Perspective of EEG Signal Analysis for Depression Diagnosis

Chendong Zou

Department of Aeronautics and Astronautics, Fudan University, Shanghai, China

19300290009@fudan.edu.cn

Abstract. Depression has long been a severe threat to mental health and to a certain extent, it precludes the regular physical mechanism of patients susceptible. As neuroscience advancing, Electroencephalogram (EEG) was put into diagnosis of depression which once highly relied on subjective judgments of doctors. The usage of EEG perfectly circumvents subjectivity and serves as a noninvasive and inexpensive measure. With algorithm advancing, the signal would be filtered after which the features of it pass through extraction and classification. The whole procedure aims to analyze the symptom of depression from the perspective of waveform and reveal the intrinsic relationship between depression and signal's feature. The paper would take a review on the current circumstances of depression, illustrating several methods based on EEG that have been proved effective in application at present stage and summarize brief drawback or limitations of current methods. This article may serve as an approach to rudimentary understanding of depression and the objective solutions using EEG.

Keywords: Electroencephalogram; Depression; Artifact; Algorithm; Deep Learning.

1. Introduction

Depression has an extremely high incidence worldwide. In China, the prevalence rate has been elevating for decades while patients of depression at the same time suffered from high recurrence rate and fatality rate. If the view is broadened to a worldwide scale, depression is the dominant mental disease across the world, with about 40% out of all mental patients, moreover, the trend has been exacerbated by COVID-19 in recent years. Of all depression patients, 6.8% have a lifelong sequela. It's predicted that by 2030, depression will have outdone any other diseases to top the list of fatal diseases.

Previously, time-consuming diagnosis and subjective treatment failed to solve this problem, so experts strive to ameliorate this problem with Brain-Computer Interface (BCI) technology, to offer timely diagnosis and individual treatment. Researches have shown that depression patients are disparate from healthy control subjects in EEG's waveforms and rhythms. Waveforms spontaneously produced from the brain contain a wide range of frequencies and might differ according to particular section of the scalp.

A variety of artifacts that interfere with normal EEG signals are obstacles before the process [1]. By reviewing various EEG artifact removal methods and the analysis of the application status, viewers can attain an overall picture of the preparing process and take a look into signal extraction and classification using specific algorithms [2]. After the artifacts are out, features of the EEG signal can be processed in plentiful types of methods, by which the researchers can obtain useful information to diagnose the presence of depression or even its extent.

This work aims to review the typical and recent research on EEG diagnosis for depression, give a picture of the principle, application and drawbacks of EEG methods. This paper presents the status quo of depression to lay the foundation for illustrating basic artifacts removal methods and how to extract features from them. After that, drawback and limitations will be introduced to depict a relatively full picture of the whole procedure.

2. Methods & Related Works

2.1 Related Works

Electricity of a single cell primarily derives from electrical properties of membrane. Given disparate density of ions in extracellular and intracellular environment, the density contrast inevitably forms diffusion between those two parts and causes potential difference which serves as the prerequisite for bioelectricity. And of course, the lipid membrane is not always open, which places interval making the membrane potential inconstant. The ions of different type, mainly Na^+,$K^+$and Cl^-.

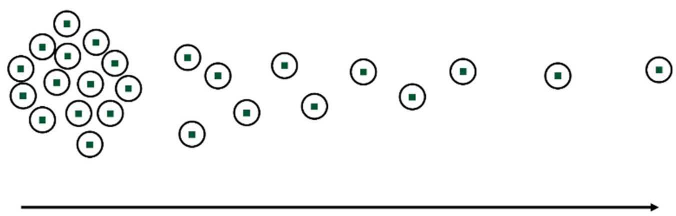

Fig 1. A demonstration of diffusion current

As is shown in figure above, ions diffuse in the form of current. When the diffusion of ions is not erratic any more, the whole procedure reaches a rather steady state. The membrane potential is at equilibrium which is constant, and the "Nernst Potential" can be calculated as below:

$$V_m=(V_i-V_e)=\left(\frac{RT}{Z_pF}\right)\ln\left(\frac{[C_p]_e}{[C_p]_i}\right) \quad (1)$$

where V_m refers to membrane potential, R represents gas constant, F represents Farady and T is a constant. So, the value of RT/F as thermal energy remains unchanged at a certain room temperature (e.g., 27°C). C_p represents concentration of ions, while the brackets of $[\ ]_e$ and $[\ ]_i$ respectively represent extracellular and intracellular ion concentration.

Given the prerequisite that Na^+, $K^+$and Cl^- are major ions involved, the equation of (1) can be specified. And since if someone is to apply Nernst equations, he must need to know variation of and in the membrane, so to predigest the situation, Goldman assumption that V varies linearly is introduced, making the equation laconic in most general environment. Though not all ions can be at equilibrium, it can be solved for steady state using the Goldman Equation:

$$V_m=\left(\frac{RT}{F}\right)\ln\left(\frac{P_{Na^+}[Na^+]_e+P_{K^+}[K^+]_e+P_{Cl^-}[Cl^-]_i}{P_{Na^+}[Na^+]_i+P_{K^+}[K^+]_i+P_{Cl^-}[Cl^-]_e}\right) \quad (2)$$

where V_m refers to membrane potential, RT/F serves as a constant thermal energy, and P represents permeability constant. As far as ideal state is concerned, (2) can calculate membrane potential to a considerably accurate extent.

After ions being stimulated for some time, action potential will fluctuate till a particular time when the depolarization process is brought in to sustain the potential, the potential comes back to resting state. Neurons carrying action potential contact each other and therefore deliver neuron signal through the means of signal, to make it familiar, brainwave. The mechanism of bioelectricity is the foundation for further research on EEG signal and thus plays indispensable role when it comes to biological currents.

2.2 Artifacts Removal

Brainwave can be readily interfered during signal acquisition; thus, artifacts are inevitable obstacles to surmount which can be cataloged into physiological and non-physiological kinds. With non-invasive brain-computer interfaces prevailing, EEG signal can be collected with much ease. However, its feebleness leads to artifacts involvement, confrontation with 'false' EEG signal can easily disturb diagnosis and features of EEG signal for depression patients may be omitted, ending up in a tragedy.

Non-physiological artifacts mainly consist of signals around 50Hz aroused by electric wire or electromagnetic interference. Physiological artifacts take place in response to physical activity, for instance, ocular artifacts such as blinks generate signal that can easily overlap with pure brainwave. Another case in point is electrocardiograph artifacts deriving from cardiac motion, but fortunately artifacts of this kind appear with certain periodicity and could be filtered comparing to ocular ones.

2.2.1 Independent Components Analysis (ICA)

EEG signal is characterized by nonlinearity and randomness, stratified by frequencies and after signal is distorted by artifacts everything seems to be assorted. Inspired by outlook of cocktail, scientists came up with the idea of separating them using specific algorithm [3]. Given the presence of a non-Gaussianity, the correction which modifies the expected Gaussian function estimate for the measurement of signal frequency, and independence of individual statistics, optimization algorithm can be used to restore original brainwave based on blended signal.

A commonly practiced modification of ICA is called InformaxICA proposed by Bell and Sejnoski in 1995 based on maximum likelihood principle of information theory [4]. ICA by now is the dominant strategy against signal artifacts, whichever artifacts including ocular, Electrocardiograph or myoelectricity can be separated from pure brainwave according to statistical independence.

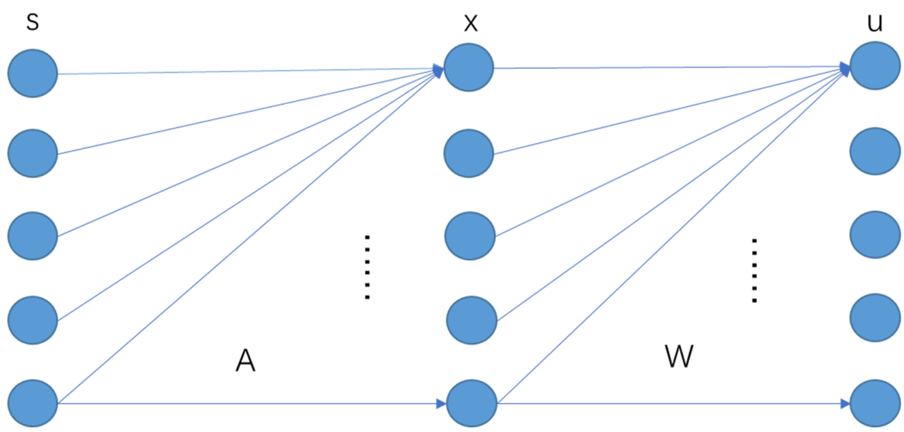

Fig 2. Brief procedure of ICA

As for the procedure above, s refers to independent signal and x refers to mixed signal under the circumstances of interferences. Respectively, A and W represents for mixing matrix and demixing matrix which are circumscribed under equations:

$$X=AS\ ;S=WX\ ;W=A^{-1} \tag{3}$$

where X and S are vector composed of signal x and s. After applying likelihood function to optimize the probability of sample, process of ICA is done.

2.2.2 Wavelet Transform (WT)

WT is another proper method for artifacts removal [5]. Wavelet is an oscillation localized in time, and it can concentrate on certain period of time domain and frequency domain to analyze its feature, which surmounts the incapability of Fourier Transform in analyze of a certain section rather than the whole.

For EEG signal, on most occasion, wavelet frequency of ocular artifact and artifact including exercise motion usually gather below 10Hz and can be insulated from pure brainwave, around 30Hz, using wavelet transform [6].

Its basic idea is to analyze how much of a wavelet is involved in a particular signal, for a particular location. Then this scale of wavelet is slid through the entire signal to access at each step to multiply the signal and wavelet. Here comes the value for the wavelet scale at every single time step. Afterwards, other scale is put into process repetitively.

Local and temporal information can be extracted simultaneously in WT, which circumvents the drawback of Fourier Transform and analyzes well confronted with low frequency signal.

2.2.3 Summary

Currently, comprehensive methods prevail. ICA and WT are combined to reach a better standard. For example, FastICA can be used together with Discrete Wavelet Transform (DWT) to elevate its accuracy and the artifact removal can be achieved on a higher level.

2.3 EEG Signal Analysis on Depression

EEG signal has been praised for high resolution ratio and sensitivity. Researches has shown that EEG signal of patients with depression is featured by hemispheric asymmetry and patients response differently towards stimulation. Since the diagnosis of depression is still a process involving subjectivity considering disparate algorithm and theory, the paper would take a brief review on four types of theoretically viable methods.

2.3.1 Method A

The first method was proposed based on dataset from more than two hundred patients including 92 depression patients and 121 healthy control [7]. The EEG signal presents weak, nonlinear, and time-sensitive characteristic, which presents typically complex dynamics. The features of EEG are divided into time domain and frequency domain. As for the time domain features, peak, variance, skewness, kurtosis, and Hjorth parameter are collected to evaluate the signal, as for frequency domain, it shows up with centroid frequency and absolute power.

Table 1. Features used in the feature extraction process

Name	Property
Centroid frequency (relative/absolute) Power (relative/absolute) Peak Variance Skewness Kurtosis Hjorth	Linear features
Power-Spectrum Entropy Shannon Entropy Correlation Dimension Kolmogorov Entropy	Nonlinear features

Then Fast Fourier Transform (FFT) is applied to compute the signal and mean amplitude of power spectrum. Researches collected EEG signal under circumstances of silence and stimulation respectively, using method including Kalman derivative, discrete wavelet transform (also applied in certain kind of artifact removal) and adaptive prediction error filter. Nearly three hundred linear and nonlinear features were extracted and put into minimal Redundancy Maximal Relevance (mRMR) method to reduce dimensions of the feature space [8]. And the accuracy has reached 80% which implies the method to be quite reliable on current stage.

2.3.2 Method B

Another proposed method for depression diagnosis using EEG signal make full use of computer science and interdisciplinary procedure. Two kinds of deep learning algorithms: Convolutional Neural Network (CNN) together with Long-Short Term Memory (LSTM) are applied to arrest temporal dependency in EEG signal and analyze the result subsequently [9].

Data in time and frequency domain are processed by FFT and modelling procedure includes layers connection and application of LSTM. Then the numbers of LTSM layers are to be decreased while the connected layers to be elevated. The output is transformed through CNN, participating in LSTM and is ultimately employed to assist the automatic detection of depression.

The method greatly retrench the time consumption and complexity of calculation, thus enjoying good reputation for depression diagnosis.

Fig 3. General steps for depression diagnostics using EEG signals

2.3.3 Method C

Depression diagnosis can also be achieved by applying Deep Learning (DL) and Machine Learning (ML) simultaneously as researches and computation have shown. The method links DL and ML together, drawing comparison between them to analyze the whole situation [10]. Three electrodes are placed on the frontal scalp to collect EEG signals, after which interference, noisy signals, are to be removed by WT and signals of varied frequency undergo features extraction as well as matrix construction to adjust to fit in the deep learning models.

As the figure3 shown above, after pre-processing features of different types are extracted. Algorithms, namely Artificial Neural Network and Deep Belief Network, are applied to the detection procedure and it turns out that Deep Belief Network together with extracted features (linear/nonlinear) exceeds the other one. Besides, this method convinces researchers that Beta wave power serves a vital role in accuracy elevating.

2.3.4 Method D

The fourth method comes into being using three-dimensional convolutional neural network to detect depression [11]. There's a section of brain called brain default mode network region (DMN) which means a brain network that includes several senior cognitive areas such as the medial prefrontal cortex, posterior cingulate cortex, and parietal regions. DMN is featured by network where regions are deactivated during cognitive tasks with clear goals.

And this specific region is located from 19-channel EEG signals. After process of artifacts removal, output of the pre-processing is collected contiguously with the interval being 2 seconds to fit into partial directed coherence algorithm. Then the results of partial directed coherence algorithm are used to overlay channels of DMN area. The network is made up of several layers to classify depression and is a rather new method requiring further observation.

3. Drawbacks and Discussion

Though methods are plentiful and data collected previously under rigorous supervision, limitations still exist as the results attained from EEG signal are featured by erratic stability when disparate sample are introduced into the diagnostics of depression. Before feature extraction and classification, artifacts removal remains erratic and thus large-scale application of EEG signal analysis for depression has a long way to go.

3.1 Major Problems

When it comes to depression detection, drawbacks are inevitable as researchers have not yet elbow through the obstacle to accurate analysis. In this paper, several common limitations are to be presented with specific cases. To begin with, researchers are always struggling against feasibility issue since any minor deviation at an earlier stage may lead to tremendous distinction ultimately. Researchers have a fantasy for accuracy not considering complexity which build up obstacles and unless clinical situations can be thoroughly improved there's no way to develop such methods compatible with practical settings.

A recent published method has trouble with implementation [12], arousing controversy among experts, and on account of its youth, the method will go through test of time to affirm its accuracy. Nineteen channels are set up for EEG signals and technologies as prerequisite for the method are hard to be imposed under clinic settings, thus making this novel idea a theoretically successful one while impractical when it comes to operation. Another case in point is a method using CNN-based models depicted above [13]. Comparison is drawn from three CNN-based models using DL approach and consequentially convolutional neural based models called MobileNet tops the three alternatives. But because of it complicacy the method is scarcely available to carry out under clinical settings either.

Another shortcoming to face is lack of data which disturbs most of the methods given that sufficient clinical manifestation really counts since the patients are reluctant to get involved at early stage. As is the common sense, diagnostics of mental diseases unlike that of physical diseases, can change accordingly since the mental state of a depression patient may take a turn for the better as the thing depressing him vanishes, on the contrary, nothing unless miracle can bring changes to physical state. A novel approach for depression detection is troubled with data paucity and there's no way for it to overcome problems of overfitting despite data segmentation and batch normalization [14].

3.2 Discussions

There's right now no method of universality can be used for depression diagnosis using EEG signals and even before feature extraction, no existing approach can remove artifacts appropriate for all kinds of EEG signals. Machine Learning and Deep Learning has already amazed researchers of its practicability and great capability to solve problems, accord with expectations of the firm, ML and DL are gradually taking the dominant role of depression detection using EEG signals.

Apart from focus on depression diagnosis, other perspectives are worth considering. Depression brings economic issues both personally and socially, patients and their family are worried about high expenses during diagnostics while the whole healthcare system may be confronted with severe difficulties if the total number of patients with depression is in great amount [15]. Given these non-scientific factors, diagnosis for depression is always delayed which results in irreversible symptoms as the depression goes from minor to major [16].

In general, polished scientific methods together with non-scientific factors contribute to proper diagnosis for depression and with the public awareness of the importance of mental health, things seem to progress in a better direction. But impediment still exist, so the public should lay emphasis on the issue from as many aspects as possible.

4. Conclusion

Depression, as the potential killer inside people's brain, is threatening human health at an unprecedented level and for the past few years diagnosis using EEG signals has come into the spotlight for its relative objectivity comparing to diagnosis through inquiry. The prerequisite for brainwave generation is bioelectricity and Nernst Potential together with Goldman Equation are used to explain the recording of EEG signals. Artifacts removal is the subsequential process which lowers the interference from both physiological and non-physiological factors. Independent Components Analysis and Wavelet Transform are commonly applied in this procedure to overcome previously unsolved nonlinearity and randomness which are exactly the characteristics of EEG signals. EEG signal analysis on depression is made up of pre-processing, feature extraction and classification. Four theoretically pragmatic methods are introduced among which deep learning and machine learning play crucial parts. The first method based on data brings in Fast Fourier Transform another algorithms to extract linear and nonlinear features while the second applies convolutional neural network together with long-short term memory to arrest the feature. Then, the third approach draws comparison between different features extracted to attain the conclusion that deep belief network outdoes others and the fourth uses partial directed coherence algorithm to build up a network classifying depression features. Drawbacks are pretty obvious if the range of application is broaden to a greater period of time. Some methods have no regard for clinical settings, thus making it impossible to implement under ordinary environments. Another limitation to be confronted with is that most methods are too novel so that data collected is far from enough. To sum up, EEG signals applied in depression diagnosis has greatly changed the situation and despite numerous obstacles ahead, this approach will definitely make its way to a better practical and universal method in days to come.

References

[1] Li Yingjie, Li Yuling, Yang Banghua. A review of EEG emotion recognition based on deep learning [J]. Beijing Biomedical Engineering, 2020, 39(6): 634-642.

[2] Luo Ruipeng, Feng Mingke, Huang Xin, Zou Renling, Li Dan. A Review of Research on EEG Signal Preprocessing Methods [J/OL]. https://doi.org/10.16180/j.cnki.issn1007-7820.2023.04.005.

[3] Jung T P, Makeig S, Humphries C, et al. Removing electroencephalographic artifacts by blind source separation[J]. Psychophysiology,2000,37(2):163–178.

[4] Hyvärinen A, Oja E. A fast fixed-point algorithm for independent component analysis[J].Neural Computation,1997,9(7):1483-1492.

[5] Hazarika N, Chen J Z, Tsoi A C, et al. Wavelet Transform[J]. Signal Processing,1997,59(1):61-72.

[6] Sharma R K.EEG signal denoising based on wavelet transform[C]. Coimbatore: Proceedings of the International conference of Electronics, Communication and Aerospace Technology,2017.

[7] Hanshu Cai, Jiashuo Han, Yunfei Chen, Xiaocong Sha, Ziyang Wang, Bin Hu, Jing Yang, Lei Feng, Zhijie Ding, Yiqiang Chen, Jürg Gutknecht, "A Pervasive Approach to EEG-Based Depression Detection", Complexity, vol. 2018, Article ID 5238028, 13 pages, 2018.

[8] Peng, H. Long, F. and Ding, C. "Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 8, pp. 1226–1238, 2005.

[9] Saeedi A, Saeedi M, Maghsoudi A, Shalbaf A. Major depressive disorder diagnosis based on effective connectivity in EEG signals: a convolutional neural network and long short-term memory approach. Cogn Neurodyn. 2021 Apr;15(2):239-252. doi: 10.1007/s11571-020-09619-0. Epub 2020 Jul 26. PMID: 33854642; PMCID: PMC7969675.

[10] Cai H, Sha X, Han X, Wei S, Hu B. Pervasive EEG diagnosis of depression using Deep Belief Network with three-electrodes EEG collector. In: 2016 IEEE international conference on bioinformatics and biomedicine (BIBM). IEEE; 2016. p. 1239–46.

[11] Khan DM, Yahya N, Kamel N, Faye I. Automated diagnosis of major depressive disorder using brain effective connectivity and 3D convolutional neural network. IEEE Access 2021;9:8835–46.

[12] Seal A, Bajpai R, Agnihotri J, Yazidi A, Herrera-Viedma E, Krejcar O. DeprNet: a deep convolution neural network framework for detecting depression using EEG. IEEE Trans Instrum Meas 2021;70:1–3.

[13] Uyulan C, Ergüzel TT, Unubol H, Cebi M, Sayar GH, Nezhad Asad M, Tarhan N. Major depressive disorder classification based on different convolutional neural network models: deep learning approach. Clin EEG Neurosci 2021;52(1):38–51.

[14] Kang M, Kwon H, Park JH, Kang S, Lee Y. Deep-asymmetry: asymmetry matrix image for deep learning method in pre-screening depression. Sensors 2020;20(22): 6526.

[15] Stewart WF, Ricci JA, Chee E, Hahn SR, Morganstein D. Cost of lost productive work time among US workers with depression. Jama 2003;289(23):3135–44.

[16] Mehltretter J, Fratila R, Benrimoh D, Kapelner A, Perlman K, Snook E, Israel S, Armstrong C, Miresco M, Turecki G. Differential treatment benefit prediction for treatment selection in depression: a deep learning analysis of STAR* D and CO-MED data. Computat Psychiatr 2020;4:61–75.