http://www.abstractsonline.com/Plan/ViewAbstract.aspx?sKey=4b4dced4-983e-42b5-9509-406113001b0a&cKey=08d405ea-516c-42c2-917f-c328e9ca8e7b&mKey={E5D5C83F-CE2D-4D71-9DD6-FC7231E090FB}.

# Application of Parallel Factor Analysis to electrophysiological data

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## INTRODUCTION

Synchronous firing of action potentials is believed to be one of the crucial mechanisms in the coding of information in the brain. Hence, the examination of the temporal structure of spike trains and the detection of patterns of synchronous firing events between the signals of multi-electrode recordings can provide fundamental insights into possible coding strategies.

We used **PARA**llel **FAC**tor analysis to investigate the effect of deactivation of the pMS cortex on the functional connectivity in area 18, based on cross correlation.

PARAFAC (Harshman & Lundy (1970) and Carroll & Chang (1970; there referred to as CANDECOMP) is a multi-dimensional decomposition method that generalizes the bilinear principal component analysis (PCA) to higher order arrays. The analysis is constrained to consider only certain interactions among the different dimensions, leading to simple mathematical models. At the same time, the obtained solution is unique - in contrast to PCA, where rotational freedom exists - allowing results to be rotated without reducing the quality of the modelling [2].
PARAFAC thus enables robust multi-dimensional analyses that allow a simple and clear interpretation.

### The PARAFAC Model

For a three-way array, the PARAFAC model is given by three loading matrices A, B and C, with elements $a_{if}$, $b_{jf}$ and $c_{kf}$. The number of components is denoted by F.
The trilinear model minimizes the sum of squares of the residuals $e_{ijk}$ in

$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + e_{ijk}.$$

## Data and pre-processing

Multi-unit spike data were recorded in area 18 of an anaesthetized cat using a 4x4 grid of electrodes. Visual stimulation was initiated by showing a grey screen for two seconds, followed by a static whole-field grating shown for two seconds, which then started moving for another four seconds.
In some phases of the experiment, the posterior middle suprasylvian sulcus (pMS) was thermally deactivated using cryoloops. There were three deactivation conditions: ipsilateral w.r.t. the recordings, contralateral and bilateral. Carried out unilaterally, the deactivation of pMS results in a visual hemi-neglect, which was confirmed before recording in the awake behaving animal.

Multi-unit data were recorded with a sampling rate of 22kHz and band-pass filtered between 800Hz-3.5kHz. Spikes were extracted using a manually chosen threshold. Analysis was performed on one-second long sections of data.
Raw correlations between the spiketrains were computed using the Matlab xcorr function with a window of 2ms, in which we considered two spikes to be synchronous. The correlograms were normalized by subtracting a jitter correlogram, obtained by convolving the original spike trains with a kernel

$$K\left(\underbrace{\frac{1}{\#Bins},\ldots,\frac{1}{\#Bins}}_{\#Bins}\right), \qquad \#Bins = \text{sampling rate} \cdot 6\text{ms}.$$

## RESULTS

### A Correlations

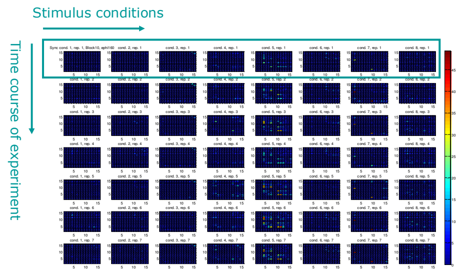



**Figure A** shows an example of the underlying correlation data for the PARAFAC analysis.
For the PARAFAC analysis, the following dimensions were selected:
1) electrode pair,
2) stimulus condition and
3) time course of experiment.

For every trial, the cross correlation between all possible pairs of electrodes was fed into the PARAFAC algorithm after subtracting the mean. One line in this plot corresponds to one data point in the loading graphs (B).
Correlation values in A correspond to repetition 14-21 in B i).

### B PARAFAC Loadings

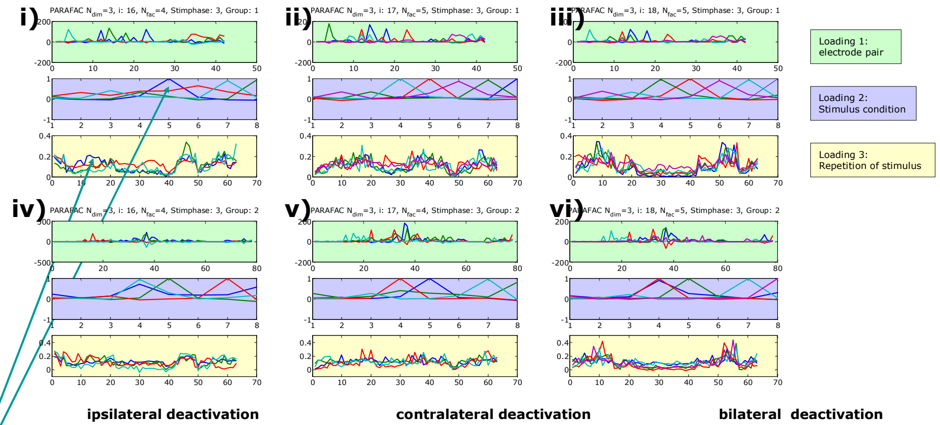
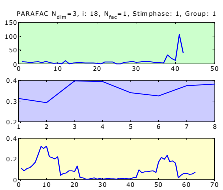



**Figure B** shows the resulting PARAFAC loading vectors for the following choice of dimensions:

- all possible **pairs of electrodes** in the array (**loading 1**), divided into "short" (42 pairs, i)-iii)) and "long" (78 pairs, iv)-vi)) distances,
- the 8 **stimulus orientations** (**loading 2**) and the
- 63 **repetitions** of the stimulus (**loading 3**).

Note: One colour in one plot corresponds to one factor but is not necessarily the same in the next plot.

### C Spontaneous activity



Already during spotaneous activity, the deactivation effect could be observed.

**Figure C** shows the PARAFAC loadings for one factor during bilateral deactivation.

### D Split-half analysis to validate the model

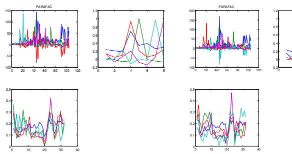


**Figure D** shows an example of a split-half experiment, which was carried out to validate the model. The data was divided into two halves; every 2nd trial belonged to the same group. PARAFAC was then applied to both halves of the data. The results are very similar, confirming that the model is appropriate for our purpose.

The loadings can be interpreted as the strength of influence on the correlation for the respective electrode pair, stimulus condition and time point.

Of the 63 repetitions showing the variation in time, the first 21 trials were recorded without deactivation. Trial 22-42 correspond to the phases of thermal deactivation of pMS. Trial 43-63 show the results for the rewarm condition.

In all data sets, we found a strong influence of pMS deactivation on the strength of correlations for both ipsi- and bilateral deactivation. Loading values for the deactivation phase were considerably lower than for the warm phases. Also, the variation in the warm phases was higher, indicating a more dynamic correlation pattern. This effect could already be observed during spontaneous activity (**Fig. C**). During contralateral deactivation of pMS, the effect was much weaker, showing that the activity in area 18 was not affected by the deactivation of contralateral pMS.

## CONCLUSION

Our approach demonstrates that feedback deactivation results in distinct changes of correlation patterns. The different PARAFAC factors (differently coloured lines in the loading plots) nicely differentiate the situations for the different stimulus conditions.
Thus, our study shows that PARAFAC is a well-suited tool to decompose multi-dimensional patterns in electrophysiological data and assign them to different biological conditions.

## References

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For PARAFAC analysis in MATLAB, we used the N-way toolbox: Andersson, C.A. and Bro, R. (2000) The N-way Toolbox for MATLAB. Chemometrics and Intelligent Laboratory Systems 52, 1-4.