A Comparative Analysis Between Standard Polysomnographic Data and In-ear-EEG Signals

Scuola universitaria professionale della Svizzera italiana
SUPSI

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IDUN Technologies

Introduction

General Context of Application

- *Polysomnography (PSG)* is the gold standard to assess sleep disorders. The PSG setting is uncomfortable and impractical to use at home and introduces bias to sleep quality assessment.
- A promising solution is the *in-ear-EEG* due to the several advantages in comfort, fixed electrode positions, robustness to electromagnetic interference, and ease of use.

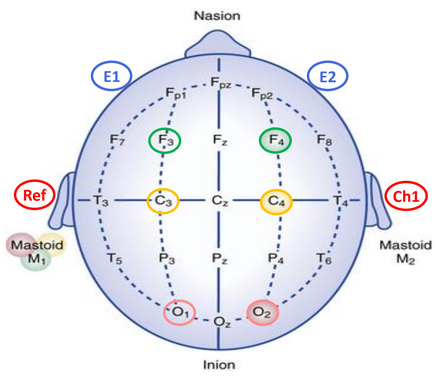
Our goals

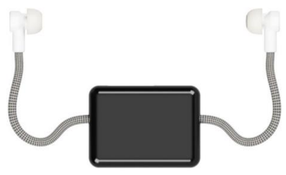
- We develop a pipeline to evaluate the similarity between in-ear-EEG and standard PSG derivations: ground truth sleep stages assessment, most relevant features identification, similarity-scores definition.

Materials and Methods

Data

- Four-hour already pre-processed signals recorded over 10 healthy subjects (males and females, age 18-60 years).
- In-ear-EEG data collected using *IDUN Guardian Development Kit (GDK)* with one unipolar channel, i.e. ch1. PSG data collected using *SOMNOmedics SOMNOscreen plus system* with 21 unipolar and bipolar PSG channels, i.e. scalp-EEG, EOG, and $M2$-$M1$ derivations.
- PSG and in-ear-EEG data scored according to *AASM guidelines (W, N1, N2, N3, REM)*





I. Hypnograms investigation

- The three Not-REM classes, i.e. N1, N2, N3 are merged under a common label '*NREM*'.
- Consensuses definition by means of *majority voting* and *soft-agreement metric*.
- Hypnograms variability analyses using *Cohen's kappa metric* to have one common reference to all signals.

II. Feature extraction and Feature selection

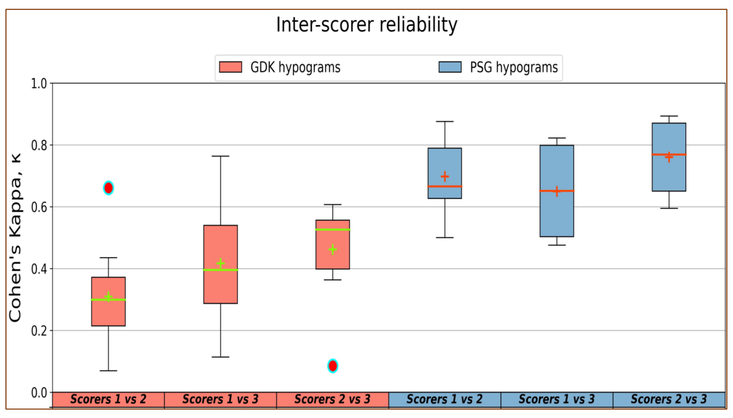
- Time-domain and frequency-domain feature extraction.
- Non-supervised feature selection based on k-NN and *Maximal Information Compression Index (MICI)*: optimization using *representation entropy* and *redundancy rate*.

III. Similarity-scores definition

- Features' distributions investigation by means of *boxplot* and *Shapiro-Wilk* test.
- Statistical comparison between PSG and in-ear-EEG features: similarity-scores defined and assigned to all the investigated channels.
- Most similar PSG derivations to the in-ear-EEG assessed separately for each sleep stage and for each subject.
- Results aggregation over the classes and then over the subjects.

Results

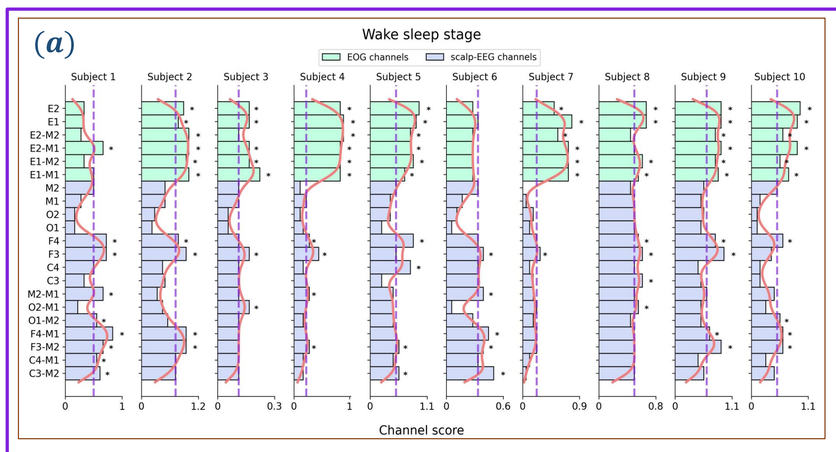
We define the ground truth as the intersection between PSG and in-ear-EEG consensuses. The small agreement between the two consensuses can be blamed on a little consistency in the in-ear-EEG labelling procedure.

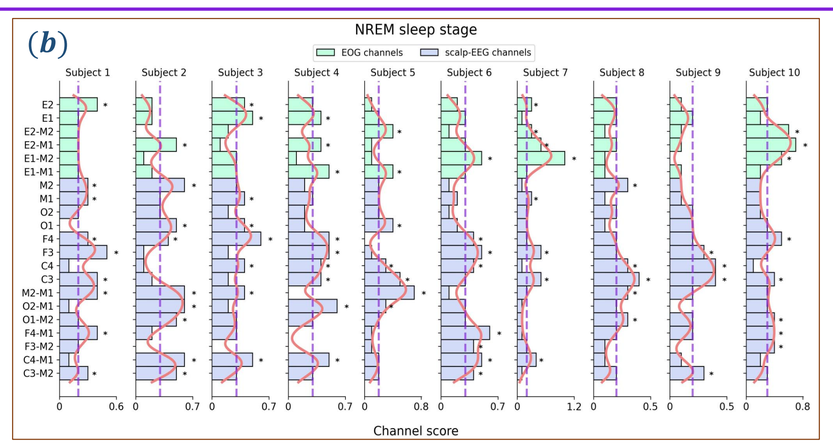


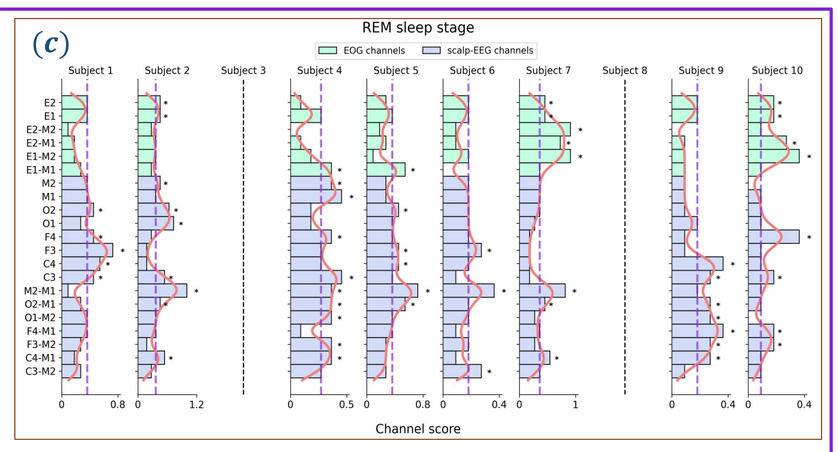
We extract 45 features from time and frequency domains. The final number of selected features is 25, 23, and 22 for wake, NREM, and REM labels. The percentage of features common to all the three classes is around 52% for wake, 56.52% for NREM and 59.09% for REM.

Frequency domain features		
Spectral energy*	δ/θ power ratio	Spectral centroid
Relative δ power band	δ/σ power ratio	Spectral crest factor
Relative θ power band	δ/β power ratio	Spectral flatness
Relative α power band	θ/α power ratio	Spectral roll-off
Relative σ power band	δ/α power ratio	Spectral spread
Relative β power band	α/β power ratio	Spectral mean*
Relative γ power band	$\delta/(\alpha+\beta)$ power ratio	Spectral variance*
Spectral entropy	$\theta/(\alpha+\beta)$ power ratio	Spectral skewness
Renyi entropy	$\delta/(\alpha+\beta+\theta)$ power ratio	Spectral kurtosis

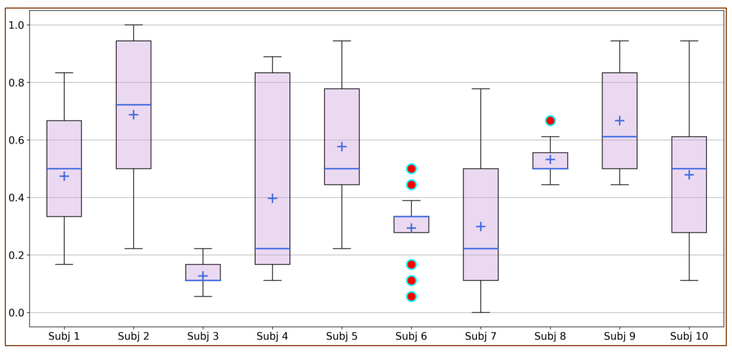
Time domain features		
Standard deviation*	DFA exponent	Hjorth activity*
Skewness	Approximate entropy	Hjorth mobility
Kurtosis	Sample entropy	Hjorth complexity
Max first derivative*	SVD entropy	Katz FD
Interquartile range*	Permutation entropy	Higuchi FD
Zero-crossings	Lempel-Ziv complexity	Petrosian FD



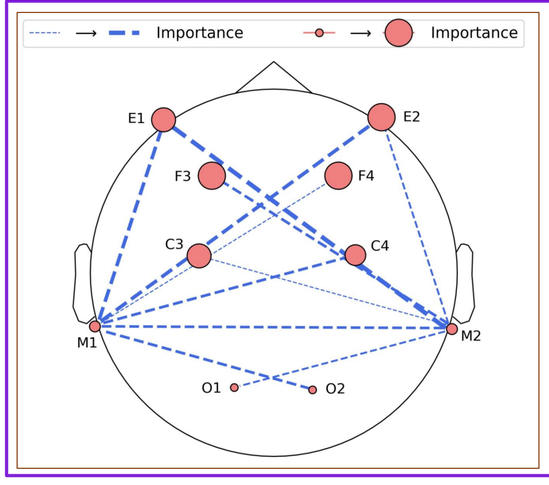


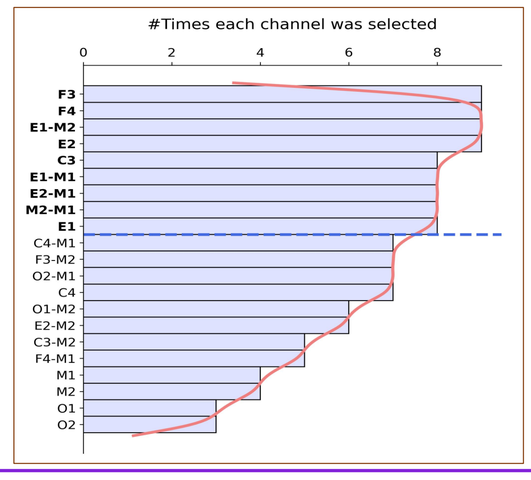


($\boldsymbol{a}$) For the wake brain state, frontal derivations are the most selected scalp-EEG channels; a high similarity is found between the in-ear-EEG and the EOG channels. ($\boldsymbol{b}$) Focusing on NREM sleep stages, central and frontal channels as well as the mastoid-to-mastoid derivation show the highest similarity scores; the affinity between in-ear-EEG and EOG signals decreases a lot with respect to the wake sleep stage. ($\boldsymbol{c}$) For the REM label, the highest affinity is found between the in-ear-EEG and both central channels and the mastoid-to-mastoid derivation; the similarity between the in-ear-EEG and the EOG is very little.



Very dissimilar ranges are found for different subjects, thus the analysis is carried out separately for each participant and for each sleep stage.





The most similar PSG channels to in-ear-EEG signals are anticipated to be the ones closer to the temporal regions. Mainly frontal and EOG channels, and the mastoid-to-mastoid derivation show the highest similarity-scores.

Conclusions and Future works

The in-ear-EEG seems a valuable solution for a home-based sleep monitoring. A customized procedure on each individual subject may turn out to be a more reasonable solution than a general analysis. The need for EOG contribution in sleep analysis cannot be excluded. In further studies, sleep stages may be weighted differently to avoid bias in results. More uniformity among contra-lateral channels could be overcome with larger and more heterogeneous datasets. This would allow to extend the analysis to the three not-REM labels separately.