The application of deep learning techniques in the electroencephalogram (EEG) analysis

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Abstract

In this paper, we show in a nutshell a characteristic of EEG signal, approaches in the analysis of this biosignal and the possible usage in the diagnosis. It will be depicted also the recent application of deep learning methods likewise the advantages of new type of neural networks: neural ordinary differential equations (ODE). ODE networks seems to be great promise to EEG analysis and its accuracy.

1 Introduction

Electroencephalography is a non-invasive diagnostic method for analyzing bioelectrical brain function. The test relies on the placement of the electrodes on the skin surface, which record changes in potential or differences in the potential of various parts of the brain and after appropriate amplification create a record from them, so-called an electroencephalogram.

This record registers the occurrence of waves, i.e. observable structures with a characteristic frequency range and repeatable shape. These are frequencies in the range 1 - 100 Hz and the amplitude five to several hundred μV.

The first study of the brain's electrical potential in humans was conducted in 1924. EEG first began to be analyzed for its pathologies. Nowadays, it finds application in a brain-computer interface (BCI), analysis of emotions, mental workload, also in psychology. For instance, the ability to concentrate may be tested or mental disorders like attention-deficit hyperactivity disorder (ADHD), schizophrenia, depression. EEG can be applied to detect epilepsy, brain tumors, Alzheimer's disease, and dementia. It is also useful in checking the depth of anesthesia, sleeping pattern analysis [1, 2].

2 The challenges in EEG analysis

The EEG signal has a low signal-to-noise ratio (SNR). For this reason, it is necessary to apply filters to eliminate artifacts to obtain a high-quality signal. The denoising is necessary to receive data, which points out brain activity uninterrupted by for instance: the eye movements, the human replacement likewise the cardiac bioelectrical activity, the movement and changes in the tension of muscles, or the technical. Importantly, the EEG is a non-stationary signal. For this reason, it is challenging to classify a given signal (statically differentiated) by the classifier, as well as learning based on an EEG fragment. What's more, this signal varies individually, which makes it even more difficult to analyze them [2].

3 Deep learning in the analysis of EEG

It is commonly used the classic signal analysis and newer solutions like the deep learning for EEG study. The transition to the frequency domain can be also applied beforehand.

Deep learning methods are used for preprocessing, feature extraction, classification, and regression of the EEG signal. Deep learning can be used directly for prediction or it is possible to first extract features using machine learning methods and then classify the data [3].

Currently, the architectures such as fully-connected layers (FC) [4], convolutional neural network (CNN) [5], recurrent neural network (RNN) [6], generative adversarial network (GAN) [7], transfer learning [8], long short-term memory (LSTM) [9], restricted boltzmann machines [10], deep belief networks (DBNs) [10], autoencoders (AEs) are being used for EEG analysis [14]. The application of GAN or transfer learning allows increasing the amount of data, which is very desirable in such a diverse signal as EEG. Data augmentation enables to significantly increase the quality of model classification [3].

4 Related work

One of the interesting applications of the EEG is the analyzing of sleeping patterns. The sleeping influences on learning, dealing with emotion or memory storage. The sleep study is called polysomnography (PSG) and consists of EEG, electrocardiograms (ECG), electrooculograms (EOG) also electromyograms (EMG) tests. Koushik, Amores and Maes [11] offered a real-time sleep staging using deep learning on a smartphone. It was only regarded as one channel of EEG (Fpz-Cz at 100 Hz) and dissected by the time-disturbed 1-D Deep Convolutional Neural Networks. The usage of wireless technique is significant because the all connection (minimum 22) to the device is uncomfortable for the patient and can disrupt the process of sleeping. In this case, the connection was achieved thanks to the Bluetooth Low Energy (BLE). The data was obtained from the Sleep-EDF database from Physionet-bank and was divided into five classes. The result of classification is available after 30 sec. The model achieved 83,5% accuracy.

Supratak et al. [12] proposed DeepSleepNet for automatic sleep stage scoring. They used raw single-channel EEG without any feature extractions. The earlier extraction of features is defective due to the resistance of the detection of transitions between sleep stages. The authors mixed CNN (to extract time invariants features) with bidirectional-LSTM (to catch the transition between the sleep stages). The data steams from public datasets Montreal Archive of Sleep Studies (MASS) and Sleep-EDF. The obtained macro F1-score is for MASS 86.2% - 81.7 % and for Sleep-EDF 78.9% - 73,7%.

One of the most frequently analyzing neurological anomaly is the detection of seizures and the diagnosis of epilepsy. The EEG is a good monitoring tool to find out this disease. The wavelet transform and energy analysis are too used to obtain features. However, Ahmedt-Aristizabal, Fookes, Nguyen, and Sridharan applied the solution to raw EEG signals [13]. They applied LSTM networks. This architecture allows remembering information from previous inputs. The data originated from the Department of Epileptology, University of Bonn. To validate data was applied cross-validation. The average accuracy was 95.54 % and accuracy (AUC) 0.9582. Whereas, Ye Yuan et al. [14] computed first the features, in this case, spectrograms. They claimed that it is better to analyze data in the time-frequency domain than only in time. This approach provides more contextual information about EEG. They used neural networks with stacked sparse denoising autoencoder SSDA and ConvA (denoising and convolutional autoencoder) to detect seizures. The data comes from the Children's Hospital in Boston. The accuracy was 94.37 % and f1-score 85.34 %.

It is needed to isolate a useful signal from the recording of brain waves to operate the brain-computer interface. Machine learning methods are used for this purpose. For the first time, Lawhern et al. extracted several features at once from a signal using a noise-resistant EEGNet. It is a flexible CNN network that has achieved high performances for four diverse datasets

(P300 Event-Related Potential, Feedback Error-Related Negativity, Movement-Related Cortical Potential, Sensory Motor Rhythm). For instance, the EEGNet gave results AUC = 0.9054 on the P300 test dataset [15].

5 Reducing number of training samples and increasing accuracy

A new groundbreaking approach was presented at the end of 2018 in the field of neural networks. This type of network is a continuous-depth model, so-called Neural Ordinary Differential Equations [16]. It is not a classical sequence of hidden layers. The outcome is calculated thanks to the black-box differential equation solver. This novelty can easily deal with a heterogeneously sampled time series, which is one of the biggest advantages. Secondly, it is parameter efficiency. It can be also regulated the depth of the model and balance between the accuracy and the cost of evaluating the model, depending on the needs. Additionally, the designed approach allows being trained with constant memory cost as a function of depth.

This ODE network could be regarded as a continuous version of the residual network. The residual blocks in a neural network are the discrete version of ODE solver. This new approach has provided a vector field of smooth transformations [16].

Mathematically, the calculations between blocks in the residual network are described by the equation:

$$h_{t+1} = h_t + f(h_t, \theta_t), \tag{1}$$

where h_t is the hidden information at time step t ($t \in \{0, \dots, T\}$) in the current block, $f(h_t, \theta_t)$ is the learned function of the current hidden information, θ_t is the set of the parameter of the model (the weights and the biases), h_{t+1} is the hidden information in the next block.

If the time step goes to zero, the following equation (ODE) will be obtained:

$$\frac{dh(t)}{dt} = f(h(t), t, \theta), \tag{2}$$

where h(t) is the change of the hidden information in the infinitely small time, $f(h_t, \theta_t)$ is the learned function of the current hidden information

6 Conclusions

The comparison of the usage neural network in the area of EEG presented in [3] depicts that the residual neural network architecture is one of the best among other applied methods. According to paragraph 5, it can be concluded that solutions with the usage of ODE networks should give better outcomes than received so far in the area of EEG classification. It is possible to obtain low-latency results, especially for time series, for example, in the case of EEG. For our future research, this approach could be applied in the field of wireless classification EEG during sleep. It also might be possible to obtain better outcomes for anomalies diseases. This type of network can learn about data as continuous function depended on time, not only discrete points.

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