Persistent Homology Based Detection of Petit-Mal Epileptic Events in EEG Data

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September 21, 2023

Supported by the German Federal Ministry of Education and Research

- Epilepsy:
  - Synchronized neuronal activity
  - Detection via electroencephalogram (EEG)
  - Difficult and time-consuming to classify data of every single patient
    $\rightarrow$ need for automated classification and interpretation
  - Shilnikov-chaos during epileptic seizure (van Veen et al. 2006 PRL; Friedrich et al. 1996 Physica D)
    $\rightarrow$ mathematical structure
- Persistent Homology:
  - Tool from Topological Data Analysis
    (intersection of data science, topology and geometry)
  - Main assumption: data has **structure**
  - Provides connectivity information of the underlying space on several spatial scales
    $\rightarrow$ robust w.r.t. small perturbations

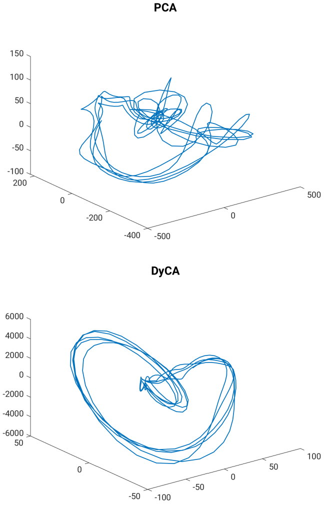
- Existence of Shilnikov chaos during epileptic seizures

$$\begin{aligned}\dot{x}_1 &= x_2,\\ \dot{x}_2 &= x_3,\\ \dot{x}_3 &= f(x_1, x_2, x_3),\end{aligned}$$

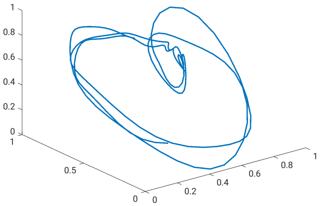
  f is a polynomial function (van Veen et al. 2006 PRL; Friedrich et al. 1996 Physica D)

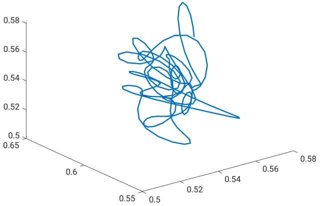
- Data used:
  - Petit-mal epilepsy:
    - abrupt beginning & end
    - seizure length: few seconds to half a minute
  - 6 time series (10s to 40s)
  - 25 channels ($\mathbb{R}^{25}$)

- Method for dimensionality reduction ($25 \to 3$)
- Inclusion of dynamics of the system
- Application to data,
  modeled by ODE system,
  linear and non-linear equations
  $\to$ no need to know exact system
- Well-suited for:
  - Classification of dynamics by eigenvalue spectrum
  - Noise-elimination
  - Modeling signal by data-driven approach



Methodology I



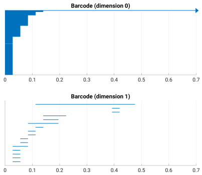


Pictures taken from Flammer et al. 2022, SciTePress

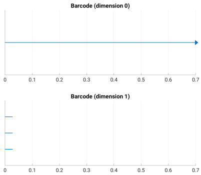
- Moving window: 0.5s length, shifted by 0.1s
- Top: trajectory (attractor) during epileptic event
  → follows ODE system
- Bottom: trajectory without epileptic event
  → no obvious structure

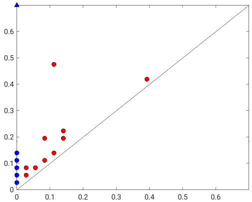
Methodology II

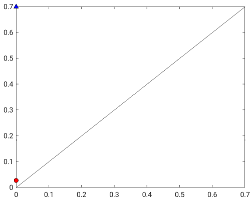
During absence



Without absence



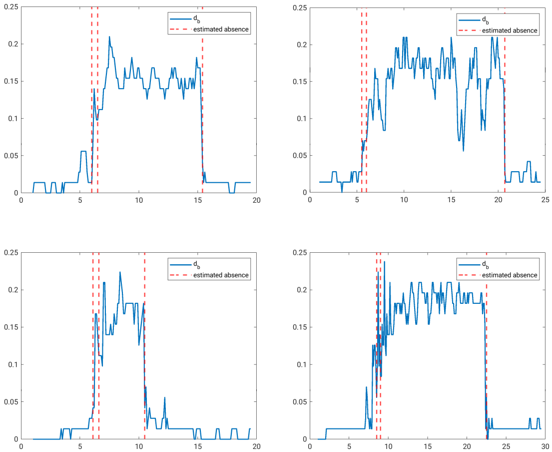




- For each window: filtration of VR-complex $\rightarrow$ PH
- Top: barcodes in dimension 0 and 1
- Bottom: persistence diagrams in dimension 0 and 1
- In persistence diagrams: blue dots: dimension 0; red dots: dimension 1; triangle: classes that live forever

Pictures taken from Flammer et al. 2022, SciTePress

Results



- Red lines: beginning/end of absence detected by an expert
- Blue line: bottleneck-distance of respective window to the empty diagram
- Table: percentage of falsely classified frames

	α	Wrong frames
TS 1	0.06	**0%**
TS 2	0.05	**0%**
TS 3	0.08	0.5%
TS 4	0.08	**2.1%**

Pictures and table taken from Flammer et al. 2022, SciTePress

Persistent Homology:

- PH detects the structure that is given by the ODE system
- No need to apply machine learning (small amount of data)
- Structure of attractor resembles more than one loop

  only a circle-like structure was regarded

  $\rightarrow$ incorporate entire information of barcode
- Current known drawback:

  not too robust w.r.t. outliers

  $\rightarrow$ making DyCA more insensitive to noise (work in progress Uhl et al.)

Thank you for your attention!

Time for questions

M. Flammer and K. Hüper.
Persistent homology based classification of chaotic multi-variate time series with application to eeg data.
In *Proceedings of the 19th International Conference on Informatics in Control, Automation and Robotics - ICINCO*, pages 595–604. INSTICC, SciTePress, 2022.