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Analysis of the Structure and Key Performance of BCI Signal Acquisition System

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Abstract. Brain-computer interfaces (BCIs) enable the brain to directly interact with external devices. At present, it has been applied in the fields of rehabilitation therapy, human-computer interaction and neuroscience research. However, different signal acquisition methods of BCI systems have significant differences in terms of invasiveness, signal quality, spatial and temporal resolution, and engineering implementation complexity. This paper focuses on three widely used brain-computer interface signal acquisition methods-electroencephalography (EEG), electrocorticography (ECoG) and intracortical recording-to compare and analyze the architecture and performance of their signal acquisition systems. Firstly, this paper introduces the basic signal processing link of BCI system and defines several key performance indicators. Then, the working principles of the three types of signal acquisition methods are analyzed respectively, and their performance is compared horizontally from the quantitative and qualitative levels. The comparison results show that from EEG to ECoG, and then to intracortical recording, the signal quality and spatial positioning accuracy are gradually increasing, but at the same time, the degree of system intrusion and the difficulty of engineering implementation are also increasing. The comparative analysis of this paper can provide a reference for researchers to select the appropriate signal acquisition scheme for specific brain-computer interface applications.

Keywords: BCI, EEG, ECoG, intracortical recording, signal acquisition

1. Introduction

With the rapid development of neuroscience and microelectronics technology, BCIs, as a technology that can establish a direct communication pathway between the brain and external devices without relying on the peripheral neuromuscular system, has shown important application value in the fields of medical rehabilitation, human-computer interaction and neuroscience research [1]. Signal acquisition is the core part of the brain-computer interface system. Different acquisition methods have significant differences in terms of invasiveness, signal quality, spatial resolution, and engineering implementation complexity. These differences largely determine the overall performance of the system and its applicable scenarios. Therefore, it is of great significance to compare and analyze the system architecture and key performance indicators of different neural signal acquisition methods.

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In this paper, the architecture and key performance characteristics of brain-computer interface signal acquisition system are compared and studied. Firstly, the overall logic flow of signal acquisition in brain-computer interface system is summarized, and the core performance indicators such as signal amplitude, signal-to-noise ratio, spatial resolution, time resolution, bandwidth and Poynting vector are determined. Then, the basic principles and hardware characteristics of three typical signal acquisition methods are introduced, including scalp EEG, ECoG and intracortical recordings. Finally, based on the above performance indicators, the quantitative and qualitative comparisons of the three acquisition methods are carried out, and their applicable application scenarios are summarized.

The comparative analysis of this paper can provide an important reference for the selection of signal acquisition methods of brain-computer interface system, and help researchers to design and optimize the front-end hardware system of brain-computer interface for different application requirements.

2. Structure and working principle of BCI system

2.1. Signal processing chain of BCI system

The signal processing chain of the BCI converts weak physiological potential signals into executable control commands through an analog-to-digital conversion pathway. The typical processes include neural activity generation, acquisition of acquisition electrodes, low-noise instrumentation amplification, filtering, analog-to-digital conversion (ADC), digital filtering, feature extraction and classification, and final device control, which is shown in Figure 1 [2].

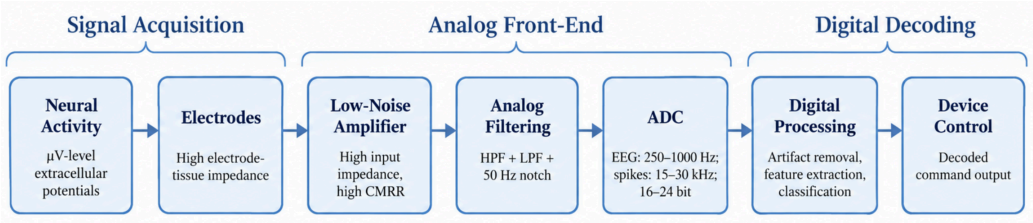


Figure 1. BCI signal processing chain

The signal source is mainly the extracellular potential generated by the discharge of synchronous neurons. Its amplitude is usually in the range of tens to hundreds of microvolts (μV), and the electrode-tissue interface impedance can reach hundreds of kΩ. Therefore, the post-stage circuit usually needs to have an input impedance of Giohm (GΩ) magnitude to reduce the signal attenuation caused by the partial pressure effect. The low-noise instrumentation amplifier is used to amplify the target differential signal and suppress the common-mode noise. Its typical performance indicators include a common-mode rejection ratio (CMRR) higher than 100 dB and an input reference noise lower than 1 μV.

Subsequently, the signal enters the analog filtering link: high-pass filtering is used to remove DC bias and low-frequency drift, low-pass filtering is used to limit high-frequency out-of-band components and prevent sampling aliasing, and 50 Hz notch filter is used to suppress power frequency interference. After the filtering is completed, the signal is digitized by the analog-to-digital converter according to the sampling frequency that meets the requirements of the Nyquist sampling theorem. Among them, the typical sampling rate of EEG signals is 250-1000 Hz, and the

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recording of nerve spike signals usually requires a sampling rate of 15-30 kHz. In order to preserve the amplitude details of microvolt neural signals, ADC usually adopts 16-24 bit resolution.

In the digital signal processing stage, algorithms such as independent component analysis (ICA) can be used to remove ocular and myoelectric artifacts; then, low-dimensional feature vectors are extracted from the original neural signals by power spectrum estimation, common spatial pattern (CSP) and wavelet transform. Finally, the classifier decodes the user 's intention according to the extracted features and converts it into the corresponding device control instruction, thus completing the closed-loop control process of the brain-computer interface system.

2.2. Main performance indicators of neural signals and acquisition system

2.2.1. Signal amplitude

The signal amplitude reflects the magnitude of the potential change in the neural electrical signal, measured in microvolts or millivolts and typically expressed as the peak-to-peak value:

$$V_{pp} = V_{max} - V_{min} \tag{1}$$

In the formula, V_{pp} is the peak-to-peak value of the signal, while V_{max} and V_{min} denote the maximum and minimum values of the signal within the observation period. The amplitude of the signal directly affects the front-end amplification factor and the input range of the ADC. This means that the acquisition system needs to strike a balance between amplifying weak signals and preventing circuit saturation.

2.2.2. Signal to Noise Ratio(SNR)

The SNR is the ratio of the signal power to the input-referred noise power. It is usually expressed in decibels (dB):

$$SNR = 10log\left(\frac{P_{signal}}{P_{noise}}\right) \tag{2}$$

In the formula, P_{signal} represents the power of the signal and P_{noise} is the power of the noise. In the front-end circuit of the brain-computer interface, due to the weak nature of neural signals, the thermal noise and 1/f noise contained in the circuit are tend to overwhelm the signal [3]. The conclusion is that the core of designing an amplifier with high signal-to-noise ratio lies in reducing the input reference noise of the amplifier0.

2.2.3. Spatial resolution and temporal resolution

Spatial resolution refers to the system's ability to distinguish adjacent neural sources, i.e., the minimum distance resolvable between two active sources during EEG source localization. Temporal resolution indicates the system's capability to capture rapid changes in neural electrical signals over time. Since neural signals vary on the millisecond or even sub-millisecond scale, electrophysiological recording methods theoretically offer high temporal resolution. In practice, however, actual temporal precision is limited by sampling rate, filter bandwidth, and signal type, with intracortical spike recordings achieving the highest temporal accuracy [4].

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2.2.4. Signal bandwidth

In the brain-computer interface system, the electrical signals from different physiological sources exhibit significant differences in the frequency domain, and this bandwidth determines the frequency response range acquisition system must cover. The signal bandwidth refers to the frequency range within which the effective energy of neural signals is concentrated.

$$B = f_h - f_l \tag{3}$$

In the formula, f_h denotes the upper cutoff frequency at which the signal power drops to half its peak value, while f_l denotes the corresponding lower cutoff frequency. Signal bandwidth directly determines the cutoff frequency settings of the filter in the analog front-end circuit. During hardware design, the filter passband must be precisely configured according to the specific signal type being acquired, striking a balance between preserving signal features and suppressing noise.

2.2.5. Sampling rate

The sampling rate is the number of times per unit time that a system samples a continuous analog neural signal, typically expressed in hertz (Hz) or samples per second (Sps). It determines how accurately the resulting discrete digital signal represents the original continuous waveform. According to the Nyquist sampling theorem, the sampling rate must be at least twice the signal's highest effective frequency to avoid aliasing:

$$f_s = 2f_{max} \tag{4}$$

where f_s is the sampling rate and f_{max} is the highest effective cutoff frequency present in the signal being sampled [3].

The sampling period—the interval between two consecutive samples—is inversely proportional to the sampling rate, given by $T_s = 1/f_s$. For a system with N channels and an ADC resolution of R bits, the total data rate is:

$$\text{Data Rate} = f_s \cdot N \cdot R \tag{5}$$

In chip and front-end circuit design, the sampling rate directly sets the ADC's operating frequency and the system's overall data throughput. While simply raising the sampling rate improves signal fidelity, it also generates a substantially larger data stream, placing considerable strain on downstream storage, computing power, and wireless transmission bandwidth. Hardware design must therefore balance waveform fidelity against data load, guided by the actual bandwidth of the signal being acquired.

3. Methods for collecting neural signals

Currently, the methods for collecting neural signals are divided into three types: scalp electroencephalogram signal collection, cortical EEG signal collection, and intracortical neural signal collection. The differences in collection methods and waveforms are shown in the following Figure 2.

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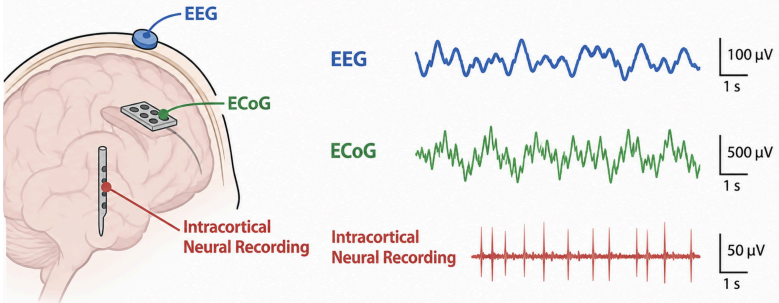


Figure 2. Neural signal acquisition methods and signal waveforms

3.1. EEG

EEG signal acquisition involves placing multiple electrodes on the scalp to measure the potential differences between different electrode positions. The electrical activity generated collectively by cortical neurons propagates through brain tissue, cerebrospinal fluid, the skull, and the scalp, giving rise to a time-varying potential on the scalp surface. The acquisition system typically uses active electrodes, reference electrodes, and common electrodes to form a measurement circuit, and the electrode positions are usually arranged according to the international 10-20 system or its extended version.

EEG electrodes mainly include wet electrodes and dry electrodes. Wet electrodes improve electrode-skin contact using conductive paste or electrolytes, whereas dry electrodes make direct contact with the scalp via metal or other conductive materials. The electrode-skin interface can be equivalently regarded as an impedance network consisting of contact resistance, interface capacitance, and half-cell potential [5]. In turn, the analog front-end needs to have a high input impedance to reduce the signal attenuation caused by the interface impedance. For example, Brain Products, a German company, is a leading player in clinical EEG technology. Its flagship product, actiCHamp Plus, mitigates the noice introduced by high contact impedance by integrating a preamplifier circuit at the electrode head.

3.2. ECoG

ECoG is a semi-invasive neural signal acquisition method. This method places the electrode array directly on the surface of the cerebral cortex without further inserting the electrode into the brain tissue. Since the electrode can be closer to the neural signal source, this method can significantly reduce the risk of direct physical damage to the brain tissue while maintaining high signal fidelity.

The traditional ECoG signal acquisition system usually uses a planar grid electrode based on silica gel and is connected to a multi-channel bioelectric amplifier to complete the acquisition and conditioning of neural signals. With the development of micro-nano processing technology, flexible organic electrode arrays with ultra-thin and high biocompatibility have been gradually applied. Such electrodes can better fit the complex sulci and gyrus structures of the cerebral cortex, thereby improving the contact quality of the electrode-cortex interface. The microvolt-scale neural electrical signal collected is first amplified by the front-end amplifier, then filtered by the band-pass filter, and converted into a digital signal by the ADC, and finally output to the subsequent decoding module for further processing [6].

Endovascular brain-computer interface can be regarded as a special extension of ECoG technology. Different from the traditional cortical electrode implantation method that requires

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craniotomy, this method implants a micro-electrode array into the venous blood vessels adjacent to the cerebral cortex through vascular intervention technology, and records the cortical potential generated by the activity of population neurons across the vascular wall. At present, Synchron is one of the more representative enterprises in the technical direction, and its core product Stentrode is an electrode array based on the design of vascular stent structure. By implanting Stentrode, paralyzed patients can use the recorded cortical neural signals to achieve text input and control of external devices.

3.3. Intracortical Neural Recording

Intracortical Neural Recording refers to the method of directly implanting micro-electrodes into the cortical, where high-frequency extracellular action potentials (spikes) and low-frequency local field potentials (LFP) can be recorded very close to the cell bodies of neurons. To address the tissue trauma and immune rejection problems caused by traditional rigid electrodes, researchers generally use flexible polymer micro-threads and, with the help of high-precision neurosurgical robots, precisely implant the micro-threads at specific depths of the cortex while avoiding blood vessels [7].

The hardware of the intracortical collection system usually consists of a high-density micro-electrode array and a front-end integrated circuit. For instance, the Neuralink architecture enhances the sampling density by integrating thousands of independent electrode contacts on flexible micro-threads; simultaneously, an embedded front-end with an ASIC is used to complete the low-noise amplification, analog-to-digital conversion (ADC), and even spike pulse detection of weak electrical signals locally, thereby effectively reducing the engineering pressure caused by the massive data transmission to the system power consumption and wireless broadband.

4. Performance comparison of different neural signal acquisition methods

4.1. Signal amplitude and Signal-to-Noise Ratio

The signal amplitudes obtained through different collection methods are mainly influenced by the distance between the electrodes and the neural source, as well as the tissue conduction path. In simultaneous recordings of somatosensory evoked potentials, Burnos et al. found median N20 amplitudes of 1.8 μV in scalp EEG versus 11.6 μV in ECoG — roughly a sixfold difference that reflects substantial attenuation of neural signals by the skull and scalp [1]. Because intracortical micro-electrodes sit much closer to individual neurons, they can resolve local field potentials and extracellular action potentials that surface recordings cannot capture.

The signal-to-noise ratio is not only affected by the signal amplitude, but also related to electrode impedance, environmental noise, physiological artifacts, and front-end circuit noise. In the same study, somatosensory evoked high-frequency oscillations showed a markedly better signal-to-noise ratio in ECoG than in scalp EEG. Besides, Parvizi's research review also pointed out that the amplitude of intracranial electroencephalogram can be approximately 10 times that of scalp EEG, and under certain conditions, the signal-to-noise ratio can be increased to about 100 times [8]. Therefore, EEG requires higher requirements for low-noise amplification and common-mode suppression, while ECoG and intracortical acquisition can obtain clearer local neural activities.

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4.2. Spatial resolution and time response characteristics

Spatial resolution depends mainly on electrode placement. Because scalp EEG signals must pass through multiple tissue layers, Burle et al. put resolution at roughly 5–9 cm, improving to 2–3 cm with surface Laplacian/current source density transforms — still coarser than ECoG (~1 cm) and intracortical microelectrodes (<100 μm) [9]. Sitting beneath the dura, ECoG avoids skull impedance and scalp current dispersion; Schalk reports standard ECoG resolution at the sub-millimeter level, further improved by high-density/micro-ECoG (HD/μECoG) [10].

Intracortical recording offers the finest spatial specificity. Khodagholy et al. show that shrinking inter-contact spacing enables precise local positioning [6]. Katzner et al. found that over 95% of LFP signal originates within a 250 μm radius of the contact, and note that spike detection requires the electrode to sit within 50–100 μm of the cell body [11]. This hundred-micron-to-tens-of-micron precision is two to three orders of magnitude finer than EEG's centimeter scale and ECoG's sub-millimeter scale, making intracortical recording the most spatially specific of the three methods.

4.3. Signal bandwidth and sampling rate requirements

Signal amplitude, bandwidth, and sampling rate all scale with electrode-to-source distance. EEG amplitudes range from 10–400 μVpp, reflecting synchronized activity across large neuron populations concentrated in low-frequency rhythms. Sitting directly on the cortical surface, ECoG reduces scalp/skull attenuation, yielding higher amplitudes (10–1000 μVpp) and access to higher-frequency oscillations [12]. Intracortical electrodes, closest to individual neurons, capture both LFPs (0.5–5 mVpp, low-frequency) and spikes (50–500 μVpp, 100 Hz–10 kHz) [2, 11].

These differences drive sampling requirements: a few hundred Hz suffices for EEG; ECoG requires kHz-level sampling to resolve high-frequency cortical activity; intracortical recording needs ≥10 kHz to capture spikes. High-density arrays such as NeuroGrid and Neuralink push this further by scaling channel count [6, 7]. Across amplitude, bandwidth, and sampling rate, the three methods follow a consistent order: EEG < ECoG < intracortical recording (ICR).

4.4. Comparative summary

Based on the above analysis, the comparisons drawn in this article are as shown in the Table 1 below.

Table 1. Three methods comparing result

Acquisition geometry	Signal amplitude	SNR	Spatial resolution	Signal bandwidth	Sampling frequency
EEG	1.8uV	Lowest	5-9/2-3cm	10-400uVpp	250-1000Hz
ECoG	About 10 times higher than EEG	Medium	3-5 mm	10-1000uVpp	kHz level
Intracortical Neural Recording	The highest	Highest	0.8-1.5 mm	Spike50-500uVpp LFP0.5-5mVpp	15-30KHz

From the comparison in the table, it can be seen that the three types of neural signal acquisition methods show a step-by-step improvement trend in terms of signal quality and information acquisition capability. EEG has the advantages of being non-invasive and easy to deploy, but it has low signal amplitude and limited spatial resolution; ECoG has improved in signal strength and

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spatial positioning ability, and it is a compromise between invasiveness and performance; intracortical acquisition, with higher signal-to-noise ratio, wider signal bandwidth, and micrometer-level spatial resolution, can achieve neural network-level information acquisition, but it has the highest invasiveness and engineering complexity. Therefore, different acquisition methods need to be weighed among signal quality, system complexity, and security based on the application scenario.

5. Conclusion

This paper conducts a study on the structure and key performance indicators of the brain-computer interface signal acquisition system, and the following conclusions are obtained. Firstly, this paper introduces the signal processing chain of the BCI system and the main parameters that affect the acquisition performance. Subsequently, it analyzes the basic principles and hardware characteristics of three acquisition methods: EEG, ECoG, and intracortical signal acquisition. On this basis, the signal amplitude, signal-to-noise ratio, spatial-temporal resolution, signal bandwidth, and sampling rate of the three acquisition methods are compared and analyzed. The results show that EEG has core advantages such as non-invasive nature, portability, and ease of batch use. However, due to the signal's transmission through multiple layers of tissues, its amplitude, spatial resolution, and signal-to-noise ratio are relatively low. ECoG effectively improves the signal quality by shortening the distance between the click and the neural source, achieving a balance between invasiveness and performance. Intracortical acquisition can directly record LFP and Spike signals, and has the best performance in terms of spatial resolution, frequency bandwidth, and time accuracy. However, it also faces higher implantation risks and engineering complexity. Therefore, different acquisition methods should be reasonably selected based on the application requirements, considering signal quality, safety, and system complexity.

The current performance comparison in this paper is mainly based on the data from existing literature, and lacks experimental verification of the century collection system. In the future, we can combine experimental testing and hardware design to further collect more accurate data collection conclusions.

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