

One-class autoencoder approach for optimal electrode set identification in wearable EEG event monitoring*

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Abstract—A limiting factor towards the wide use of wearable devices for continuous healthcare monitoring is their cumbersome and obtrusive nature. This is particularly true in electroencephalography (EEG), where numerous electrodes are placed in contact with the scalp to perform brain activity recordings. In this work, we propose to identify the optimal wearable EEG electrode set, in terms of minimal number of electrodes, comfortable location and performance, for EEG-based event detection and monitoring. By relying on the demonstrated power of autoencoder (AE) networks to learn latent representations from high-dimensional data, our proposed strategy trains an AE architecture in a one-class classification setup with different electrode combinations as input data. The model performance is assessed using the F-score. Alpha waves detection is the use case through which we demonstrate that the proposed method allows to detect a brain state from an optimal set of electrodes. The so-called wearable configuration, consisting of electrodes in the forehead and behind the ear, is the chosen optimal set, with an average F-score of 0.78. This study highlights the beneficial impact of a learning-based approach in the design of wearable devices for real-life event-related monitoring.

Index Terms—wearables, EEG, autoencoder, optimal electrode set, tattoo electrodes.

I. INTRODUCTION

Electroencephalography (EEG) recording is the defacto approach to brain functions assessment with diagnostic or monitoring purposes (e.g. epilepsy, sleep studies). It is performed through electrodes placed along the scalp that non-invasively transduce the brain's electrical activity. The standard international system for electrodes placement, with a configuration of 32/64 electrodes, is depicted in Fig. 1(a). The need of such a dense electrodes' locations is a limiting factor in-view of real-life monitoring applications. Wearable EEG represents a promising solution to achieve ubiquitous monitoring [6], for which there exist some commercial solutions (e.g. Emotiv headset¹). These devices rely on a

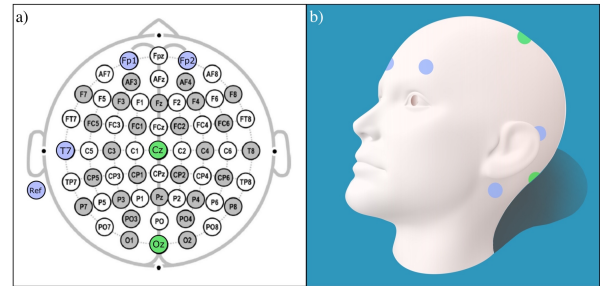


Fig. 1. The EEG headset. a) International 10-20 system with 32/64 (grey/all) electrodes [22] and highlighted the electrodes adopted in this study (green and violet). b) 3D representation of the headset, with green electrodes (Cz-Oz) and the wearable configuration, in violet (the reference electrode is placed on the left mastoid bone in this representation).

simplified electrodes scheme and are showing great results in the Brain-Computer Interface field. However, they have a cumbersome interface, in terms of materials and setup of the electrodes. To overcome the limitations of traditional bulky and rigid materials, promising alternatives have been proposed in the field of epidermal [16] and tattoo electronics [8]. Despite their seamless interface, there is still a need of multiple electrodes in uncomfortable or non-discrete locations. An optimized electrode set, i.e. a minimum number of electrodes in comfortably and discrete locations, which can grant a realistic use of wearable EEG is still missing.

In this work, we propose to use a deep neural network to identify the optimal electrode set to monitor a given state or condition from EEG recordings. To this end, we model EEG recordings acquired through tattoo electrodes [9] as multi-variate time series. Under the hypothesis that collected electrophysiological signals are a representation of a latent condition, we train an autoencoder (AE) network to learn a model of the variability of such condition. To avoid the class imbalance problem during training [7], we formulate our problem as a one-class classification one [19]. At inference time, the trained AE detects the presence or absence of the condition/state of interest in unseen data points. Using this configuration, we propose to alter the number of variables of the multi-variate time series, i.e. the EEG channels, to define the optimal electrode set that identifies the condition of interest in unseen data with acceptable performance. We investigate alpha waves detection, the most studied brain rhythm, as a use case to validate the proposed approach.

The remaining of this paper is organized as follows. Section II introduces our use case, the alpha waves detection.

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Section III describes the proposed method. In Section IV we present the experimental setup, followed by the obtained results (Section V). The paper concludes with a summary of our contributions, a discussion of the related works and perspectives.

II. USE CASE: ALPHA WAVE DETECTION

Alpha waves are a spontaneous brain activity that appears in the 8–12 Hz frequency band. They are induced by relaxation with closed eyes and abolished by eye opening or alerting (e.g. thinking, calculating) [21]. In relaxation or drowsiness, alpha activity is known to rise and, if sleep appears, the power of the lower frequency bands increases [21]. Alpha wave detection finds applications as an indicator of sleepiness in high risk professions, such as long-distance driving [14], and as a marker of sleep depth [3].

Alpha waves typically arise in the occipital region and they are well visible in the EEG’s CzOz channel, where a channel represents the acquisition from two electrodes. The CzOz channel is impracticable for compact and comfortable wearable devices, as it involves the whole back part of the head (Fig. 1). Considering that the cerebral activity arises inside the brain and it is spread all over the scalp surface, we hypothesize that it is possible to infer the presence or absence of alpha waves from other channels, through a learnt latent representation. In particular, we are interested in identifying a subset of locations of the 10-20 international system that are more feasible for wearable implementation, such as behind-the-ear (T7 location, Fig. 1), which has been explored for seizure detection [10], or forehead EEG (Fp1-Fp2 electrodes, Fig. 1).

III. METHOD

This section formulates the AE based one-class classification problem (III-A) for alpha wave detection and presents the optimal electrode set selection strategy (III-B).

A. AE based One-class Classification of Alpha Waves

Let us denote $\mathcal{T} = \{\mathbf{x}_t\}_{t \in T}$, $\mathbf{x} \in \mathbb{R}^m$ is a multivariate time series, representing an EEG recording corresponding to m channels, with each point \mathbf{x}_t being an observation at a specific time t . One-class time-series classification trains a model under the assumption that the training data \mathcal{T} comes from a single class, denoted the positive class. At inference time, the goal is to identify if unseen observations $\hat{\mathbf{x}}_t \notin \mathcal{T}$ belong to the positive class or not, under the assumption that $\hat{\mathbf{x}}_t$ belongs to the positive class if it is similar to the observations from \mathcal{T} , according to some (dis-)similarity metric. In this work, we consider alpha waves as the positive class since they represent the condition of interest.

An AE is a neural network combining an encoder E and a decoder D . The encoder part takes an input X and maps it into a set of latent variables Z . The decoder maps from the latent space back into the input space as a reconstruction. The difference between the original input vector and its output is denoted the reconstruction error

$$\|X - AE(X)\|_2 \quad (1)$$

Type	Features
Time-domain	Mean, Standard deviation, Median, Minimum, Maximum, Root-mean-square (RMS)
Frequency-domain	Maximum Power Spectral Density (PSD), Mean PSD

where $\|\cdot\|$ the L_2 norm, and

$$AE(X) = D(Z), \quad Z = E(X). \quad (2)$$

Trained with data \mathcal{T} from the positive class, the AE estimates a model that captures the dynamics of such class [5]. At inference time, the AE reconstructs well data similar to \mathcal{T} , while failing to do so with data that it has not encountered, thus resulting in large reconstruction errors. This error is used as a score to classify new points into the positive (low error) or negative class (high error).

To model the dependence between a current time point and previous ones it is common to define, at every t , a time window of length $K < |T|$, i.e. $W_t = \{\mathbf{x}_{t-K+1}, \dots, \mathbf{x}_{t-1}, \mathbf{x}_t\}$. This means that the original time-series \mathcal{T} is transformed into a sequence of windows $\mathcal{W} = \{W_t\}_{t \in T}$ used as training input. Raw electrophysiological signals, however, are generally noisy [11]. To avoid spurious effects linked to the nature of the data, we do not build the standard time windows W of raw time points \mathbf{x}_t . Instead, we transform raw time point windows $W^{m \times K} \rightarrow W^{m \times L}$, by extracting a set of L time- and frequency-domain features per time window (Table I).

The windows \mathcal{W} are used as input to an AE based topology conceived for multivariate time series analysis [2]. The network is composed of a common encoder E connected to two decoder networks D_1 and D_2 : $AE_1(X) = D_1(Z)$, $AE_2(X) = D_2(Z)$, with Z as in Eq 2. The network is trained using a two-phase adversarial training scheme to allow the AEs to learn how to amplify the reconstruction error as detailed in [2]. At inference time, the score of unseen data \hat{X} is estimated as a linear combination of the reconstruction error of the two AEs:

$$S(\hat{X}) = \alpha \|\hat{X} - AE_1(\hat{X})\|_2 + \beta \|\hat{X} - AE_2(AE_1(\hat{X}))\|_2, \quad (3)$$

where $\alpha + \beta = 1$ are two hyper-parameters that control sensitivity and specificity.

B. Optimal Electrode Set Selection

AEs are good at extracting low-dimensional subspaces (latent spaces) representing the dynamics inside a high-dimensional dataset. The proposed method uses this property to identify the best set of EEG channels to use, i.e. the minimum set of comfortable and discrete channels, which is able to detect the presence/absence of an alpha state. We vary m , the number of input EEG channels, to train candidate models and assess their performance using an evaluation metric. We choose to use the F-score as it is a well-suited evaluation metric for class imbalanced data, but any other

performance measure could be used.

$$F\text{-score} = \frac{2TP}{2TP + FN + FP} \quad (4)$$

with TP denoting true positives, FP a time point misclassified as the positive class, and FN a false negative.

In alpha waves detection, we expect a maximal performance using the CzOz channel as input channel, since it is the one normally used to measure alpha activity. We adopt it here as the reference. The optimal wearable design is chosen among all candidate models based on performance (closest to the reference), number of channels (the least the better) and comfort (at the least, avoid Cz).

IV. EXPERIMENTAL SETUP

This section describes the data and our experimental setup.

a) Data: The EEG dataset was acquired as described in [9]. The tattoo electrodes were placed in T7, Cz, Oz, Fp1, and Fp2 locations (Fig. 1). A tattoo reference electrode (ref) was placed on the right mastoid bone, while the ground was located at the highest point of the head, near the Cz position. For the alpha session, the participant, comfortably seated in an isolated room, was asked to close the eyes to produce alpha waves and, when requested, to open the eyes to stop their appearance. The non-alpha sessions had the same setup with open eyes at all time. A total of 13 recordings were acquired, from which 9 have been used in this study, with a length of ~ 2 minutes, accounting for 3.07M raw sample points. For each recording, the time points are labeled by an expert rater.

b) Setup: We assessed five different EEG channel configurations to identify the optimal electrode set. These are: 1) *all*: T7Cz, Fp1Fp2, refCz, refT7, refOz, refFp1; 2) *noCz*: Fp1Fp2, refT7, refOz; 3) *wearable*: Fp1Fp2, refT7; 4) *refT7*: and 5) *Fp1Fp2*: also known as forehead EEG. We used the signals without any pre-processing, thus the dataset can be noisy and with typical EEG artefacts. We transformed it into a sequence of windows using a window size $K=4$. The resulting set was split into training/testing set over 6 different folds. The training set of the AE based network only used positive class samples. The optimal set was selected by estimating the average F-score (Eq. 4) on the test set, over the 6 folds.

We compared the performance of the proposed method with two classical machine learning approaches: a random forest (RF), with 500 trees and maximum depth of 5, and a Gradient Boosted Tree (GBT). Both RF and GBT made use of alpha and non-alpha samples. Therefore, we performed a 6-fold cross-validation using \mathcal{W} , but assuring to have the training set as balanced as possible on each fold and using the remaining as test set.

The AE based network used a publicly available implementation² with $\alpha=\beta=0.5$ and latent space dimension $|Z|=0.5m \cdot L$. RF and GBT were coded in Python using the Scikit-learn implementation.

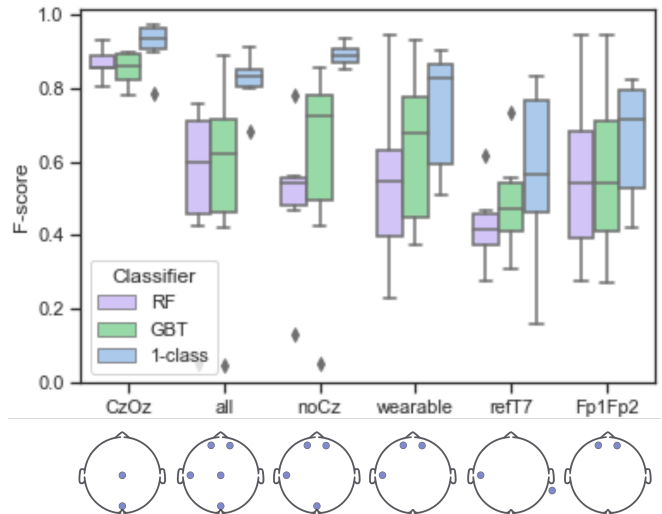


Fig. 2. F-score from the 6 experiments performed with Random Forest (RF), Gradient Boosted Trees (GBT) and one-class methods, across all the evaluated setups.

V. RESULTS

Table II reports the best F-scores obtained by the AE based network using different EEG channel setups. We include the CzOz channel result as reference. With alpha as the positive class, the NoCz configuration reports a good performance (F-score=0.81), close to the all combination, making it an affordable solution in view of a comfortable design and performance. Although this configuration demands 3 channels, corresponding to 5 electrodes, it avoids the Cz electrode that is impractical (Fig. 1). The wearable configuration reports good results (F-score=0.78), but a higher variance. The results using non-alpha as the positive class do not show significant differences in the observed results. This indicates that one-class training can be done using either class. The easiest class to collect in large amounts should be favored.

Figure 2 compares the use of the AE based architecture to RF and GBT. The AE based network shows a consistent superior performance. These results are in-line with the demonstrated power of neural networks to learn latent representations and indicate that the AE based network is a more reliable tool for EEG event detection with an optimal electrode set.

VI. DISCUSSION AND CONCLUSIONS

We presented a one-class autoencoder-based framework to identify an optimal electrode set to detect and monitor events from EEG recordings. We define the optimal set in terms of number of electrodes, comfortable location and event detection/monitoring performance. Using alpha wave detection as a use case, we investigated five electrode sets. The results indicate that the NoCz (F-score=0.81) and wearable (F-score=0.78) configurations are viable solutions for realistic monitoring of the studied use case. Although our results indicate that the proposed architecture is able

²<https://github.com/robustml-eurecom/usad>

TABLE II

F-SCORE FOR DIFFERENT ELECTRODE SETS, USING ALPHA AND NON-ALPHA AS POSITIVE CLASS

Positive class	CzOz	all	noCz	wearable	refT7	Fp1Fp2
Alpha	0.94±0.06	0.82±0.11	0.81±0.12	0.78±0.21	0.74±0.26	0.71±0.24
Non-alpha	0.84±0.14	0.85±0.13	0.78±0.17	0.71±0.27	0.72±0.18	0.72±0.16

to detect the presence/absence of alpha without using the CzOz channel, we observe that there is an increased variance in the performance as the number of channels is reduced. This indicates that avoiding the most performing, but least comfortable channel (i.e. CzOz), comes at the cost of an increase in the number of alternative used channels to maintain the performance. For instance, the smallest electrode sets (refT7 and Fp1Fp2) reported poor results, suggesting there is a minimal number of such alternative channels required to guarantee an acceptable performance in the absence of CzOz. As such, it is worth to explore additional configurations, including other comfortable electrode locations, and/or other electrophysiological measurements.

Our work is closely related to the more general problem of feature selection [1], [4], [7], which accounts to select the EEG channels achieving the highest performing accuracy. In the scope of sleep studies, some methods have explored comfortable EEG channels, e.g. forehead electrodes, among the pool of features, reporting a performance accuracy of 76-77% [7], [13]. Our work differs from these previous approaches in two ways. Firstly, these methods focus on performance accuracy. As our final aim is to enable wearable EEG design, our optimal electrode set definition goes beyond performance, comparing multiple configurations that consider comfort and discreteness as criteria. Secondly, from a pure technical perspective, our one-class formulation avoids the problem of class imbalance, common to EEG analysis [7]. Although not directly comparable, this formulation allows our method to achieve a higher accuracy (83%) than that one reported in previous works, in forehead electrodes.

This work is a proof-of-concept on how learning-based techniques can assist the conception, development and implementation of wearable devices, which may go beyond the presented use case. Nevertheless, this framework represents just a small component of the infrastructure required to conceive a wearable device using an optimal set of electrodes. For instance, alpha waves monitoring with the identified set needs to be done in conjunction with the AE based network. Whether a light-weight network is deployed in the wearable itself or in a remote device (i.e. a phone) is an important design choice that remains to be addressed as part of our future work.

REFERENCES

- [1] T. Alotaiby, F. E. Abd El-Samie, S.A. Alshebeili, and I. Ahmad. A review of channel selection algorithms for EEG signal processing. *EURASIP Journal on Advances in Signal Processing*, 2015, pp.1-21.
- [2] J. Audibert, P. Michiardi, F. Guyard, S. Marti, and M.A. Zuluaga. USAD: UnSupervised Anomaly Detection on Multivariate Time Series. *Proc. of the 26th ACM SIGKDD Intl. Conference on Knowledge Discovery & Data Mining*, 2020, pp. 3395–3404.
- [3] M.H. Asyali, R.B. Berry, M.C. Khoo, and A. Altinok. Determining a continuous marker for sleep depth. *Computers in biology and medicine*, vol. 37, 2007, pp.1600-1609.
- [4] R. P. Balandong, R.F. Ahmad, M.N.M. Saad, and A.S. Malik. A review on EEG-based automatic sleepiness detection systems for driver. *IEEE Access*, 2018, pp. 22908-22919.
- [5] A. Blázquez-García, A. Conde, U. Mori, and J.A. Lozano. A review on outlier/anomaly detection in time series data. *ACM Computing Surveys*, 2021 vol 54, pp. 1-33.
- [6] A.J. Casson, S. Smith, J. S. Duncan and E. Rodriguez-Villegas. Wearable EEG: what is it, why is it needed and what does it entail? 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2008, pp. 5867-5870.
- [7] S. Chambon, M. N. Galtier, P. J. Arnal, G. Wainrib and A. Gramfort. A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2018, vol. 26, pp. 758-769.
- [8] L.M. Ferrari, K. Keller, B. Burtcher and F. Greco. Temporary tattoo as unconventional substrate for conformable and transferable electronics on skin and beyond. *Multifunctional Materials*, IOP Science, vol. 3, 2020, pp.46.
- [9] L. M. Ferrari, U. Ismailov, J. M. Badier, F. Greco and E. Ismailova. Conducting polymer tattoo electrodes in clinical electro- and magneto-encephalography. *npj Flexible Electronics*, vol. 4, 2020, pp. 1-9.
- [10] Y. Gu, E. Cleeren, J. Dan, et al. Comparison between scalp EEG and behind-the-ear EEG for development of a wearable seizure detection system for patients with focal epilepsy. *Sensors*, vol 18, 2018, pp. 29.
- [11] M. Hakonen, H. Piitulainen, and A. Visala. Current state of digital signal processing in myoelectric interfaces and related applications. *Biomedical Signal Processing and Control* vol. 18 2015 pp. 334-359.
- [12] J. Heikenfeld et al. Wearable sensors: modalities, challenges, and prospects. *Lab on a Chip*, 18.2, 2018 pp. 217-248.
- [13] C. S. Huang, C.L. Lin, L. W. Ko et al. A hierarchical classification system for sleep stage scoring via forehead EEG signals. *IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)*, 2013, pp. 1-5.
- [14] Y. Jiao and B.L. Lu. Driver sleepiness detection from EEG and EOG signals using GAN and LSTM networks. *Neurocomputing*, vol. 408, 2020 pp. 100-111.
- [15] Y. Khan, A. E. Ostfeld, C. M. Lochner, A. Pierre and A. C. Arias. Monitoring of vital signs with flexible and wearable medical devices. *Advanced Materials* vol. 28, 2016, pp. 4373-4395.
- [16] D.H. Kim, N. Lu, R. Ma, et al. Epidermal electronics. *Science*, vol. 333, 2011, pp.838-843.
- [17] T.M. Krummel. The rise of wearable technology in healthcare. *JAMA network open* 2.2, 2019, pp. e187672-e187672.
- [18] P. Lukowicz, T. Kirstein, G. Tröster. Wearable systems for health care applications. *Methods of information in medicine*. 2004, vol. 43, pp. 232-8.
- [19] M. A.F. Pimentel, D. A. Clifton, L. Clifton, and L. Tarassenko. A review of novelty detection. *Signal Processing*, vol. 99 2014, pp. 215-249.
- [20] Y. Roy, H. Banville, I. Albuquerque et al. Deep learning-based electroencephalography analysis: a systematic review. *Journal of neural engineering*, vol. 16 2019, pp.051001.
- [21] M. Teplan. Fundamentals of EEG measurement. *Measurement science review* vol. 2, 2002 pp. 1-11.
- [22] H.J. Yoon and S.Y. Chung. EEG-based emotion estimation using Bayesian weighted-log-posterior function and perceptron convergence algorithm. *Computers in biology and medicine*, vol. 43, 2013, pp.2230-2237.