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EEG signal denoising and arifact removal using machine learning techniques

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dedication

Abstract

This thesis aims to investigate the use of machine learning techniques for EEG signal denoising. The first part of the thesis is dedicated to the introduction of the problem, the statement of the research questions and an overview of the basic concepts. The second part is dedicated to history and the state of the art of the signal analysis, and more specifically of the EEG signal analysis and denoising methods. The third part is dedicated to the machine learning techniques. The fourth part is dedicated to the experimental results and the last part is dedicated to the conclusions and future work.

Contents

Chapter 1

Introduction

The chapter is built as follows: in the first section there is a brief introduction of the problem, the reasons that led to the choice of the topic and the outline of the thesis. In the second section there is the statement of the research questions. In the third section there is a brief description of the basic concepts.

1.1 Problem statement

What is EEG in the first place and why is it important? Electroencephalography (EEG) is a non-invasive technique used to measure the electrical activity of the brain. EEG signals are still among the less explored ones in the field of signal processing, despite their widespread use in clinical practice and research. In recent years, there has been a growing interest in developing denoising methods for EEG data to improve their quality and reliability.

The main objective of this thesis is to investigate and compare different EEG denoising methods, and to evaluate their performance in terms of signal quality, artifact removal, and preservation of underlying brain activity. Specifically, we will focus on the most recent machine learning techniques, such as generative adversarial networks (GANs), autoencoders (AEs), and deep learning (DL) models. We will also investigate the potential of combining different denoising methods to improve the performance of EEG denoising.

Overall, this thesis aims to provide a better understanding of the strengths and limitations of different EEG denoising methods, and to help researchers and clinicians make informed decisions when selecting the most appropriate denoising method for their EEG data analysis. By improving the quality of EEG signals, we can enhance our understanding of brain function and ultimately contribute to the development of more effective diagnostic and therapeutic tools for neurological disorders.

1.2 Research questions

The research questions are the following:

- How can we remove artifacts from EEG signals?

- How can we exploit the most recent machine learning techniques for EEG denoising?
- What are the strengths and limitations of these new methods?
- What are the performance of these new methods?

1.3 Basic concepts

In this section we will introduce the basic concepts that will be used in the thesis. The first part is dedicated to the EEG signal, the second part is dedicated to the EEG denoising.

1.3.1 EEG

When talking about EEG,in this thesis, we are referring to the electroencephalogram, in particular we are interested in the EEG waves. Electroencephalogram (EEG) waves are the patterns of electrical activity that are recorded by EEG measurements. These waves have different frequencies and amplitudes, and they reveal different states of brain activity. We divide the EEG waves in 5 main categories depending on their frquency:Alpha, Beta, Theta, Delta and Gamma waves.

Alpha waves are typically observed when someone is relaxed and awake, with a frequency of 8-13 Hz. Beta waves, on the other hand, are associated with active cognitive processing and have a higher frequency of 14-30 Hz. Theta waves are usually observed during drowsiness or light sleep and have a frequency of 4-7 Hz, while delta waves are typically observed during deep sleep and have a frequency of less than 4 Hz.

Gamma waves have a frequency of 30-100 Hz and are associated with higher cognitive functions such as attention and memory. Mu waves, with a frequency of 8-13 Hz, are observed in the sensorimotor cortex during movement and motor planning.

It's important to remember that EEG waves are not distinct entities but represent a continuous spectrum of activity that can be influenced by various factors such as task demands, attention, and emotion. Interpreting EEG waves requires expertise and context since different patterns of EEG activity may reflect different states of brain activity depending on the individual and the experimental conditions. Furthermore, research has shown that EEG waves can be useful in clinical diagnosis and prognosis, as well as in the assessment of cognitive function and brain injury. Therefore, understanding the various EEG waves and their characteristics can provide valuable insights into brain function and activity.

1.3.2 EEG denoising

EEG signals can be influenced by various factor that alter the real waves originated from neural activities, those factors are defined as artifacts. The artifacts can be classified as [1]:

- intrinsic artifacts: artifacts that depend on physiological sources, such as ocular artifacts (EOG) that come from eye movement and blinking, muscle artifacts (EMG) and cardiac artifacts (ECG)
- extrinsic artifacts: artifacts generated from external electromagnetic such as power line noise sources.

Denoising of EEG data is an essential task to be able to work on data and to extract meaningful information from it. The denoising process is complex and it does lead to different level of quality of the data depending on the method used, the quality of the data and the type of artifact.

There are several challenges[2] related both to single methods characteristic and general artifact removal. For example, some methods are computationally expensive and require a lot of time to be applied, some methods are not able to remove all kind of artifacts, some methods require a lot of data to be applied. On a general level, there is the problem of the lack of a standard method to evaluate the quality of the denoised data and the EEG applications are not yet fuly commercial, so there hasn't been a sufficient investment in hardware and software to make the denoising process easier.

However the main goal of latest studies is to find a method that can denoise from all kind of artifacts and that can be used in a flexible and fast way, to accomodate the needs of all the different EEG applications.

Chapter 2

Literature review

In this chapter we will present the main methods used for the denoising of EEG data. In the first part we will focus on the methods used for the removal of artifacts from signals in general, in the second part we will present the ones specifically deveolopped for the denoising of EEG data and in the third part we will explore the latest, machine learning related, methods.

2.1 Signal analysis

In this section we will present the basic techniques used for the analysis of signals that constituted a base for the ones developed for the analysis of EEG data.

2.1.1 Fourier transform

The first method used for the removal of artifacts from signals is the Fourier transform[3]. The Fourier transform is a mathematical tool used used to decompose a signal into sine and cosine functions, that are used as basis functions for the original signal. It is defined as:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}dt \tag{2.1}$$

where $f(t)$ is the signal and ω is the frequency. The Fourier transform of a signal is a complex number, which can be decomposed into its real and imaginary parts. The real part of the Fourier transform is called the amplitude and the imaginary part is called the phase.

2.1.2 Fast Fourier transform

The Fourier transform is a very useful tool for the analysis of signals, but it is computationally expensive. The Fast Fourier transform (FFT)[4] is an algorithm that is used to calculate the Fourier transform of a signal in a shorter time: it reduces the time nedded to Nlog (N), obtaining a speed-up of a factor of N/log (N). The FFT is used in many different fields of science such as signal processing, image processing, etc...

2.1.3 Short Time Fourier Transform

The Short Time Fourier Transform (STFT)[5][6] is a method used to calculate the Fourier transform of a signal. It is used with non stationary signals to find the frequency components of a signal over time. The STFT equation is defined as:

$$S(\tau) = s(t) \cdot h(t - \tau) \tag{2.2}$$

where $s(t)$ is the signal, $h(t)$ is the window function and τ is the time.
The STFT can be used to find the frequency components of a signal:

$$S(\omega) = \frac{1}{2\pi} \cdot \int_{-\infty}^{\infty} s(\tau) \cdot h(t - \tau) e^{-i\omega t} d\tau \tag{2.3}$$

where $s(\tau)$ is the signal, $h(t)$ is the window function and ω is the frequency.

2.1.4 Wigner-Ville distribution

The Wigner-Ville distribution (WVD)[7] is a method used to provide the description of a signal in the time-frequency domain with higher resolution. It is described by the following equation:

$$W(\tau, \omega) = \int_{-\infty}^{\infty} s(t - \tau) \cdot s^*(t - \tau) e^{-2\pi\omega\tau} d\tau \tag{2.4}$$

where $s(t)$ is the signal, τ is the time and ω is the frequency. The main problem of the WVD is that it introduces the so called cross terms. In fact, for a signal

$$x(t) = x_1(t) + x_2(t) \tag{2.5}$$

the corresponding WVD is:

$$WVD(t, f) = WVDx_1(t, f) + WVDx_2(t, f) + 2Re[WVDx_1x_2(t, f)] \tag{2.6}$$

where $2Re[WVDx_1x_2(t, f)]$ is the cross term which is removable at the expense of a loss of resolution.

2.1.5 Wavelet transform

The wavelet transform[8] is a method used to find the frequency components of a signal over time. It is used with non stationary signals and it provides a better time-frequency resolution than the STFT and the WVD since it gives a better simultaneous time-frequency localization.
It expresses the signal as a linear combination of mother wavelets. The wavelet transform is defined as:

$$W(\tau, \omega) = \int_{-\infty}^{\infty} s(t - \tau) \cdot \psi(t - \tau) e^{-2\pi\omega\tau} d\tau \tag{2.7}$$

where $s(t)$ is the signal, τ is the time, ω is the frequency and $\psi(t)$ is the wavelet function.
A possible choice for the wavelet function is the Morlet wavelet:

$$\psi(t) = \frac{1}{\sqrt{2c\pi}} \cdot e^{-\frac{t^2}{2c^2}} \cdot e^{i\omega_0 t} \tag{2.8}$$

where ω_0 is the central frequency of the wavelet and c is the width of the wavelet.

2.1.6 Matching Pursuit

The Matching Pursuit (MP)[10] is a greedy algorithm used to approximate a signal with a linear combination of basis functions called time-frequency atoms, selected from a dictionary of functions.
A general family of time-frequency atoms can be generated by scaling, translating and modulating a single window function $g(t)$ as follows:

$$g_\gamma(t) = \frac{1}{\sqrt{s}} \cdot g(\frac{t-u}{s}) \cdot e^{i\xi t} \tag{2.9}$$

where γ is the tuple (s, u, ξ) s is the scale, u is the translation and ξ is the frequency modulation.
The algorithm aims to find a set of atoms $\gamma_1, \gamma_2, \ldots, \gamma_N$ that best approximate the signal $f(t)$, i.e.:

$$f(t) \approx \sum_{i=1}^{N} a_i \cdot g_\gamma(t) \tag{2.10}$$

where a_i are the expansion coefficients.
The vector f can be decomposed into

$$f(t) =< f, g_\gamma > g_\gamma + Rf(t) \tag{2.11}$$

where R_f is the residual vector after approximating f in the direction of g_γ.
MP iteratively decomposes the residue R_f by projecting it on a vector of D that matches R_f at best.

2.2 EEG denoising

The denoising of EEG signals is performed using techniques developed from the field of signal processing, but more suited to the specific characteristics of EEG signals and artifacts. Here we present the most common methods.

2.2.1 Regression

The regression method[11], considers the EEG signal to be a linear combination of the artifacts and the clean EEG signal. In particular, the EEG signal is modeled as:

$$EEG = \alpha \cdot EMG + \beta \cdot EOG + \gamma \cdot ECG + \delta \cdot CEEG \tag{2.12}$$

where EEG is the registered EEG signal, EMG is the muscle artifact , EOG is the ocular artifact, ECG is the cardiac artifact and $CEEG$ is the clean EEG signal. The regression coefficients $\alpha, \beta, \gamma, \delta$ are estimated using the least squares method. The regression method is simple and fast, but it doesn't take into account the temporal correlation between the artifacts and the EEG signal, the so called cross terms. Furthermore it requires the knowledge of the artifacts signals.

2.2.2 Blind source separation

Blind source separation (BSS)[12] is a class of methods used to separate a mixture of signals into their individual components. There are several BSS algorithms, all based on an unsupervised component separation. The most common BSS algorithms are the Principal Component Analysis (PCA), the Principal Component Analysis (ICA) and the Canonical Correlation Analysis.

Principal Component Analysis

The PCA[13] is a method used to find a linear transformation of the mixture signals that maximizes the variance of the transformed signals. First, data are standardized by subtracting the mean and dividing by the standard deviation.

$$\mathbf{Z} = (\mathbf{X} - \mathbf{m})/\mathbf{s} \tag{2.13}$$

Then, the covariance matrix is computed.

$$\mathbf{C} = \frac{1}{n-1}\mathbf{Z}^T\mathbf{Z} \tag{2.14}$$

The eigenvectors of the covariance matrix are the principal components of the data while the eigenvalues are the variances of the principal components.

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i \tag{2.15}$$

The principal components found by projecting x onto those perpendicular basis vectors are uncorrelated, and their directions orthogonal. This scheme is very efficient in redundancy reduction, and can be said to maximize the amount of information spanned by a subset of dimensions of the initial vector.

Independent Component Analysis

The ICA[14] is a method used to find a linear transformation of the mixture signals that maximizes the non-Gaussianity of the transformed signals. It consists in decomposing the signal in Independent components and discarding the ones containing artifacts. In blind source separation, the original independent sources are assumed to be unknown, and we only have access to their weighted sum.[15]
The signal is modeled as:

$$x(t) = \sum_{i=1}^{N} a_i \cdot s_i(t) \tag{2.16}$$

where $x(t)$ is the mixture signal, $s_i(t)$ is the i-th source signal and a_i is the mixing coefficient.
The ICA algorithm aims to find the source signals $s_i(t)$ and the mixing coefficients a_i that maximize the non-Gaussianity of the mixture signal $x(t)$. It is based on the assumption that the sources are statistically independent.

Canonical Correlation Analysis

The CCA[16] is a method used to find a linear transformation of the mixture signals that maximizes the correlation between the transformed signals. More specifically, CCA identifies two sets of variables, X and Y, and finds linear combinations of X and Y that are maximally correlated. These linear combinations are called canonical variates. The first canonical variate is the linear combination of X and Y that has the highest correlation, and each subsequent canonical variate is the linear combination that has the highest correlation subject to being orthogonal to the previous canonical variates.

2.2.3 Empirical Mode Decomposition

The EMD[17] is a method used to decompose a signal into a set of intrinsic mode functions (IMFs). The EMD is a data-driven method that does not require any prior knowledge of the signal.
It decomposes a signal into a finite number of intrinsic mode functions (IMFs), which are functions that capture the local behavior of the signal. EMD is based on the concept of sifting, which involves iteratively extracting the local maxima and minima of the signal to generate IMFs. The basic steps of EMD are as follows:

- Given a signal $x(t)$, find all of its local maxima and minima.
- Interpolate between the local maxima and minima to create an upper and lower envelope for the signal. This step effectively eliminates the high-frequency components of the signal and captures its slowly varying behavior.
- Calculate the mean of the upper and lower envelopes to obtain a first IMF, $c_1(t)$.
- Subtract $c_1(t)$ from the original signal to obtain a new signal, $r_1(t) = x(t) - c_1(t)$.
- Repeat steps 1-4 on the residual signal $r_1(t)$ to obtain the second IMF, $c_2(t)$.
- Continue this process until a stopping criterion is met, such as the number of IMFs or the amplitude of the residual signal falling below a certain threshold.

The resulting IMFs are functions that oscillate around zero with a characteristic scale and capture the local behavior of the signal at different scales. The final residual signal is a monotonic function that represents the long-term trend of the signal.

2.2.4 Filtering techniques

2.3 Machine learning

2.3.1 Fully connected neural network

2.3.2 Convolutional neural network

2.3.3 Recurrent neural network

2.3.4 Long short-term memory

2.3.5 Generative adversarial network

2.3.6 Autoencoder

Chapter 3

Methodology

3.1 Data

The data used in this thesis are the EEG signals of the EEGdenoiseNet dataset[18]. It is comprehensive benchmark dataset that proves to be an exemplary resource for training and evaluating deep learning-based EEG denoising models. It is composed of 4514 clean EEG epochs, 3400 EOG epochs, and 5598 EMG epochs, making it an inclusive and extensive dataset that caters to the needs of researchers and practitioners alike.

The incorporation of these various types of epochs in the dataset enables to generate a considerable number of noisy EEG epochs with their corresponding ground truth data. As a result, this compilation has proven to be an invaluable resource for model training and testing, facilitating an enhanced understanding of EEG denoising.

3.2 Preprocessing

3.3 Denoising

3.4 Machine learning

Chapter 4

Experimental results

4.1 Results

4.2 Discussion

Chapter 5

Conclusions and future work

5.1 Conclusions

5.2 Future work

Chapter 6

Appendix

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