This single layer model can solve linear classification problems but to solve nonlinear problems a multilayer perceptron or MLP (ie, feed forward network with hidden layers), is required.[88] Each result at the output layer of an MLP is compared with a target and the mismatch (or error) is sent back into the network using a backpropagation algorithm. This error is then used to readjust the connection weights so that the mismatch in the final output is minimized. Because of this error feedback mechanism, MLPs are also referred to as backpropagation neural networks.

*Deep Neural Networks.* Deep learning methods are machine learning techniques that involve a large number of nonlinear data processing layers. Accordingly, deep neural networks (DNNs) refer to ANNs with many hidden layers (ie, deep architecture) that are organized in a hierarchical fashion.[89] Convolutional neural networks (CNN), deep belief networks (DBN), recurrent neural networks (RNN), and stacked autoencoders (SAE) are the DNNs commonly employed for P300 detection.[90-92]

Cecotti and Graser[93] developed a VP3S based on CNN, which achieved 95.5% recognition rate for 15 epochs by operating in temporal domain without channel selection. Kshirsagar and Londhe[94] used deep CNN in their VP3S for Devanagari script, which achieved a maximum classification accuracy of 94.18% with 8 epochs.

## Distance-Based Classifiers

The most common distance-based classifier is the k-nearest neighbors (kNN) algorithm, which is a nonparametric data-driven method. Its basic principle is to assign an unclassified data point, say $q$, to the predominant class among the $k$ nearest labeled-neighboring points. The algorithm involves 2 steps. In the first step, $k$ nearest neighbors of $q$ are identified using some metrics like Euclidian distance (sometimes normalized) or Mahalanobis distance,[95] which evaluate the similarity criteria between data points. For a dataset $\{x_i\}$ with class labels $\{y_i\}$, the Euclidian distance from each point in $\{x_i\}$ to $\{q\}$ is given by

$$d(x_i, q) = \| x_i - q \| \tag{13}$$

The second step is the classification of $q$, with the help of the $k$ identified nearest neighbors from the first step. For this, usually a weighted voting method is used, which gives more weightage to the class of the closest among the $k$ identified nearest neighbors. A simple discriminant function used for classification in kNN is given by

$$f_{kNN}^*(x) = \sum_{n \in N_k(x)} \frac{y_n}{d(x_n, q)} \tag{14}$$

where $N_k(x)$ is the index of the $k$ nearest labeled-neighboring points (in training set) of $x$ and $d(x_n, q)$ is a distance measure from $\{ x_i \}$ to $q$. The kNN decision boundary is strongly nonlinear and it does not require iterative training process since no data need to be fit to a model.

Fira[96] has developed a VP3S based on nearest neighbor method that uses Euclidian distance metric. This speller achieved 64.7% classification accuracy for 12 signals using 3 electrodes. Channel sensitivity of the classifier is an issue with this system that need to be addressed properly for achieving better performance.

### Ensemble of Classifiers

Ensemble of classifiers refers to a framework comprising a set of subclassifiers (typically of the same type), which work together to classify input data. In some VP3S literature, it is referred to as the multiple-classifier system (MCS). However, an MCS may contain different types of subclassifiers and thus is a generalized version of the ensemble of classifiers. Each subclassifier in the ensemble contributes toward the ensemble prediction, after being trained separately by select subset of the training dataset. Bagging and boosting are the common methods used to create an ensemble.[97] In bagging, the subclassifiers operate in parallel and the individual results are aggregated to generate the ensemble prediction[98] whereas in boosting, the subclassifiers operate sequentially so as to minimize the bias (or error) in ensemble prediction.[99]

If the probability that an input data $x_i$ belongs to class $y_i$ for the $j$th subclassifier of the ensemble (with M subclassifiers) is $P_j(y_i \mid x_i)$, where $j = 1, 2, \ldots, M$, then the probability of the ensemble can be estimated as

$$P_{Ens}(y_i \mid x_i) = \frac{1}{M}\sum_{j=1}^{M} P_j(y_i \mid x_i) \tag{15}$$

*Ensemble of LDAs and SVMs.* In ensemble of LDAs (ELDA) and SVMs (ESVM), the sub-classifiers are based on LDA and SVM algorithms respectively. Salvaris and Sepulveda[50] have implemented and compared the performance of 2 VP3S systems, one based of ELDA and the other based on ESVM. This study revealed that, for fewer trials (<5), ELDA system is more accurate than that of ESVM however, with more trials, ESVM system outshines that of ELDA.

Rakotomamonjy and Guigue[39] developed a VP3S based on ensemble of SVMs that demonstrated the best performance for the BCI Competition III (dataset II). Li et al[52] applied ensemble of SVMs to a modified VP3S that used familiar faces to improve the speller accuracy. In comparison with single SVM classifier, the system was able to achieve a slightly better performance. The above speller was modified by Li et al[47] by introducing a randomized strategy for the selection of the training dataset, which yielded a higher classification accuracy compared with the traditional approach.

Kulasingham et al[100] have introduced an enhanced VP3S using ensemble of SVMs with added support for Sinhala and Tamil languages, compared with the conventional English-only VP3S. This speller achieved 83.76% and 90.68% mean accuracies for letter and P300 classifications respectively. Kundu and Ari[101] applied PCA-based feature extraction together with a weighted version of ensemble of SVMs classifier in their VP3S. This speller demonstrated comparable performance (for 5 and 15 epochs), with regard to VP3S based on LDA and SVM classifiers.

*Multiclassifier Neural Network.* Zhang et al[102] have applied AdaBoost algorithm[99] to create a boosting NNs that calculate a posteriori class probabilities of the input EEG data. This result was then used to classify spatial and temporal patterns for their VP3S, after feature enhancement through ICA projection. They found that the use of temporal patterns gave higher mean speller accuracy than that of spectral patterns. This was also evident from the fact that temporal patterns for electrode channels near Pz demonstrated better feature stability and discriminability than that of spectral maps. Mousavi et al[103] used a multiclassifier NN to obtain 93% mean classification accuracy with 15 trials for their VP3S speller.

*Fuzzy Integral Ensemble.* Cavrini et al[60] have developed a VP3S, which uses a classification framework based on fuzzy integrals that selectively combined artificial NN, SVM (linear and RBF), BLDA, shrunken regularized LDA and SWLDA classifiers. This system achieved 60.8% mean efficiency with Nykopp's ITR[59] of 16 868 bits/symbol.

*Random Forest.* Random forest is an ensemble learning technique with decision tree subclassifiers, each of which is trained with random subsamples of the input dataset.[104] Farooq and Kidmose[105] compared the accuracy and bitrate of VP3Ss based on random forest, SVM, SWLDA, multiclassifier CNN, and ESVM. For fewer trials (ie, <10), the speller based on random forest outran all others whereas for more trials (ie, >10), the spellers based on random forest, multiclassifier CNN and ESVM exhibited similar performances, which were comparatively higher than others. The dictionary-based VP3S developed by Akram et al[106] was able to type 10 words (random) using only one-half of the average time taken by a conventional speller. Also, the random forest classifier demonstrated high accuracy with few repetitions compared to that of SVM, confirming the previous findings by Farooq and Kidmose.[105] Akram et al[106] identified the low outlier sensitivity of random forest as a possible reason for its improved accuracy.

## Discussion

VP3Ss are primarily intended for clinical applications, especially communication and movement assistance for motor-disabled patients. However, the speller designs in most of the literature we surveyed are applicable only for healthy individuals. Studies indicate that motor neuron impaired subjects will not be able to operate these systems as effectively as that of healthy individuals.[107,108] Moreover, the speller paradigms have direct impact on the user acceptability and performance of

VP3Ss. These factors suggest that further researches are necessary to adapt VP3S systems to meet their intended purpose. This survey identified that the electrode configuration, and paradigm design are two important considerations in this context.

The studies of Krusienski et al[15] and McCann et al[16] have identified that the electrodes Cz, Pz, Oz, PO7, and PO8 are relevant for the detection of P300 component in normal subjects and most VP3S implementations in literature follow these findings. However, Ijichi and Tanaka[17] found that the electrodes Cz and CP4 are the effective ones in VP3S for ALS patients. The gaze-dependency of RCP, RBP, and CBP could result in user inconvenience as they require continuous and regular eye movements for character selection while gaze-independent paradigms like Hex-o-Spell and RSVP could be comparatively more comfortable. Furthermore, asynchronous paradigms like ASP could significantly improve user acceptability of VP3Ss and also, they are quite relevant while assisting people with severe disabilities. Considering these findings, we suggest that an asynchronous VP3S with gaze-independent paradigm, which employs dynamic electrode selection, could effectively achieve its intended purpose.

The VP3S process flow consists of preprocessing, feature extraction, and classification stages. In preprocessing, majority of the EEG artifacts and noises are removed through filtering. However, ocular artifacts, which have signal characteristics similar to that of the P300 component, need to be eliminated using EOG recordings. For feature extraction, EEG channels are segmented into epochs of around 800 ms duration. In some of the researches, prestimulus segments up to 200 ms were used for the baseline correction of epochs. The epochs of each channel are then concatenated and subsequently averaged across channels to obtain a single feature vector that is used for training the classifier. In case of high sampling rate signals, decimation is used to reduce bit rate. Automatic segmentation in VP3S is an area which require further research and development.

Accuracy, bitrate or ITR, and character selection or typing time (TT) are the metrics that are commonly used to evaluate the performance of VP3Ss. The paradigm design has direct correlation with the CA and ITR of the system. While CA quantifies the correctness of the VP3S, ITR quantifies the quality of communication between the user and system. With more the number of trials, CA of the system increases but on the contrary its ITR is reduced. VP3S performance metrics like reliability, confusion matrix, and area under curve (AUC) require surveying.

Classification algorithms based on discriminant analysis, SVM, neural network, distance-based and ensemble of classifiers are commonly used in VP3S implementations. The classifier usage statistics in Figure 5 (pie chart) indicates that majority (~70%) of VP3Ss are based on either discriminant analysis or support vector machine. This could be due to their ease of implementation and comparatively good accuracy.

Unlike FLDA, SWLDA uses a feature reduction approach that makes it non-exhaustive thereby giving faster convergence without overfits. Consequently, it offers comparatively stable performance with large feature set and thus preferred over FLDA. Compared with MLPs, DNNs have improved feature learning capability, which gives them the edge while handling nonlinear classification problems in higher dimensions. However, increased processing time requirement for DNNs adversely affects VP3S typing speed and thus a major performance bottleneck. Though backpropagation algorithms are prone to vanishing gradient issue,[109] they are still being used for training DNN-based VP3Ss. Ensemble of classifiers combine a number of single classifier units that work together toward the common goal of classifying input data. Because of the imbalanced nature (intrinsic) of VP3S datasets, ensemble of classifiers is a better choice as it prevents classification biases to significant extents. For VP3S applications with fewer trials, EFLDA and random forest classifiers are recommended since they demonstrated higher accuracy and bitrate than SVM, SWLDA, NN, and ESVM. However, for more trials ESVM was found to be the better performer.

This survey was limited to P300 mind-speller BCIs based on the visual stimulus. However, there exist sensory and cognitive stimuli that could invoke P300 signals. Mind-speller systems based on these stimuli require surveying.

## Conclusion

Over the past 2 decades, BCIs based on the P300 component have undergone intense researches that yielded many promising results. The visual P300 mind-speller, which is a highly reliable BCI with great application prospects, is the most popular among them. In this article, we reviewed the recent developments in the VP3Ss with a specific focus on their classifiers. Our study revealed that the electrode configuration and paradigm design are the 2 important determinants of user acceptability and performance of VP3Ss. We identified different classifiers used in VP3Ss, namely the discriminant analysis, support vector machine, artificial neural network, distance-based method, and the ensemble of classifiers. However, most VP3Ss (~70%) in literature used either discriminant analysis or SVM classifiers. Although none of these classifiers delivered excellent performance in all the evaluation metrics, each of them is suited for some specific conditions. For example, the SWLDA classifier gives good accuracy for large feature-set classifications, while the FLDA classifier does not. Also, we found that the ensemble of classifiers is the best choice for VP3Ss, as they combine the advantages of multiple classifiers while accurately classifying the imbalanced P300 dataset.

### Author Contributions

Jobin. T Philip and S. Thomas George have contributed to the concept and design of the study. Both the authors were part of the data collection, processing, analysis, and its interpretation. Moreover, both of them were involved in drafting, revising, and approving the manuscript.

### Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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