# Brian Electrical Activity Acquisition and Decoding Algorithms For Using BMIs

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**Abstract.** Physical disabilities in limbs often lead to severe impacts on personal life and work. However, BMI technology offers hope for amputees or paralyzed individuals to regain control and motor abilities. By reading signals from the brain's motor cortex, BMI technology enables the control of robotic arms, cursors, and more, facilitating functional recovery. The key lies in identifying and extracting information related to specific tasks or intentions from brain signals, where the decoder determines the accuracy, reliability, and sensitivity of the final movements. This paper aims to provide a brief overview of the decoding steps in BMIs. The paper will discuss how the raw signals are acquired from the brain, including invasive BMI and noninvasive BMI, along with the respective advantages and disadvantages of these two approaches. Then, it will explore how these signals are processed into specific commands through both linear and nonlinear algorithms. Additionally, the paper will discuss the strengths, limitations, and feasibility of different decoding methods in human-computer interaction applications. This review offers researchers a preliminary understanding of the acquisition and decoding algorithms for brain electrical activity in BMIs. By evaluating the strengths and limitations of different algorithms, we can provide guidance for designing and improving BMI systems, thereby supporting the achievement of more accurate and efficient human-computer interaction.

**Keywords:** Brain-computer interface, ECoG, EEG, linear algorithm, deep learning.

## 1. Introduction

The human ability to control movements is crucial for everyday life and social interaction. Individuals who have lost their motor functions due to amputation or paralysis may face significant limitations in independently performing daily activities and achieving mobility. In 1999, Chapin and his team successfully utilized a Brain-Machine Interface (BMI) to allow mice use its mind to control a robotic arm and retrieve a water reward by thinking and being aware of the target position [1]. Their work demonstrated the possibility of controlling external mechanical devices through brain activity using a BMI.

Over the past few decades, BMI technology has rapidly evolved from further advancement in 2D movement [2], to the three-dimensional (3D) movement of neuroprosthetic devices [3], and there have been practical examples of paralyzed patients successfully controlling 7D robotic arm movements through BMIs [4]. As a result, the hope for applying this technology to restore motor abilities in amputees and paralyzed individuals in their everyday lives is increasing.

To achieve the interaction between brain activity and external devices through the acquisition and interpretation of brain neural signals, BMIs go through several steps. First is signal acquisition, where brain neural activity is obtained through implantable or noninvasive electrodes. Next is signal decoding, which converts the collected neural signals into understandable movement commands. Finally, external device control is realized to achieve the intended outcomes. In these three steps, decoding brain signals is a crucial step that involves effectively analyzing and interpreting the movement intentions or instructions contained in neural signals.

Initial research primarily focused on decoding arm or finger movements by recording electrical signals and converting them into movement commands for prosthetic limbs. However, with technological advancements, researchers have started exploring more complex tasks, including cursor movement and clicking [3, 5, 6], as well as other tasks such as restoring human functionality through stimulation of muscles [7].

The accuracy of these tasks largely depends on the performance of the decoder and how clear and rich the brain signal collected is. Advanced signal processing methods and machine learning algorithms can significantly improve decoding accuracy and precision, while also reducing training time and costs, bringing this technology closer to practical applications in daily life [8]. The following sections of this article will be divided into two parts. Firstly, signal acquisition will be introduced, followed by a discussion of various algorithms used in decoders and their advantages and disadvantages.

## 2. Research Works

### 2.1. Brain Electrical Activity Acquisition

#### 2.1.1 Invasive devices

Currently, the overwhelming majority of BMI systems utilize implanted electrodes to acquire brain signals, with the main techniques being electrocorticography (ECoG) [2, 5, 9] and implanted electrodes [1, 3, 4, 6, 7, 10, 11]. ECoG implants electrode arrays onto the surface cortex, while implanted electrodes are used for signal acquisition in deeper brain regions. Both of these techniques require subjects to undergo surgery to have the electrode arrays implanted in specific areas of the brain. These electrodes are usually made of stainless steel, platinum, or rigid silicon etc. The number of electrodes can be tailored to the needs of the study. Figure 1 is an example of implanted BMIs, it is a seven-dimension Implanted BMI which can control a prosthetic limb to reach and grasp. Picture a shows a paralyzed patient who underwent an electrode implantation surgery. Picture b displays the patient controlling a mechanical prosthetic to perform grasping tasks. Picture c demonstrates the training process, where the patient's performance in grasping tasks improves gradually despite increased task complexity and reduced computer assistance. The gray trace indicates the chance level of performance given the level of assistance.

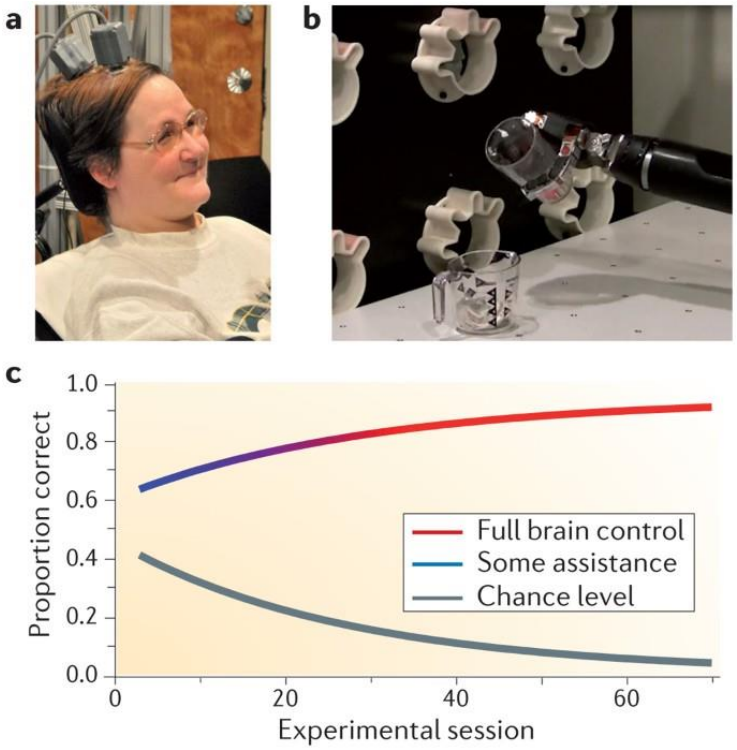



**Fig. 1** a seven-dimension prosthetic limb which can reach and grasp [12]

Implanted BMIs offer higher signal quality and accuracy compared to noninvasive methods like electroencephalography (EEG) because they can directly record neural activity from the brain cortex. Although ECoG provides advantages such as high spatial resolution, good signal quality, strong temporal resolution, and anti-interference capabilities, it also has some drawbacks. Firstly, ECoG

requires invasive surgery to implant the electrodes into the brain, which carries risks and may result in cell death. These invasive surgeries pose certain risks, including infection, bleeding, and other surgery-related complications. Furthermore, after the electrodes are implanted, their durability and stability become issues. Over time, because of the rejection of immune system, the quality of the signals collected by the electrodes may deteriorate, and their position may also change. These drawbacks hinder the application of implanted BMI systems in everyday life. Moreover, implanted electrodes are limited to specific brain regions and can only record specific ranges of brain activity.

### 2.1.2 Non-invasive devices

Noninvasive BMIs primarily utilize electroencephalographic (EEG) as a means of collecting signals [13, 14].

EEG is a noninvasive technique used to measure brain electrical activity. By placing electrodes on the surface of the scalp, weak electrical signals from the brain cortex can be recorded when neurons are active. The position and number of electrodes can be adjusted based on the desired measurement area and experimental design. Figures 2 shows one of noninvasive BMIs at use. This figure illustrates a noninvasive BMI that utilizes EEG signals. Users can control a mobile robot to navigate freely within a room using their thoughts through the BMI. The interface enables them to perform actions such as turning and moving forward. Additionally, users can also control processes of certain programs on a computer using EEG brainwave signals.



**Fig. 2.** A noninvasive BMI that can control external mechanical movements and program processes[8]

Compared to invasive electrodes that require surgery and have serious side effects and durability issues, noninvasive EEG-based BMIs are more suitable for practical applications in daily life outside of the laboratory. Additionally, EEG has the advantage of being able to monitor activity across the entire brain.

However, there are reasons why EEG has not become the mainstream signal acquisition method for BMIs. Firstly, there are issues with spatial resolution and signal interference. The signals obtained from EEG are affected by the impedance of the scalp and skull, resulting in relatively low spatial resolution. This means that EEG is challenging to accurately locate and identify specific neural activity, limiting the accuracy and sensitivity of BMI systems. Moreover, EEG signals are prone to various sources of interference, such as muscle movements, power line interference, eye movements, etc. These interferences can degrade signal quality and disrupt accurate signal analysis. Additionally, for many BMI applications, real-time and fast processing is crucial, and the speed of EEG signal acquisition, processing, and decoding is slower compared to methods like ECoG.

Despite these drawbacks, EEG still holds the most potential as a mainstream signal acquisition method in future practical applications. Recent research has found that we can compensate for the shortcomings in signal processing of EEG signals by combining machine learning techniques and intelligent interaction designs in the analysis process [8]. Additionally, through mutual learning, where the user and the system adapt to each other, the required learning time for individuals to adapt to BMIs can be significantly reduced [8].

## 2.2. Decoding Algorithms

### 2.2.1 Linear decoder

Linear decoder is the earliest and most commonly used decoder in BMIs, which establishes an association model between brain signals and corresponding movements or operations. It assumes a linear relationship between brain signals and movements or operations and uses this relationship to decode unknown brain signals. Linear algorithms applied in BMIs include Linear Discriminant Analysis (LDA), Linear Regression, etc.

The advantages of linear decoders are high computational efficiency and easy implementation. Linear algorithms, relatively speaking, do not require complex models or parameter adjustments, thereby reducing computational costs. This makes them relatively easy to implement and adjust, reducing the complexity of system development and debugging. Additionally, the interpretability of feature weights and coefficients during the decoding process of linear decoders helps understand the relationship between brain signals and control signals.

For example, the ridge regression algorithm is suitable for solving ill-conditioned regression analysis problems. It can be applied to decode the relationship between electrical brain signals in the brain and limb movement purposes, velocity, and position, and has many characteristics suitable for brain signals. When dealing with brain signals, we often need to process data containing activity from a large number of neurons or brain regions, while facing interference from many other unrelated brain regions and neural activities. There are challenges such as collinearity, overfitting, high noise levels, and limited number of participants in BMIs, i.e., inadequate sample size. The ridge regression algorithm introduces a regularization term to prevent overfitting and reduce the influence of noise. It can handle collinearity issues and provide reliable analysis results even with a small number of samples.

Another commonly used algorithm is the Kalman filter, which is a recursive algorithm. Although it is linear, it can update estimates based on previous state estimates and observed data at each time step, making it adaptable to dynamic and nonlinear systems. In practical applications, to handle nonlinear systems, modified Kalman filters such as Unscented Kalman Filter are often used, which linearly approximates the nonlinear functions to adapt to nonlinear systems.

The Kalman filter is also frequently combined with other linear algorithms. For example, in a BMI study where a trained monkey controlled a cursor movement using visual feedback, researchers combined the Kalman filter with ridge regression. By utilizing the Kalman-filtered data to improve the ridge regression, the estimation of the cursor motion results has been improved quite a bit [5]. In another experiment where paralyzed patients moved and controlled cursor clicks, a linear classifier determined whether to click the cursor, while the Kalman filter determined the cursor's velocity.

### 2.2.2 Nonlinear decode

Although linear decoders are widely used in BMIs, they are limited by their assumption of a linear relationship. Therefore, they have limitations in capturing complex or nonlinear brain activity.

Nonlinear decoders handle the nonlinear relationship between neural signals and control signals better. They use nonlinear models to capture more complex nonlinear relationships and patterns, enabling them to handle more complex tasks and data. They possess stronger model-fitting and generalization abilities. Additionally, nonlinear decoders can filter out noise and interference through nonlinear transformations and feature selection, improving the stability of decoding results.

Nonlinear decoders include Bayes quadratic and Hidden Markov Models (HMM), as well as more cutting-edge machine learning algorithms widely applied in various fields in recent years, such as Convolutional Neural Networks (CNN) and Support Vector Machines(SVM).

For example, EEGNet is a recent research achievement. It is a compact CNN architecture optimized and adjusted for EEG signals. There have been cases where CNNs have been used to decode single-trial EEG BMIs [15], but EEGNet goes further by designing a single CNN architecture with high generalization capabilities to accurately classify signals of EGG from different BCIs [16].

EEGNet is optimized and adjusted for the characteristics of EEG signals. Traditional CNNs typically use convolution operations in the spatial domain, where a single kernel slides over the input in different spatial positions. EEGNet introduces channel-wise convolution, where convolution operations occur between different channels (electrodes). This allows EEGNet to capture spatial correlations between different channels and better utilize the information from multi-channel EEG data. EEGNet also employs depthwise separable convolution, which consists of two steps: spatial convolution in each channel followed by channel-wise linear combinations using 1x1 convolution. This operation reduces the number of model parameters and improves computational efficiency. Additionally, the authors utilize regularization techniques and batch normalization to improve model stability and generalization abilities.

Another example is the Berlin Brain-Computer Interface (BBCI). It aims to address the long training time required by traditional EEG-based BCIs [17]. In the BBCI, training is performed on previously collected training data to learn patterns for extracting relevant features from EEG signals and performing classification. Once the training is completed, these algorithms can be used for real-time or new input EEG signals to perform classification and decoding, converting brain activity into control commands. With continuous feedback and adjustments, machine learning algorithms can gradually optimize and improve outcomes of BBCI. Ultimately, untrained individuals can quickly achieve high BMI performance.

### 2.2.3 Combination of decoders

Of course, in practical applications, different decoders are often combined and used together, using strategies such as Boosting, Voting, Stacking, etc. By combining different algorithms and leveraging the advantages of each, decoding and analysis can be improved, and the final results often outperform the use of a single decoder [18]. For example, in the previously mentioned example of combining Kalman filters and ridge regression [5], and in the case of hybrid BMIs, such as combining P300 and SSVEP for wheelchair control [19].

P300 is a BMI that uses presented stimuli to elicit event-related potentials in the brain, which are then used for target recognition and command identification. SSVEP, on the other hand, utilizes visually presented stimuli of different frequencies to elicit visual cortex potentials, which are used for command recognition by monitoring the corresponding frequency of the brain's electrical response. Both of these BMIs collect signals through EEG.

In wheelchair control, the experimental team simultaneously collects P300 and SSVEP signals and processes these signals using different algorithms. They utilize P300 for target selection and command identification while utilizing the additional information provided by SSVEP to enhance the performance and stability, such as adjusting the stimulus sequence and parameters for optimization and improving the detection accuracy of P300. Ultimately, this combination of P300 and SSVEP in the BCI performs relative excellence when it comes to terms of detection accuracy and response time.

## 3. Discussion

The current progress of BMI technology is rapid, but it still faces many issues. In terms of current technology, implanted devices cause serious brain damage, are expensive, and inevitably lead to problems like immune rejection and infection, while noninvasive devices have issues with the efficiency and accuracy of signal reading. The speed and precision of movement controlled by BMIs for mechanical prosthetics also fall short of satisfaction.

Even if we set aside these problems with current technology, we need to note that most BMIs are currently implemented in laboratories. In the lab, we can use heavy and expensive equipment for data collection and analysis, but it is unrealistic to apply them in everyday life.

Furthermore, due to the risks and limitations in effectiveness of current BMI surgeries, it is difficult to find enough subjects to gather sufficient data. Noninvasive BMIs are the focus of future development. They can solve the health damage caused by implant surgeries and attract more subjects. The signal detection disadvantages can also be addressed through the development of new generation decoding algorithms. Reducing the cost and miniaturizing the devices are also key directions for future development.

Aside from technical issues, we must also consider ethical concerns, including the risks to health from using implanted BMIs, the invasion of privacy through reading brain signals, and the risk of reversing input signals to control personal thoughts. These are all issues that need to be taken into consideration in the future. We can follow past medical ethics, prioritize privacy protection and informed consent. Ensure patients are aware of the risks of BMIs and set appropriate informed consent standards for patients who have difficulty expressing their own wishes. Find a balance between violating privacy and necessary information gathering in the use of BMIs. It is inevitable that BMIs will infringe on privacy during use, but we must ensure that it does not go too far. At the same time, for the enhancement of human functionality by BMIs, we may need philosophical intervention to help us establish ethical standards in this previously uncharted territory [20].

## 4. Conclusion

BMI technology, as an emerging medical technology, offers hope for restoring motor function to amputees or paralyzed individuals. Every step, from the collection of brain signals to signal decoding, plays a critical role in the outcome of movement restoration. This article provides a brief introduction from the perspectives of brain signal acquisition and decoding algorithms.

In terms of brain signal acquisition, implantable electrodes and noninvasive techniques are the main methods. Implantable electrodes offer higher signal quality and accuracy but come with surgical risks and durability issues. Noninvasive techniques such as EEG are more suitable for practical application in daily life and have the advantage of monitoring the entire brain activity.

In terms of decoding algorithms, both traditional signal processing methods and machine learning techniques play important roles. Traditional signal processing methods have the advantages of simplicity and interpretability but may be limited in complex tasks and noisy environments. Machine learning methods are more flexible and adaptive, but they are more complex and require more training data for modeling.

In conclusion, BMI technology has tremendous potential to restore motor function in amputees and paralyzed individuals. By continuously improving brain signal acquisition and decoding algorithms, the accuracy, sensitivity, and real-time performance of decoding can be further enhanced, making this technology more applicable to daily life. It is hoped that this article will inspire further research and development of BMI technology.

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