P300 event-related potentials classification from EEG data through interval feature extraction and recurrent neural networks

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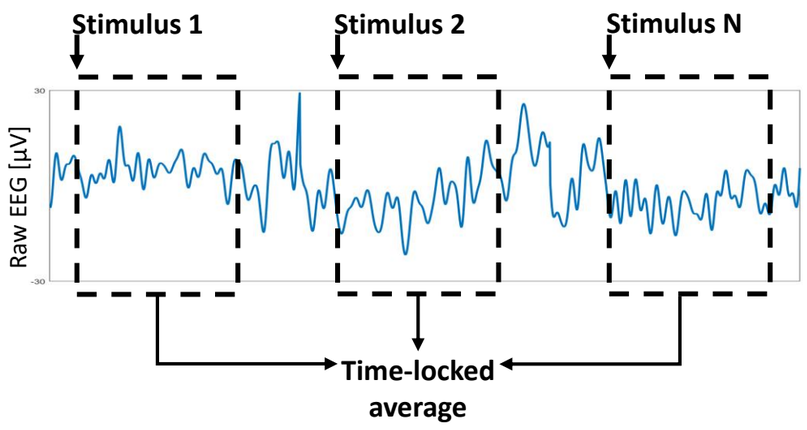
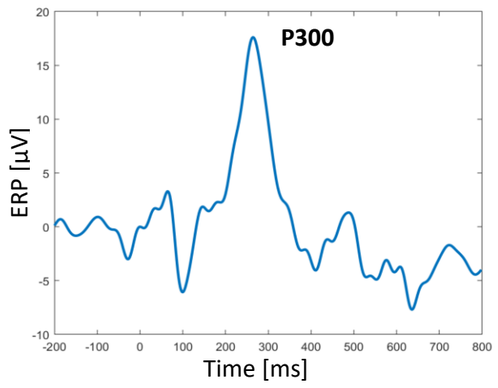
Introduction

- Event-related potentials (ERPs) are reproducible electrophysiological responses after the administration of an external stimulus.
- Due to their low amplitude and SNR, the extraction of ERPs is usually achieved by processing multiple presentations of the same kind of stimulus using time-locked average of the signal epochs.



- P300 component is a positive deflection appearing around 300 ms after the stimulus presentation.



P300 component is representative of the evaluation and the categorization of the stimuli, allowing to discriminate among the subject's brain states.

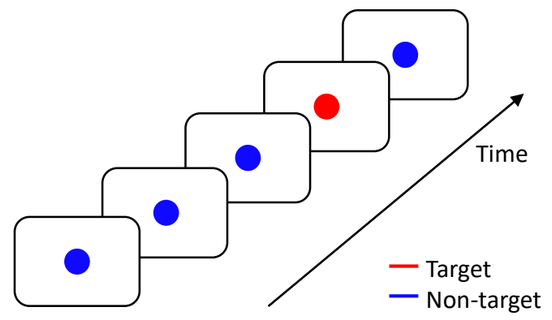
- P300 neural responses can be useful to examine impairments in sensory and cognitive processing. To reduce the number of trials (fatigue issue), novel signal processing and machine learning algorithms are needed to also achieve robust automatic ERPs classification.

Methods

Objective: to test the performance of a Long Short-Term Memory (LSTM) network to classify P300 component between target and non-target stimuli in an auditory oddball paradigm.

Experimental protocol: *(CHU Pasteur, CERNI 2019-4)*

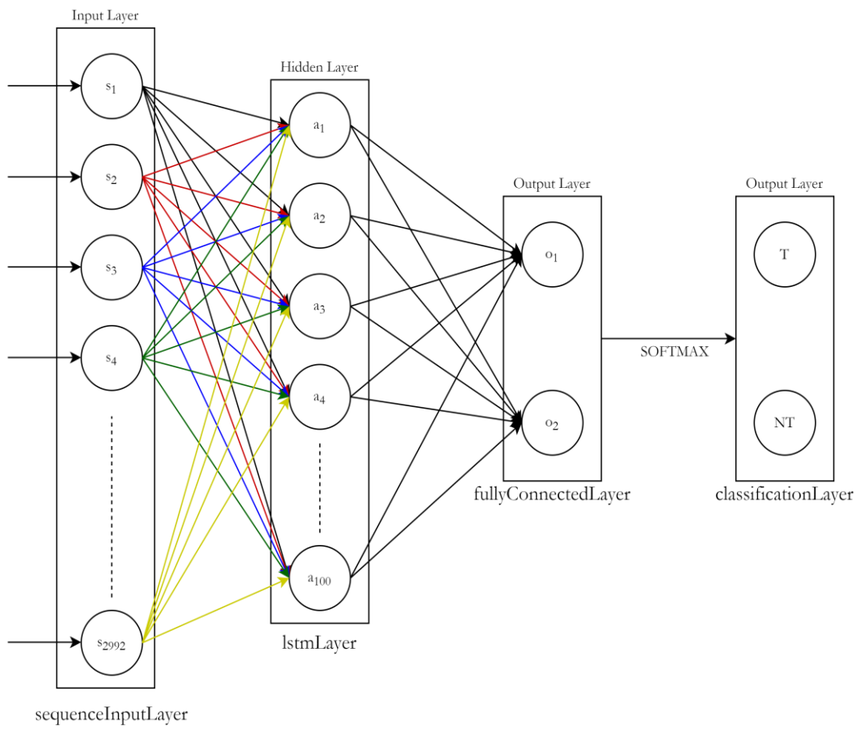
- sequences of low frequency pitch tones (non-target) are infrequently interrupted by a deviant high pitch tone (target), i.e. 80% stimuli are non-target and 20% target.
- 2 subjects (S1, S2) for a total of 324 trials
- 19-channels EEG recordings



Interval features extraction:

For each time *i* of the trial, segments with length varying as the power of 2 were formed, by keeping always *i* as the starting point and including the rest of the time series until the length of the interval exceeds the epoch. Then, for each interval µ and σ were calculated and used as features to feed the network.

$$\text{Length } 2{:}\{x_i, x_{i+1}\} \rightarrow \mu, \sigma$$
$$\text{Length } 4{:}\{x_i, x_{i+1}, x_{i+2}, x_{i+3}\} \rightarrow \mu, \sigma$$
$$\text{Length } 8{:}\{x_i, x_{i+1}, \ldots, x_{i+7}\} \rightarrow \mu, \sigma$$
$$\ldots$$
$$\forall x_i \text{ with } i = 1,\ldots,T \text{ with } T = \text{length}(\boldsymbol{x})$$



Classification:

Use of a single-layer LSTM network, followed by a fully connected layer and a softmax activation function. A different classification problem was solved for each electrode.

Two approaches were tested:

- a *subject-dependent* one, by using 75% of S1 samples as training set and the other 25% as test;
- a *subject-independent* one, by using 200 samples (100 S1 + 100 S2) as training set and the remaining ones as test.

Results

Table 1. % accuracy for each electrode classification problem for the *subject-dependent* approach

Fp1	84.00	**Fp2**	82.00	**F7**	76.00	**P8**	78.00
F3	84.00	**F4**	82.00	**T7**	80.00	**Fz**	88.00
C3	86.00	**C4**	80.00	**P7**	76.00	**Cz**	82.00
P3	80.00	**P4**	84.00	**F8**	80.00	**Pz**	84.00
O1	84.00	**O2**	80.00	**T8**	72.00	**Mean**	81.16

Table 2. % accuracy for each electrode classification problem for *subject-independent* approach

Fp1	73.23	**Fp2**	75.59	**F7**	74.02	**P8**	75.59
F3	76.38	**F4**	77.95	**T7**	73.23	**Fz**	74.80
C3	77.17	**C4**	77.17	**P7**	70.08	**Cz**	74.02
P3	75.59	**P4**	74.80	**F8**	75.59	**Pz**	75.59
O1	78.74	**O2**	77.17	**T8**	78.74	**Mean**	75.55

Conclusion

- Results **in line** with the previous literature studies, in which recurrent neural network outperformed other common algorithms, such as SVM.
- F3, F4, Fp1 and Fp2 allow globally the best accuracies. Indeed, P300 is typically stronger on the **frontal lobes**.
- Compared to other feature extraction methods, the interval feature extraction is **intuitive** and **easy-to-implement**, and does not rely on any other parameter.
- The use of this classifier is quite **encouraging**, but further analyses need to be done: data collection with a more balanced number of events, combination of the interval feature extraction to other features, and implementation of a LSTM bidirectional layer.

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