Identifying epileptic spikes using ear-EEG


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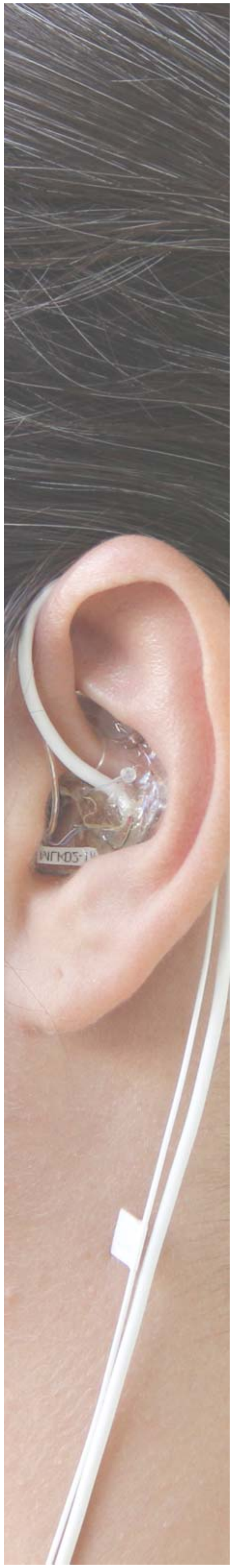
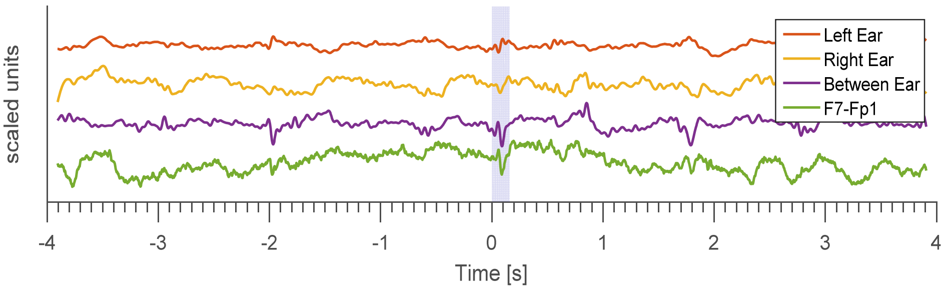


Background

Epilepsi is characterized by a host of changes to the EEG signal; the most well-known of these are the clinical seizures which can last up to several minutes, but other changes can also be observed. These are, collectively, called Interictal Epileptiform Discharges. In this project, we focus on the so-called spikes, which are well-defined, short discharges, of duration up to 70 ms (see example in Figure 1). It is theorized that fluctuations in spike frequency within a given patient could be linked to the effectiveness of epilepsi treatment.

To obtain maximal benefit of spike recordings, it is important to be able to record them easily over long times, without long visits to the hospital. As such, a mobile EEG platform that is easy to use and which can reliably register spikes is necessary. One solution to this is the ear-EEG platform [1], shown in Figure 2.

Figure 1
Example of a spike event.



Setup

EEG

13 patients were admitted to the epilepsy monitoring unit at Roskilde Sygehus, following normal procedures, including a 24-electrode EEG-cap. Additionally, 4-channel ear-EEG was placed in each ear, using ear pieces modeled from individual ear impressions. All electrodes had a common reference, and were sampled at 256 Hz.

Classifier

An ensemble of 30 decision-tree classifiers were used, as implemented in the Matlab Statistics and Machine Learning Toolbox, v. 10.1. Before feature extraction, the ear-EEG data was reduced from 8 channels to 3, describing within-ear variation of each ear, and between-ear variation. To this was added the ECG, making 4 time series.

These time-series were cut into 70 ms-long epochs, spaced 35 ms apart. For each epoch, 36 features were calculated, described in the box to the right.

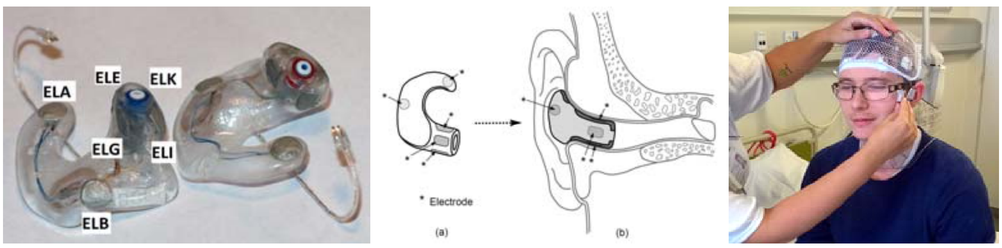
To compensate for the extreme imbalance in the data set between relevant and irrelevant epochs (roughly 1 in 1000 epochs contains a spike), additional epochs were extracted around the previously identified spikes, reducing the imbalance to about 1 in 100.

Rundown of the 36 features calculated per epoch

For each ear-EEG channel:
- 3 wavelet-based features to detect spike waveforms
- 1 for EMG artifacts
- 1 for discarding ”half-spikes”
- 1 for discarding spike trains
- 5 for various frequency bands

Additionally:
- 1 single feature describing between-channel variation.
- 2 features detecting ECG-artifacts.

Figure 2
The ear-EEG platform. Pictures taken from [2].



Results

In the dataset used for testing, 45 spikes were present. Of these, the classifier successfully marked 25, giving a success rate of 56%. Unfortunately, given the imbalanced nature of the problem, even the quite low false-positive rate resulted in 546 additional markings. We are, however, confident that this problem will be remedied by increasing the set of training examples, which we are in the process of doing.

Bibliography

[1] Looney, D., Kidmose, P., Park, C., Ungstrup, M., Rank, M., Rosenkranz, K., Mandic, D., 2012. The in-the-ear recording concept: User-centered and wearable brain monitoring. IEEE Pulse 3 (6), 32-42.
[2] Mikkelsen, K. B., Kappel, S. L., Mandic, D. P., Kidmose, P., Nov. 2015. EEG recorded from the ear: Characterizing the Ear-EEG method. Frontiers in Neuroscience 9.