Analysis of Different Algorithms for EEG Signal Feature Extraction in BCI

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Abstract: Brain-Computer interface (BCI) technology has made important breakthroughs in neuroscience and human-computer interaction in recent years, allowing the brain to communicate directly with external devices. In recent years, advances in feature extraction algorithms, signal processing methods, and deep learning models have greatly improved the effectiveness of BCI in medical rehabilitation, cognitive enhancement, and neuroprosthetics. However, bidirectional BCI (BBCI) is still in its infancy and research content is limited, which limits its application in sports rehabilitation and cognitive intervention. In this paper, the algorithms commonly used to extract EEG signal features in the field of BCI are discussed, and combined with the experiments of several researchers, the key algorithms in time-frequency analysis, deep learning, and spatial feature extraction are analysed, and their effects on BCI performance are analysed. The results show that Short Time Fourier Transform (STFT), Tunable Q-Factor Wavelet Transform (TQWT), Long-Short-Term Memory (LSTM), BiLSTM and Filter Bank Common Spatial Pattern (FBCSP) have significant accuracy advantages. This paper also expected that BBCI would have promising applications in the fields of neural rehabilitation, cognitive enhancement. Future research should focus on solving the individual differences of EEG signals, optimization of denoising technology and real-time computing efficiency, to further improve the practicability of BBCI. At the same time, the data privacy and neurosecurity of brain-computer interfaces also need to receive more attention to ensure the safety and ethical compliance of BBCI technology.

1 INTRODUCTION

As artificial intelligence technologies become more and more advanced and people insisting exploration the brain of their body, in recent years, Brain-Computer Interface (BCI) technology based on neural technology and computer science, which directly connects human brainwaves with computer systems, has become a new promising research direction.

The technology of BCI is used in neural experiments initially, aiming to enable patients who are suffering from paralysis causing difficulty in communicating with others to have communications with others again by using a device that has some cursors being put on relevant parts of their head, reading active electronic signals in their brain, decoding those data and express these patients' thoughts. Gradually, this technique is used in pragmatic applications, including medical, entertainment fields. As a subpart of BCI, Bidirectional BCI is also attracting a glut of research attention, which could execute more complex interactions and more accurate control, not only reading brainwaves but also giving responses to people's brains.

There are several research directions of BCI. One of those directions is collecting signals and improving the technique of resolving. Conventional signal collection method of electroencephalography (EEG) was used widely because of the convenient and non-invasive quality. But the spatial resolution was relatively low and signal-to-noise ratio was limited, so, researchers introduced advanced signal processing algorithms to raise the accuracy and efficiency of extracting features of brain signals, including Filter Bank Common Spatial Pattern (FBCSP) and deep learning models (Lin et al., 2023).

Another direction is applications on neural rehabilitation, studies have shown that BCI-based neurological recovery equipment and electrical stimulation can apparently improve the rehabilitation effect for patients of stroke, Parkinson's disease and other diseases. For instance, if the patients of stroke use the unilateral lower-limb exoskeleton robot to

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train the ability to walk and use Neural Muscle Electronic Stimulation (NMES) to help them, their balance of walking would be improved. This research revealed that the process of re-moulding neural systems through electronic stimulations could effectively help patients' neural functions recover (Huo et al., 2024).

Apart from more advanced algorithms and medical applications, there are also some applications of Bidirectional BCI. Unlike traditional one-way BCI, Bidirectional BCI could not only read signals in people's brain, but also send signals to those subjects' brain by electronic stimulations and other methods, creating more interactions between people and devices (Lee et al., 2021).

This essay will analyse research on BCI and give critical thinking about the use of different advanced technologies in different areas, including helping to recover from several kinds of diseases or disability, and the current situation of wearable devices, and identification of medical images. Simultaneously, this essay will analyse the theory and the promise of Bidirectional BCI, combined with the current development of this technique.

2 IMPORTANT RESEARCH PART OF BCI

The important part of techniques used for BCI is how to extract characteristics of EEG signals. The process involves putting electrodes on subjects' head, and those electrodes would detect the electronic activities of neuron system, and devices would be used for collecting brainwave data, solving them and extracting useful information. However, EEG signals are relatively easily affected by noises, which would have deleterious effects on the accuracy of interactions between human and devices. Therefore, there is a need to use advanced algorithms to solve those collected data and improve the accuracy of extracting data and make results reliable.

2.1 Time Frequency Algorithm of BCI

In the field of BCI, EEG signals are unstable signals, and there are time frequency algorithms which could overcome the unstable quality of the signals and describe the relationship between signals and time intervals. Short Time Fourier Transform (STFT), Tunable Q-Factor Wavelet Transform (TQWT) are typical time frequency algorithms. This kind of algorithm could provide information of the frequency distribution on different time intervals of EEG signals, especially TQWT, which could not only provide high frequency resolution in low frequency band, collecting signals which change slowly and have various details including recognition situation, but also high time resolution in high frequency band, collecting signals which change fast including muscle activities.

2.1.1 STFT

STFT can divide signals into many time intervals and apply Fourier Transform on each interval. In the formula of this algorithm, s(t) represents signals which should be solved and h(t) means window function which usually regard 0 as the centre. The formula indicates that by changing the time window function h(t), the frequency distribution on various time intervals could be determined. In addition to that, STFT is suitable for analysing EEG signals (Zhang et al., 2022).

$$STFT(t,f) = \int_{-\infty}^{+\infty} [s(\tau)h(\tau - t)]e^{-j2\pi f\tau}d\tau \quad (1)$$

In fields of processing voice signals and recognizing emotion, STFT could effectively transfer voice signals to the representation of time frequency. For instance, there is research that used techniques based on STFT, named Mel Spectrogram with Short-Time Fourier Transform (Mel-STFT). The method extracted features about voice by using the formula of STFT, transferring signal amplitude distribution into the Mel scale and researchers also introduced Improved Multiscale Vision Transformers (MViTv2) as their classifier (Ong et al., 2023). Compared with the previous versions of classifiers, this classifier enhanced the ability of space-time interaction modelling and reduced the loss of information during pooling. When the team of these researchers was testing the method, they used some speech emotion datasets, and all of them covered various kinds of emotions and over 1000 audio samples, the result showed that the accuracy datasets applied with Mel-STFT had the highest accuracy among all datasets, around 90.57%, 81.75% and 63.49%, indicating that the method using techniques based on STFT is an effective approach which could be used for extracting and analysing features of information of human-computer interaction.

2.1.2 Limitations of STFT and Mel-STFT

While the method used by the researchers obtained an outstanding effect, there are still some limitations of this kind of approach. The limitation of STFT is that if the window function was fixed, then the adaptability to different signal bands would not meet the expectation. Different parts of the voice signal may need different relevant shapes and lengths of the window functions. As for Mel-STFT, the characteristics would be influenced by background noises and neglect some information about the high frequency. Using Wavelet Transform could help solve the problem because it can retain more information of high frequency and improve the ability to solve unstable signals.

2.1.3 TQWT

TQWT could decompose complex unstable signals into multiple scale sub-bands, and the Q-factor means the quality factor which could be adjusted, with different values of Q representing different types of signals. Zhang, et al. used the datasets of epileptic patients and other healthy subjects, applying TQWT to their EEG signals and extracting features of sub-bands on different frequencies (Zhang et al., 2022). They adjusted Q-factor to adapt to the characteristics of signals, and decomposed signals from high frequency to low frequency to capture some information of a certain frequency band when epilepsy started seizure. In the experiment, the combination of TQWT and deep learning, TQWT with deep residual shrinkage network (TQWT-DRSN), had better performance than only time-frequency TQWT methods, with the accuracy of 99.92%, 95.20% and 90.46% on different classifications. The result shows that the combination could be used in multiple fields such as detection for epilepsy and Parkinson, because of its effective extraction from useful frequency bands and automatic extraction from higher level through deep learning.

2.1.4 Limitations of TQWT

In the experiment of the research, as the difficulty of classification becomes higher, the accuracy becomes lower, and under this situation, TQWT should be combined with the deep learning algorithm to raise the accuracy. Moreover, TQWT is sensitive to the noise in signals, which should be solved by preprocessing to reduce noise.

2.2 Deep Learning Algorithms Applied to EEG Signals

In deep learning algorithms, there are some typical algorithms such as Long-Short-Term Memory (LSTM). Unlike traditional algorithms, deep learning algorithms could automatically learn features from raw data of EEG signals, reducing the workload of the extraction. Besides, in the classification of EEG signals, this algorithm has higher accuracy and has the ability to recognise patterns, which could be applied to the domain of emotion recognition, sleeping-level classification.

2.2.1 LSTM

LSTM is a type of deep learning algorithm that is used to process constant time series signals and could automatically extract features of EEG signals about reliability in terms of time, reflecting the continuous characteristics of human brain activities. This algorithm is suitable for analysing long-time signal patterns.

In research of automatically detecting EEG signals in Parkinson's disease (Göker et al., 2023), an extension version of LSTM, BiLSTM was used for extracting features of time series in EEG signals and making the classification for those features. BiLSTM can calculate forward and backward simultaneously, which is more effective than the normal kind LSTM. This research used datasets from Parkinson's patients and other healthy subjects and calculated the power spectral density (PSD) of EEG signals between 1Hz to 49Hz and used 4 classification algorithms to extract features of PSD. Compared to other algorithms, BiLSTM algorithm had the highest performance in their experiments when it is combined with Welch method, with the sensitivity of 99.4%, a specificity of 96.5%, a precision of 96.4% and an accuracy of 97.92%, which means that algorithms based on deep learning could have an extraordinary performance on extracting features of EEG signals and offer an important and significant access to diagnose neural diseases.

2.2.2 Limitations of LSTM

Although the performance of results of BiLSTM is more accurate and precise than others, the cost of calculation would be relatively higher than other algorithms because of simultaneously processing forward and backward data. And similar to LSTM, they both have complex network structures, including a quantity of variables. Moreover, if there are noises or some artifacts including eye tracking and electromyographic disruptions, the performance of these models would degrade. Thirdly, overfitting should not be neglected, because sometimes the model is too complex, causing those unnormal values also fit. To address the potential problem, researchers could introduce some lightweight models to reduce the complexity of calculations and enhance preprocessing techniques to avoid interruptions of irrelevant information, and they can also use the technology of Dropout in the LSTM model to turn off some nodes, reducing the overfitting problem.

2.3 Spatial Feature Extraction from EEG Signals

EEG signals are distributed in various parts of human brain, so the spatial distribution of those signals could represent neural activities. In addition, spatial feature extraction could identify coordinated activity patterns in different brain regions, which could also extract characteristics of those signals. This kind of algorithm could improve the accuracy of classification of those signals, so there is a need to apply this type of algorithm on the domain of medical recovering, motor imagery and emotion recognition.

2.3.1 Filter bank common spatial pattern (FBCSP)

FBCSP is an algorithm which could analyse multiple frequency bands, by applying Common Spatial Pattern (CSP). CSP could improve spatial filter by determining the ratio of maximized and minimized standard deviation of EEG signals, which could raise the accuracy of classifications. FBCSP would decompose signals into multiple frequency bands, and then it could take advantages of CSP to extract the feature of each band. At last, the feature of highest identity would be selected. In the domain of motor rehabilitation, movement-related cortical potentials usually appear at two bands, α bands (8-12 Hertz) and β bands (13-30 Hertz), so advantages of FBCSP could match the feature of these signals, which could help patients train their brains when patients are imagining exercising, typically such as raising hands.

In the research of applying 3 different algorithms including FBCSP on 2 datasets about EEG signals in motor imagery field (Meng et al., 2024), researchers compared those data of accuracy and found that FBCSP performed the best, with an accuracy at 91.57% for dataset A, and an accuracy with 83.32% for dataset B. But due to the redundancy of results of FBCSP, researchers applied a stepwise discriminant analysis (SDA) on FBCSP, making the accuracy of both datasets increase to 98.47% and 95.2%. The result illustrated that FBCSP could perform an outstanding accuracy than other algorithms, the feature of motor imagery could be extracted effectively, and if the algorithm could be combined with SDA, the accuracy would be higher.

2.3.2 Limitations of FBCSP

FBCSP would generate a considerable number of extracted features, among of which may include some abundant information affecting the attributes of classifications, such as discrete difference brought by various subjects, irrelevant neural activities and useless noises, so there is a need to apply some methods to select features more effectively, and applying SDA is an appropriate way. SDA could remove features which could not contribute to classifications to reduce complexity of calculations, reduce noise to improve accuracy for different subjects in the research.

3 SITUATIONS OF APPLICATION OF BCI

BCI is widely used in multiple fields, including medical care and entertainment, providing people an easier way to observe data and ease mental stress.

In medical care domain, BCI technology could be used in clinical situations, helping doctors know about patients' mental activity and behaviours, making the diagnosis and treatment easier. Taking neural science as an example, the technique could be used to observe and evaluate patients' brain activity and behaviour recognition, providing a non-invasive detection for EEG signals (Zhang et al., 2021). On the other hand, BCI could be used as a rehabilitation method, enabling patients to control their limbs and recover their perceptual functions. Khan et, al discussed some Motor-Imagery BCI strategies (Khan et al., 2020), including functional electric stimulation, robotics assisted systems and virtual reality technique based hybrid models, which can help people suffering from stoke or other diseases recover motor function, enhance the effect and improve the immersive experience. With the help of BCI, EEG signals would be converted into mechanical command to help people train their body.

In entertainment domain, by collecting EEG signals and analysing, a glut of BCI applications could be created. There are some devices which could draw people's dream, by collecting their EEG signals when those subjects are dreaming, and making relevant drawings, which could not only demonstrate the scene of dream to people, but also stimulate their curiosity to explore more knowledge about dream. Furthermore, BCI is also used in game developing. Game developers could take advantages of various algorithms to analyse features of EEG signals in different game experiences to design a game with a better interactivity and immersion.

4 PROBLEMS AND EXPECTATIONS OF BCI

Although there are many fields introducing BCI to help do research, some issues about the technique should not be neglected. For example, because EEG signals are data which record personal emotion and memory, there is a need to protect personal privacy, avoiding being attacked by hackers. Moreover, regulations about how to use BCI should be announced. Given the fact that BCI could control brain activities, limiting the use of BCI should be taken into account.

As for the future development of BCI, although some branches of BCI research are in a nascent stage, including applications on virtual reality, enhancing users' experience including communications with analysing their EEG signals (Zhu et al., 2023) and bidirectional BCI (BBCI), the technology has started being used for some more realistic fields, such as helping more people regain abilities. BBCI could not only receive and collect signals from brain but also transmit the response signals back to the body, which could be used in motor rehabilitation and memory enhancement. For instance, BBCI makes patients feel their strength when they are touching or holding some objects, aiming to make them realize the existence of their assistant legs, enable them to memorize such feeling and help them control their behaviours, and additionally accelerate the process of recovering. On the other hand, BBCI could also be used in mental recovering fields, create positive dreams to provide some virtual experience, helping post-traumatic stress disorder (PTSD) patients release stress.

5 CONCLUSIONS

This paper focuses on BCI, explores advanced algorithms of EEG signal feature extraction, and combines the application of many researchers in medical rehabilitation, emotion recognition and brain control devices, including the three methods, which are time-frequency analysis, spatial feature extraction and deep learning. In the analysis, STFT, TQWT, LSTM, FBCSP algorithms are summarized, and their shortcomings and improvement measures are critically considered, and the driving effects of these algorithms in the field of neuroscience. In addition, the potential applications of BBCI in motor rehabilitation, neural regulation and cognitive enhancement are also discussed. By analysing the results of this paper, based on the summary and analysis of existing algorithms, the concept of typical advanced algorithms could be understood, and it would be explicit to know when to use different algorithms to improve the accuracy of EEG signals, and make ideas about the field of BCI.

However, because there are too many kinds of algorithms, this paper cannot list them all and make analysis and evaluation. There are many other outstanding algorithms to extract features in an effective way. In conclusion, BBCI has high application value in the fields of medical rehabilitation, neural regulation and human-computer interaction.

In the future, with the development of neuroscience, artificial intelligence and material engineering, the technology is expected to make further breakthroughs to achieve human-computer integration in a true sense, and improve human perception, memory and movement ability.

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