

# ***Algorithmic Enhancement of Brain-Computer Interface Control: Harnessing Thought for Precise System Management***

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**Abstract.** Brain-computer interface (BCI) control technology is a cutting-edge technology that allows users to control computers, mechanical devices, and other electronic devices with their minds by directly connecting the brain to external devices. This manuscript examines the methodologies employed in signal acquisition and decoding. A comparative analysis is conducted between two distinct approaches to signal acquisition: invasive and non-invasive techniques. The discussion encompasses their respective advantages, limitations, and contextual applications. Then, this paper cross-sectionally compares the application of several different machine learning (ML) algorithms in BCI control awareness, such as Autoregressive (AR), Long Short-Term Memory (LSTM) in Temporal Model; Support Vector Machines (SVM), Neural Network (NN), Ridge regression (RR) in Regression model. All these algorithms play an important role in signal decoding for BCI. Finally, this paper successfully decodes and analyzes the signals using the Hidden Markov Algorithm (HMM) as an example, which will show some value for future applications in various fields such as consciousness control and medical rehabilitation.

**Keywords:** BCI, EEG, ML, HMM

## **1. Introduction**

Brain-computer interface (BCI) technology is a transformative advancement in the field of human-computer interaction that enables direct communication between the brain and external devices by decoding neural signals. In recent years, BCI has revolutionized the technology for controlling consciousness, with far-reaching applications of this technology ranging from medical rehabilitation of paralyzed patients [1] to immersive gaming [2], smart home control, and augmented reality (AR/VR) systems [3]. Despite its enormous potential, BCI faces significant challenges, including signal noise [4], individual differences, and trade-offs between invasiveness and signal fidelity. Mitigating these constraints necessitates the implementation of advanced computational techniques, particularly machine learning (ML) algorithms, to enhance the precision and real-time efficacy of signal decoding. In this paper, we focus on comparing different signal acquisition methods that BCI systems rely on, and cross-sectionally compare a variety of machine learning algorithms. The inherently dynamic characteristics of neural signals necessitate the utilization of sophisticated

machine learning models that are adept at managing temporal, nonlinear interactions as well as high-dimensional datasets. While traditional algorithms such as support vector machine (SVM) [5] and autoregressive (AR) models [6] have shown promise, emerging techniques such as long short-term memory (LSTM) networks [7] and hidden Markov models (HMM) [8] offer new ways to improve state prediction and control accuracy. In the future, with the continuous optimization of algorithms and the upgrading of computing hardware, BCI technology will certainly show broader application prospects.

## 2. BCI control technology

### 2.1. The use of BCI control technology

BCI control technology is a cutting-edge technology that enables direct communication between the brain and external devices, allowing users to control computers, machinery, and other electronic devices through their minds. Brain-Computer Interface (BCI) systems capture and interpret the electrical activity of the brain, converting these neural signals into actionable control commands. This innovative technology holds significant promise for diverse applications, including medical rehabilitation, gaming and entertainment, smart home automation, as well as augmented reality (AR) and virtual reality (VR) environments [3]. In medical rehabilitation, BCI offers significant advantages for paralysed patients or amputees to regain control of assistive devices, thereby enhancing quality of life [1]. Although BCI technology has made significant progress, it still faces challenges such as signal stability, reliability, and user comfort. As BCI technology continues to evolve, it is expected to revolutionise human-computer interaction in the future, bringing more convenience and possibilities.

### 2.2. The basic principle of BCI control technology

#### 2.2.1. Invasive

Invasive BCI technologies record neural activity by implanting electrodes directly in the brain, providing higher signal resolution and quality [9]. Cortical electroencephalography (ECoG) involves the placement of electrodes beneath the dura mater, facilitating the capture of intricate electrical activity for clinical applications, including epilepsy monitoring and brain function mapping. Invasive BCIs, due to their highly precise control and monitoring capabilities, show great potential for applications in neuroscience research, neurorehabilitation, and human-computer interaction, but are accompanied by surgical risks and biocompatibility challenges.

#### 2.2.2. Non-invasive

Non-invasive BCI technologies allow users to interact with computers or other electronic devices without surgical intervention by monitoring neural activity outside the brain. One widely used non-invasive method is electroencephalography (EEG), which records the electrical activity of the brain by attaching multiple electrodes to the scalp [10]. EEG is a cost-effective and straightforward method that captures real-time fluctuations in brain states, proving highly effective for diagnosing disorders like sleep disturbances and epilepsy. In addition, EEG has demonstrated a remarkable ability to parse the user's intent and state of consciousness, and by translating brain activity into specific commands, the user can control a drone [1], an automated wheelchair [11], a computer cursor, or other interactive devices, greatly enhancing the quality of life and autonomy of people

with mobility impairments. This technology not only provides new communication and control tools for people with disabilities, but also shows a wide range of applications in the fields of neuroscience research, human-computer interaction, and augmented reality technology.

### 2.2.3. Main processes

The BCI control principle encompasses four essential steps: signal acquisition, processing, decoding, and countermeasures, with acquisition involving both invasive and non-invasive techniques. The acquired signals usually contain a large amount of noise and irrelevant information, and the purpose of signal processing is to filter and enhance these signals to extract useful feature values. The process of filtering eliminates high-frequency noise and low-frequency drift by employing bandpass filters [12]. Through Fourier and wavelet transforms, feature extraction obtains time-frequency domain signal characteristics. Signal decoding translates processed EEG signals into actionable commands, often via pattern recognition—employing machine learning like support vector machines and neural networks for feature classification and intent interpretation—or regression analysis, which predicts subsequent control commands through regression modeling [13]. The feedback mechanism enables the BCI system to operate external devices based on user-issued EEG control commands, providing timely results through various modalities, including visual, auditory, and tactile feedback. For example, visual [14] feedback can display the operation results or progress through the screen, auditory feedback can prompt the user through sound to indicate the success or failure of the operation, and haptic feedback can convey information to the user through vibration or pressure changes. Through this feedback, users can see in real time whether their control commands are being executed correctly, so that they can make adjustments and improvements if necessary. Timely feedback helps users learn and adapt as they use the BCI system, improving overall control accuracy and stability.

## 3. Machine learning algorithms

### 3.1. Temporal model

#### 3.1.1. Autoregressive modelling

The autoregressive (AR) model is a statistical model used in time series analysis that uses past observations to predict future values. The AR model plays an important role in brain-computer interface (BCI) applications for controlling consciousness. It can analyze EEG signal features over time to identify the user's consciousness state and facilitate intelligent control of external devices [15]. The AR model efficiently captures characteristic patterns of consciousness states by modeling the autoregressive structure of EEG signals. Its simplicity facilitates real-time signal processing, allowing for rapid decoding of conscious states and immediate feedback. In addition, AR models can be used to predict and classify EEG signals, e.g., to predict motor intentions in motor imagery tasks [6], as well as to further improve signal quality and analysis through noise processing and combining with other models (e.g., ARMA and ARIMA models) [16]. In summary, the application of AR models in BCI systems not only simplifies the signal processing process, but also significantly enhances the reliability and performance of the system.

### 3.1.2. Long Short-Term Memory network

Long Short-Term Memory (LSTM) networks are crucial for brain-computer interface (BCI) control of consciousness, as they effectively manage long-term dependencies in time-series data, making them ideal for analyzing complex, non-linear, and noisy EEG signals [17]. LSTMs can capture, through their unique gating mechanisms [18] (input gates, oblivion gates, and output gates) and remember important information in long time sequences while ignoring irrelevant information, thus decoding the user's state of consciousness more accurately and enabling intelligent control of external devices [7]. LSTM models enhance real-time processing and prediction in applications like motor imagery BCI, emotion recognition, and brainwave control by autonomously extracting complex EEG features. Despite challenges related to computational demands and data needs, LSTM demonstrates significant potential in advancing BCI system intelligence and efficiency, establishing it as a crucial tool in the BCI domain.

## 3.2. Regression model

### 3.2.1. Support Vector Machine

Support Vector Machines (SVMs) play an important role in Brain-Computer Interface (BCI) control, which is mainly used to identify and decode the user's state of consciousness to achieve the control of external devices. By analysing the features of EEG signals, SVMs can accurately classify different states of consciousness [19], e.g., distinguishing between left-handed and right-handed motor imagery in a motor imagery BCI system. In dealing with nonlinear relationships and high-dimensional features, SVM significantly improves the recognition accuracy by using kernel functions (e.g., RBF kernel and polynomial kernel). SVM excels in managing noisy and limited datasets, making it ideal for real-time applications that facilitate rapid classification for decoding states of consciousness. In addition, SVM combined with feature selection methods (e.g., recursive feature elimination, RFE) can effectively select the most discriminative features and improve the model performance and computational efficiency. SVM shows its strong performance in practical applications such as motion imagery BCI [20], P300 Speller [21], and emotion recognition [5], which provides a broad prospect for further development of BCI systems in the future.

The formulas outline the fundamental mathematical framework of SVM, frequently employed in binary classification tasks. In BCI control systems, SVM differentiates user intentions by analyzing distinct brainwave patterns [22].

$$y_i = [(w \cdot x_i) + b] - 1 \geq 0, i = 1, 2, \dots, l \quad (1)$$

The decision function of SVM is used to calculate the classification result. In this function,  $w$  denotes the weight vector,  $x_i$  is the input vector, and  $b$  is the bias term. This formula determines the classification (positive or negative class) of the input vector  $x_i$ . When  $y \geq 1$ , it means that  $x_i$  is classified as the positive class.

$$\min Q(a) = \frac{1}{2} \sum_{i,j=1}^l a_i a_j y_i y_j \cdot K(x_i, x_j) - \sum_{i=1}^l a_i \quad (2)$$

The optimal weight vector  $w$  is solved by an optimisation problem. In this problem,  $a_i$  is the Lagrange multiplier designed to solve the optimisation problem with constraints. The kernel

function  $K(x_i, x_j)$  is used to map the input data to a higher dimensional space so that the data can be linearly differentiated.

$$K(x_i, x_j) = \frac{\exp(-|x-x_i|^2)}{g^2} \quad (3)$$

The Gaussian kernel (or radial basis function kernel) employed is capable of handling nonlinearly differentiable data. The degree of smoothing of the kernel function is controlled by the parameter  $g$ , which determines the width of the kernel and thus affects the degree of model fit.

### 3.2.2. Neural Network model

Neural Network (NN) models are extensively utilized in Brain-Computer Interface (BCI) control, particularly for decoding and recognizing user consciousness states for external device operation. Their hierarchical architecture enables automatic extraction of high-level features from EEG signals, effectively capturing intricate relationships between EEG data and consciousness states via nonlinear activation functions [23]. Models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) have significantly improved recognition accuracy and real-time processing in applications such as Motor Imagery BCI, P300 Speller, and Emotion Recognition [24]. Despite the substantial data and computational demands of training neural networks, optimization strategies like data augmentation and transfer learning, alongside innovative architectures such as Generative Adversarial Networks (GANs) and Graph Convolutional Networks (GCNs), are advancing BCI technology, establishing neural networks as essential for developing more intelligent and efficient brain-computer interface systems.

### 3.2.3. Ridge Regression

The application of Ridge Regression (RR) in brain-computer interface (BCI) control awareness is of great significance, which effectively prevents overfitting by introducing the L2 regularisation term, and especially performs well in processing high-dimensional EEG signal data with multiple covariates and noise. The high-dimensional nature and complexity of EEG signals frequently result in model overfitting; however, Ridge Regression enhances model generalization by regularization, constraining regression coefficients [25]. Ridge regression enhances model interpretability and predictive accuracy by attenuating irrelevant features and accentuating those most salient for decoding user intent. In continuous variable prediction, this method enables precise forecasting of user movement intentions and facilitates seamless control of external devices via EEG signal features [26]. By preventing overfitting, feature selection, and dimensionality reduction, continuous variable prediction and robust data processing performance, ridge regression becomes an important tool for intelligent and efficient control in BCI systems.

Table 1. Comparing five different ML algorithms

Model Type	Advantages	Disadvantages	Application Status
Autoregressive model (AR)	suitable for analyzing time series data; simple and easy to implement	Limited expression of nonlinear relationships; susceptible to outliers	In BCI control based on time series prediction
Long Short Memory Network (LSTM)	Suitable for dealing with long-term dependence in time series; adapts to different time scales of data	High computational complexity; requires a large amount of data and a long training time	Widely used in continuous action recognition and prediction
Support Vector Machine (SVM)	Powerful classification capability, especially in high-dimensional space; excellent generalization performance; good robustness to noise; can effectively deal with nonlinear classification problems	When dealing with very large datasets, the training speed may be slow	Sensitive to parameter selection, widely used in BCI systems for pattern recognition and classification tasks
Neural network modeling (NN)	Capable of learning very complex patterns and relationships; applicable to various types of BCI control tasks	Requires a large amount of data; prone to overfitting; high cost of model tuning and training	Commonly used in complex BCI control tasks.
Ridge regression (RR)	It can reduce the data covariance problem; more stable compared to ordinary least squares	Limited ability to deal with nonlinear problems	Used in BCI applications that require robust predictive modeling

## 4. Hidden Markov Model

### 4.1. Basic model

The machine learning model talked about in the previous chapter needs inputs and outputs for algorithmic analysis. This paper examines brainwave signals as inputs, with outputs comprising the waveforms and frequencies of smaller brainwaves derived from decoupling to extract intention-based information. And Hidden Markov Model (HMM) is a model that decouples and reduces the units of measurement. (Figure 1)



Figure 1. EEG data processing flow

The HMM is a statistical model for describing sequences of states that are not directly visible in a system and inferring state changes from observed events. The HMM efficiently analyzes and classifies EEG signals by modeling distinct EEG states and decomposing continuous data into potential state transformations. This model assumes that each state depends only on its previous state (Markovian property) and has a probability of generating observations [8]. The HMM utilizes state transition and observation probability distributions to predict state sequences for unknown data, facilitating applications in brain-computer interface design and the identification of specific EEG patterns, such as sle

ep phases [27], seizures, or thought activity), and greatly enhancing the ability to extract information from complex EEG data. equation

$$\pi = [\pi_i]_{1 \times N} \quad (4)$$

$$\pi_i = P(i_{t-1} = S_i) \quad (5)$$

The initial state distribution(4) [28] describes the probability that the system is in state  $S_i$  at the beginning of the time series. In BCI systems, this distribution corresponds to a particular type of brainwave onset state.

$$A = [a_{ij}]_{N \times N} \quad (6)$$

$$a_{ij} = P(i_{t+1} = S_j | i_t = S_i) \quad (7)$$

The state transfer probability matrix (6) [29] represents the probability that the system will transfer from state  $S_i$  to state  $S_j$  at any given point in time. This matrix has an important role in the BCI system as it helps the model to learn how to transition from one EEG state to another, which is crucial for predicting the user's behaviour or reaction.A

$$B = [b_j(o_t)]_{N \times M} \quad (8)$$

$$b_j(o_t) = P(o_t | t_t = S_j) \quad (9)$$

The observation probability matrix consists of two formulas [28] that represent the probability of observing an observation  $o_t$  when the system is in state  $S_j$  at a given point in time. Here,  $o_t$  is a measurement of the subject's electrical brain activity, usually expressed as a waveform or pattern of a specific frequency, reflecting the current state of the system.

## 4.2. Arithmetic example

This study uses the EEG dataset provided by Faller et al. riment on Neurofeedback (NFB) training. The experiment employed a high-density EEG system to capture neural signals from participants engaged in cognitive or attention-related tasks, aimed at eliciting distinct EEG patterns during data acquisition.

Since the prefrontal cortex (PFC) plays a key role in consciousness regulation, I selected the data from Fp1, Fp2, AF3, and AF4 channels for analysis [30]. The prefrontal cortex, governing higher cognitive functions, underpins the examination of BCI control's influence on consciousness regulation. Utilizing the Faller et al. dataset, this study employs the HMM algorithm to assess the neurodynamic characteristics and modulability of this region during neurofeedback training. By identifying fluctuation patterns and decomposing them into hidden states, the HMM effectively discerns EEG state transitions, particularly between focused and unfocused states, crucial for BCI control.

Table 2. Three different BCI states

BCI state	EEG waveform	Transition mode of state
S1 (concentration state)	High $\beta$ wave (14-30 Hz) and $\gamma$ wave (>30 Hz), low $\alpha$ wave (8-12 Hz).	Has a high probability of self-looping ( $a_{11}$ is larger) and will remain focused for a short time if the user is already in that state.
S2 (light concentration state)	Medium $\alpha$ and $\beta$ waves, lower $\theta$ waves (4-7 Hz).	They are more prone to state transitions, i.e., they may transition to a focused state (S1) or a fatigued state (S3), with relatively high transition probabilities $a_{21}$ and $a_{23}$ .
S3 (fatigue state)	High $\theta$ and $\alpha$ waves, low $\beta$ waves.	Tends to be maintained for some time, but may return to a state of mild concentration (S2) if the individual takes certain steps (e.g., deep breathing, changing the task).

#### 4.2.1. Optimisation direction of HMM in Eeg prediction

Future research should investigate the application of Hidden Markov Models (HMM) in EEG prediction, particularly for real-time monitoring and regulation of attentional states. Utilizing the Viterbi or forward-backward algorithms, HMM can determine the most probable EEG state sequences and forecast subsequent state transitions [31]. If the HMM demonstrates sufficient training, subsequent studies can validate its efficacy in prospectively detecting attentional decrement, such as the issuance of timely alerts contingent upon an increased probability of EEG state transition from S1 (concentration) to S3 (fatigue). Further investigation into the application of HMM within BCI is warranted, especially concerning the dynamic modulation of task difficulty based on EEG predictions to attenuate user fatigue and augment interaction efficiency. Concurrently, HMM can be employed for longitudinal trend analysis to examine patterns of individual attentional variation during sustained tasks, thereby furnishing a foundation for personalized neurofeedback training.

## 5. Conclusion

In this study, by adopting advanced machine learning algorithms such as HMM, an important breakthrough has been made in the field of BCI consciousness control, which realizes certain decoding of motor imagery consciousness and improves the real-time and reliability of consciousness control. The findings demonstrate significant applicability in medical rehabilitation, particularly in stroke recovery and limb function restoration. Future research will focus on the development of the universal decoding model, the exploration of brain-computer collaborative enhancement learning paradigm and the optimization of system wearability, etc. These advancements will facilitate the transformative evolution of brain-computer interface technology within human-computer interaction. However, this is also accompanied by some ethical issues and great challenges. With continued technological advances, the brain-computer interface is expected to become a key technology that will change the way humans interact with technology.

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