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Artifact Elimination of Eeg Signals Based on Deep Learning：Survey

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A B S T R A C T

Electroencephalogram (EEG) plays an important role in measuring human status and activities. EEG signals come from weak currents and are very vulnerable to artifact pollution, which affects the performance of many EEG tasks. It is crucial to develop methods that can effectively identify and remove artifacts. In the past, researchers have proposed a variety of methods to eliminate artifacts, but there is still no method to achieve the best effect. With the rapid development of deep learning, the new method has made excellent progress in eliminating artifacts. Compared with traditional methods, it is fast and can be automatically processed. This paper explores a new method to eliminate artifacts using deep learning technology. First, it discusses the characteristics and types of artifacts of EEG data, reviews the traditional elimination methods, then introduces the application of new and new methods of deep learning, and introduces the relevant data sets. In the future research, the method of artifact elimination relying on data automation has great potential.

Keywords:EEG; Artifact Alimination Technology; Noise Elimination; Deep Learning

1. Introduce

Electroencephalogram (EEG) is the epidermal electrical signal collected from the human head by a non-invasive instrument. The microvolt level voltage on the scalp is obtained through a sensitive sensor, and is converted into one-dimensional time sequence content that can be collected and stored through signal amplification and digital analog conversion hardware equipment [1]. These special signal contents reflect human physiological and psychological conditions, from which important human characteristics can be extracted to identify human emotions, instructions or diseases [2]. In recent years, EEG has made great contributions to neuroscience, psychology, cognitive science and other research fields, and the development of technologies that can mine information hidden in the brain is a research hotspot in many fields. However, because EEG signal is very sensitive in the process of collection, the signal is very vulnerable to noise pollution, resulting in invalid artifact content. 【3】 Artifacts will affect people's interpretation of neural signals and hinder the task in practical applications, such as misdiagnosis in disease diagnosis [4], misjudgment in emotion recognition, and incorrect instructions in motion imagination [5]. The sources of artifacts include signal acquisition equipment and human physiological status, which is an inevitable problem. In order to make EEG signals available for practical use, preprocessing must be carried out to eliminate artifacts.

Artifact elimination can reduce artifacts as much as possible from the physical level. Preventive measures should be taken before signal collection. The experimenter and the subject should follow the corresponding instructions to reduce artifacts generated by movement, but this is not practical in practical applications. It has been studied for a long time on the algorithm level to remove artifacts. The traditional algorithms include regression, blind source separation, combination methods, etc. With the excellent performance of depth learning technology in image, sound, and text denoising [6], the use of depth learning technology to remove artifacts from EEG signals has increased year by year. Using Google Scholar as the collection platform, we set the key words: EEG, artifact elimination, neural network, deep learning, and denoising. We searched the percentage of the number of relevant documents in the past five years. Figure 1 shows that the number of documents involving deep learning technology is close to 31% of the number of EEG artifact elimination documents, indicating that it has a very wide range of applications. Figure 2 shows the changes in the number of documents in the past five years. Deep learning technology and EEG artifact elimination have maintained the same growth. Although the number of studies is increasing year by year, there is still no unified solution.

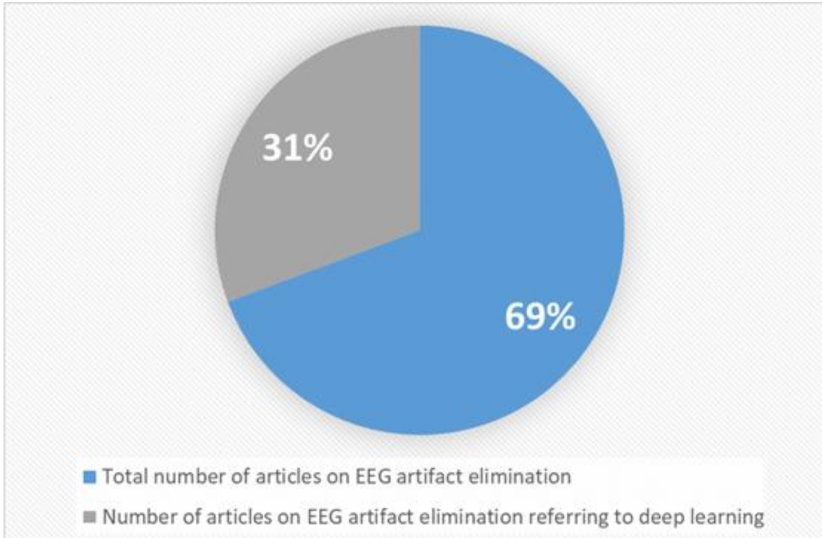

Fig. 1 - The ratio of the number of articles on EEG artifact elimination to the number of articles on deep learning technology in recent 5 years

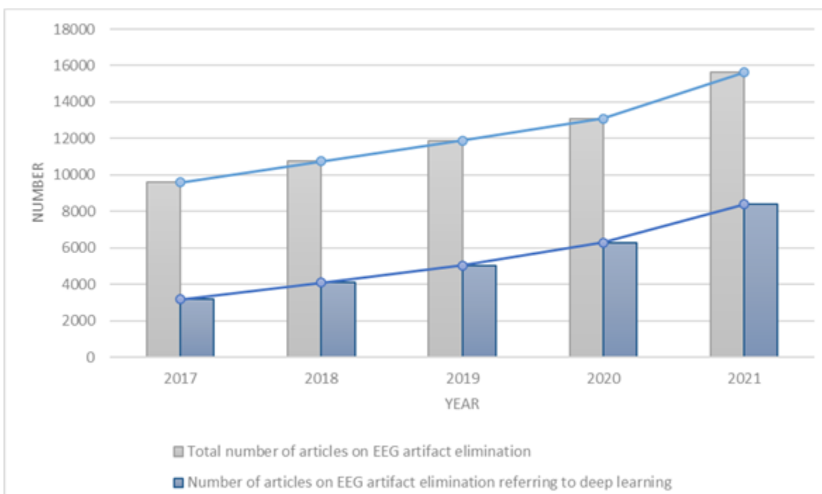

Fig. 2 - Changes in the number of articles related to elimination of EEG artifacts in recent 5 years

In order to promote the development of deep learning technology in EEG artifact elimination, we try to conduct a comprehensive investigation of the main methods mentioned in the literature. First, we summarize the characteristics of EEG signal and the types of noise. Next, we introduce and analyze the advantages and disadvantages of traditional elimination techniques. Then, we discuss in detail the current deep learning techniques mainly used for elimination. Finally, we introduce the EEG artifact data set that is important for deep learning. We hope that this article can help researchers better understand the application of deep learning technology in artifact elimination and develop more efficient methods.

2. Artifact Description

EEG is an electrical signal record collected from the human head epidermis. A large number of nerve cells in the brain will produce very weak electrical signals when they are active. The frequency of the signal is related to the activity of the brain. The effective frequency of EEG signal is 0.5HZ to 50HZ, and the voltage is about 50 microvolts. The signals beyond these ranges are invalid signals. 【7】 EEG signals are generally divided into five frequency bands. Table 1 summarizes the characteristics of these bands.

Table 1 - Frequency Band Distribution of Brain Signals.

Band	Frequency	Occurrence
δ	0.1 – 3Hz	When in infancy or during deep sleep
θ	4 - 7 Hz	When people's emotions are suppressed, meditate or create
α	8 – 14 Hz	When people are awake and relaxed or close their eyes
β	14 - 30 Hz	When people are nervous, wake up ,excited or anxious
γ	>30 Hz	When the eyes are under strong light, motion control and imagination

A comprehensive understanding of the types and characteristics of artifacts can better find ways to eliminate artifacts, which mainly come from the environment, collection instruments, and human body. 【8】 The controllable environment and well maintained equipment can reduce the appearance of artifacts. The artifacts of human movement can be reduced through subjective behavior, but the artifacts generated by the physiological activities inside the human body are inevitable. Artifacts are generally divided into two types according to their sources. Table 2 records the distinction and types of artifacts. The artifact elimination algorithm is mainly aimed at human physiological artifacts.

Table 2- Type of Artifact

Type	Name	Source
Physiology Interior	EOG ECG EMG Breathe Disease	Blinking, opening, eye movement, facial or head muscle activity, heart beating, speaking, breathing, and diseases related to the brain or skin.
External	motion electric power Equipment aging	Human movement, seat field displacement, AC point interference, sensor electrode and line equipment aging.

The artifact removal algorithm focuses on physiological internal signals. At present, the research on eye artifacts, muscle artifacts and heart artifacts is the most extensive. These three artifacts have obvious regularity and can be recognized and processed by programs. External artifacts will produce very obvious signal fluctuations, which can be eliminated by electronic filters or filtering algorithms. These noises act on multiple channels of the brain at the same time, with obvious consistency. 【9】

Three main categories of artifact elimination in EEG research:

- 1) The source of eye artifacts is the movement of the eyes and eyelids, and the nerve signals needed for the movement will be transmitted through the scalp. The electrical signals generated by the eyes have large amplitude, which can be collected and recorded through electrodes, and are called electrooculography (EOG). 【10】 The frequency of EOG is similar to that of EEG. The interference between the two is not unidirectional, but mutual. When collecting EOG, there will also be artifacts generated by EEG. In the artifact elimination operation, such bidirectional interference needs to be considered.
- 2) The noise pollution caused by muscle activity is not single, but multiple muscle groups. Nerve signals generated by muscle stretching and contraction can be collected on the skin near the muscle, which is called electromyography (EMG). Due to the large distribution of muscle groups, EMG is usually collected through multiple channels. The degree of muscle activity determines the frequency and amplitude of the signal. The EMG signal has obvious statistical independence in time and space. Independent component analysis is very suitable for removing these artifacts. 【11】
- 3) The electrical signals generated by heart beating are very strong, and these signals are called ECG. ECG can be collected near the blood vessels of the body. The heart beats to deliver blood with a stable regularity. The frequency of ECG is about 1.2Hz.【12】 The frequency characteristics similar to those of ECG can be seen in EEG, and they exist all the time, which is very difficult to eliminate. However, due to the single regularity of ECG, these artifacts can be eliminated through the reference waveform information.

3. Artifact Elimination

3.1. Traditional Artifact Elimination

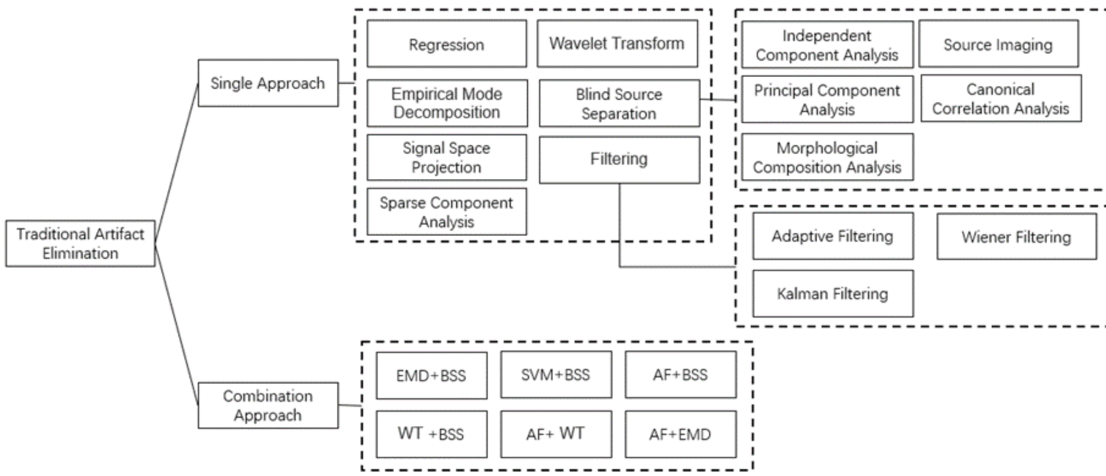

Fig. 3 -Classification of traditional denoising methods.

In previous studies, denoising methods are divided into separate methods and combined methods. The figure shows the classification of these methods. Individual methods include regression analysis, wavelet transform (WT), empirical mode decomposition (EMD), sparse decomposition (SCA), signal space projection (SSP), blind source separation (BSS), and filtering. BSS includes principal component analysis (PCA), independent component analysis (ICA), and EEG source imaging (ESI) morphological component analysis (MCA). There are three filtering methods: adaptive filtering (AF), Wiener filtering and Kalman filtering. The combination method is innovated and improved on the individual method, and better results are obtained by combining the advantages and disadvantages of different methods. BBS combined with wavelet changes can eliminate jitter and retain effective changes. BBS combined with support vector machine (SVM) can effectively eliminate artifacts generated by blinking. BBS combined with EMD can remove muscle artifacts in low channel situations. Adaptive filtering combined with blind source separation or wavelet transform can also remove eye artifacts, while adaptive filtering combined with empirical mode decomposition can remove ECG artifacts. Different combinations can be used for different artifact types to complement the characteristics of each individual method. The traditional method is not the focus of this paper. Here, we will analyze its shortcomings.

Traditional methods have these shortcomings: each method has its own characteristics, but can not fully meet the various conditions of artifact removal. Because traditional methods require manual judgment and selection of processing methods when facing different artifacts, this process is very laborious. When there are many types of pollution or high pollution levels, a lot of manual work is required to review the data. In addition, in different periods of data, consistent denoising methods will lead to effective data content being treated as noise removal. These methods cannot automatically identify the noise differences between data, reducing the amount of effective data. In the face of cross individual data, the features of noise content such as ECG and eye movement noise cannot be processed uniformly, and manual correction is still required. Traditional denoising methods can not get effective solutions as a key step of preprocessing on cross dataset and multiple downstream tasks. Deep learning improves the defects of traditional denoising methods in an end-to-end manner.

3.2. Deep learning artifact elimination

In order to explore a method that can automatically and quickly remove artifacts, we investigated the research progress of using depth learning to remove artifacts and recorded it in the table. The types of methods can be classified as artificial neural network (ANN), automatic encoder (AE), convolutional neural network (CNN), and countermeasure generation network (GAN). The types of artifacts that the research focuses on removing are eye artifacts (EOG), muscle artifacts (EMG), and electrocardiogram artifacts (ECG). Next, we also outlined each method in the table.

Table 1 -Comparison of Several Methods of Artifact Elimination in Depth Learning

Study	Year	Method	Method Type	Artifact Type	Aapplication
Vaibhav *et al.*	2011	SWE+ RQNN	ANN	Denoising	Motor Signal
Nguyen	2012	WT+ANN	ANN	EOG	Data Recovery /Enhancement
Jing Hu	2015	ANFIS+ANN	ANN	EOG,EMG	Data Recovery /Enhancement
J. Li	2015	DAE	ANN	Denoising	Motor Signal
Mateo	2016	SPM+ANN	ANN	EMG	Data Recovery /Enhancement
Robin	2017	deepConvNets	CNN	EOG,EMG, ECG	Decoding Toolbox
Banghua	2018	SSAE	AE	EOG,EMG	Decoding Toolbox
Hartmann	2018	Wasserstein GAN	GAN	/	Data Recovery /Enhancement
Niago	2018	DCAE	CNN	EOG,EMG	Data Recovery /Enhancement
S Yang	2019	EL-SDAE	AE	EOG,EMG	Motor Signal
R Ghosh	2019	SVM+ AE	AE	EOG	Data Recovery /Enhancement
Sun, W	2020	1D-ResCNN	CNN	EOG,EMG, ECG	Data Recovery /Enhancement
H. Zhang	2021	Full-DCNN	CNN	EMG	Data Recovery /Enhancement
F Lopes	2021	DCNN	CNN	EOG,EMG, ECG	Epilepsy Signal
Sawangjai	2021	EEGANET	GAN	EOG	Data Recovery /Enhancement
Y an	2022	SETET+GAN	GAN	EOG, EMG	OnlineEEG Analysis

Vaibhav Gandhi et al. [13] used the Schrodinger wave equation (SWE) to enhance the original EEG signal in 2011. Based on the recursive quantum neural network (RQNN), they constructed an alternative neural information processing architecture, which can eliminate artifacts in an unsupervised way, while strengthening the effective moving image features in EEG. Nguyen H.A.T et al; This method requires a priori signal to denoise. Jing Hu et al. [15] constructed a filter capable of processing fuzzy data to eliminate EOG and EMG artifacts by combining functional neural network applications and adaptive neuro fuzzy inference systems in 2015. This method requires a priori signal. J. Li et al. [16] used Lomb Sculle periodogram to describe EEG signals containing artifacts in 2015, and then used automatic encoder (DAE) to initialize neural network weights according to feature information. The trained network can identify and eliminate artifacts, and the denoised EEG is still useful for recognizing motion commands again. Mateo, J et al. [17] developed a growing artificial neural network for muscle artifact removal in 2016. Its network optimizes the number of nodes in the hidden layer, and optimizes the sparse matrix through simultaneous perturbation, which realizes EEG signal denoising under low distortion. After updating parameters, EEG signal denoising can adapt to multiple tasks. This method needs to know the noise type before training. Robin et al. [18] used deep ConvNets to eliminate EEG artifacts in 2017, built a model in a similar way to image denoising, and created three convolutional networks with different architectures. The model also learned to automatically analyze and extract three frequency bands α, β, γ The frequency characteristics of are aligned in the local space for visualization. Banghua Yang et al. [19] built a deep learning network based on Stacked Sparse Automatic Encoder (SSAE) in 2018. By learning EEG data without EOG, they can remove eye artifacts without relying on EOG data, and can also be used in low channel numbers. This method lost a lot of EEG data details. Hartmann et al. [20] proposed to use GAN to generate EEG signals in 2018. The model was improved based on Wasserstein GAN and combined with EEG data training, which verified that GAN is also very useful in time series generation, and the generated EEG data can be used for data enhancement and damage recovery, which is also applicable to EEG artifact elimination. Niago et al. [21] built an automatic denoising method of depth convolution automatic encoder in 2018 to remove artifacts generated by eyes and jaw muscles. This model can extract spatio-temporal features and is superior to traditional band-pass filters and full connected neural networks in peak signal to noise ratio performance. S Yang et al. [22] proposed an integrated deep learning model EL-SDAE in 2019 to identify human psychological load. In this algorithm, motion and muscle artifacts in multi-dimensional features are removed by using an automatic encoder with superimposed de-noising to enhance the stable feature content in EEG signals while retaining local features. R Ghosh et al. [23] used sliding windows in combination with support vector machines to identify eye artifacts in 2019, and used an automatic encoder constructed by three-layer neurons to convert part of the artifact signals into highly correlated pure EEG signals. The trained model retained most of the signal information and supported 64 channel artifact elimination. Sun, W et al. [24] first applied CNN method to noise reduction in 2020. A one-dimensional residual convolution neural network (1D-ResCNN) is constructed to train the model of automatic removal of EEG artifacts. The network is divided into three parts: feature extraction, combined output, and loss function optimization error. Different residual blocks can extract different features and filter continuously in each convolution layer transmission. Remove eye, muscle and heart artifacts. H. Zhang et al. [25] built a deep neural network with multiple convolutional layers and a fully linked layer in 2021. The model reconstructed EEG signal is used to eliminate muscle artifacts, and the feature dimension and time series are gradually increased to conduct de sampling, so as to avoid over matching after the increase of network layers. But it does not support long-time EEG signal de-noising. F Lopes et al. [26] proposed a deep convolution network in 2021 to eliminate artifacts in epileptic data. The EEG data of experts separating artifacts are used for learning. The effect of model learning is equivalent to that of experts separating, and it can automatically process long-term collected EEG signals. Sawangjai et al. [27] put forward the generation countermeasure network model EEGANET for EEG de-noising in 2021. Based on the discriminator, they can judge whether it is the mutual confrontation between artifacts and artifact signals generated by the generator, and constantly learn to improve the recognition ability of EEG artifacts. The trained model can be used to identify eye artifacts without new prior knowledge or correction. This method is suitable for multi-channel eye artifact elimination. In 2022, Yan et al. [28] put forward the method of generating countermeasure network (GAN) to build discriminator to judge whether the noise is filtered. The generator constantly changed the denoising method, and used sample entropy threshold and energy threshold based normalization method (SETET) to limit the range of EEG signals, so as to achieve cross individual EEG artifact removal.

3.3. DataSet

Deep learning technology depends on the quality and quantity of data, and data sets are essential. Although unsupervised learning and transfer learning can reduce the demand for data to a certain extent, the training of network models cannot be without data. EEG data is different from text, image and sound data, which can be obtained in large quantities through simple ways, often relying on complex and professional equipment to collect. Public data sets are particularly important for algorithm research and development. We summarized the open EEG data sets that can be used for artifact elimination at present to promote the further development of this direction.

CHB-MIT data set [29], released in 2000, recorded epileptic EEG signals of 22 subjects, with a total of 664 records, 23 signal channels, and a sampling frequency of 256HZ, collected by Boston Children's Hospital.

BCI competition IV Data sets 1 [30], published in 2008, contains EEG data of 7 subjects. The data set is mainly used for motor imagination tasks. It records 200 motor imagination signals of each subject, which are divided into three categories. Each signal lasts for 6 seconds. There are 59 channels in total, and the signal frequency is 0.5 to 200 Hz,

The DEAP dataset [31] was released in 2011. There were 32 subjects, 48 channels in total, including 32 EEG channels, 4 EOG channels, 4 EMG channels and other channels. The sampling rate was 512HZ. Each subject watched 40 one minute video content, mainly for emotion recognition tasks.

EPILEPSIAE data set [32], released in 2012, recorded epileptic EEG signals of 275 patients, including 222 scalp EEG, 49 intracranial EEG, and 4 intracranial and scalp EEG. The upper sampling frequency is 250HZ-2500HZ. The data were obtained at Freiburg University (Germany), Goimbra University Hospital Center (Portugal), and the Hotel Saint Pierre Salpatriere (France) in Paris.

The Halt data set [33], released in 2018, has a total of 12 subjects, recording 950 records of each subject for 1 second. The data set mainly records motion imagination signals, divided into 6 categories, 22 channels in total, including 2 reference signals, 1 pulse signal, and the data sampling frequency is 200Hz.

The SEED-VI data set [34] was released in 2019. There were 15 subjects, each subject had three sessions, and each session had 24 experiments. Each recording duration was 4 seconds, including 62 EEG channels and eye tracking signals. The data sampling rate was 200HZ, and four categories of recognition were conducted, mainly for emotion recognition tasks.

EEGnowerateNet [35], released in 2020, is a data set specially used for deep learning denoising tasks, including 4514 pure EEG signal records, 3400 eye artifact records, and 5598 muscle artifact records. The EEG recording method is the same as that of the motor imagination task. There are 64 channels, 256HZ sampling rate, and each recording time is 2 seconds.

The multimodal EEG signal data set [36], released in 2020, has 25 healthy subjects, each subject has three sessions, a total of 82500 experiments, 60 EEG signal channels, 4 EOG signal channels, 7 EMG channels, a sampling rate of 2500HZ, and 11 motor tasks for motor imagination tasks.

When denoising is required for datasets, some need artifact reference channels and the other need to manually mark artifacts. At present, there are few EEG public data sets that are purely used for deep learning and denoising. Most EEG signals have their own focused tasks, and the denoising process should also take into account the preservation of information about the main tasks. In the future, the artifact channels in different types of tasks, as well as EEG data sets specially used for denoising, have sufficient potential.

4. Discussion

The general flow of EEG artifact elimination based on deep learning technology is shown in the figure. After the original signal is obtained, it will undergo a simple preprocessing stage, such as down sampling, band-pass filtering, etc., to reduce the amount of data and remove obvious invalid signals. The preprocessed signal is converted into two-dimensional graph, matrix and other characteristic forms, and then sent to the deep network model for learning. During the learning process, the model updates the parameter content, realizes the recognition of artifacts, and then removes the artifacts. At the same time, pure EEG related data is reconstructed. The new data and original data constructed are judged by the scoring system to determine the effect of noise removal, and iterative training is repeated. After the model learning is completed, it can be deployed to new data for testing tasks and downstream tasks.

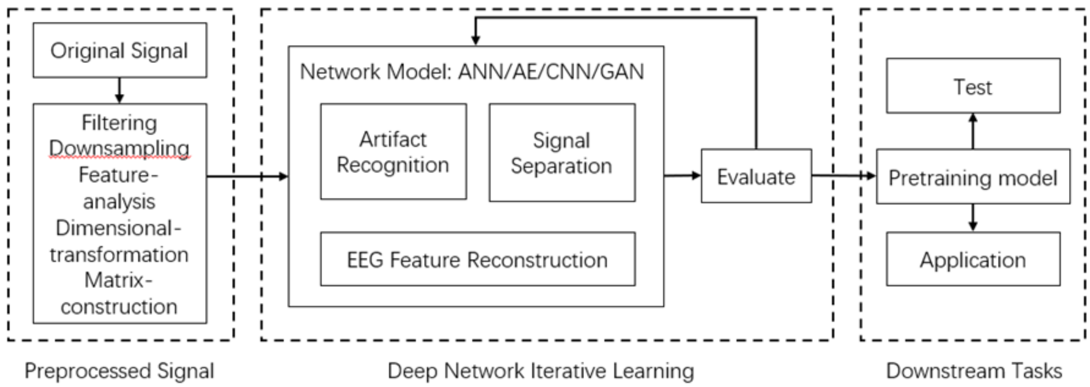

Fig. 4 - Process of Artifact Elimination Method of Deep Learning tTechnology.

The effect of deep learning denoising is consistent with that of manual denoising. The former process is automatic, requiring less time and reducing manual work. The latter takes more time to process different artifacts and EEG signals. After the network model training, the deep learning method can adapt to the processing of cross individuals and cross artifact types without redesigning the preprocessing process when transferring to the downstream tasks. On some models, once the network model is trained, prior artifact data is not required, and unsupervised identification can be realized on different data sets, which is more convenient than traditional methods. The model can separate nonlinear pure signals under various conditions such as channel number, signal density and reference channel, which has better performance and greater scalability than traditional methods. The deep network can not only realize denoising, but also realize the expansion and enhancement of EEG data. The generated content makes up for the shortage of pure EEG data and is difficult to obtain. Compared with multiple tasks of EEG signals, artifact elimination is actually to recognize invalid EEG features and reconstruct the original signal, just like autonomous recognition of effective EEG features. In addition, the deep learning model can realize online operation, and has broad application prospects in real-time EEG applications.

The development direction of depth based de-noising is to break away from the dependence of training data type. The training of deep network needs a lot of data support. If the model is limited to a specific data range, it is not widely applicable. The separated EEG data type has the following aspects: a The characteristics of EEG artifacts and signal artifacts are different for individual subjects, and individual independence is the basic ability of the model; b. Artifact type: it is difficult to have separate artifacts in real EEG data, and the temporal distribution of artifacts is uneven. An efficient model can handle a variety of different artifact types; c. For data sets, there are differences in the collection environment, number of channels, experimental methods, collection equipment, etc. for each data set. De noise is a necessary step for all data sets. The de noise model trained by one data set can be applied to the test of other data sets; d. Downstream tasks and artifact elimination are generally used as the preprocessing stage of EEG recognition tasks. For different downstream tasks, the pre trained denoising model can be quickly and efficiently adapted.

Improved network model and technology of deep learning artifact elimination: a The enhancement and generation of pure EEG with GAN and the generation of adversary network for data generation have achieved excellent performance in many directions. The de-noising of EEG signals is also a way to generate pure EEG data based on original data [37], which makes up for the defect of less pure signals in the actual collection of EEG data. The characteristics of the generated EEG signals are widely adapted to the data of cross individuals, cross tasks and multiple artifacts; b. CNN is adapted to other denoising methods. EEG signal is a one-dimensional time series, which is the same dimensional conversion method as one-dimensional time series such as voice, ECG signal and radar. It is converted into two-dimensional or multi-dimensional types such as complex networks and images, and then the convolutional neural network model of multi-dimensional data is adapted to transfer the efficient denoising method to EEG signal. c. Unsupervised learning: EEG signals cannot run on a large amount of data in actual tasks. The artifact features of the human brain are consistent in a wider range of data. The model needs to be updated when encountering new data. EEG signals that have never been encountered are processed by clustering, reinforcement learning, segmentation, etc. The unsupervised way can directly identify artifacts in the consistent feature domain and further learn. D. Migration learning: the denoising model learned from a certain task can be quickly transferred to other tasks, and the artifact content contained in it has different manifestations in different tasks. The EEG signal focusing on epilepsy and the EEG signal focusing on motion can be extracted from the artifact with the same model, In the future, it can also be applied to EEG artifact elimination with the help of other data transfer learning methods.

5. Conclusions

In various tasks of EEG signal, artifact elimination is always required. Because traditional methods are not competent for automatic processing tasks, previous research has not found the best way to remove artifacts. The development of deep learning provides a possibility for this. Data driven end-to-end learning can provide a way to automatically and quickly process multiple artifacts, reducing the manual work of researchers. This paper summarizes the progress of deep learning technology used to eliminate artifacts of EEG signals. At first, the technology of combining ANN with traditional methods was popular, and the research gradually developed to more complex deep learning networks such as GAN and CNN. With the help of excellent denoising technology of video, text, audio and other data, it can also be applied to EEG automatic denoising, based on the preprocessing model as artifact elimination and pure signal generation, It can be better applied to downstream task operation. As deep learning is used to identify effective EEG data for downstream tasks such as motion, disease and emotion, the same way is used to identify invalid EEG data for artifact elimination. However, there are still problems in this development. The lack of data sets is an obstacle to the emergence of new methods. The expansion of data quality and quantity affects the effect of artifact elimination of deep learning. The contribution of this survey is to provide a reference for researchers to develop a broader path of EEG artifact elimination technology.

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