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A review of EEG acquisition, processing and application

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A review of EEG acquisition, processing and application

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Abstract. As the study about the human body goes forward, some breakthrough in human biological signals is made, especially in EEG signal. At the same time, people are getting to know more about the benefits of EEG. Therefore, EEG research is enjoying a stronger demand around the world. Nowadays, EEG research is carried in several fields and different stages, such as the acquisition of EEG, the processing of EEG, energy recovery of EEG, etc. Scholars are mainly searching for behavioral and electrophysiology, neural network, multi-lead electroencephalogram, non-invasive brain imaging technology, etc. And the current research frontier and the main trend is the comprehensive study of brain function and disease at the molecular, cellular, and global levels and the understanding of the brain structure principle from the brain development process. In this review, three aspects are chosen to study: the processing of EEG, the acquisition of EEG and EEG application. Four EEG acquisition methods, five ways of EEG processing system and three patterns of application are introduced. EEG acquisition system comprises scalp electrodes, a signal isolation amplifier, an analog-to-digital converter, and a wireless transmission module. Low power consumption, small size and portability are the main directions. The research status and difficulties of suitable electrodes, high integration acquisition chip, and analysis algorithm are analyzed and predicted. Due to the rapid development of EEG signal processing, the application of EEG has developed from medical rehabilitation to driving safety, education assistance, and entertainment consumption.

1. Introduction

With the development of technology, people are pursuing a healthy and convenient life. Human biological signals are paid attention to detect health information. Therefore, the subject of human biological signal research is becoming more and more important. There are some common signals: ECG signal, EEG signal, EMG signal, EOG signals, pulse signal, respiratory signals, blood pressure [1], etc. EEG signal attracted more concentration because it comes from brain's vital operating. And researchers can analyze it to get different states of brain function. EEG is a typical time-varying non-stationary signal whose amplitude is at the micro-volt level. The common methods of EEG signal analysis and processing are frequency-domain and time-domain analysis, wavelet transform [2], wavelet entropy [3], improved multi-scale entropy algorithm [4], EEG feature extraction based on constrained independent component [5]. In the future, EEG will develop into a deeper stage not only in the traditional medical field but also in the military, sports, educational psychology, entertainment, etc. And the application in these aspects will dramatically change our society.

From Adolf Beck observing brain waves [6], human exploration of EEG never stopped [7]. The first human EEG was recorded by Hans Berger, which is seen as a monument of clinical neurology [8]. Then Gibbs and Jasper found that interictal spike could be seen as the focal signature of epilepsy [9]. After that, people began to use EEG to diagnose diseases. With the development of the brain-computer interface (BCI), people first controlled external objects to accomplish a maze [10]. Furthermore, tetraplegic Matt Nagle became the first person to control an artificial hand using BCI [11]. Nowadays, many researchers make EEG devices smaller to effectuate the so-called "Wearable EEG" [12]. This development also promotes the disease diagnosis and the BCI. To diagnose diseases more accurately, current EEG is often combined with machine learning for the data can be analyzed automatically.

This paper summarizes the research direction of EEG, including the introduction of acquisition and common data of EEG, as well as the processing methods of removing artifacts, summarization the feature extraction methods of EEG from the frequency domain, time domain, and nonlinear dynamics, and the main application fields of EEG. Finally, the existing problems in EEG research are discussed, and the future development direction has prospected to bring some references for related researches.

2. Methods of EEG acquisition

The first part of this paper involves some methods of collecting EEG. It expounds on four ways to collect EEG and put forward corresponding precautions and examples according to their principles.

2.1. Electroencephalogram (EEG)

EEG is a graph obtained by amplifying and recording the brain's spontaneous biological potential from the scalp with precise electronic instruments. EEG records the electrical activity of the brain through electrodes, which are usually embedded in electrode caps. The paper gets the conclusion that commonly used biological electrodes are disposable electrode, limb electrode, portable electrode, and metal shell electrode [13]. The equivalent circuit model of common electrodes is shown in **Figure** 1 [14].
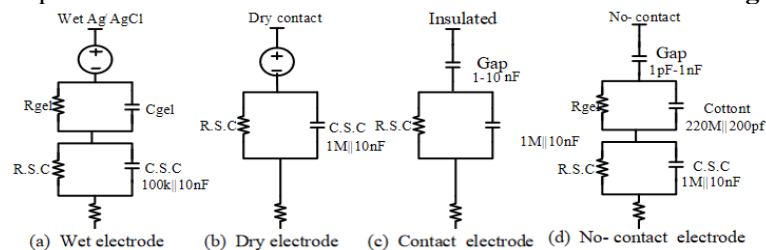

Figure 1. Equivalent circuit model for various bioelectrodes.

2.2. Electrocorticogram (ECoG)

A cortical electroencephalogram involves recording electrical activity by surgically implanting electrodes into the surface of the brain. Compared with the EEG sensor, the ECoG sensor has better spatial resolution and can accurately detect high-frequency brain activity, which is also invisible , as shown in **Figure** 2 [15]. Once implanted, the electrode can be prepared for BCI or other tasks.
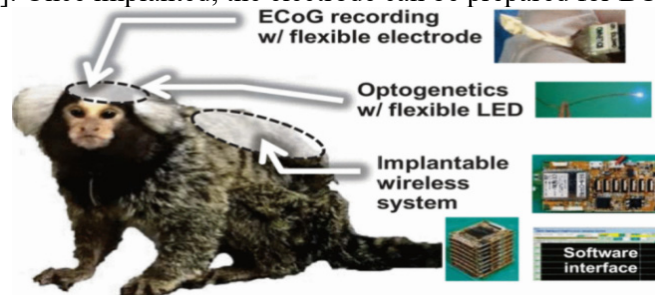

Figure 2. Conceptual diagram of the proposed implantable wireless electrocorticogram (ECoG) recording system with a flexible sheet electrode, flexible LED probe, and software interface.

The flexible thin plate electrode can be used for minimally invasive ECoG recording with soft materials, as shown in **Figure** 3a [16]. Flexible plate electrode has biocompatibility and mechanical flexibility, which supports long-term monitoring. The neural operation function can be realized in the small system with the latest low power consumption and LED devices. Besides, the implantable sensor system has attracted researchers, which can carry out long-term and remote monitoring of organisms because wireless systems can easily monitor online biological signals in the body.

Figure 3b [17] shows an ECoG recording with a flexible sheet electrode, the mainboard, and an ADC board, which can record ECoG signal. The electrode sheet has a grounding electrode, a sensing electrode, and a reference electrode. The ground electrode and the reference electrode were placed at the surface of the brain. Sensing electrodes were inserted into the brain to monitor the ECoG signal.
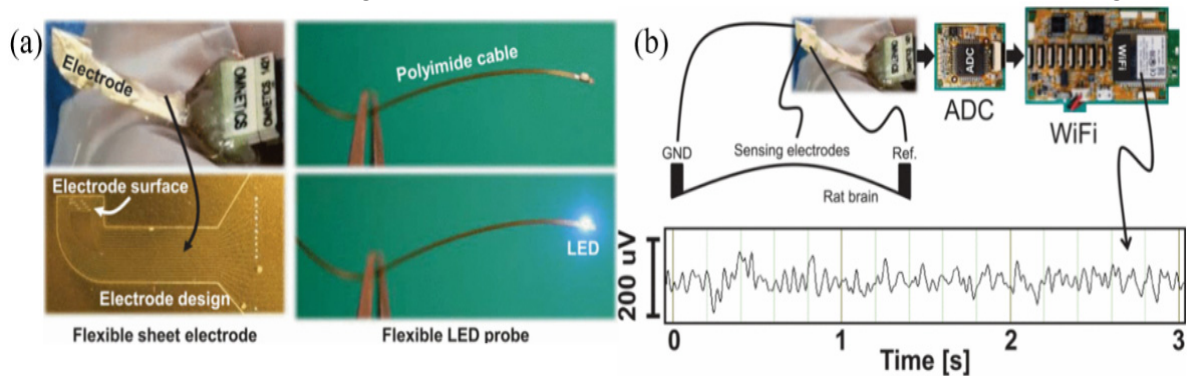

Figure 3. a) Flexible electrode and LED probe with biocompatible parylene-C passivation b). ECoG recording with the developed flexible electrode and the wireless system.

2.3. Functional Magnetic Resonance Imaging (fMRI)

Functional magnetic resonance imaging (fMRI) is a new neuroimaging method, as shown in **Figure** 4a [18]. The principle of fMRI is to measure the changes in hemodynamics caused by neurons' activity . At present, it is mainly used in the study of human and animal brain or spinal cord.

Functional magnetic resonance imaging cannot directly detect neurons' activity but reflect the oxygen saturation and blood flow through the measurement of MR signal as shown in Figure 4b [19], thus indirectly reflecting the energy consumption of the brain. Therefore, to a certain extent, it can reflect neurons' activity and achieve the purpose of functional imaging.
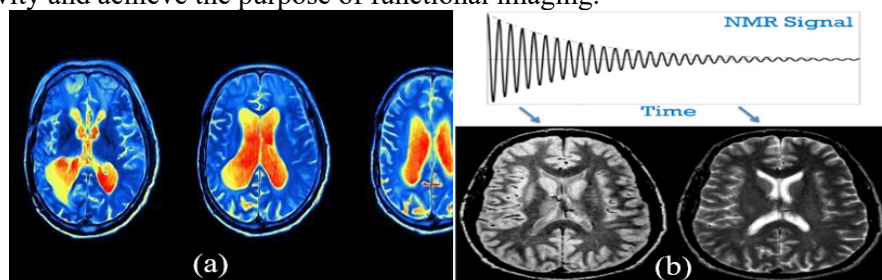
Figure 4. a) fMRI. b) Using the phenomenon of nuclear magnetic resonance (NMR), the hydrogen nuclei can be manipulated so that they generate a signal that can be mapped and turned into an image

In the simplest fMRI experiment, the subjects alternated between the period of performing a specific task and the control state. The fMRI data was analyzed to identify brain regions with matching patterns of change in the MRI signals and treat them as areas activated by stimuli (in this case, the visual cortex at the back of the head) in **Figure 5** [20].

Figure 5. Fox MD, Raichle ME. Spontaneous fluctuations in brain activity observed with fMRI.

Now, functional magnetic resonance research mainly focuses on the regional association and neural pathway of the brain. For example, the excitation of a certain brain area caused by peripheral nerve impulses can cause the excitation effect or inhibition effect of other brain areas successively.
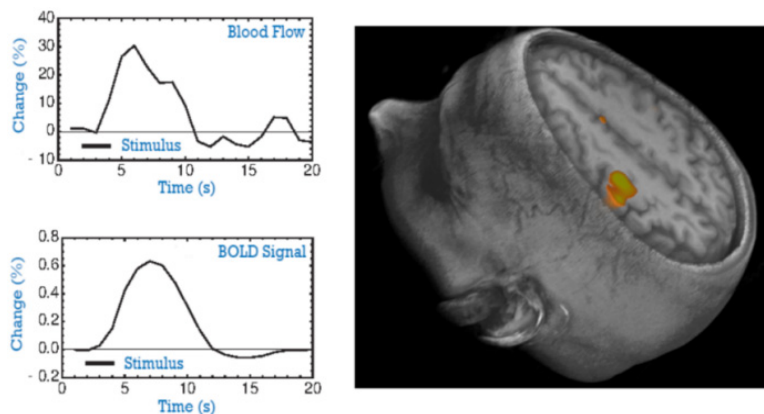
2.4. Depth electrode

There are many ways to collect EEG signals through deep electrodes. This paper selects a typical example to illustrate. Deep brain stimulation (DBS) is a clinical technique used to treat neurological disorders [21]. DBS is performed using neural electrodes placed in specific target regions of the brain to deliver current or voltage through an implantable pulse generator [22].

3. Signal processing technology of EEG

The second part of this paper involves some circuits to process EEG and characteristics of EEG.

3.1 .The characteristic of EEG

Depending on the frequency, EEG can usually be categorized into five groups, and each group shows different neural activities. Their frequency limits have different classifications, as **Table 1** shows [23].

Table 1. Different classifications of the frequency band

Frequency（Hz）	IFCN 1999 (II)	IPEG 2012	IFCN-2017 Glossary
Delta	0.5 - 4	1.5 - <6	0.1 - <4
Theta	5 - 7	6 - <8.5	4 - <8
Alpha	8 - 12	α1: 8.5-<10.5	
		α2: 10.5-<12.5	8 - 13
Beta	β1: 14 - 20	β1: 12.5-<18.5	
	β2: 21 - 30	β2: 18.5-<21	14 - 30
		β3: 21-<30	
		30-<40	
Gamma	γ1: 30 - 40	γ1: 30-<65	>30-80
	γ2: 40 -. . .	γ2: 65-<90	
		γ3: 90-<135	

3.2 .Non-ideal factors of EEG measurement

3.2.1 .Interference. Several kinds of interference challenge the measurement of EEG, which mainly consists of thermal noise, flicker noise, power line interference (PLI) and electrode offset voltage. The spectral density of some interference is showing in the **Figure 6**.

Thermal noise is generated by the random thermal motion of charge carriers inside an electrical conductor, which happens regardless of any applied voltage. The amplitude of it has nearly a Gaussian probability density function. Flicker noise, also known as 1/f noise, is a signal with a frequency spectrum that falls off steadily into the higher frequencies. It occurs in almost all electronic devices. Power Line Interference (PLI) is generated by power line, so the frequency of it is around 50/60 Hz.   The electrode offset voltage is generated from charge accumulation between the metal and electrode gel caused by chemical interaction. It may saturate the amplifier.
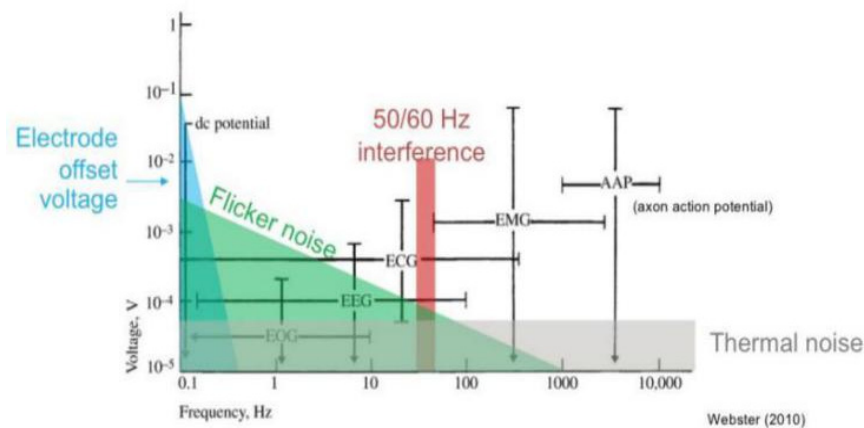

Figure 6. Several interference's spectral densities.

3.2.2 .Interference reducing techniques. To obtain a pure EEG signal, reducing interference is necessary. Some interference reducing techniques in amplifier design are also effective, mainly consisting of auto-zeroing (AZ) and chopper stabilization technique (CHS).

Auto-zeroing (AZ) technique samples and stores the offset voltage and noise during a sampling phase. During the signal-processing phase, the amplifier will subtract the stored signal from the instantaneous value of the contaminated signal either at the input or the amplifier's output. The topology is shown in **Figure 7 (a)** [24]. AZ can cancel the offset voltage and reduce the low-frequency noise. AZ is a sampling technique. So the wide-band noise(thermal noise) is aliased down to the base-band [25]. This may cause fold-over noise [26].

Unlike AZ, the chopper stabilization technique (CHS) does not use sampling and it is a continuous-time modulation system. CHS modulates the signal to a higher frequency where there is no 1/f noise. The next modulation, which has the same frequency as the first, will demodulate the useful signal back to the original band. Meanwhile, the noise and offset voltage are transposed to the odd harmonic frequencies of the modulation signal [27]. The whole procedures are shown in **Figure 7 (b)**.
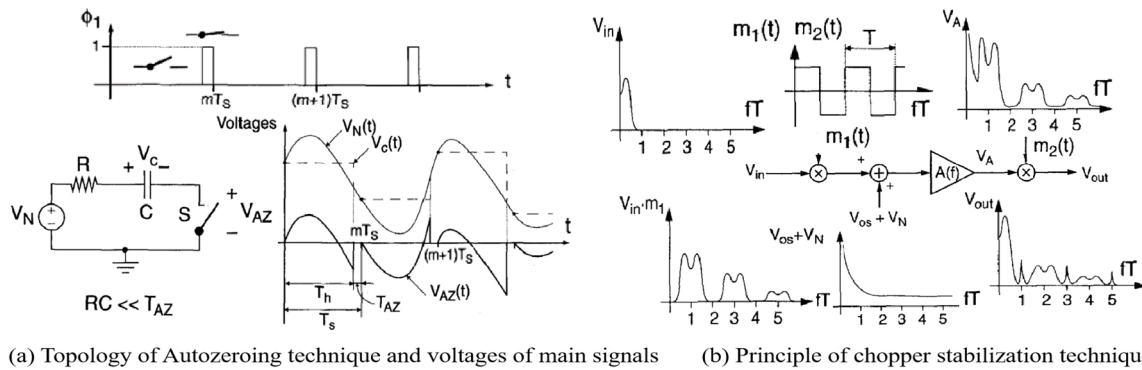
(a) Topology of Autozeroing technique and voltages of main signals   (b) Principle of chopper stabilization technique

Figure 7. Interference reducing techniques

3.3 .EEG measurement circuit

After collecting the signal from electrodes, the EEG signal will be processed by the measurement circuit. Most of the measurement circuit consists of instrumentation amplifiers, filters, A/D converter (ADC), signal processor, and power supply.

3.3.1 Instrumentation amplifiers. The EEG signal is tiny and hard to be detected by ADC, so the amplifiers should have a large gain and CMRR in order to separate the EEG signal from noise.

Figure 8 (a) shows a topology of IA called Three Op-Amp instrumentation amplifier. Its first stage is two fully-differential buffers. The second stage is a differential to the single-ended amplifier. This topology has a high input impedance but energy-consuming. Because of the mismatch, the CMRR of this topology is not too high, so the common-mode input may saturate the amplifier. And the modified circuit Driven-Right-Leg Circuit as shown in **Figure 8 (b)** can set the input to the common-mode range of the IA and reduce common-mode noise, such as power-line interference [28]. But the Driven-Right-Leg Circuit doesn't help the electrode offset voltage (EOV). To solve the issue of EOV, the topology called Capacitively-Coupled Instrumentation Amplifier (CCIA) can be used. The gain of it is set by the ratio of capacitors, which are easier to match on-chip than resistors [29]. For the topology of **Figure 8 (c)**, the gain is: $A_V = -(C_1 / C_2)$. To overcome the 1/f noise, a modified topology based on CCIA and incorporated with CHS has been designed called Capacitively-Coupled Chopper Instrumentation Amplifier (CCCIA). And the gain of it shown in **Figure 8 (d)** is $G = \dfrac{A_O}{1 + A_O C_{fb1,2} / C_{in1,2}}$, A0 is the open-

loop gain of the op-amp [30]. The Switched-capacitor Instrumentation Amplifier in **Figure 8 (e)** uses a capacitor as feed-back. It is intended to be used as a sample-and-hold amplifier for low-level signals in data acquisition systems. This topology has a very high CMRR because the new sampling technique can prevent the common-mode signal from entering the amplifier [31]. In the topology of **Figure 8 (f)**, the output voltage is coupled back to the input of Gm2 by a current, and this current can reduce the common-mode input. According to this, Current-Feedback Instrumentation Amplifier (CFIA) has a larger CMRR [32]. The Current-Mode Instrumentation Amplifier (CMIA) is a kind of modified 3-opamp amplifier and a kind of topology is shown in **Figure 8 (g)**. It has two main advantages, the first is that the CMRR depends on the match of the current mirror, which means no resistor matching is required. And the second advantage is that the CMIA only requires the op-amps to be identical, not ideal [33].

Combining the above structures, some more advanced structures have also been proposed in recent years, like **Figure 8 (h)**. It is an architecture that uses both input coupling capacitors and CHS , it also can be seen as a current-mode amplifier. The later stage is a capacitive integrator which can convert the current-mode signal back to voltage-mode signal [34].
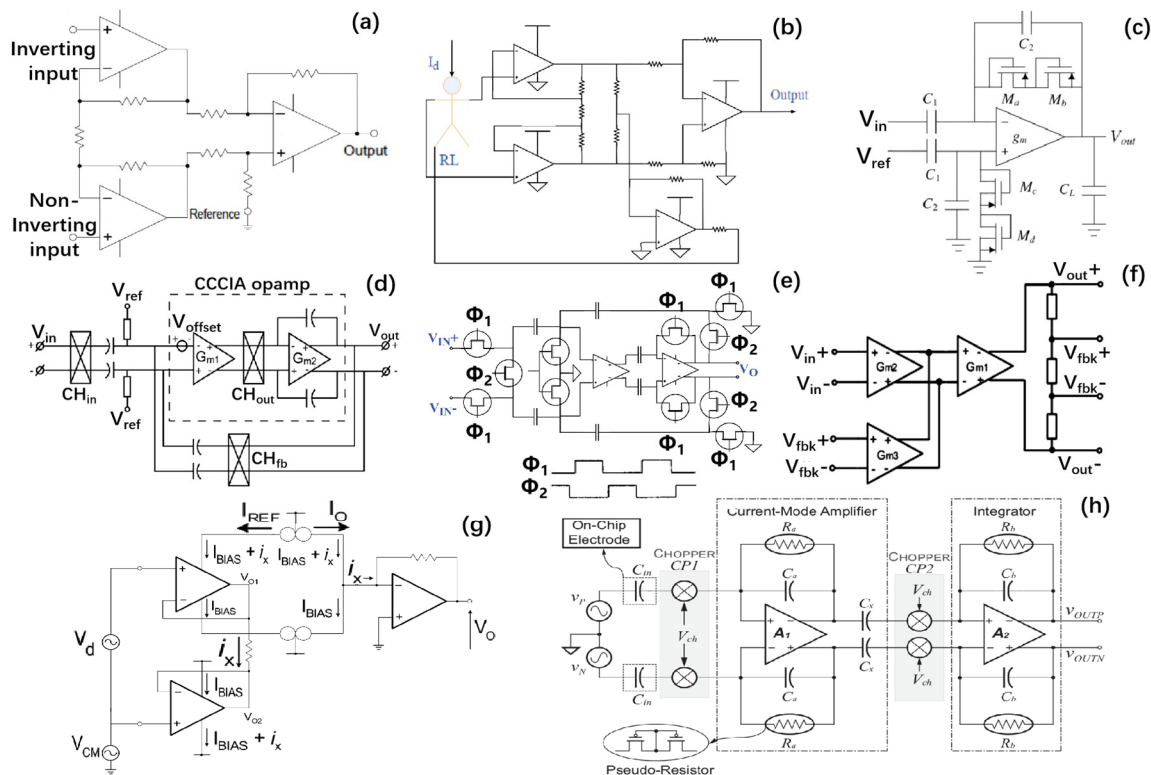
Figure 8. Topology of Instrumentation Amplifier

3.3.2 .A/D converter. Using ADC, the amplified EEG signal can be changed into digital form. The performance of ADC is determined by its bandwidth and signal-to-noise ratio (SNR). There are several types like Sigma-Delta ADC, Successive-Approximation ADC (SAR ADC), Pipe-lined ADC. In bio-electricity signal measurements, SAR ADC and Sigma-Delta ADC are commonly used [35].

4. Application of EEG

The third part of this paper introduces some modern applications of EEG. It contains a brief working principle and some application examples.

4.1 .Brain disease detection

4.1.1 .Application of diagnosis for brain edema. The non-invasion brain edema monitor shown in **Figure 9a** is used to detect EEG and spectrum of different spaces in the brain of normal people shown in **Figure 9b** and typical brain edema individuals shown in **Figure 9c** with their eyes closing.
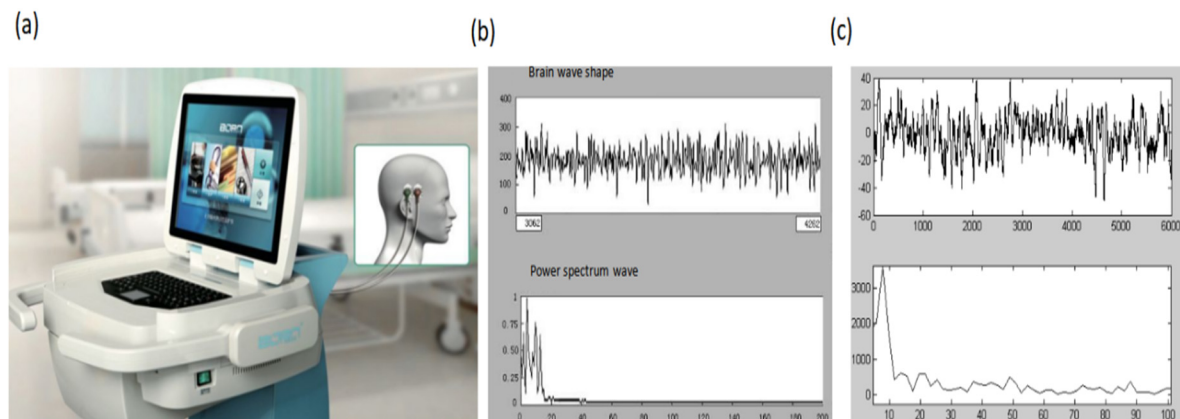
Figure 9. a) non-invasion brain edema monitor. b) EEG and spectrum of different spaces in normal people's brains [36]. c) EEG and spectrum of different spaces in patients' brains [36].

Comparing the EEG and spectrum between normal people and brain edema patients, it can be concluded that EEG from normal people is clear around 5Hz while patients' around 10Hz. So in amounts of clinical tests, the EEG differences between normal people and patients are regular.

4.1.2 .Application in the diagnosis of Parkinson's disease. Using deep learning, combining the feature extraction of instantaneous frequency and power spectrum entropy with LSTM neural network model [37] to judge the EEG signals of Parkinson's disease then diagnose whether there is Parkinson's disease with the people. The overall framework is shown in **Figure 10**.
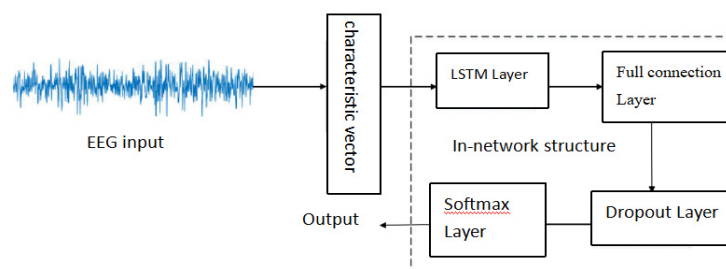

Figure 10. Fusion feature LSTM network model framework

The input signal is the EEG signal of the slow-wave sleep period (SWS) extracted after the sleep stage. Then extract slow-wave sleep 2D temporal characteristics of instantaneous frequency and power spectrum entropy as the input of the whole LSTM neural network model.

4.1.3 .Application in Diagnosis of Epilepsy Scots. The method combines time-frequency analysis with nonlinear analysis. First, it segments the original epileptic EEG signals and decomposes the segmented sub-signals by variational mode decomposition [38], and gets refined composite multiscale dispersion entropy [39] as well as refined composite multiscale fuzzy entropy. Then support vector machine (SVM) is used to classify the focal and non-focal signals. After classification, three indexes of accuracy, sensitivity, and specificity are used to measure the final classification results to realize automatic detection and evaluation of EEG signals. The overall research flow is shown in **Figure 11**.
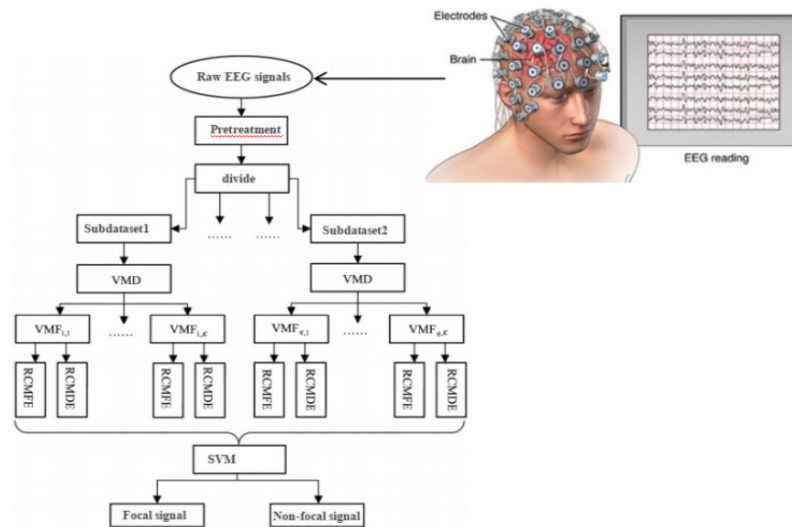
Figure 11. Research methodology overall process

4.2 .Brain-computer interface (BCI)

BCI is a way to convert electrical signals from the thinking activity of the brain to control signals in order to realize the control system for the peripheral equipment. The application of BCI based on three important potentials is usually put into use.

The first one is the application of BCI based on visual evoked potential (VEP). It can be used in the situation of choosing options. In the BCI system based on VEP, subjects are required to stare at different target stimulation. Simultaneously, neural activity modulation in the brain's visual cortex can be detected clearly, which is shown in **Figure 12a**. Researchers can confirm the target's characters through analysis of spectral characteristics of visual cortical EEG signals. Then the BCI system makes corresponding operations. **Figure 12b** is the power spectrum obtained from 13Hz photic stimulation.
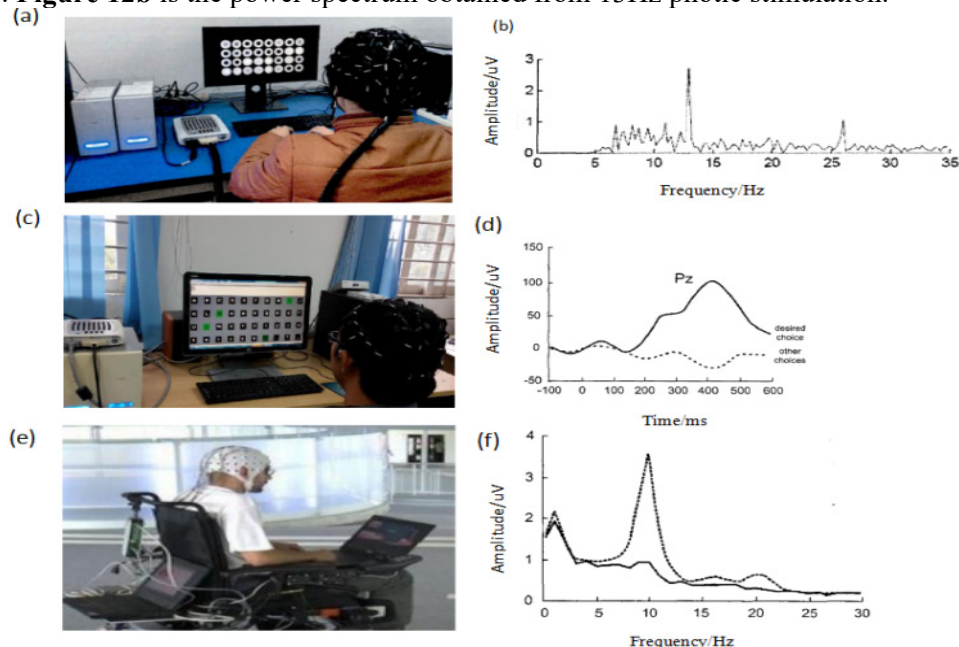

Figure 12. a) detect the neural activity modulation through visual stimulation. b) Spectrum of 13Hz SSVEP [42]. c)input character through stimulus based on P300[42]. d)P300 potential waveform [43]. e) direction control of the wheelchair based on mu and beta rhythm [44]. f) Motion imagination power spectrum and resting state EEG.

The second is the application of BCI based on P300[40]. As shown in **Figure 12c**, the system chooses options by the content of the stimulus to input character functions and so on. The P300 potential waveform at the position of PZ is shown in the following **Figure 12d**. The most classic application based on P300 is the character speller designed by Farewell and Donchin. By the flicker from the P300 target stimulus, devices can detect the EEG in the presence of the P300 component, then determine whether a target stimulus appears. Finally, the character can be typed out.

The third is the application of BCI based on Mu and Beta rhythm. Movement imagined EEG signals are based on different brain electrical states. Each EEG state corresponds to a single output controlling command for a specific control device, equal to a code or mapping process. It can be used for motion control of mechanical equipment as shown in **Figure 12e**. In **Figure 12f**, the solid line is the power spectrum of motor imagination EEG, and the dotted line is resting EEG. The energy of the power spectrum of ERD/ERS[41] is significantly reduced in the Mu rhythm and Beta rhythm, which is related to subjective motor awareness and can be put into use in the study of BCI systems.

4.3 .Application of EEG in emotion detection and recognition

External stimuli such as pictures and music are used to induce different emotions in the subjects. After the stimulation, researchers get an EEG signal, then analyze and process the signal to judge people's emotions.With the research going forward, databases like emotional picture system [45] has been established. Some of the ways to recognize emotions based on EEG signals are as follows.

4.3.1 .EEG emotion recognition based on MEMD. EEG signal is a multi-channel signal in most cases, and there is important mutual trust between each channel signal. So, it is necessary to select multiple channels to study EEG signals. The MEMD algorithm is used to decompose the multi-channel EEG signal, then the decomposed IMF[46] components are extracted, and finally, the emotion classification is realized according to the features.

The research extracts 32 subjects in the DEAP database (80 samples per subject) as the experimental data. So there are 2560 samples in this experiment, respectively belong to HAHV (high arousal high pleasure class mood) class, LAHV (low awake high pleasure), LALV (low arousal low pleasure) and HALV (high arousal low pleasure). Then construct four dichotomous problems. The specific classification task description is shown in **Table 2**. The classification accuracy of the four tasks is 64.4%, 67.5%, 63.3% and 65.3%.

Table 2. Dichotomous task description

Task1	Task2	Task3	Task4
HALV/HAHV	HAHV/LAHV	LAHV/LALV	LALV/HALV

4.3.2 .Emotion Recognition Based on Multiple EEG Characteristics. The basic time-domain features, frequency domain features, and the nonlinear features are extracted from the EEG signals. All the extracted features are simply spliced to obtain the emotional feature sets of the EEG signals. Then two feature fusion methods, namely feature selection algorithm based on random forest algorithm [47] and RF-SFFS [48], are used to obtain effective emotional features that can represent the degree of emotional difference. Finally, the obtained emotion feature training set is trained as the input of the SVM to produce a suitable classifier. Then the final emotion classification results are obtained.

The specific performance on three sub-classification tasks of the final trained classifier support vector machine is shown in **Table 3**.

Table 3.   Multi-feature EEG Classification and Identification Based on Feature Fusion （%）

Emotional features	HAHV/LAHV	LAHV/LALV	LALV/HALV	HALV/HAHV	average
Combination features	60.4	62.5	61.5	63.8	62.05
RF fusion features	67.3	70.2	65.8	71.4	68.68
RF-SFFS fusion features	68.8	74.0	72.5	71.8	71.78

5. Conclusion:

Among the EEG acquisition methods in this article, EEG is the most common neuroimaging method in BCI research. The ECoG sensor can accurately detect high-frequency brain activities invisible to EEG electrodes. Functional magnetic resonance imaging can measure changes in cerebral blood flow related to different intellectual activities. The FMRI system requires a very strong magnetic field. The application of the time-frequency analysis method in EEG signal processing makes up for the shortcomings of time-domain and frequency-domain analysis methods in nonlinear signal analysis. It can accurately extract the characteristic information of nonlinear signal changes with time. When dealing with nonlinear signals and suppressing Gaussian noise, the power spectrum of high-order spectrum based on second-order statistics is better than the power spectrum. Through automatic zeroing technology and chopper stabilization technology, interference can also be greatly reduced.

Although various EEG technologies have made a huge progress in recent years, many challenges should be paid attention to. In terms of the dry electrode needs a good contact to have a low impedance for collecting high-precision signals. The acquisition and transmission of EEG signals should be integrated into one chip as far as possible to achieve the lowest power consumption. As for applications, many EEG applications need the users to be well trained to produce steady EEG signals.

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