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Review on Automatic Ocular Artifacts Removal in EEG Using Deep Learning (Combinations of CNNs and Long Short-Term Memory (LSTM)

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Abstract - **Electroencephalography (EEG) is very tedious for analysis of the dynamic behaviour of human brain. Practically, the analysis of the biomedical signal is no simple as those signals are very dynamic with respect to time, researcher have to make many computations on the different static and dynamic parameters which consumes much time. Accuracy of the signal from object depends on the experimental environment setup and environmental conditions. Enhanced research is conducted on automated EEG signal analysis using artificial intelligence and computer-aided technologies. This would make fast and accurate results. The main objective of this research is to remove unwanted and noisy signals which are mixed in the original signal generated by human brain using deep learning (DL) architectures. We can use the databases available on Kaggle, Web of science which are made free for testing purpose. All datasets and samples will be collected, then analysed and will be processed with different neural architectures and compared. DL in biomedical signal processing is efficient in various research applications. It is very helpful diagnosing the common neurological disorders diagnosis.**

Keywords: EEG, DL, OAs, EOG, DCNN, ICA.

1.Introduction

Automatic ocular artifacts removal in EEG using deep learning

Ocular artifacts (OAs) are one the most important form of interferences in the analysis of electroencephalogram (EEG) research. OAs removal/reduction is a key analysis before the processing of EEG signals. For classic OAs removal methods, either an additional electrooculogram (EOG) recording or multi-channel EEG is required. To address these limitations of existing methods, this paper investigates the use of deep learning network (DLN) to remove OAs in EEG signals. The proposed method consists of offline stage and online stage. In the offline stage, training samples without OAs are intercepted and used to train an DLN to reconstruct the EEG signals. The high-order statistical moments information of EEG is therefore learned. In the online stage, the trained DLN is used as a filter to automatically remove OAs from the contaminated EEG signals. Compared with the exiting methods, the proposed method has the following advantages: (i) non use of additional EOG reference signals, (ii) any few number of EEG channels can be analyzed, (iii) time saving, and (iv) the strong generalization ability, etc. In this paper, both public database and lab individual data for EEG analysis are used, Researcher will compare the proposed method with the classic independent component analysis (ICA), kurtosis-ICA (K-ICA), Second-order blind identification (SOBI) and a shallow network method.

Electroencephalogram (EEG) is a nonlinear and time variable signal test that measures the electrical activity of the brain [1], [2]. It is widely used in tasks involving the study of the brain dynamics such as cognitive tasks, development of epileptic seizure prediction models, and sleep stage detection. It is used in diagnosing many brain disorders.

Electrical signal generated by brain propagates over the entire scalp. Therefore, several electrodes are required to capture those signals with high spatial resolution [3]. Apart from brain information, these electrodes often capture noise, such as environment interference, experimental errors, and physiological artifacts [4].

Environmental interference is generated by external disturbances, e.g., main power leads, electromagnetic waves and different activity of organs [5]. Experimental errors are usually related with poor electrode and its installation, incorrect scalp cleansing while testing, and experimental subject motion resulting from daily life routine. These errors, that frequently distort the EEG signal, are quite difficult to remove, even with artifact removal approaches [4], [6]. Physiological artifacts are alterations generated from other physiological processes, such as eye movements, muscle activity (chewing, swallowing, talking, and scalp contraction), and cardiac activity. Therefore, these artifacts cannot be fully avoided even in controlled environments. Physiological artifacts generally present a spectrum overlapping the frequencies of interest of the EEG signals [5].

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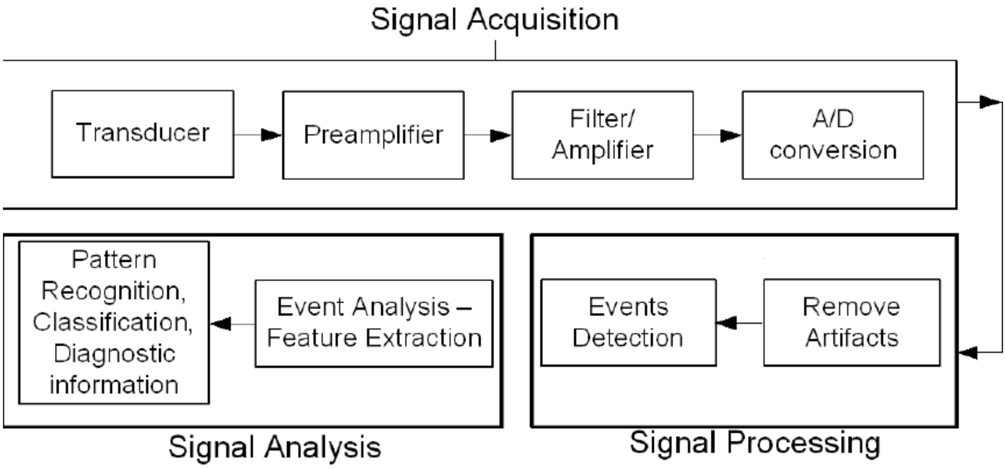

Figure 1: Biomedical Signal Acquisition System

In signal data acquisition transducers converts activity signal to equivalent electrical signals. Isolation Preamplifiers isolates the subject from physical set up of experimental setup which is again followed by amplifiers , filters and Analog to digital convertor for signal strengthening and conditioning which comes under instrumentation process. Next part is artfact removal which is the main aim of experiment.

In general, EEG artifacts can be minimised when signal acquisition is performed under supervised conditions. However, in tasks such as epileptic seizure prediction, EEG signals have to be continuously acquired over several days [11], [12] but practically it is impossible to avoid artifacts during such long observation process. Although a possible solution would be to detect and to remove noisy segments, this removal would result in a high loss of information. It needs to develop artifact removal techniques to eliminate, or at least attenuate, noisy data from the EEG signals while preserving neural Signal information [4], [6].

Simple digital filters can be used for removing undesired frequency spectrum bands from the EEG signals, e.g., power-line component. However, these filters may not be used to separate EEG from artifacts with overlapped frequency spectra, as it is the case of experimental errors and physiological artifacts. For this reason, other techniques have been considered to improve EEG filtering. Linear regression algorithms were the most used methods for artifact removal until the 1990s due to their lower computational complexity. Source decomposition methods, such as wavelets and empirical mode decomposition (EMD) approaches, aim at separating the neural information from the artifacts by means of decomposing each signal channel into different waveforms. However, similarly to simple digital filtering, wavelets cannot remove artifacts that overlap frequencies of interest without removing important data. Also, although the EMD is able to adapt itself to nonlinear and non- stationary signals, such as EEG, it is computationally complex and thus difficult to be used in real-time. Furthermore, both approaches require thresholds tuning to select the components of interest [4]–[6].

Linear blind source separation (BSS) methods are the most used for artifact attenuation [5], [6], [13]. These methods focus on the separation of the signals into their independent sources, by assuming that the measured signals result from the sum of the linear mixture of sources. Generally, EEG signals are considered to be generated by independent dipolar sources that linearly mix together. Thus, linear BSS algorithms tend to perform well when separating brain signals from artifacts [13], [14]. These methods do not require any external information about the type of artifacts, making them an important solution whenever artifact template signals are not available. However, these methods require visual inspection to distinguish between brain and noisy sources. Some authors have overcome this drawback by developing classifiers to label the independent sources [15]. Although these classifiers may solve the visual inspection task, linear BSS approaches still require expensive computational time, which makes these ones difficult to be used in real-time scenarios.

2. Materials and Methods

This section presents the methods which can be considered to prepare the dataset used in this study as well as the procedures followed to develop and evaluate the targeted approach.

A) Dataset

Dataset will contain long-term epileptic EEG signals from N number of patients, along with seizure metadata acquired during pre surgical monitoring. From these datasets, some of contain scalp EEG, some contain intracranial EEG, and few contain both types of EEG recordings. These recordings Researcher can obtain with different sampling

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rates, which vary from few Hz to kHz, over several days. This study is framed in the context of epileptic seizure prediction. To develop epileptic seizure prediction models, Researcher have to consider data ranging from 4.5 hours before the beginning of the leading seizure until its onset. This selection was made based on the assumption that EEG signals, within the mentioned period, contain information from both normal and pre-seizure brain states.

Before proceeding to the development of seizure prediction models, Researcher believe it is crucial to remove artifacts that may be present over the long-term EEG signals. However, performing visual inspection of the ICs of the EEG signals is a tough and time-consuming task, therefore demanding for an automatic procedure to remove noise from this type of data. Based on this, Researcher have to use the aforementioned data to develop EEG denoising models, which can be later used to preprocess data before applying further specific methods in any EEG-based application (eg. Epileptic seizure prediction models).

B) Data Preparation

We can filter the 4.5-hour EEG signals using a 0.5-100 Hz bandpass 4th-order Butterworth filter and a 50 Hz 2nd-order notch filter, with the purpose of removing DC component, high frequency noise and power line interference, respectively. Researcher can use Notch filter and Comb filters to reduce periodic artefact Then, Researcher have to remove noise generated by experimental errors, such as flatlines, saturated segments, and abnormal peaks. Afterwards, Researcher can divide the 4.5-hour EEG signals in 10-minute segments. Later, Researcher can identify channels with experimental errors that Researcher can remove and fixed them using spherical interpolation method available in EEGLAB toolbox. Researcher can present the duration of both raw data and data after the described preprocessing steps (preprocessed EEG data).

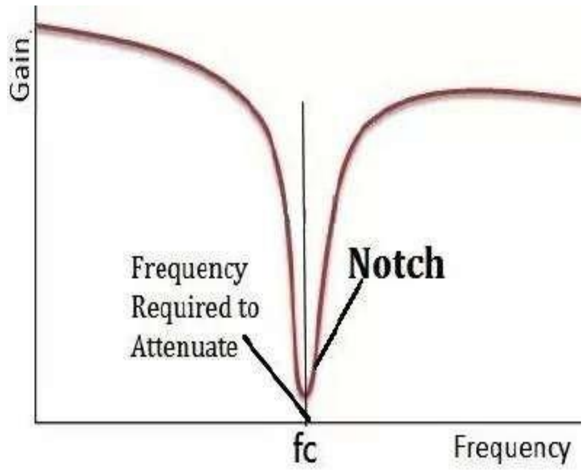

Figure 2

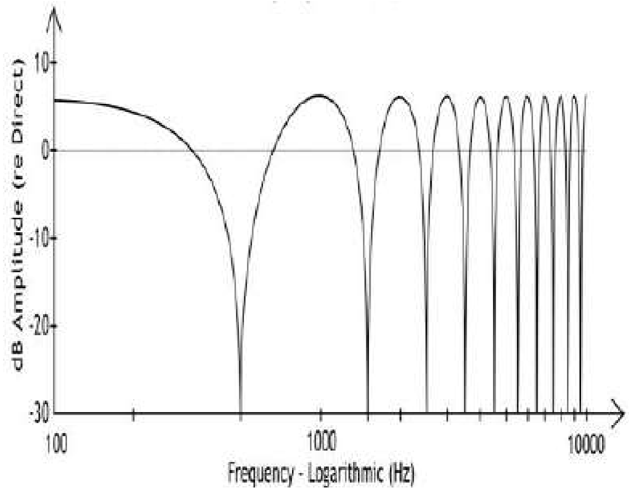

Figure 3

After removing experimental errors, Researcher will re-reference the EEG segments to average reference and processed them using extended-infomax ICA (Independent Component Analysis) available in EEGLAB. Afterwards, two experts visually inspected the ICs of the EEG segments of both training and test sets with the purpose of eliminating noisy ICs. However, two different procedures were performed for both sets. EEG segments that were already analysed by one expert were not analysed by the other, i.e. each expert analysed different segments from the training set. Test set was, firstly, analysed by both experts, independently. Then, discordant samples were inspected by the two experts together with the purpose of producing a set, validated by both, to evaluate our approach. After the visual inspection, the segments from training and test sets were reconstructed using the non-noisy ICs. Finally, Researcher will have a training set and a test set with two different versions for the same EEG segment: the segment before visual inspection of the ICs (noisy segment), and the segment after the visual inspection of the ICs (target segment).

C) EEG Artifact Removal Deep Convolutional Neural Network

The proposed EEG artifact removal method, based on deep convolutional neural networks (DCNNs), was designed to automatically remove noise from EEG segments. Although the ICA reconstruction is linear, the decisions performed by the experts to classify the ICs are nonlinear. Therefore, a nonlinear model is required to automatically remove noisy artifacts from the EEG segments.

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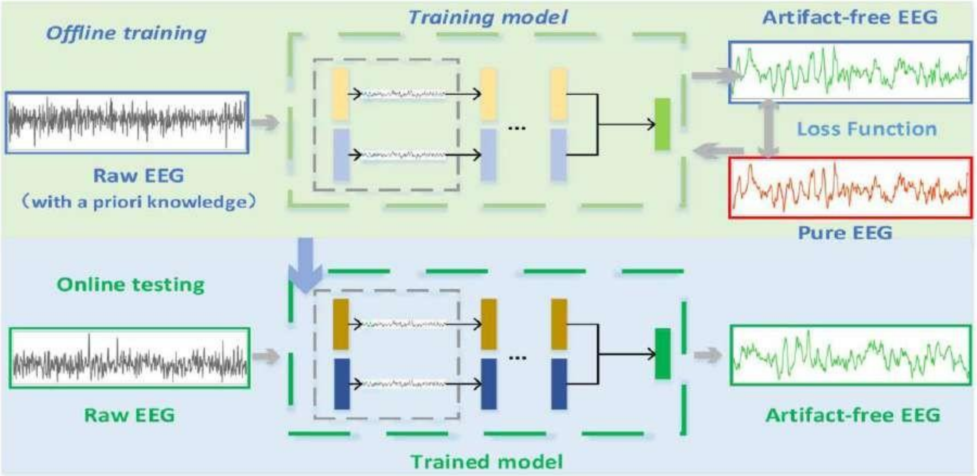

Figure 4: CNN (Convolutional Neural Network)-LSTM (Long Short-Term Memory) model

DCNNs contain convolutional layers and layers with several possible activation functions. Convolutional layers [28] include several filters, used for extracting features from the input data, optimised during learning process. Layers with activation functions are used for controlling the information which is transferred to the following layer. Rectified linear unit (ReLU) function is commonly used given its nonlinear behaviour and fast computation [28]. However, this nonlinear function can produce dead neurons, which means that some neurons of the network will output a zero value for different inputs. Leaky ReLU function was introduced in order to overcome this disadvantage [29]. It solves the problem by outputting a smaller portion of the negative inputs instead of nullifying them.

We can develop an architecture based on three convolutional blocks, i.e., three sets of three convolutional layers followed by leaky ReLU activation function. The convolutional layers, used in each block, become wider as DCNN depth increases. ICA may be viewed as a single convolutional layer with a linear filter that covers all channels at a time. Therefore, researcher considers that more than one nonlinear convolutional layer is required to allow the model to better learn such task.

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We have to develop an architecture based on three convolutional blocks, i.e., three sets of three convolutional layers followed by activation (leaky ReLU) function which may vary on researchers' methodology. The convolutional layers in each block, become wider as DCNN depth increases. ICA may be viewed as a single convolutional layer with a linear filter that covers all channels at a time. Therefore, researcher considers that more than one nonlinear convolutional layer is required to allow the model to better learn such task. Since the various scalp EEG channels are not independent from each other, and as ICA processing covers all channels at the same time, Researcher will produce a model able to remove artifacts from all the channels, simultaneously.

As we know that deep learning models improve with the increasing of depth and width. Thus, Researcher can an architecture that combine both factors taking into account the available computational resources (4 GPU NVIDIA Quadro P5000 with 16 GB GDDR5 RAM). The number of filters per layer starts at 32 and doubles from one block to the next. The last convolutional layer is used for converting the data back to the initial dimensions. Small filters are useful for exploring fine details of the data and have less computational cost than large filters. Filters with size 1 were not considered because these ones are not able to analyse the values around the unit under analysis. Filters with an even size were also not used

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because these ones cannot maintain the symmetry around the unit under analysis resulting in data distortions across the layers. Finally, Researcher will perform grid-search experiments using filters with size 3 and filters with size 5 and verify that the results were similar or not. Therefore, all convolutional layers comprise filters with size 3 making the training of the model faster and less prone to over fit. As researcher does not want to reduce the sample size across the layers, a stride of 1 for every convolutional layer must be used. All activation layers use leaky ReLU function and consider an α of 0.2 as suggested by Xu et al. [22].

D) Training and Validation

The training set can be further filtered by the number of eliminated ICs. Therefore, the EEG segments, with more than half of their ICs classified as noise can be discarded. For training the DCNN, Researcher will need to use optimisation function, Loss function usually used root mean squared error (RMSE) gives more significance to larger reconstruction errors, thus leading the algorithm to focus in artifacts with larger amplitude, independently from the range of values of the target signal . For reducing this bias, Researcher can replace RMSE by the relative root mean squared error (RRMSE). RRMSE [6] normalises the RMSE by dividing it by the root mean square (RMS) of the target EEG segments. Simultaneously, the model can be evaluated, every new epoch, using the validation subset, with the purpose of saving the one that obtained the lowest validation loss. At the end of each run, the model with the intention of being tested with the completely independent test set.

E) Comparison with Different Artifact Removal Models

We need compare our DCNN model with 1D-ResCNN model from [26] and with an automatic ICA model based on extended Infomax ICA and MARA classifier. As the 1D-ResCNN is not publicly available; Researcher developed it following the procedures presented by the authors. The MARA model is publicly available in EEGLAB toolbox. All models can be tested in a computer with an AMD Ryzen 5 2600 CPU 3.4 GHz, 64 GB of RAM, NVIDIA RTX 2060 Super, and Linux Ubuntu 20.04 LTS. The extended Infomax ICA-MARA can be tested in Matlab 2019b whereas the DCNN and 1D-ResCNN models Researcher have to teste using Tensorflow 2.0 and Keras 2.3 from Python 3.8 in Anaconda Spyder 4. The inference phase of the DCNN models can be performed using CPU rather than GPU with the purpose of comparing it with the extended Infomax-MARA model, which has to be performed in CPU. Additionally, testing the models on the CPU allows approximating the simulation to a real environment where GPUs are usually less available.

F) Evaluation Metrics

Standard statistical metrics Researcher can use are , RMSE for measuring reconstruction error, RRMSE for measuring normalised reconstruction error, Pearson correlation coefficient (PCC) for measuring the linear correlation between the denoised and the target segments ,and Signal- to-noise ratio (SNR) difference for measuring the noise attenuation. We need to calculate RMSE, RRMSE, and PCC for both noisy and denoised segments. In other words, Researcher can compare the noisy segments and the denoised segments with the target segments. In this way, Researcher can inspect whether the DCNN model approximates the noisy data to the target data.

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