The power of tensors in ECG processing

Griet Goovaerts

griet.goovaerts@esat.kuleuven.be

31-8-2018

Contents Overview

1. Introduction

- Biomed and ECG
- Heart and ECG
- Tensors and ECG

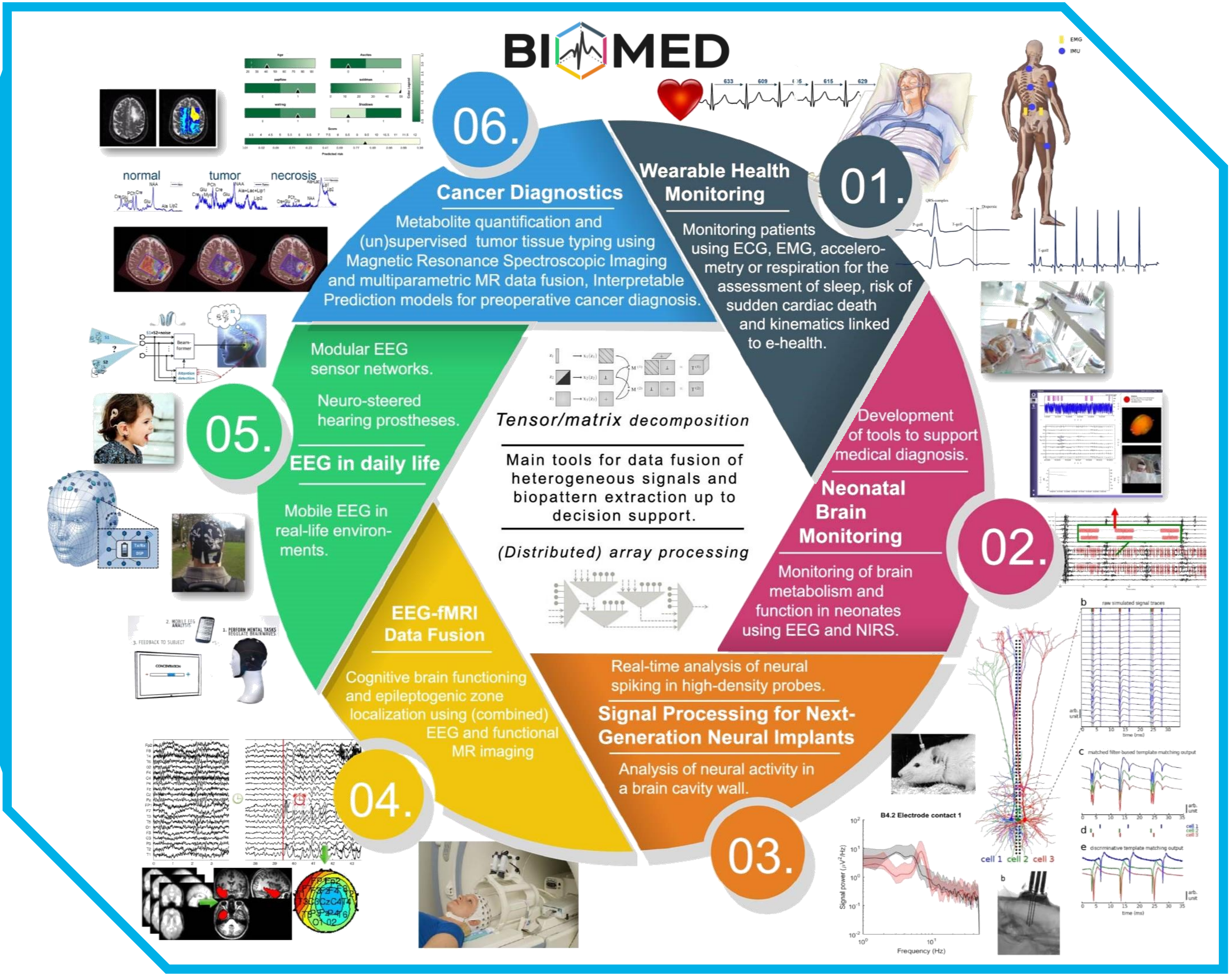
2. CPD applications

- Irregular heartbeat detection
- T wave alternans detection
- ECG morphology analysis

3. Conclusions and Future Directions

Research in close collaboration with

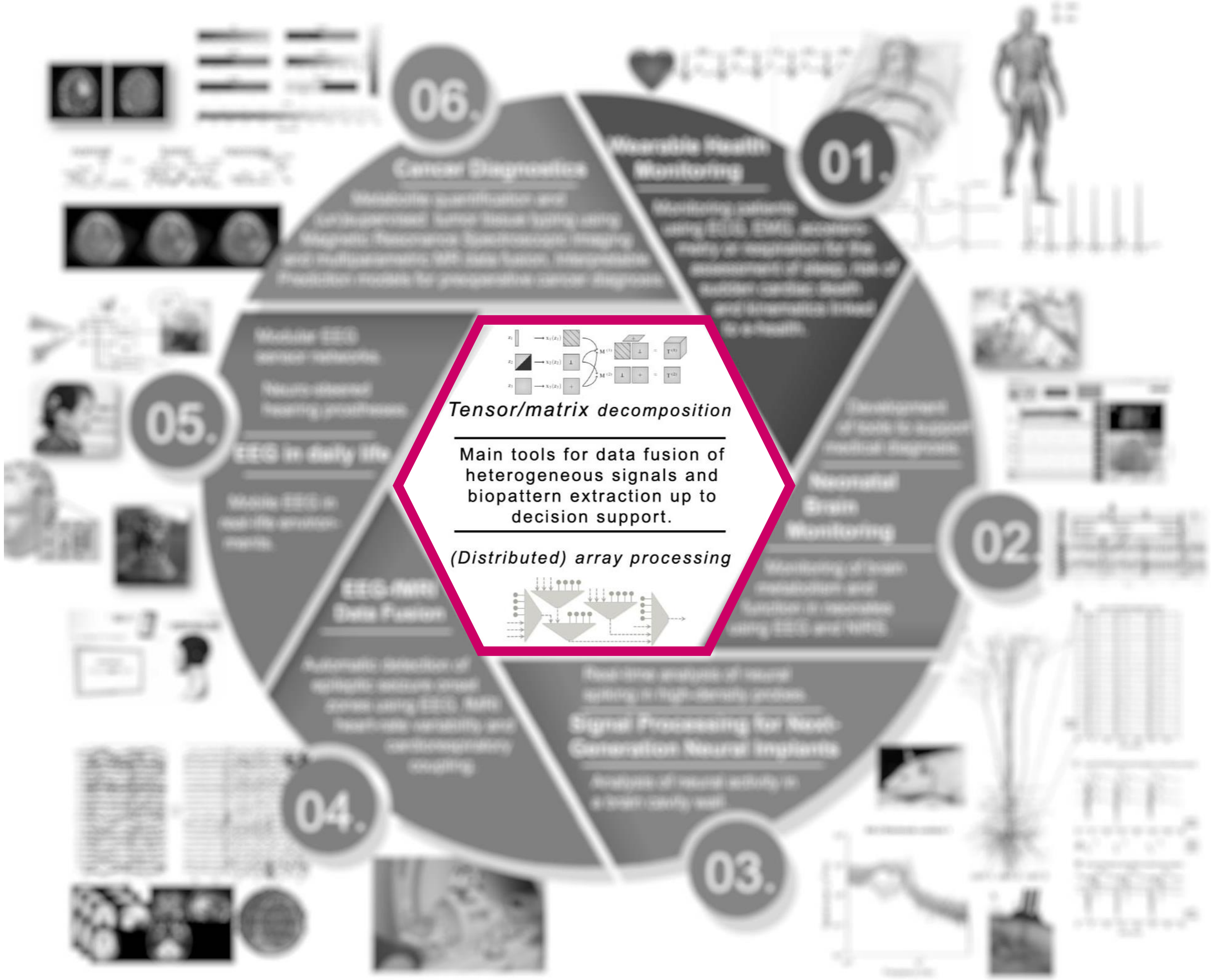
UZ LEUVEN



erc
European Research Council
Established by the European Commission

imec

KU LEUVEN


06.
01.
05.
Tensor/matrix decomposition
Main tools for data fusion of heterogeneous signals and biopattern extraction up to decision support.
(Distributed) array processing
02.
04.
03.

Wearable
Health Monitoring

UZ Leuven departments:

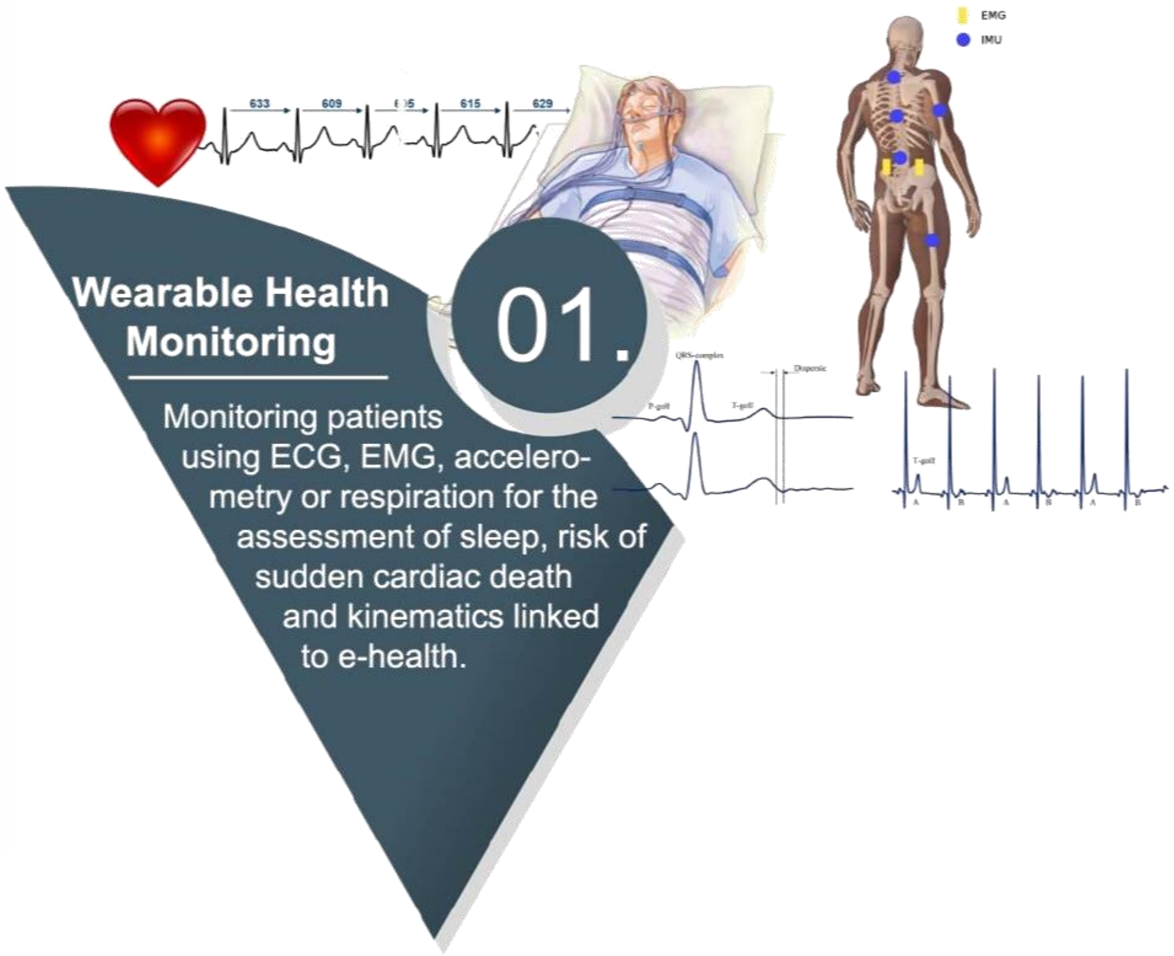
Cardiology

Neurology

Pneumology

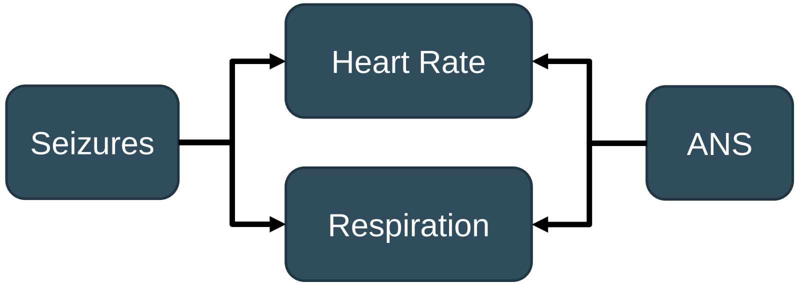
Rheumatology

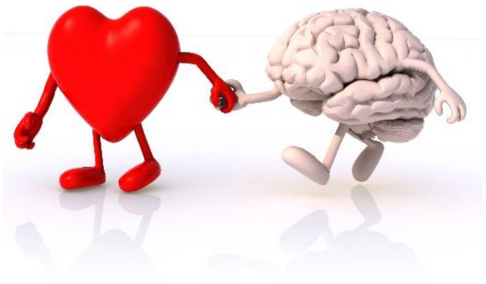
Pulderbos Revalidation Center



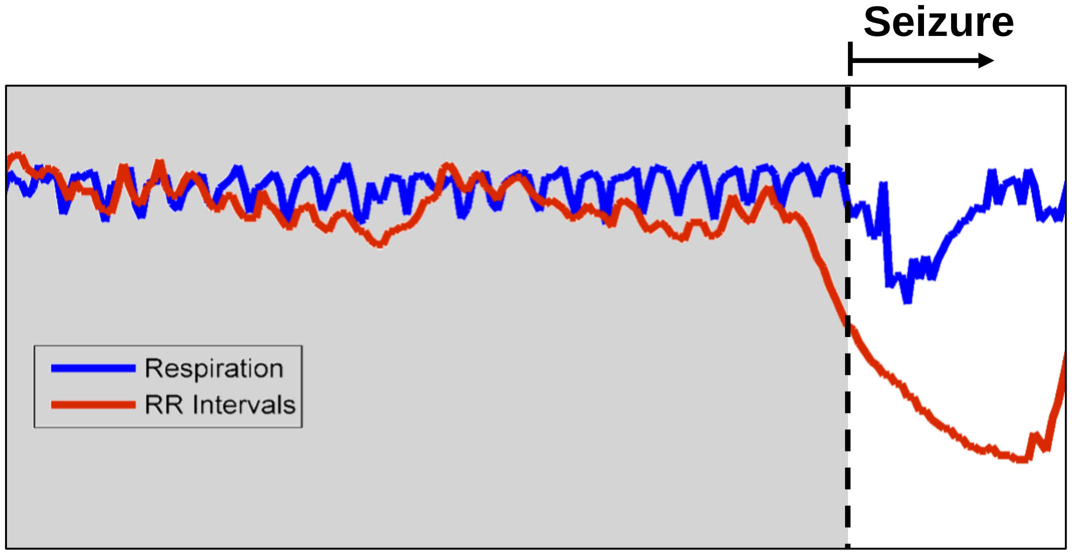
Epileptic seizure detectors based on ECG

Seizures and the autonomic nervous system (ANS)





Goal: Detect cardiac and respiratory changes caused by seizures



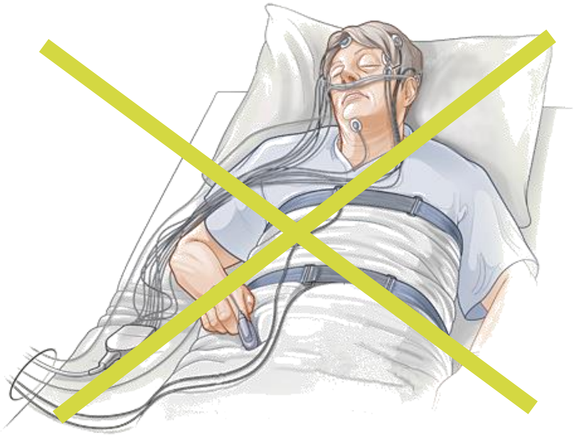
Seizures

- ✓ Pre-ictal changes
- ✓ Autonomic symptoms
- ✓ Motor activity
- ✓ Stress response
- ✓ Apnea episodes
- ✓ Reduced HRV
- ✓ Tachycardia or bradycardia

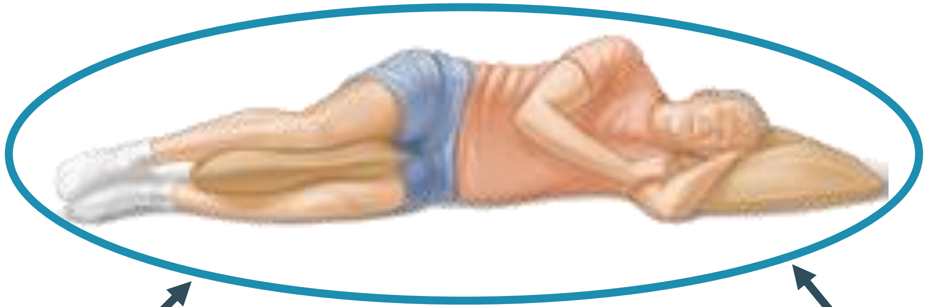
Sleep Monitoring

PPG

SpO_2



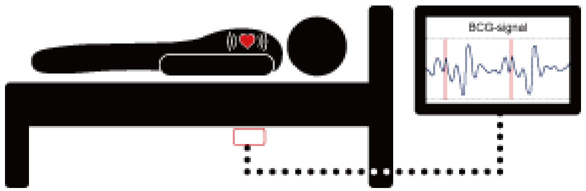
Classical in-hospital polysomnography



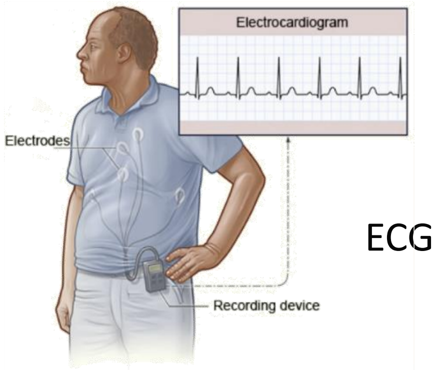
Unobtrusive (home) monitoring

Sleep staging

OSA detection and phenotyping



Ballistocardiography



ECG

KU LEUVEN

Sudden cardiac death

Introduction

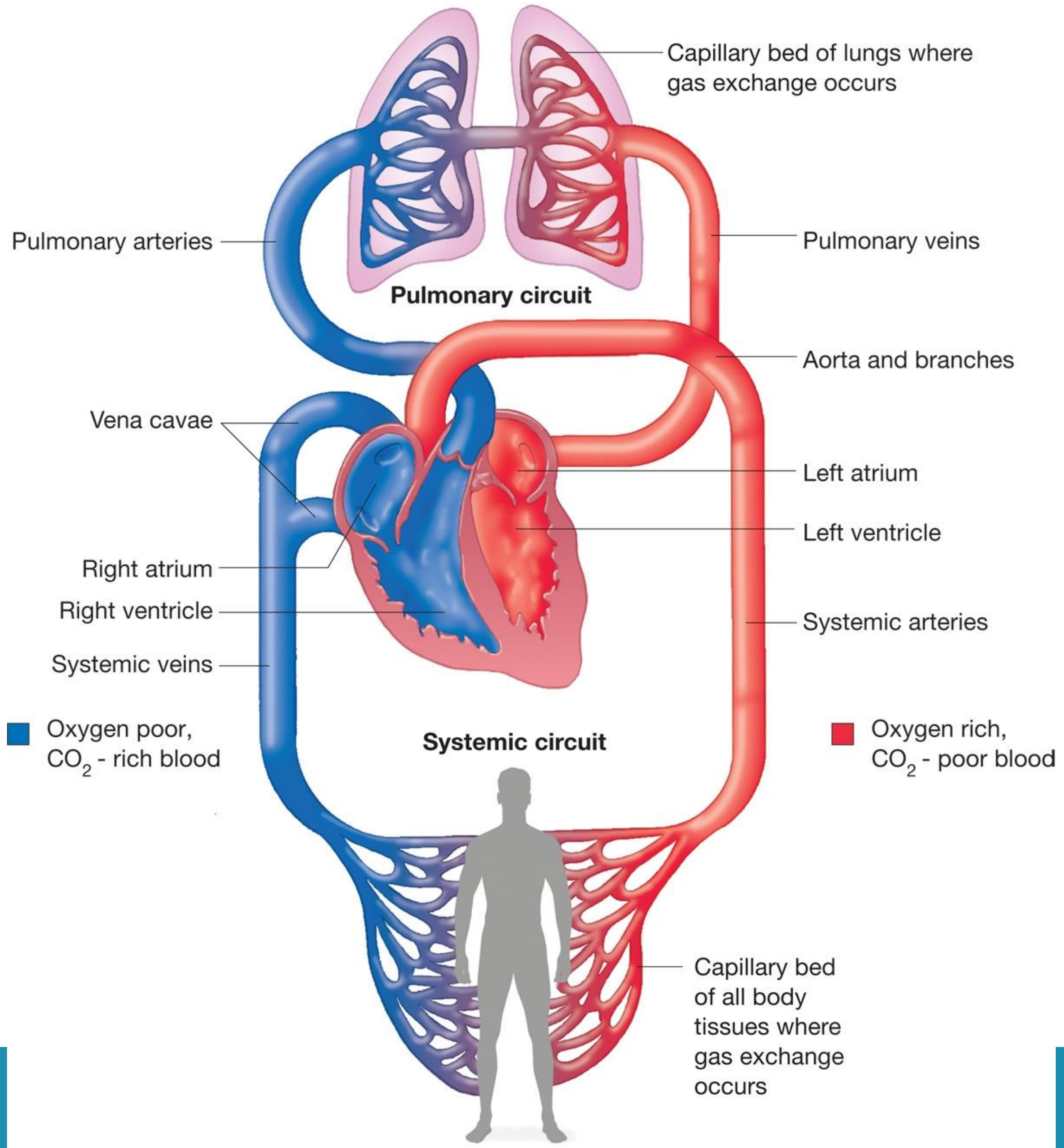
- Sudden cardiac death: 2nd most important cause of death (~ 30% of deaths)
  - 180 000 – 450 000 deaths/year in US
  - Cause: often cardiac arrythmia

- Prevention: implantable cardioverter-defibrillator

  ➔ Main problem: **Patient selection!**

Goal: Automatically detect features in the electrocardiogram that **are** expected to be predictive for sudden cardiac death

Heart and ECG

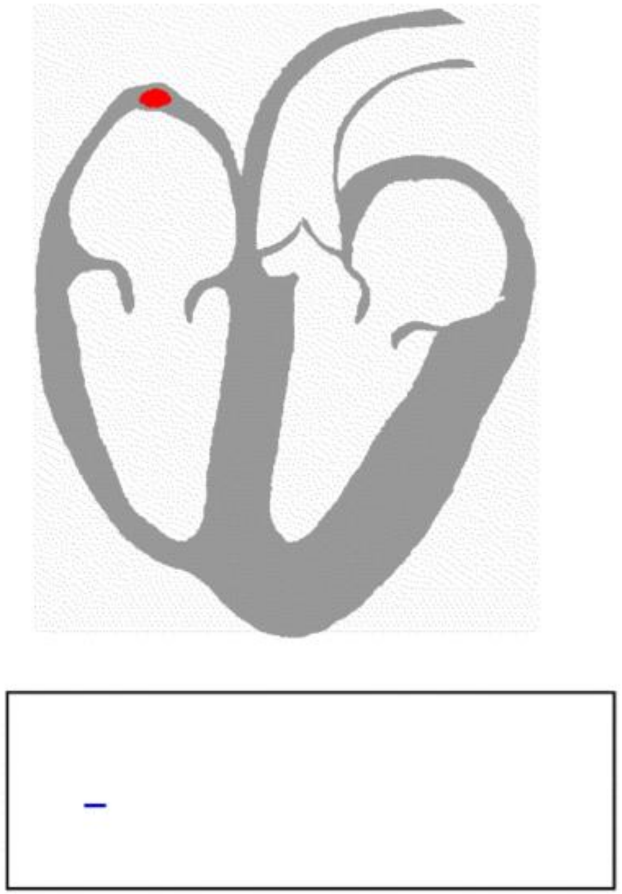

Capillary bed of lungs where gas exchange occurs
Pulmonary arteries
Pulmonary veins
Pulmonary circuit
Aorta and branches
Vena cavae
Left atrium
Left ventricle
Right atrium
Right ventricle
Systemic arteries
Systemic veins
Oxygen poor, CO_2 - rich blood
Systemic circuit
Oxygen rich, CO_2 - poor blood
Capillary bed of all body tissues where gas exchange occurs

KU LEUVEN

Electrocardiogram

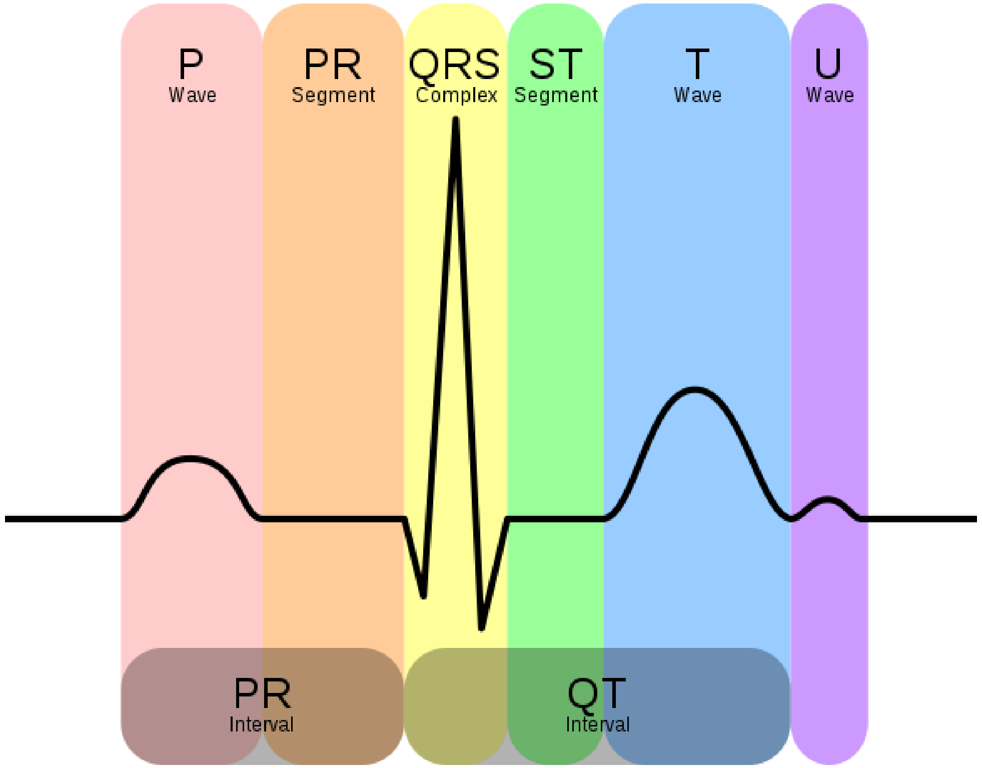
ECG : recording of electrical activity of the heart

- Cheap
- Widely available
- Quick to measure



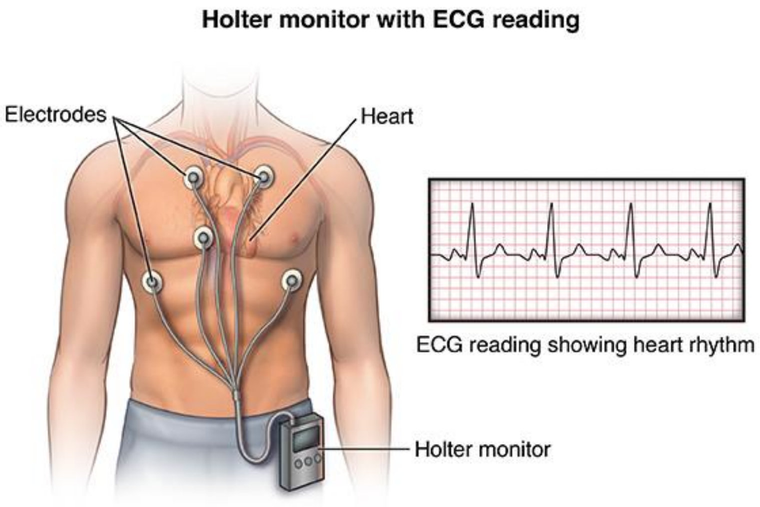
Electrocardiogram

Cardiac event	ECG segment
Atrial contraction	P wave
Electrical conduction	PR segment
Ventricular contraction	QRS complex
Plateau phase	ST segment
Ventricular relaxation	T wave
(Relaxation fibers?)	(U wave)

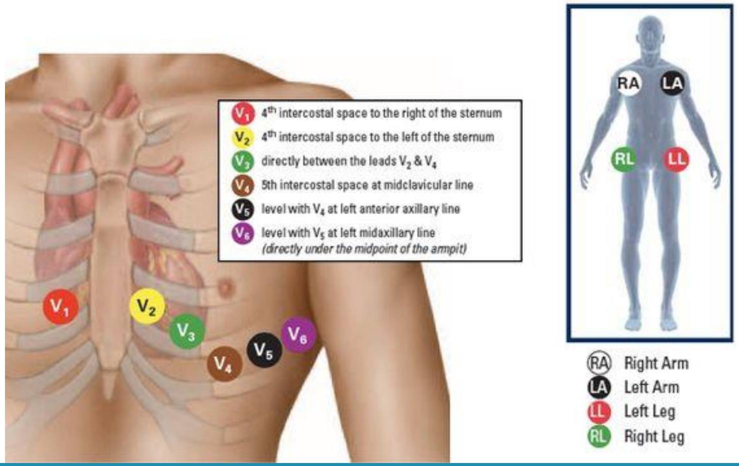


ECG measurements

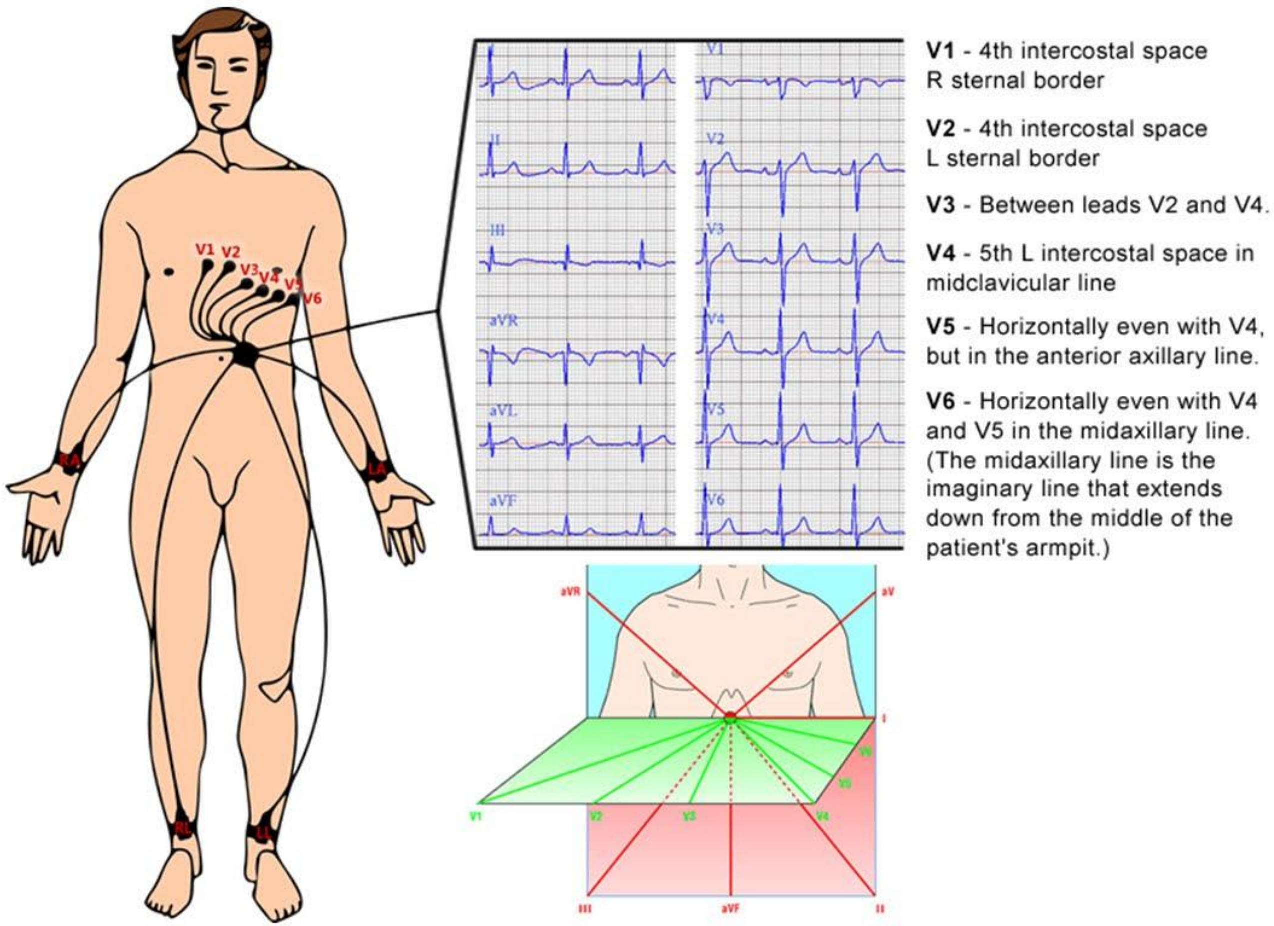
- Holter measurements:
  - 2/3 channels
  - Long-term measurements
  - Detection of acute events

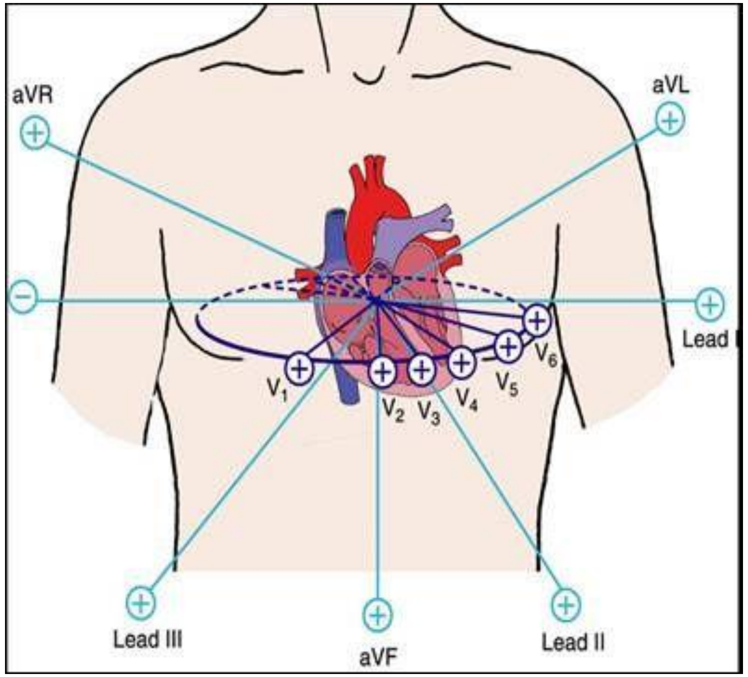


- Clinical measurements
  - 12 channels
  - Shorter measurements (~10s)
  - Detection of chronic events



ECG measurements





12-lead ECG : channels give complementary 3D view

➔ Analyze simultaneously

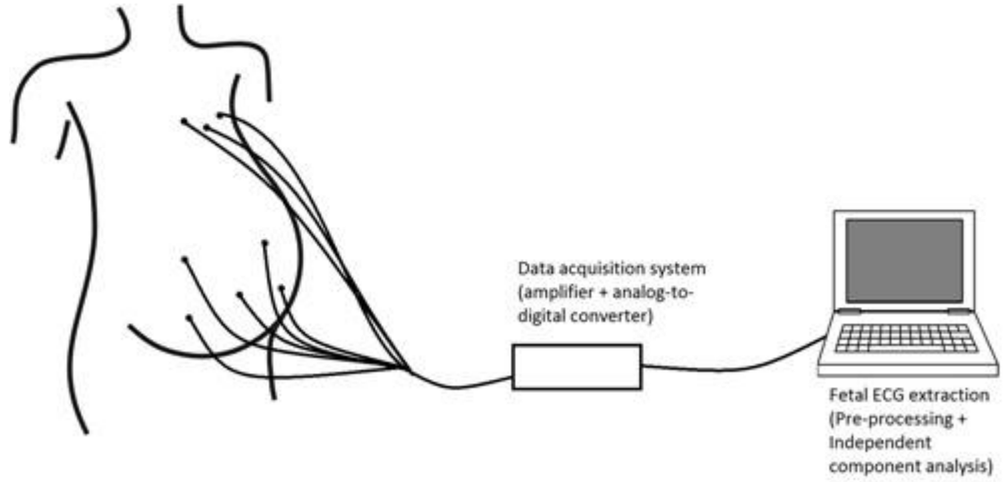
➔ Tensors!

KU LEUVEN

Tensors and ECG

Tensors and ECG

1. Fetal ECG extraction : separate maternal and fetal ECG = BSS
    - Independent Component Analysis
    - Block term decomposition
    - CPD
    - Multilinear Singular Value Decomposition
    - PARAFAC2
    - Segmentation
    - Löwnerization
    - …



Tensors and ECG

Other applications :

- Irregular heartbeat detection
    - MLSVD : *Sibasankar Padhy*
    - LS-CPD : *Martijn Boussé*
    - UMPCA
- Atrial fibrillation detection/extraction
    - MLSVD : *Simon Geirnaert*
    - BTD
- Classification of myocardial infarction
    - MLSVD + wavelets : *Sibasankar Padhy*
- Compression
    - MLSVD : *Sibasankar Padhy*

Tensors and ECG

Canonical Polyadic Decomposition (+ variants)

1. Irregular heartbeat classification
2. T wave alternans detection
3. Analysis of ECG changes prior to in-hospital cardiac arrest

Goal : 1. Extract clinically relevant features

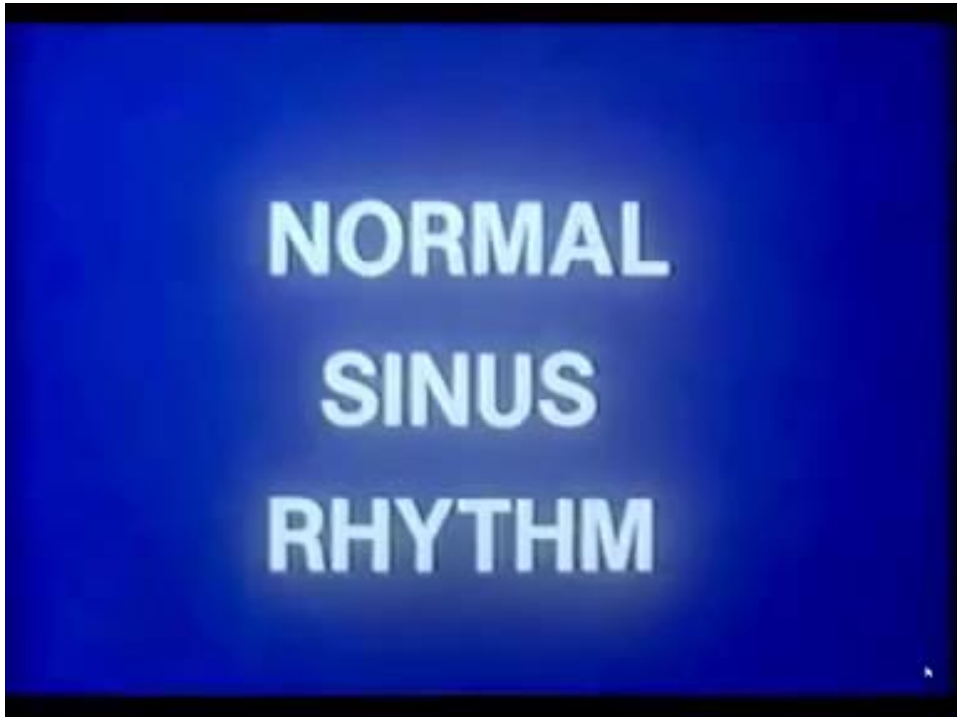
2. Adapt tensor decomposition according to signal characteristics

Irregular heartbeat classification

Irregular heartbeats

3 main types of heartbeats:

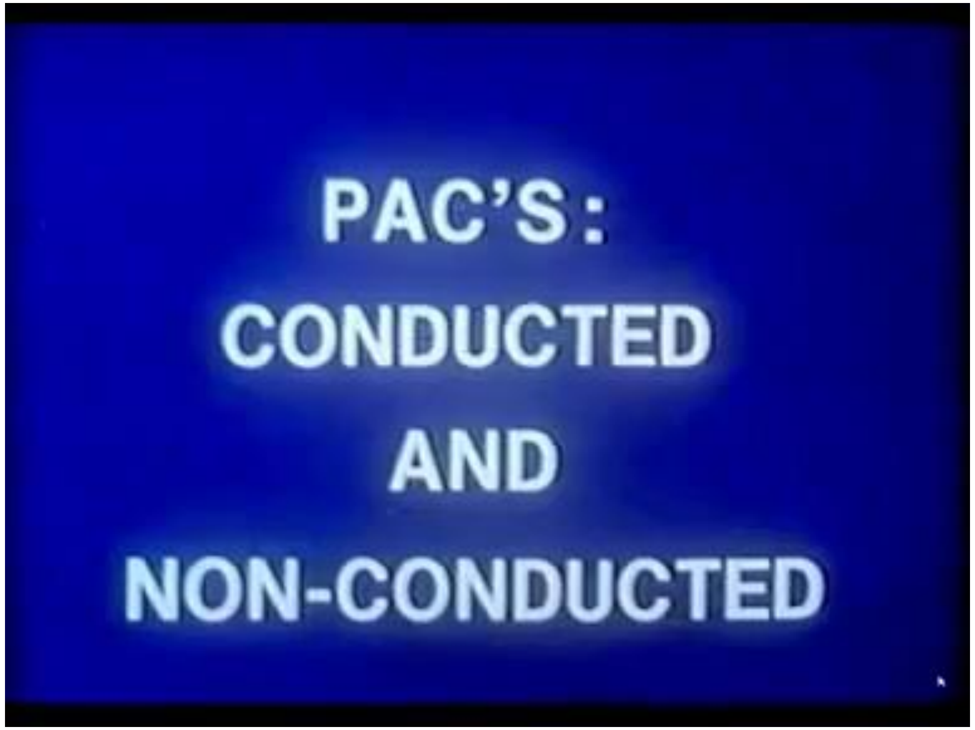
1. Normal beats : constant rhythm, constant morphology



Irregular heartbeats

3 main types of heartbeats:

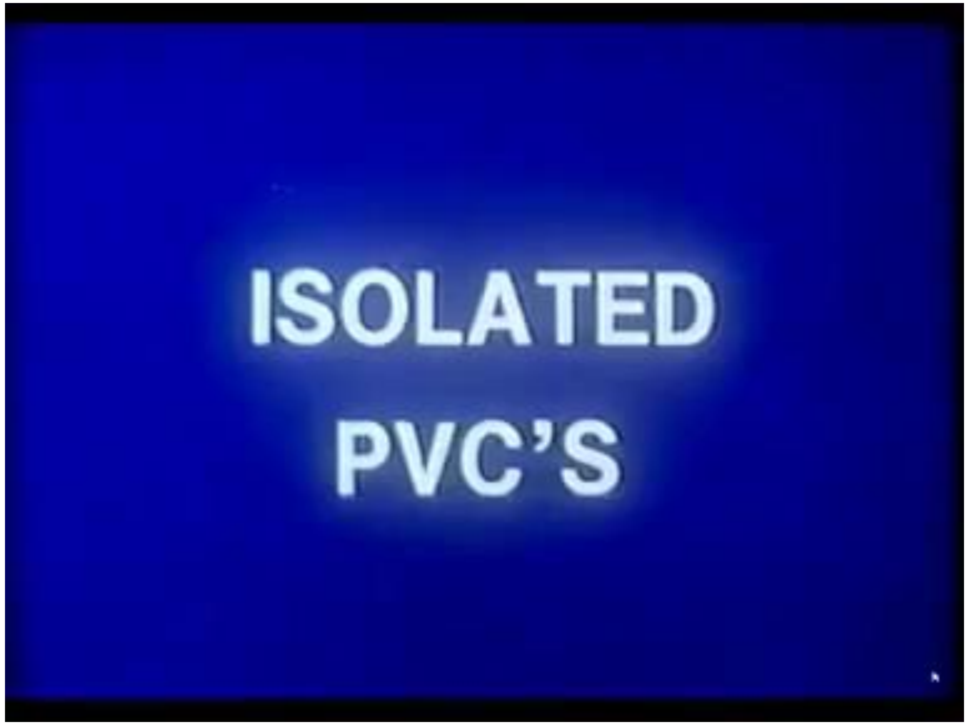
2. Supraventricular beats: originate in atria



Irregular heartbeats

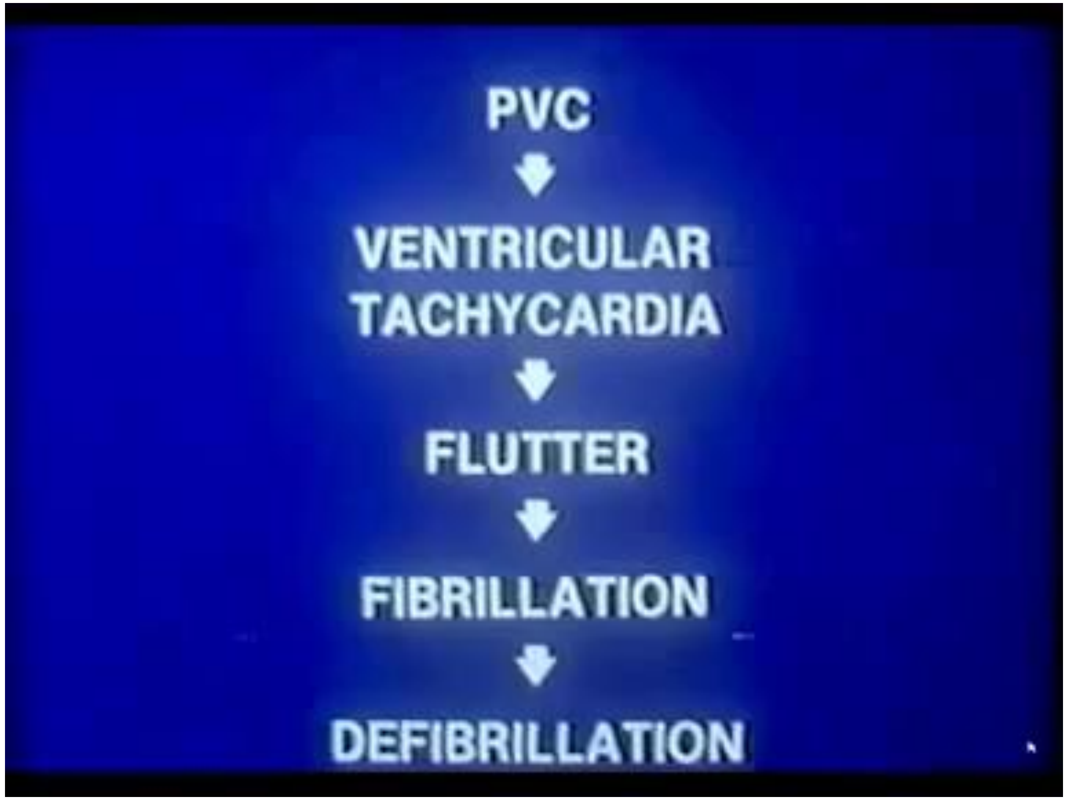
3 main types of heartbeats:

3. Ventricular beats : originate in ventricles



Irregular hearbeats

- Intermezzo : sequence of chaos



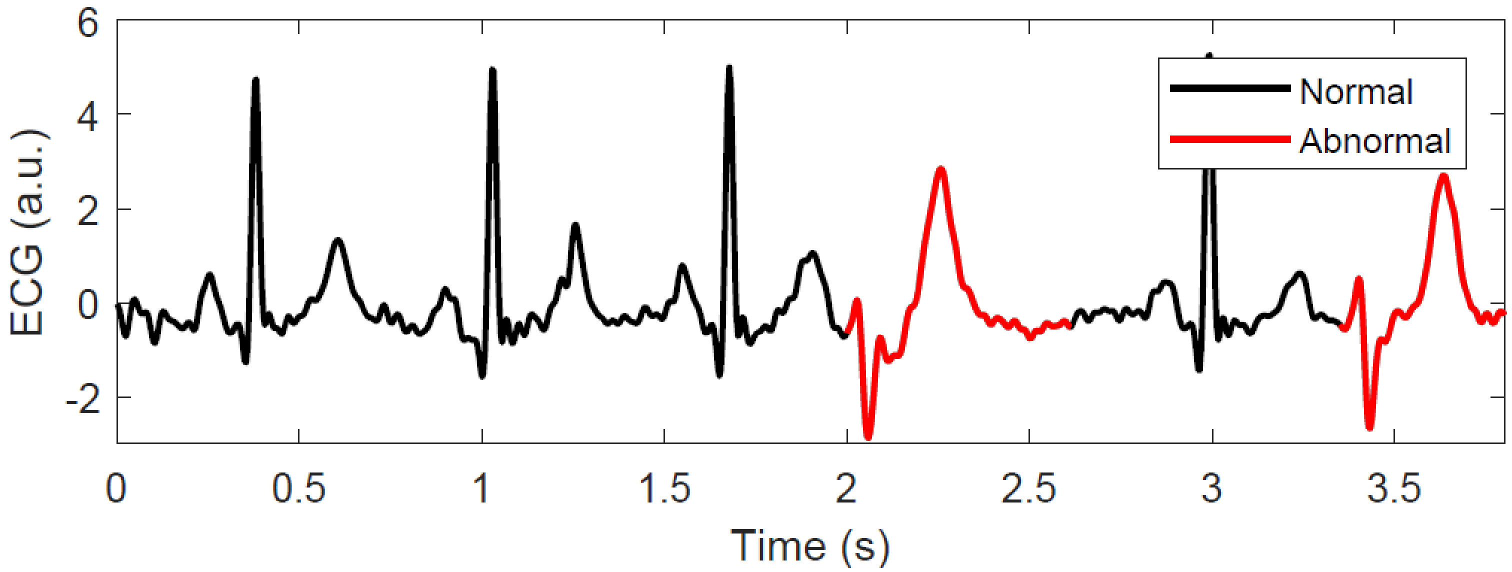
Irregular heartbeat detection

1. Heart rate variability studies : only use normal beats

2. Ventricular beats
    - Initiators of most ventricular arrhythmia
    - Frequency has prognostic value in ischemic heart disease
    - Not necessarily dangerous ☺

Irregular heartbeat classification

Goal: Unsupervised classification of irregular heartbeats



Preprocessing → Tensor construction → CPD : tensor decomposition → Clustering

Goovaerts, G., De Wel, O., Vandenberk, B., Willems, R., & Van Huffel, S. Detection of irregular heartbeats using tensors. In *Computing in Cardiology Conference, 2015* (pp. 573-576)

KU LEUVEN

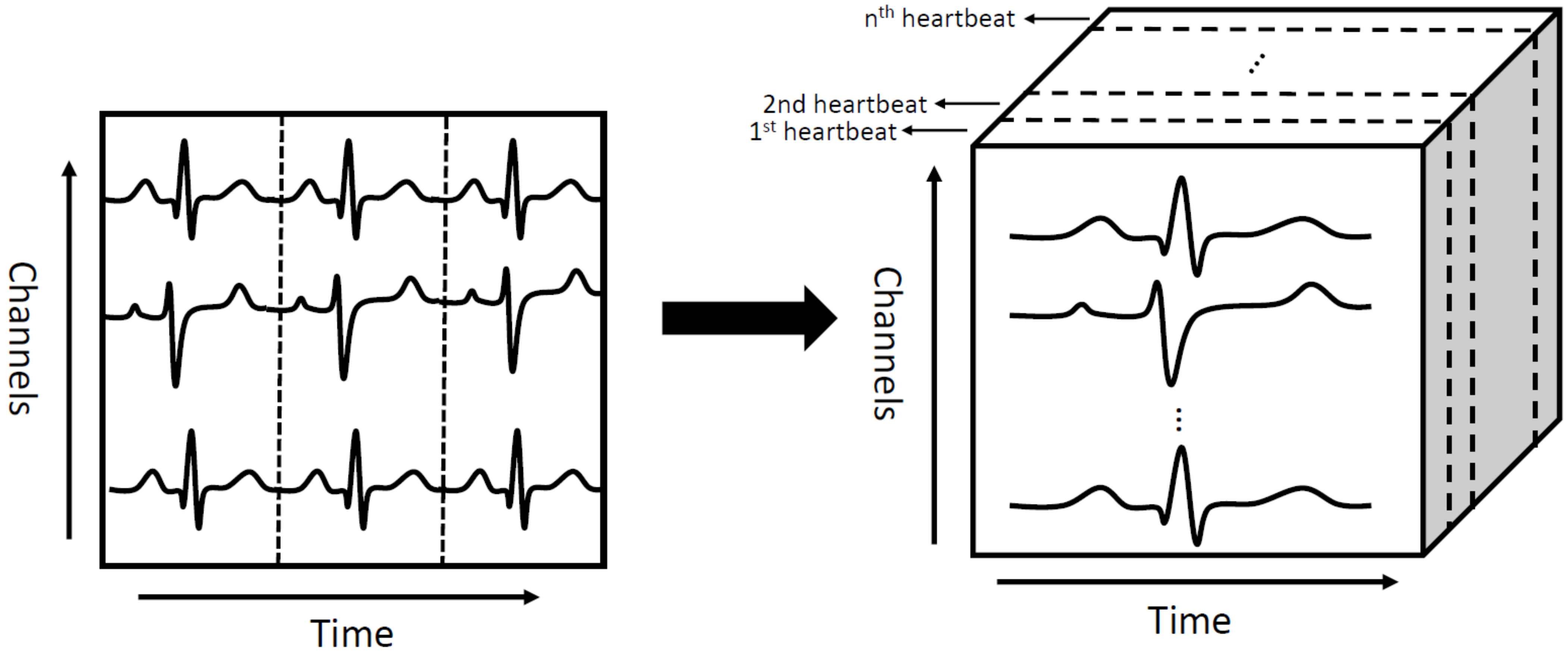
Preprocessing

Remove different noise source from the ECG:

1. Baseline wander : 2 consecutive median filters (200ms/600ms)
2. Powerline interference
3. High frequency noise

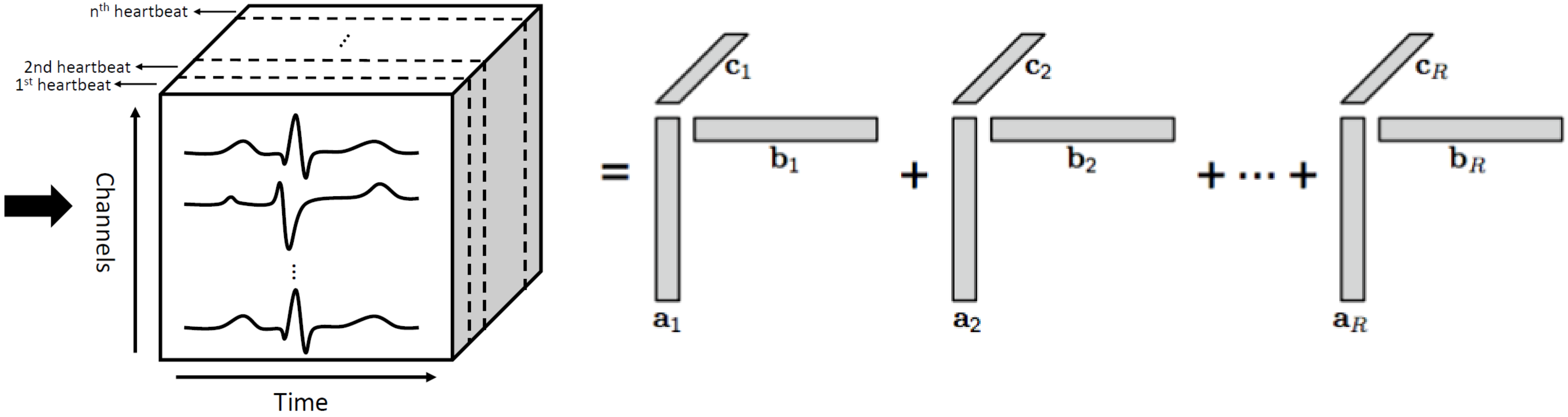
Butterworth low-pass filter at 35Hz

Tensor construction



KU LEUVEN

Tensor decomposition



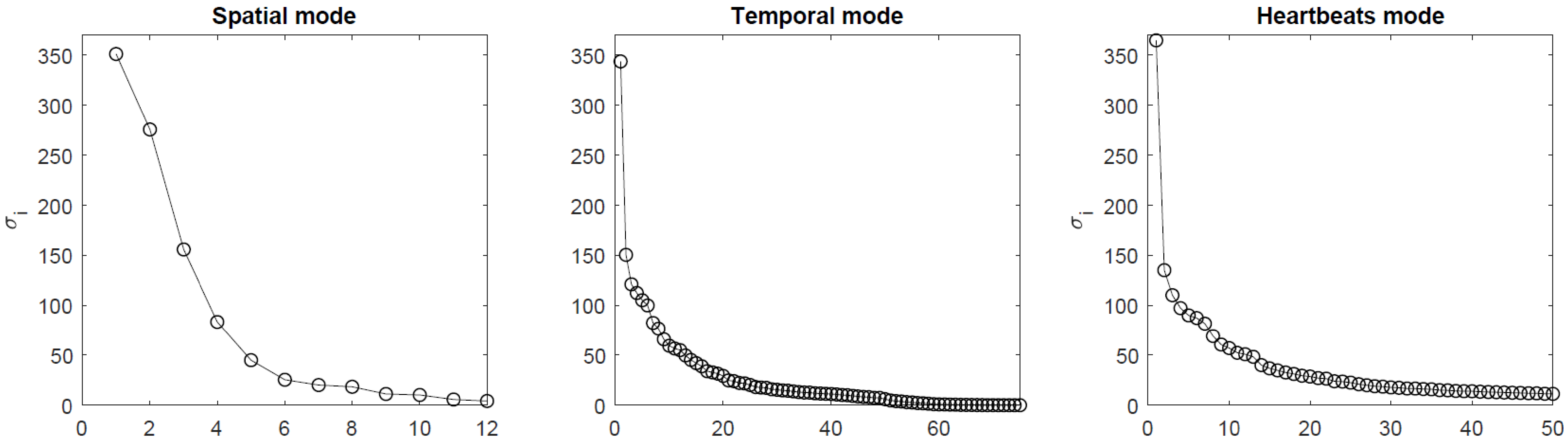
Why CPD?

- Interpretable components
- Few parameters to optimize
- It works…

KU LEUVEN

CPD rank estimation

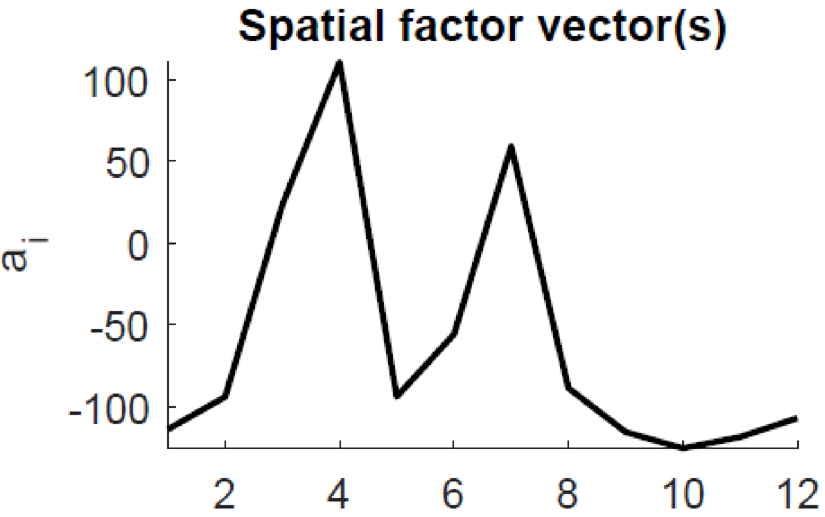
Inspect multilinear singular values:

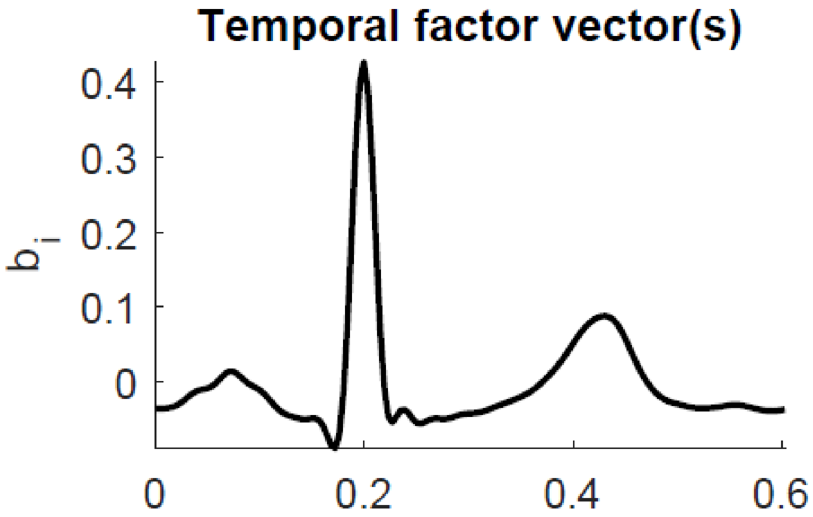


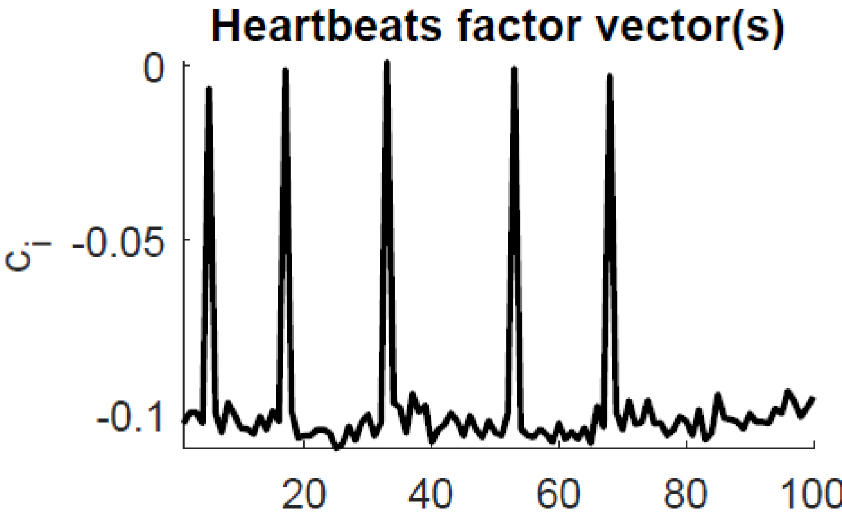
KU LEUVEN

CPD rank estimation

r = 1

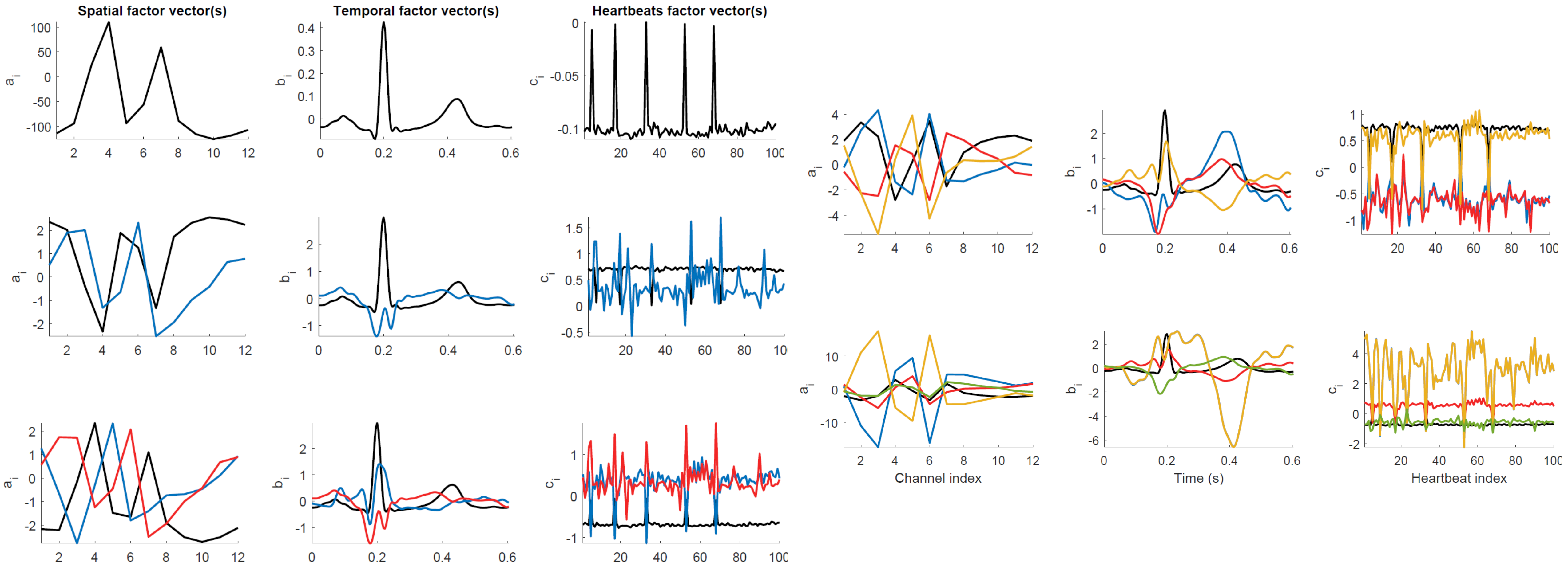






KU LEUVEN

CPD rank estimation



KU LEUVEN

Clustering

Hypothesis :

1. Values of heartbeats factor vector(s) different for different heartbeat types
2. Most signals : only two types of beats : regular + irregular

    ➔ Detect 2 clusters

3. Most heartbeats are normal

Compare 4 clustering approaches :

1. K-medoids clustering
2. Hierarchical clustering
3. Density-based clustering
4. Spectral clustering

Dataset

St. Petersburg Institute of Cardiological Technics 12-lead Arrhythmia dataset:

- Publicly available
- 75 recordings, 12 leads, 30 minutes
- Patients undergoing tests for coronary artery disease
- R peak locations + heartbeat type annotations provided

Questions:

- Optimal rank?
- Optimal clustering method?
- Optimal number of channels?
- Stability?

$$F_1 = \frac{2TP}{2TP+FN+FP}$$ for each class

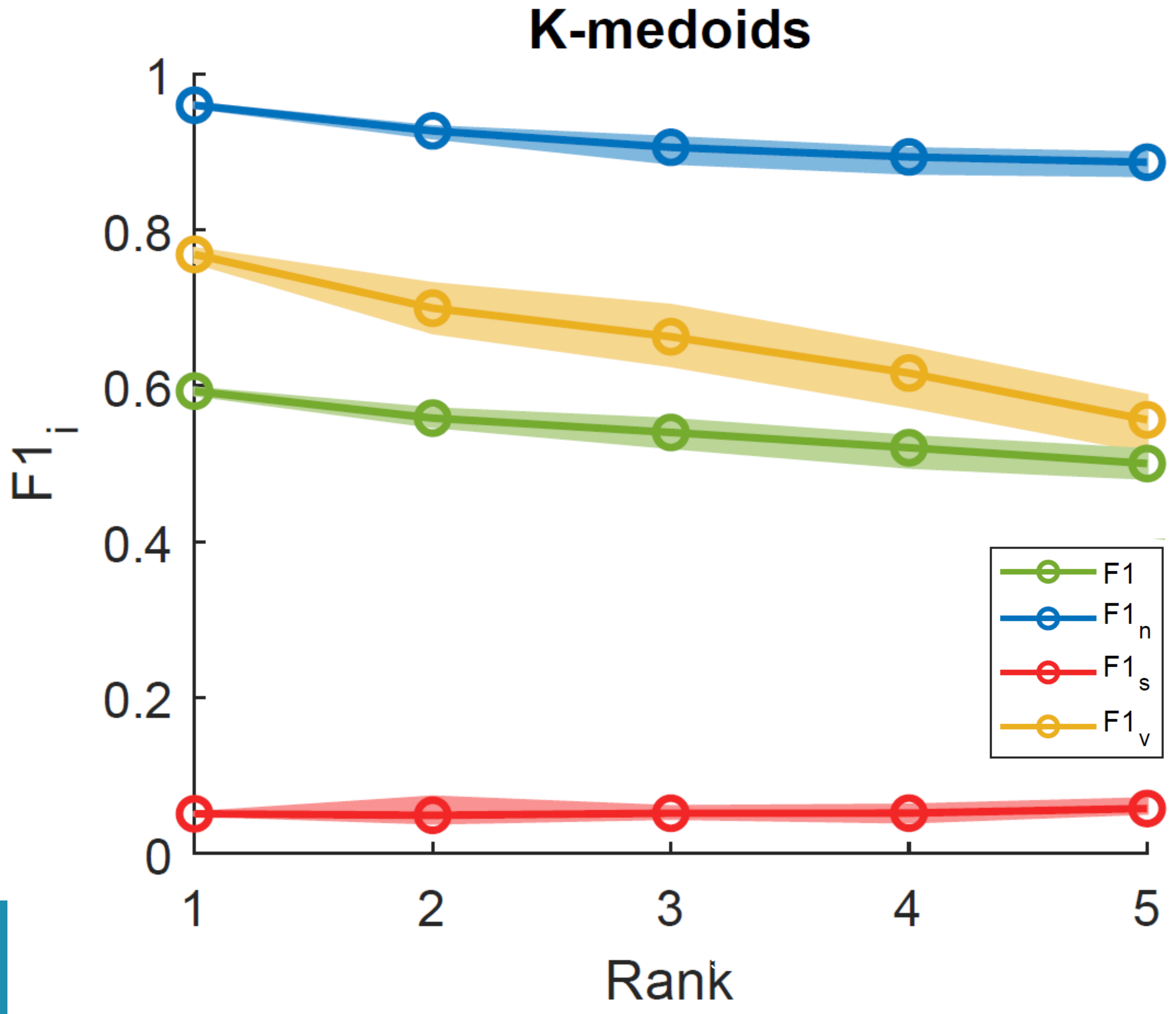
KU LEUVEN

Results rank

1. Results normal, ventricular beats >> supraventricular beats

2. Rank 1 gives best results

3. Little variance over different runs

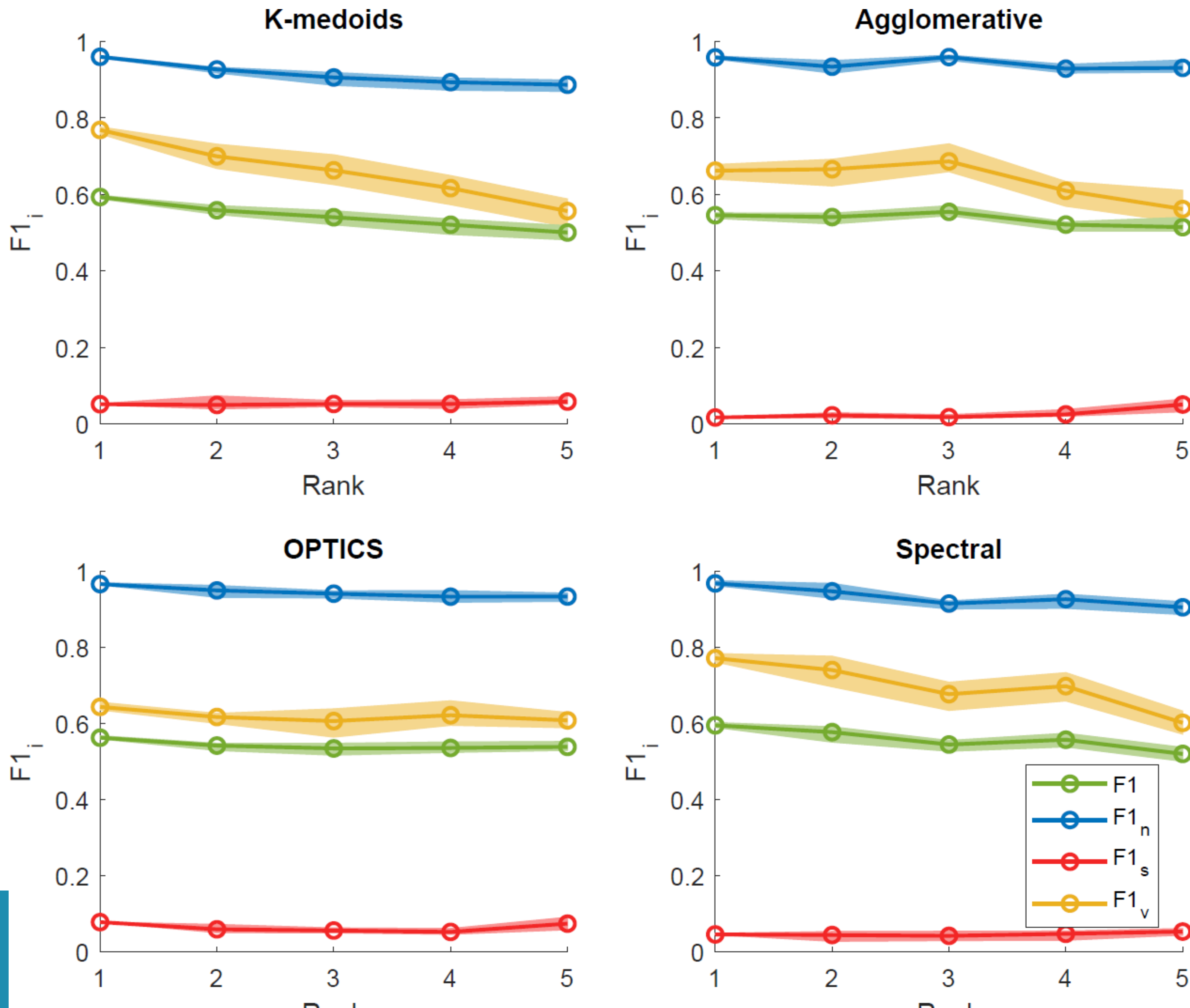


Results clustering

- Same trend for all clustering methods
  - r = 1
  - Ventricular, normal > supraventricular

- K-medoids, spectral clustering obtain superior results

- Overall results quite good (without considering supraventricular beats)



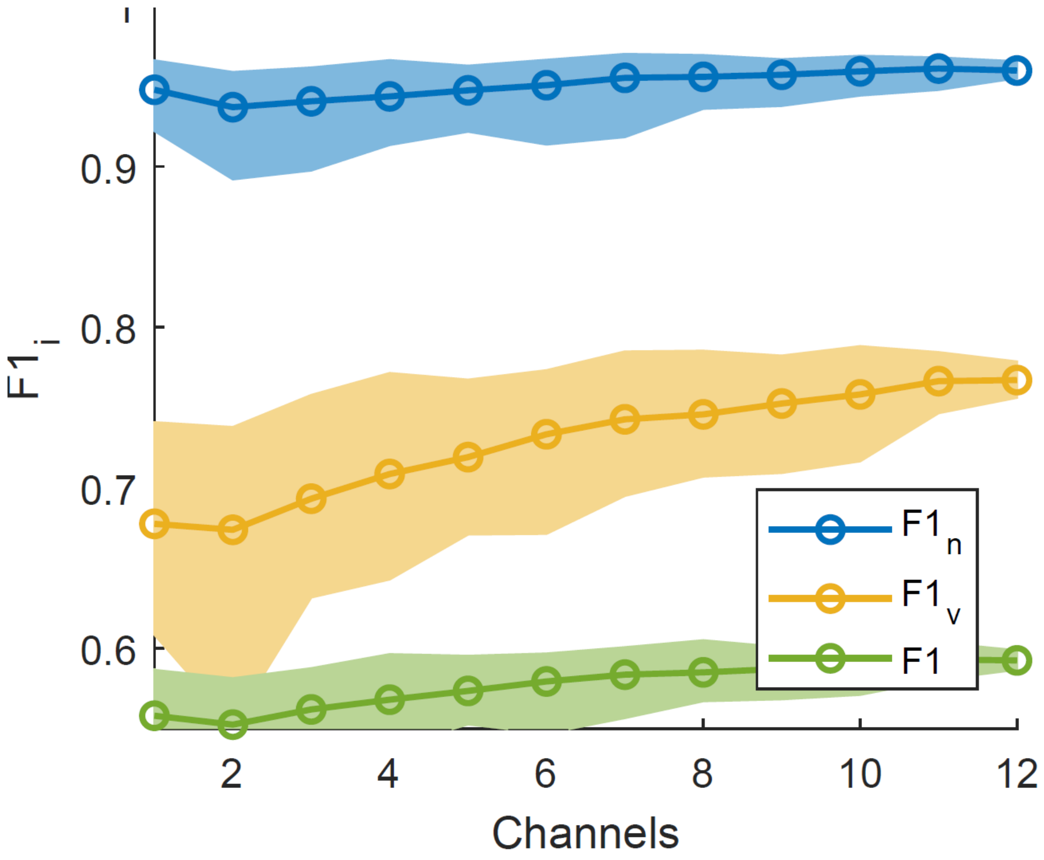
Results channels

- 12 lead signals: randomly select *n* channels, for *n = 1,..,12*

- Combining more channels – better results

- (Supraventricular beats : similar results)

- Disadvantage : few 12-lead databases publicly available…



KU LEUVEN

Future work

- Increase performance for supraventricular beats
  - Add heart rate variability features
  - Move to semi-supervised/supervised techniques

- Examine other feature vectors

- Correlate results with clinical outcome

Conclusion

CPD can be used to detect (some) irregular heartbeats

- Rank 1 is sufficient
- Factor vectors can be physiologically interpreted

Detection of ventricular beats yields good results (> standard unsupervised methods)

- Clinically more relevant than atrial beats
- ‘Easier’

KU LEUVEN

T wave alternans detection

Introduction

T wave alternans: amplitude of T wave changes beat-to-beat

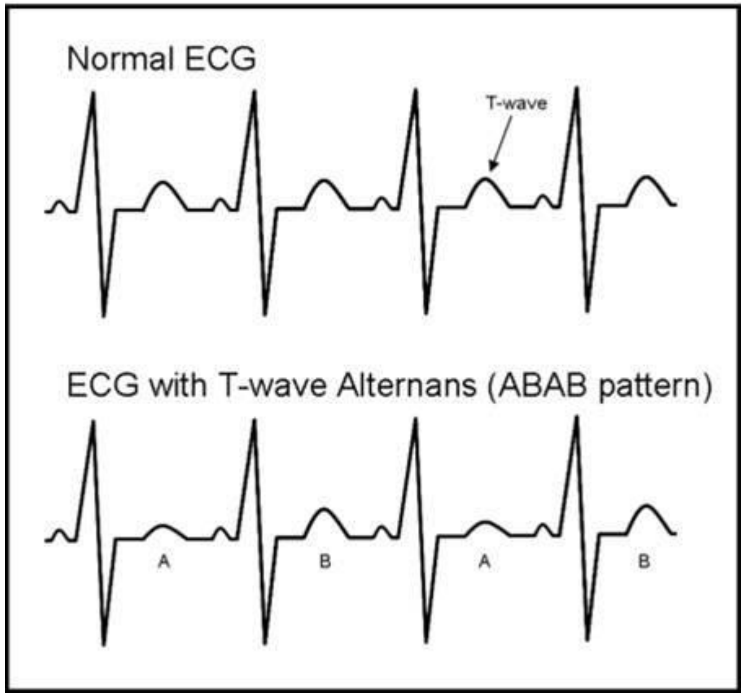
➔ ABABAB …

➔ Dangerous if HR < 110bpm

Sign of electrically unstable tissue, with risk of SCD up to 10 times higher

µV TWA : not visually detectable

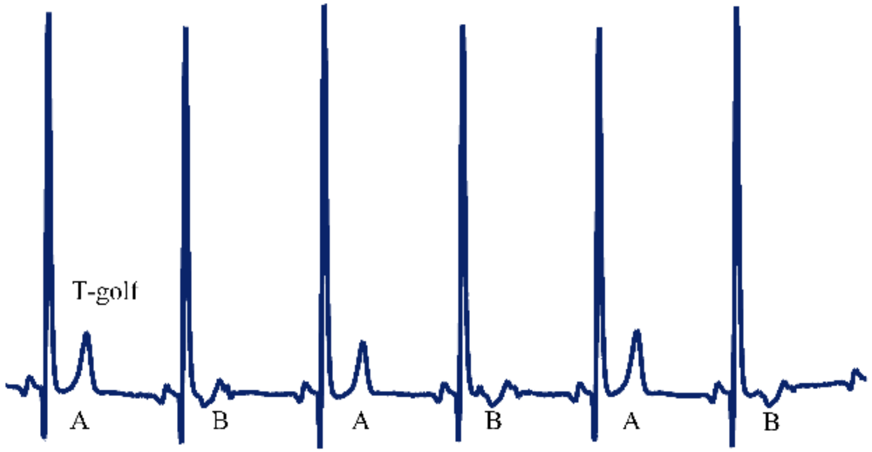
➔ Automated methods



KU LEUVEN

Methods

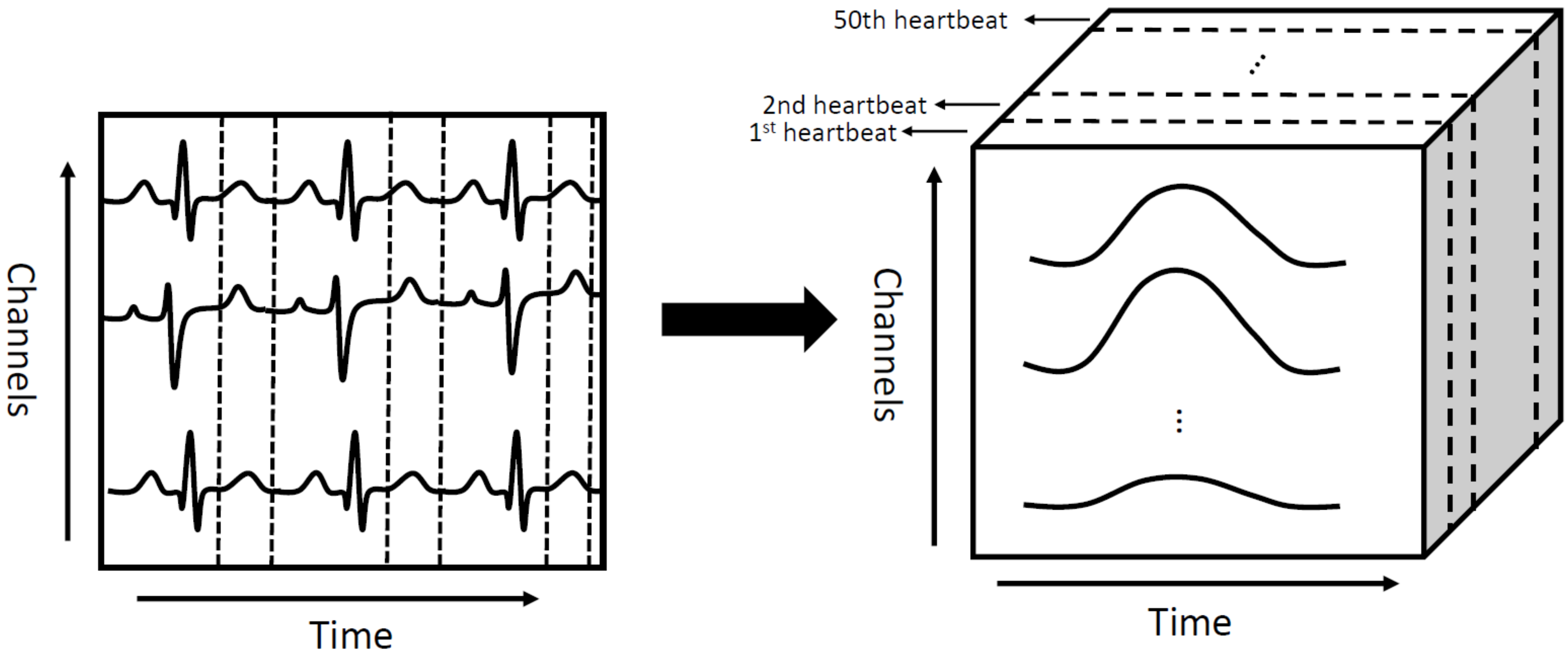
Goal: Automatic detection of T wave alternans



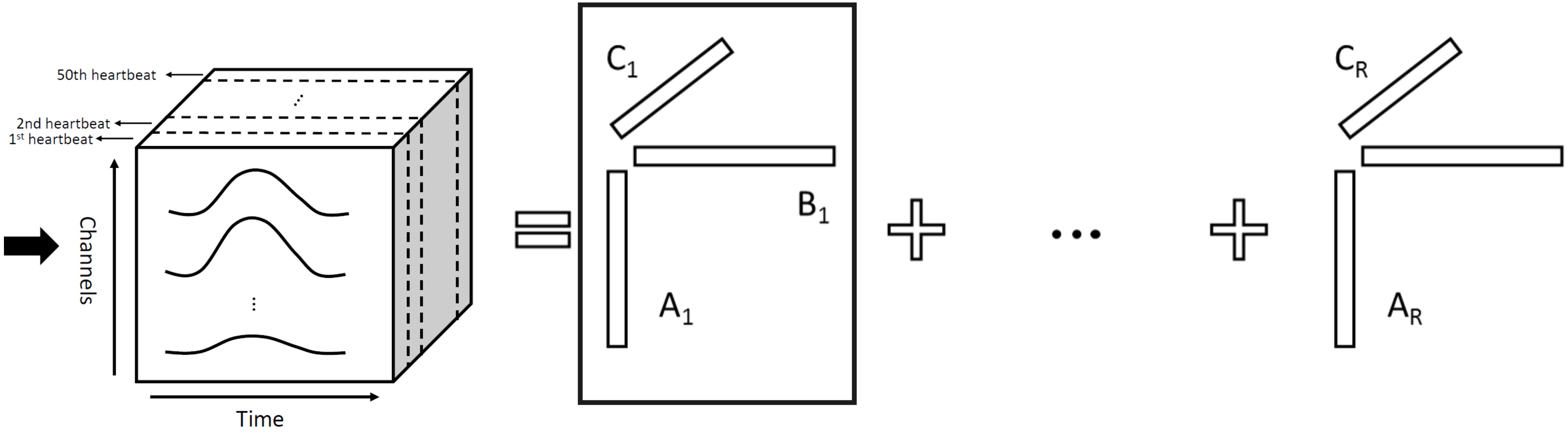
T wave segmentation → Tensor construction → Tensor decomposition → TWA detection

Goovaerts, G., Vandenberk, B., Willems, R., & Van Huffel, S. (2017). Automatic detection of T wave alternans using tensor decompositions in multilead ECG signals. *Physiological measurement*, *38*(8), 1513.

Tensor construction



Tensor decomposition

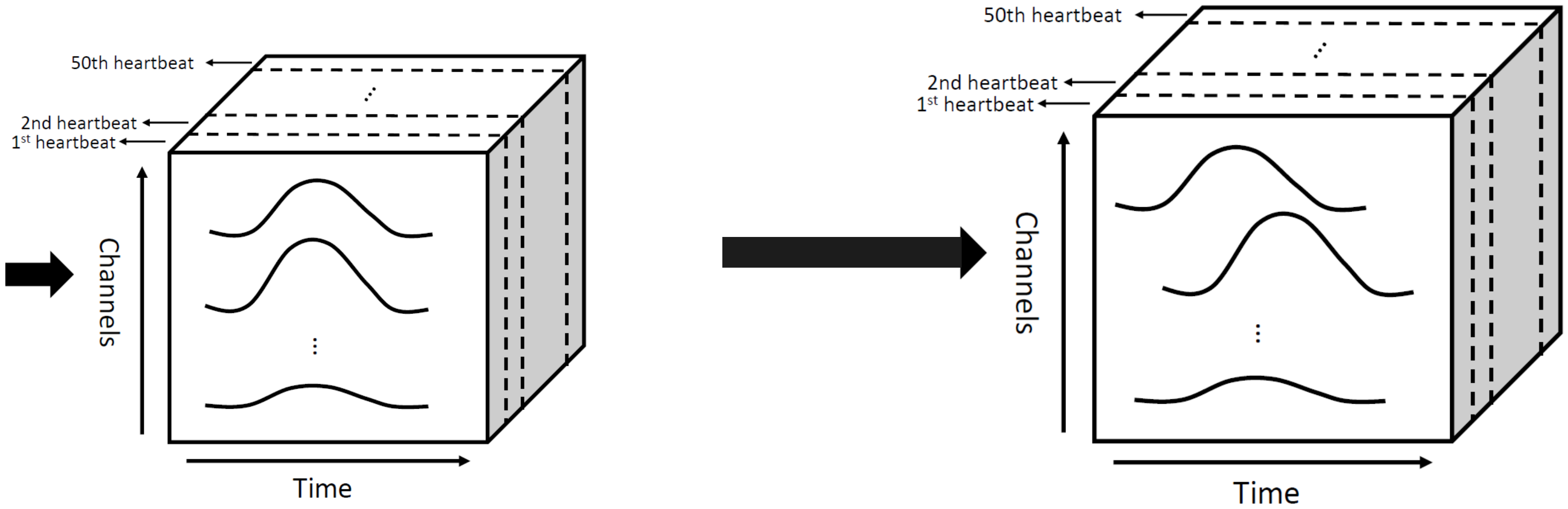


KU LEUVEN

Tensor decomposition

Practically :

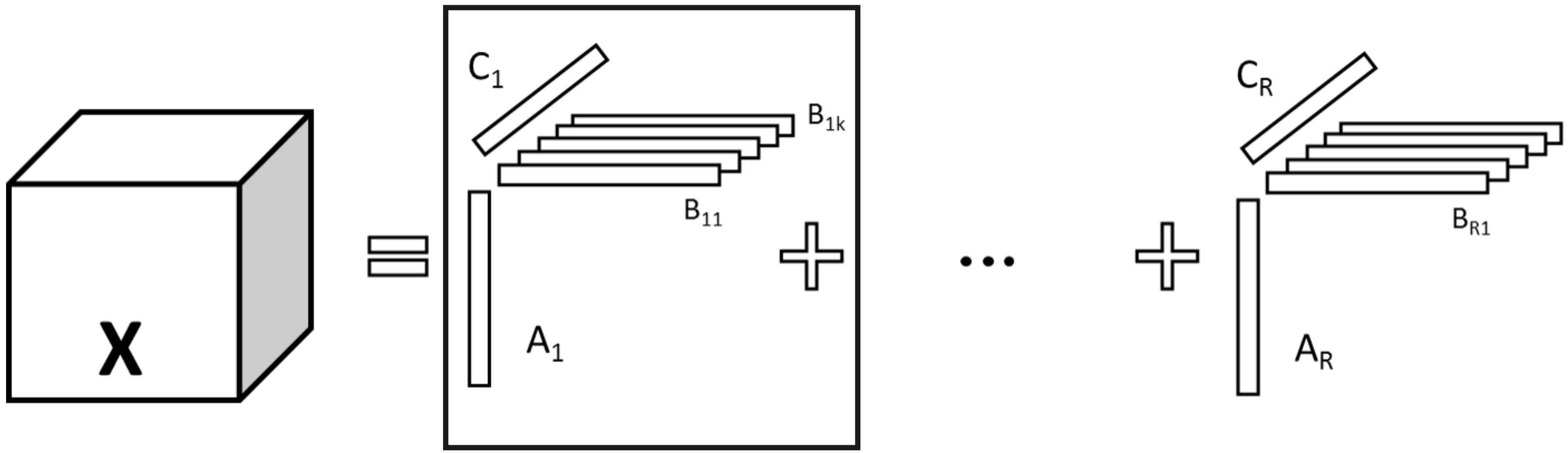
1. TWA mainly manifests at high HR
2. Clinical tests : stress test on bycicle
3. Changing heart rate ➔ changing distance R peak – T wave



Tensor decomposition

Alternative decomposition : PARAFAC2

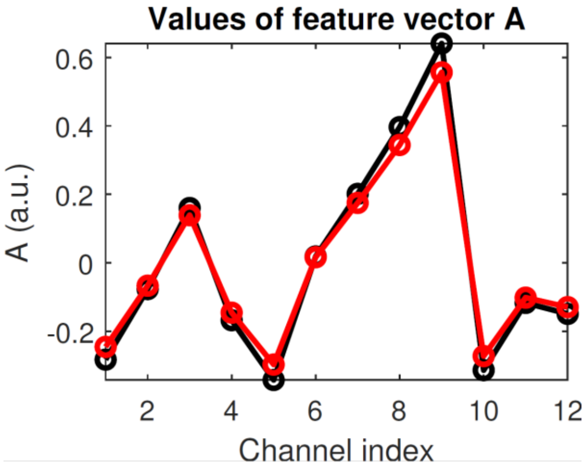
= allow variations in factor vectors of one mode

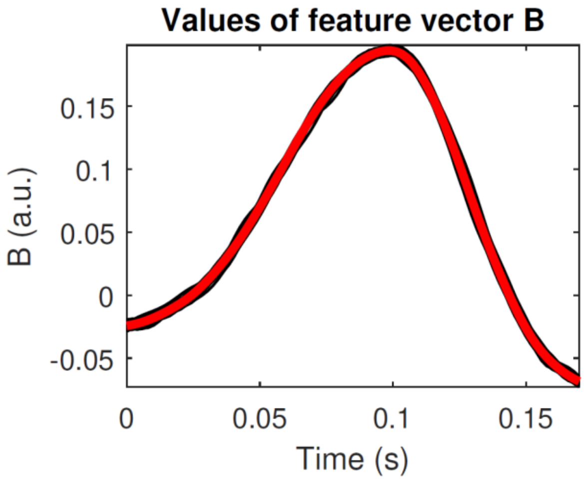


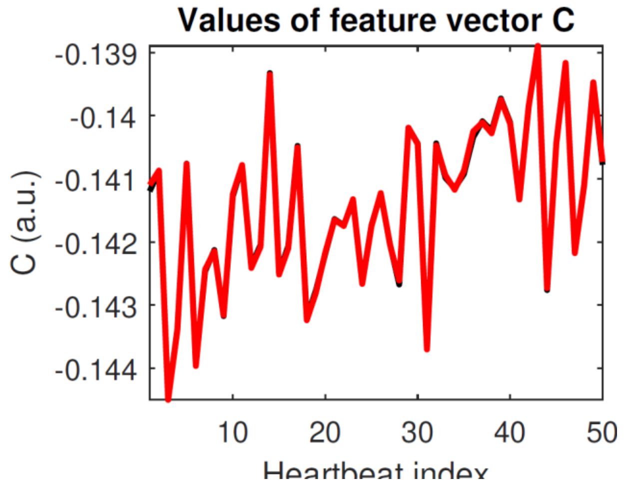
Example – clean vs. TWA

Red – CPD
Black – PARAFAC2

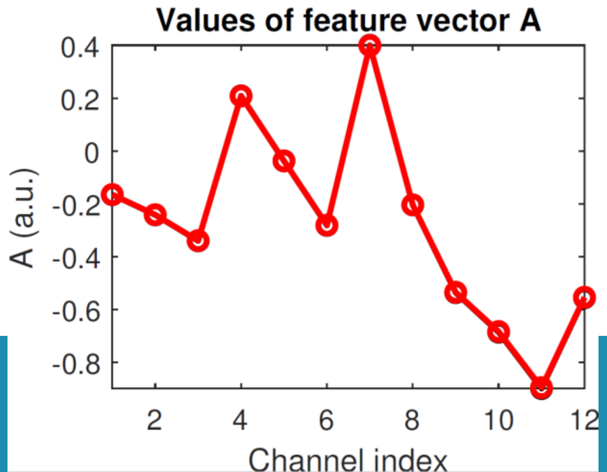
Clean

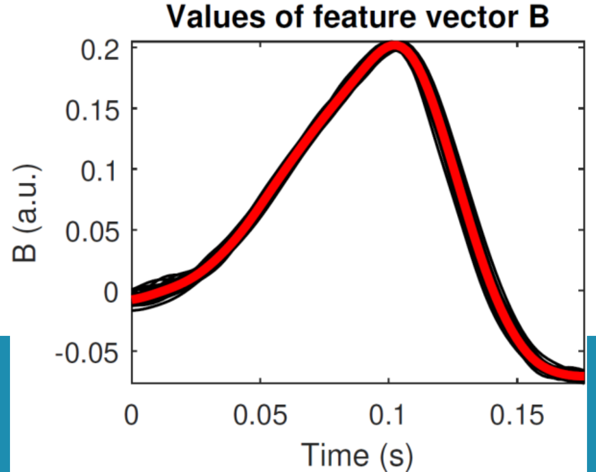


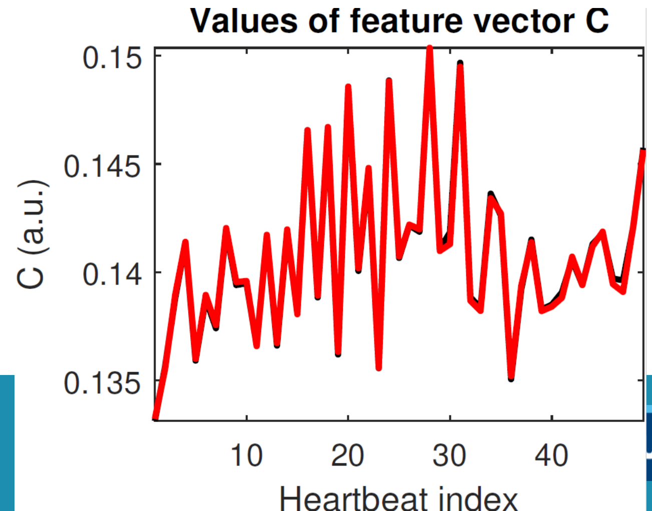




TWA

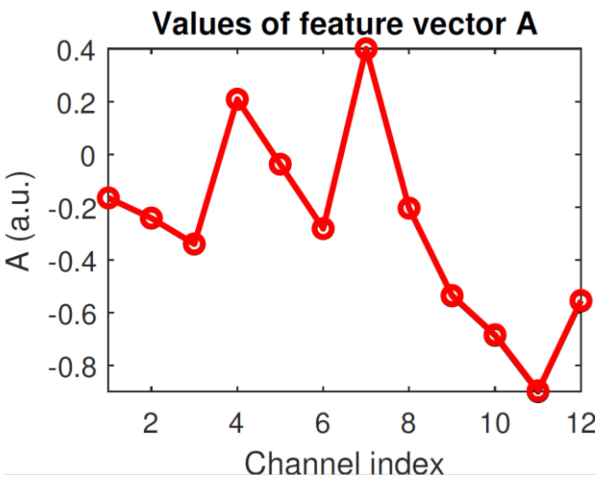


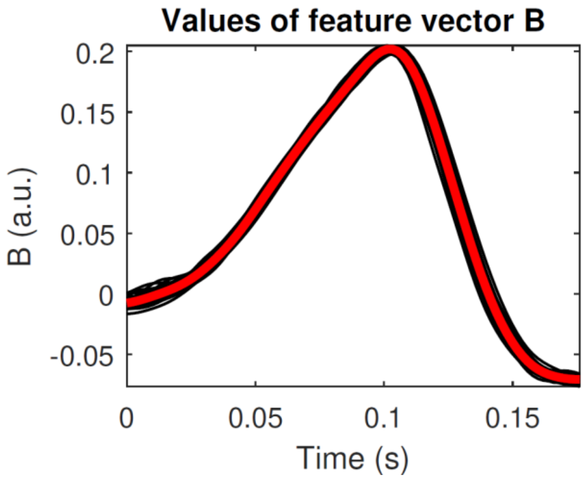


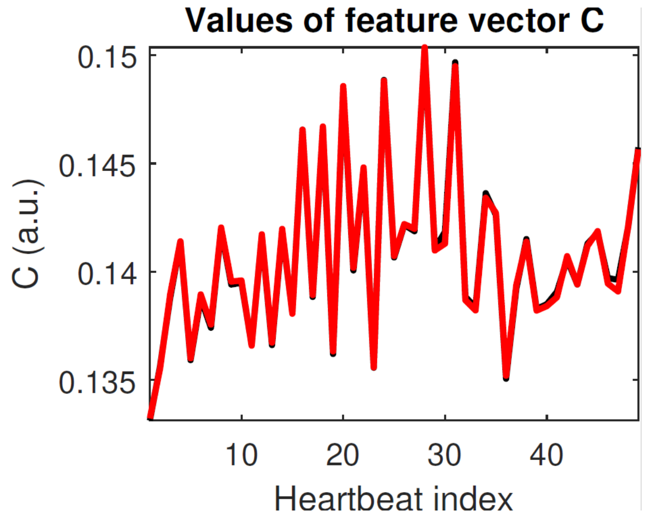


Example – shift vs. no shift

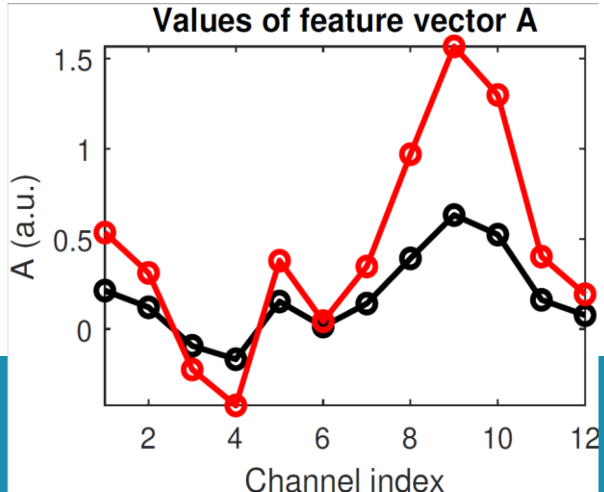
No shift

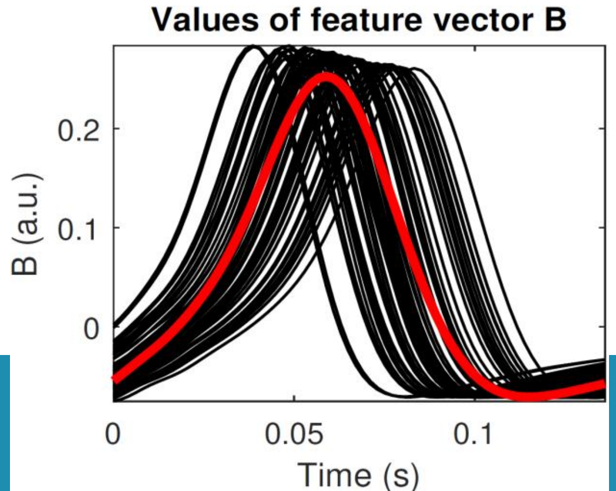


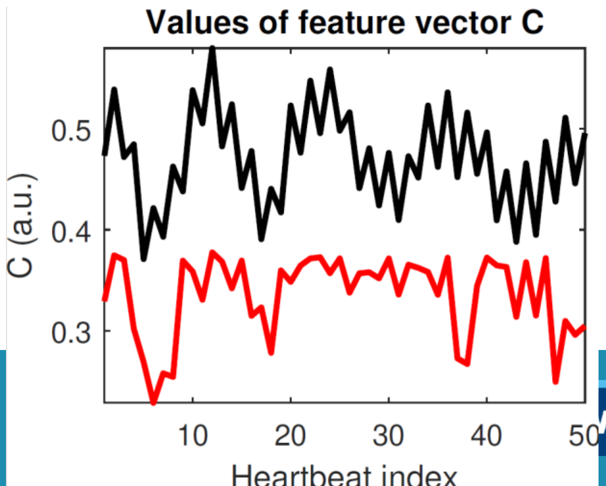




Shift

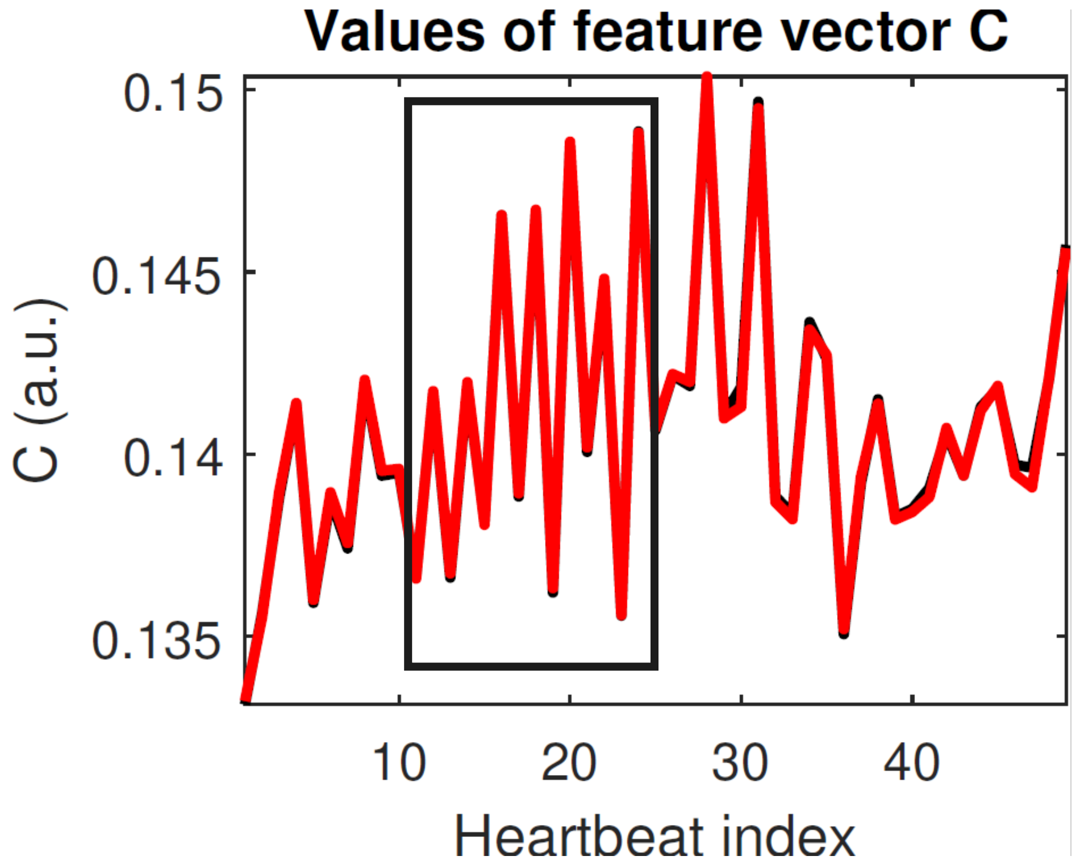






T wave alternans detection

- Third feature vector : changes in T wave between subsequent heartbeats
- TWA-pattern visible as ABAB-pattern in amplitude of **c**
- Quantification:
  1. Detect turning points (min 10)
  2. Calculate average amplitude difference

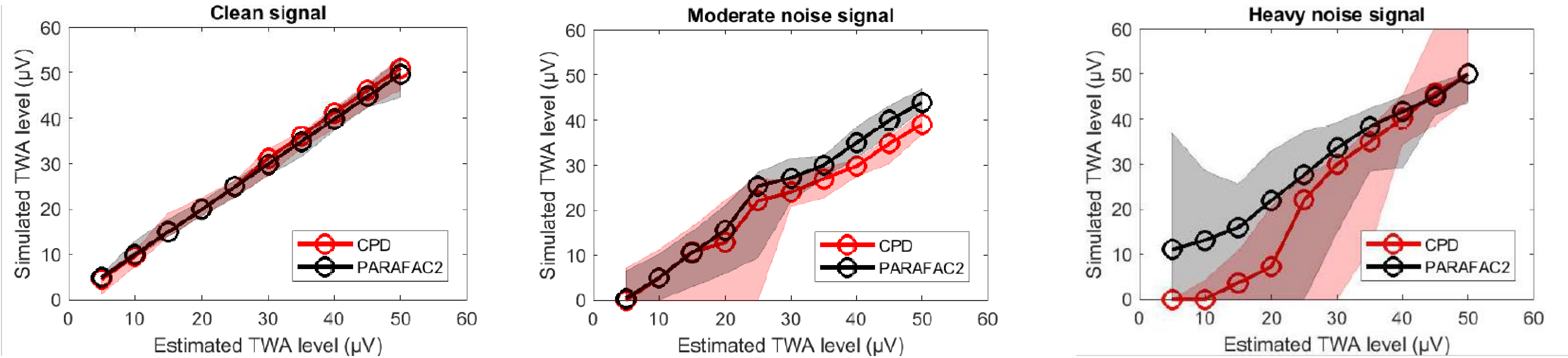


Datasets

1. Artificial signals with known amount of TWA and varying noise
   - 30 (simulated) patients
   - TWA : 5-50μV
   - Clean signals, moderate noise, heavy noise
   - 12 channels

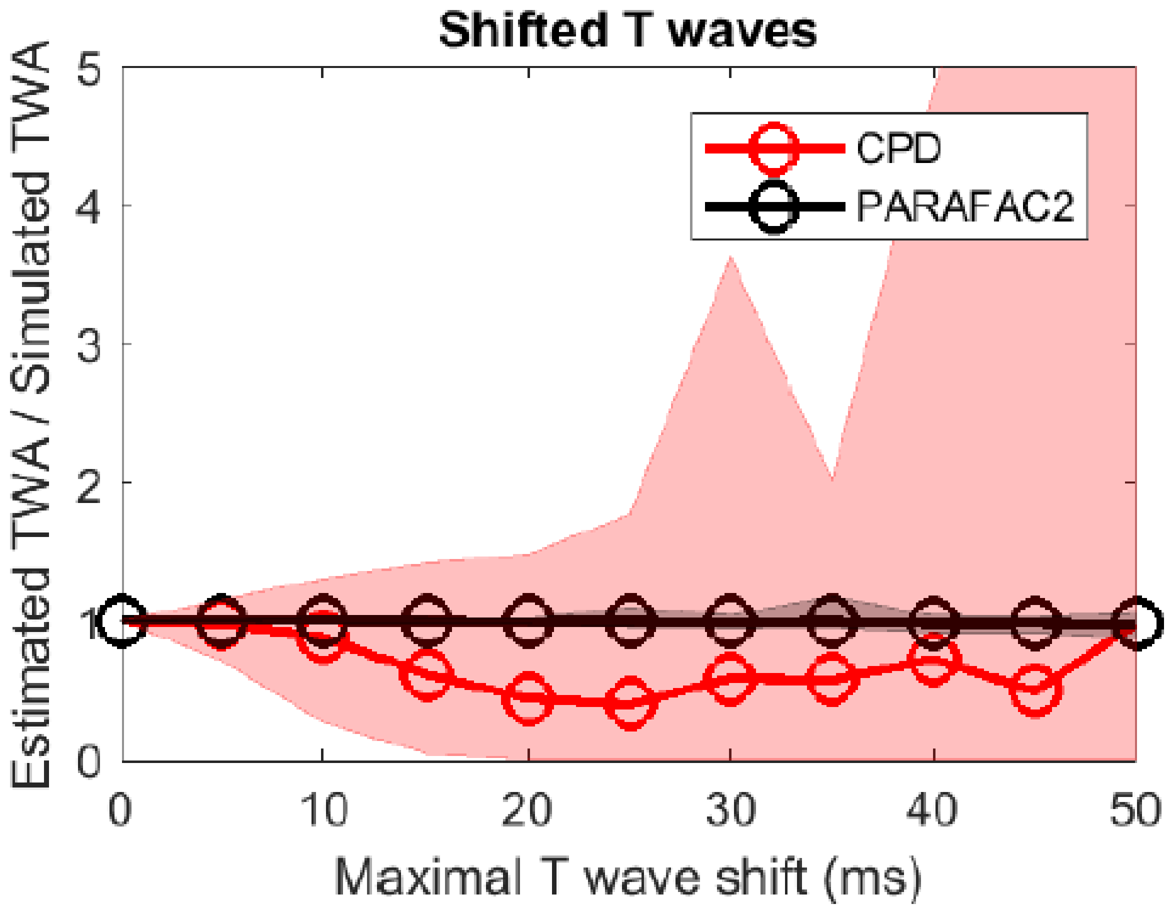
2. Clinical dataset : patients from UZ Leuven undergoing clinical TWA test
   - 33 Holter ECG signals (2/3 channels) from nine patients
   - 4 positive patients, 5 control patients
   - Only patients with multiple positive/negative tests

Results – simulated data

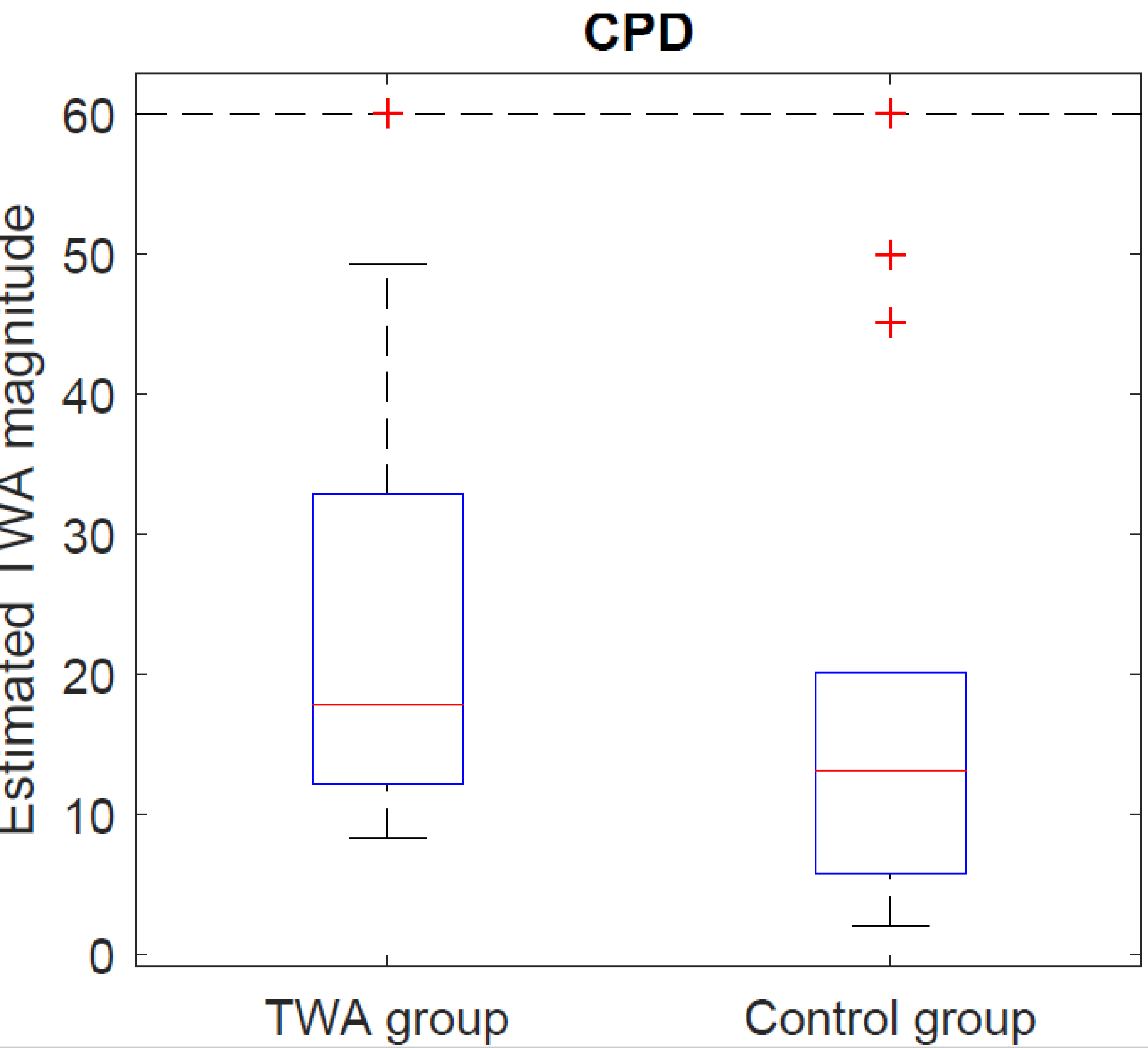


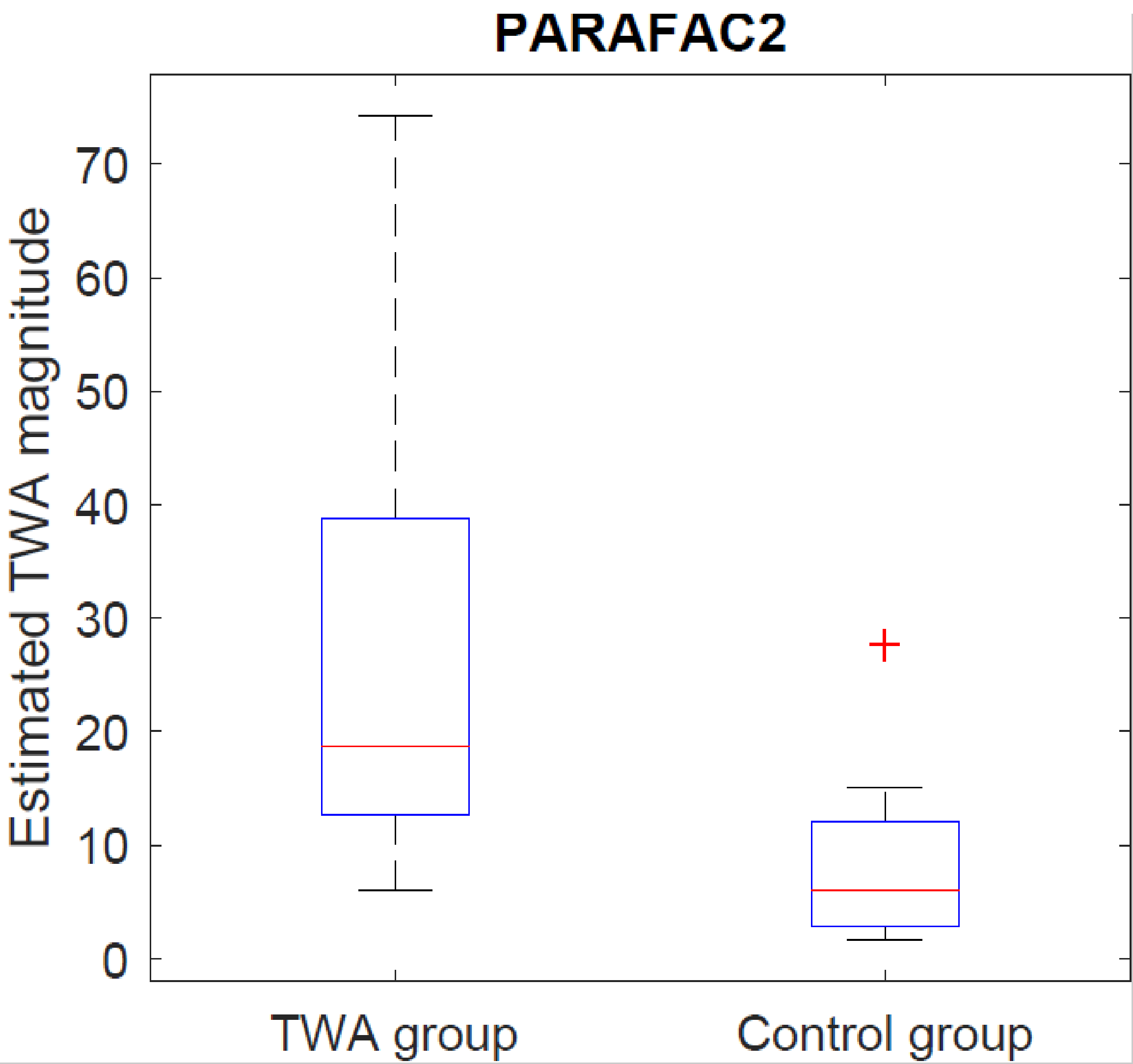
KU LEUVEN

Results – simulated data



Results – clinical data





Conclusion

- PARAFAC2 can be used to deal with shifts in T wave
- TWA successfully detected in both artificial and clinical signals
- Clinical signals : small amounts of TWA detected in control signals
  - Not detected by clinical test
  - Clinically relevant?

Analysis of ECG changes prior to in-hospital cardiac arrest

Introduction

University of California
San Francisco

- In-hospital cardiac arrest :
  - 40% of all cardiac arrests
  - 25% survives to discharge

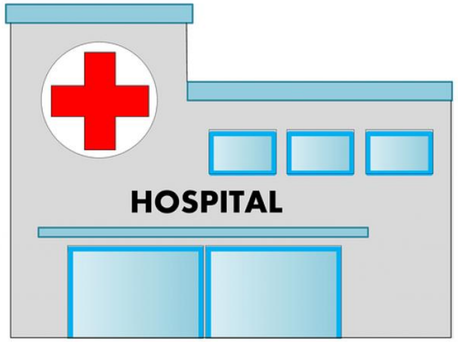
Early patient identification!

- Code blue : medical emergency

- Strategy : continuously monitor vital signs (ECG), give early alarm when patient starts deteriorating

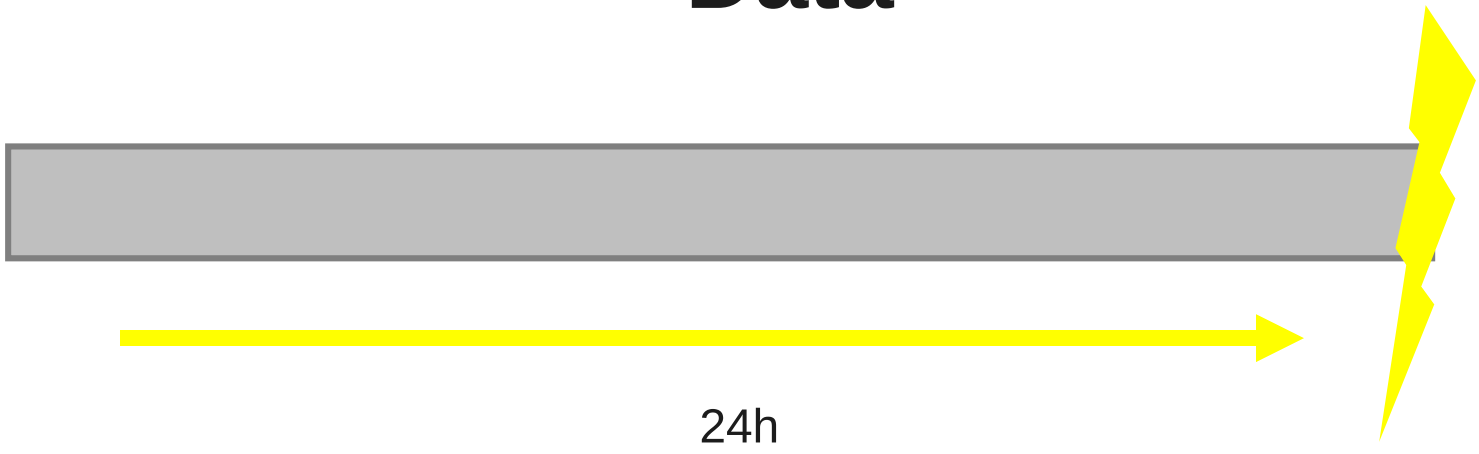
  ? Which parameters to monitor?

  ? What changes are relevant?



Goovaerts G., Boussé M., Duc D., De Lathauwer L., Van Huffel S., Hu X. Analysis of changes in ECG morphology prior to in-hospital cardiac arrest using weighted tensor decompositions, submitted to IEEE TBME

Data

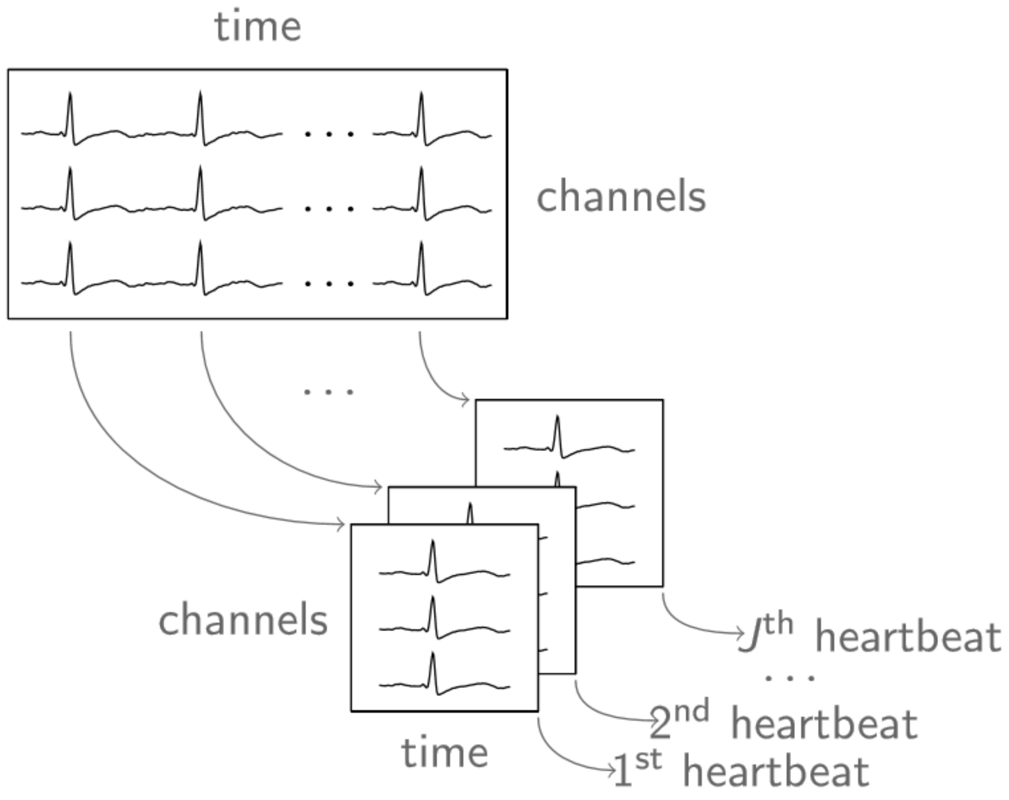


160 patients from intensive care unit UCSF/UCLA hospital

- ECG signal 24 hours before code blue
- 4/7 channels, sampling frequency 240Hz
- Information about date, time, type of code and survival

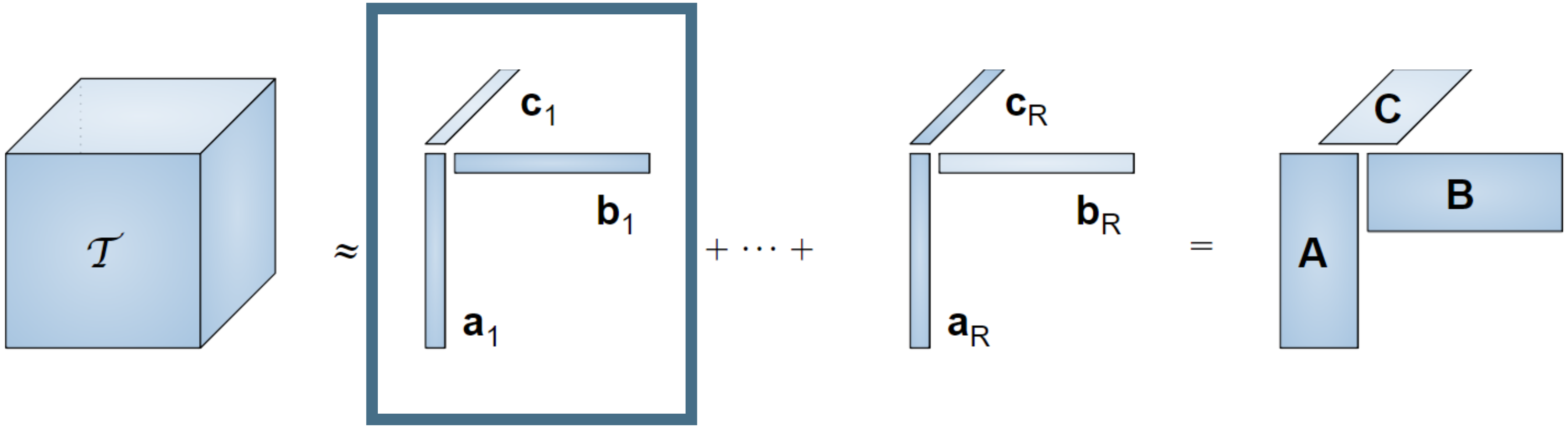
GOAL : analyse changes in ECG morphology over time

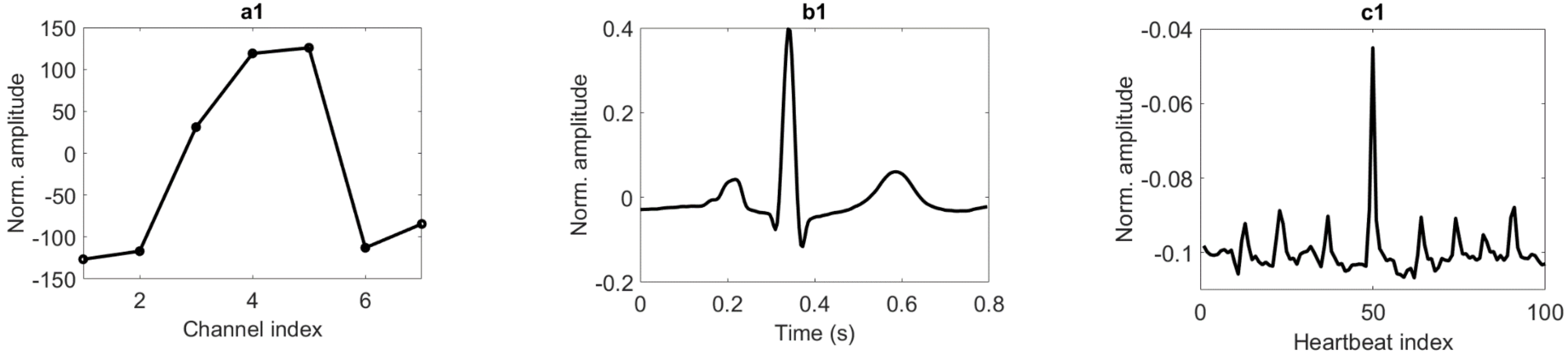
Methods



Tensor construction → Tensor decomposition → Feature extraction → Statistical analysis

Methods





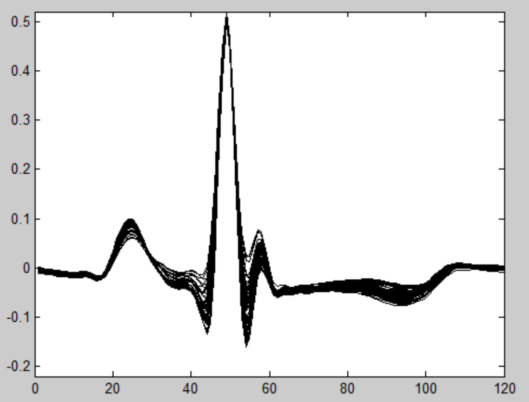
Tensor construction → **Tensor decomposition** → Feature extraction → Statistical analysis

KU LEUVEN

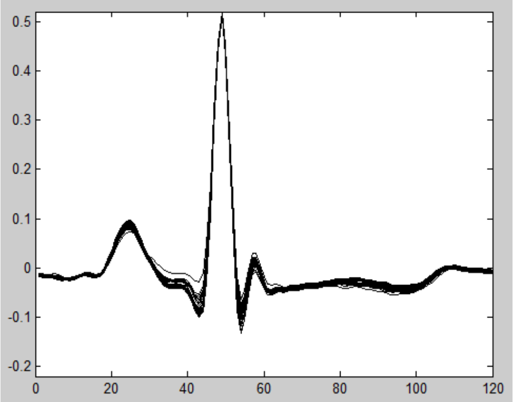
Changes in time

Template heartbeats for 1 patient:

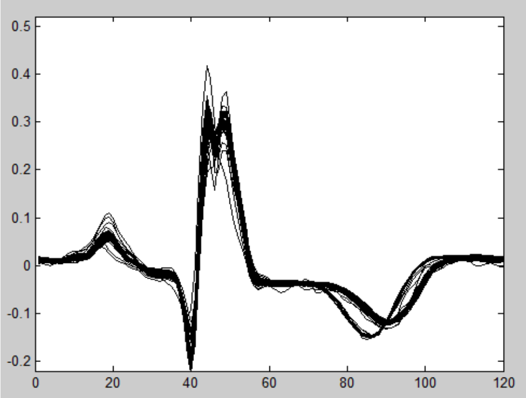
Stable



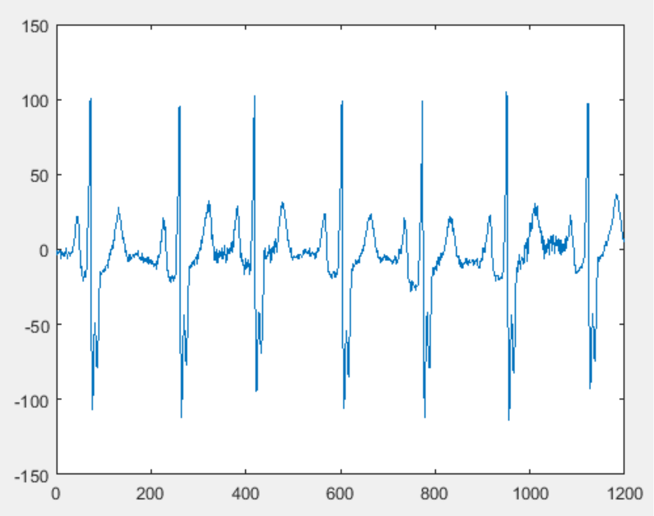
Intermediate



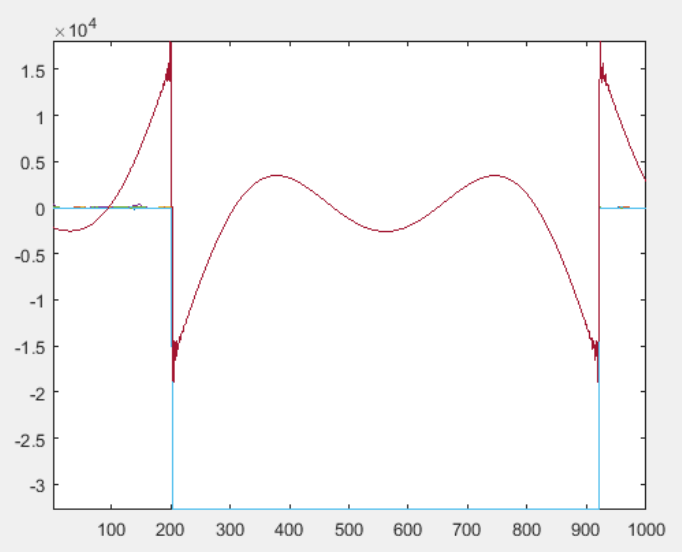
Unstable



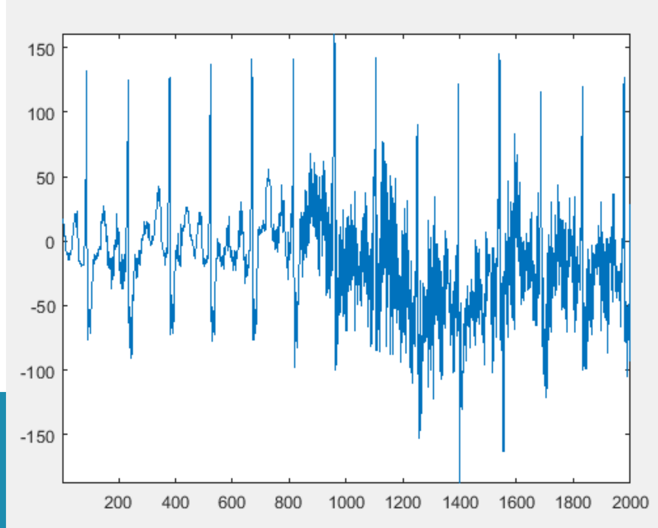
Problem: signal quality



Clean signal



Technical artifacts



Physiological artifacts

Solutions

- Cut out noisy pieces

  ☹ Lose signal information

- Heavy preprocessing

  ☹ Potentially change ECG morphology, leading to false results

- Incorporate signal quality in tensor decomposition

  ➔ Weighted CPD

Weighted CPD

- Signal processing : data perturbed by noise

➔ Include prior knowledge about noise in least-squares cost function!

$$\min_{\mathbf{A},\mathbf{B},\mathbf{C}} \frac{1}{2}||\mathcal{W} * (\mathcal{T} - [\![\mathbf{A},\mathbf{B},\mathbf{C}]\!])||_F^2$$

$\mathcal{W}$ = weight tensor : (prior) knowledge about noise
= $[D, E, F]_L$

- Calculated efficiently with NLS approach
- Calculation of $\mathcal{W}$: assume signal quality is constant for each heartbeat in each mode

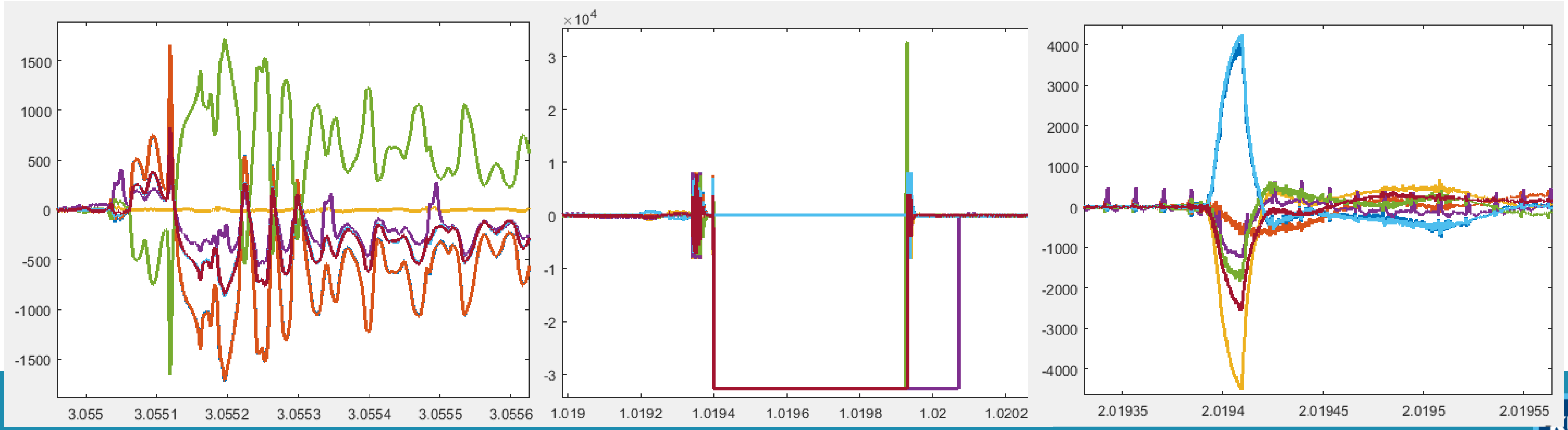
➔ 1 value per mode-2 fiber

Boussé, M., & De Lathauwer, L. (2017, December). Nonlinear least squares algorithm for canonical polyadic decomposition using low-rank weights. In *2017 IEEE 7th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*

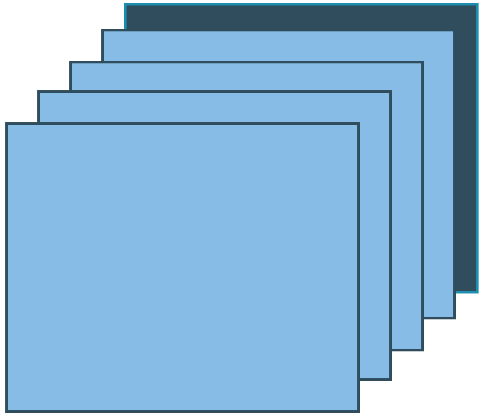
Technical artifact

- Artifacts due to (technical) malfunctions : loose electrodes, machine errors
  - High amplitudes / no signal
  - Often very structured morphology
  - No ECG is measured

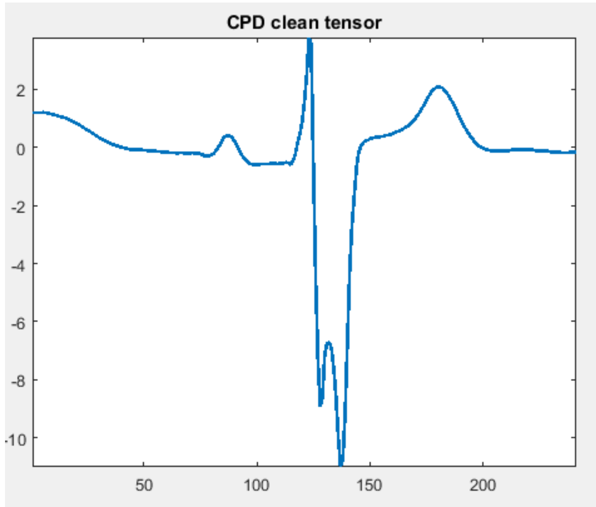
Remove completely!
Weight = 0

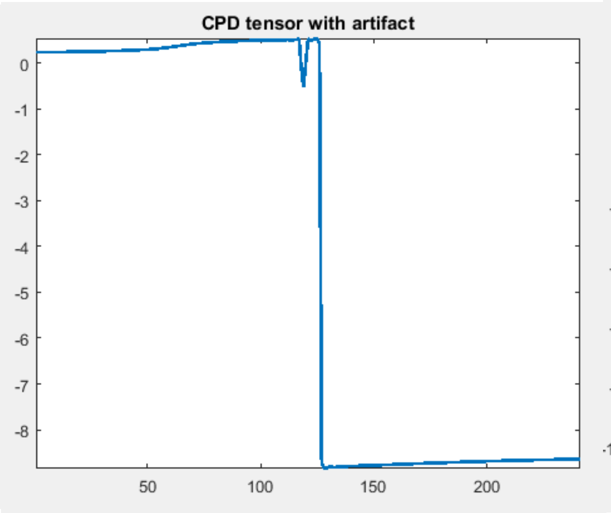


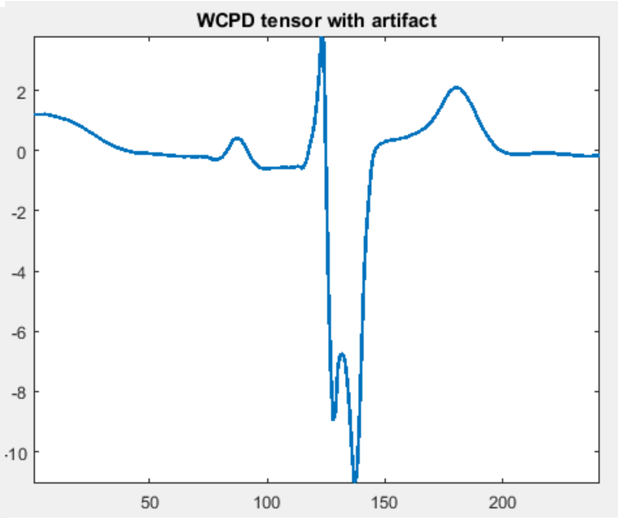
Technical artifact



- 100 normal slices (e.g. clean ECG)
  = normal tensor
- 1 slice with technical artifact
  = tensor with artifact
- Weight tensor : 1, with 0s in last slice



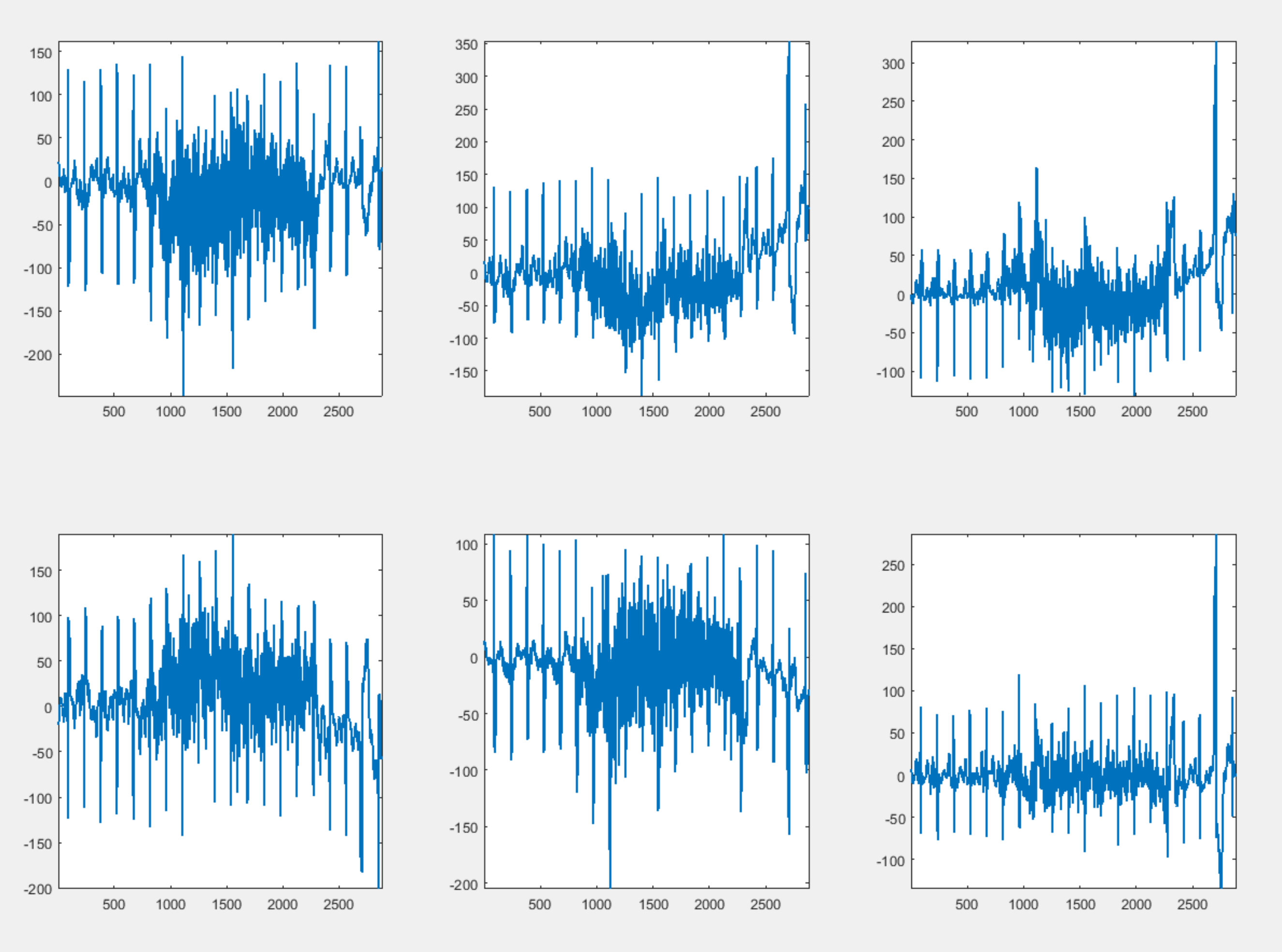




Physiological artifacts

- Noise coming from physiological sources : breathing, muscle artifacts
  - Amplitudes varies depending on noise level
  - ‘Random’
  - Changes between channels and in time
  - Is added to ECG : useful signal is measured

- Construct weight tensor : calculate SNR for <u>each heartbeat</u> (e.g. mode-2 vector)



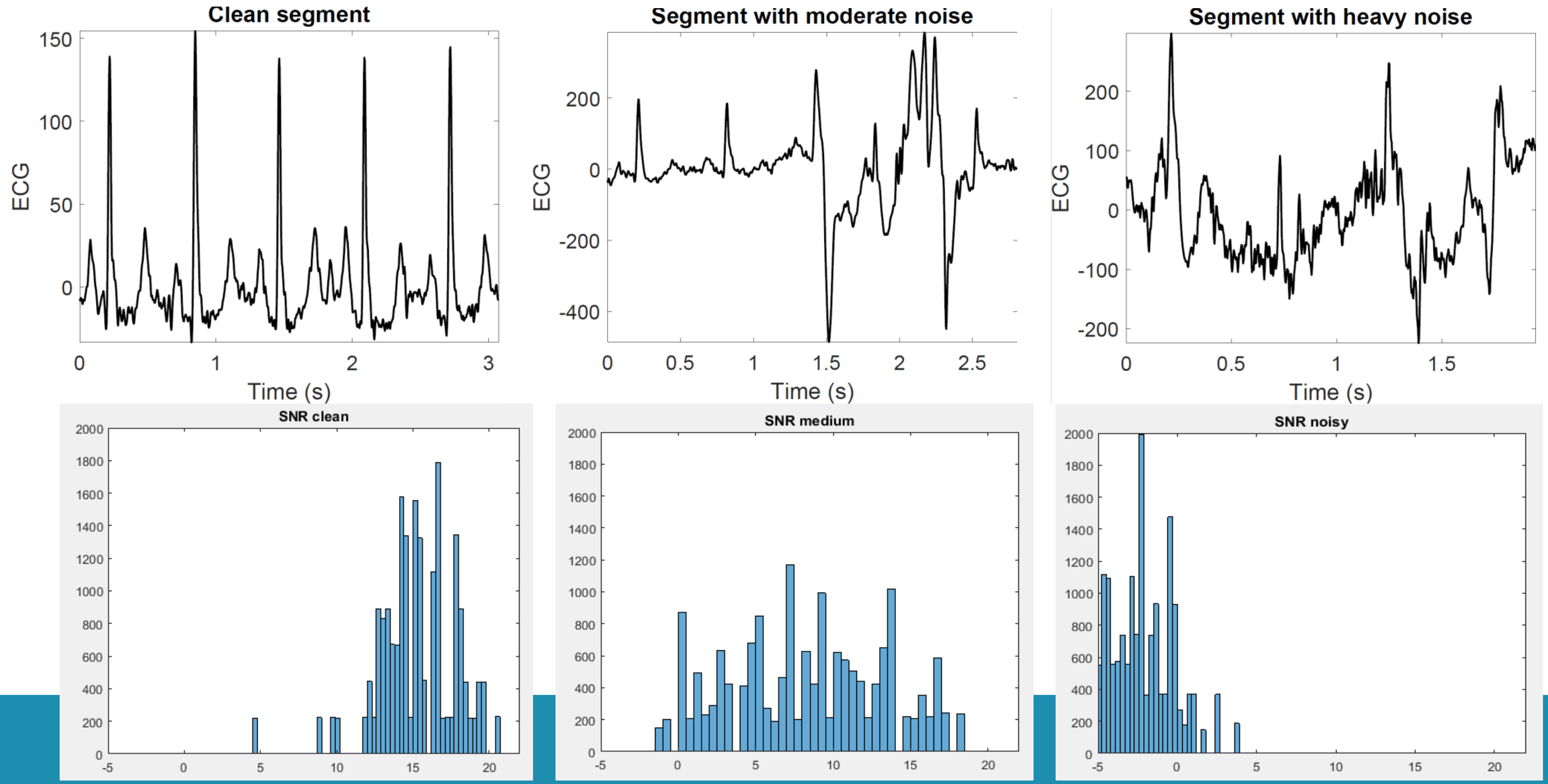
SNR estimation

- MIT-BIH Noise Stress Database: 2x6 signals with known SNR (clean signal + calibrated noise) between -6 and 24
- From literature: select 8 useful features
  - Skewness
  - Kurtosis
  - Power in 6 subbands 0-10Hz, 10-20,20-48,48-52,52-100,100+

- Fit linear regression model using 6 signals, tested on other 6 signals

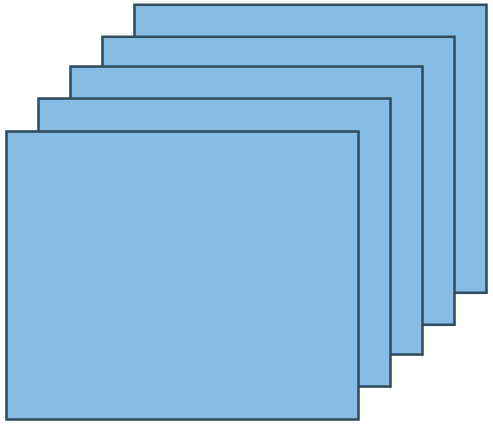
SNR estimation

Application on UCSF data: selection of segments of 1m

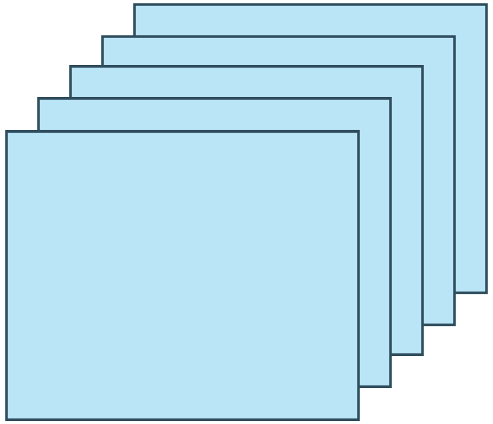


Weighted CPD

Comparison of CPD and WCPD on three previous segments

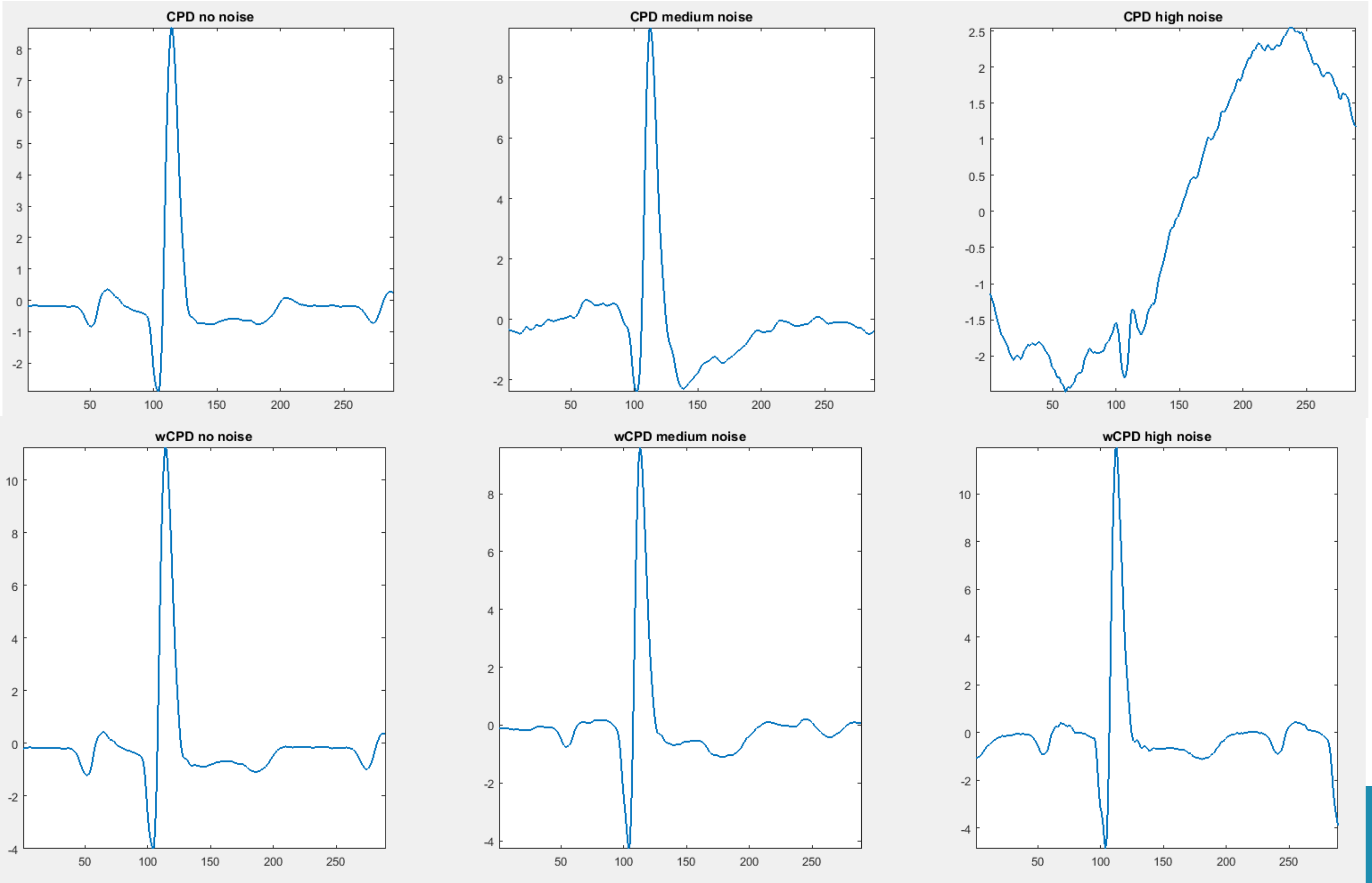


Heartbeats tensor:
channels x time x heartbeats



Weights tensor:
channels x ***SNR*** *x heartbeats*

Weighted CPD



Conclusion

wCPD can drastically improve results for noisy signals

Final weight tensor construction : 2 steps

1. Detect technical artifacts : weight = 0
2. Calculate SNR of each heartbeat : weight = (normalized) SNR

Clinical : analyse ECG interval/amplitude in time

- ECG amplitude waves change drastically in all patients prior to cardiac arrest
- ECG intervals change differently in different patient groups

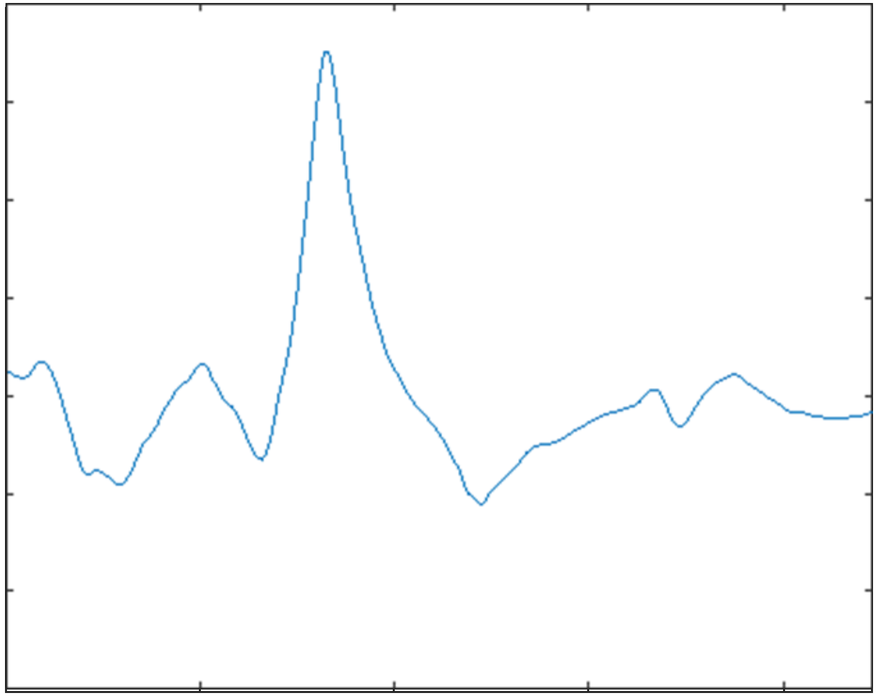
➔ Could be used for monitoring patients at risk

Future work

Current method : sliding window of 100 heartbeats

~ semi real-time : 1 output every 1-1.5 minutes

Improvement : tensor updating : real time monitoring



Vandecappelle, M., Boussé, M., Vervliet, N., & De Lathauwer, L. (2018, January). CPD Updating Using Low-rank Weights. In *Proc. of the 2018 IEEE International Conference on Acoustics, Speech and Signal Processing* (No. accepted).

KU LEUVEN

Conclusions and Future directions

Conclusion

Use of CPD in various ECG applications

- Interpretable components
- Results ≥ state-of-the art methods
- Adapt (computation of) CPD to deal with typical ECG characteristics

Many other applications possible with minimal changes

- Different types of alternans

Future directions

CPD : easy to interpret, but limited..

- Only assessment of ‘global’ ECG features
- Channel-by-channel assessment : BTD/MLSVD

Updating : can be used in many patient monitoring applications

Multimodal analysis : combine ECG with other physiological signals

e.g. sleep analysis, epilepsy

Thank you!

Acknowledgments

| University Hospitals Leuven Gasthuisberg

| Prof. dr. Rik Willems, dr. Bert Vandenberk

| University of California, San Francisco, Department of Nursing

| KU Leuven, Dept. Electrical Engineering-ESAT, division STADIUS & MICAS

| Tensor group of Lieven De Lathauwer; Martijn Boussé, Michiel Vandecappelle