Automated assessment of sleep in healthy pediatrics from simulated behind-the-ear EEG

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GUEG SEPILOG

INTRODUCTION

The properties of sleep architecture are an under-evaluated but highly relevant aspect for children with epilepsy [1,2]. Conventional recording methods for assessing sleep, which require EEG, EMG and EOG electrodes, are quite cumbersome and limit the examinations to single-night recordings. A more discreet and practical setup would open the path towards easier and longer-term recordings, additionally allowing to investigate daytime naps and multi-night correlations [3]. **The current study explores the feasibility of adopting a behind-the-ear EEG montage for automated sleep staging in a pediatric**

METHODS

- 50 overnight-recordings with conventional 10-20 set-up from pediatric patients (without epileptic abnormalities during the recorded period) were selected from a dataset from Saint-Luc University Hospital (Brussels, Belgium).
- 3 independent experts manually scored sleep staging (Wake, N1, N2, N3, REM).
- **Behind-the-ear montage was simulated** from 9 additional recordings which had simultaneous 10-20 and behind-the-ear EEG (provided by Byteflies). For each recording, the ordinary least-squares solution (OLS) was obtained. The average OLS solution was used to simulate a behind-the-ear montage for the 50 pediatric

population.

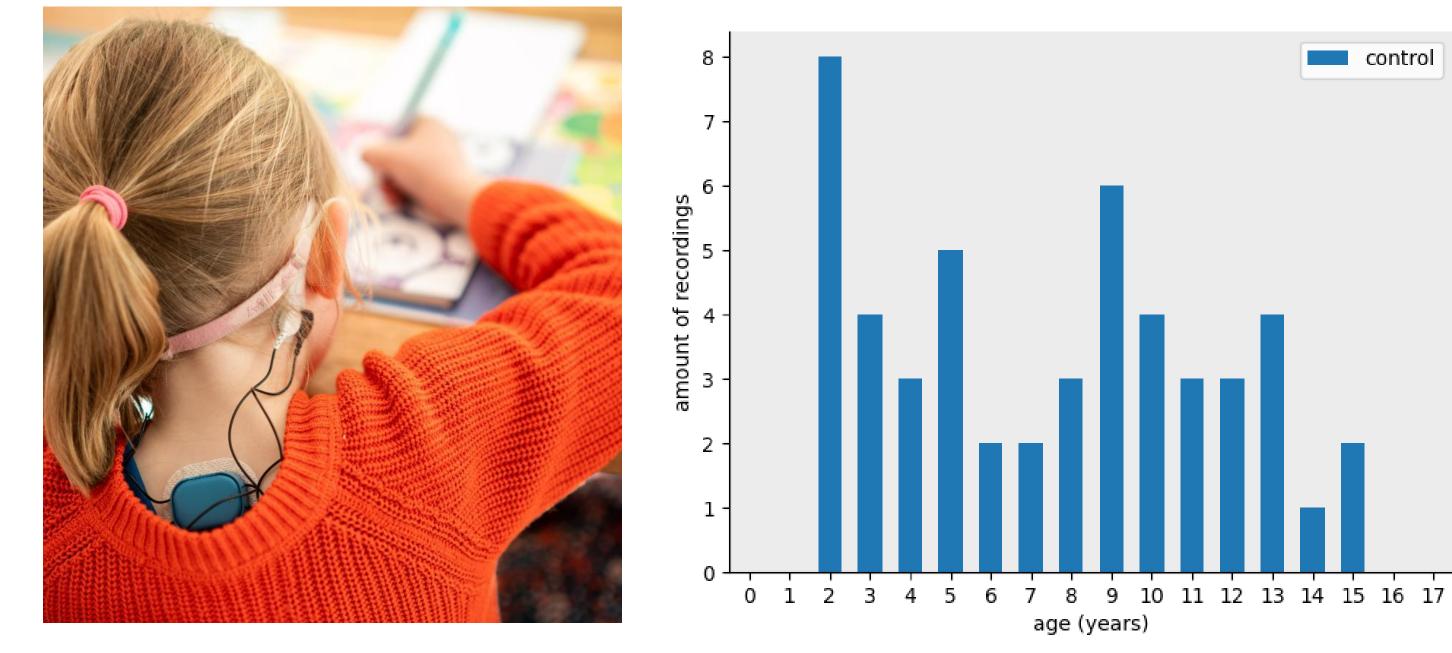


Figure 1. Behind-the-ear EEG was simulated in 50 pediatric patients from 10-20 EEG. Left panel: Example of a behindthe-ear EEG setup in a pediatric subject. Right panel: The histogram of the pediatric patients included in the study.

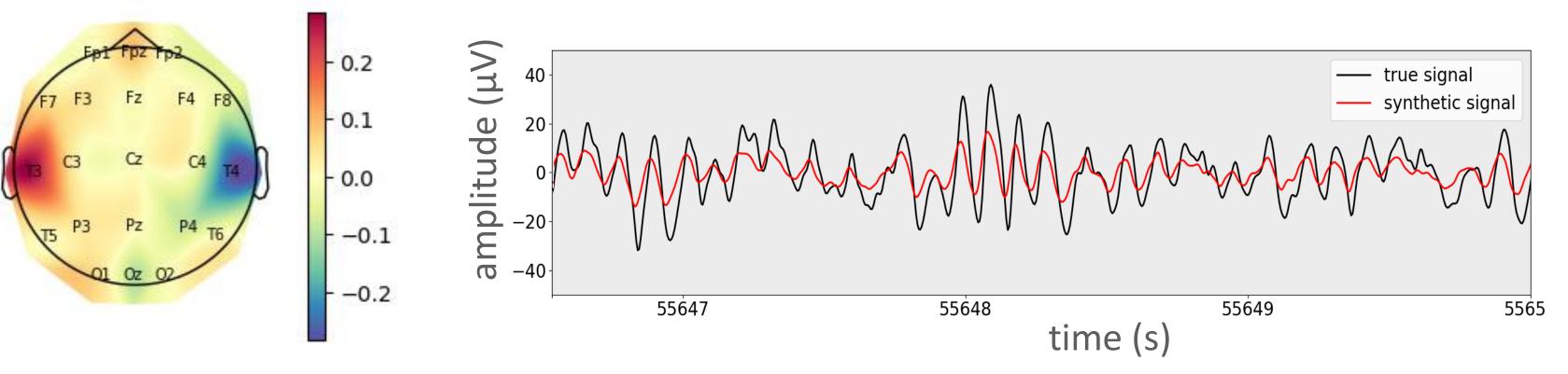
patients.

- Sleep staging models were trained for automated sleep scoring (Wake, NREM, REM) for the 10-20 set-up as well as the behind-ear-simulation. This algorithm included the extraction of several features and a gradient boosting model for classification.
- **Performance evaluation** was based on Cohen's kappa coefficient (κ) using a 5fold cross-validation strategy. The inter-expert agreement was used as baseline performance.
- **Statistical comparisons** was done with the two-tailed Wilcoxon signed-rank test and a significance threshold of 0.01.

RESULTS

Simulating behind-the-ear EEG from 10-20 EEG

The average OLS solution to simulate the behind-the-ear from full scalp EEG montage uses a bipolar reference of channels T3 and T4. The amplitude of the



bipolar signal is furthermore reduced by 70% to match the reference behind-

the-ear signal.

Figure 2: Left panel: Average OLS solution to simulate a behind-the-ear montage from 10-20 scalp EEG. Colors indicate the weights that were assigned to each channel. Tight panel: Overlay of true and synthetic behind-the-ear signal show a good match.

Automated sleep staging

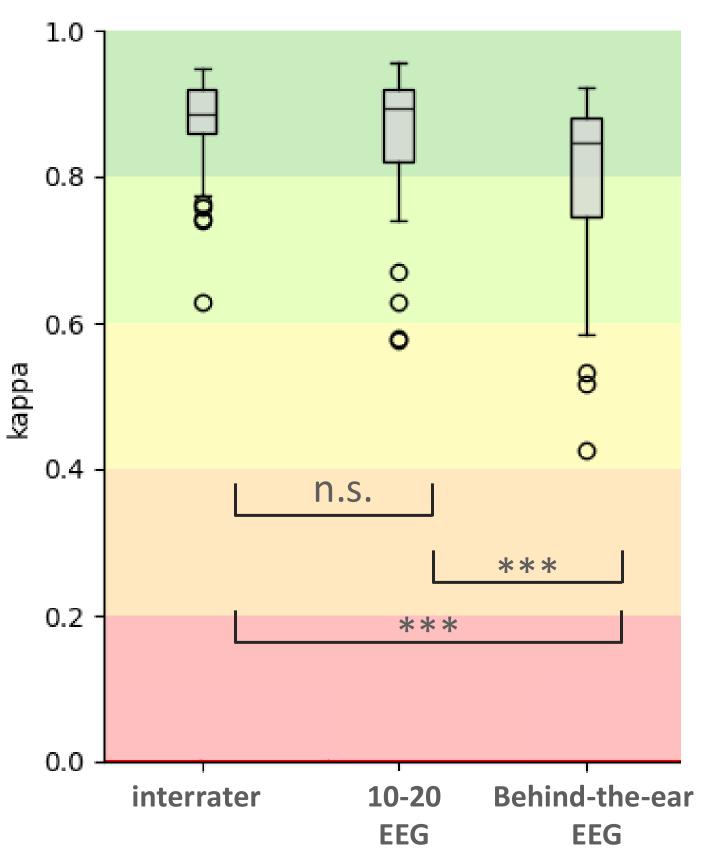


Figure 3: Cohen's kappa coefficients of the agreement between readers (left), the full-scalp staging model

The average agreement among the three experts for full-montage recordings was high ($\kappa = 0.87\pm0.06$). Note that this is higher than in literature due to the many Wake stages (~50%, 24-hour recordings) and the grouping of N1, N2 and N3 stages in one NREM group. The model that uses the **full-scalp EEG** achieves near-perfect agreement with the consensus scoring ($\kappa=0.87\pm0.09$), which was not significantly different compared to the interrater agreement (p=0.74). From **behind-the-ear EEG**, the model reached a slightly lower, albeit still high, agreement compared to consensus scoring ($\kappa=0.81\pm0.1$). This is significantly different from the full-scalp model and the interrater agreement (both p<0.001).

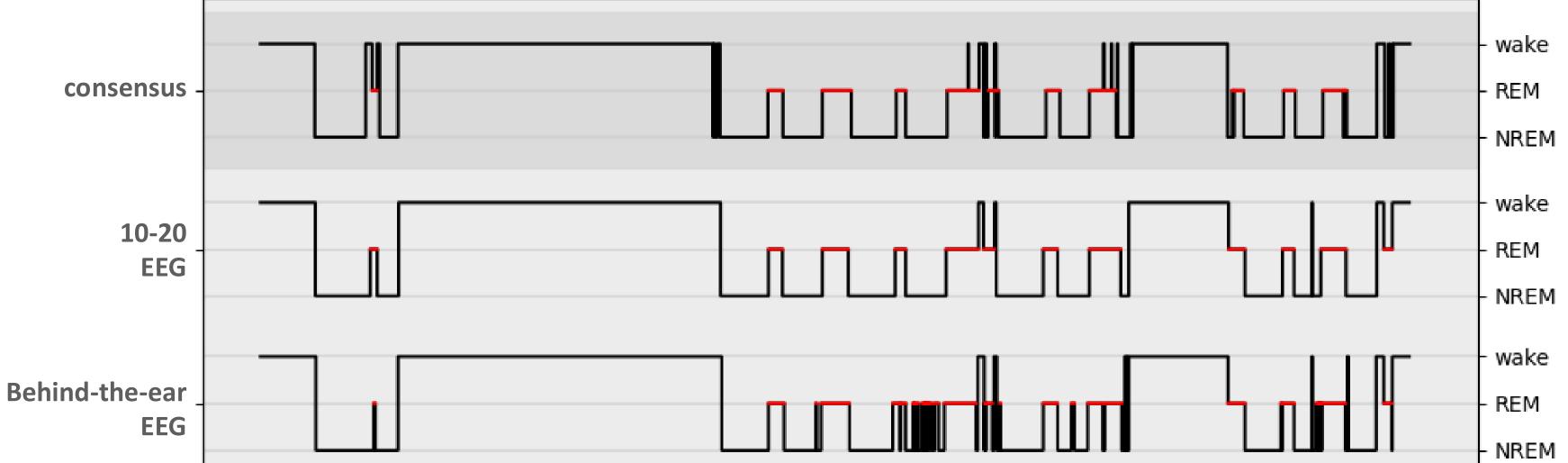


Figure 4: Example of similarity between hypnograms obtained by the expert consensus scoring, the automated scoring based on the 10-20 scalp EEG and the automated scoring based on the simulated behind-the-ear EEG.

	(middle) and the behind the ears staging model						- NREM	1M	
	(middle) and the behind-the-ears staging model (right).	0 1 2 3 4 5 6	7 8 9 1 time (hours)	0 11 12	13 1	14 15 16			
	CONCLUSION						LIMITATIONS		
•	Sleep staging can be reliably assessed automatically from a behind-the-ear EEG setup.				• N	 No assessment on actual behind-the-ear recordings. 			
•	The algorithm reliably detects NREM stages and wakefulness, detection of REM stage is less reliable, likely due to limited spatial sampling.			, likely	 Cross-validation within one datasets does not allow to assess generalizability across population and hardware. 				
•	This holds promise toward a broader clinical utility and ease-of-use of long-term sleep assessment (incl. its use in ambulatory settings) combining non-intrusive wearable hardware with automated analysis.			incl. its		Ļ	ACKNOWLEDGEMENTS		
					This study was funded by UCB Inc				
	References								
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