Tensor-based ECG Signal Processing Applied to Atrial Fibrillation Detection

Simon Geirnaert

Joint work with G. Goovaerts, S. Padhy, M. Boussé, L. De Lathauwer, S. Van Huffel

Asilomar Conference on Signals, Systems, and Computers
October 30, 2018

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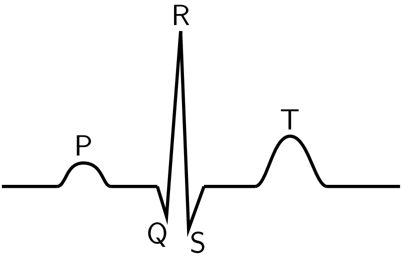
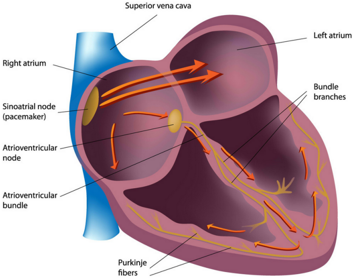
Opening new horizons

The electrocardiogram (ECG): measuring the electrical activity of the heart



A normal ECG-signal



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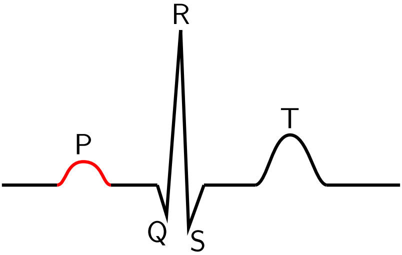

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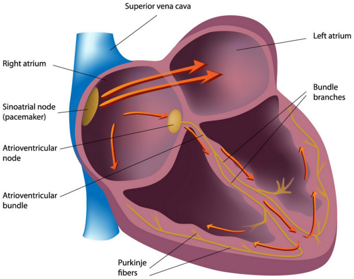

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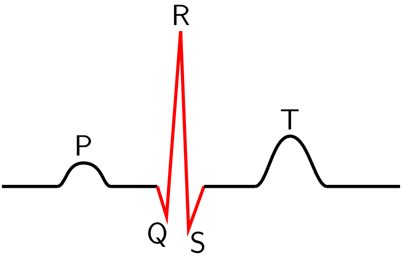

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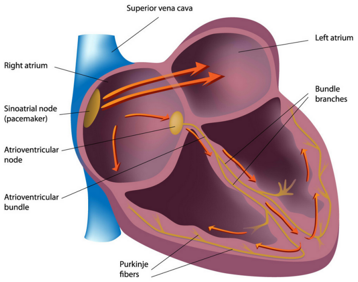

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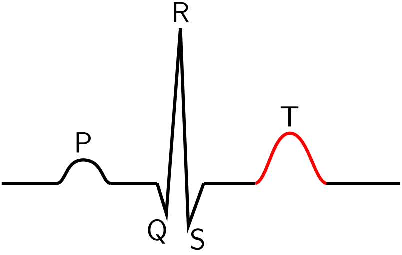

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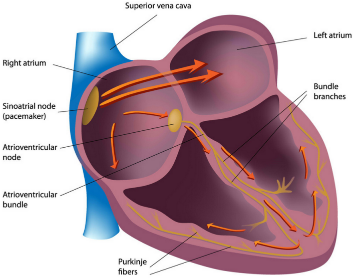
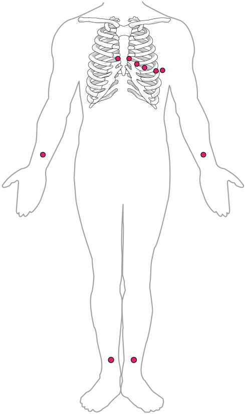


The electrical activity of the heart

Recording the ECG

Multi-channel (e.g. Holter)



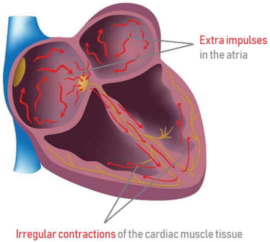
Positioning electrodes

Single-channel (*mHealth*)

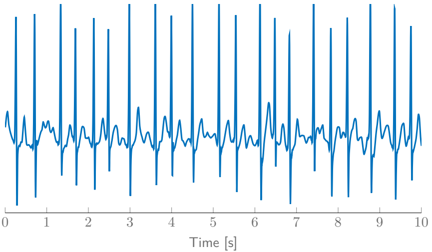
KardiaMobile™ of AliveCor®

The Apple Watch®

Atrial fibrillation (AF): a cardiac arrhythmia

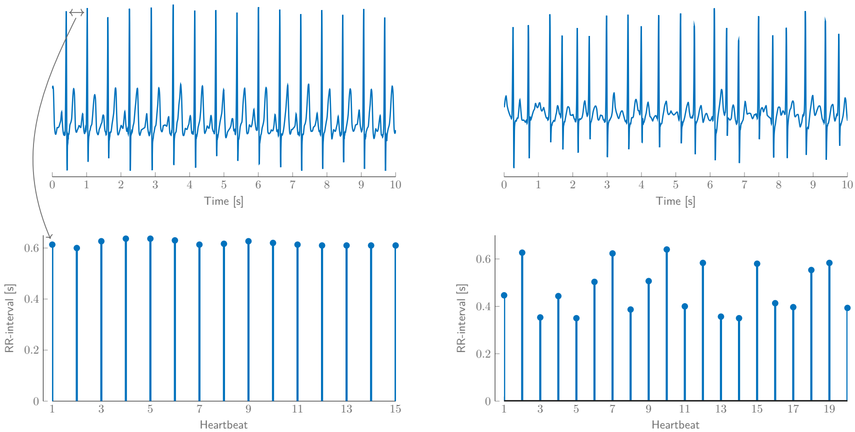


The electrical activity of the heart when AF is present



An ECG-signal with AF

Atrial fibrillation (AF): a cardiac arrhythmia



Atrial Fibrillation: the most common cardiac arrythymia

Prevalence

- 1 out of 4 will develop AF
- 1% of general population

Risks

Latently: cloths of blood $\rightarrow$ pulmonary embolism, stroke, ...

Treatment

Often medication, sometimes electrical cardioversion, ...

How to improve?

Need: accurate and early detection of AF

More and more data available (*mHealth*)

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Impossible to process for cardiologists?

Not i.c.w. *automatic detection of AF*!

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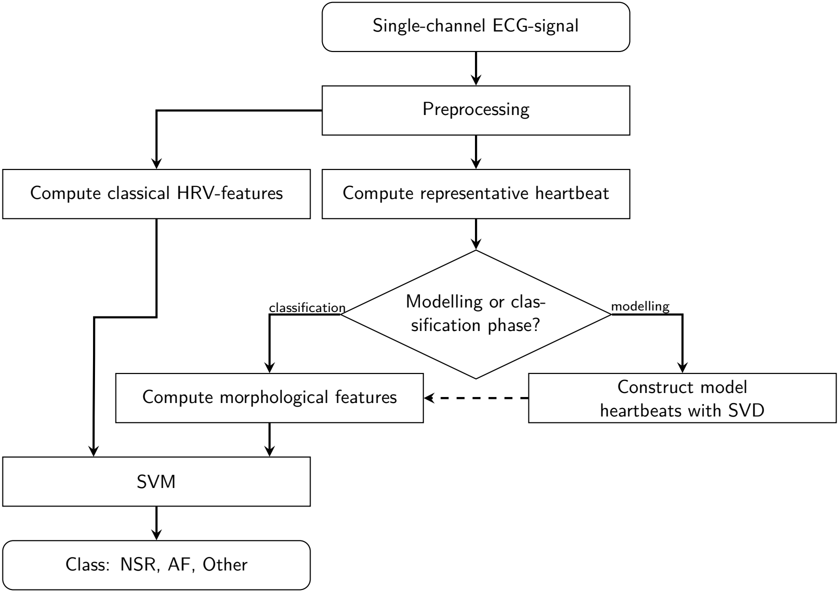
Goal

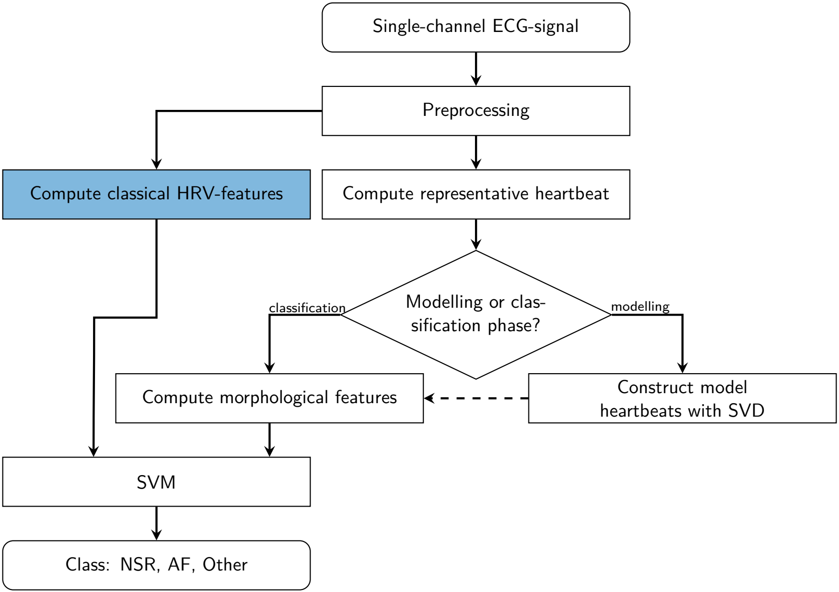
The development of matrix- and tensor-based methods for the automatic detection of AF in single- and multi-lead ECG.

Outline

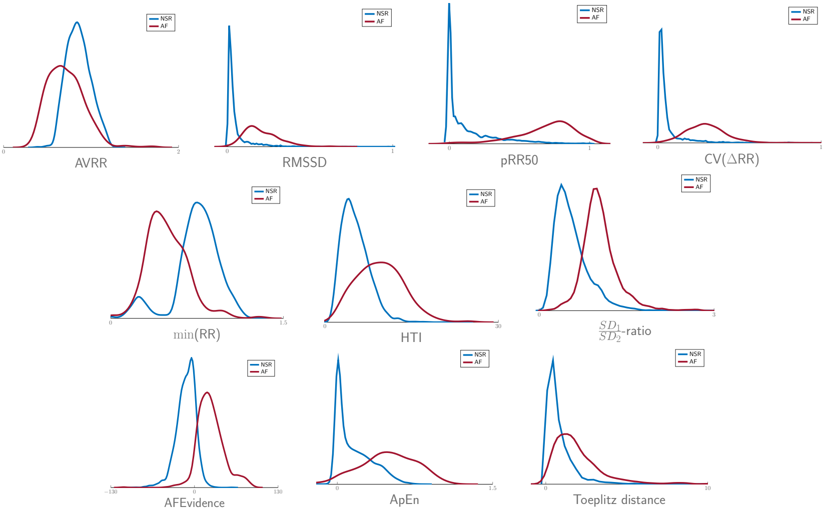
Overview of the algorithm



Classical HRV-features

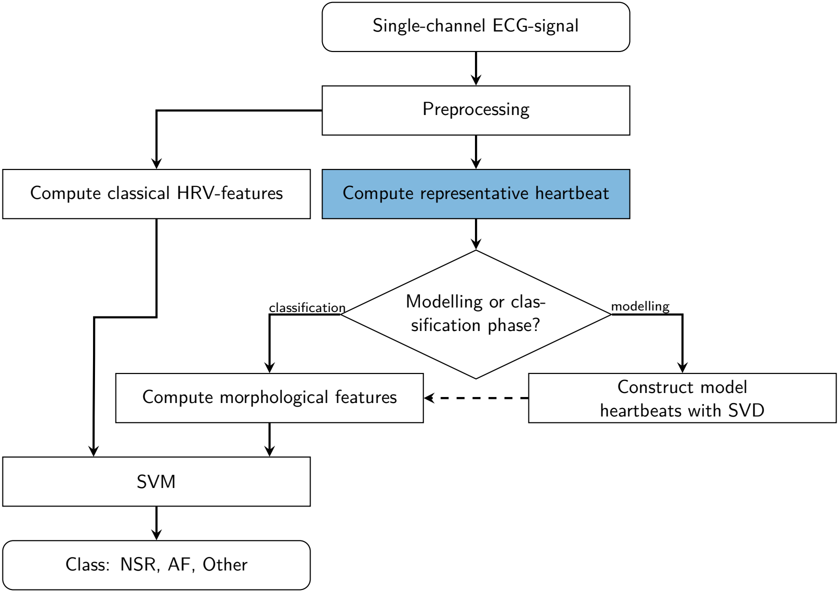


Classical HRV-features: densities



NSR = Normal Sinus Rhythm, AF = Atrial Fibrillation

Computation representative heartbeat



Computation representative heartbeat

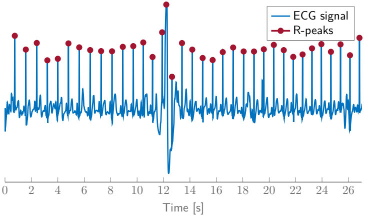
Three steps:

1. R-peak detection (Pan-Tompkins) and noise removal
2. Segmentation and alignment
3. Compression in one representative heartbeat

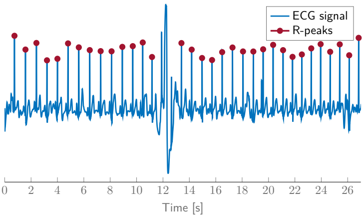
Computation representative heartbeat

Three steps:

1. *R-peak detection (Pan-Tompkins) and noise removal*
2. Segmentation and alignment
3. Compression in one representative heartbeat



Without noise detection

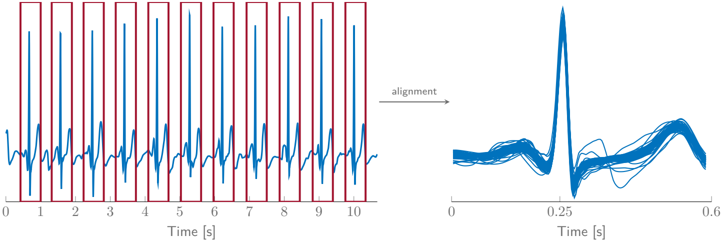


With noise detection

Computation representative heartbeat

Three steps:

1. R-peak detection (Pan-Tompkins) and noise removal
2. *Segmentation and alignment*
3. Compression in one representative heartbeat

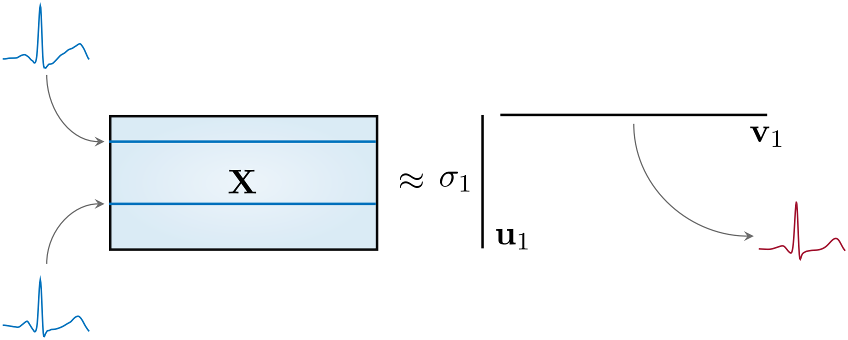


From window-based segmentation to cross-correlation based alignment

Computation representative heartbeat

Three steps:

1. R-peak detection (Pan-Tompkins) and noise removal
2. Segmentation and alignment
3. *Compression in one representative heartbeat*



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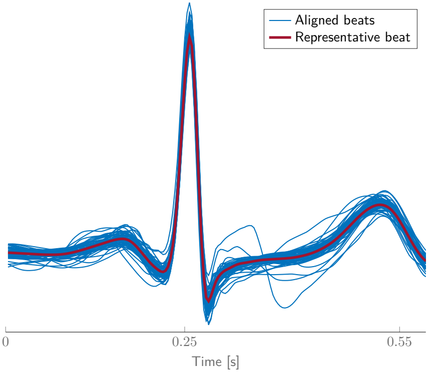
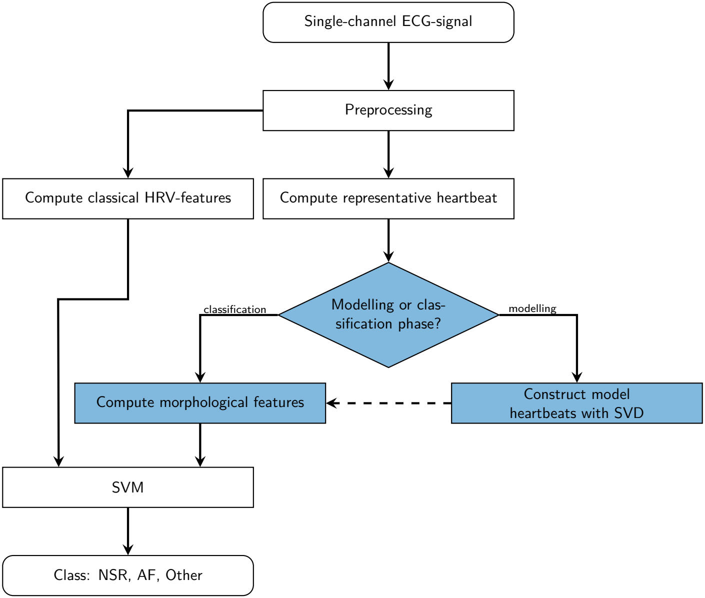


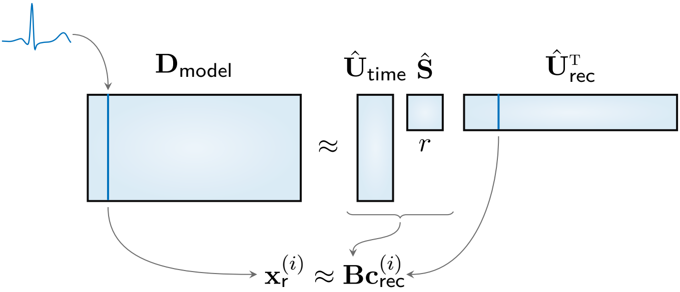
Compression

Modelling and classification



Matrix-based modelling

Given a model set:



For $\mathbf{x}_{\text{r}}^{(\text{new})}$:

$$\mathbf{x}_{\text{r}}^{(\text{new})} = \mathbf{B}\mathbf{c}_{\text{rec}}^{(\text{new})} \rightarrow \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})}.$$

Compute $\mathbf{f}^{(\text{new})}$ based on:

$$s_i = \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})^{\text{T}}} \tilde{\mathbf{c}}_{\text{rec}}^{(i)}, \forall i : 1 \leq i \leq M.$$

For each class C: $f_c^{(\text{new})} = \sum_{i \in C} w_i s_i$

Results: PhysioNet/CinC Challenge 2017

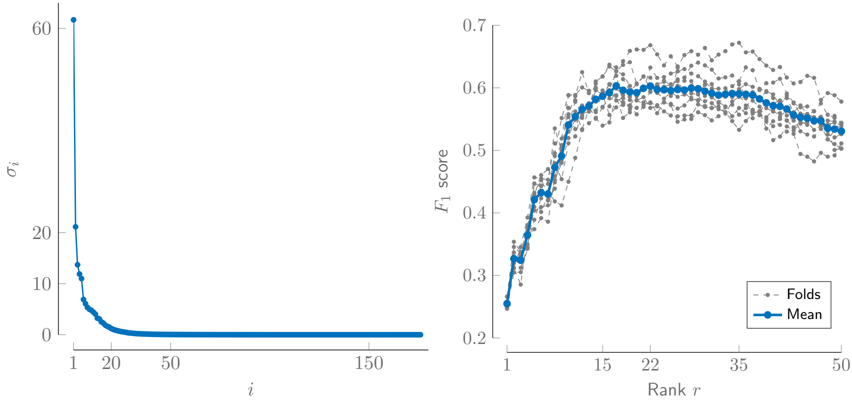
- Data: 8244 signals from AliveCor®

KardiaMobile™ of AliveCor®

- Three classes: NSR > Other > AF
- Model set of 4946 signals (60%), training and test set have equal sizes

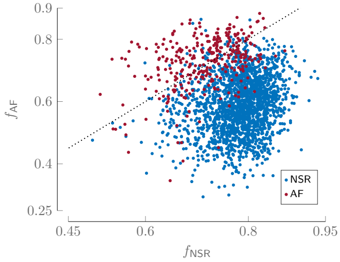
Results: the optimal rank

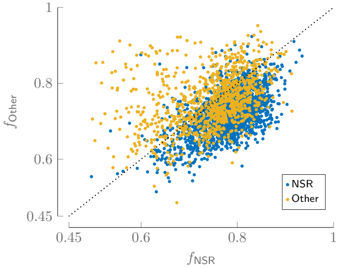
Optimal rank: 22

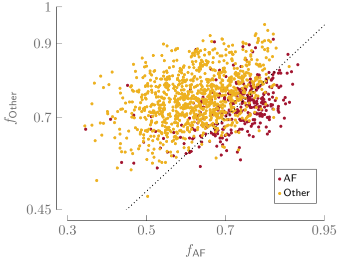


Singular values and optimal rank

Results: the morphological features





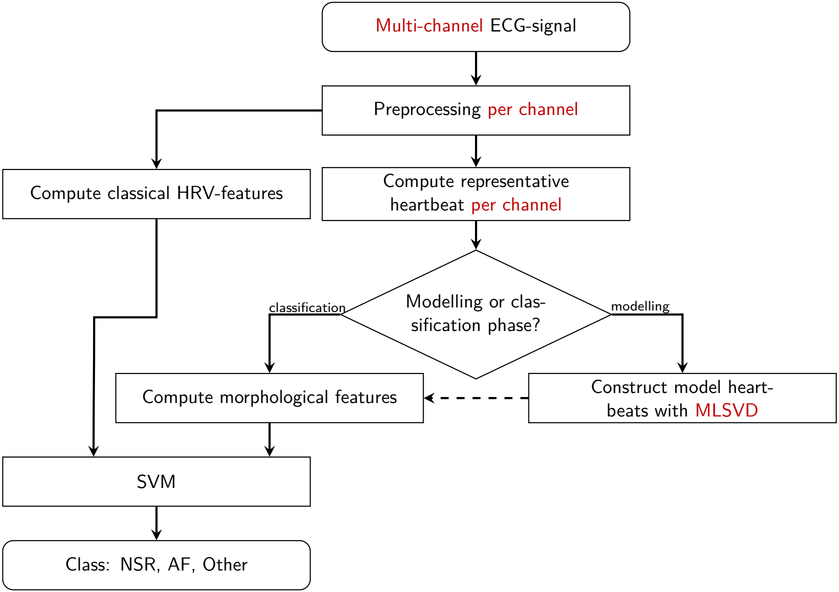


Results: the numbers

Method	$P(\%)$	F_{1n}, F_{1a}, F_{1o}	F_1
SVD	70.0	0.81, 0.57, 0.40	0.59
HRV	77.7	0.85, 0.76, 0.59	0.73
SVD + HRV	80.2	0.87, 0.80, 0.65	0.77

Outline

Overview of the algorithm

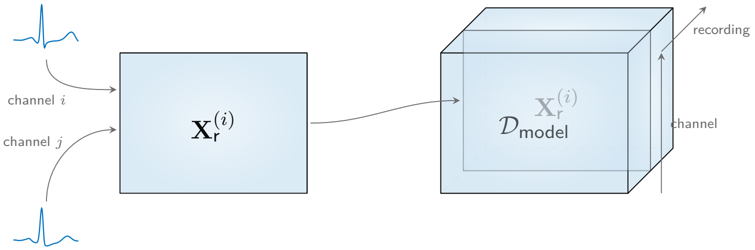


Tensor-based modelling

- Tensorization
- Modelling
- Optimal rank

Tensor-based modelling

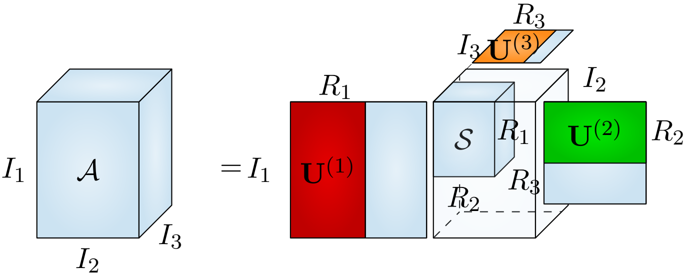
- *Tensorization:*



  $\mathbf{X}_\mathsf{r}^{(i)}$ by collecting representative heartbeats channel-by-channel, followed by $\mathbf{X}_\mathsf{r}^{(i)} \to \mathcal{D}_\mathsf{model}$
- Modelling
- Optimal rank

Tensor-based modelling

- Tensorization
- *Modelling*: the multilinear singular value decomposition:



- Optimal rank

Tensor-based modelling

- Tensorization
- *Modelling:* the truncated MLSVD gives:

$$\mathcal{D}_{\text{model}} \approx \hat{\mathcal{S}} \cdot_1 \hat{\mathbf{U}}_{\text{channel}} \cdot_2 \hat{\mathbf{U}}_{\text{time}} \cdot_3 \hat{\mathbf{U}}_{\text{rec}}.$$

For $\mathbf{X}_{\text{r}}^{(i)}$:

$$\mathbf{X}_{\text{r}}^{(i)} \approx \underbrace{\hat{\mathcal{S}} \cdot_1 \hat{\mathbf{U}}_{\text{channel}} \cdot_2 \hat{\mathbf{U}}_{\text{time}}}_{\mathcal{B}} \cdot_3 \mathbf{c}_{\text{rec}}^{(i)\,\mathrm{T}}$$

$$\Leftrightarrow \text{vec}\left(\mathbf{X}_{\text{r}}^{(i)}\right) \approx \mathbf{B}_{(3)}^{\mathrm{T}} \mathbf{c}_{\text{rec}}^{(i)}.$$

For $\mathbf{X}_{\text{r}}^{(\text{new})}$:

$$\text{vec}\left(\mathbf{X}_{\text{r}}^{(\text{new})}\right) = \mathbf{B}_{(3)}^{\mathrm{T}} \mathbf{c}_{\text{rec}}^{(\text{new})} \rightarrow \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})},$$

similarly $\mathbf{f}^{(\text{new})}$.

- Optimal rank

Tensor-based modelling

- Tensorization
- Modelling
- *Optimal rank:* solution for complexity is sequential optimization (with cross-validation):

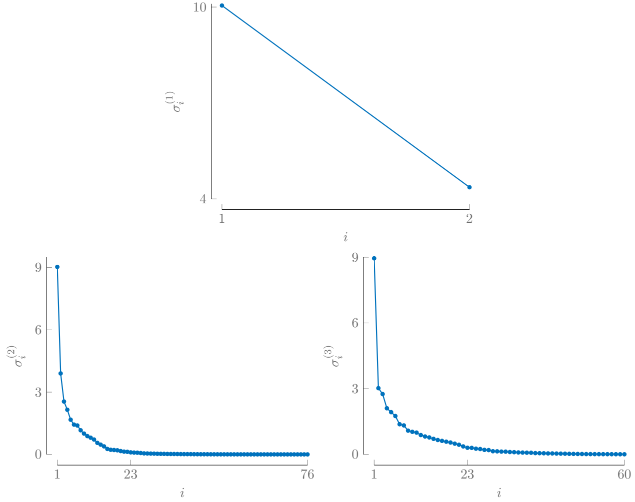
$$\cdots \rightarrow \left.\begin{array}{l} r^{(i)}_{\text{channel}} \\ r^{(i)}_{\text{time}} \\ r^{(i)}_{\text{rec}} \end{array}\right\} \xrightarrow[r^{(i)}_{\text{time}}]{\text{Vary}} \left.\begin{array}{l} r^{(i)}_{\text{channel}} \\ r^{(i+1)}_{\text{time}} \\ r^{(i)}_{\text{rec}} \end{array}\right\} \xrightarrow[r^{(i)}_{\text{rec}}]{\text{Vary}} \left.\begin{array}{l} r^{(i)}_{\text{channel}} \\ r^{(i+1)}_{\text{time}} \\ r^{(i+1)}_{\text{rec}} \end{array}\right\} \xrightarrow[r^{(i)}_{\text{channel}}]{\text{Vary}} \left.\begin{array}{l} r^{(i+1)}_{\text{channel}} \\ r^{(i+1)}_{\text{time}} \\ r^{(i+1)}_{\text{rec}} \end{array}\right\} \rightarrow \cdots$$

Results: MIT-BIH AFIB & AFTDB dataset

- $23 + 80$ two-channel Holter signals, long duration
- MIT-BIH AFIB: no independence, only NSR
- AFTDB: independence *in-between* sets and *within* test set

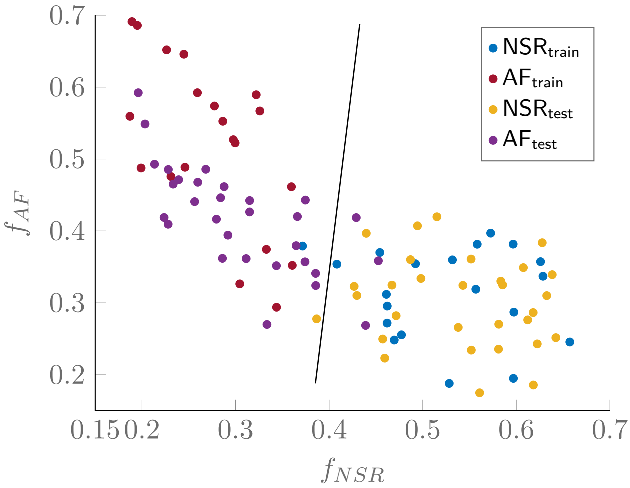
Results: the optimal multilinear rank

Optimal multilinear rank: (1,23,23)



Multilinear singular values

Results: the morphological features



Results

Method	AUC	F_1
MLSVD	0.99	0.933
HRV	1.00	0.983
MLSVD + HRV	1.00	1.00

Results: analysis linear SVM

Linear SVM:

$$y(\mathbf{f}) = \mathsf{sign}(\mathbf{v}^{\mathrm{T}}\mathbf{f} + b),$$

with $\mathbf{f} \in \mathbb{R}^{12}$ and $\mathbf{v} = \sum_{k=1}^{\#\text{SV's}} \alpha_k y_k \mathbf{f}_k \in \mathbb{R}^{12}$.

Results: analysis linear SVM

Linear SVM:

$$y(\mathbf{f}) = \text{sign}(\mathbf{v}^{\mathrm{T}}\mathbf{f} + b),$$

with $\mathbf{f} \in \mathbb{R}^{12}$ and $\mathbf{v} = \sum_{k=1}^{\#\text{SV's}} \alpha_k y_k \mathbf{f}_k \in \mathbb{R}^{12}$.

$$\mathbf{v}^{\mathrm{T}} = \begin{bmatrix} \overset{f_{\text{NSR}}}{\mathbf{-0.55}} & \overset{f_{\text{AF}}}{\mathbf{0.42}} & \overset{\text{AVRR}}{-0.22} & \overset{\text{RMSSD}}{0.26} & \overset{\text{pRR50}}{0.50} & \overset{\text{HTI}}{0.47} & \overset{\min(\text{RR})}{-0.14} & \overset{\text{SD1/SD2}}{-0.12} & \overset{\text{ApEn}}{0.45} & \overset{\text{Toeplitz}}{0.27} & \overset{\text{CoV}(\Delta_{\text{RR}})}{0.29} & \overset{\text{AFEvidence}}{0.51} \end{bmatrix}$$

Conclusion and outlook

To conclude:

- The designed features, based on SVD and MLSVD, quantify morphology and can be used as such
- Morphological + HRV-features > HRV-features when other classes are present

Outlook:

- MLSVD-method should be tested on larger datasets
- Extension to long-term signals
- Use Higher-Order Discriminant Analysis to perform supervised subspace learning
- Coupling of datasets (across modalities) by using coefficients as features

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Opening new horizons

[1, 2] [3, 4, 5, 6, 4, 7, 8, 9, 10] [11, 12, 13] [14, 15] [16, 17, 18, 19] [20] [21, 22, 23, 24, 25]

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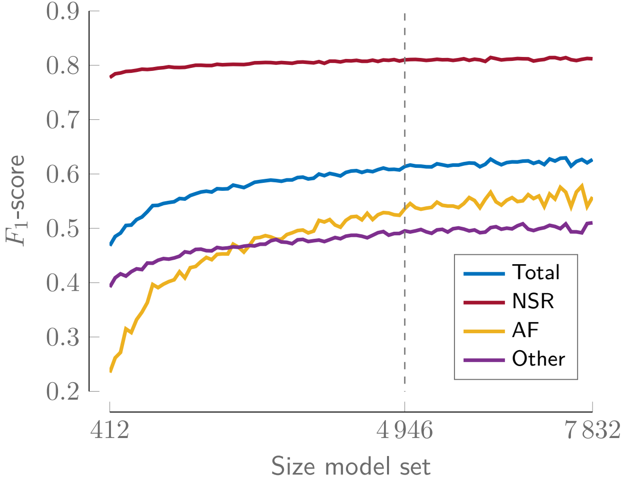
Results: analysis size model set



Multi-lead ECG: alternatives

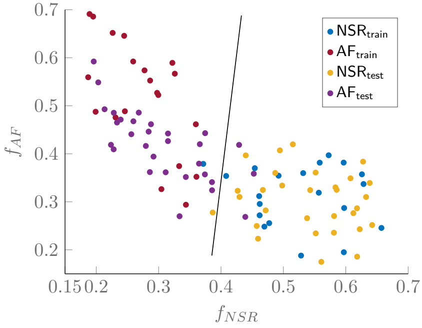
- Tensor-based: see ▸ Tensor-based modelling
- Tensor-based: solution per channel

$$\mathbf{x}_{\mathsf{r}}^{(i,k)} \approx \hat{\mathcal{S}} \cdot_1 {\mathbf{c}_{\mathsf{c}}^{(k)}}^{\mathrm{T}} \cdot_2 \hat{\mathbf{U}}_{\mathsf{time}} \cdot_3 {\mathbf{c}_{\mathsf{rec}}^{(i)}}^{\mathrm{T}}$$

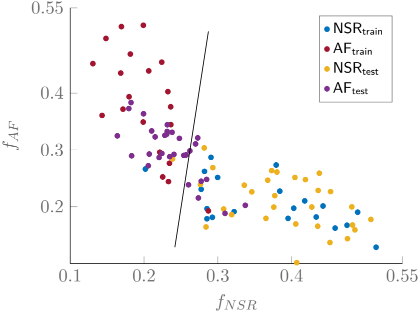
- Matrix-based:

$$\mathbf{D}_{\mathsf{model},(3)}^{\mathrm{T}} \approx \hat{\mathbf{U}}_{\mathsf{tc}} \hat{\mathbf{S}} \hat{\mathbf{U}}_{\mathsf{rec}}^{\mathrm{T}}$$

Multi-lead ECG: alternatives



MLSVD



SVD

Morphological features

Multi-lead ECG: alternatives

Method	AUC
MLSVD	0.99
SVD	0.97
MLSVD, per channel (all/1/2)	0.97/0.91/0.91