



ADVANCED TIME-VARIANT, NON-LINEAR APPROACHES FOR ANALYSING BRAIN DYNAMICS

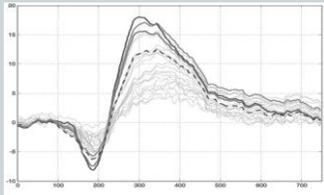
**Karin Schiecke, Diana Piper, Britta Pester, Lutz
Leistritz, Herbert Witte**



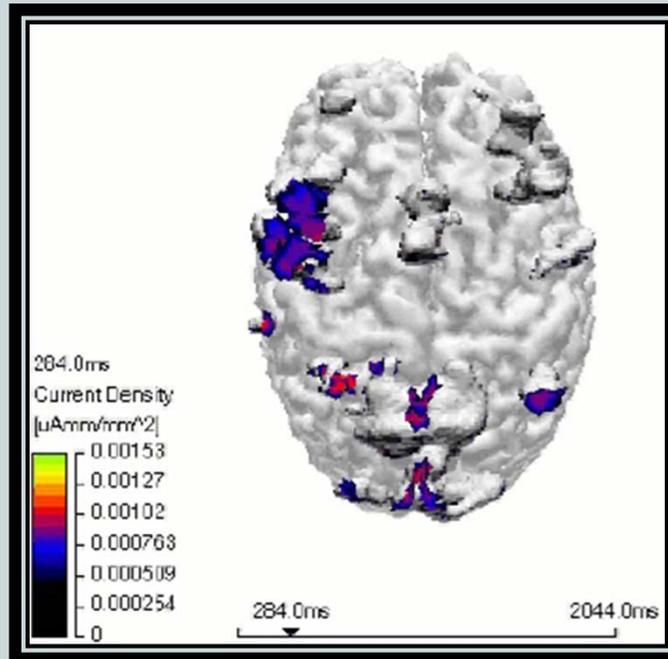
Bernstein Group for Computational Neuroscience,
Institute of Medical Statistics, Computer Sciences
and Documentation, Jena University Hospital,
Friedrich Schiller University Jena, Germany

↓ MRI (head model)

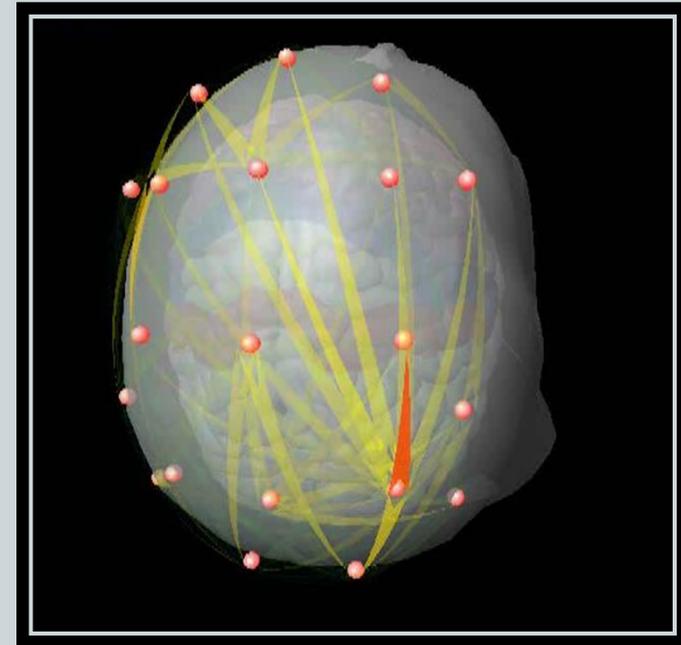
EEG /
MEG



source model
(e.g. CDR)



system and/or
process models



A. Brzezicka et al.: *Brain Topography* 24(2011)

neural mass
activity,
sensor space

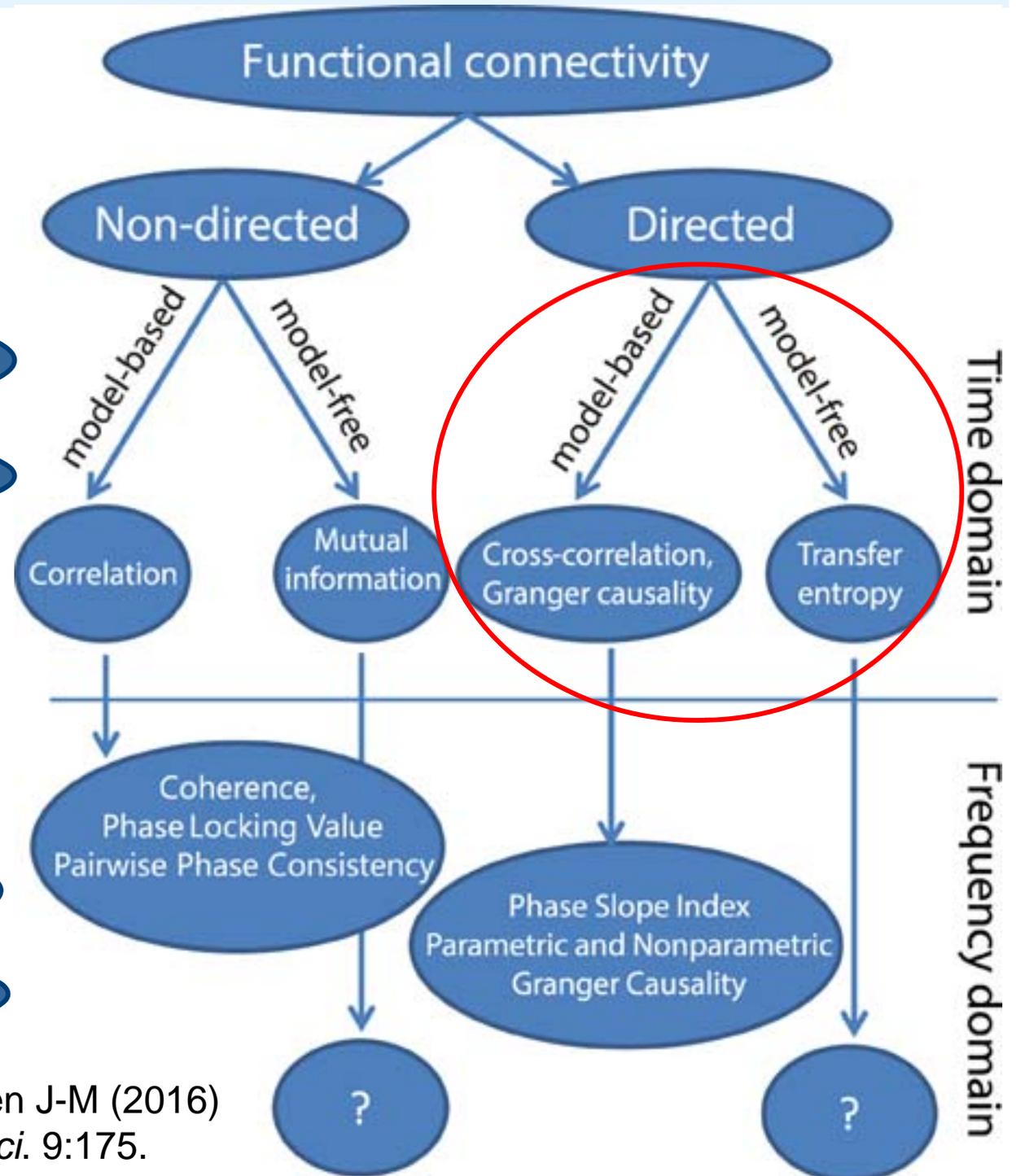
source space
activity

connectivity,
sensor and source space

- Multivariate
- Time-variant
- Frequency-selective
- ...

Representation and Interpretation of Results:

- Tensor Decomposition
- Network Analysis
- ...



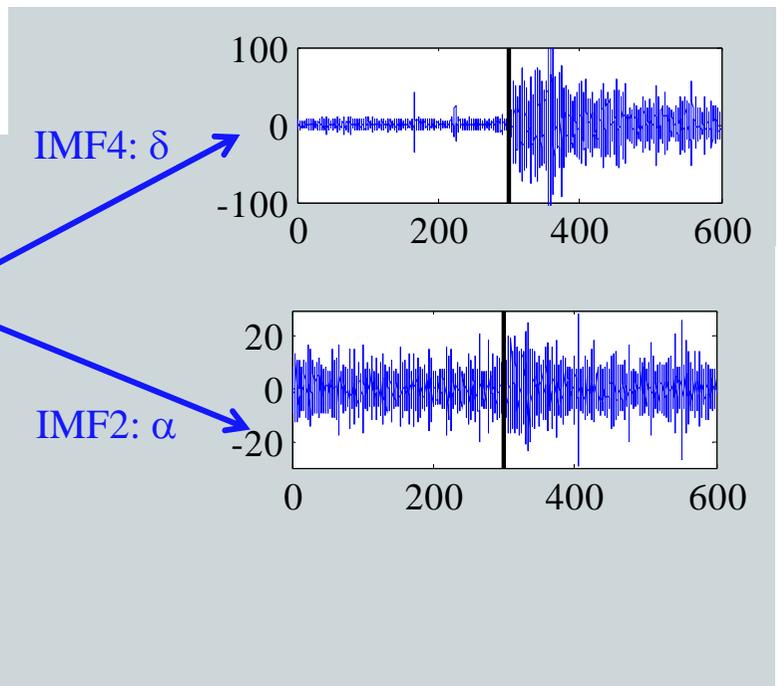
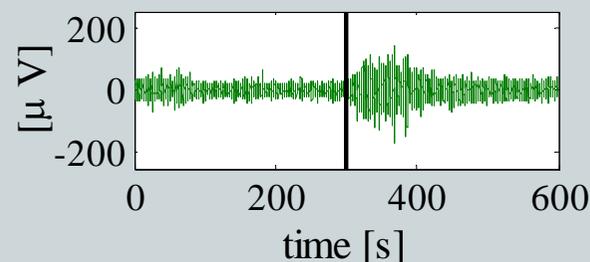
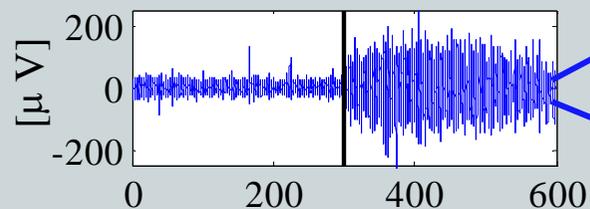
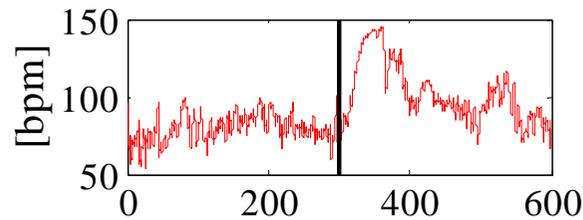
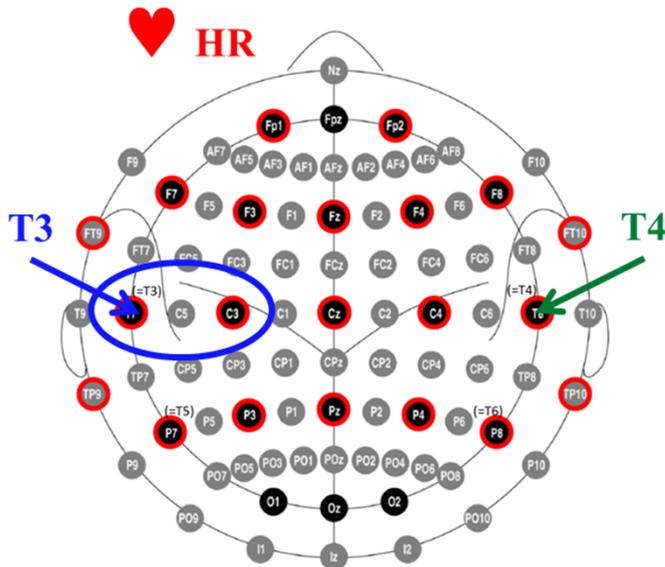
Epilepsy Monitoring Unit Vienna: temporal lobe epilepsy (TLE); 18 children, 9 left-sided, 9 right-sided seizures; video monitoring, 21 channels EEG, ECG; 1 seizure per child, 10 min recordings ($f_s=256$ Hz), seizure onset at 5 min;

EEG

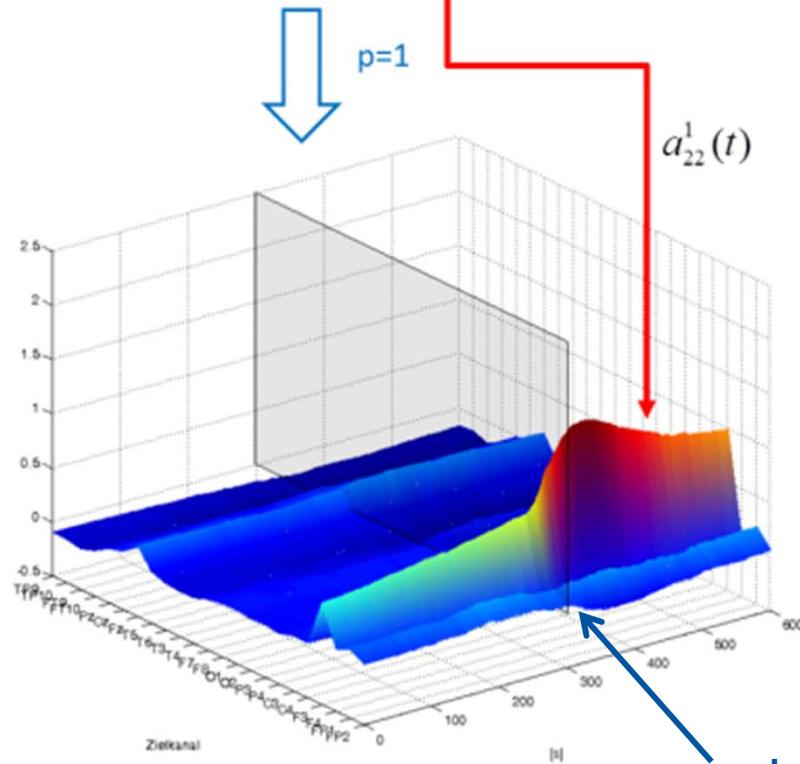


MEMD: **EEG_{IMF4}** and **EEG_{IMF2}**

example (focus left):



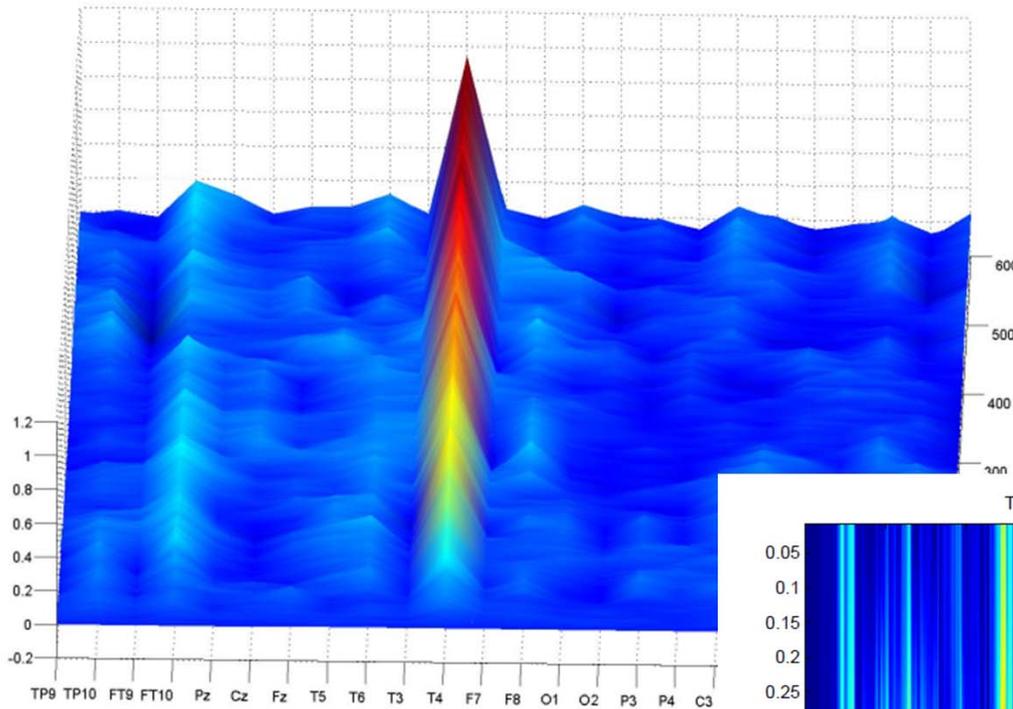
$$\begin{bmatrix} x_1(t) \\ \vdots \\ x_N(t) \end{bmatrix} = \sum_{p=1}^P \begin{bmatrix} a_{11}^p(t) & a_{12}^p(t) & \dots & \dots & a_{1N}^p(t) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{N1}^p(t) & a_{N2}^p(t) & \dots & \dots & a_{NN}^p(t) \end{bmatrix} \begin{bmatrix} x_1(t-p) \\ \vdots \\ x_N(t-p) \end{bmatrix} + \begin{bmatrix} w_1(t-p) \\ \vdots \\ w_N(t-p) \end{bmatrix}$$



example 1:
 EEG during TLE
 F3-related column of AR coefficients
 for $p=1$ (time-variant, multivariate
 approach)

**each channel / electrode is best
 explainable by itself !!!**

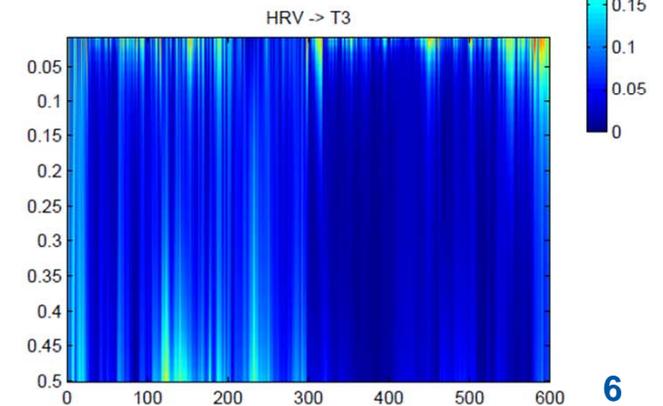
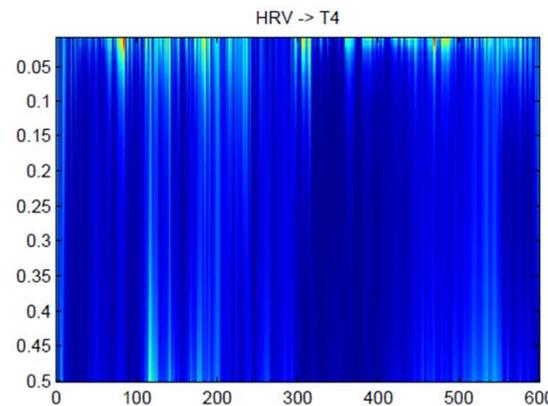
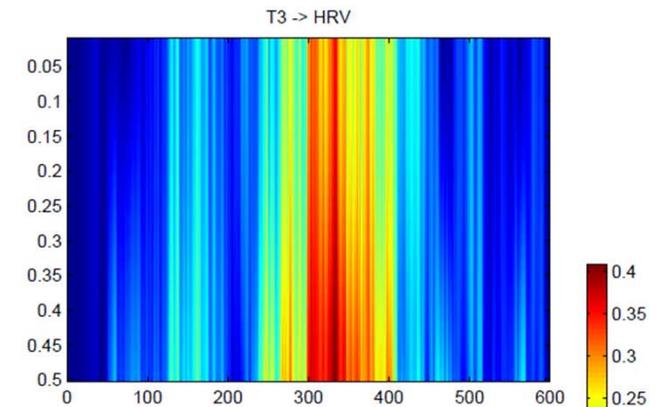
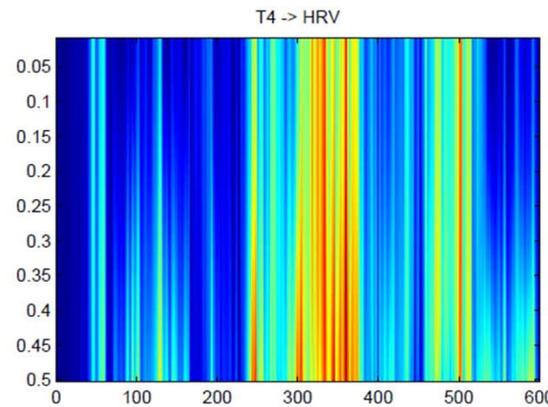
Example 2:
 EEG-component-envelope / HRV
 during TLE
 T4-related column of AR coefficients
 for $p=1$ (time-variant, multivariate
 approach)



Example 2:
 EEG-component-envelope
 / HRV during TLE
 resulting time-variant,
 multivariate estimation of
 PDC



**no interpretable /
 meaningful results!!!**



interaction / coupling between EEG components, EEG and HR ...: adaptation of (TVMVAR) GC-based approaches

TLE data: AR-based models fail !

nonlinear, non-AR-based alternatives

- ✓ **directed causation**
- ✓ **time-variant**
- ✓ **frequency-selective**
- ✓ **multivariate**
- ✓ **robust concerning noise**
- ✓ **statistically quantifiable**

Convergent Cross Mapping ?

Convergent Cross Mapping (CCM) [Sugihara et al. 2012] :

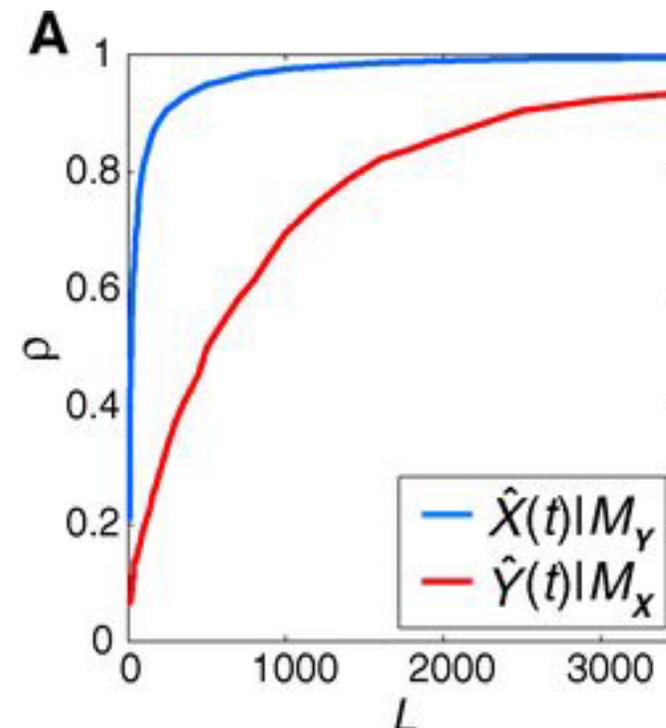
- **correspondence between “shadow manifolds” M_X and M_Y (nonlinear state space reconstruction by lagged coordinates) of time series X and Y**
- **measures to which extent historical record of Y values can estimate states of X or vice versa**
- **cross mapping: X by $M_Y (X/M_Y)$ and Y by $M_X (Y/M_X)$**
- **X drives $Y \Rightarrow$ possible estimation of X from Y , but not of Y from X (contrary to intuition and Granger causality!)**

estimation of CCM:

- correlation coefficient ρ between X and X/M_Y or Y and Y/M_X (or other error metrics) by using basic algorithm
- use of increasing data length („library length L “)
- X drives Y stronger than vice versa $\Rightarrow \rho$ between X and X/M_Y converge faster/reach a higher plateau than ρ between Y and Y/M_X

performance of CCM:

- embedding dimension
- time lag
- library length
- used error metrics
- system noise

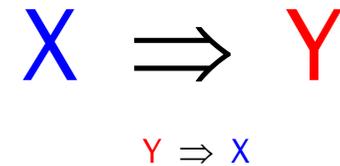


G Sugihara et al. Science 2012;338:496-500

- 2-species logistic model:**

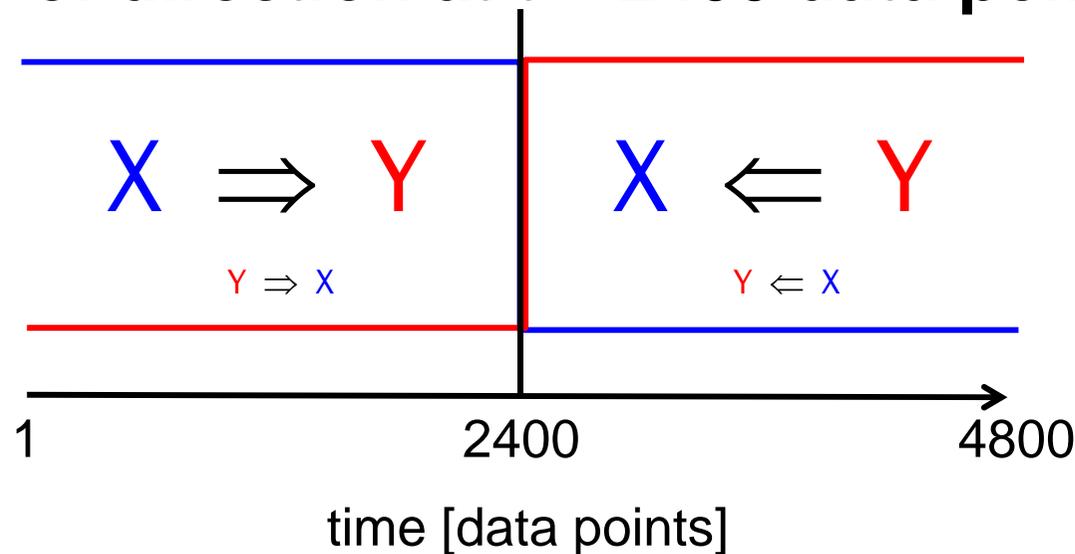
$$x(t + 1) = x(t)[3.8 - 3.8 x(t) - 0.02 y(t)]$$

$$y(t + 1) = y(t)[3.5 - 3.5 y(t) - 0.1 x(t)],$$

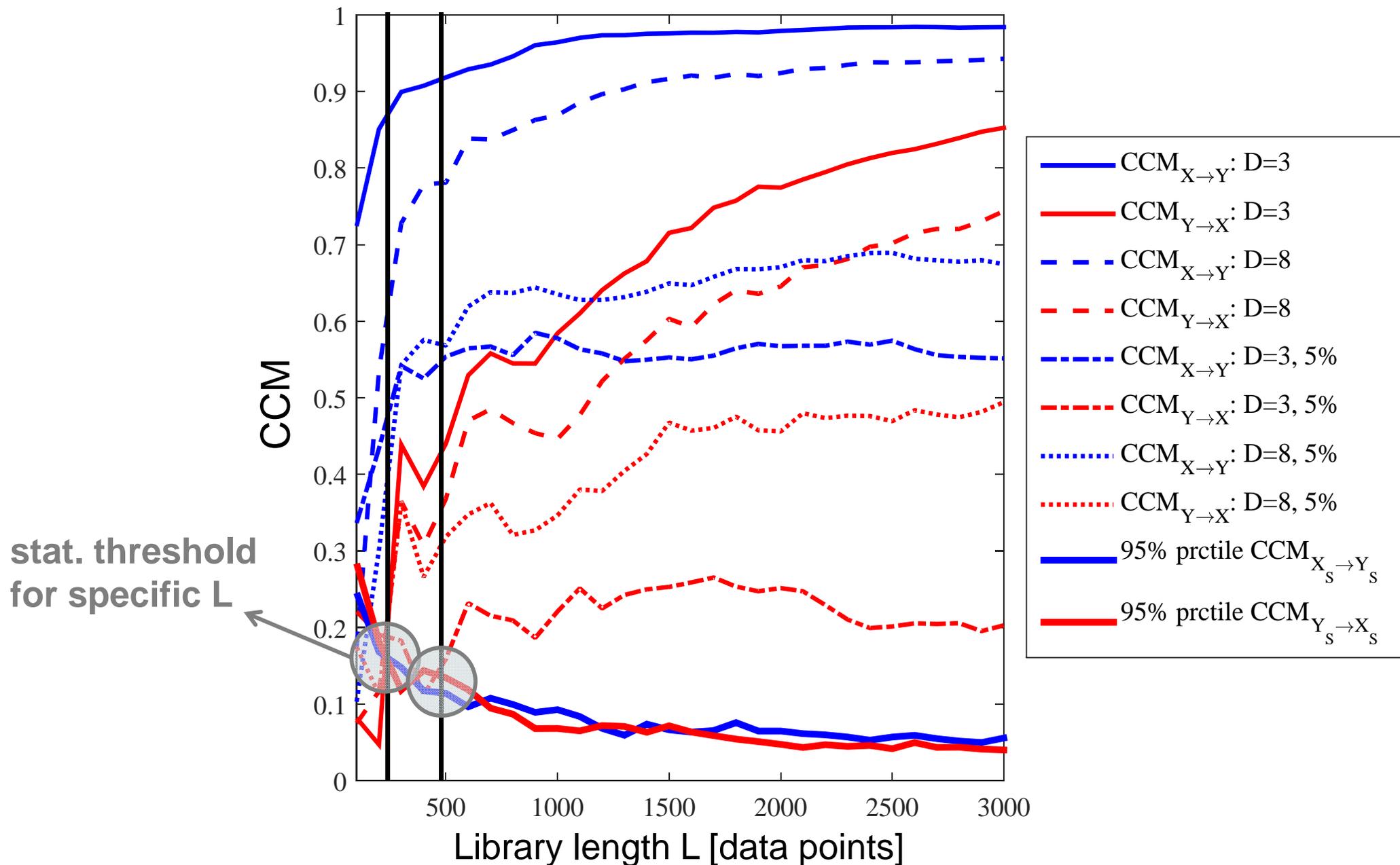


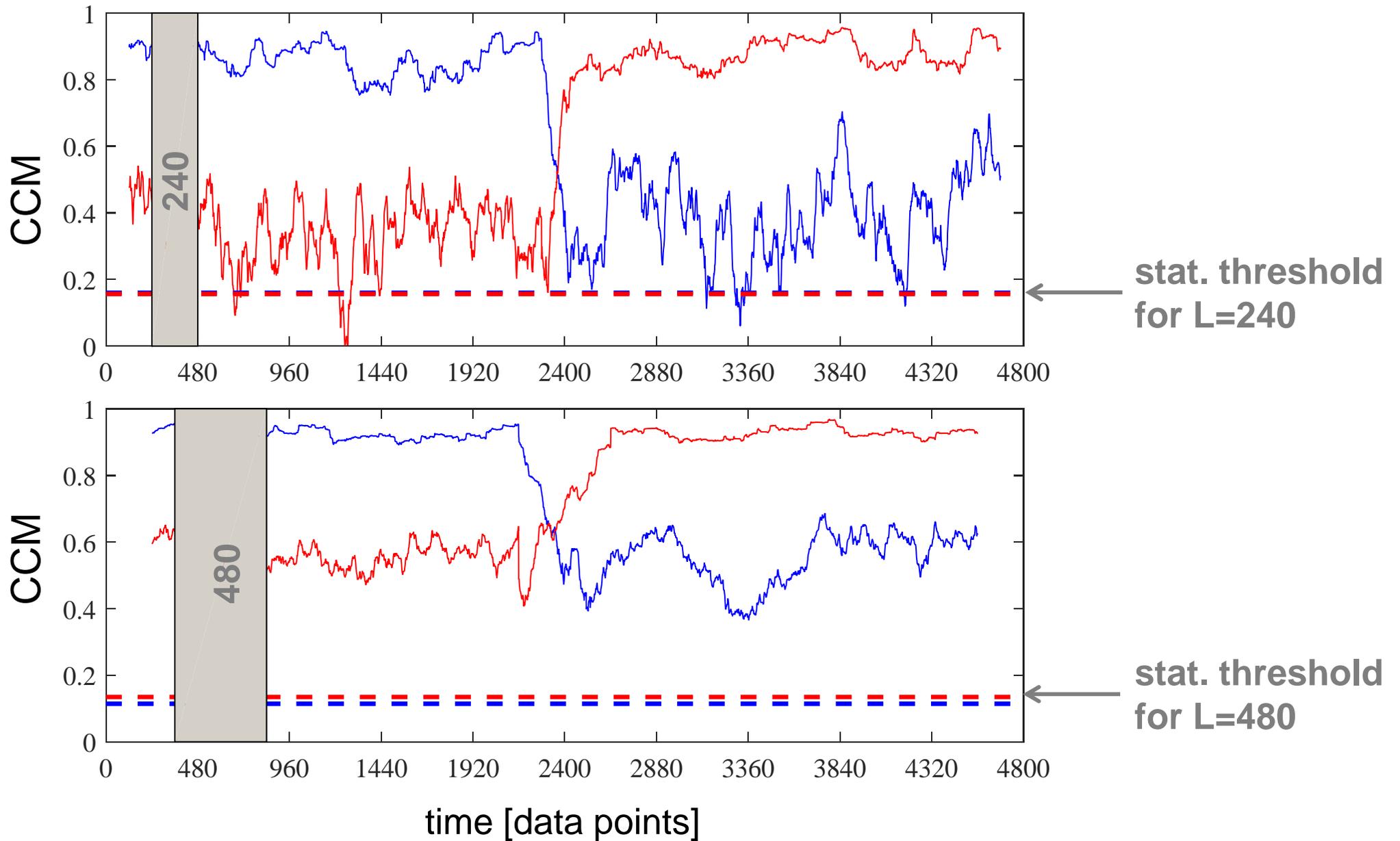
(„X drives Y stronger than vice versa“)

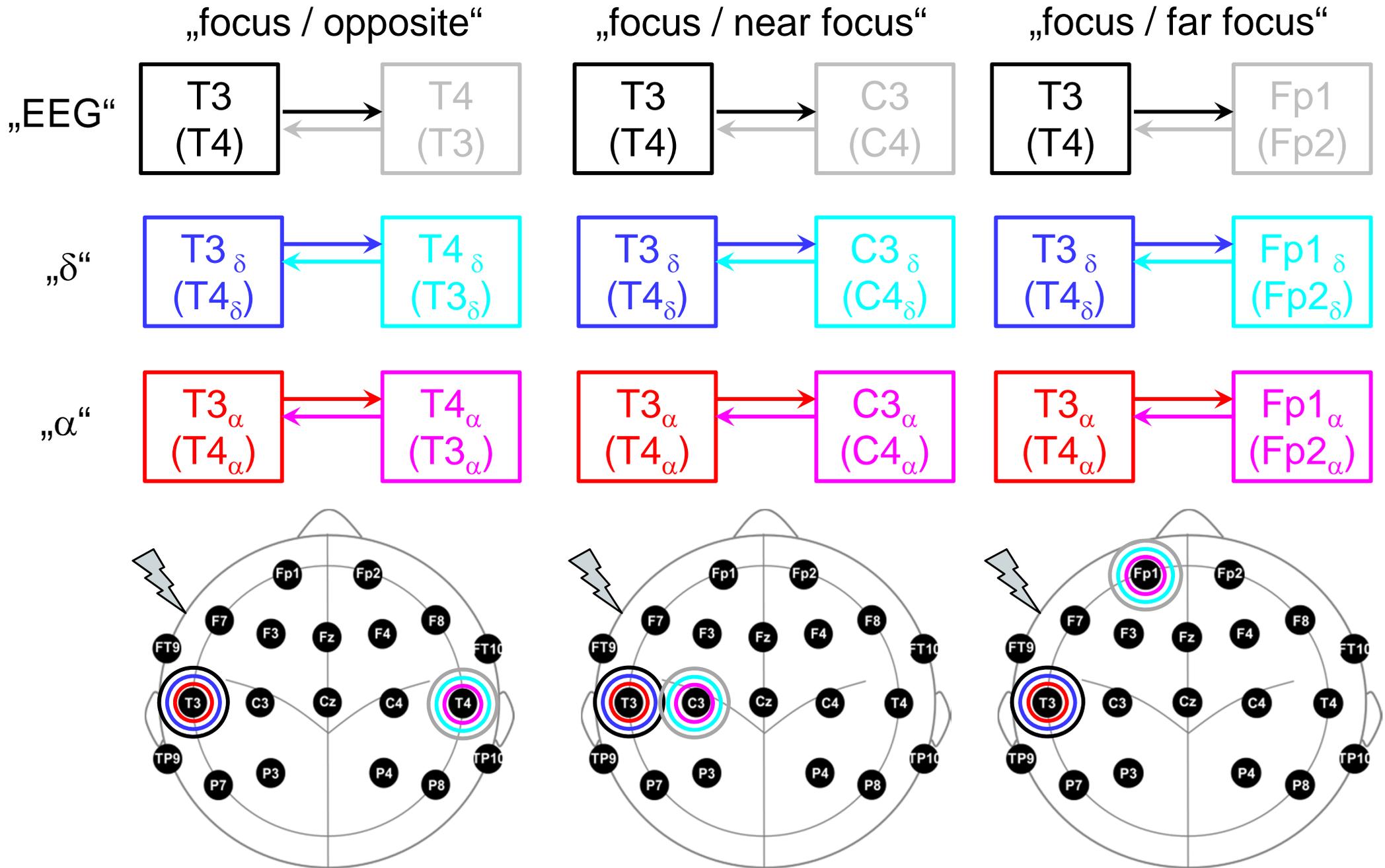
- change of direction at t = 2400 data points:**

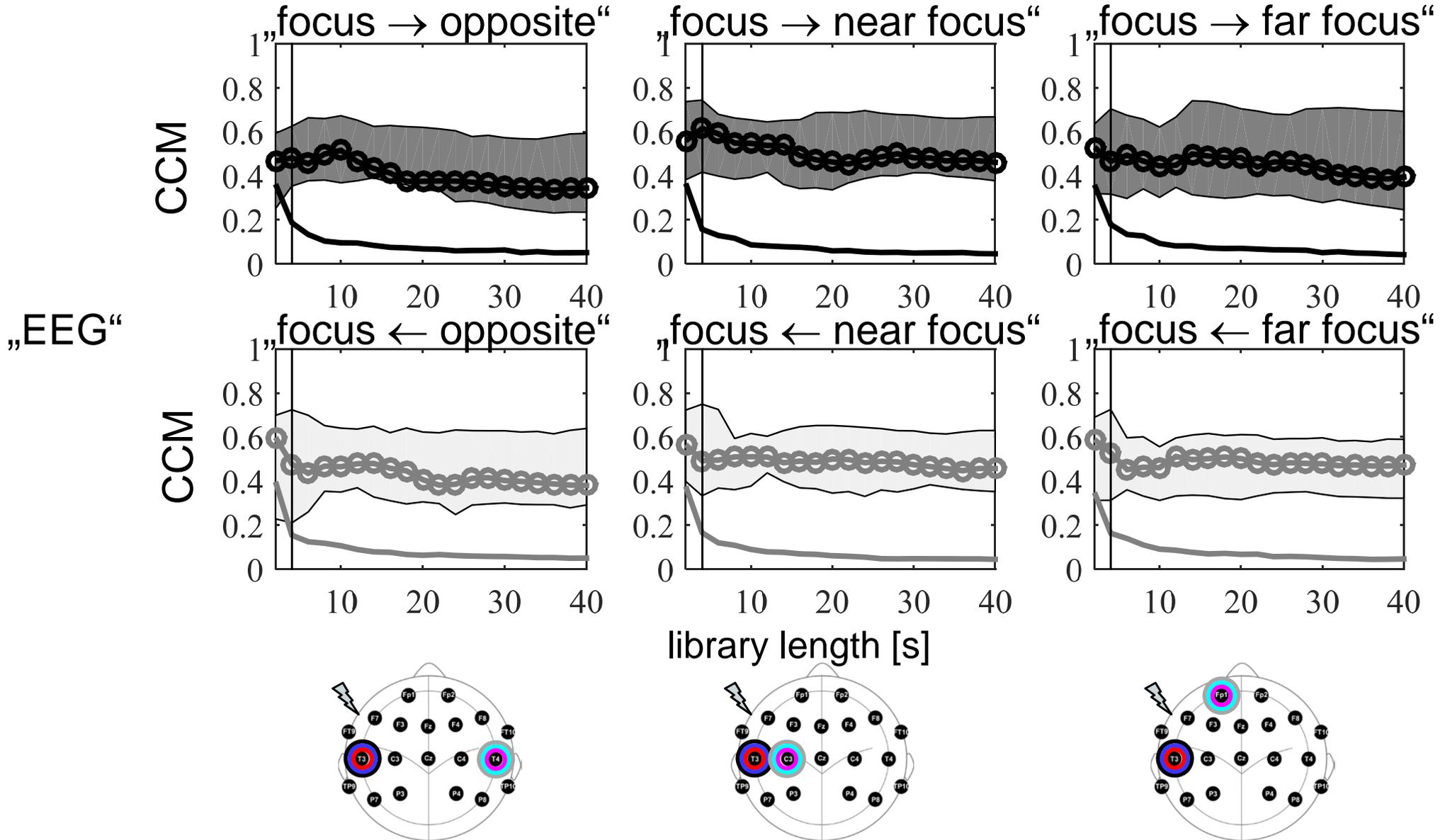


- **influence of different levels of additive noise (% of STD of original signals)**
- **influence of embedding dimension**
- **surrogate data test for statistical validation**
- **influence of window-length on interval-based performance**



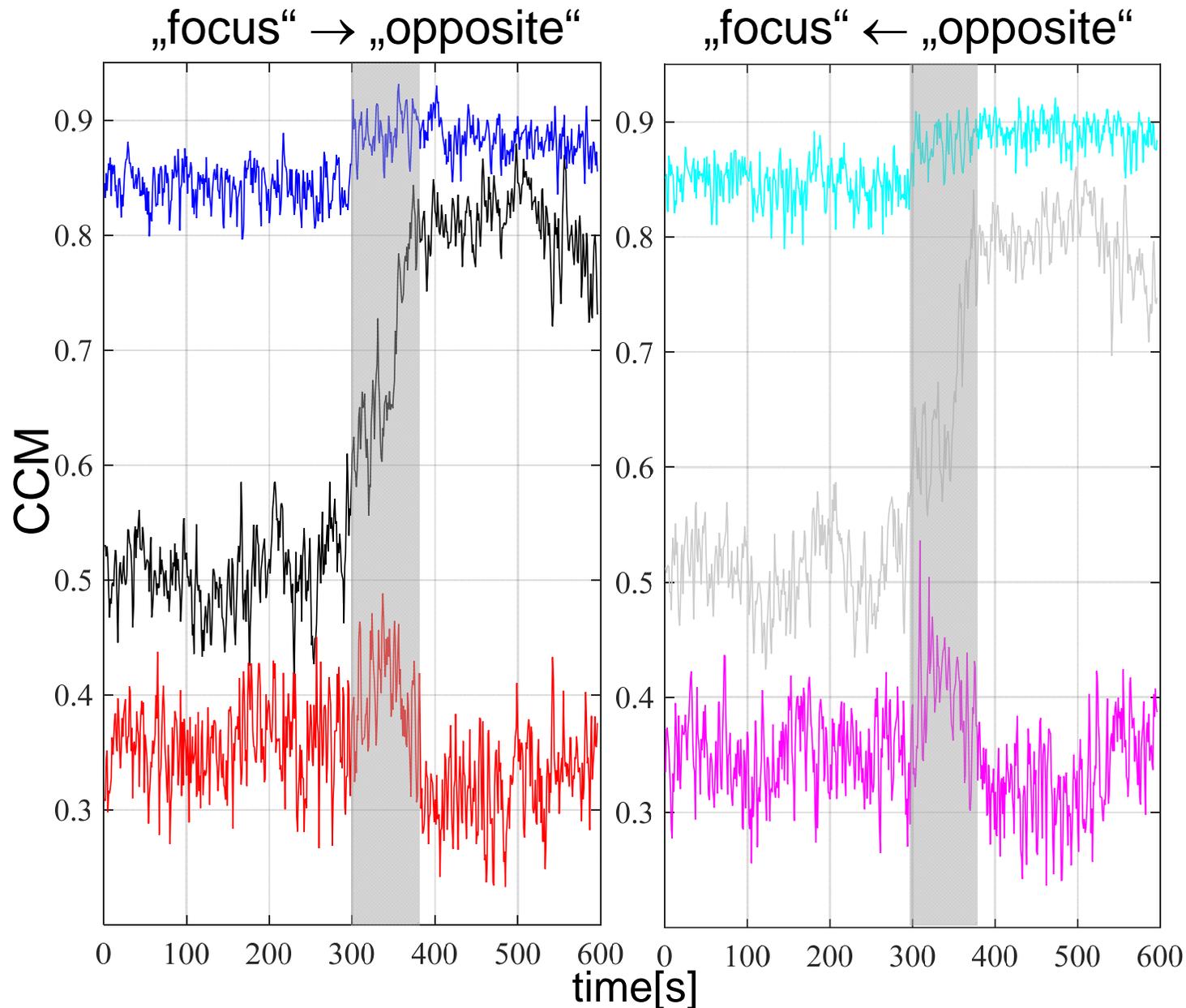
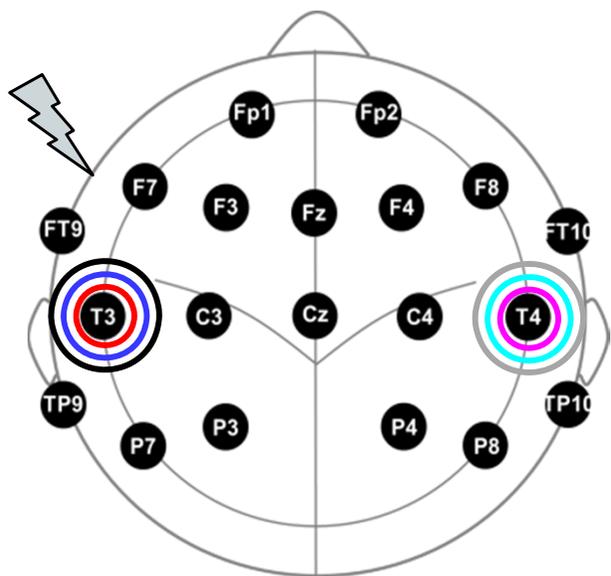






18 children, median and 95% CI-tube (bootstrap), stat. threshold (surrogates), data: [200 - 240 s], L=128, 256, ..., 2560, (2 s, 4 s, ..., 40 s)

median duration of seizure = 90 s

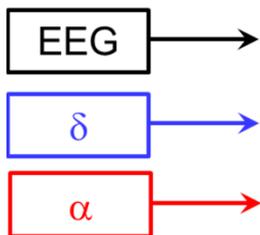
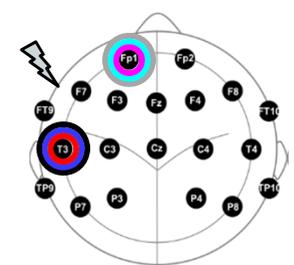
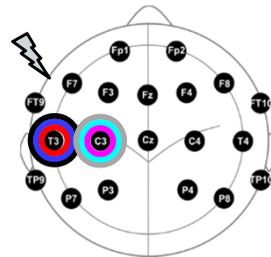
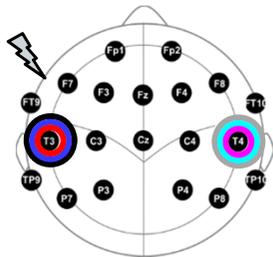
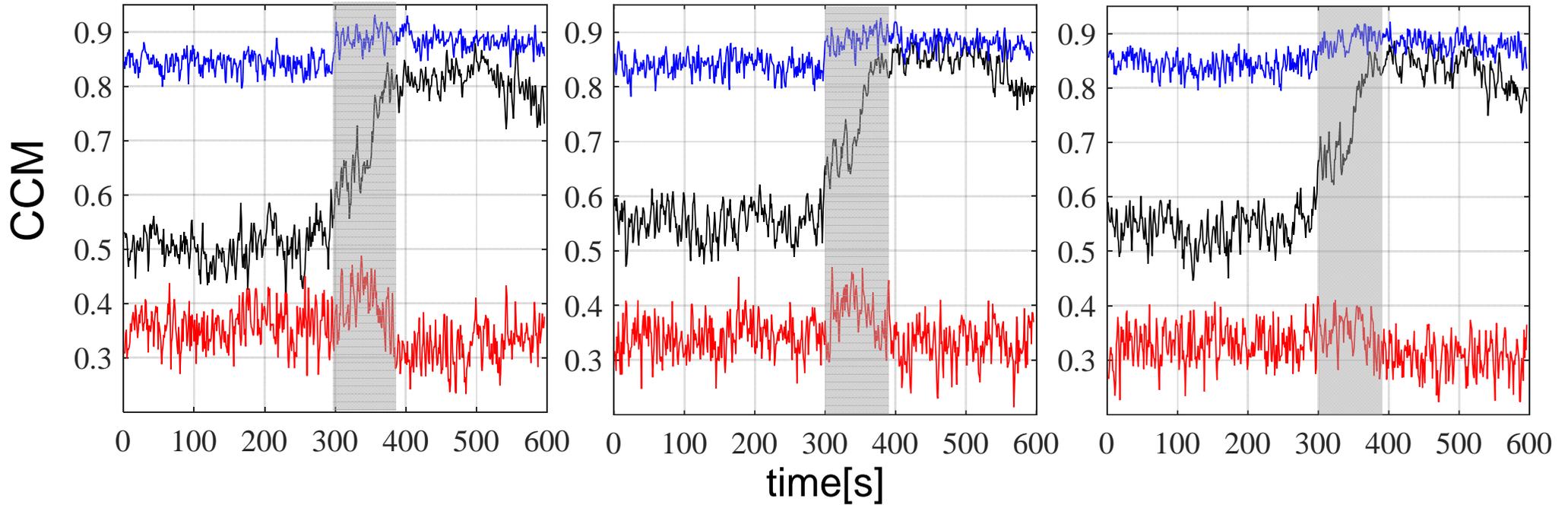


mean of 18 children, moving window: 4 s (256 data points)

„focus → opposite“

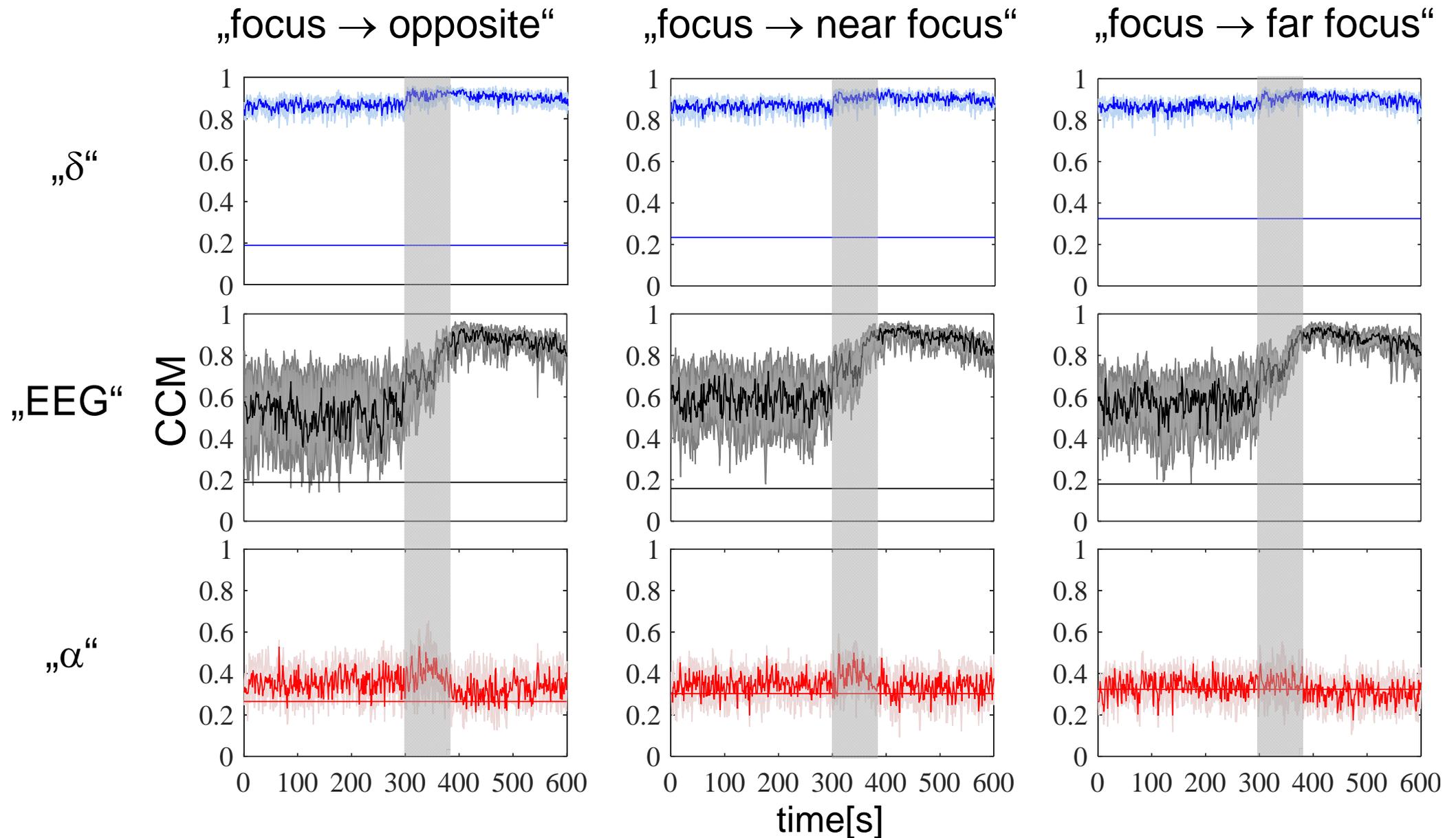
„focus → near focus“

„focus → far focus“



median duration of seizure = 90 s

mean over 18 children
moving window: 4 s (256 data points)



18 children, median and 95% CI-tube (bootstrap), stat. threshold (surrogates) , moving window: 4 s (256 data points)

CCM:

- **nonlinear** ✓
 - **directed causation** ✓
 - **time-variant** (✓)
 - **frequency-selective** ✓
 - **multivariate** ?
 - **noise** ✓
 - **statistical measures** ✓
- **considerable nonlinear alternative to (TVMVAR) GC-based approaches**
 - **needs further improvements (bivariate! error metrics?)**
 - **comparison to other nonlinear (model-free) approaches (TE)**

EEG during TLE:

- **direction and strength of interactions vs. time-varying changes of (frequency-selective) network measures?**
- **concept epileptic focus vs. epileptic network?**
- **other models (DDEs and derived meta-parameters)?**

9th meeting of

European
Study
Group on
Cardiovascular
Oscillations



April 10th-14th 2016
Lancaster, UK

THANK YOU FOR YOUR ATTENTION!



Cooperation with Epilepsy Monitoring Unit, Department of Child and Adolescent Medicine, University Hospital Vienna, Austria

Prof. Martha Feucht
Dr. Franz Benninger



Supported by the DFG (Grant Wi 1166/12-2 and Le 2025/6-2)