Review of Drowsiness Detection Machine-Learning Methods Applicable for Non-Invasive Brain-Computer Interfaces

Marjan Gusev, Nevena Ackovska, Vladimir Zdraveski
Emil Stankov, Mile Jovanov, Martin Dinev, Dejan Spasov
Faculty of Computer Sciences and Engineering,
Sts Cyril and Methodius University in Skopje,
North Macedonia

Xiaoyan Gui, Yanlong Zhang,
Li Geng, Xiaochuan Zhou
School of Electronics and Information Engineering,
Xian Jiaotong University,
Xiâan, China

***Abstract*—This review focuses on the analysis of non-invasive BCI methods, and in particular in the state-of-the-art machine learning-based methods for EEG acquisition. EEG as a tool can be used to detect various states concerning human health, but it can also be used to detect the human's states such as alertness, interest and even drowsiness. In this paper we focus on this important issue and present some of the ML techniques that can be used, as well as the methodology for noise detection and elimination while using EEG.**

***Index Terms*—EEG, Brain-Computer Interfaces, Noise elimination**

I. Introduction

This paper aims at reviewing a non-invasive brain-computer interface (BCI) by applying Machine Learning (ML) algorithms on an Electroencephalography (EEG) signal for drowsiness detection. In addition, we also present state-of-the-art techniques comparing the Neural Networks (NN) and Deep Learning (DL) methods.

Brain-computer interfaces (BCIs) are used to translate brain signals into commands that the device can understand [1]. In invasive BCIs a surgical implantation of electrode arrays is directly implanted into the subject's brain, being risky since the electrodes are connected with the neurons of the subject's brain, although they result with high accuracy.

Non-invasive BCIs use EEG signals, which do not require surgery and are measured through the surface of the scalp, which introduces a low signal-to-noise ratio compared to that of invasive BCIs, such as poor spatial resolution, limitations with usage of higher-frequency signals, as well as blurring and/or dispersing the electromagnetic waves obtained by the neurons. However, they are easy to wear, require no surgery and other invasive activities, and therefore the ethical principles of their usage are more easily obtained.

These BCI devices can detect the person's intent, even before the action is performed. Even more so, BCI devices can be used in affective computing, in entertainment and game research, multimodal interaction research etc [2].

There is significant previous work that refers to the concept of Non a invasive BCI, the first mention starting in 1973 [3]. The initial published reports on non-invasive BCI approach include applications such as the control of a cursor in 2D using visual evoked potential [4], and the control of a buzzer using CNV [5]. The first control of a physical object, a robot, using a brain alpha rhythm is reported in 1988 [6], and a control of a text written on a screen using P300 is reported in 1988 [7]. The other significant findings in this area follow after these pioneering results. In the 2000s this topic becomes increasingly important and many scientists become involved in BCI research. Today there are even commercial BCI devices from different companies, such as NEUROSKY [8] and EMOTIV [9] that can be used for research and other uses.

On the other hand, the machine learning techniques are becoming a great tool for BCI support. Most of the applied NN, ML and DL methods include Random Forest (RF), Convolutional Neural Network (CNN), Hidden Markov Model (HMM), Multilayer Perception (MLP), Recurrent neural network (RNN), DBN (Deep Belief Network), and Fully-connected networks (FCNN). Additional methods use discrete wavelet transform (DWT), linear discriminant analysis (LDA), Linear Regression (LR) and Liquid State Machine (LSM).

We review state-of-the-art in ML-based drowsiness detection, and analyse deeper the EEG research and acquisition, along with analysis of noise detection and elimination methods in EEG signals. The application barrier of EEG as a brain-computer interface is that the user should perform offline training before using it. At the same time, the accuracy of the drowsiness degree is too low when using a classifier (such as two or three classifications) for drowsiness detection.

II. ML-based drowsiness detection

Many concepts and proof of concepts have been designed in the past focusing on the ML application to the drowsiness detection. Mainly, there are three approaches, such as (1) recognizing the movement or driving pattern of the vehicle, (2) drivers' health/psychophysical measurements and (3) advanced driver monitoring using camera or computer vision based technique [10].

Driving behaviour was a very frequent subject of analyses. Authors in [11] analyze the driver-vehicle-environment and prove the ML-based techniques capability. A system that uses the real-time monitoring to ensure a safe driving in [12] does not include any expensive sensors, and therefore, it is cost effective compared to biometric or vision based techniques. At the end, the drowsiness detection process is modelled as a binary classification problem with a ML-based classification scheme. DB ML-approach recognition developed on top of an existing threshold-based monitoring system is explored in [13] where RF and NN are used as a hybrid solution.

Pupil-based and gaze metrics are used for driver's psychophysical measurements [14] to detect the driver's cognitive state on the simulations and in-car environments. The efficiency of different ocular parameters can estimate the cognitive load and derive the driver's cognitive state, while classifying varying states and psychometric tests in different light conditions. Brain signals are used to classify the emotions in a human brain [15], targeting valence and arousal classes examining the data produced by the brain itself. DL models are used in the form of CNN and NN to analyze the brain waves data and classify them.

Following the recent trend of vision and camera based approaches, a CNN solution embedded in smart connected glasses [16] detects the driver's drowsiness based on the eye blinks. A methodology for drowsiness detection [17] is based on the eye patterns of people, who are monitored by video streams. Computer vision and ML were used to implement a real-time system, using a web camera, making it a quite low-cost approach. Drowsiness rules for blink patterns are applied, retrieved from the neuroscience literature. A yawning detection model [10] is suggested to prepare advanced, more realistic datasets that will include pictures from real driving conditions.

III. EEG Research

The historical landmark of EEG in 1929 provided a novel neurologic and psychiatric diagnostic tool at the time [18] introducing alpha and beta waves. Later on, in 1934 epileptiform spikes were specified, and clinical use was founded in 1935, spreading the technology as a trustworthy indication of brain activity quickly proven to be extremely useful.

Since then the EEG research is becoming increasingly popular due to the non-invasive nature of obtaining signals which carry a large amount of information about the human condition. Interpreting these states is complex and demands large processing resources to implement training to obtain reliable results. In addition, the data quality and data processing methods play significant role[19].

Two approaches are addressed among ML processing of EEG data; the first based on training and classifying on raw measured EEG data, while the second based on preprocessing the EEG data to extract better features. While some networks are trained on EEG data from individual subjects, there are networks which target to classify EEG data from subjects that have not supplied any training data. Availability of data sources depends on the approached problem, besides the opensource EEG data, such as PhysioNet database, Temple University Hospital (TUH) Abnormal EEG Corpus, Sleep Heart Health Study, SEED, MAHNOB-HCI, DEAP, and others.

Several methods have been developed for the ML-based classification of EEG recordings. The existence of abnormalities is analyzed by developing a deep CNN [20], HMMs and CNN-MLP model [21] and RNN architecture [22]. The detection of epileptic seizures has been investigated by applying DWT [23], CNN [24], and unspecified a DL classifier [25]. Traumatic brain injuries were addressed by a LDA [26], emotion recognition by a CNN [27], or LSM [28]. Depression recognition uses hybrid models of KNN, LDA and LR [29], KNN, SVM, ANN and DBN [30], while Alzheimer's disease uses a hybrid model of 8 methods [31].

EEG-related research can be based on different ML architectures, including HMM [21]. Decomposition of EEG was performed by FCNs with CNN and MLP [32]. Emotion estimation was done using DL [33] and emotion recognition by LSTM RNN [34]. A deep CNN was added to include a sleep phase [20] and a pretrained CNN to increase the subject-independent recognition [27]. DBN was applied on high resolution multichannel EEG data [35], or integrated with HMM [34].

IV. EEG acquisition

Non-invasive measuring of EEG signals allows a portable and affordable monitoring, as novel systems require less preparation time to yield EEG data with sufficient quality [36]. The most common approach for EEG acquisition is a method where electrodes are placed on the scalp of the subject and recordings last about 20 minutes. Although, the typical number of electrodes is 64, about 70% use less than 40 electrodes [19]. Longer EEG recordings concurrent to daily activities are realized with reduced number of electrodes to increase the subjects' comfort, such as the approach of using a three-electrode pervasive EEG colector [30]. Though, EEG data can suffer from noise, a new method involves a modified ear electrode and electrode placement protocol [37] .

The placement of the electrodes also affects the classification performance, and practical electrodes placement is recommended for systems with different number of electrodes [38].

ML classification methods can improve their performance as further research is applied to continuous EEG sampling. The application of EEG analysis in Brain Computer Interfaces extends the use of EEG data from medical classifications to everyday assistance. But this requires that the measurement of EEG signals should be more resistant to noise and be implemented in a lifestyle compatible manner. Again, invasive EEG acquisition methods may provide the necessary qualities, but other methods are also considered such as unobtrusive wearable devices. A review of bio-amplifier architectures and circuits design techniques addressed wearable EEG acquisition is given in [39]. Miniature electrodes placed in and around the human ear are a feasible solution for data acquisition with minimum disturbance to the user's daily activities [40]. A textile-based EEG headband system [41] uses materials and methods for fabrication of multi-layer stretchable e-textile.

Among the noninvasive acquisition methods there are also Electrocorticography (ECoG) and clinical acquisition methods like Functional magnetic resonance imaging (fMRI) [42]. EcoG applies electrodes externally to the scalp or implanted into the surface of the brain. fMRI on the other hand measures EEG signals indirectly as a reflected neurons' activity on the MR signal. fMRI may be used to examine the brain's functional anatomy [43]. EEG data can be coupled with these additional information sources as to provide more training data to the ML architecture. Such approaches have been made in coupling fMRI with EEG recording. However, the data collected this way contains artifacts that make it difficult to interpret the data. The research toward removing these artifacts contributes to the precision of the trained ML model. Success in developing new methods that process EEG data and produce artifact-free results is evident [44] making them superior to results from existing methods. Removing artifacts has been a subject of interest for at least two decades now [45], aiming at producing artifact free EEG recordings that differed in only 10-18% with the EEG recorded without fMRI.

V. Noise detection and elimination in EEG signals

Sources of noise that corrupts the EEG signals may be classified as physiological (originating from the person that is EEG recorded) and environmental (originating from the surrounding sources of electromagnetic waves). Physiological noise may be coming from eye movements (ocular noise), heartbeats (cardiac noise), and other muscle movements. Power lines, electrical appliances, and computer equipment usually produce environmental noise.

Interpretation and analysis of the EEG recordings are influenced by the presence of noise due to small signal-to-noise ratio of EEG signals. The most obvious way to remove noise from the EEG signals is to eliminate possible sources, although we are aware that we can not always control the presence of noise. Since we focus on drowsiness detection, we are aware that in vehicles there are many sources of environmental noise. In addition, eye movements and blinking contribute to the noise amplitude and introduce changes to the EEG signal [46]. Another approach to remove noise is to increase the sample size, hoping that on average, the noise will cancel itself, an approach with several drawbacks, since In some situations, increase of the sample size may be impossible.

A well-known method for removing noise is based on linear regression [47] [48]. Here the eye movements by electrooculogram (EOG) and heartbeats by the electrocardiogram (EGG) signal are simultaneously recorded on separate channels.

Another approach may be to transform recorded EOG signal into frequency domain, and to filter the EOG signal from noisy frequencies above and below certain threshold frequencies (for example between 0.01 Hz and 100 Hz).

Algorithms based on blind source separation are another approach for noise removal from EEG recordings without using additional electrodes, usually realized by Independent Component Analysis (ICA), which statistically derives EEG signals from highly correlated EEG recordings [49].

Another important problem is automated noise removal from the EEG recordings. Algorithms for automated noise removal utilize one or more of the above methodologies. Hybrid algorithms combine two or more algorithms to obtain better signal-to-noise ratio. However, some algorithms still require expert knowledge to identify artefacts in the EEG recordings, while other algorithms may introduce additional noise during the automated noise removal. ML is also used to improve the accuracy of the algorithms for automated noise removal and to achieve full automation [50].

VI. Conclusion

BCI devices play a great role in contemporary daily activities. They becoming less intrusive and are increasingly accepted by the users. As one of the non-invasive BCI techniques, EEG analysis is becoming a great tool and it is used in many applications that obtain knowledge of the medical issues of the subject. However, in the last decade EEG devices are used for obtaining other types of knowledge about the subjects, such as their alertness state, their satisfaction, interest etc. Many of these methods include machine learning techniques, as presented in this overview. One of the important aspects of people's everyday life is their safety, an it can be seriously compromised by drivers that are facing drowsiness. The EEG methods that address this issue are presented in this paper. In addition, we address the problems of the acquisition of the signals, and the ways of noise detection and elimination that can be applied on EEG signals. A successful methodology can be defined by a specific EEG acquisition method, data format, feature engineering process, training process, and selection of the ML-method.

Acknowledgement

This work has been supported by the bilateral project between China and North Macedonia entitled: "An Adaptive Multi-Channel Non-Invasive Brain-Computer Interface SoC with Machine-Learning for Drowsiness Detection" 2019-2021.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, pp. 767 – 791, 2002.

[2] A. Nijholt, "The future of brain-computer interfacing (keynote paper)," in *2016 5th International Conference on Informatics, Electronics and Vision (ICIEV)*, 2016, pp. 156–161.

[3] J. Vidal, "Toward direct brain-computer communicationg," *Annual Review of Biophysics and Bioengineering*, vol. 2, no. 1, pp. 15–780, 1973.

[4] ——, "Real-time detection of brain events in eeg," *Proceedings of the IEEE*, vol. 65, no. 5, pp. 633–641, 1977.

[5] L. Bozinovska, G. Stojanov, M. Sestakov, and S. Bozinovski, "Cnv pattern recognition: step toward a cognitive wave observation," in *Signal Processing V: Theories and Applications*, L. Torres, E. Masgrau, and E. Lagunas, Eds. Elsevier, 1990, pp. 1659–1662.

[6] S. Bozinovski, M. Sestakov, and L. Bozinovska, "Using eeg alpha rhythm to control a mobile robot," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1988, pp. 1515–1516 vol.3.

[7] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988.
[8] "Neurosky," acessed 9.11.2021. [Online]. Available: http://neurosky.com/
[9] "Emotiv," Sep 2021, acessed 9.11.2021. [Online]. Available: https://www.emotiv.com/
[10] F. Hasan and A. Kashevnik, "State-of-the-art analysis of modern drowsiness detection algorithms based on computer vision," in *2021 29th Conference of Open Innovations Association (FRUCT)*. IEEE, 2021, pp. 141–149.
[11] Z. E. Abou Elassad, H. Mousannif, H. Al Moatassime, and A. Karkouch, "The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review," *Engineering Applications of Artificial Intelligence*, vol. 87, p. 103312, 2020.
[12] K. Vasudevan, A. P. Das, B. Sandhya, and P. Subith, "Driver drowsiness monitoring by learning vehicle telemetry data," in *2017 10th International Conference on Human System Interactions (HSI)*. IEEE, 2017, pp. 270–276.
[13] F. Lindow, C. Kaiser, A. Kashevnik, and A. Stocker, "Ai-based driving data analysis for behavior recognition in vehicle cabin," in *2020 27th Conference of Open Innovations Association (FRUCT)*. IEEE, 2020, pp. 116–125.
[14] G. Prabhakar, A. Mukhopadhyay, L. Murthy, M. Modiksha, D. Sachin, and P. Biswas, "Cognitive load estimation using ocular parameters in automotive," *Transportation Engineering*, vol. 2, p. 100008, 2020.
[15] A. Bishnoi, *Emotion Recognition Using Deep Learning*. California State University, Long Beach, 2019.
[16] A. A. Jordan, A. Pegatoquet, A. Castagnetti, J. Raybaut, and P. Le Coz, "Deep learning for eye blink detection implemented at the edge," *IEEE Embedded Systems Letters*, 2020.
[17] C. B. S. Maior, M. J. das Chagas Moura, J. M. M. Santana, and I. D. Lins, "Real-time classification for autonomous drowsiness detection using eye aspect ratio," *Expert Systems with Applications*, vol. 158, p. 113505, 2020.
[18] H. Berger, " "U about the human electrenkephalogram," *DMW-German Medical Weekly*, vol. 60, no. 51, pp. 1947–1949, 1934.
[19] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: a systematic review," *Journal of neural engineering*, vol. 16, no. 5, p. 051001, 2019.
[20] K. Van Leeuwen, H. Sun, M. Tabaeizadeh, A. Struck, M. Van Putten, and M. Westover, "Detecting abnormal electroencephalograms using deep convolutional networks," *Clinical neurophysiology*, vol. 130, no. 1, pp. 77–84, 2019.
[21] L. de Diego and S. Isabel, "Automated interpretation of abnormal adult electroencephalograms," Ph.D. dissertation, Temple University. Libraries, 2017.
[22] S. Roy, I. Kiral-Kornek, and S. Harrer, "Chrononet: a deep recurrent neural network for abnormal eeg identification," in *Conference on Artificial Intelligence in Medicine in Europe*. Springer, 2019, pp. 47–56.
[23] H. U. Amin, M. Z. Yusoff, and R. F. Ahmad, "A novel approach based on wavelet analysis and arithmetic coding for automated detection and diagnosis of epileptic seizure in eeg signals using machine learning techniques," *Biomedical Signal Processing and Control*, vol. 56, p. 101707, 2020.
[24] M. Hügle, S. Heller, M. Watter, M. Blum, F. Manzouri, M. Dumpelmann, A. Schulze-Bonhage, P. Woias, and J. Boedecker, "Early seizure detection with an energy-efficient convolutional neural network on an implantable microcontroller," in *2018 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2018, pp. 1–7.
[25] I. Kiral-Kornek, S. Roy, E. Nurse, B. Mashford, P. Karoly, T. Carroll, D. Payne, S. Saha, S. Baldassano, T. O'Brien *et al.*, "Epileptic seizure prediction using big data and deep learning: toward a mobile system," *EBioMedicine*, vol. 27, pp. 103–111, 2018.
[26] B. Albert, J. Zhang, A. Noyvirt, R. Setchi, H. Sjaaheim, S. Velikova, and F. Strisland, "Automatic eeg processing for the early diagnosis of traumatic brain injury," *Procedia Computer Science*, vol. 96, pp. 703–712, 2016.
[27] Y. Cimtay and E. Ekmekcioglu, "Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset eeg emotion recognition," *Sensors*, vol. 20, no. 7, p. 2034, 2020.
[28] O. Al Zoubi, M. Awad, and N. K. Kasabov, "Anytime multipurpose emotion recognition from eeg data using a liquid state machine based framework," *Artificial intelligence in medicine*, vol. 86, pp. 1–8, 2018.
[29] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from eeg signal," *Computer methods and programs in biomedicine*, vol. 109, no. 3, pp. 339–345, 2013.
[30] H. Cai, X. Sha, X. Han, S. Wei, and B. Hu, "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, pp. 1239–1246.
[31] C. Lehmann, T. Koenig, V. Jelic, L. Prichep, R. E. John, L.-O. Wahlund, Y. Dodge, and T. Dierks, "Application and comparison of classification algorithms for recognition of alzheimer's disease in electrical brain activity (eeg)," *Journal of neuroscience methods*, vol. 161, no. 2, pp. 342–350, 2007.
[32] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, and K. Dizdarevic, "Energy distribution of eeg signals: Eeg signal wavelet-neural network classifier," *arXiv preprint arXiv:1307.7897*, 2013.
[33] A. Frydenlund and F. Rudzicz, "Emotional affect estimation using video and eeg data in deep neural networks," in *Canadian Conference on Artificial Intelligence*. Springer, 2015, pp. 273–280.
[34] W.-L. Zheng, J.-Y. Zhu, Y. Peng, and B.-L. Lu, "Eeg-based emotion classification using deep belief networks," in *2014 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE, 2014, pp. 1–6.
[35] J. Turner, A. Page, T. Mohsenin, and T. Oates, "Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection," in *2014 aaai spring symposium series*, 2014.
[36] M. O'Sullivan, J. P. Pena, A. Bocchino, C. O'Mahony, D. Costello, E. Popovici, and A. Temko, "Comparison of electrode technologies for dry and portable eeg acquisition," in *2017 7th IEEE International Workshop on Advances in Sensors and Interfaces (IWASI)*. IEEE, 2017, pp. 15–20.
[37] C. Kumaragamage, B. Lithgow, and Z. Moussavi, "A new low-noise signal acquisition protocol and electrode placement for electrocochleography (ecog) recordings," *Medical & biological engineering & computing*, vol. 53, no. 6, pp. 499–509, 2015.
[38] J. Montoya-Martínez, A. Bertrand, and T. Francart, "Optimal number and placement of eeg electrodes for measurement of neural tracking of speech," *bioRxiv*, p. 800979, 2019.
[39] J. Xu, S. Mitra, C. Van Hoof, R. F. Yazicioglu, and K. A. Makinwa, "Active electrodes for wearable eeg acquisition: Review and electronics design methodology," *IEEE reviews in biomedical engineering*, vol. 10, pp. 187–198, 2017.
[40] M. G. Bleichner and S. Debener, "Concealed, unobtrusive ear-centered eeg acquisition: ceegrids for transparent eeg," *Frontiers in human neuroscience*, vol. 11, p. 163, 2017.
[41] M. R. Carneiro, A. T. de Almeida, and M. Tavakoli, "Wearable and comfortable e-textile headband for long-term acquisition of forehead eeg signals," *IEEE Sensors Journal*, vol. 20, no. 24, pp. 15 107–15 116, 2020.
[42] B. Li, T. Cheng, and Z. Guo, "A review of eeg acquisition, processing and application," in *Journal of Physics: Conference Series*, vol. 1907, no. 1. IOP Publishing, 2021, p. 012045.
[43] R. a. ACR, "Magnetic resonance, functional (fmri) - brain," Feb 2019. [Online]. Available: https://www.radiologyinfo.org/en/info/fmribrain
[44] R. K. Niazy, C. F. Beckmann, G. D. Iannetti, J. M. Brady, and S. M. Smith, "Removal of fmri environment artifacts from eeg data using optimal basis sets," *Neuroimage*, vol. 28, no. 3, pp. 720–737, 2005.
[45] P. J. Allen, O. Josephs, and R. Turner, "A method for removing imaging artifact from continuous eeg recorded during functional mri," *Neuroimage*, vol. 12, no. 2, pp. 230–239, 2000.
[46] R. Verleger, "The instruction to refrain from blinking affects auditory p3 and n1 amplitudes." *Electroencephalography and clinical neurophysiology*, vol. 78 3, pp. 240–51, 1991.
[47] X. Jiang, G.-B. Bian, and Z. Tian, "Removal of artifacts from eeg signals: A review," *Sensors*, vol. 19, no. 5, 2019.
[48] G. Repov, "Dealing with noise in eeg recording and data analysis," *Informatica medica slovenica*, no. 15, p. 18, 2010.
[49] S. Makeig, A. J. Bell, T.-P. Jung, and T. J. Sejnowski, "Independent component analysis of electroencephalographic data," in *NIPS*, 1995.
[50] T. Radüntz, J. Scouten, O. Hochmuth, and B. Meffert, "Automated eeg artifact elimination by applying machine learning algorithms to ica-based features." *Journal of neural engineering*, vol. 14 4, p. 046004, 2017.