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Exploring High- and Low-Density Electroencephalography for a Dream Decoding Brain-Computer Interface

Mithila Packiyanathan[1], André Torvestad[1], Luis Alfredo Moctezuma[2]*and Marta Molinas [1]

1- Department of Engineering Cybernetics, Norwegian University of Science and Technology. Trondheim, Norway

2- International Institute for Integrative Sleep Medicine, University of Tsukuba. Tsukuba, Ibaraki, Japan

Abstract. A high-performance real-time brain-computer interface system capable of identifying dreams has potential for healthcare applications. To address this, we use electroencephalogram (EEG) data from non-rapid eye movement sleep to classify *dream experience* and *no-experience*. Using 58 EEG channels, we achieve an accuracy of 0.94, an AUROC of 0.91, and a kappa score of 0.84, accomplished by first filtering the data through multivariate empirical mode decomposition followed by a combination of principal component analysis and common spatial patterns for feature extraction and K-nearest neighbors classifier. Interestingly, comparable results are obtained using 29 or 10 EEG channels selected by permutation-based channel selection.

1 Introduction

Neurological disorders and diseases often manifest during sleep before symptoms occur during waking conditions [1–3]. Given that the content of dreams can be influenced by one's mental health, research suggests that dreams could offer insight into the mental and emotional well-being of an individual [4, 5]. In light of this, the development of a tool capable of determining if a subject is dreaming and analyzing its emotional content could prove essential in healthcare facilities. Such a dream decoder could help psychologists diagnose and monitor patients with conditions such as depression, anxiety disorders, and various neurological disorders [5–7].

A brain-computer interface (BCI) is one way to build a dream decoder. Artificial intelligence (AI) and signal processing algorithms have contributed significantly to the advancement of BCI systems in general. However, achieving robustness remains a challenge, primarily due to the difficulty of obtaining a good trade-off between high performance and real-time speed, as well as the use of low-density electroencephalogram (EEG) systems [8, 9]. Currently, there are no BCI solutions for dream decoding in real-life applications, as research has focused mainly on analyzing dreams through the power spectrum, and only recently using machine learning (ML) techniques [2, 6, 10, 11].

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Moving towards the development of a BCI system for dream decoding using EEG signals, we propose the use of multivariate empirical mode decomposition (MEMD) as a filter to then *1)* extract features using principal component analysis (PCA) and common spatial patterns (CSP) and use them as input to the K-nearest neighbors (KNN), or *2)* use a convolutional neural network (CNN) called EEGNeX, both to classify *dream experiences* and *no-experiences* during non-rapid eye movement (NREM) sleep. To identify the most important EEG channels and minimize their numbers while maintaining classification performance, we employ permutation-based channel selection. This technique also sheds light on the regions of the brain that are important to identify dream experiences.

2 Materials and Methods

2.1 EEG dataset

The dataset comprises high-density EEG recordings collected in 28 participants using a 58-electrode cap positioned according to the 10-10 international system with a sampling rate of 400 Hz and configured with a high-pass filter set at 0.1 Hz [10].

Participants were instructed to provide dream reports upon awakening. They were encouraged to verbally give all details of their experience, regardless of whether they had a dream experience or not. The study defined dreams as any mental experience recalled from sleep and the reports were judged by two independent raters, who labeled the reports as *dream experience* or *no-experience*. The awakenings were performed during sleep onset, N2 and rapid eye movement (REM) sleep stage. The awakenings during sleep onset were performed by awakening the subjects after 30, 60 or 90 seconds of elapsed sleep during the first hours of sleep, collecting up to 10 reports per subject. At least one hour after the last sleep onset report, the subjects were awakened when N2 was detected and then at least 30 minutes later when REM sleep was detected.

Our experiments consider the data collected during the N1 and N2 sleep stages, here referred to as NREM data. In total, we used 181 NREM epochs: 76% belonging to *dream experience* and 24% to *no-experience*.

2.2 Preprocessing, feature extraction and classification

To minimize high-frequency noise in the signals, a low-pass filter with a cutoff frequency of 45 Hz, experimentally selected, was applied to the EEG data. The EEG channels are referenced using the average between the left and right mastoids $\frac{(A1+A2)}{2}$.

We considered two experiment configurations: *1)* the low-pass filtered data, referred to as the raw data. *2)* The application of MEMD to low-pass-filtered recordings, choosing the three intrinsic mode functions (IMFs) closest to the original signal, in terms of Euclidean distance, and combining them to reconstruct a MEMD-filtered signal. For both configurations, the epochs

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were segmented into 0.5-second instances, selected experimentally based on the classification performance using different segment sizes (0.5, 1, 2, 5 and 10 second segments).

For the classification process, two methods were used. The first method involved PCA and CSP for feature extraction and the KNN classifier. The number of neighbors in KNN was selected experimentally, checking the optimal value when $k = \{1, 10\}$. The second approach used EEGNeX, a CNN that outperforms existing state-of-the-art methods in EEG-based BCI classification tasks [12].

We used 5-fold cross-validation with a train-test split ratio of 80-20. The models were evaluated using accuracy, Fscore, precision, recall, area under the receiver operating characteristic curve (AUROC), and kappa.

To analyze which channels are more relevant and thus decrease the number of required EEG channels for the classification task, we used permutation-based EEG channel selection. For each channel, we randomly shuffled the EEG data within the channel, changing the information that was used during the training of the baseline model. The subdataset containing the shuffled channel was then evaluated using the baseline model. If the kappa score decreased when changing the data for a particular channel, it meant that the channel was important to obtain the baseline classification performance. Then, this process was repeated for all 58 channels. In this way, the algorithm identified the most important channels based on a comparison of the kappa score of the baseline model performance and the other performances; the performance delta.

3 Results

3.1 Classification performance under different experiment configurations

For the first approach to classifying dream experiences during NREM, we used 58 EEG channels with raw data and MEMD-filtered data. The process used KNN and the EEGNeX models.

To see the performance development when the number of channels is reduced, the classification task was also performed using 10 and 29 EEG channels.

The results of the classification using PCA, CSP, and KNN, and EEGNeX with both experiment configurations as input are presented in Fig. 1. The important brain regions obtained using the permutation-based channel selection are presented in the topographic maps in Fig. 2 where the 10 most important EEG channels are indicated with a yellow circle.

Fig. 1 shows a high classification performance for both KNN and EEGNeX; however, the standard deviation for the AUROC and kappa is higher for EEGNeX, showing less robustness than the KNN model. Furthermore, using MEMD-filtered data with 29 channels gives a higher performance than the raw data with 58 channels.

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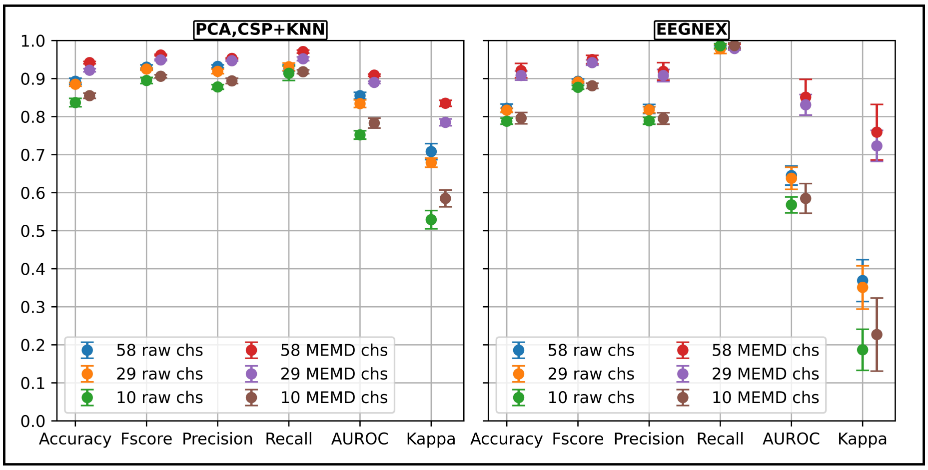

Fig. 1: Average classification performance of *dream experiences* and *no-experiences* using PCA, CSP and KNN (left), and EEGNeX (right), with both the raw data and the MEMD-filtered data.

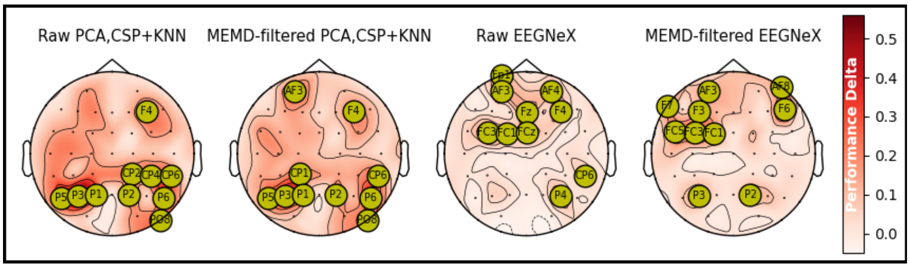

Fig. 2: Channel importance derived from classification experiments presented in Fig. 1. The 10 most important channels are indicated with yellow circles.

4 Discussion

We have presented experimental results using EEG signals for automatic classification of *dream experience* or *no-experience* during NREM.

In general, our results show that using MEMD-filtered data, instead of raw data, helps to obtain higher performance to classify when a subject is dreaming, both when using KNN or EEGNeX. Using KNN, performance increases 0.13 in kappa, 0.04-0.05 in accuracy, recall, and AUROC and 0.02-0.03 in Fscore and precision. For EEGNeX, 0.39 in kappa, 0.21 in AUROC, 0.1 in accuracy and precision, 0.06 in Fscore, and 0.002 in recall.

In the best case, we obtain up to 0.94 accuracy, 0.96 Fscore, 0.95 precision, 0.97 recall, 0.91 AUROC, and 0.84 kappa when using MEMD-filtered data and PCA, CSP for feature extraction and KNN classifier. This indicates that feature extraction techniques and the classical ML algorithm are better able to capture the features of EEG signals with dream content during NREM than EEGNeX.

Original signals are represented by three IMFs, which indicates that the removal of unnecessary frequency components makes the MEMD-filtered signal contain more important and valuable information for the classification process [13].

From the topographic maps in Fig. 2, we see the important regions of the dream classification experiments employing PCA, CSP and KNN. The 10 most important channels are located primarily in the parietal lobe, while some are distributed throughout the frontal and parieto-occipital regions. The parietal region is responsible for creating a spatial understanding of the surrounding environment and our location in it, and it is also where most sensory information is interpreted [14]. However, aspects related to prospective memory, future planning, and decision-making occur in the frontal lobe [14]. The map highlighting the parietal and frontal areas indicates that these are key areas to distinguish between *dream experiences* and *no-experiences*. When applying the MEMD-filtered data, the left parietal and front regions are emphasized.

For EEGNeX, the highlighted channels are predominantly located in the frontal, central, and parietal regions. The frontal region emerges as the most important area, suggesting that CNN captures activity in this area rather than in the parietal region, as observed with PCA, CSP, and KNN. The MEMD-filtered EEGNeX map is of more importance in the left frontal region. This could mean that dreams incorporate elements of logical reasoning, as research suggests that the left brain is associated with logical thinking [7, 15].

The topographic maps of PCA, CSP, and KNN exhibit notable differences compared to those of EEGNeX, both in important regions and in the performance delta. The maximum performance delta is lower when using EEGNeX (0.33) than when using KNN (0.56). That means that the subset of channels used is not as relevant for EEGNeX as for KNN, where the removal of specific channels greatly decreases performance.

Classification using PCA, CSP and KNN with MEMD-filtered data yields the highest performance; therefore, the associated topographic map is more reliable. The observations of the topographic map also align with the reported findings of frequency changes in the parieto-occipital, medial, and lateral frontoparietal regions while dreaming in NREM [6].

The classification using 10 channels instead of 58 results in less than 0.06 of a decrease in Fscore, precision, and recall, 0.09 of accuracy, 0.13 in AUROC and 0.25 in kappa, when using PCA, CSP, and KNN with MEMD-filtered data. This result holds promise as a first step towards the development of a BCI system for dream decoding applications. However, since the analysis is limited to NREM data, the findings for REM data may vary and need further investigation.

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