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Add-on **patient-specific seizure detection** when the generic approach fails

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Introduction

The performance of automatic seizure detection methods is reaching a satisfactory level on a population basis. However, due to the interindividual seizure heterogeneity, there are still people with epilepsy (PWE) for whom the generic algorithm works inadequately. Therefore, we aim to develop a patient-specific seizure detection algorithm based on one single seizure that uses the individual's most distinguishable subset of features to address seizure heterogeneity.

Methods

- A 55-years-old PWE was monitored for a period of 299 days with a two-channel subcutaneous EEG (sqEEG) device.
- Device adherence of 98%, 7109 hours of continuous EEG recorded.
- 9 seizures were identified by visual inspection

Feature Extraction:

- A general feature space with 22 frequency and non-linear features were extracted from each epoch (4 seconds, 3 seconds overlap) of EEG.
- The training data consisted of a single seizure as well as samples of random interictal data corresponding to the same duration as the training seizure from the same PWE.
- The training seizure revealed 7 minutes of ictal activity. However, only 6 minutes with clear morphology changes were used for training and thereby also, 6 minutes of background data were selected.

Feature Selection

- Permutation feature importance was used for individualized feature selection to select the most distinguishable features for developing a classification model.

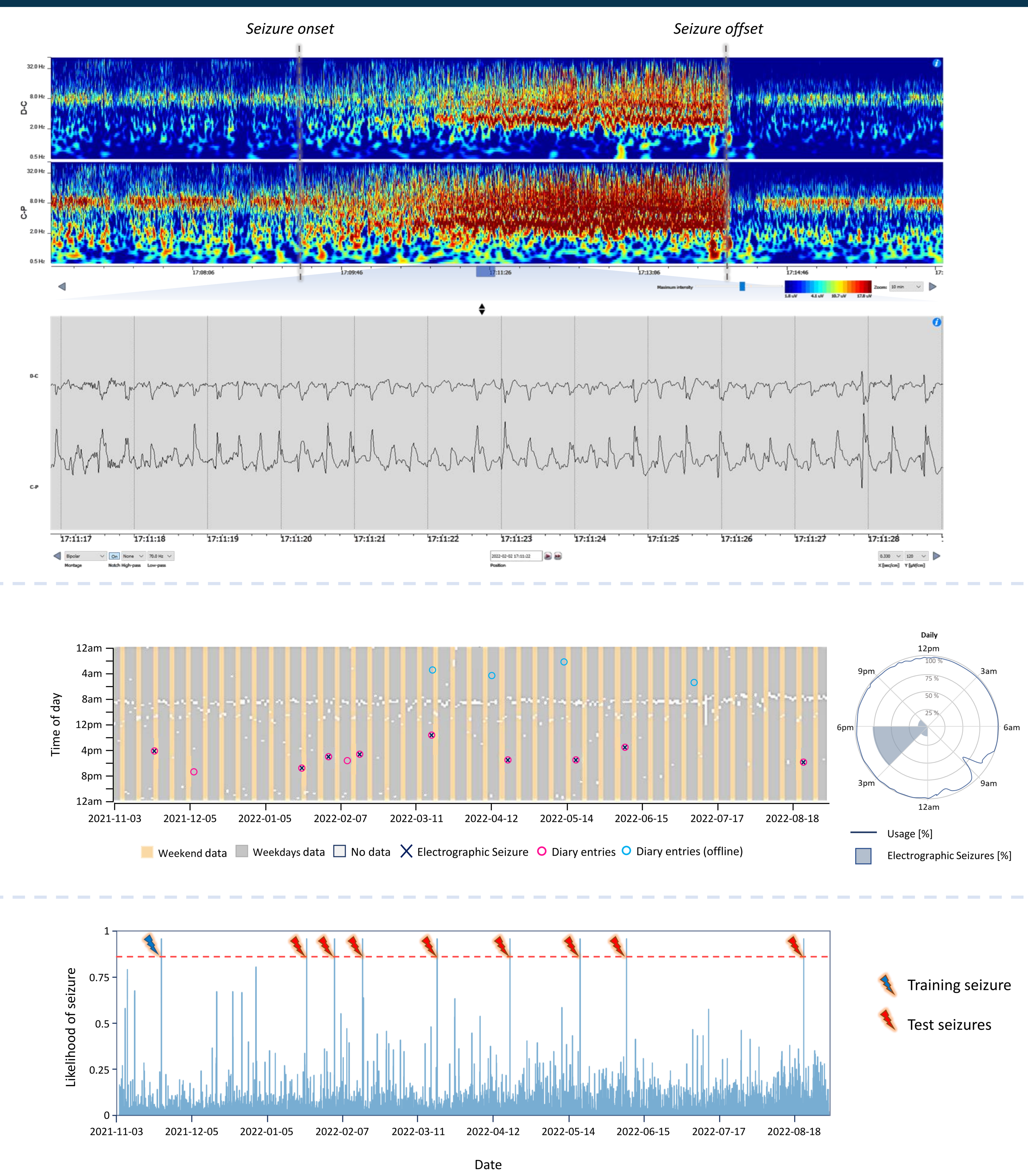
Classification

- An SVM classifier based on these individualized features was trained and then tested on the rest of the recording. A linear moving average filter and thresholding process were adjusted based on the duration of the training seizure and applied to the predicted labels to acquire the final results.

A.

B.

C.



A. Illustration of the two-channel sqEEG data from a sample seizure in the time domain (below) and time-frequency.
B. Seizure event report with the recording device adherence over 299 days. All diary entries without electrographic correlate was found to be false.
C. Classifier output following a linear moving average filter. The orange line depicts the individualized threshold for the seizure's likelihood. All 8 test seizures were correctly identified by the classifier with no false detections.

Results

- Eight frequency features were found to be optimal in distinguishing ictal from interictal data.
- When testing the algorithm on all 7446 hours of sqEEG, a total of 8 seizures were correctly detected, giving a sensitivity of 100% with no false positive detections.

Conclusions

Our results show that a single-seizure-trained model using an individualized feature-based method could address the interindividual heterogeneity of seizure characteristics while considering intrasubject homogeneity. Although our results demonstrate precise patient-specific seizure detection, this only holds true if the seizure signatures throughout the recording are identical to the identified training seizure. A future study with more subjects is needed to evaluate the performance of the proposed method.

Further reading:

- *Duun-Henriksen, et al., 2020. A new era in electroencephalographic monitoring? Subscalp devices for ultra–long-term recordings. Epilepsia.*
- *Weisdorf et al., 2019. Ultra-long-term subcutaneous home monitoring of epilepsy—490 days of EEG from nine patients. Epilepsia.*
- *Boonyakitanont et al., 2020. A review of feature extraction and performance evaluation in epileptic seizure detection using EEG, Biomedical Signal Processing and Control.*

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