Mathieu LEMAY
Signal Processing and AI Group Leader

12.09.2024

EE512 – Applied Biomedical Signal Processing
Module 01 - Introduction

csem
40 YEARS OF INNOVATION

EE512 – Applied Biomedical Signal Processing

General context
CSEM
Course's module contents
Motivations
Applications based on:
- Electrocardiogram (ECG)
    + Labo on raw signals
- Photoplethysmography (PPG)
    + Labo on raw signals
    + BP demo
- Electroencephalogram (EEG)
FAQ

General context

- The goal of this course is to **introduce** the **most used approaches** for the processing of biomedical signals and **illustrate** their **utility on real signals (time series)** and real health/medical applications.
- Note that these approaches, although sometimes tailored for specific biomedical applications, are **widely used in many context** (speech, communication, control, ...).
- **Prerequisite** on:
  - Analysis, linear algebra, fundamentals on Fourier analysis and digital filtering
  - Signal processing for telecommunications COM-303 (recommended)
  - Signal processing EE-350 (recommended)

CSEM, a public-private partnership

CSEM mission

Development and transfer of **micro-technologies** and **micro-electronics** to the industrial sector to reinforce its competitive advantage via

- Cooperation agreements
- Creation of start-ups
- Licensing (technology, IP, algorithms)

Status

Incorporated, **not-for-profit RTO**, supported by Swiss Government and with a strong heritage of the **Swiss watchmakers** (majority shareholders)

Possible collaboration

- Internship
- Master thesis projects
- PhD thesis

550+ experts

97 MCHF turnover

46 start-ups &spin-off

Technology transfer - success stories

SAPHENUS®

DECATHLON

ActiGraph

Touch CONNECT SOLAR

bellabeat

csem

ICON HEALTH & FITNESS

SIGMA GERMANY MED

FESTINA Watches since 1902

PULSE ON

csem

iFIT

AKTIIA

biospectal

GE

Module 01- Introduction - 12.09.2024

- General context and module structure
- The important of biomedical signal processing field
- Examples of applications
- Introduction to labo

Dr. Mathieu LEMAY

Module 02 - Basics - 19.09.2024

Dr. Philippe RENEVEY

- Sinusoids and complex exponentials
- Continuous time Fourier transform
- Normalized frequency
- Discrete time Fourier transform
- Linear filter design
- Labo + Exercise

Module 03 - Basics II - 26.09.2024

- Stochastic signals and filtering
- Auto- / cross-correlation functions
- Power spectral density
- White noise
- Labo + Exercise

Dr. Philippe RENEVEY

Module 04 - Time-frequency - 03.10.2024

- Motivation for time-frequency analysis
- The short-term Fourier transform (STFT)
- Spectrograms in practice
- Wavelet analysis
- Labo

Dr. Martin PROENCA

Module 05 - Linear model - 10.10.2024

- Autoregressive (AR) signal modeling
- AR model estimation
- Linear prediction
- Model order selection
- High resolution spectral estimate
- Labo + Exercise

Dr. João JORGE

Module 06 - Linear model II - 17.10.2024

- Moving average (MA) signal modeling
- ARMA signal modeling
- Linear system identification
- Adaptive identification
- Labo + Exercise

Dr. Adrian LUCA

Module 07 - Frequency tracking - 31.10.2024

- Concept of instantaneous frequency
- Hilbert transform
- Teager-Kaiser operator
- Short-term Fourier transform
- Adaptive filter frequency tracking
- Labo

Module 08 - Midterm exam (optional) - 07.11.2024

White exam + corrections

Module 09 - SVD - 14.11.2024

- Matrix rank
- Singular value decomposition (SVD)
- Least-squares solution using SVD
- Singular spectrum analysis
- Labo

Dr. Guillaume BONNIER

Module 10 - PCA- 21.11.2024

Dr. Karen ADAM

- Basics of classical principal component analysis (PCA)
- PCA and SVD
- Dimensionality reduction, blind source separation
- Example: PCA on signals
- Labo

Module 11 - Classification & regression - 28.11.2024

Dr. Ramin SOLTANI

- Linear/non-linear regression
- Classification/clustering
- Feature selection
- Training/testing/validation
- Labo

Module 12 – Introduction to NN - 05.12.2024

Dr. Clémentine AGUET

- Perceptron
- Multilayer perceptron (MLP)
- Activation functions
- Gradient descent and backpropagation
- Labo

Module 13 - NN architecture - 12.12.2024

- Convolution neural network (CNN)
- Recurrent neural network (RNN)
- Regularization (dropout, batch normalization, weight decay, early stopping)
- Labo

Dr. Clémentine AGUET

Module 14 - Course recapitulation - 19.12.2024

Open questions (optional)

Dr. Mathieu LEMAY

Laboratories

Duration of **approx. 2h** with **Matlab/Python** exercises + **Exercises** + Open discussion

Useful commands/scripts are **provided**

Each exercise defines:

- Operations to perform
- Figures/results to interpret

Software requirements:

- Matlab with Signal Processing toolbox
- Python -> a requirements.txt for each lab (incl. NumPy, Matplotlib, Jupyter, ScipPy, Ipython, Plotly, scikit-learn, pandas, and PyTorch libraries)

Some Labo with include **optional tasks** (script to be written)

!!! **Teams of 3-5** need to provide their lab report (.pdf) in the following week on Moodle

EE521 - FAQ

- How do you compute the final score?
  - Final exam: 65% of the final score. Lab reports: 35% of the final score. The 11 reports will be equally distributed on this 35%.
- Does the midterm exam count in the final score?
  - No, The midterm exam will provide you an idea about what to expect from the final exam in terms of questions/exercises.
- What should be the format of the lab report?
  - The report must be a .pdf. It must contain answers to the questions provided in the lab description. Copy/paste of figure and script text can be added to the report.

EE521 - FAQ

- Could we submit one .pdf for the lab team?
    - No, every team member must submit a.pdf file. It can be the copy of their team members if the .pdf file mentioned the other team members
- I have two courses at the same time, Is it mandatory to attempt the lectures and labs?
    - No, it is not mandatory.
- Do you record the lectures?
    - No, it is not compatible with the room setup.

EE521 - FAQ

- **Is there any digital processing books to support the course?**
  - There is plenty of interesting books. You can use the following ones: (1) Discrete-Time Signal Processing by Alan V. Oppenheim or (2) Digital Signal Processing by John G. Proakis and Dimitris G. Manolakis
- **How should I name the lab report?**
  - Please respect the following file name: name1_name2_name3_lab_XX.pdf
- **I am registered but don't have access to moodle. Is it possible to force my enrollment?**
  - Yes, please contact me (mathieu.lemay@csem.ch).

EE521 - FAQ

- Can I have the technical background to follow the course (rephrased in numerous ways)?
  - The only good answer is the following: follow modules Basics I and II, do the labo and exercise. If you find it adapted for you, then the rest will be OK.

EE512 – Applied Biomedical Signal Processing

Motivations

Biomedical Signal Processing - What for?

- **Living organisms** are composed of many interacting **subsystems** (nerve system, cardiovascular system, ...).
- The associated **physiological processes** include stimulation and hormonal/nerve control, and electrical, chemical and mechanical **inputs/outputs**.
- These processes/activities can be **monitored** using **sensors** that map pression, concentration, temperature, ... into **electrical signals** that can be acquired and analyzed.
- **Pathologies** (diseases, congenital problems) may manifest themselves through **modifications** of these signals or their **relations**, and the delineation of these changes can be **helpful for diagnosis**.

Biomedical Signal Processing - What for?

Why analyze these signals on a computer instead of relying on visual observation only?

- The human visual system is well suited for **feature extraction**, but it is often impossible to **accurately extract parameters values** (such as frequency ones) or even to quantify them.
- **Interferences** may hamper visual observation.
- Human analysis is always **partially subjective**.
- It is sometimes necessary to analyze **tens** or **hundreds of recordings**, which becomes clearly fastidious.

Biomedical Signal Processing - Main fields of application

- **Cardiovascular activities**: electrocardiogram (ECG), photoplethysmography (PPG), arterial pressure, respiration via bio-impedance or strain gauge, audio-cardiograms (valve sounds) …
- **Brain activities**: electroencephalogram (EEG), …
- **Bio-mechanical activities**: electromyogram (EMG), movement analysis / human kinetics (e.g., accelerometer, gyroscope, barometer, magnetometer, camera)

Biomedical Signal Processing - Main goals

- Signal pre-processing (**enhancement**)
- Design of **monitoring tools**
- Design of **diagnosis tools**
- **Decision support systems**
- **Fundamental research**: interpretation of physiological phenomena, process modeling...

Biomedical Signal Processing - Main challenges

- **Signal distortions** (saturation, artefacts, ...)
- **Interferences** due to other physiological processes
- **Non stationarity**
- **Signal variability**, both intra- and inter-subjects/patients

EE512 – Applied Biomedical Signal Processing

Applications

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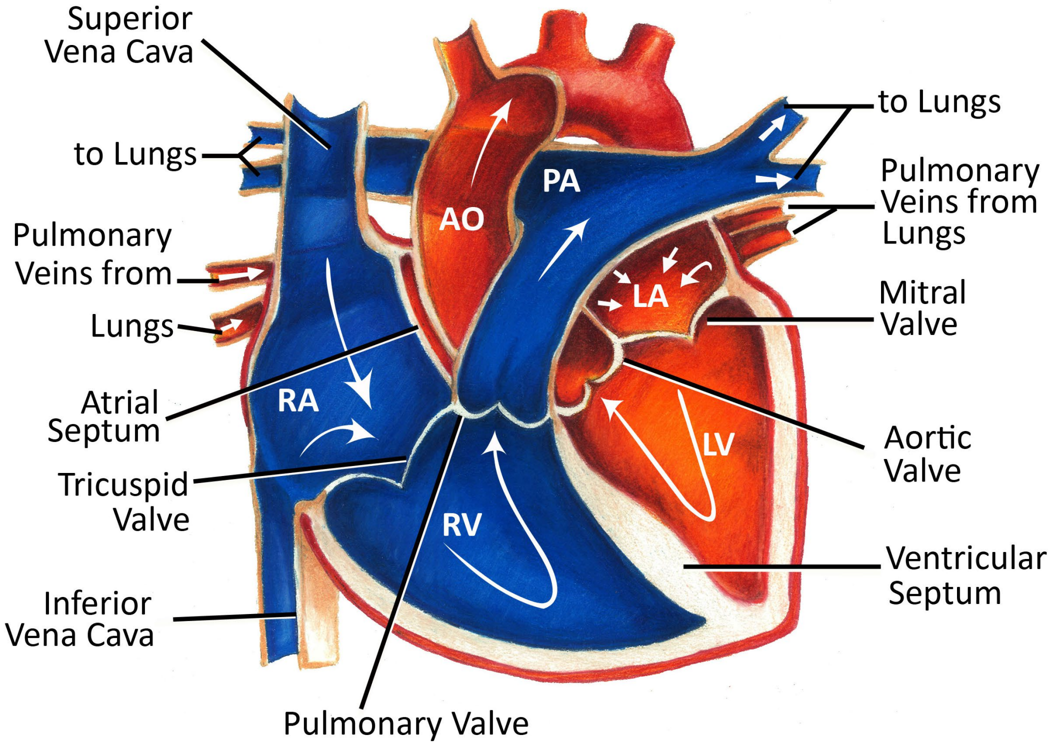
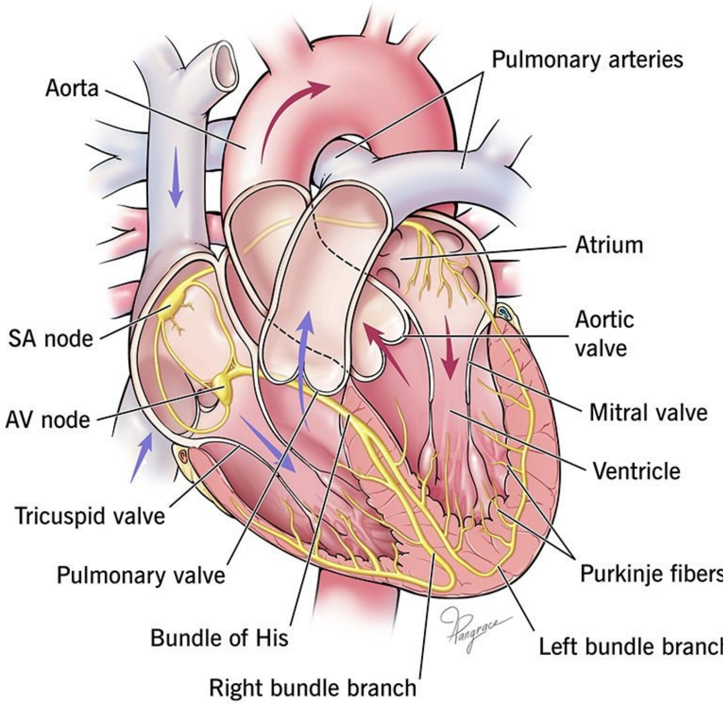
Electrocardiogram and relevant biomedical signal processing applications

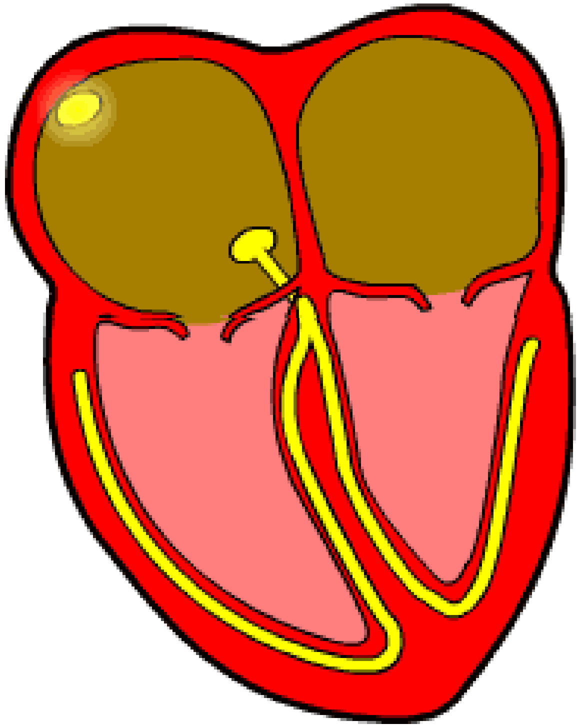
Heart: physiology and electrical activity

Blood flow



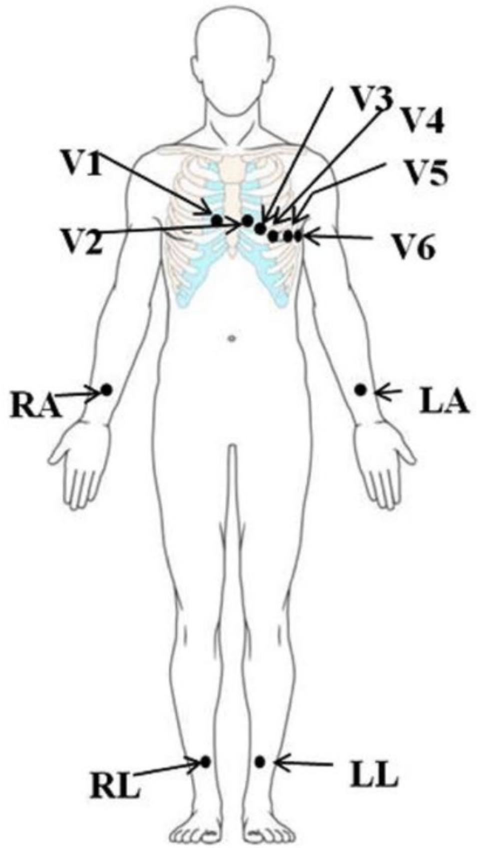
Electrical conduction



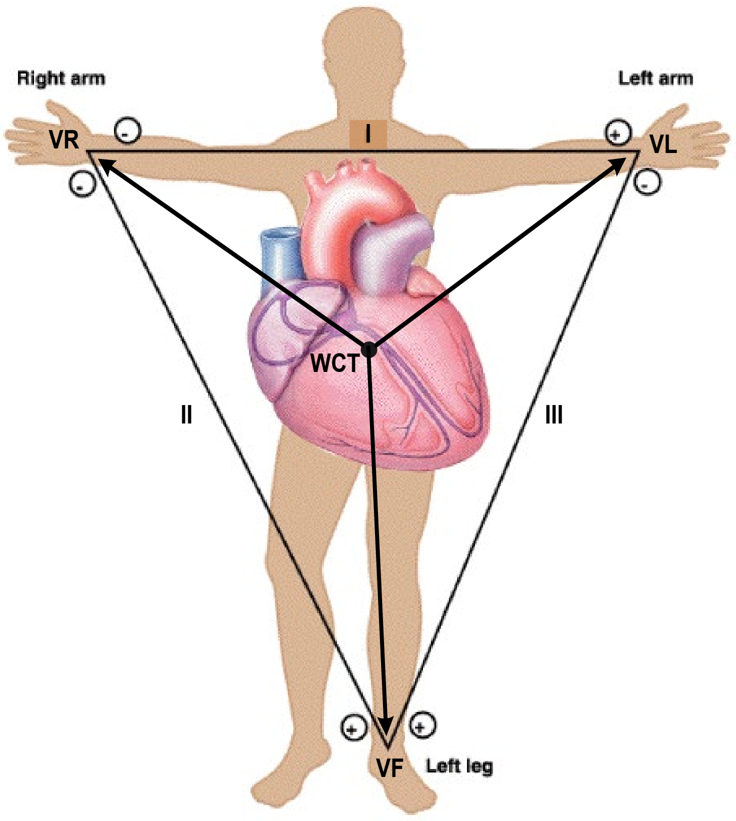


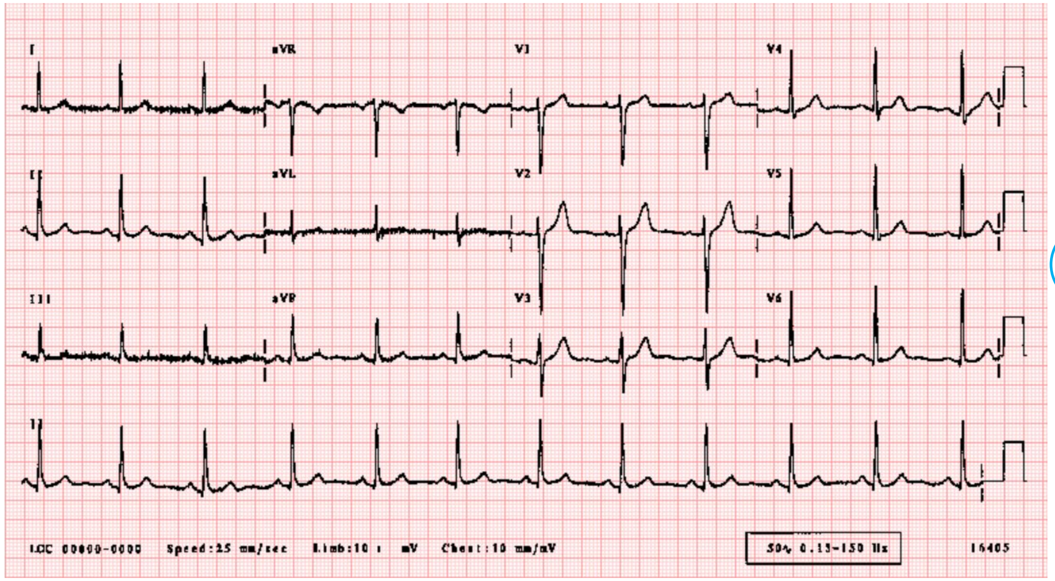
Electrocardiogram (ECG or EKG)

Standard 12-lead ECG

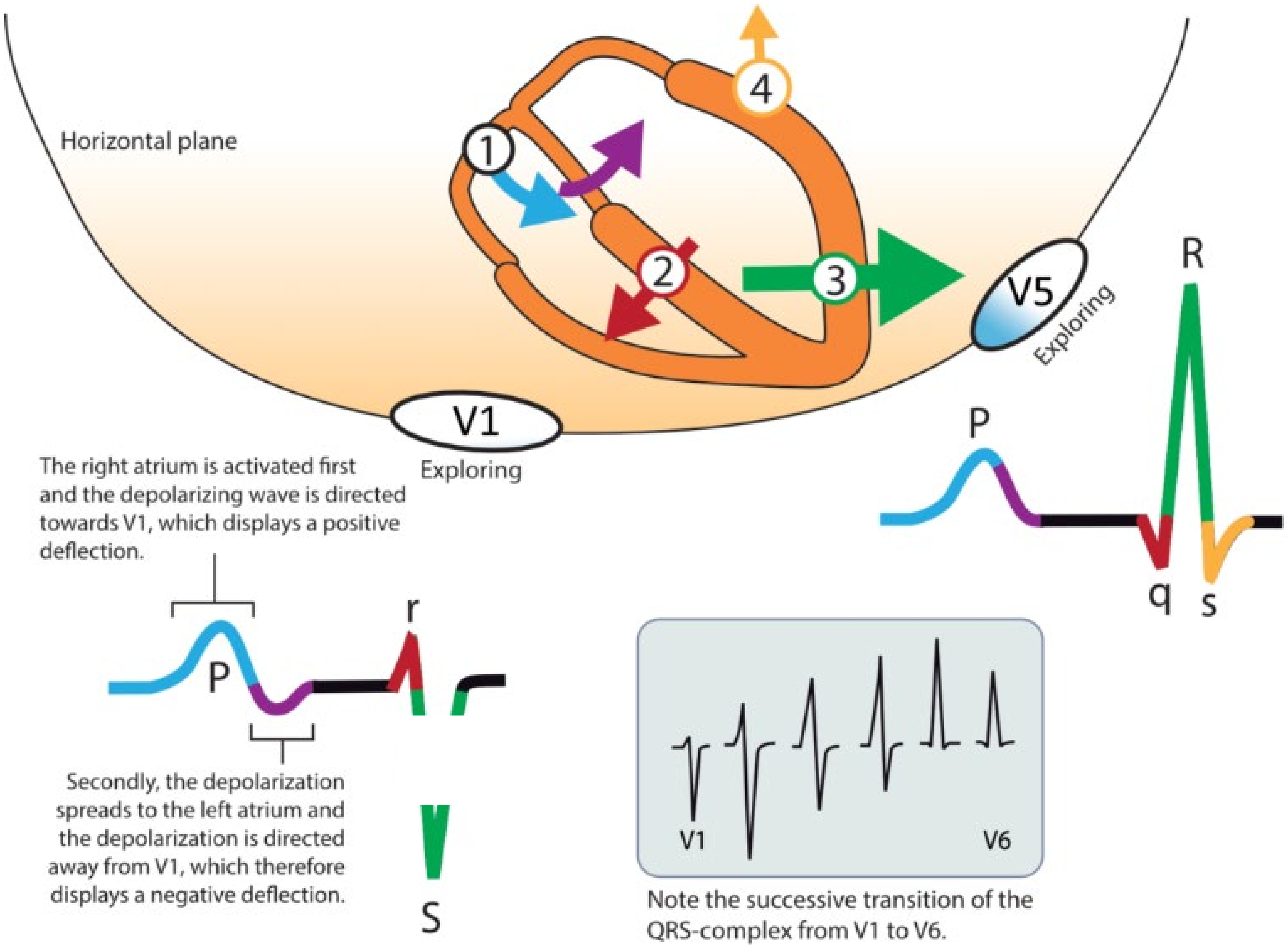


Einthoven’s triangle





Electrocardiogram (ECG or EKG)



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Electrocardiogram - signal processing applications

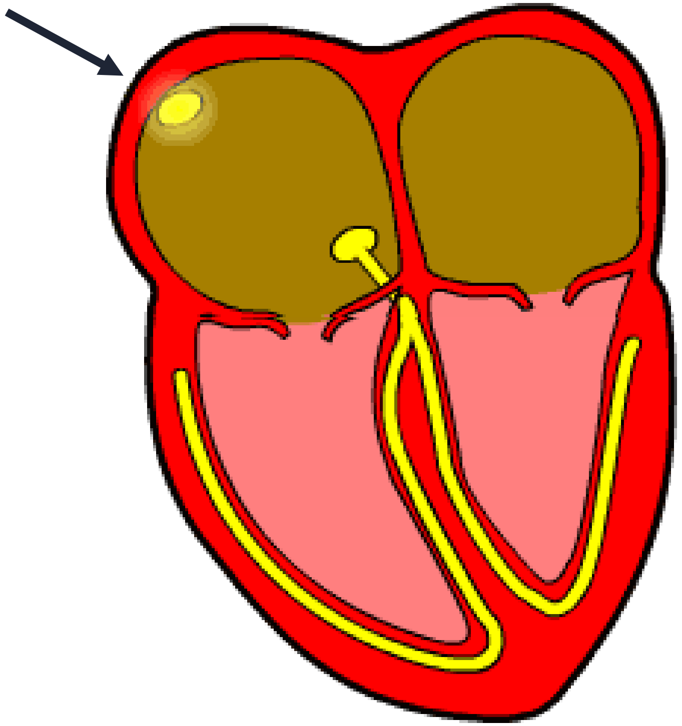
Atrial fibrillation facts:

- Prevalence of **3-7%** in elderly population
- Symptoms: syncope, chest pain, fatigue, palpitations, **heart failure and stroke**
- Diagnostic & treatment challenges: **intermittent and asymptomatic at its early stage**
- Signal processing challenges: **improve diagnostics** and **corresponding treatment** through **ECG information enhancement**

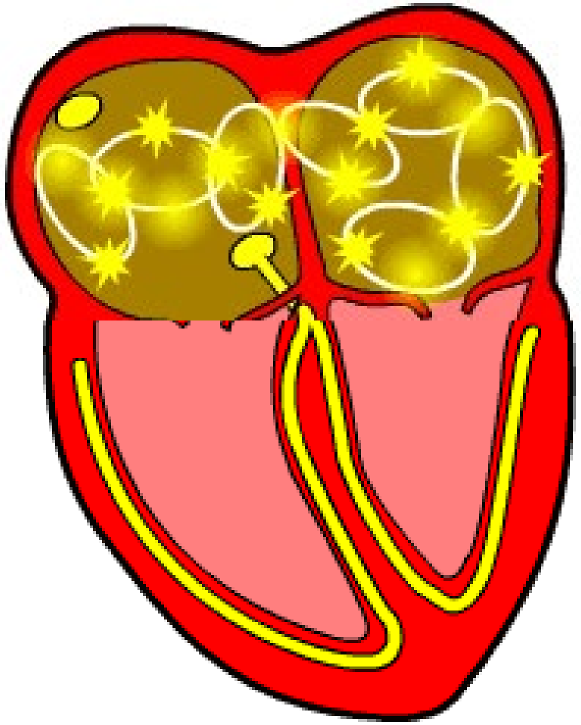
Cardiac arrythmias - Mechanisms

Sinus (normal) rhythm

Sinus node



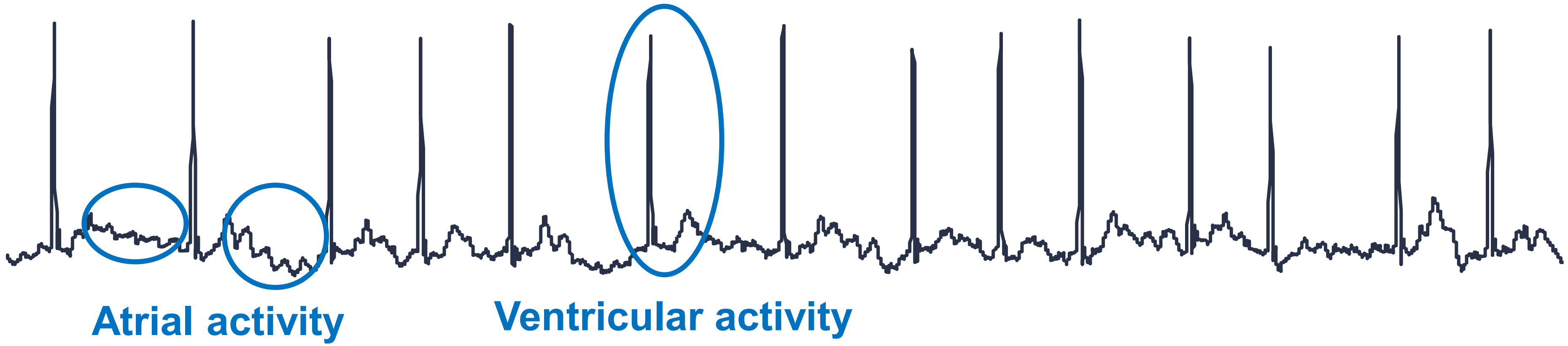
Atrial fibrillation



Electrocardiogram during cardiac arrythmias

Surface ECG during atrial fibrillation (AF or Afib)

The most common tool used for the **clinical evaluation** of arrythmias



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Electrocardiogram - other arrhythmias

Ventricular bigeminy:

- is a cardiac arrhythmia in which there is a **single ectopic beat** (e.g., premature ventricular contraction), following each regular heartbeat

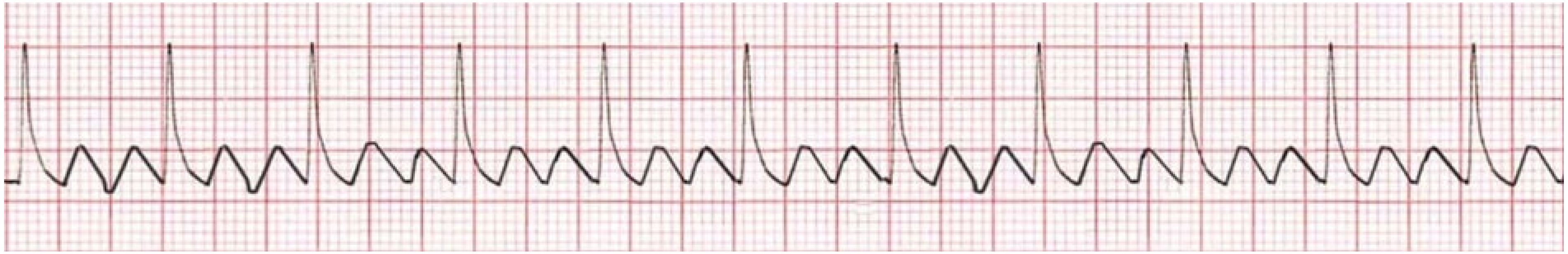
Ventricular trigeminy:

- same as bigeminy with a **pattern of three beats**

Electrocardiogram - other arrhythmias

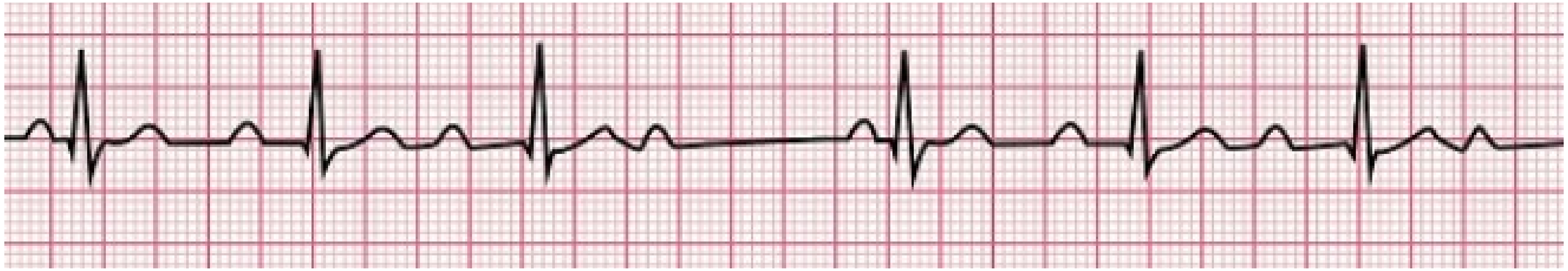
Atrial flutter:

- is a cardiac arrhythmia in which the heart's **upper chambers** (atria) **beat too quickly**



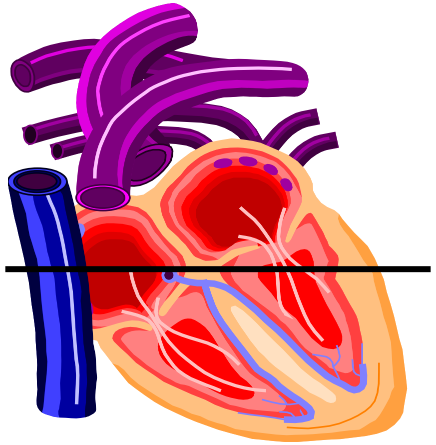
Second-degree AV block:

- is a **conduction block** between the atria and ventricles

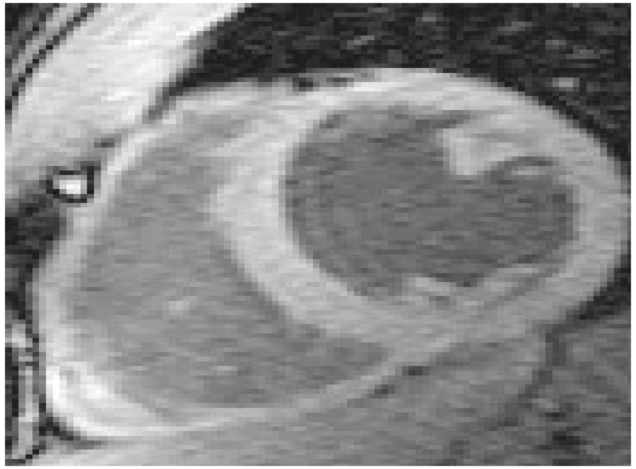


Simulation - ionic model of cardiac electrical activity

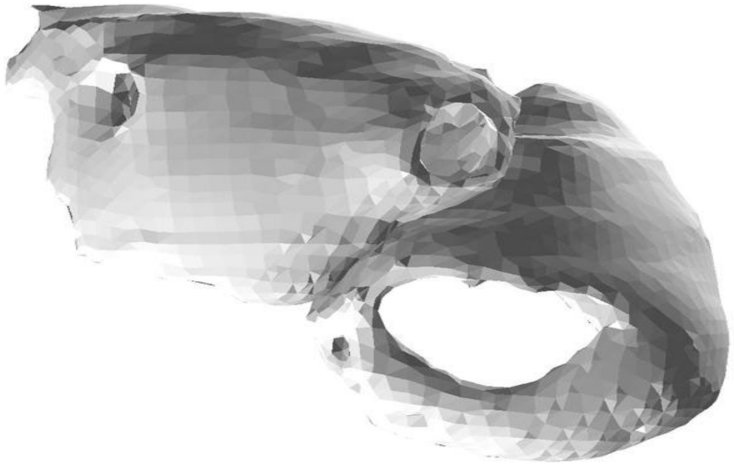
Human heart



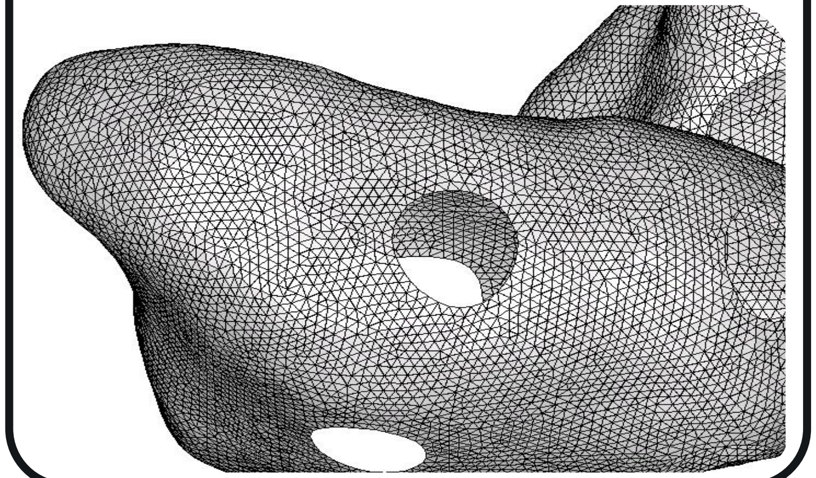
Magnetic resonance images



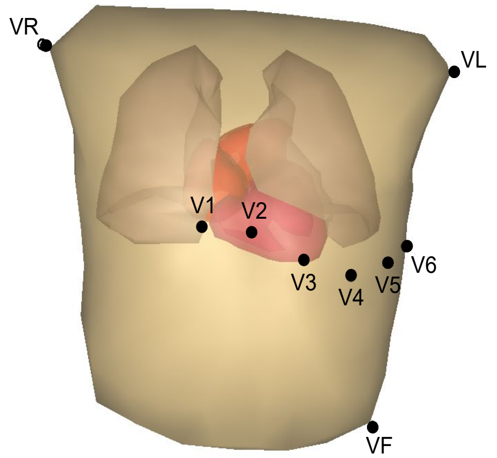
3D reconstruction



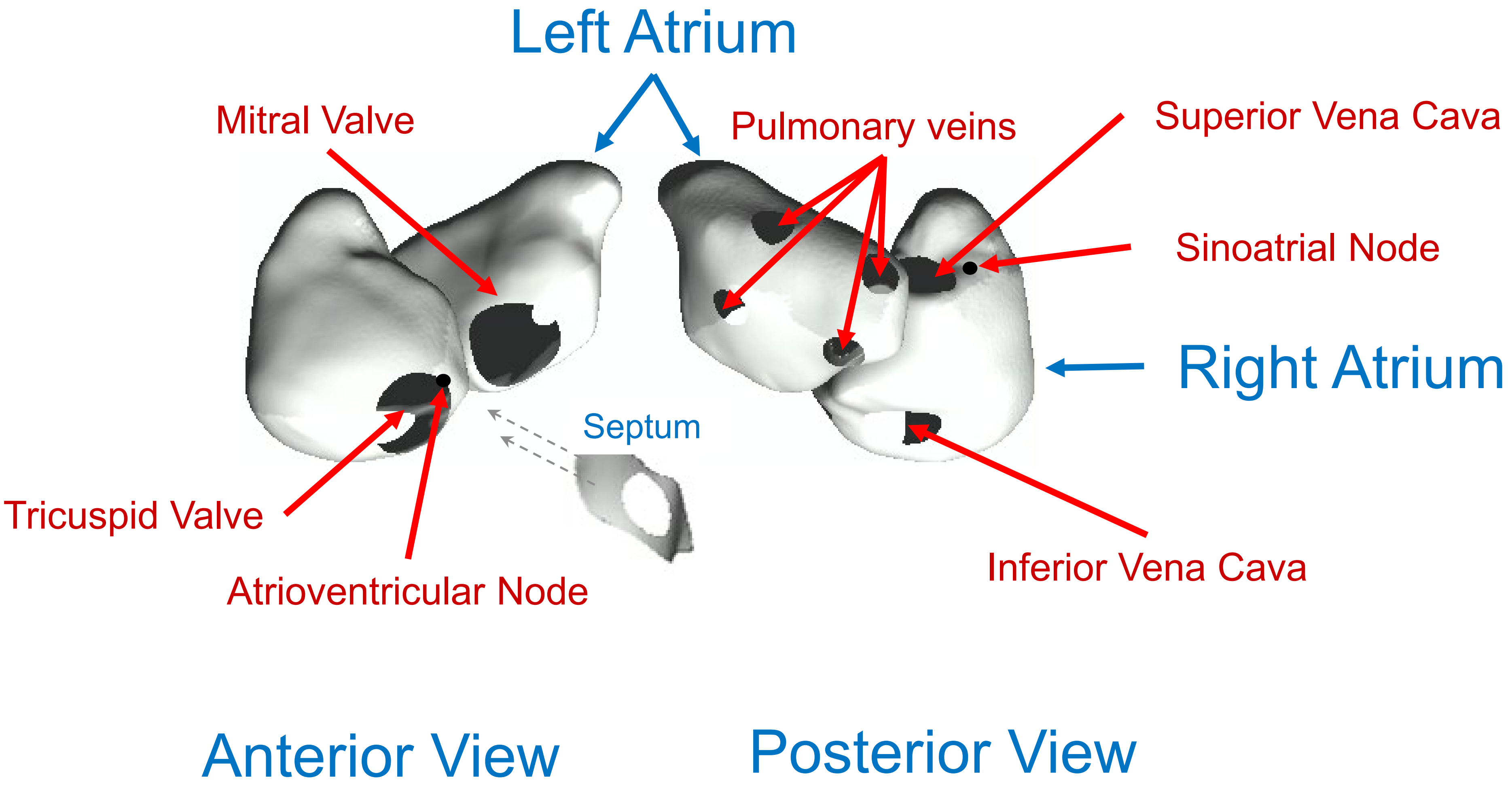
Mesh generation



Surface ECG model

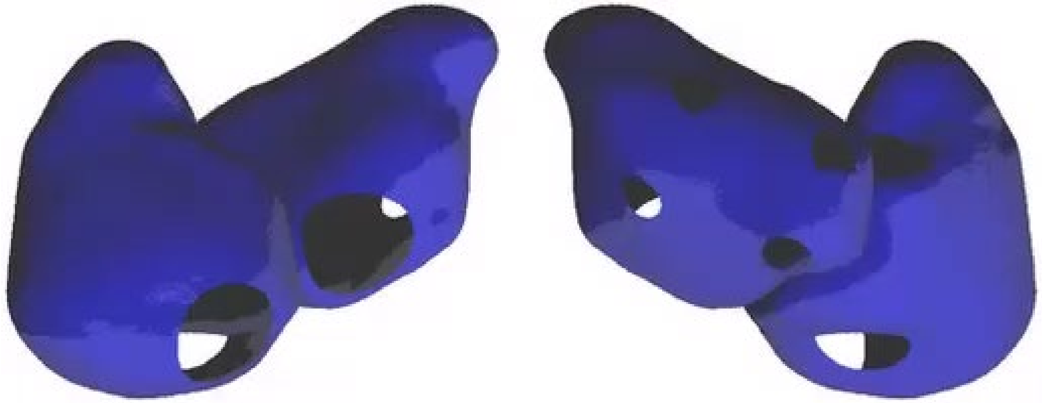


Simulation - ionic model of cardiac electrical activity



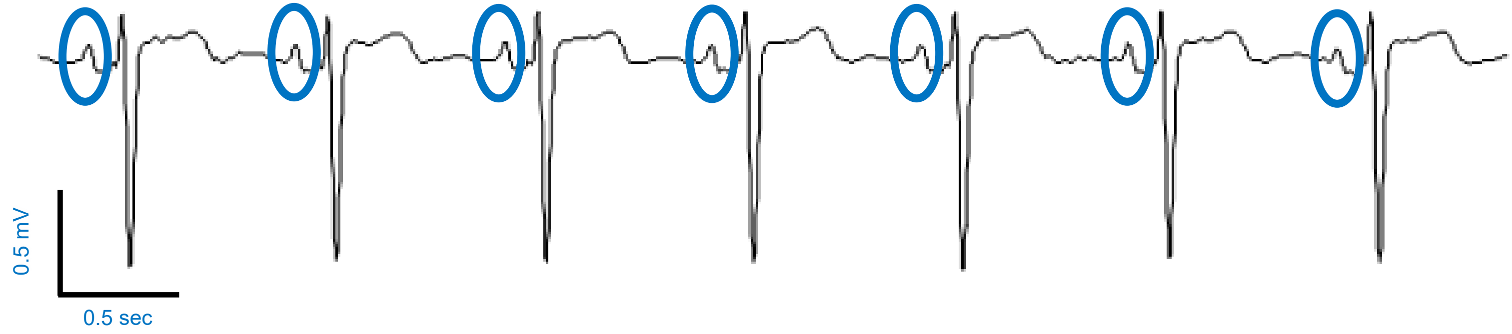
Simulation - ionic model of cardiac electrical activity

Normal atrial electrical propagation produces P waves



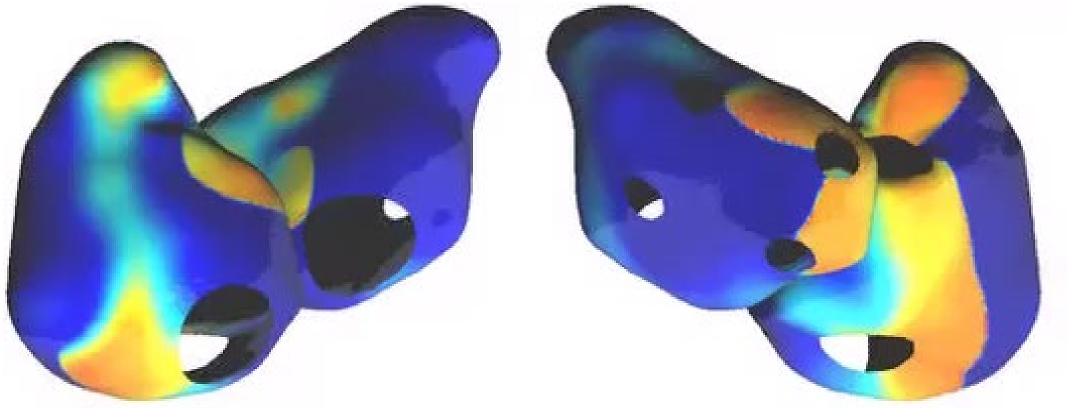
Anterior View

Posterior View

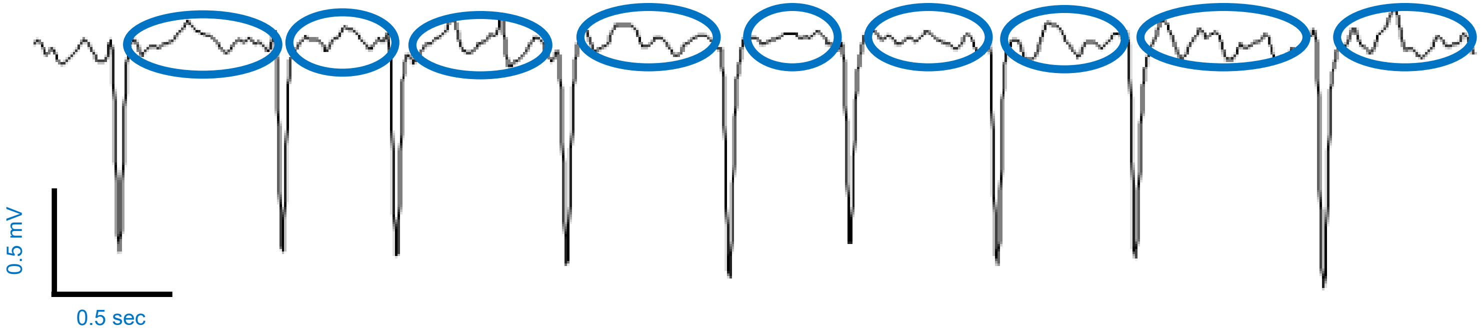


Simulation - ionic model of cardiac electrical activity

Atrial electrical propagation with **self-sustained reentrant waves** produces fibrillatory waves



Anterior View **Posterior View**



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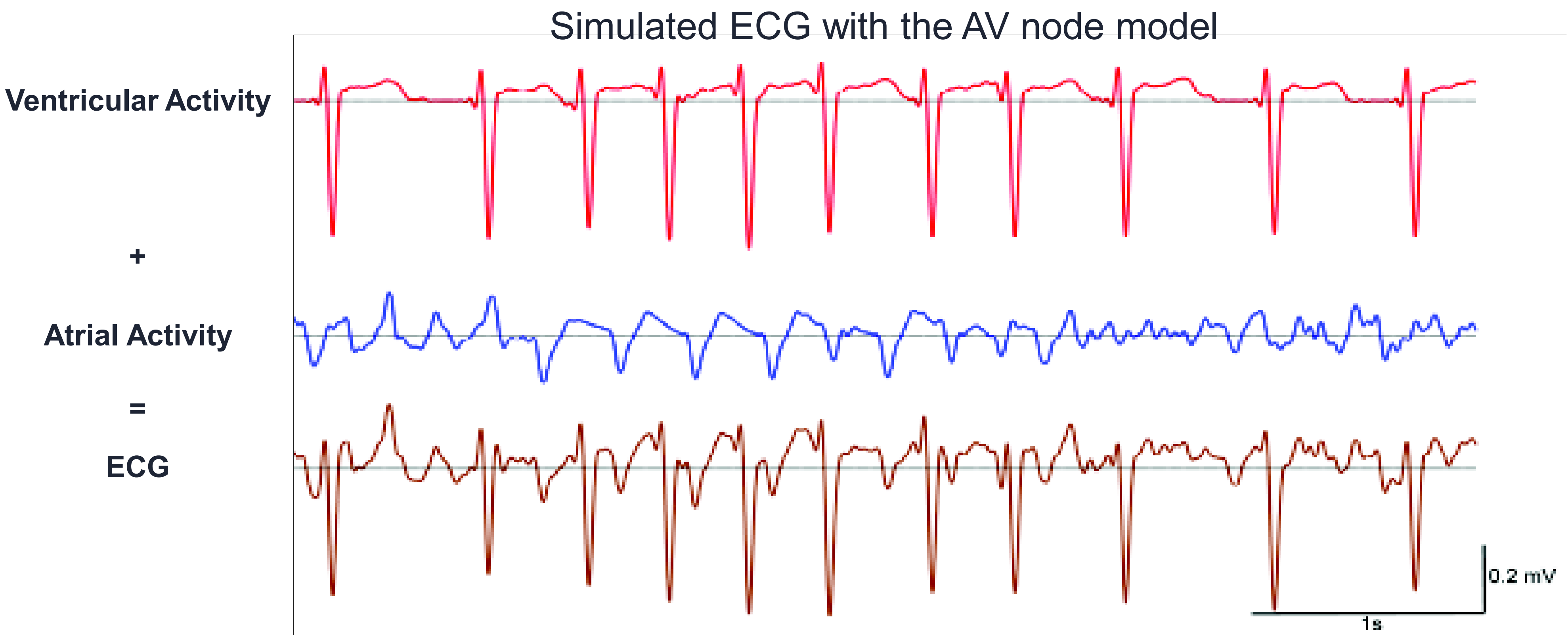
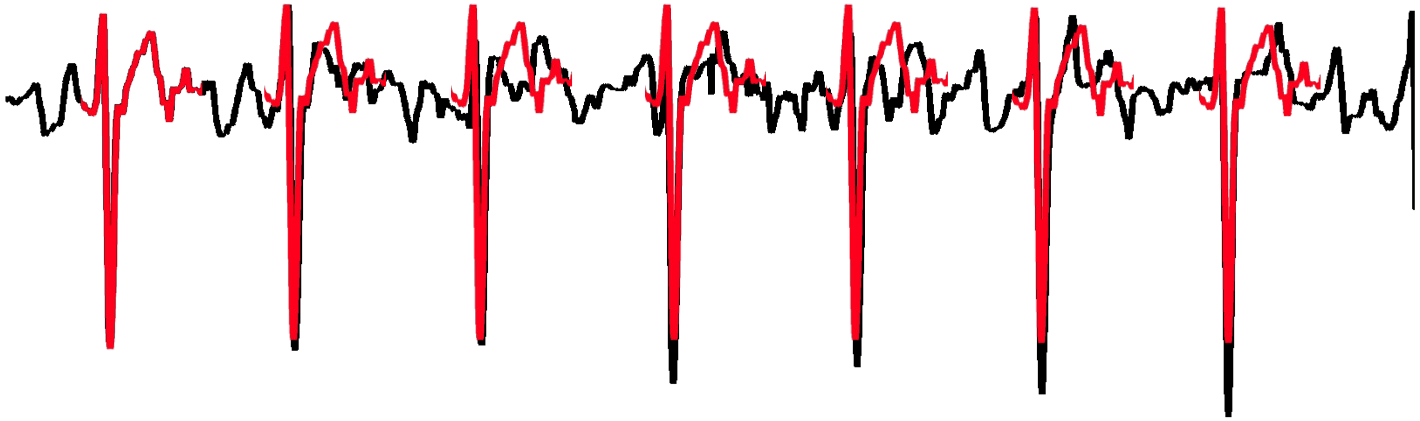
Electrocardiogram - signal processing applications

Simulated 12-lead ECG:



Electrocardiogram - signal processing applications

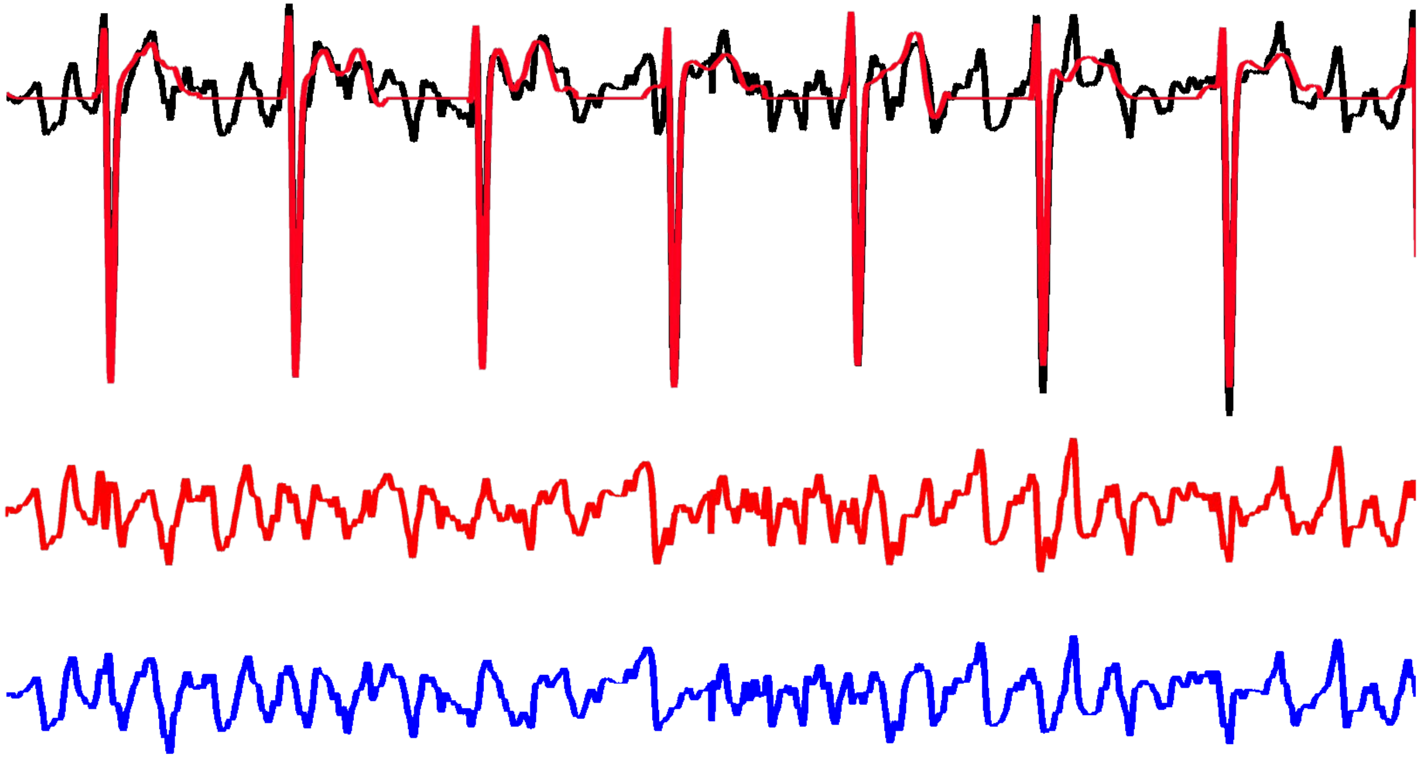
1st challenge: separate atrial and ventricular activities



Electrocardiogram - signal processing applications

Filter design, wavelet analysis, instantaneous frequency & adaptive filter frequency tracking, PCA & blind source separation, classification

1st challenge: separate atrial and ventricular activities



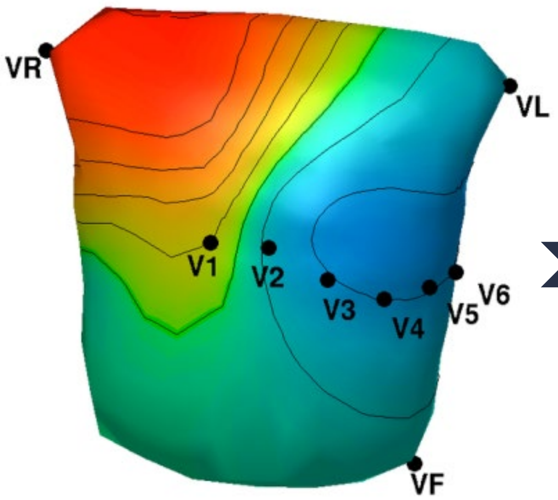
Electrocardiogram - signal processing applications

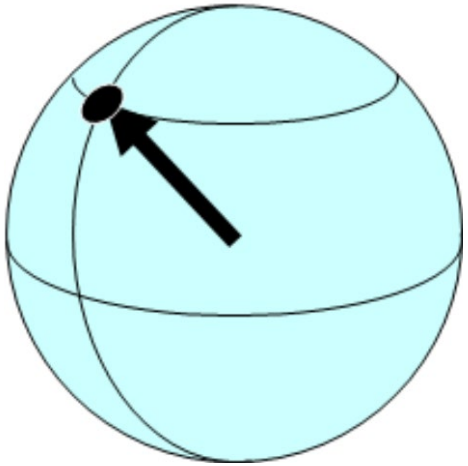
2nd challenge: cardiac arrhythmia classification

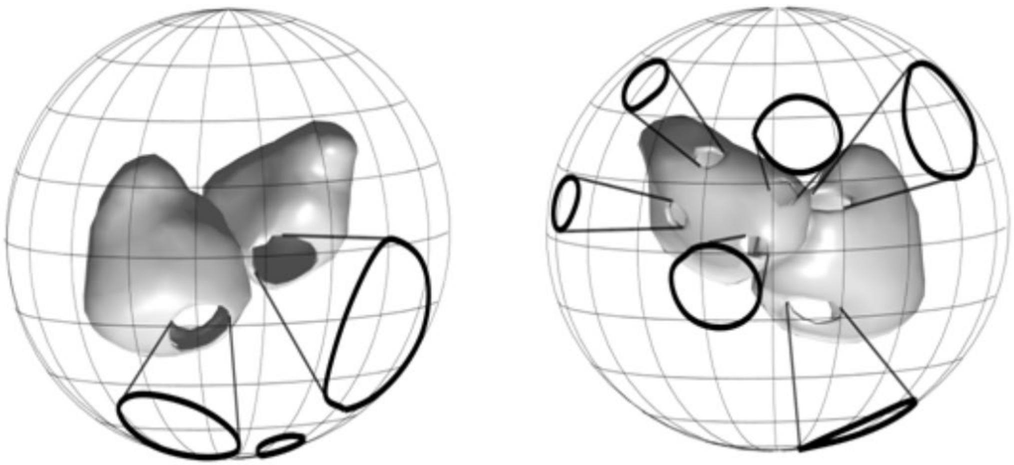
How to extract spatial information

- One can compute a vectorcardiogram (VCG on X,Y,Z components) from 12 lead ECG signals $\vec{V}(t) = \mathrm{T}\Phi_{ECG}(l,t)$

Body surface potential **VCG (dipole)** **Spatial references**





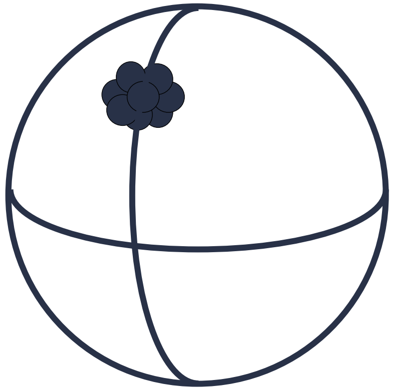


Electrocardiogram - signal processing applications

2nd challenge: cardiac arrhythmia classification

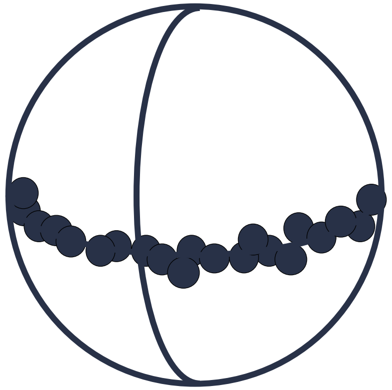
- Eigenvalues λ_1, λ_2 and λ_3 are computed ($\lambda_1 + \lambda_2 + \lambda_3 = 1$)

$\lambda_1 = 1$
$\lambda_2 = \lambda_3 = 0$



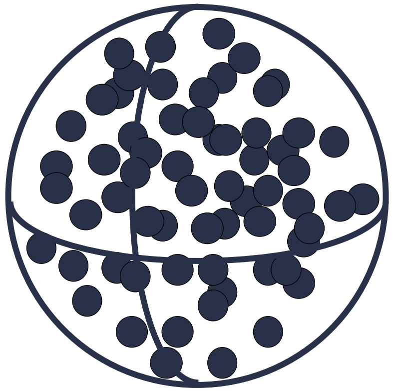
Peak distribution

$\lambda_1 = \lambda_2 = 1/2$
$\lambda_3 = 0$



Distribution along a great circle

$\lambda_1 = \lambda_2 = \lambda_3 = 1/3$

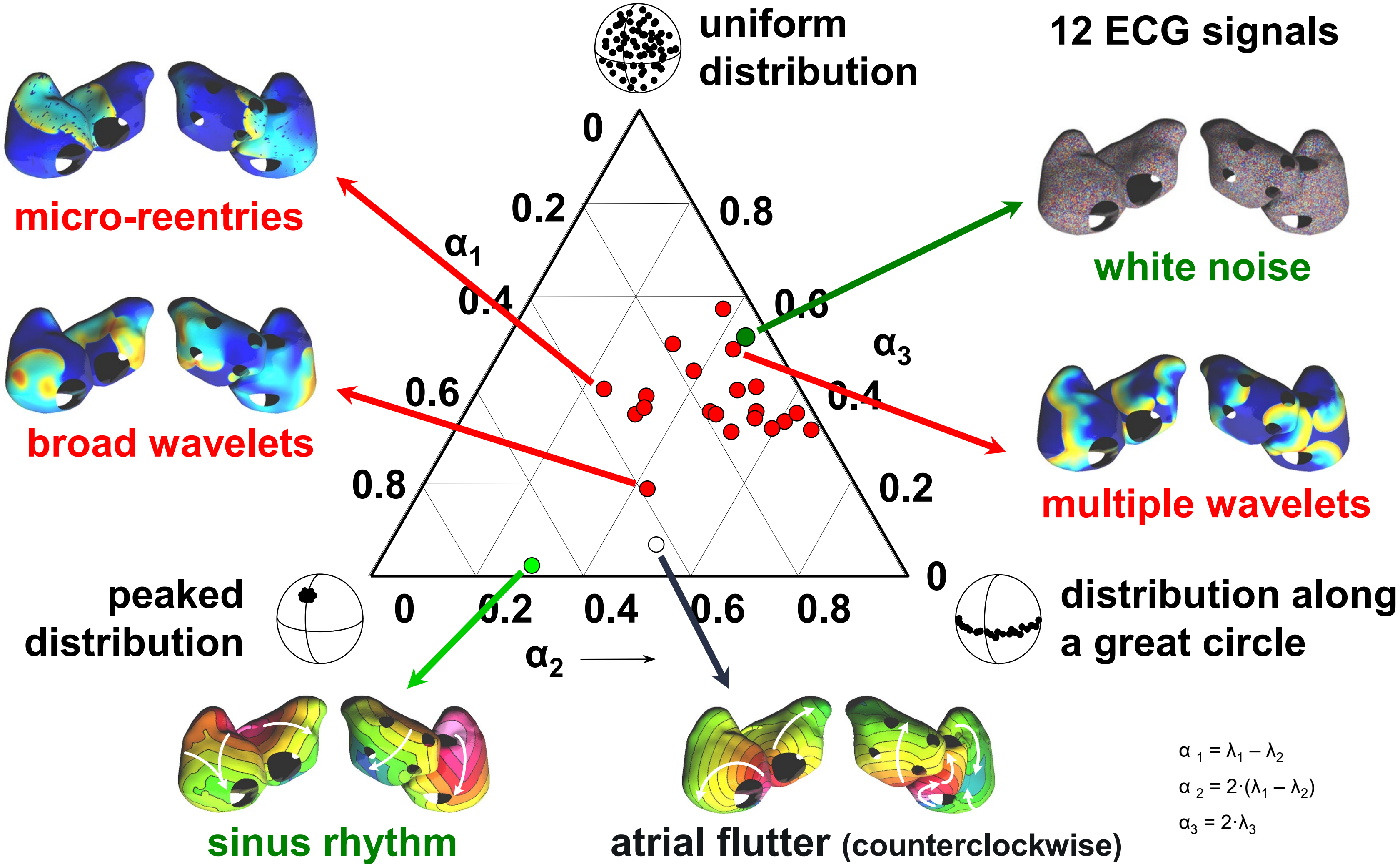


Uniform distribution

Electrocardiogram - signal processing applications

SVD and its eigen values, classification, clustering, NN

2nd challenge: cardiac arrhythmia classification



$\alpha_1 = \lambda_1 - \lambda_2$

$\alpha_2 = 2\cdot(\lambda_1 - \lambda_2)$

$\alpha_3 = 2\cdot\lambda_3$

Electrocardiogram - signal processing applications

3rd challenge: ECG monitoring of foetus

Maternal heart

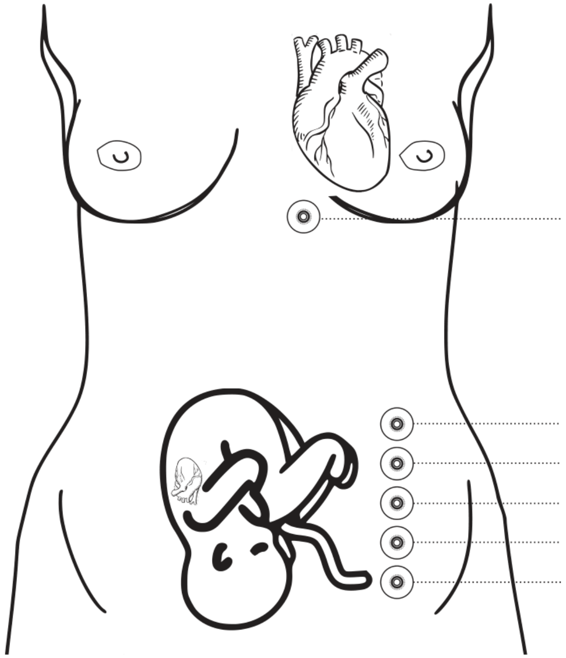
$U_m = 50\ \mu\text{V} - \mathbf{5\ mV}$

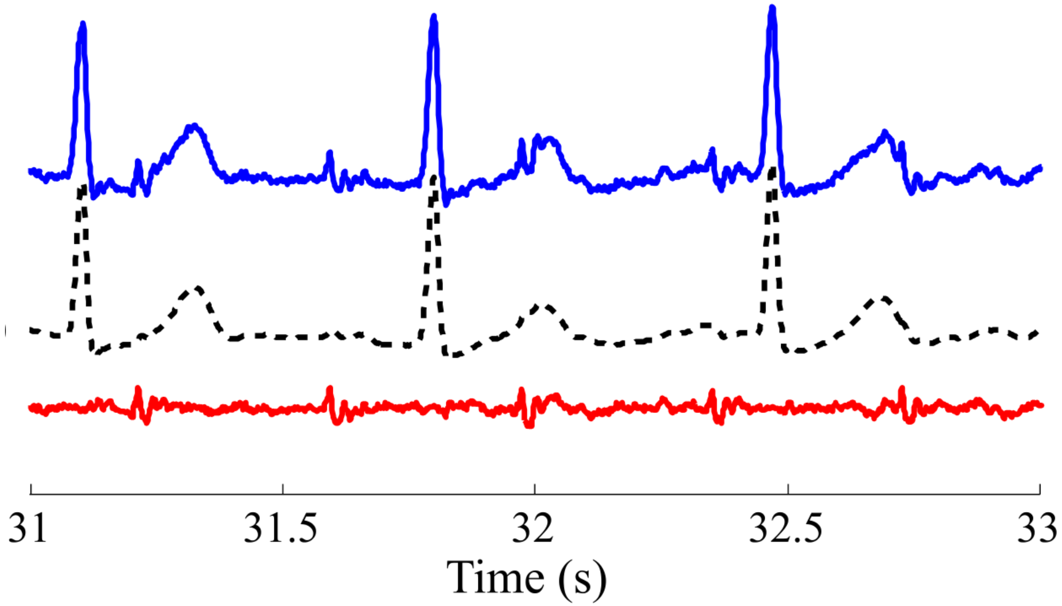
$\text{HR}_m = 60 - 80\ \text{bpm}$

Fetal heart

$U_f = \mathbf{10\ \mu V} - 300\ \mu\text{V}$

$\text{HR}_f = 110 - 180\ \text{bpm}$

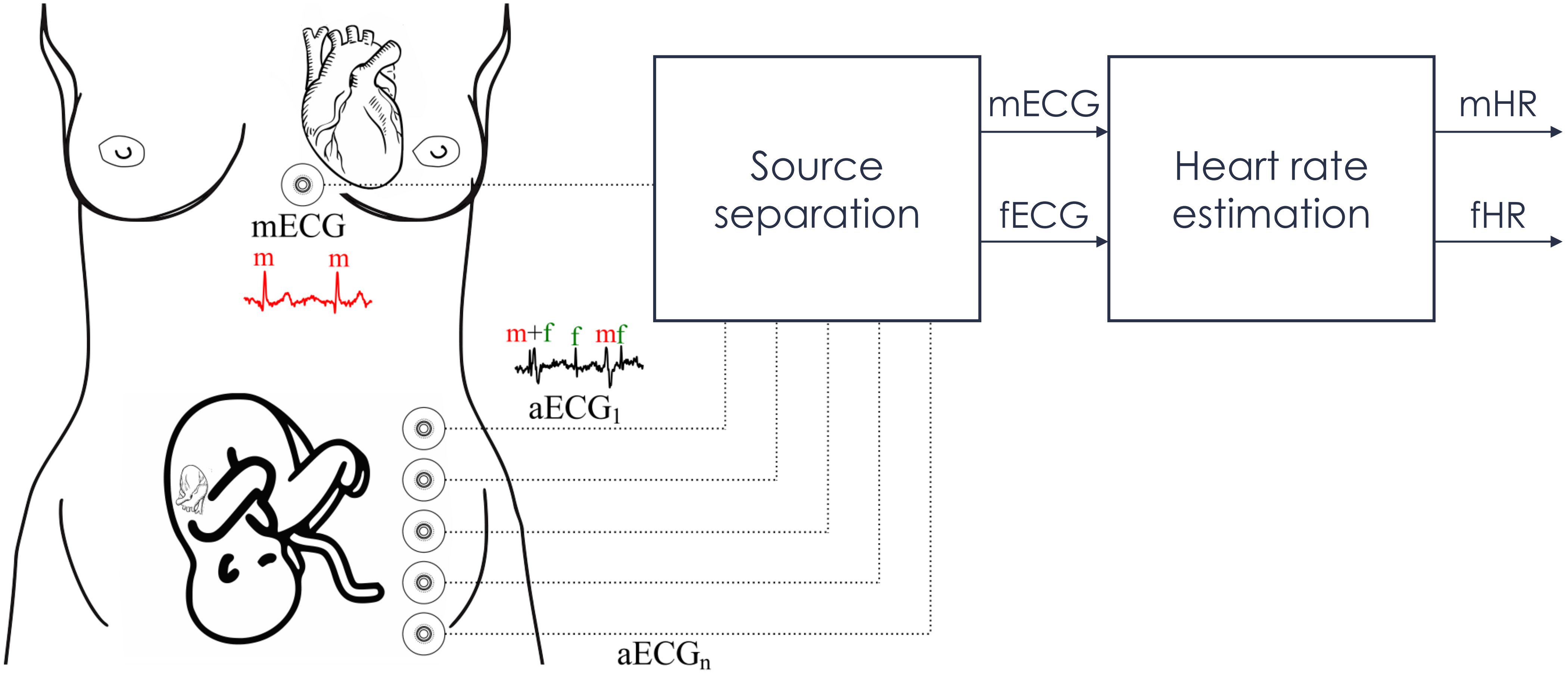




Electrocardiogram - signal processing applications

PCA & blind source separation, adaptive filter frequency tracking, power spectral analysis

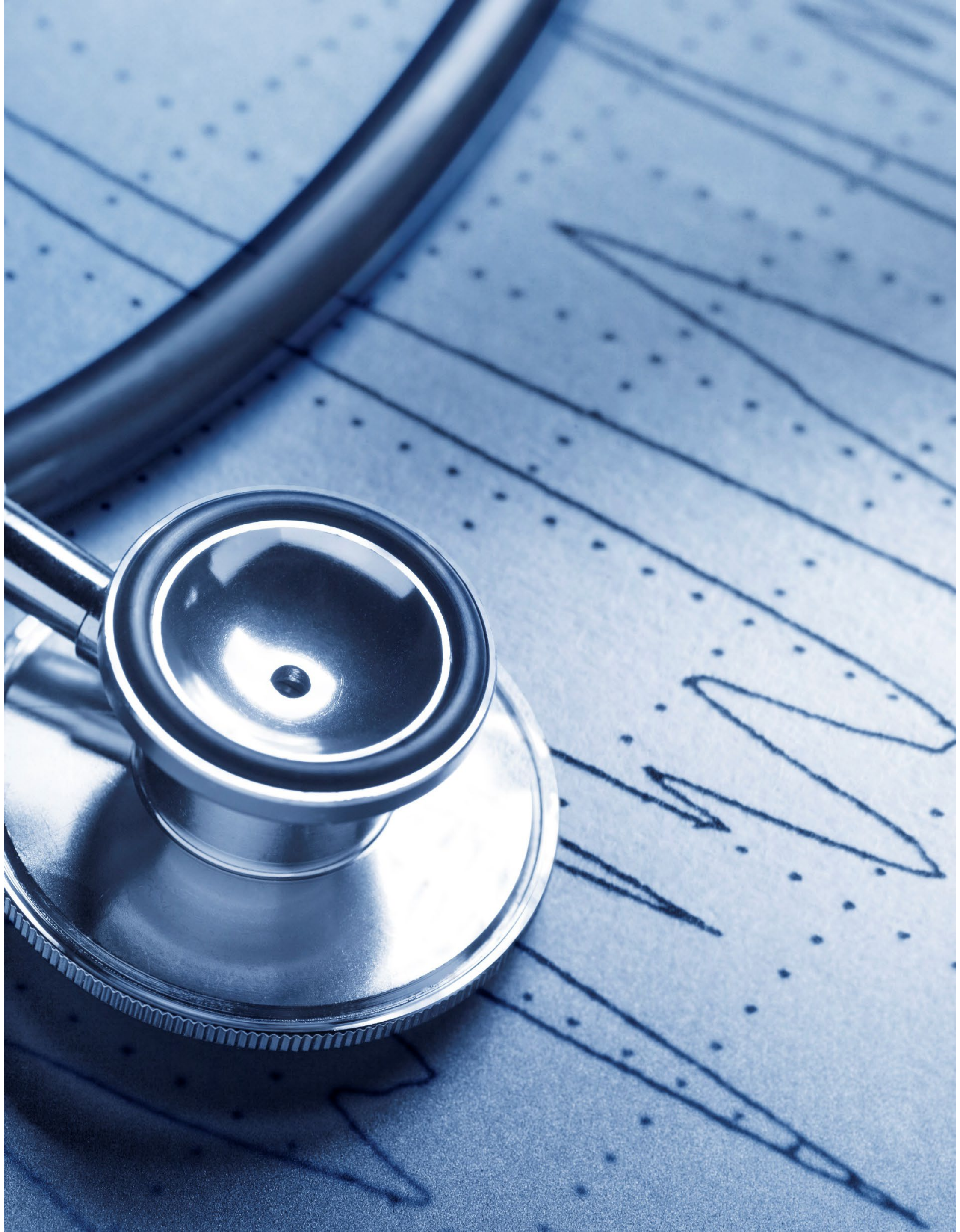
3rd challenge: ECG monitoring of foetus



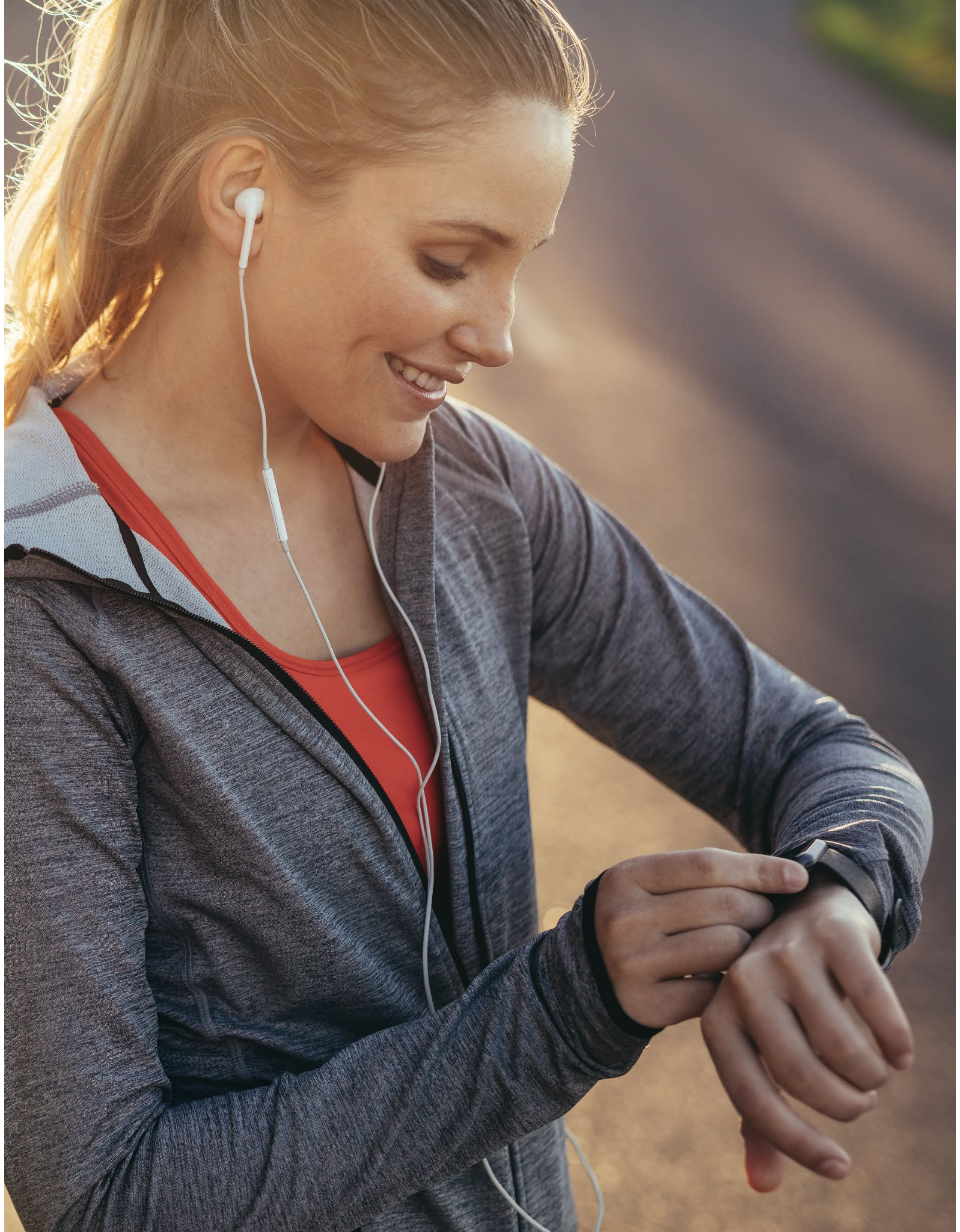
Labo 01 - Electrocardiogram & Cardiac Arrythmias

1) Download the .zip on moodle
2) Use Jupyter note to execute ecg_data.ipynb

   https://noto.epfl.ch/



Photoplethysmography and relevant biomedical signal processing applications



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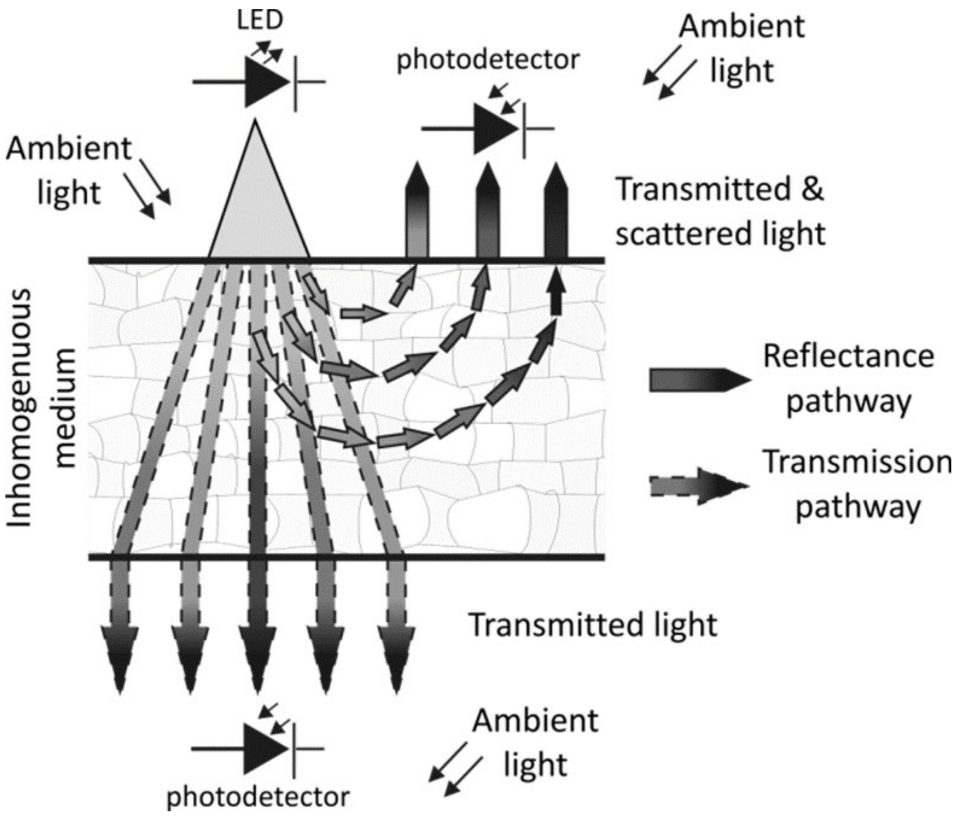
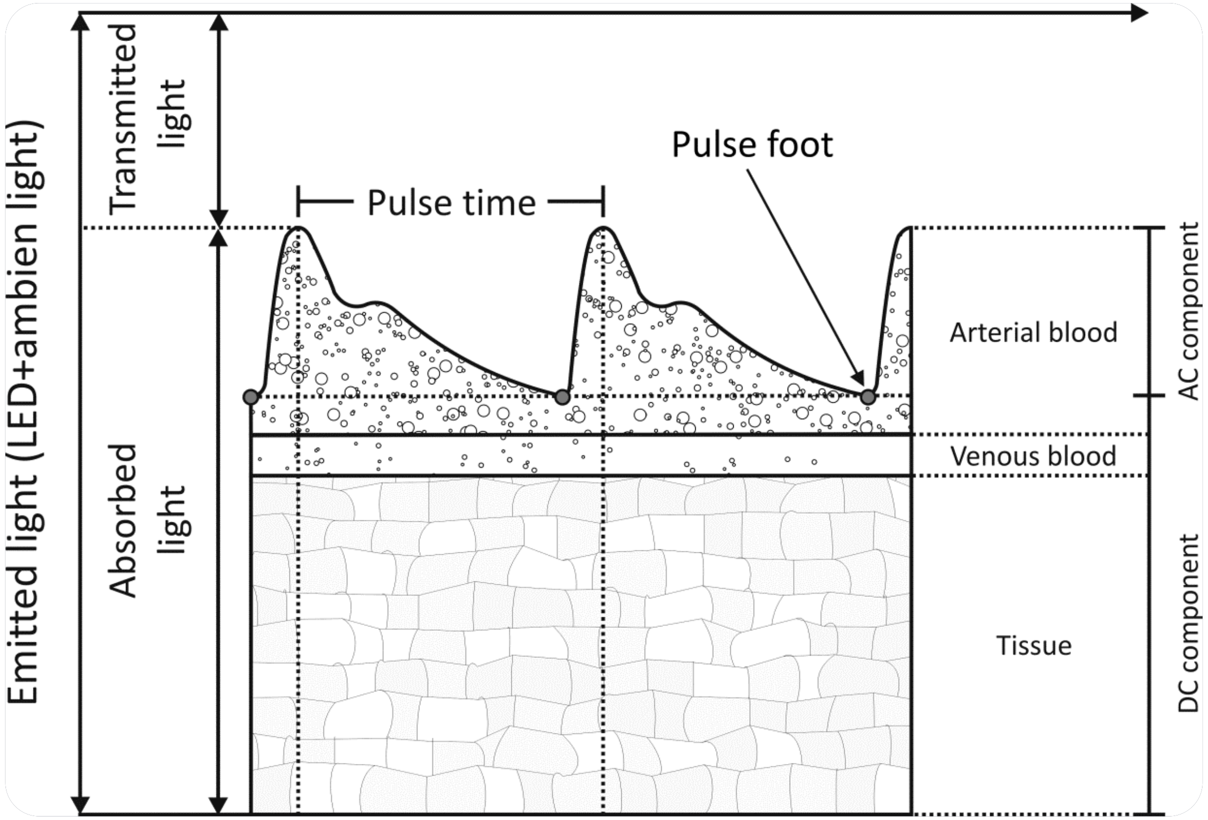
Photoplethysmography (PPG) - Basics

Pulse oximeter

PPG bracelet





Measurement of volume changes by optical means

Blood volume variations modify light absorption

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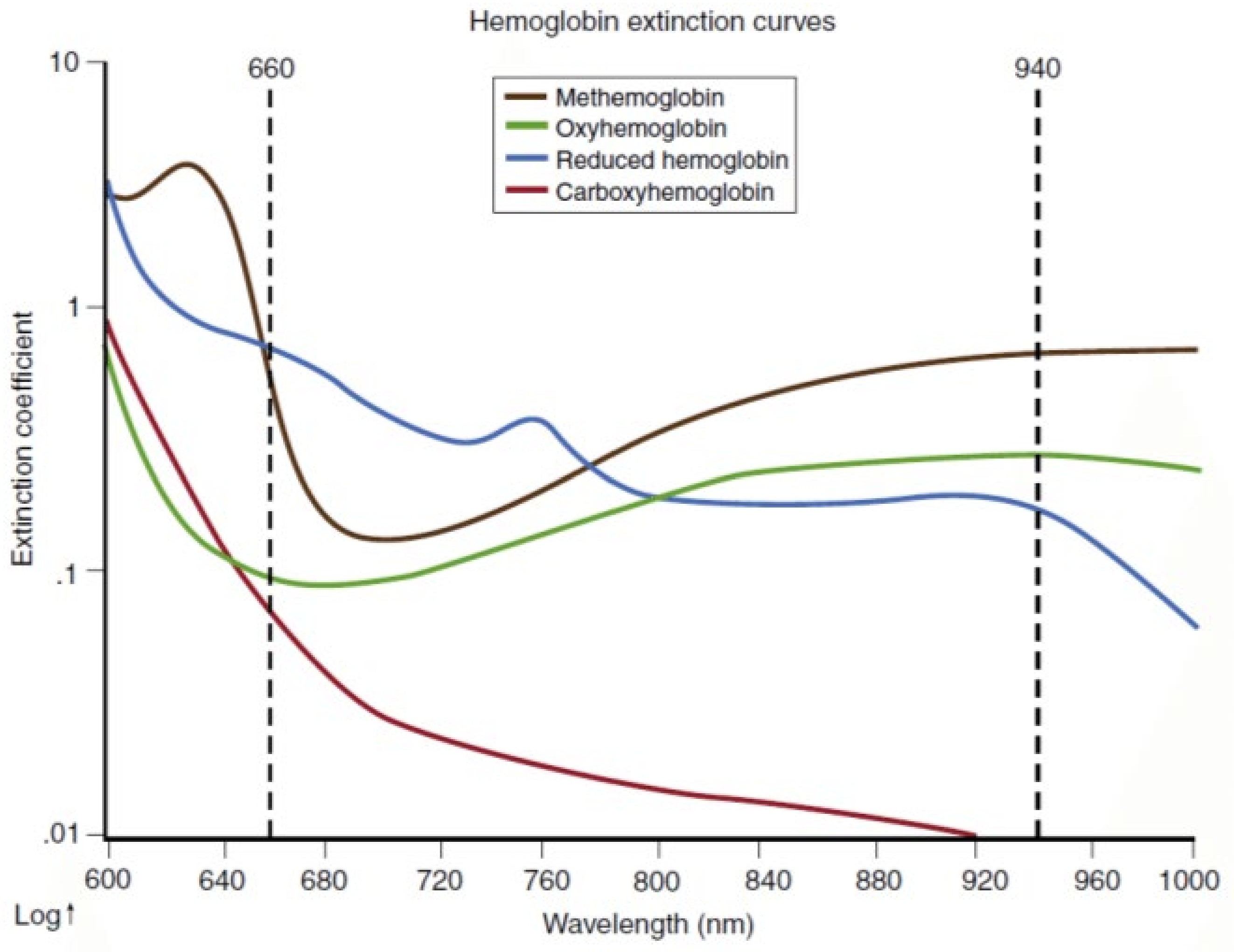
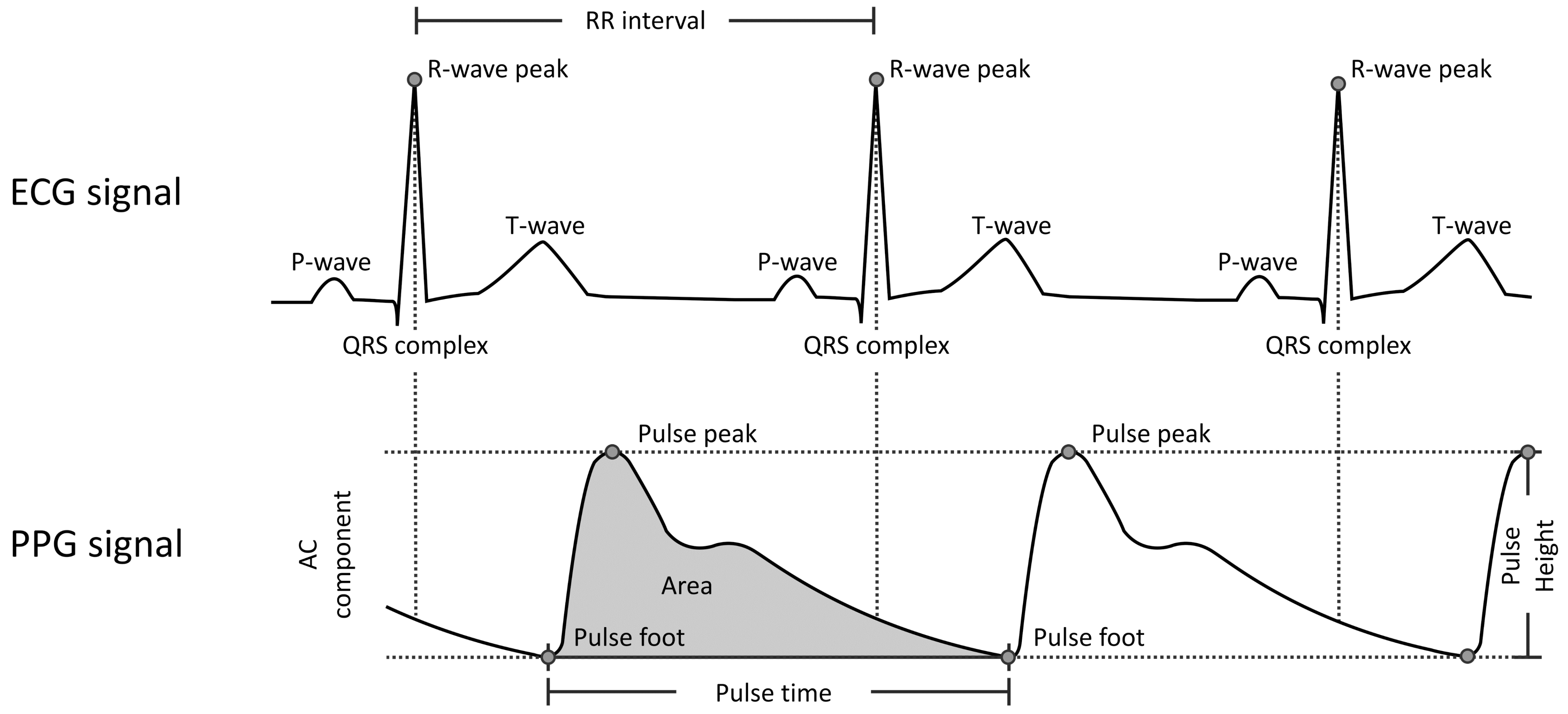
Photoplethysmography (PPG) - Oxygen saturation



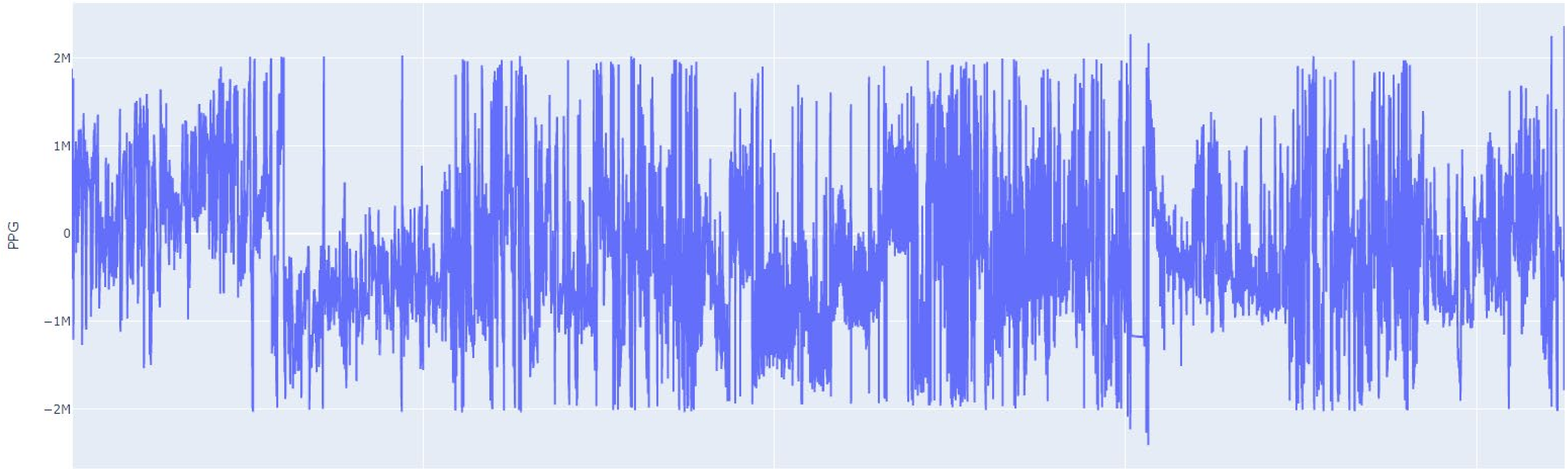
$$R = \frac{A_{AC_{660}} / A_{DC_{660}}}{A_{AC_{940}} / A_{DC_{940}}}$$

Photoplethysmography (PPG) - Basics



Photoplethysmography - signal processing applications

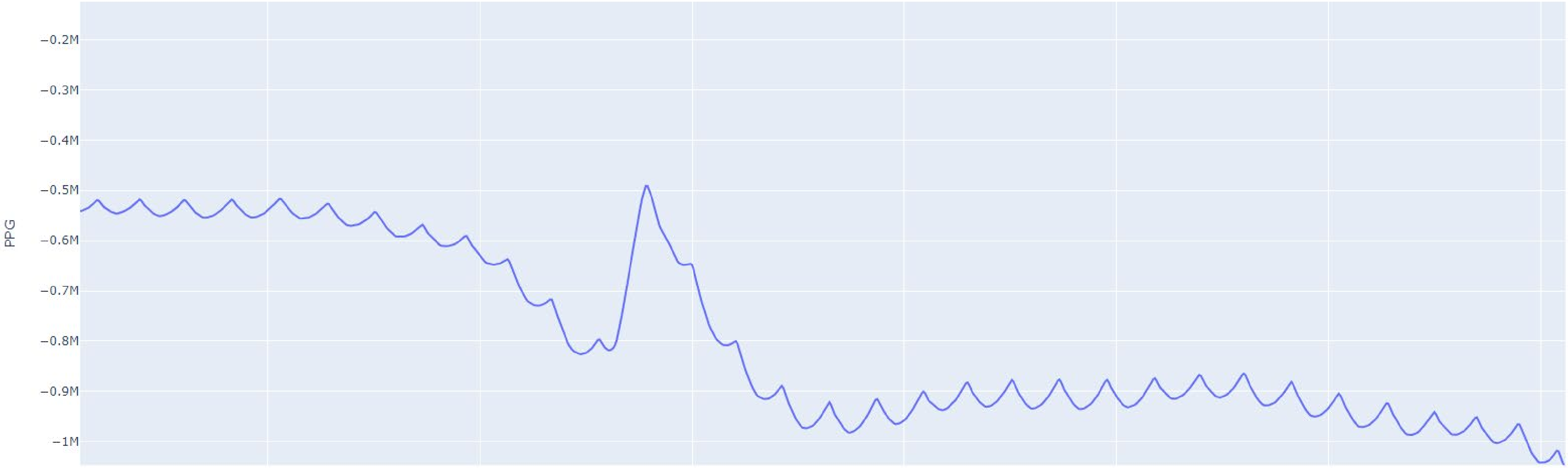
1st challenge: track heart rate during physical activities



Raw PPG signals
(daily activities)

Photoplethysmography - signal processing applications

1st challenge: track heart rate during physical activities



Raw PPG signals
(at rest)

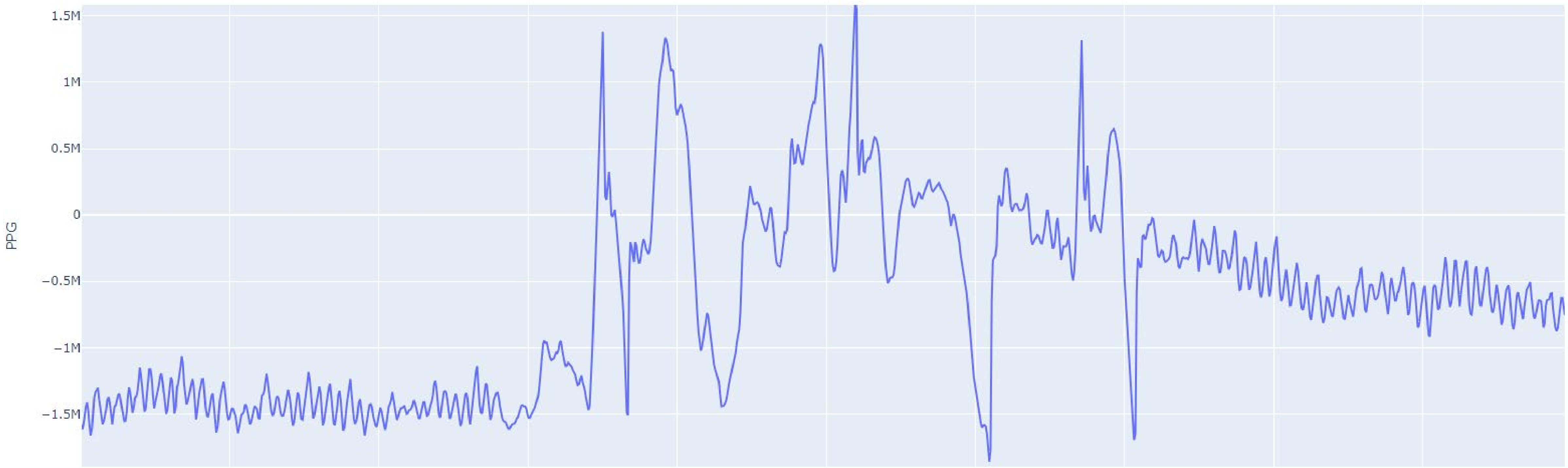
Photoplethysmography - signal processing applications

1st challenge: track heart rate during physical activities

Raw PPG signals
(running with motion)

Photoplethysmography - signal processing applications

1st challenge: track heart rate during physical activities



Raw PPG signals
(running with motion + artefacts)

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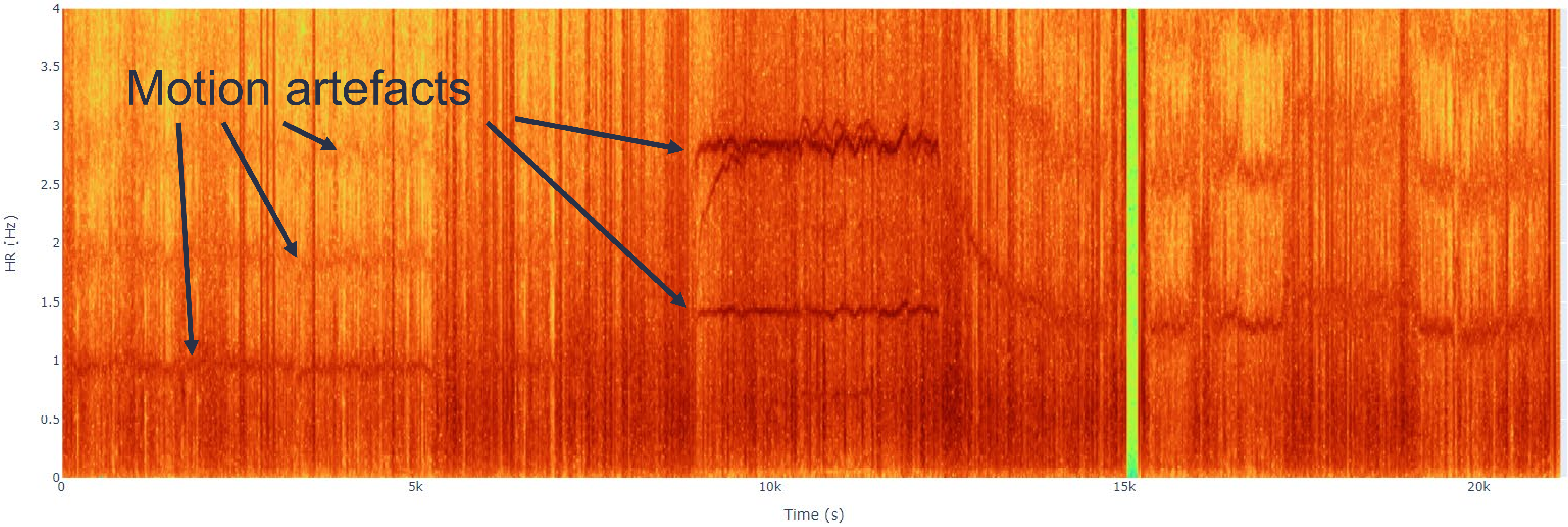
Photoplethysmography - signal processing applications

1st challenge: track heart rate during physical activities



Time frequency analysis

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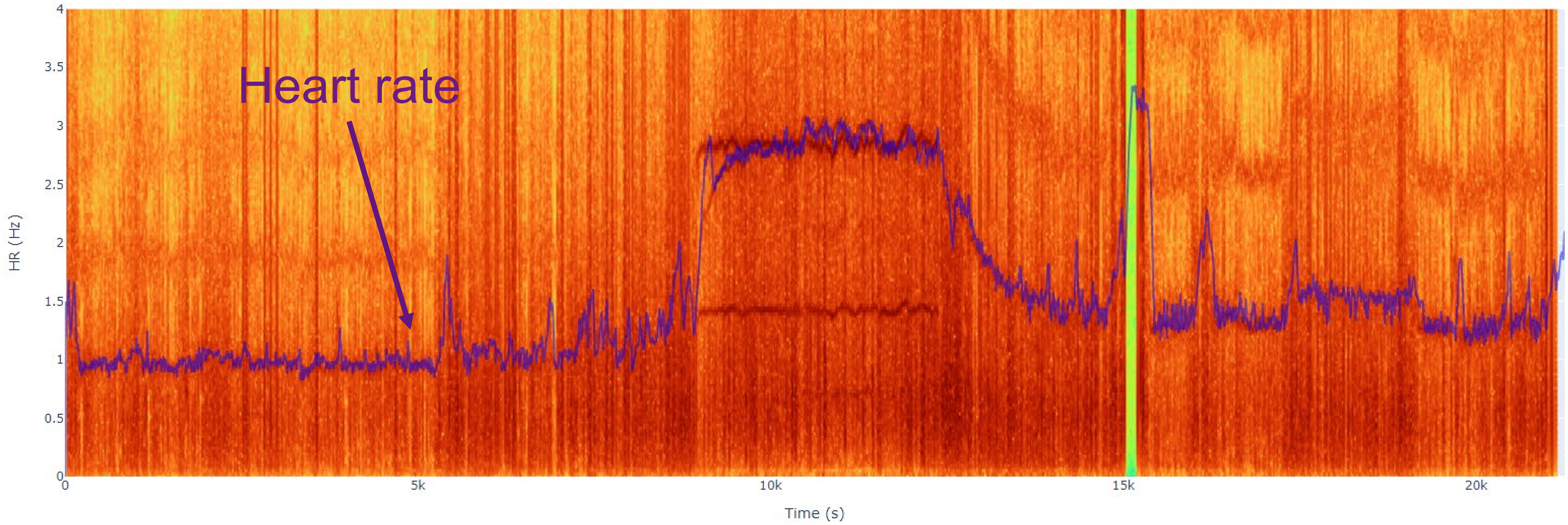
Photoplethysmography - signal processing applications

1st challenge: track heart rate during physical activities



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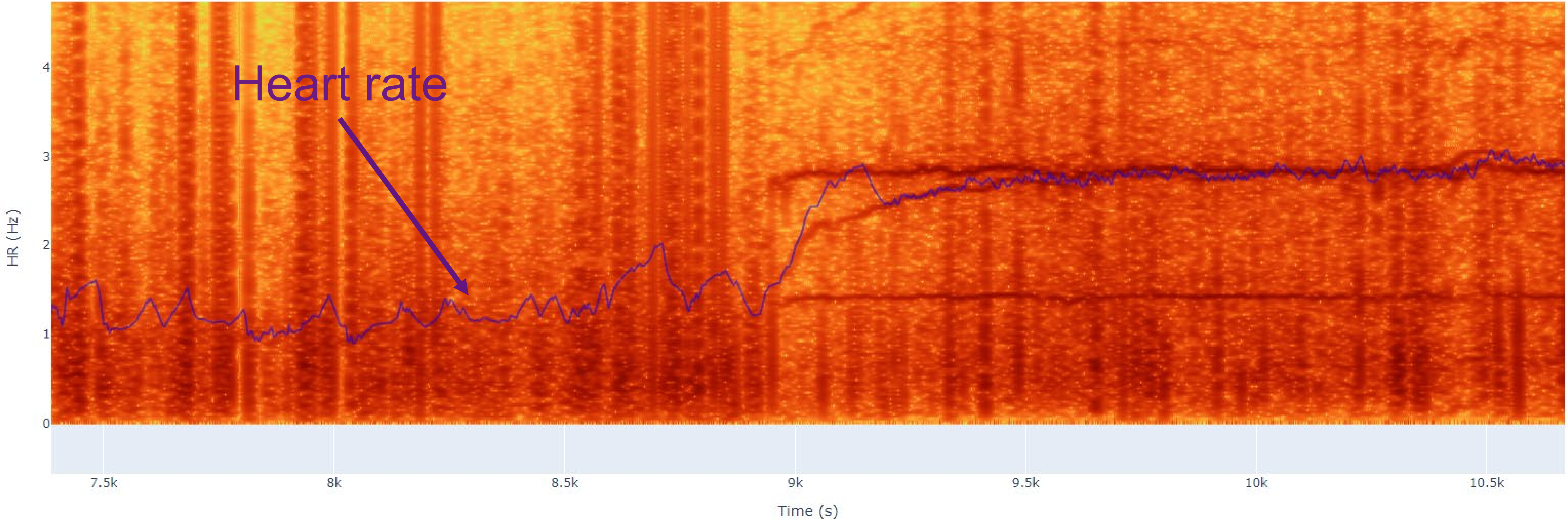
Photoplethysmography - signal processing applications

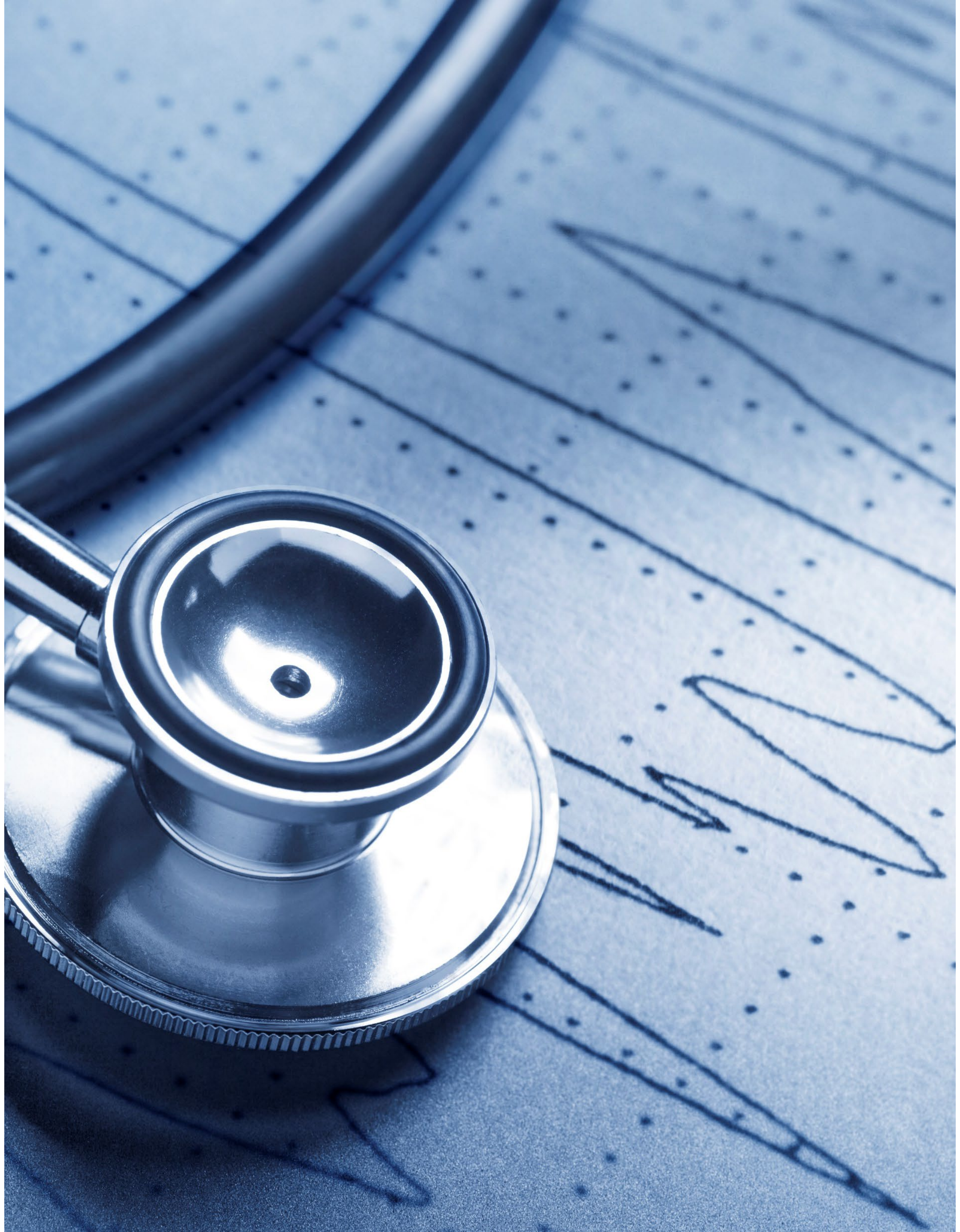
Time frequency, adaptive filter frequency tracking, power spectral analysis

1st challenge: track heart rate during physical activities



Labo 01 - Photoplethysmography & Motion artifacts

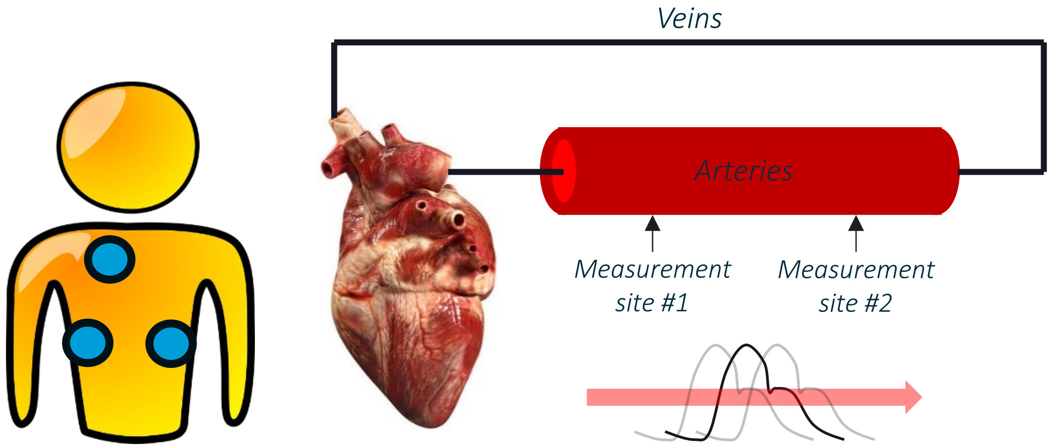
activity_data.ipynb



Photoplethysmography - signal processing applications

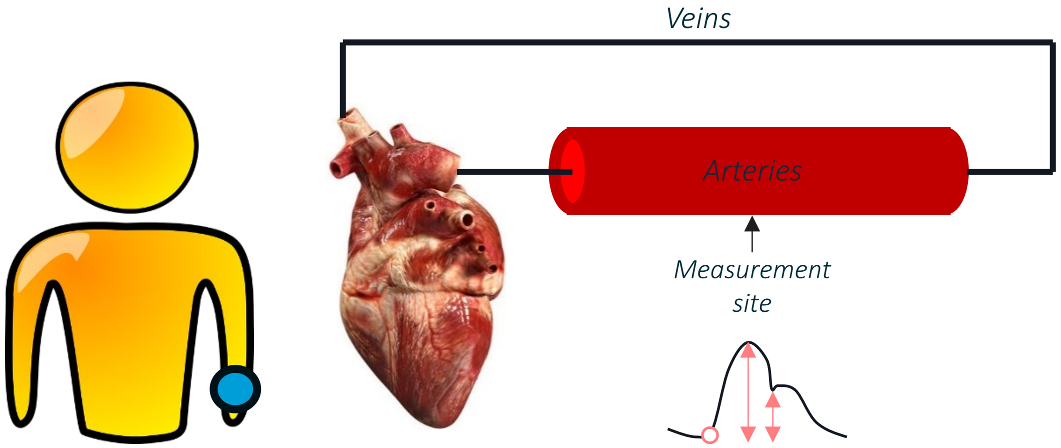
2nd challenge: blood pressure monitoring

Technologies based on **pulse wave velocity (PWV)**



*Measurement of the **velocity** of the pressure wave*

Technologies based on **pulse wave analysis (PWA)**



*Measurement of the **morphology** of the pressure wave*

oBPM® – optical blood pressure monitoring

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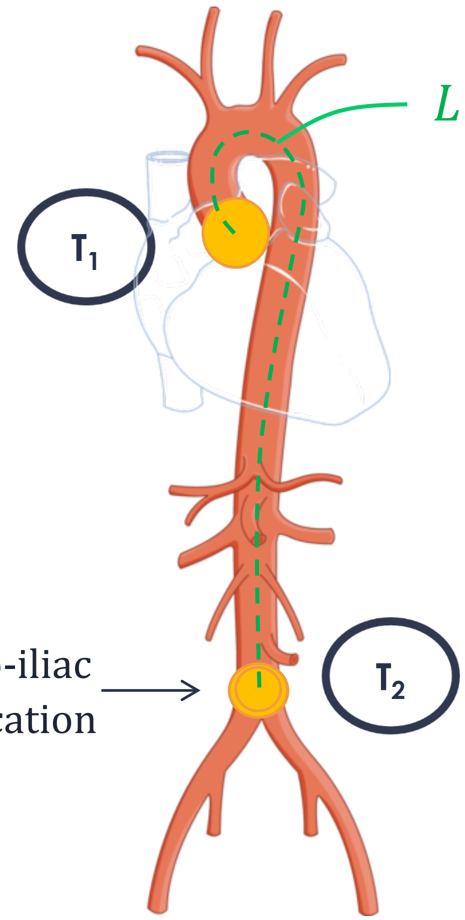
Photoplethysmography - signal processing applications

2nd challenge: blood pressure monitoring

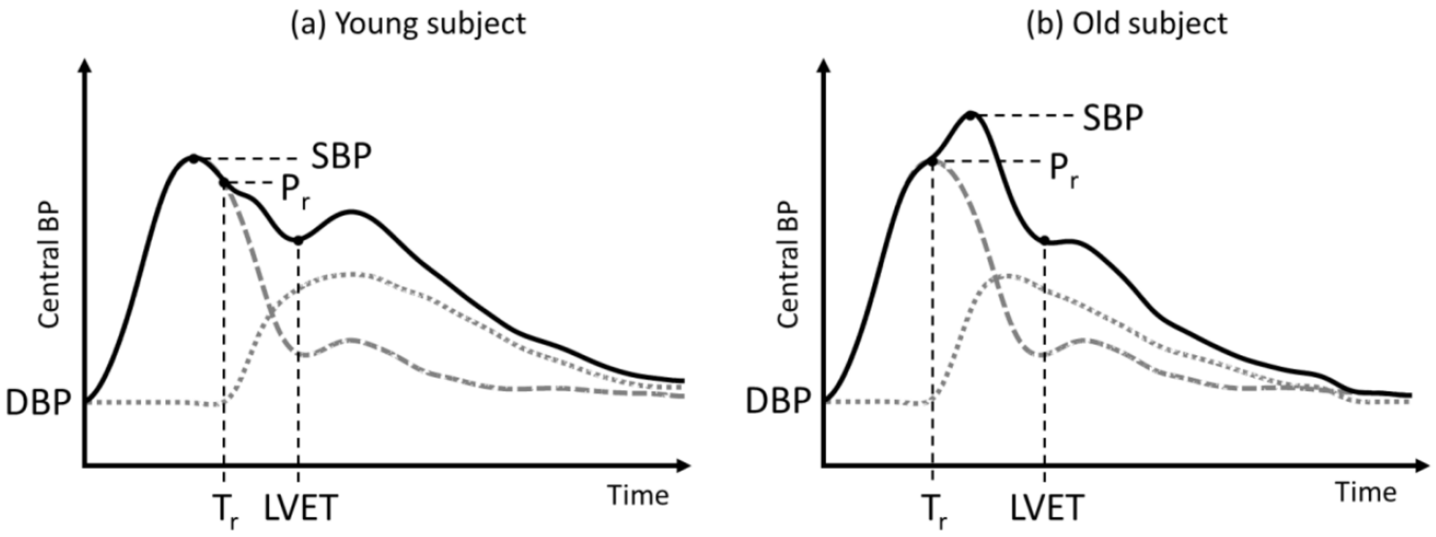
oBPM®: Physiological background & algorithm pipeline



Aorto-iliac Bifurcation

$$\text{Central Pulse Wave Velocity} = \frac{L}{T_2 - T_1} = \sqrt{1/(\rho\delta)} \propto \sqrt{1/\delta} \qquad \text{(Bramwell-Hill equation)}$$

- δ = Aortic distensibility
- ρ = Density of blood (constant)
- L = Aorta length (constant)

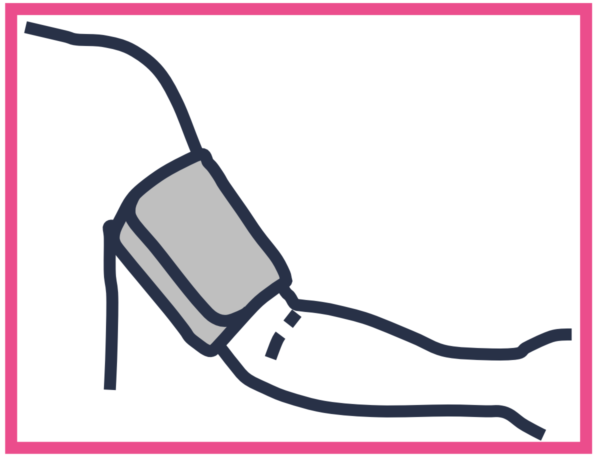


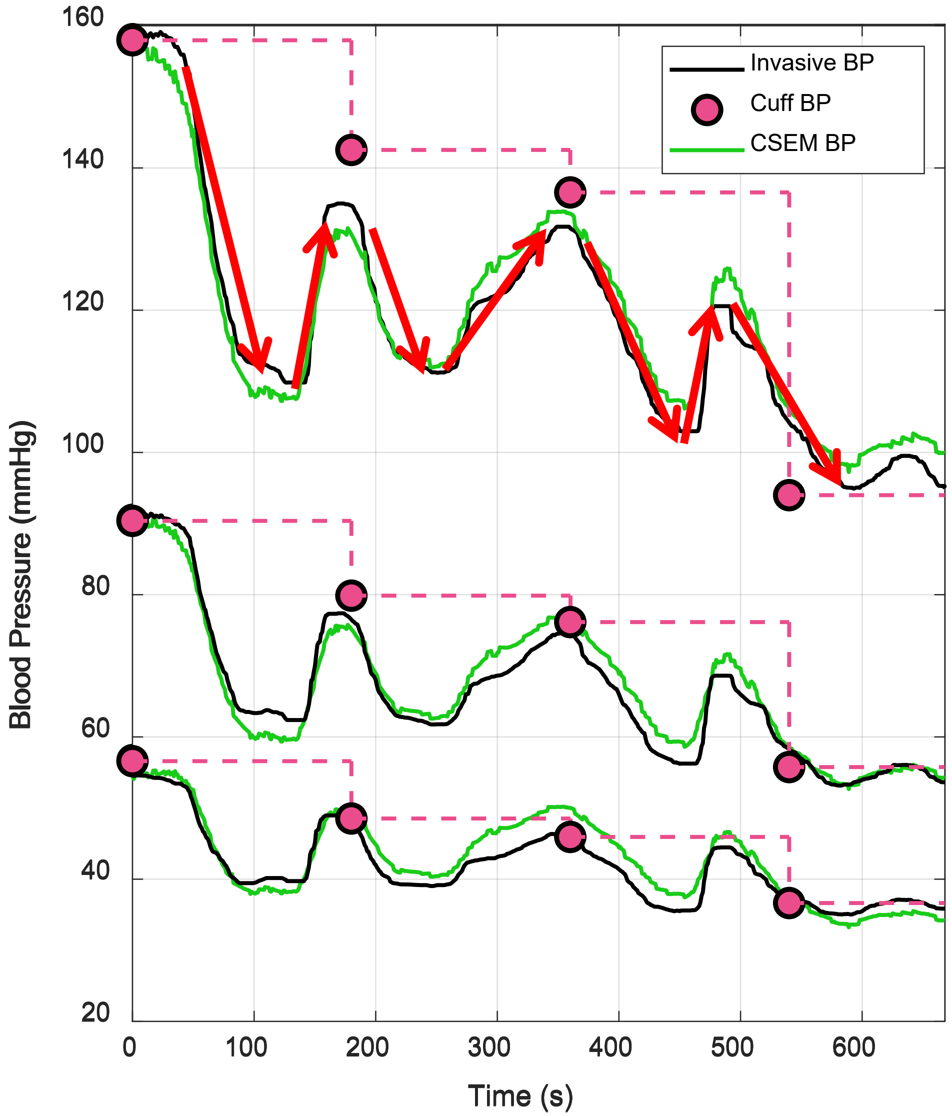
$T_r = 2(T_2 - T_1)$ = Aortic time to reflection

Photoplethysmography - signal processing applications

Regression, feature selection, NN

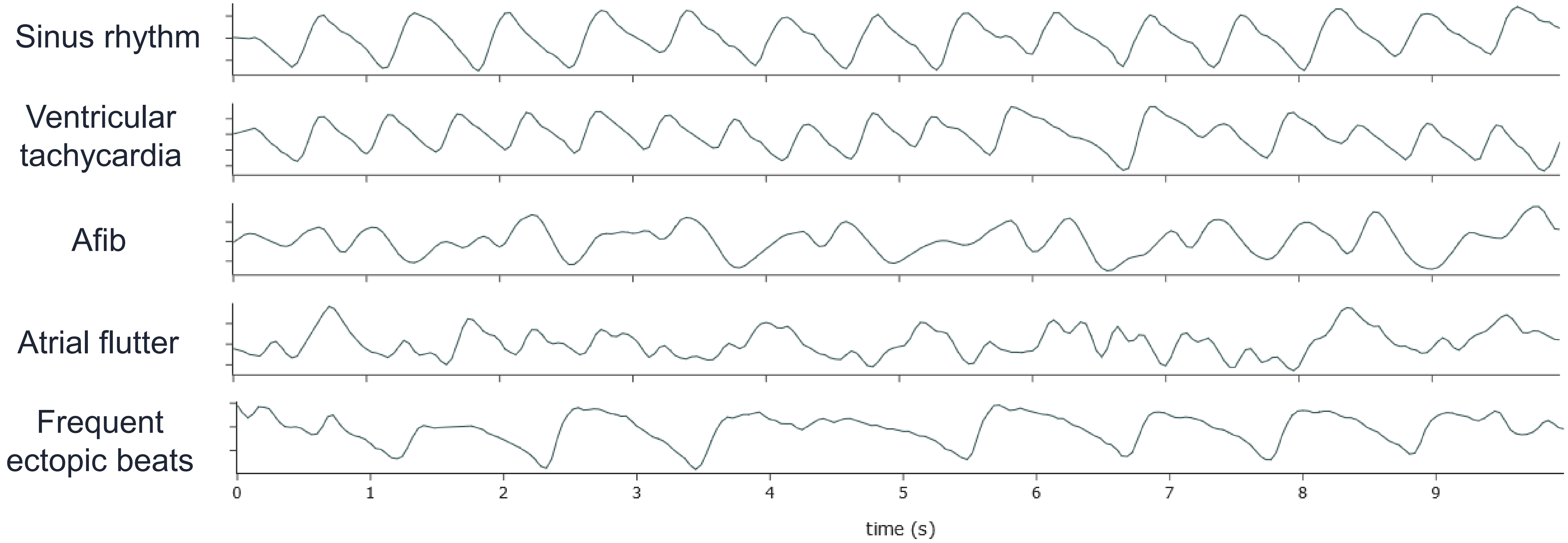
2nd challenge: blood pressure monitoring





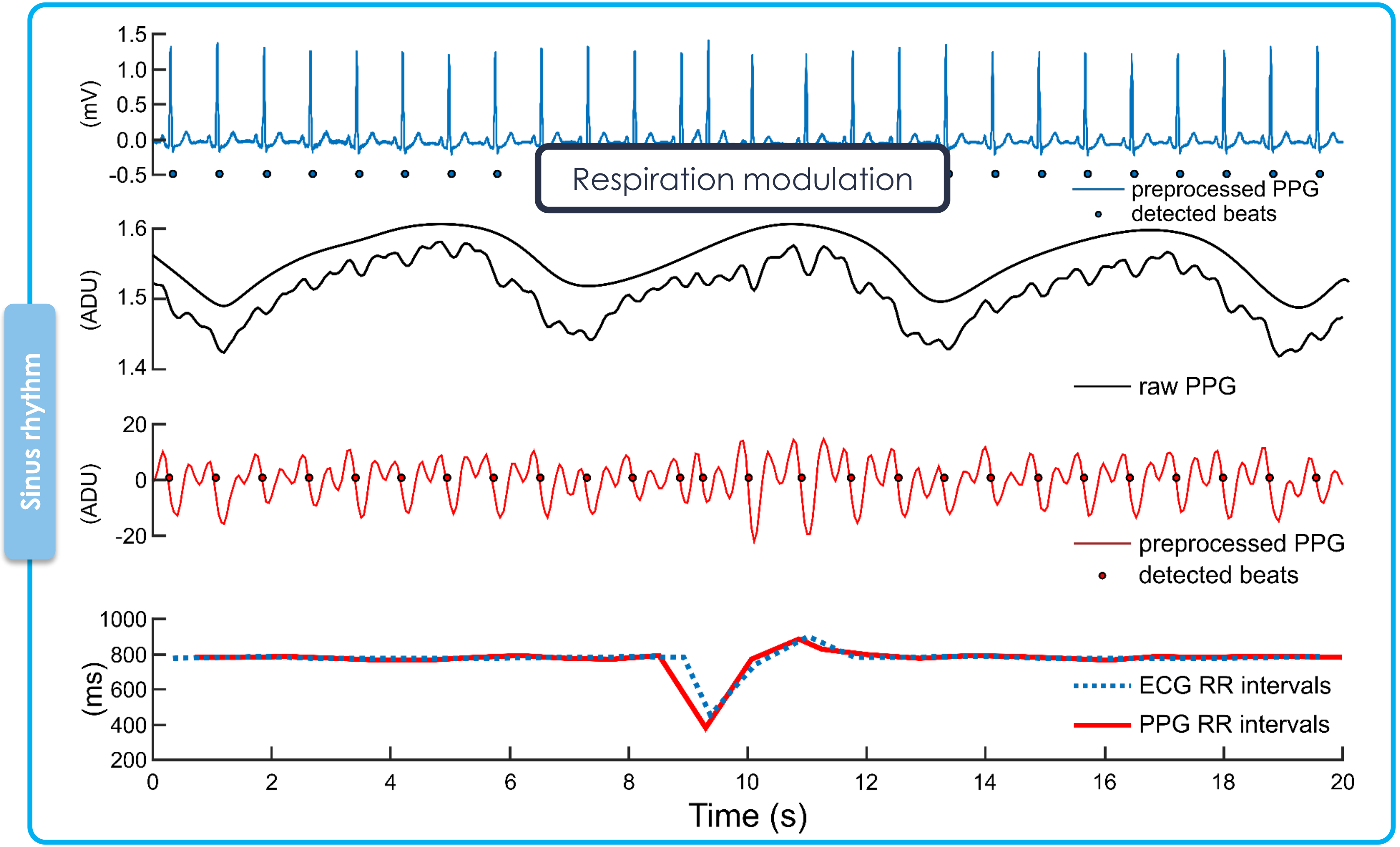
Photoplethysmography - signal processing applications

3rd challenge: classify cardiac arrhythmias



Photoplethysmography - signal processing applications

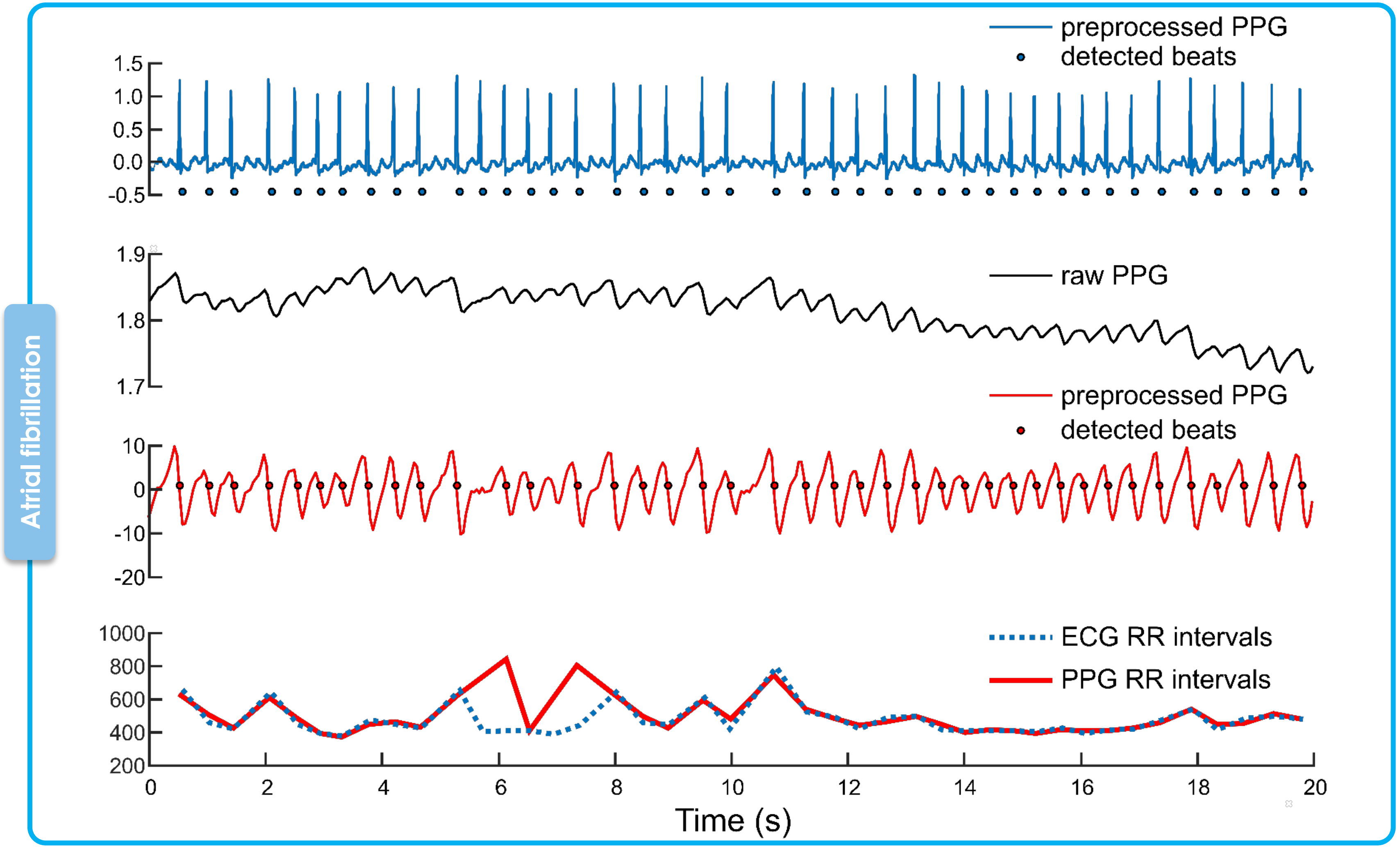
3rd challenge: classify cardiac arrhythmias



Photoplethysmography - signal processing applications

Power spectral density, classification, clustering, feature selection

3rd challenge: classify cardiac arrhythmias



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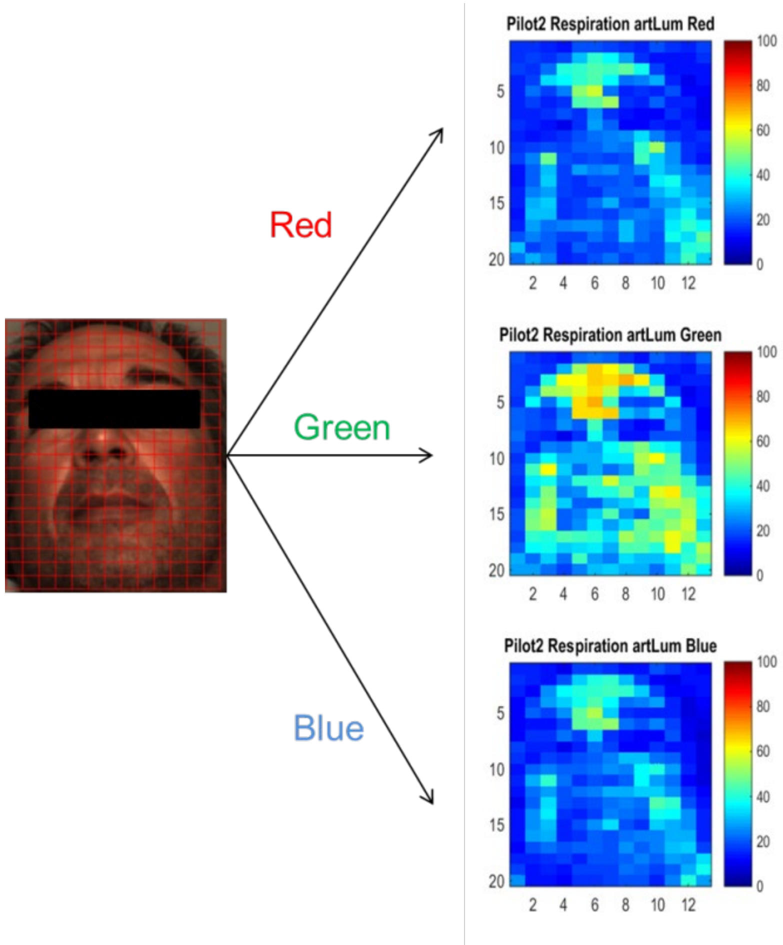
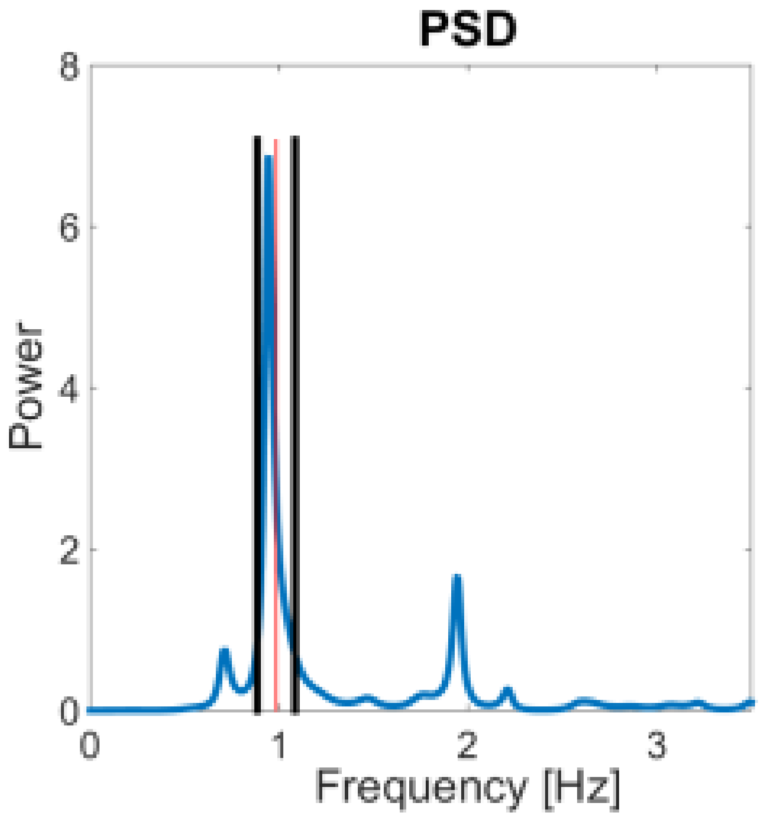
Photoplethysmography - signal processing applications

4th challenge: track vital signals remotely



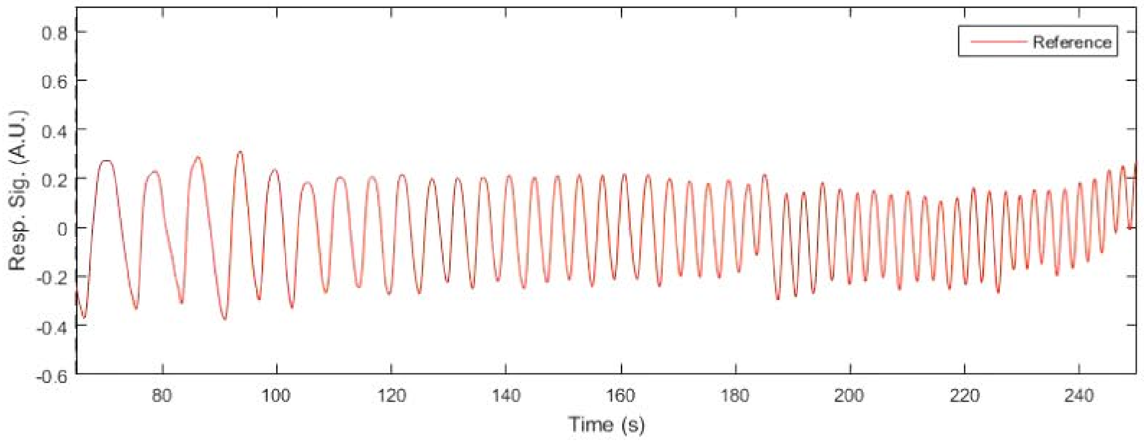


Power around the true heart rate

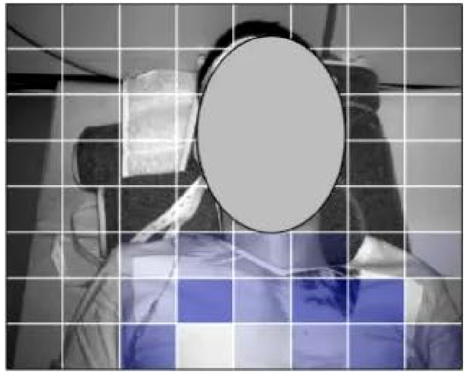
Photoplethysmography - signal processing applications

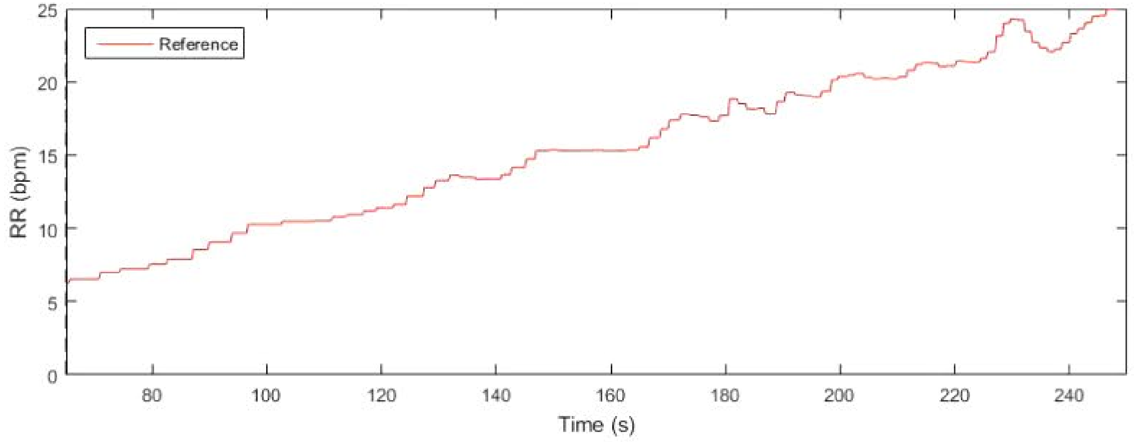
4th challenge: track vital signals remotely

Raw Video



Estimated Motion

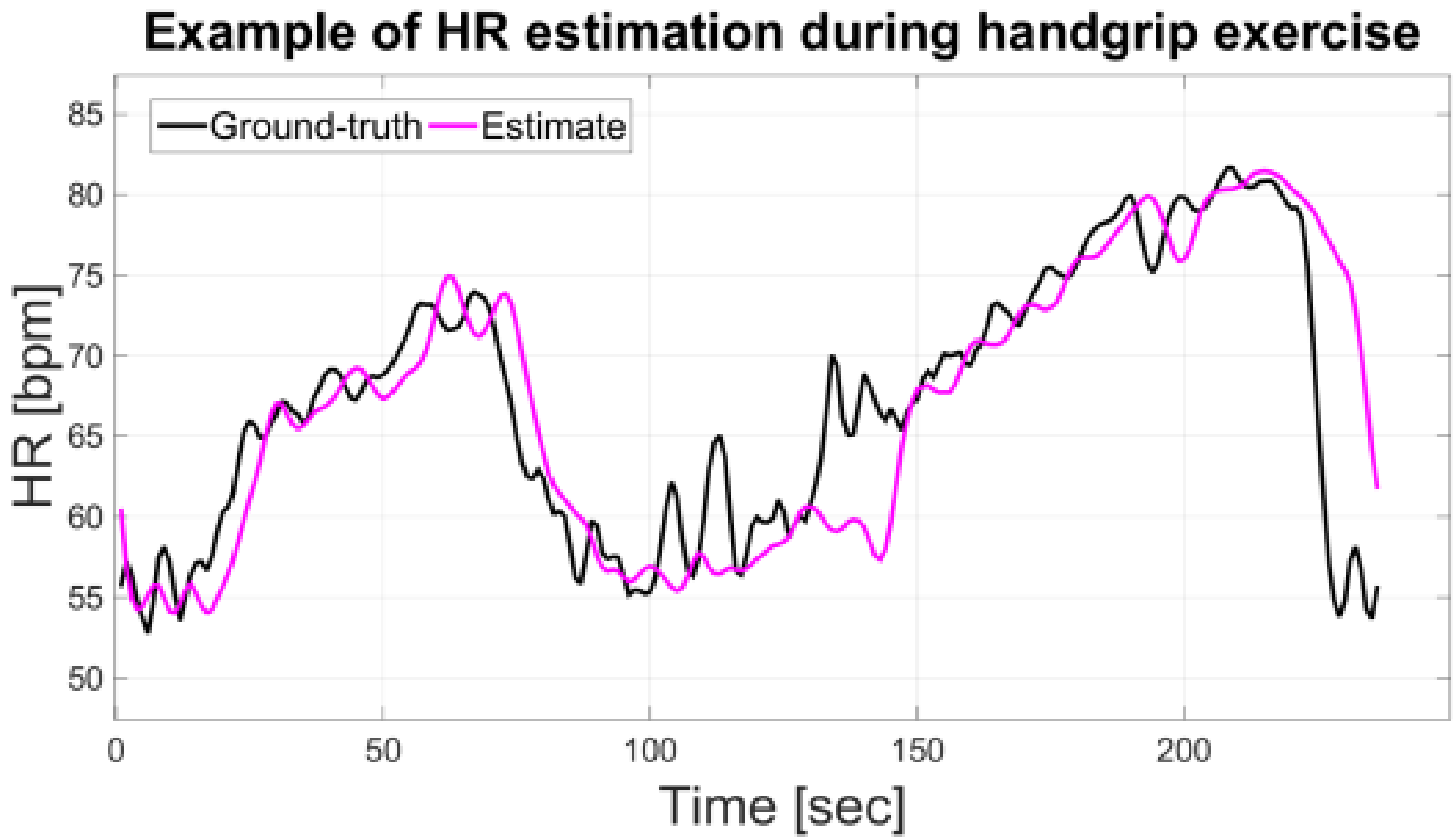




Photoplethysmography - signal processing applications

Adaptive filter frequency tracking

4th challenge: track vital signals remotely



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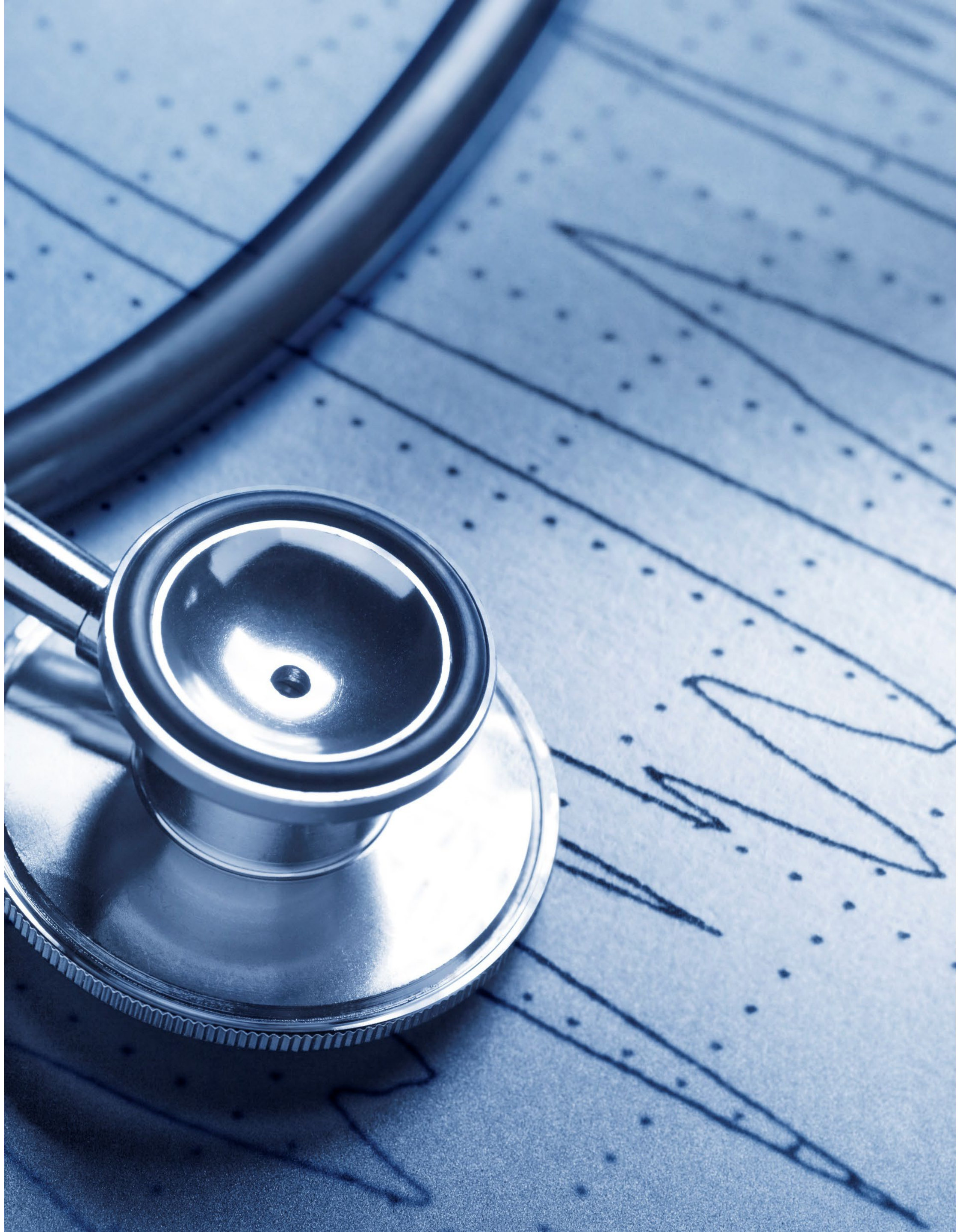
Labo 01 - Electrocardiogram, Photoplethysmography & Cardiac Arrythmias

ecg_ppg_data.ipynb

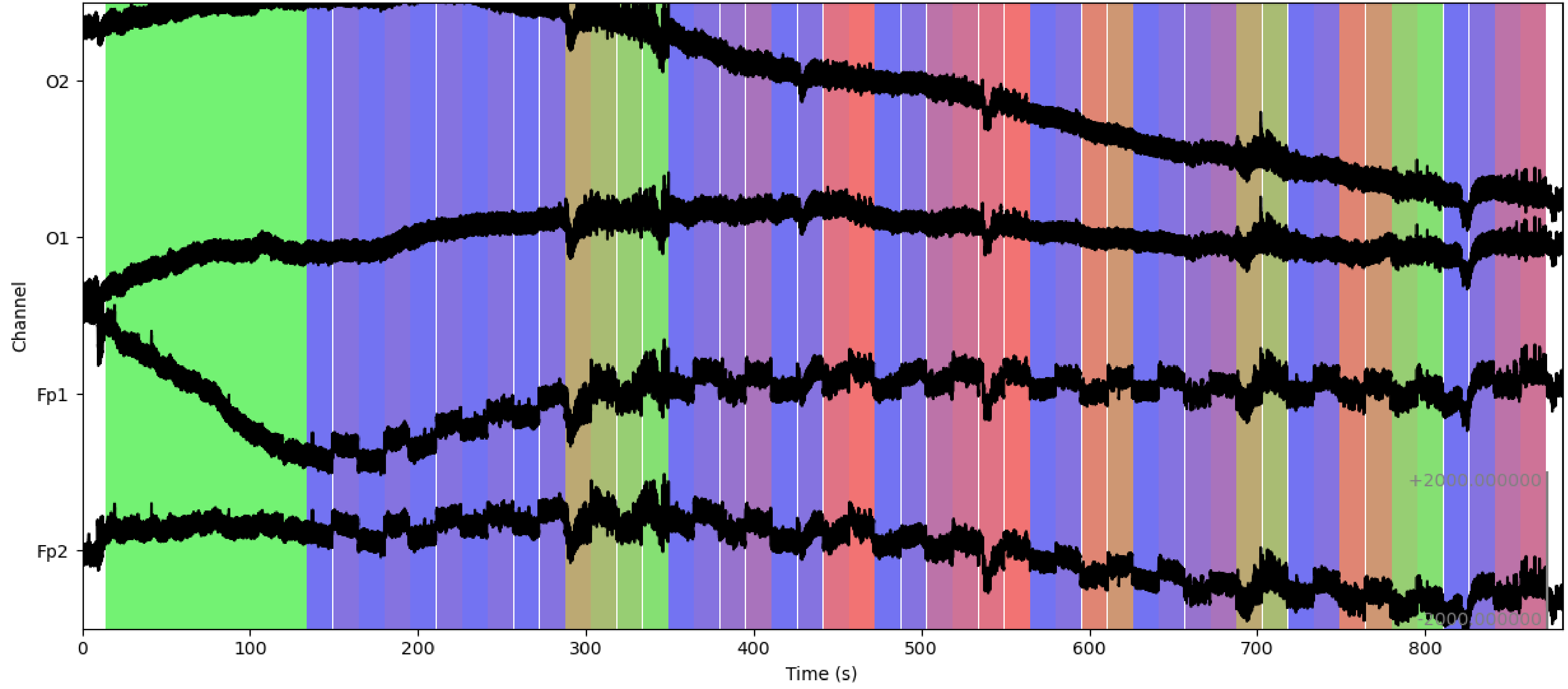


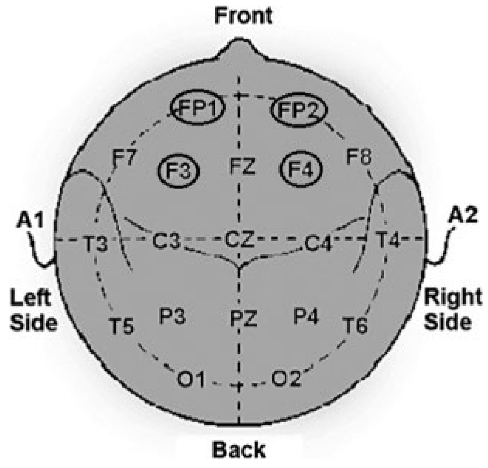
Electroencephalogram and relevant biomedical signal processing applications

Electroencephalogram - signal processing applications

1st challenge: human-computer interaction

Raw EEG signals from different locations



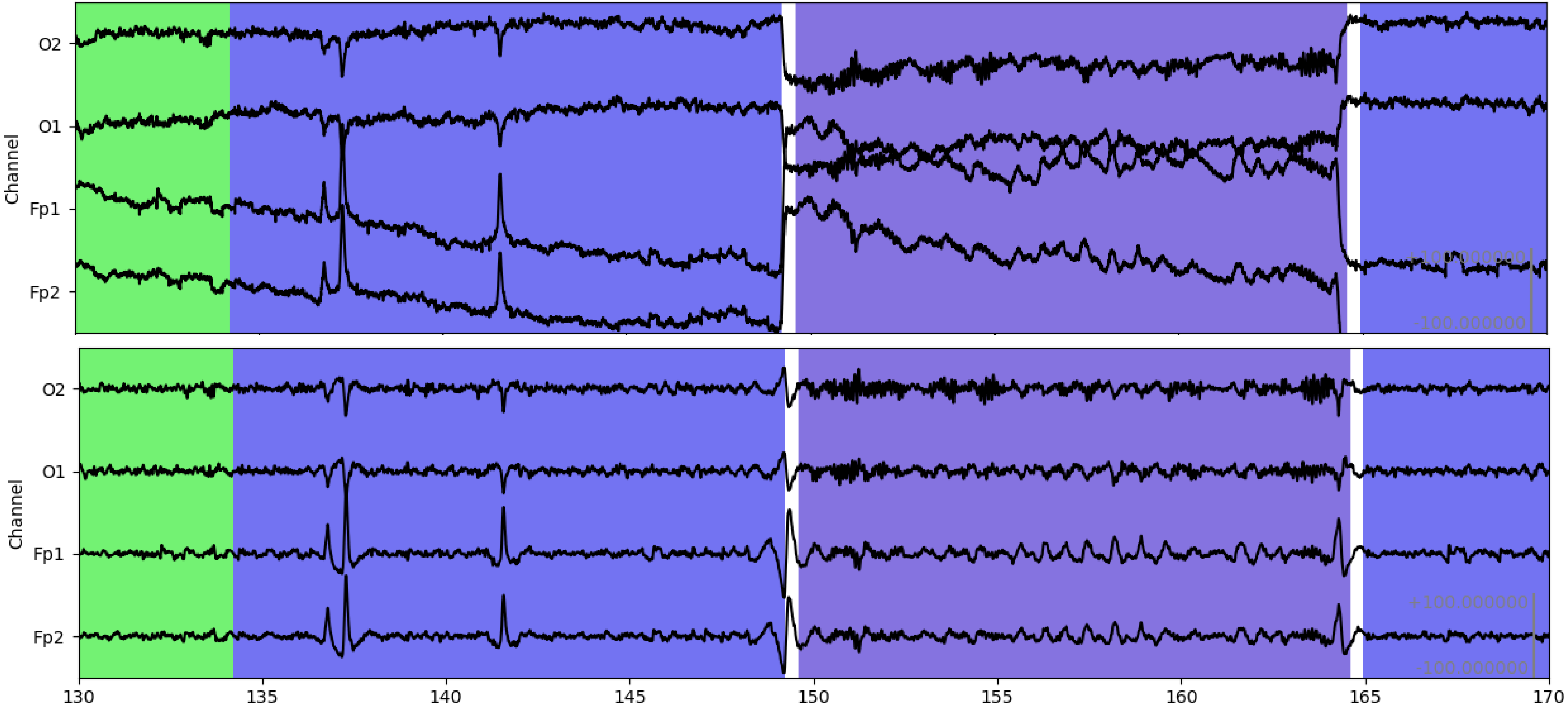


Electroencephalogram - signal processing applications

1st challenge: human-computer interaction

Before filtering

After filtering

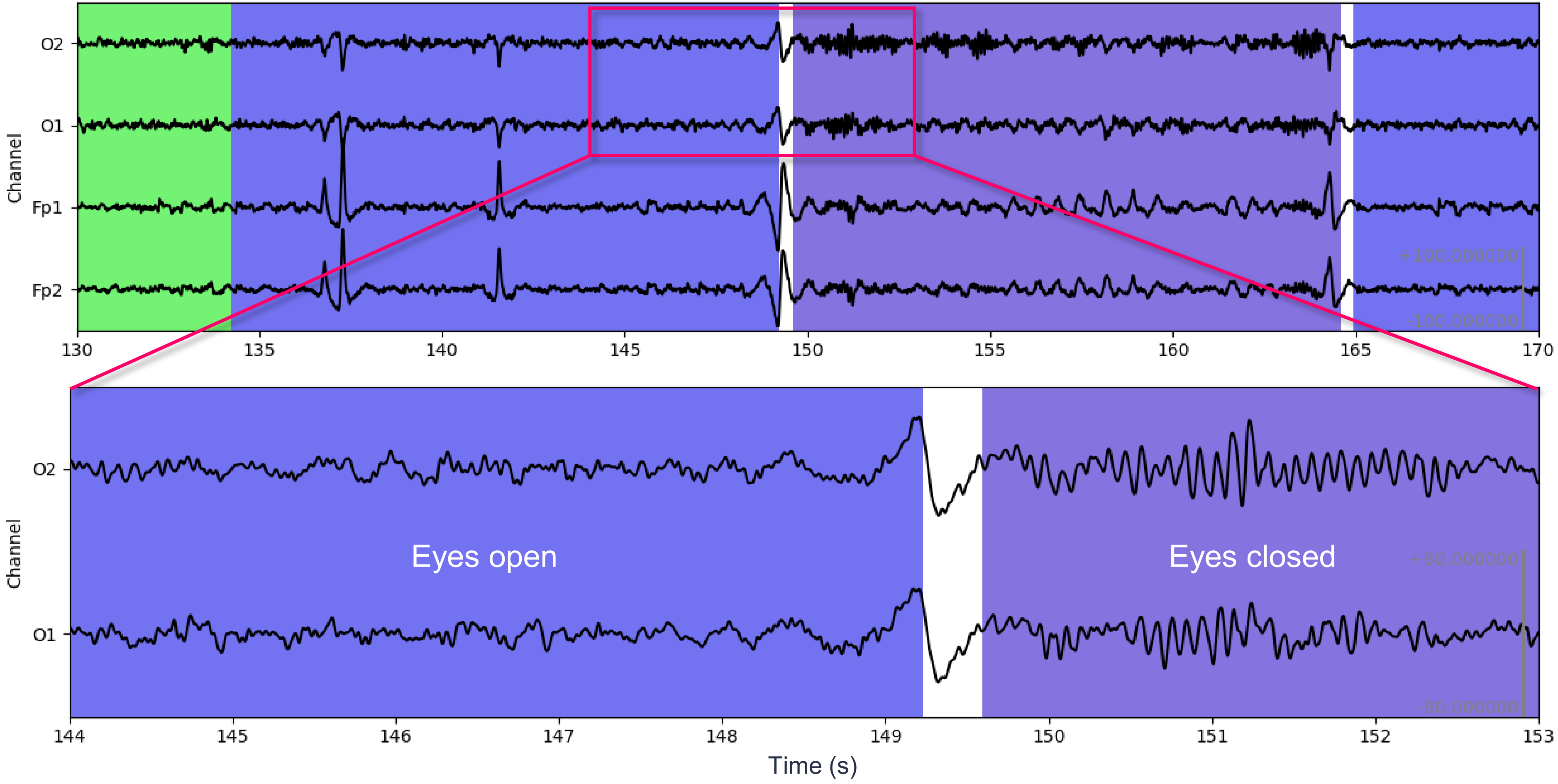


Electroencephalogram - signal processing applications

Filter design, power spectral density, classification, feature selection, NN

1st challenge: human-computer interaction

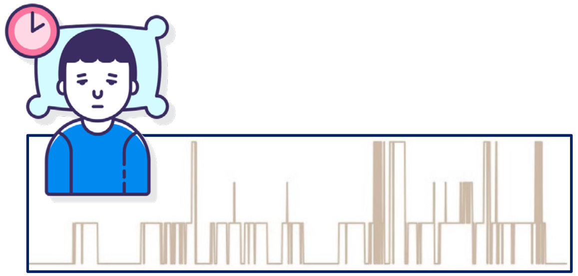
After filtering



Brain activity - signal processing applications

2nd challenge: sleep staging

- Why Sleep Staging ? → To diagnose sleep disorders



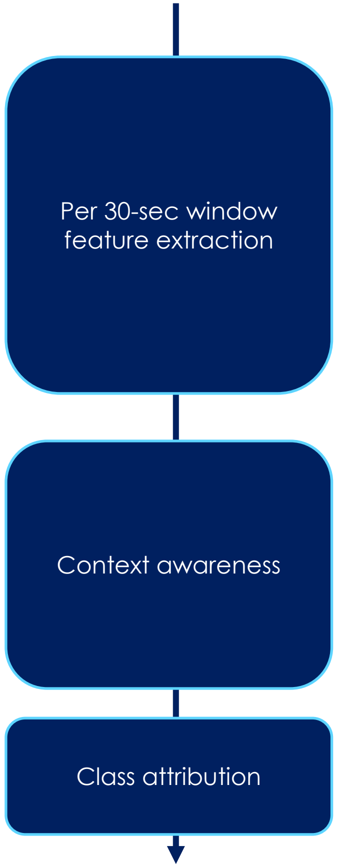
- Why use Deep Learning ? → Rich and complex problem, less labor-intensive, offline, scalable ✓

- Objective ? → **Train a DL algo for Ambulatory Sleep Staging which perform on various type of signals (EEG, ECG, PPG)**

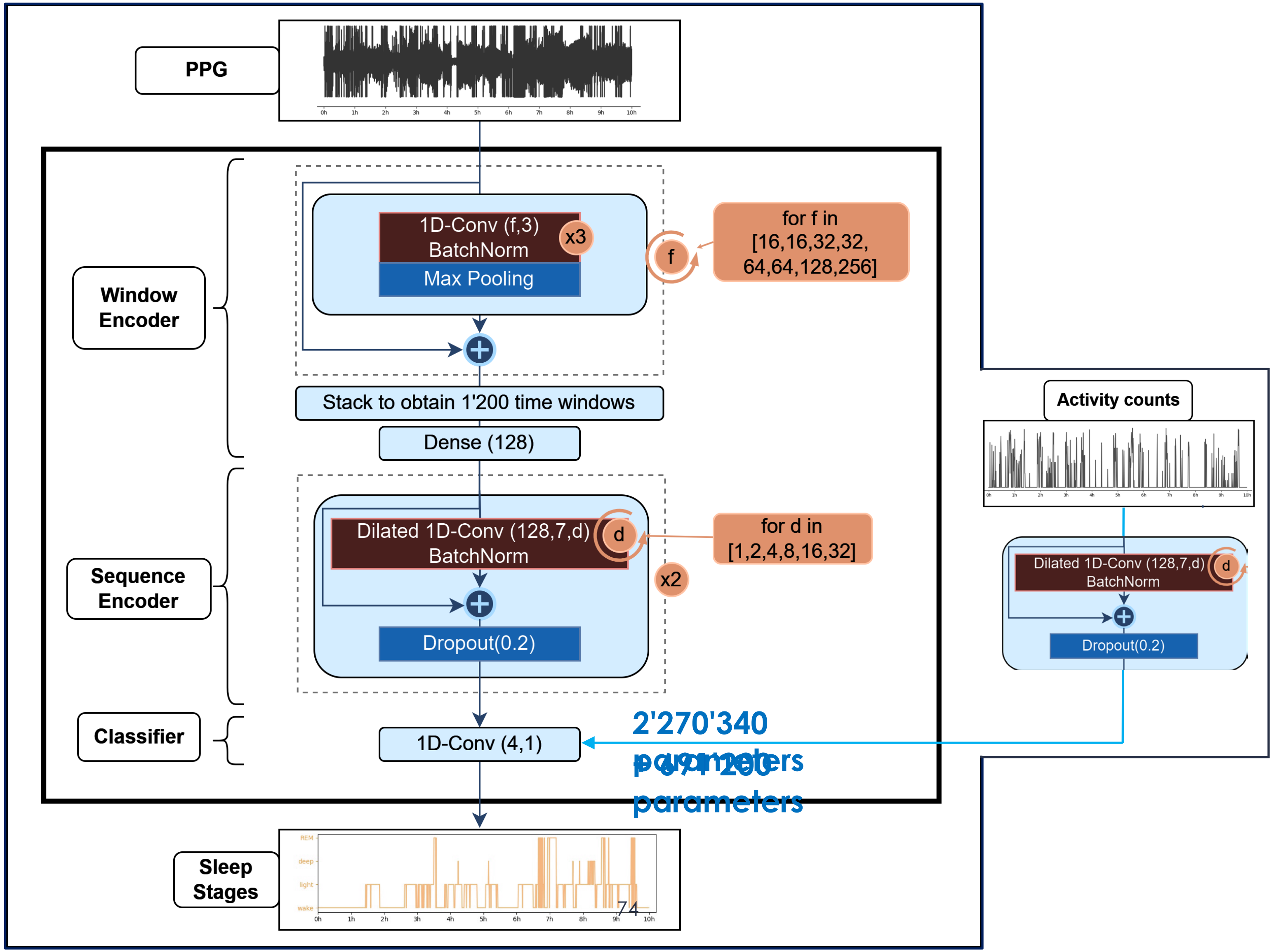
Brain activity - signal processing applications

2nd challenge: sleep staging

10h of PPG at 34.13 Hz



Sleep Stages each 30s
(Wake/Light/Deep/REM)



Brain activity - signal processing applications

2nd challenge: sleep staging

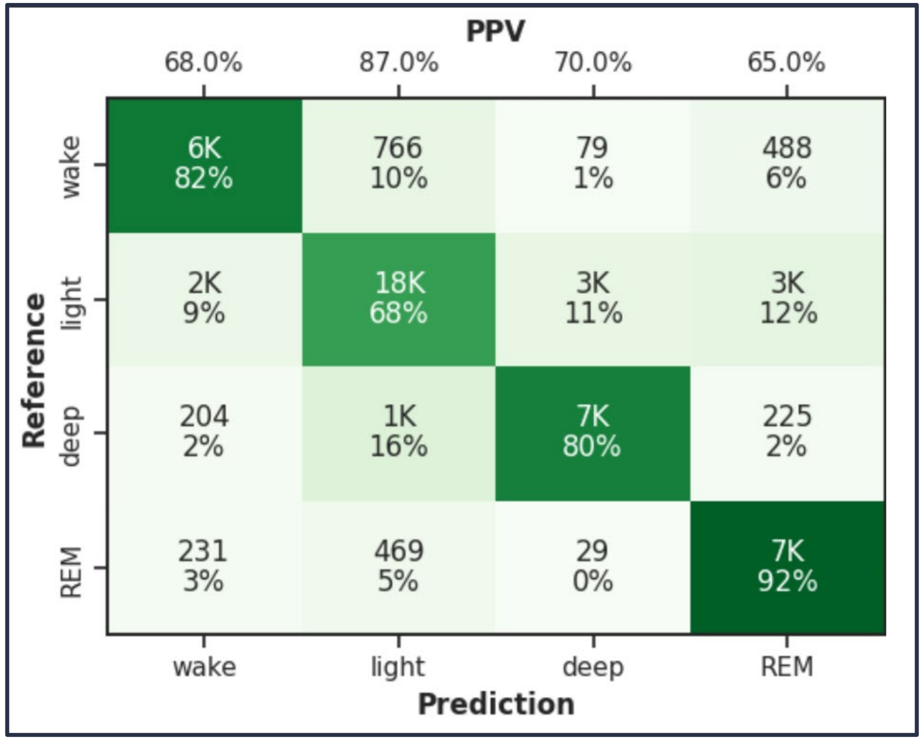
classification, NN

EEG

ECG

PPG

Accuracy: 78.1%



EE512 – Applied Biomedical Signal Processing

Module 01 - Introduction

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