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Research on Local Field Potential Signal Classification Algorithm Based on Transfer Learning

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Abstract: The local field potential signals (LFPs), as a vital signal for studying the mechanisms of deep brain stimulation (DBS) and constructing adaptive DBS contain information related to the motor symptoms of Parkinson’s disease (PD). This paper proposed a Parkinson’s disease state recognition algorithm based on the idea of transfer learning.The algorithm uses continuous wavelet transform (CWT) to convert one-dimensional LFPs into two-dimensional gray-scalogram images and color images respectively, and adds a Bayesian optimized random forest (RF) classifier to replace the three fully connected layers used in the classification task in the VGG16 model, to realize the pathologic status identification of PD and normal state of parkinsonian patients. It was found that consistently superior performance of gray-scalogram images over color images. The proposed algorithm achieved an impressive accuracy of 97.76%, outperforming feature extractors such as VGG19, InceptionV3, ResNet50, and the lightweight network MobileNet. This algorithm has high accuracy and can monitor the status of patients in real time without manual feature extraction, and only apply DBS stimulation when in PD state, effectively improving the closed-loop adaptive DBS treatment effect.

1. Introduction

Within the past two decades, DBS has been widely recognized as an effective therapy for treating PD [1-3]. Currently, bilateral subthalamic nucleus deep brain stimulation (STN-DBS) is commonly employed for PD treatment [4-5]. While STN-DBS stands out as a viable therapeutic option for advanced stages of PD [6], continuous DBS may still be associated with some side effects, such as language difficulties, sensory abnormalities, and mood changes [7]. Compared with traditional DBS, adaptive DBS (aDBS) is based on a closed-loop stimulus pattern, which automatically adjusts stimulus parameters in response to feedback signals that can represent symptoms, aiming to reduce side effects and improve therapeutic efficacy [8]. Researchers have identified LFPs as valuable for gaining insights into the mechanisms of DBS and potential feedback signals for aDBS [9]. It had been confirmed that LFPs collected at the subthalamic nucleus in PD patients exhibit significantly enhanced beta band oscillations (13-30Hz) [10], which were believed to be related to motor impairments in PD. Recent reports [11] suggest that the application of levodopa and DBS can attenuate this activity, suppressing beta oscillations in LFP and accompanying improvements in clinical symptoms.

In the current research on LFP signals, Wang Shouyan et al. [12] used correlation analysis to identify and distinguish the abnormal state of LFP in PD patients. Wang used bispectral analysis to study the nonlinear interaction between LFP oscillations in the PD deep brain, which is helpful to distinguish the pathological state of Parkinson’s disease[13-14]. Zhang Kun extracted signal frequency domain features and combined them with a naive Bayes classifier to identify LFPs of PD patients before and after medication. Sun Qifeng used the improved EMD method to separate the frequency bands containing abnormal oscillating signals from LFP and extracted the envelope characteristics of the abnormal oscillating signals[15]. Peter Brown’s team at the University of Oxford used threshold stimulation strategies to control the pulse stimulation time of DBS after filtering, noise reduction, smoothing, and other processing of LFPs of PD patients and studied other potential feedback markers to improve the current adaptive DBS framework. In the above works of literature, LFP signal feature extraction usually relies on the subjective judgment and experience of experts for algorithm design, which leads to the subjective and knowledge limitation of EEG features. At the same time, when combining traditional machine learning classification methods such as Naive Bayesian support vector machine (SVM) , and random forest (RF) for signal recognition, the classification effect is likely to be unsatisfactory due to the small amount of data, inaccurate feature selection or too high or too low feature dimension. In contrast, a deep convolution neural network (DCNN) can automatically extract features from input signals without manual intervention, and meet the requirement of automatic feature extraction through semi-supervised or unsupervised means. However, the small amount of biomedical signal data limits the advantages of the DCNN algorithm [16-19].

Transfer learning (TL) solves problems such as data scarcity, domain adaptation, feature representation learning, and model initialization by applying previously learned knowledge and experience from one task to another[20-23]. This technique is gradually being used in different fields of machine learning. The core idea is to use the knowledge learned on a task to speed up or improve learning on new data or tasks through trained models. Mainstream pre-trained models for image tasks include VGG, ResNet, MobileNet, Inception, etc. The models are pre-trained on the ImageNet dataset, which contains millions of images, and the trained model can accurately classify 1000 different classes of objects. By adjusting the weight of the pre-trained model, it can be used to solve the problems of classification and segmentation in different fields. There are two main strategies for transfer learning[24]: The feature extraction strategy utilizes a DCNN model pre-trained on a large dataset to be used as a feature extractor in a new target domain. Typically, this strategy involves selectively freezing the convolutional layer of the DCNN model, removing the fully connected layer, and leaving the rest to be used as a fixed feature extractor to accommodate new tasks, such as ECG signal classification tasks [25]. Another one is fine-tuning, which typically involves setting the convolutional layer weights of a pre-trained model to be trainable, allowing the weights to be updated during training, or adding new layers to the top of the model to fit a specific task. In the process of fine-tuning, the weight of the whole network will be updated in the training process [26].

Therefore, based on feature extraction strategy, the present study attempted to use the pre-trained model VGG16 as a feature extractor and combined it with the RF classifier to identify the pathologic status of PD and normal state of parkinsonian patients. By adding an RF classifier to replace the three fully connected layers used for classification tasks in the VGG16 model, the Bayesian optimization algorithm was used to optimize the hyper-parameters, further improved the model performance and generalization ability.

2. Materials and methods

2.1. Data

The data of local field potential signals of PD patients came from the public data set [9] of Peter Brown's team at Oxford University. All subjects underwent DBS surgery, where stimulation electrodes were implanted at the STN of patients and their LFP signals were recorded. The experiment was approved by the local ethics committee. A total of 52 groups of data were collected the states of receiving DBS stimulation (on-stimulation) and without getting stimulation (off-stimulation) for 26 PD patients. The sampling time of each group was about 60 s. The sampling frequency of signals off-stimulation and on-stimulation states was 2048Hz and 4096Hz respectively, and was uniformly downsampled to 1000Hz, and the sampling points of each group was 60,000.

The amount of data obtained from hospitals is limited, not enough to train an effective deep learning model, and increasing the amount of data in a clinical setting is not practical [27]. To solve this problem, this paper enriches the data set by slicing operations. Each LFP signal segment with a length of 60,000 is divided into 60 parts, that is, each segment contains 1000 sampling points and lasts for 1s. These segments are independent signals for generating deep-learning models. As a result, the dataset was expanded from 52 to 3120, with 1,560 on- and off-stimulation data sets.

2.2. Signals preprocessing

In the present study, the collected LFPs were pre-processed by denoising, filtering, and downsampling, to improve the quality of the signals, reduce interference, highlight the characteristics of the target frequency band, and provide more accurate and reliable input for subsequent analysis and model building. Firstly, a 50Hz notch filter was used to remove power frequency interference. Then a 4-order IIR digital filter was used to filter the LFPs in the target band (3-50Hz) and remove the low-frequency noise. Finally, the filtered signal was downsampled and sliced. The one-dimensional LFPs were converted into two-dimensional gray-scalogram images using Continue Wavelet Transform (CWT) and then converted into color images [28]. The converted images contain sufficient disease information, which is conducive to the status classification of PD patients. Both these distinct forms of images are used as inputs for a deep neural network to conduct a comparative analysis for the classification of LFPs. The scalogram is the absolute value of the continuous wavelet transform coefficient, showing time and frequency in both horizontal and vertical directions, and the pixel values in a color image indicate the intensity or amplitude of the signal at different times and frequencies.

The CWT of a signal $f(t)$ is taken given by the equation (1) [29],

$$CWT(a,b) = \langle f(t), \psi_{a,b}(t) \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

Where $\langle f(t), \psi_{a,b}(t) \rangle$ is the inner product. The results of the CWT are many wavelet coefficients, which are a function of a and b. Here a and b represent the scale and position parameters respectively [18]. The basic wavelet function $\psi_{a,b}(t)$ is usually called the mother wavelet function, and Morlet as the wavelet function can fully capture the signal[18] features and obtain good resolution in both time and frequency domains [29]. By convolving the wavelet function with the input signal for the combination of different scale and position parameters, the local characteristics of the signal can be obtained in different time and frequency ranges, and the time-frequency characteristics and dynamic changes of non-stationary signals like the LFPs can be better captured.

To comply with the VGG16 model's specifications, all input images must be resized to a fixed dimension of 224×224 and normalized before employing the model for feature extraction. Each continuous set of 1000 sample points (1s duration) is individually converted into gray-scalogram images and color images, as depicted in Figure. 1.

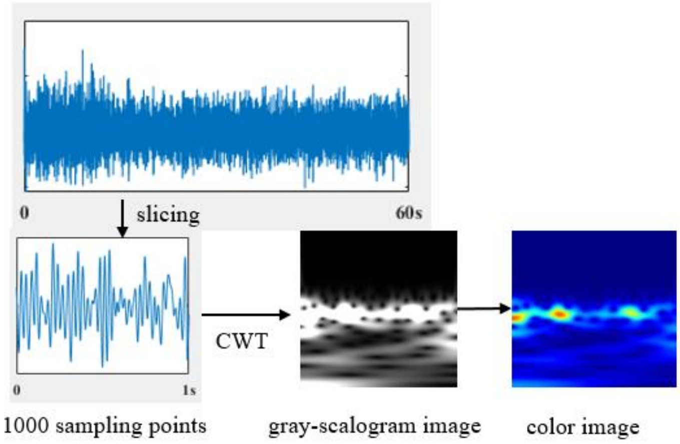

Figure 1: The conversion process of LFP signal to images.

2.3. Improved transfer learning classification model

TL utilizes models pre-trained on large-scale datasets, allowing the migration of their robust feature extraction capabilities to medical image tasks. Benefiting from training on extensive data, transfer learning is widely applied in medical image classification, identification, and segmentation models, consistently demonstrating high accuracy. In the present study, a DCNN based on VGG16 is employed, which has a smaller convolutional kernel and a deeper network structure, and can effectively extract image details and semantic information. Generally, the full connection layer of VGG16 uses the sigmoid activation function to solve the image binary classification problem. In our study, the scarcity of electrophysiological signal data poses challenges in fulfilling the classifier's training prerequisites. In addition, the sigmoid function is prone to saturation when the input value is large or small, which makes it difficult for the model to converge or learn features effectively during training, and thus performs poorly in unbalanced.

RF classifier is an integrated learning algorithm based on a decision tree, which has nonlinear modeling ability and can effectively capture complex nonlinear features in electrophysiological signals. Besides, RF has a strong anti-interference ability to noise. By integrating the results of multiple decision trees and reducing the influence of noise, the accuracy and generalization performance of the classifier can be improved, and it is not easy to overfit electrophysiological signals[30]. Therefore, this study constructs an improved VGG16-RF combined classification model by adding an RF classifier to replace the three fully connected layers used for classification tasks in the VGG16 model.

The classification model of the PD state proposed is shown in Figure. 2. First, LFPs are converted into 224×224×3 2D images and sent to the VGG16 for efficient feature extraction. The numerical value 16 corresponds to a configuration of 13 convolutional layers and 3 fully connected layers. The convolution and pooling layers collectively play a role in extracting features. The convolutional process involves the first stage with two rounds of 64 3×3 filter convolutions, followed by a pooling (stride 2); the second stage with two rounds of 128 filter convolutions, followed by a pooling; the third stage with three rounds of 256 filter convolutions, also followed by a pooling. This pattern is repeated twice with 512 filters, each undergoing three rounds of convolution before a final pooling. Finally, a ‘flatten’ layer is applied to convert the features into a one-dimensional format, reducing storage space. The one-dimensional feature vetors are fed into an RF classifier trained using Bayesian optimization, yielding classification results. This newly developed classifier undergoes dedicated training and operates independently within the neural network throughout the training process. To enhance classification accuracy, this study employs the Bayesian optimization algorithm to automatically search for the optimal parameter combination for the RF classifier. Finally, the model’s generalization ability is evaluated using test data, and a comparative analysis of evaluation metrics for different models is conducted, contributing to the refinement of the overall structure and coherence of the research.

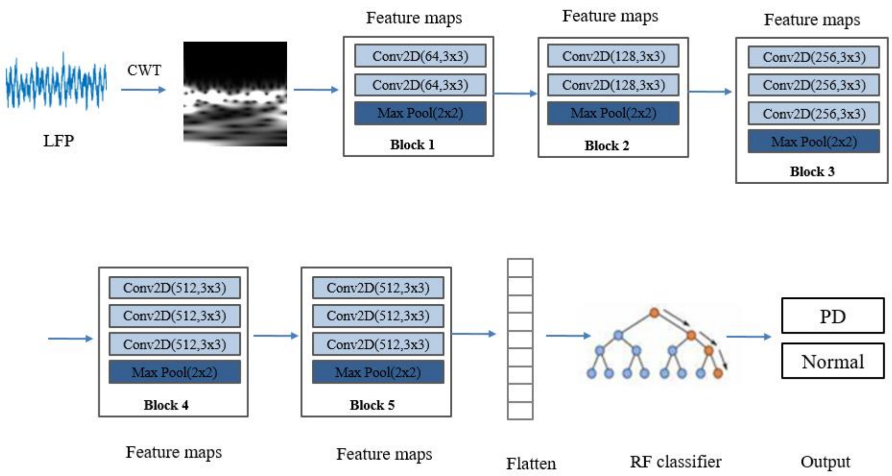

Figure 2: Improved VGG16 random forest classification model

3. Experimental results and analysis

3.1. Experimental settings

To verify the effectiveness of the proposed method in this study, we conduct in-depth experiments and comparative analyses using a variety of strategies:

(1) The comparison of two different presentation forms, gray-scalogram images and color images, fed into different feature extraction networks.

(2) Construct deep neural network VGG16 and use sigmoid activation function to complete binary classification task;

(3) Other mainstream DCNN architectures VGGNet, InceptionV3, ResNet50, and lightweight MobileNet serve as feature extractors;

(4) Compared with traditional feature extraction methods, the power spectral density (PSD) features of LFP signals are extracted according to experience.

3.2. Evaluation indexes

In classification tasks, commonly used indexes for assessing model performance include accuracy (ACC), precision (PRE)、recall (REC) and F1-score, defined as follows[31]:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$PRE = \frac{TP}{TP + FP} \tag{3}$$

$$REC = \frac{TP}{TP + FN} \tag{4}$$

$$F1 - score = 2 * \frac{REC * PRE}{REC + PRE} \tag{5}$$

where TP, FP, TN, and FN denote the number of samples for true positives, false positives, true negatives, and false negatives, respectively. The F1-score is the reconciled mean of precision and recall, which measures the comprehensive performance of the classification model.

3.3. Results and analysis

In this study, we used different networks to automatically extract features combined with different classification methods to identify the pathologic status identification of PD and normal state of parkinsonian patients. The results listed in the table are averages of 10 experiments performed on the test set. Firstly, two image forms of LFP signals, gray-scalogram images, and color images, are fed into different classification networks respectively for feature extraction and classification. The accuracy of the test set is shown in Table 1 and Figure. 3. clearly presents a line graph of accuracy comparison. The observed trend indicates that the accuracy of classifying gray-scalogram images consistently surpasses that of color images, and it can better retain the key information in the time domain, which helps the model focus more on effective feature extraction. On the contrary, although the color image can clearly reflect the amplitude intensity and other information, it may also lead to the introduction of some noise or redundant information, increasing the risk of overfitting and making the model training accuracy unsatisfactory.

Secondly, the results of the proposed method in this paper with networks such as VGG19, InceptionV3, lightweight MobileNet, and ResNet50 as feature extractors to classify the target task are shown in Table 2. The experimental findings reveal that the suggested approach outperforms the classification indexes of other deep DCNN architectures on the test set, and the Bayesian-optimized RF classifier achieves the best results in Accuracy, Precision, Recall, and F1 score evaluation indices, which reach 97.76%, 99.01%, 96.47%, and 97.73%, respectively. At the same time, the classification performance difference of the RF classifier for feature vectors extracted from different DCNN architectures is compared. The differences in the classification performance of the

Table 1: Test set accuracy of two image forms

Method	gray-scalogram image(%)	color image[28](%)
VGG16+sigmoid	88.62	77.56
Proposed Method	97.76	92.47
VGG16+LR	85.74	77.08
VGG16+SVM	84.46	71.47
VGG19+RF	92.63	87.34
InceptionV3+RF	96.15	88.14
MobileNet+RF	95.99	83.17
ResNet50+RF	83.49	75.00

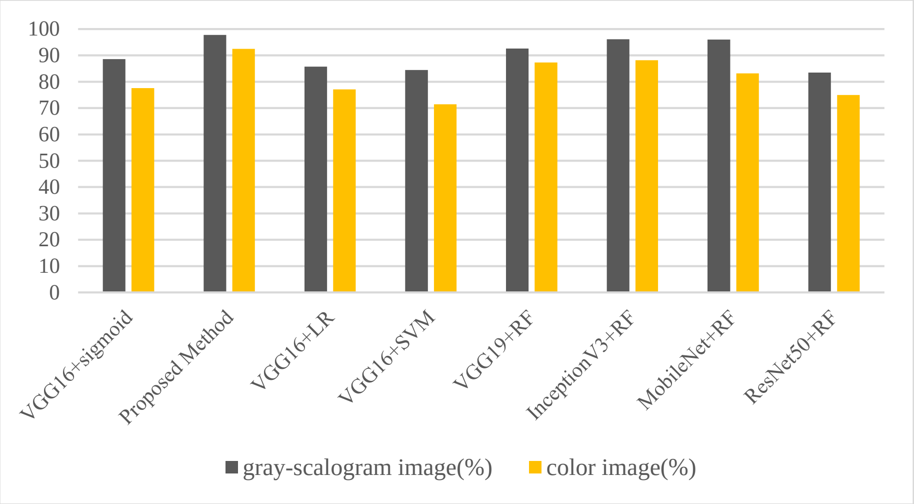

Figure 3: The corresponding accuracy line chart

Table 2: The results of different classification models based on gray-scalogram images

Method	ACC(%)	PRE(%)	REC(%)	F1-score(%)
VGG16+sigmoid	88.62	87.31	90.38	88.82
Proposed Method	**97.76**	**99.01**	**96.47**	**97.73**
VGG16+LR	85.74	85.40	86.22	85.81
VGG16+SVM	84.46	81.16	89.74	85.23
VGG19+RF	92.63	92.90	92.31	92.60
InceptionV3+RF	96.15	97.06	95.19	96.12
MobileNet+RF	95.99	98.97	92.95	95.87
ResNet50+RF	85.26	83.33	88.14	85.67

RF classifier on the feature vectors extracted from different DCNN architectures are also compared, and it outperforms VGG19, InceptionV3, ResNet50, and MobileNet in the Accuracy index by 5.13%, 1.61%, 12.5%, and1.77%, respectively. In addition, the VGG16+sigmoid method, VGG16+LR method, and VGG16+SVM method compare the classification effect of using sigmoid activation function, logistic regression (LR), and support vector machine (SVM) as the classifier respectively under the premise of the same feature extraction. The findings indicate that RF exhibits superiority in dealing with imbalanced data and resisting noise, and it has strong anti-interference ability and better generalization to new data. By comparing the feature extraction and classification methods of different pre-trained networks, it is found that feature extraction is more important for classification accuracy, which in turn has a great impact on the results.

4. Discussion

In this work, a transfer learning classification algorithm based on the combination of pre-training model VGG16 and random forest is investigated to address the two key problems of using electrophysiological signals for disease state recognition of PD patients in the clinic, i.e., feature extraction and small and unbalanced data volume. By fully mining the features learned by the pre-trained model of VGG16 on large-scale data, the sensitivity of the model to the disease state of the patient is improved. At the same time, the introduction of random forest effectively alleviates the challenge of data imbalance and makes the algorithm more suitable for small sample situations. This study provides a feasible solution for the application of electrophysiological signals in disease state recognition of Parkinson’s patients.

In this paper, after performing a 1D to 2D image conversion of LFP signals, we have investigated by experimentally comparing the two forms of time-frequency images for feature extraction and classification using several pre-trained models. The experimental results show that a high level of accuracy can be obtained for both grayscale and color images. However, the grayscale image has low information complexity because it contains more layers of time-frequency information, which makes it easier for the model to capture key features that help in classification.

Compared to other DCNN models, VGG16 shows better feature extraction capability on the target domain studied in this paper. Although the deep structure can better capture the complex features of the image, the results show that in the feature extraction task of non-smooth signals such as electrophysiological signals, the deeper network structure may lead to overfitting or computational burden, on the contrary, VGG16's relatively shallow network structure and moderate model complexity make it show better performance in the medium-sized image classification task. This shows that the VGG16 network outperforms other models in terms of feature extraction capability and has been well transferred in the field of medical signaling. In the algorithm research based on VGG16 deep transfer learning[32][33], the extracted features are usually passed to softmax classifier for training, and fine-tuning the fully-connected layer of the model to improve the accuracy of the target task. Therefore, in practical applications, since the characteristics of different tasks and datasets may affect the effectiveness of the model, the solution for a specific problem still needs to be evaluated and selected in detail according to the actual situation.

Traditional machine learning relies on the knowledge and experience of domain experts and requires the design of algorithms to extract features of relevant information, such as time- and space-domain information [34], Lyapunov exponents [16], etc. This approach suffers from difficulties in feature engineering and requires a lot of time and effort to select and construct appropriate features. The models used are usually linear or statistically based with limited expressive power to capture complex nonlinear relationships in the data. In contrast, the deep transfer learning algorithm proposed in this study can use multi-layer neural networks for feature learning, thus learning higher-level abstract feature representations without any manual extraction. The powerful representational ability of deep learning to capture complex nonlinear relationships in data makes it perform well on tasks in many domains.

The amount of data for electrophysiological signals such as LFP is too small to meet the training requirements of large-scale deep learning models. To address this problem, this study, based on the idea of transfer learning, utilizes a model that has been trained on a large-scale dataset and migrates its knowledge to a small dataset to improve the classification performance on the small dataset, based on which an RF classifier is added to solve the overfitting problem related to unbalanced data. In addition, the selection of the RF classifier's hyper-parameters is very important to the model performance, and the setting of the hyperparameters directly affects the model's complexity, generalization ability and fitting degree to the training data. Compared with traditional methods such as manually adjusting parameters or grid search, the Bayesian optimization algorithm can automatically search the parameter space, reducing the workload of manual parameter tuning. By establishing a probabilistic model between the parameters, the correlation between the parameters can be taken into account, and the optimal parameter combination can be found more efficiently, which in turn improves the performance of the RF classifier.

5. Conclusion and future work

STN-DBS is an effective treatment for advanced PD patients, LFP signals recorded by electrodes implanted at the STN contain rich information related to the disease as well as the patient's state. In this paper, a new deep transfer learning method was proposed to identify the PD state and normal state of Parkinsonian patients, so as to realize real-time monitoring of patients' disease, trigger stimulation when they are in PD state, and stop stimulation when they are in the normal state, which does not need to extract features manually and effectively solves the overfitting problem associated with too small or unbalanced data. Compared with other deep pre-trained models, the proposed method has good classification accuracy, and the evaluation metrics in all aspects are better than other experimental strategies with DCNN architecture as a feature extractor. In the field of medical signaling, the superposition of deep learning's automatic feature extraction and random forest classifier yields a better classification accuracy, which effectively solves the performance of the classifier under small data volume and far surpasses the traditional machine learning methods. In addition, the experimental process found that the conversion to gray-scalogram images is more suitable for classification studies of electrophysiological signals.

Due to the lack of human electrophysiological data for technical and ethical reasons, which is prone to overfitting, is one of the reasons for the lower classification accuracy, so increasing the experimental samples of the disease is the focus of the next step. Multimodal feature fusion[35] is also a research direction for the studies related to the disease state of Parkinsonian. Apart from the LFPs, other multimodal data can be utilized, such as brain images, motion data, etc. Fusion of LFPs with other data can provide more comprehensive and accurate identification and monitoring of Parkinson's disease state.

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