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Article

Research Progress of Content Generation Model Based on EEG Signals

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Abstract: The EEG-based content generation model holds great promise in areas such as emotion recognition, thought decoding, and multimodal interaction. EEG signals can monitor the state of brain activity in real time, thereby enabling the decoding of information related to brain activity, such as emotional states or thought patterns. However, there exist problems such as noise interference, low recognition accuracy, difficulty in signal synchronization, and time delay with action signals. To address these issues, this paper proposes using Independent Component Analysis (ICA) for noise reduction, deep convolutional neural networks for spatial feature extraction, and Dynamic Time Warping (DTW) and Long Short-Term Memory (LSTM) networks for signal alignment. These methods aim to improve signal processing accuracy and alignment efficiency, thereby advancing brain-computer interface technologies.

Keywords: EEG signal; content generation; brain-computer interface

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1. Introduction

With the development of brain-computer interfaces, content models generated based on EEG signals have broad application prospects in applications such as emotion computing, thinking decoding, and multimodal interaction. EEG signals can record brain activity in real time and decode key information related to cognition and emotional states. However, due to limitations such as low signal-to-noise ratio, noise interference, individual differences, and the difficulty in synchronizing EEG signals with data of other patterns, its practical application is restricted. To improve the accuracy and real-time performance of EEG signals in content generation, multiple schemes such as noise reduction based on independent component analysis, feature extraction based on deep learning, and signal synchronization using dynamic time warping or long short-term memory networks have been proposed. These methods are likely to promote the more efficient application of EEG signals in the fields of brain-computer interfaces and intelligent interaction.

2. Basic Characteristics of EEG Signals

2.1. Frequency Characteristics of EEG Signals

The spectral characteristics of EEG signals represent multiple frequency bands of brain activity, and each frequency band represents different types of cognitive and physiological states. EEG signals are routinely divided into several frequency bands, with specific typical values being δ waves (0.5-4Hz), θ waves (4-8Hz), α waves (8-13Hz), β waves (13-30Hz), and γ waves (30-40Hz). δ waves usually occur in a state of deep sleep or unconsciousness, representing a lower frequency of brain activity. Theta waves are usually accompanied by non-deep sleep, meditation, relaxation states, and often represent some emotional or recall processes. Alpha waves typically occur in a waking and relaxed environment, especially when the eyes are closed, and usually indicate that the brain is in a quiet and free state. Beta waves typically occur during the processes of concentration, problem-solving, and advanced cognitive behaviors (thinking, language, and decision-making), often accompanied by increased tension, excitement, and agitation. Gamma waves are typically associated with high-level cognitive processes in the brain, especially during complex sensory tasks or information integration. They are characterized by high frequency and are considered indicative of intense mental activity. From the frequency-domain analysis results of EEG signals, people's psychological and physiological states can be known, which are applied in the fields of emotion analysis, cognitive analysis, and human-computer interaction. (See Table 1).

Table 1. Frequency Characteristics of EEG Signals.

Frequency band	Frequency range	Corresponding to the state of electroencephalogram activity	Main functions/performance
δ wave	0.5-4 Hz	Deep sleep, coma, deep relaxation	The brainwave activity is the least, mainly related to deep sleep and restorative rest.
θ wave	4-8 Hz	Relaxation and rest, meditation, chatting idly, anxiety, innovative behavior.	It is related to memory processing, meditation, emotion regulation and light sleep.
α wave	8-13 Hz	Rest: Lie flat, rest in bed, and lie still.	It is associated with relaxation, concentration and attention control in the resting state.
β wave	13-30 Hz	Attention, thinking, problem-solving, tension.	It is related to cognitive behavior, concentration and anxiety.
Γ wave	30-40 Hz	Abstract logic, information fusion and attention.	Attention dysfunction is related to advanced cognitive activities and perceptual processing.

The above table shows the main frequency domain range of the EEG signal and the corresponding frequency range, as well as the state of the electroencephalogram. Each frequency domain range is associated with specific psychological and physiological states, as established by extensive empirical studies.

2.2. Spatial Characteristics of EEG signals

The spatial characteristics of EEG reflect neural activity across different brain regions, providing information about specific anatomical locations based on the brain's regional divisions. The commonly used international 10-20 electrode placement system helps researchers observe changes in neural activity across different brain regions under various conditions. For example, the frontal lobe is associated with emotion regulation, decision-making, and planning. The parietal lobe is related to spatial processing, sensory input and motor control. The occipital lobe is mainly responsible for visual processing. For the analysis of EEG spatial features, the main focus is on extracting the changes in the activities of various parts of the brain, so as to facilitate the activity responses of each part of the brain and the completion of corresponding cognitive activities. In the research of human-computer interaction, in terms of spatial feature analysis, it is conducive to the localization research of brain activity responses, that is, to study the relationship between brain activity responses and the thinking responses and content correspondence of brain activities to specific tasks. Meanwhile, EEG signals primarily capture cortical surface activity, making it difficult to observe neural processes occurring in deeper brain regions. This directly affects the temporal and spatial analytical ability of electroencephalogram.

3. Research Status of Content Generation Models Based on EEG Signals

3.1. Noise Interference and Signal Accuracy Decline in Affective Computing

Emotion computing based on EEG signals is confronted with noise interference caused by various reasons, such as eye movement, motor electromyography signals and surrounding noise, which leads to the distortion of EEG signals and affects their accuracy. Among them, eye movement artifacts and electromyography signal artifacts have high frequencies and are prone to aliasing with the frequencies of emotional signals, thereby affecting emotional signals. These artifacts significantly impact the accuracy of emotion computing models, particularly in quiet or low cognitive stress states where emotional features in EEG signals are inherently weak, making them more susceptible to noise interference. Furthermore, due to the different electroencephalogram (EEG) activities of each individual, the EEG signals respond uniquely to the emotions of each individual, making it difficult for the emotion calculation model to transfer among individuals and affecting the accuracy of the model. To solve the above problems, various noise removal strategies for suppressing false signals and improving the accuracy of emotion calculation have been proposed. However, even so, noise signals still cause great computational pressure for real-time data processing. Efficiently removing noise while preserving the integrity of emotional information remains a major challenge in the field of affective computing research.

3.2. The Signal Decoding Accuracy in the Decoding of Thinking Content Is Low

Although decoding thought content from EEG signals is feasible, the accuracy remains very low. This is mainly due to the low signal-to-noise ratio and limited spatial resolution of EEG signals, making it difficult to understand the activities of brain regions. This is not conducive to understanding complex cognitive processes. Moreover, physiological noises such as muscle movement and eye movement can also cause thought signals and reduce the accurate decoding of thought signals. Especially in the performance of complex cognitive tasks, the fluctuations of electroencephalogram (EEG) are tiny and unpredictable, and how to effectively distinguish the relevant characteristics is the core difficulty of the research. In recent years, deep learning methods such as convolutional neural networks and Long Short-Term Memory (LSTM) networks have achieved breakthroughs in automated feature extraction and accurate decoding. However, there are still certain deficiencies in multi-task decoding and generalization decoding. The key challenge lies in enhancing the spatial and temporal resolution of EEG signals within their inherent physical limitations to improve decoding accuracy.

3.3. Inconsistency of Time and Space in Multimodal Signal Fusion

Temporal and spatial inconsistencies between EEG signals and other modalities (such as vision, hearing, and language) often pose challenges for multimodal signal fusion. EEG signals have high temporal resolution, whereas other modalities such as video and auditory signals generally have lower temporal resolution for real-time processing. Therefore, when conducting real-time processing, it is difficult to synchronize the data of each modality, which also results in low quality of signal aggregation and content generation. Furthermore, the spatial resolvability of EEG signals is relatively weak. It is also difficult to pair EEG with visual information with strong spatial resolvability (such as facial expressions or gestures, etc.), which will also make data fusion more complex. To solve these problems, the time synchronization problem is addressed by Dynamic time warping (DTW), and the spatial domain requirements are solved by cross-modal learning. Although the above-mentioned methods have brought about some improvements, there is still a lot of room for enhancing efficiency in practical applications.

3.4. Time Delay in the Synchronization of Electroencephalogram (EEG) Signals and Behavioral Data

In terms of BCI and game interaction design, how to handle the synchronization between EEG signals and behavioral data is a key issue. Limited by the high temporal resolution of EEG signals, on the other hand, behaviors are collected by external sensors, presenting characteristics of lower temporal resolution and response time. This may cause certain delays, and in the interactive scenarios of virtual reality or augmented reality, the impact of delays is very obvious. Therefore, to handle this problem, Dynamic Time Warping (DTW), Long Short-Term Memory Networks (LSTM), and other methods are used to coordinate the synchronization between EEG signals and behavioral data by analyzing temporal relationships. Although the above-mentioned methods can effectively eliminate delays and ensure the coordination among data, they also face high computational costs and the problem of real-time efficiency in scenarios with multi-channel data or high sampling rate data.

4. Research Strategies for Content Generation Models Based on EEG Signals

4.1. Use Independent Component Analysis for Denoising

Due to artifacts caused by eye movements, muscle activity, and electrode grounding, EEG signals are usually contaminated by noise, and the purity of EEG signals has a negative impact on their application in emotional computing, cognitive understanding, and multi-information processing, etc. Independent Component Analysis (ICA) is widely used for noise suppression in EEG signals. The general steps of ICA for noise suppression in EEG signals are as follows: First, the EEG signal needs to be preprocessed, such as using a bandpass filter to remove low-frequency and high-frequency noise. Then, the ICA is used to decompose the complex signal into multiple independent components, which can distinguish the components of neuronal signals and other noises in the EEG signal. During this process, by examining the nature of each component, the components related to artifacts can be separated, such as the illusions produced by eye movement and muscle movement, and then the noise components can be removed, retaining only the signal components related to the brain. The EEG signals decomposed by ICA into independent components are relatively clear. The EEG signals denoised by ICA can better reflect functions such as emotions and cognition, and improve the task accuracy and reliability of functions such as emotion computing and thinking decoding. (See Table 2).

Table 2. Denoising Steps of Independent Component Analysis (ICA).

Steps	Method description	Function/Purpose	Application example
Signal preprocessing	Perform preliminary preprocessing on the EEG signal (remove noise and standardize, such as bandpass filtering).	Filter out the low-frequency interference and high-frequency noise irrelevant to the EEG signal (such as electromyography interference, eye movement artifacts, etc.).	Signal preprocessing applied to eliminating false signals and baselines.
Signal decomposition	The independent component analysis of EEG signals was carried out using the ICA algorithm.	Separate the compound signal into independent signals and separate the noise source and effective information.	ICA can extract independent components related to brain activity and remove interfering signals
Identification of noise	The noise sources are discriminated based on the inherent	Identify and label isolated components related to false signals, such as eye	Identify eye movement and electromyographic pseudo-signals, and mask

components	characteristics of the signal components (such as frequency, time waveform, etc.).	movement false signals and electromyographic components.	them during the process of calculating emotions.
Noise removal	Remove the noise related to the occurrence of some of the obtained signals, and what remains is the electroencephalogram (EEG) signal.	Retain the components related to memory, sensation, etc. in the EEG signal, and remove the confounding components.	Eliminate the components related to eye movement and electromyographic artifacts to improve the recognition effect of emotional signals.
Reconstruct the signal	Reshape the EEG using independent components for noise reduction.	Therefore, after the signal is reconstructed through denoising, a clear EEG signal can be reconstructed.	The reconstructed EEG signals are applied in processing tasks such as emotion computing and decoding thinking.

Therefore, the denoising function of ICA is crucial and can improve the quality of EEG signals, providing high-quality signal support for subsequent data generation and brain-computer interface implementations.

4.2. Use Deep Convolutional Neural Networks to Extract Spatial Features

Deep Convolutional Neural Networks (CNNs) are powerful feature learning tools widely applied in computer vision and speech processing. They are also effective for extracting spatial features from EEG signals. When extracting spatial features from EEG signals, convolution operations in deep CNNs automatically capture features at multiple spatial scales. The core formula of the convolution operation is as follows:

$$y(t) = (x * w)(t) = \sum_{i=1}^{N} x(t-i)\, w(i) \qquad (1)$$

x(t) represents the input EEG signal (time-domain signal), w(i) represents the convolution kernel or filter, which automatically extracts features from the data through learning, $*$ represent the convolution operation, y(t) represents the output after convolution, that is, the extracted spatial features. The advantage of convolution operation lies in its ability to automatically learn the most representative spatial features from the data without the need for manual feature design. Based on the adaptability of CNN, the analysis of EEG signals is better and it has important applications in aspects such as emotion computing and brain-computer interfaces. In the study of EEG signals, generally speaking, spatial attributes refer to the distribution of electrical activity in various regions of the brain, which can reflect the activation carried by the brain when performing a certain operation or expressing a certain emotion. EEG signals are usually data information obtained through a set of electrodes, and this set of electrodes can record the electrical activity of the cerebral cortex. The data obtained through these electrodes have relatively high spatial attribute information. CNN can obtain the spatial attributes and features of EEG signals based on convolutional layers and aggregation layers. Especially for the analysis of complex problems, the relevant feature patterns of the activity connections of each brain region can be extracted from EEG signals. The trained deep convolutional neural network can obtain the spatial attributes of EEG signals and apply them in the subsequent content generation.

4.3. Dynamic Time Warping Synchronization Signals Are Adopted

Signal synchronization using Dynamic Time Warping (DTW) involves addressing timing signal synchronization and multimodal signal fusion, while also considering computational complexity and optimization methods. Regarding the synchronization of temporal signals, DTW solves the delay problem between EEG signals and other data types by finding an optimal alignment that minimizes the cumulative distance between sequences, allowing flexible temporal matching, ensuring the accurate positioning and registration of the signals. For the fusion of multiple modalities, DTW helps coordinate the timing sequences in each mode, thereby increasing the learning efficiency across modalities. Furthermore, it solves the synchronization problem between EEG signals and other signals, ultimately enabling the creation of high-quality interactive products. Due to the high computational complexity of DTW, especially in real-time applications, optimization techniques such as windowing constraints (e.g., Sakoe-Chiba band) and parallel processing are employed to improve efficiency to improve the computational complexity in order to meet the requirements of real-time synchronization. Through this method, DTW can provide reliable signal synchronization services in the production of real-time brain-computer interfaces and multimodal (Figure 1).

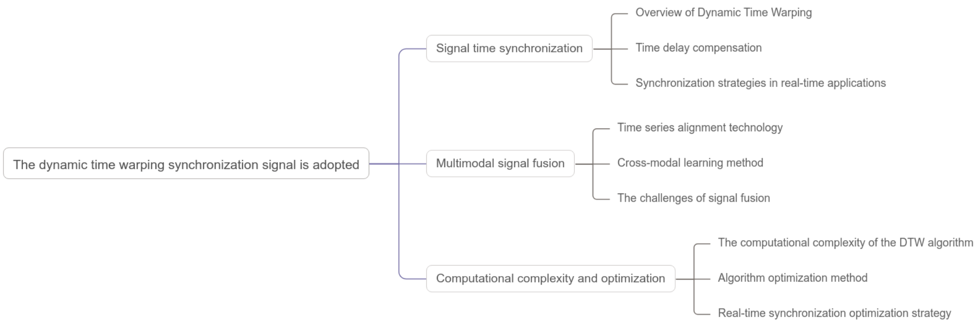

Figure 1. Adopts the Dynamic Time Warping Synchronization Signal.

4.4. Synchronize EEG Signals and Behavioral Data Using Long Short-Term Memory Networks

Synchronizing EEG signals with behavioral data is a critical issue in brain-computer interfaces and multimodal content generation. EEG signals have a relatively high temporal resolution and can provide real-time information on brain activities. However, the collection of behavioral data usually has a relatively low temporal resolution, which leads to a time delay problem when synchronizing these two types of signals. LSTM is a deep learning model suitable for time series data and can effectively capture temporal dependencies between EEG signals and behavioral data. Through its unique gating mechanism, LSTM is capable of capturing short-term and long-term dependencies in signals and is particularly suitable for synchronization of time series data. LSTM's gating mechanisms enable it to learn temporal dependencies, facilitating effective synchronization between EEG and behavioral signals. The key formulas of LSTM are as follows:

Forget Gate: $f_t = \sigma\left(w_f \cdot \left|h_{t-1,}x_t\right| + b_f\right)$ (2)

Among them, $\mathrm{f_t}$ is the output of the forgetting Gate. σ is the sigmoid activation function. w_f is the weight matrix. h_{t-1} is the hidden state of the previous moment. x_t is the input at the current moment (such as EEG signals or behavioral data), b_f is the bias term.

Input gate: $i_t = \sigma\left(w_i \cdot \left|h_{t-1,}x_t\right| + b_i\right)$ (3)

Among them, i_t is the output of the input gate, control which information will be stored in the cellular state. When synchronizing EEG signals with behavioral data, LSTM can predict behavioral data based on past signal states, thereby solving the problems of time delay and synchronization between signals. By using LSTM, the model can learn and adjust the time deviation between EEG signals and behavioral data in real time, ensure the synchronization of these two types of data, and thereby improve the accuracy and real-time performance of content generation.

5. Conclusion

The content generation model based on EEG signals has the prospect of wide application in functions such as emotion computing, thinking decoding and multimodal interaction. Although there are still problems such as signal noise, decoding accuracy and data synchronization of EEG signals, the adoption of ICA to eliminate noise, CNN to extract spatial information, DTW signal synchronization and LSTM to synchronize EEG signals and behavioral data can further improve the processing effect and efficiency of EEG signals. With the development of technology, EEG signal-driven content generation models have more possibilities and can bring new impacts on brain-computer interfaces, intelligent interaction, personalized medical care, etc., further promoting the development of intelligent systems.

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