Acquisition and Analysis of Biosignals DTEK0042

Biosignal analysis III

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Introduction

So far, we learned:

- ❑ Time domain analysis and Frequency domain analysis
- ❑ Analysis of ECG, PPG, EMG, and PCG

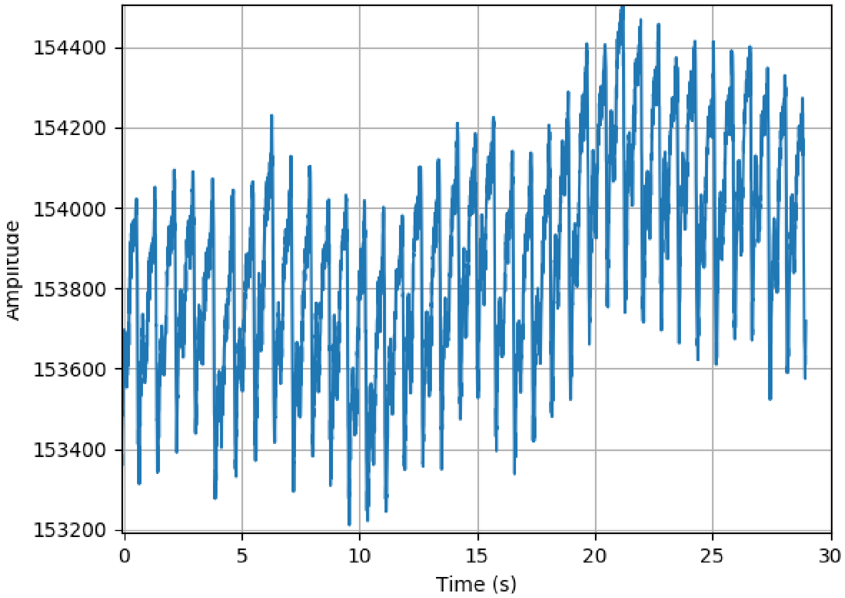
In this session, we will learn:

- ❑ Time-frequency analysis
- ❑ Analysis of SCG and GCG
- ❑ Classification and decision-making

Time domain analysis

- ❑ Different time-domain techniques are used to analyze the events
- ❑ Feature Extraction:
    - Wave shape
    - Intervals between events
    - Energy distribution
    - …

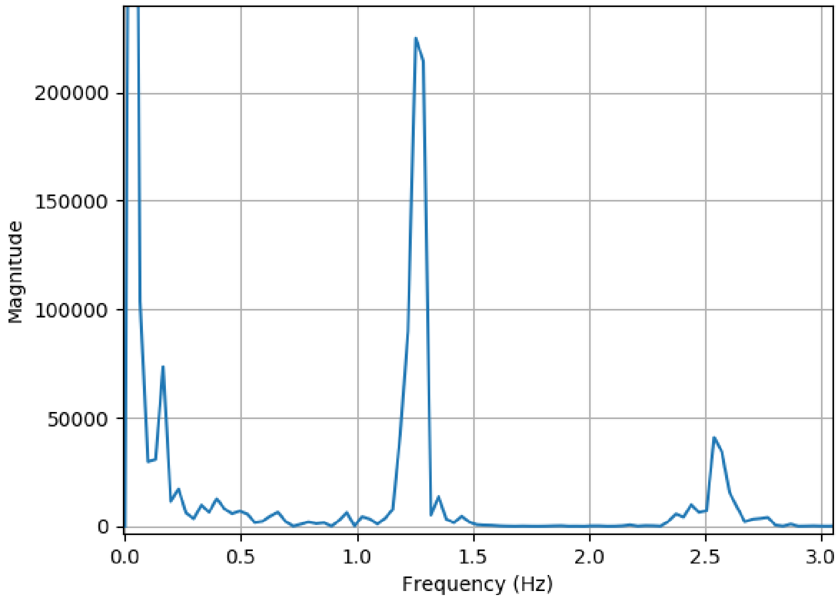
PPG signal (IR)



Frequency domain analysis

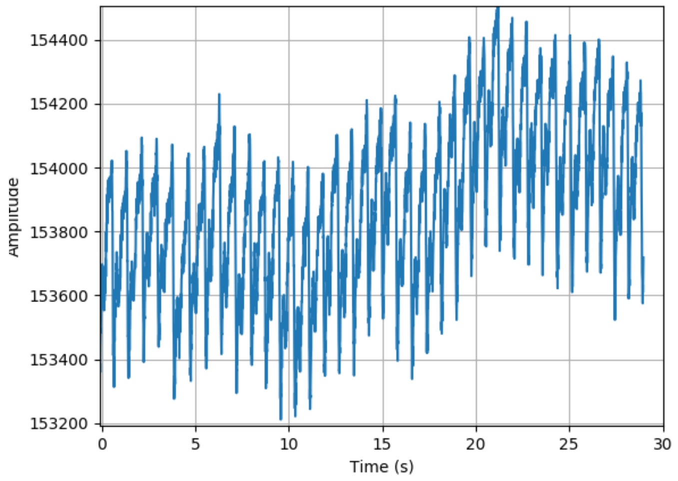
- ❑ Different frequency-domain techniques are used to analyze the events
- ❑ Feature Extraction:
  - Mean frequency
  - Dominant frequency (resonance frequency)
  - Power band
  - …

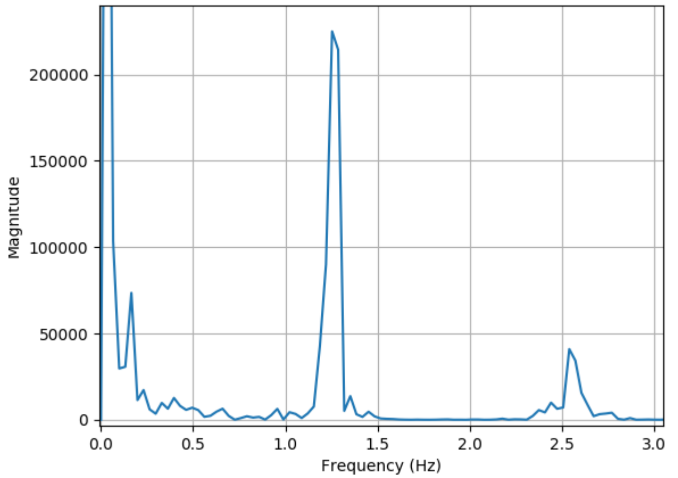
PSD of the PPG signal



Time domain analysis and Frequency domain analysis

- **Time domain analysis**: We know when the event starts and when it ends, but it is difficult to understand the patterns, repetitive events, rhythms, etc.
- **Frequency domain analysis**: We know about the resonance frequency, but we do not know when the event starts and when it ends.
- How to use both the time and frequency information?

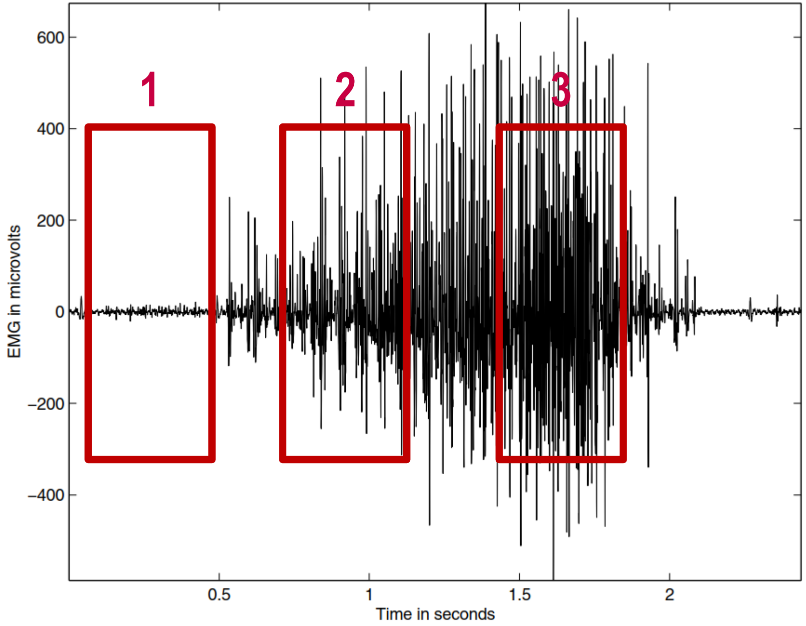




Time-Frequency Analysis

Nonstationary signals

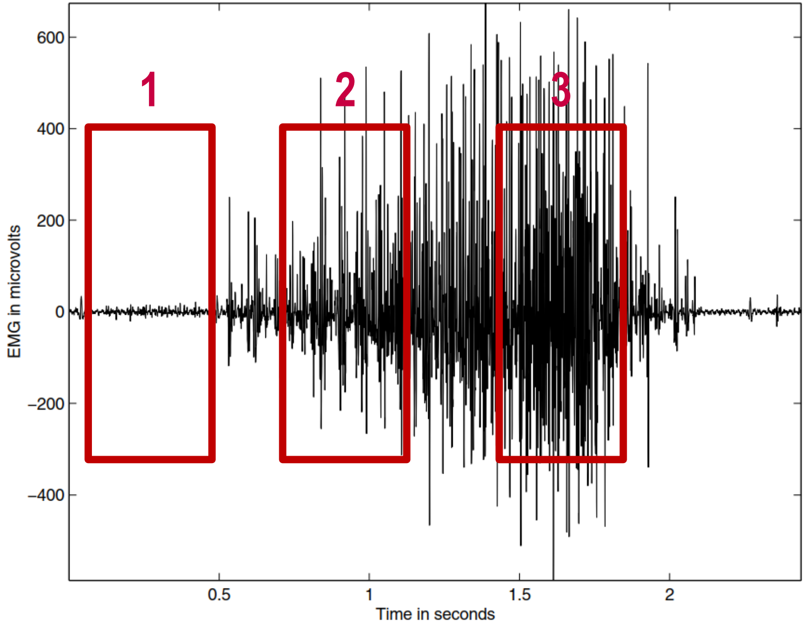
- A nonstationary signal possesses statistics that vary with time
- Various short-time statistical measures computed over moving windows may be used to characterize a nonstationary signal
  1. Mean
  2. Variance



Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

Nonstationary signals – Cont.

3. Measures of activity
   - Nonstationary: turning points and zero crossing rate vary with time
4. Auto-correlation function (ACF) and power spectral density (PSD)
   - Nonstationary: ACF varies with time
   - If nonstationary in ACF, also nonstationary in its PSD



Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

Fixed Segmentation

- Given a nonstationary signal, the simplest approach to break it into quasistationary segments would be to consider small windows of fixed duration.
- Let's consider the signal as $x(n)$ for $n = 0,1,2, \dots, N-1$
- We could consider a fixed segment duration of M samples that $M \ll N$ and break the signal into $K = \frac{N}{M}$ parts as

$$x_k(n) = x[n + (k-1)M]$$

$$0 \le n \le M-1 \quad and \quad 1 \le k \le K$$

- With the assumption that the signal does not change its characteristics in the segment

Short time Fourier transform

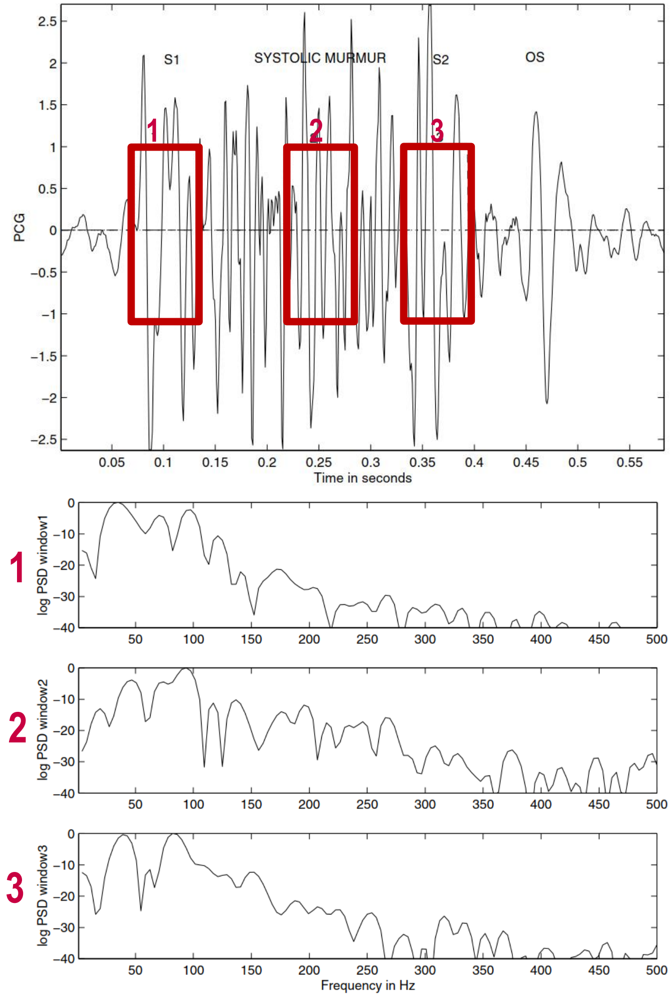
- Short time Fourier transform (STFT) is a sequence of Fourier transforms of a windowed signal
- For example:
  1. A given signal has been segmented into quasistationary parts $x_k(n)$
  2. We compute the DFT of each segment:

$$X_k(\omega) = \sum_{n=0}^{M-1} x_k(n)e^{-i\omega n}$$

- $X_k(\omega)$ for $k = 1,2, \dots, K$ describe the time-varying spectral characteristics of the signal.

Example – PCG signal

- PCG signal (nonstationary) with systolic murmur and opening snap of the mitral valve
- The duration of each window is 64 samples, equal to 64ms with *fs = 1 kHz*
- The second window displaying the largest amount of high-frequency power due to the murmur



Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

STFT – Moving analysis window

- Segmentation of the given signal may be interpreted as the application of a moving window to the signal where:

Any time instant

$$x_k(n) = x(n)w(n - m)$$

- We need to state how the window is moved from one segment to another.

STFT – Spectrogram

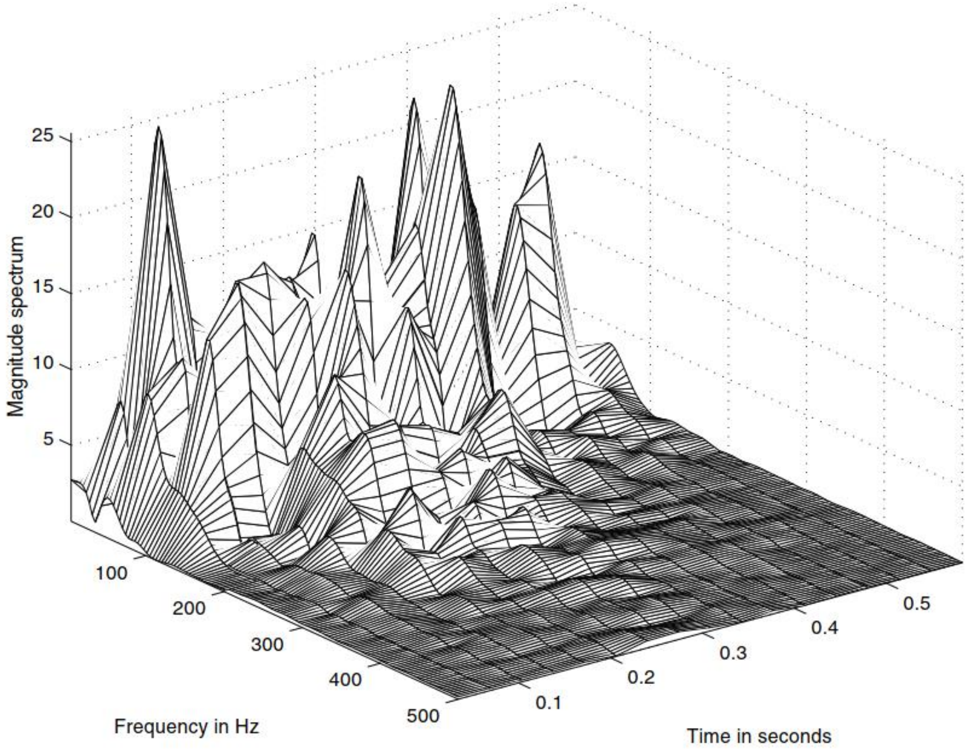
- We may then compute the Fourier transform of the segments:

$$X(m, \omega) = \sum_{n=0}^{M-1} [x(n)w(n-m)]\, e^{-i\omega n}$$

- The spectrum is now expressed
  - not only as a function of **frequency** $\boldsymbol{\omega}$,
  - but also as a function of **time** $\boldsymbol{m}$
- The magnitude of the STFT (squared) is known as the spectrogram of the signal.

Example – PCG signal

- PCG signal (*fs* = *1 kHz*) with systolic murmur and opening snap of the mitral valve
- The duration of each window is 64 samples
- The window advance interval is 32 samples



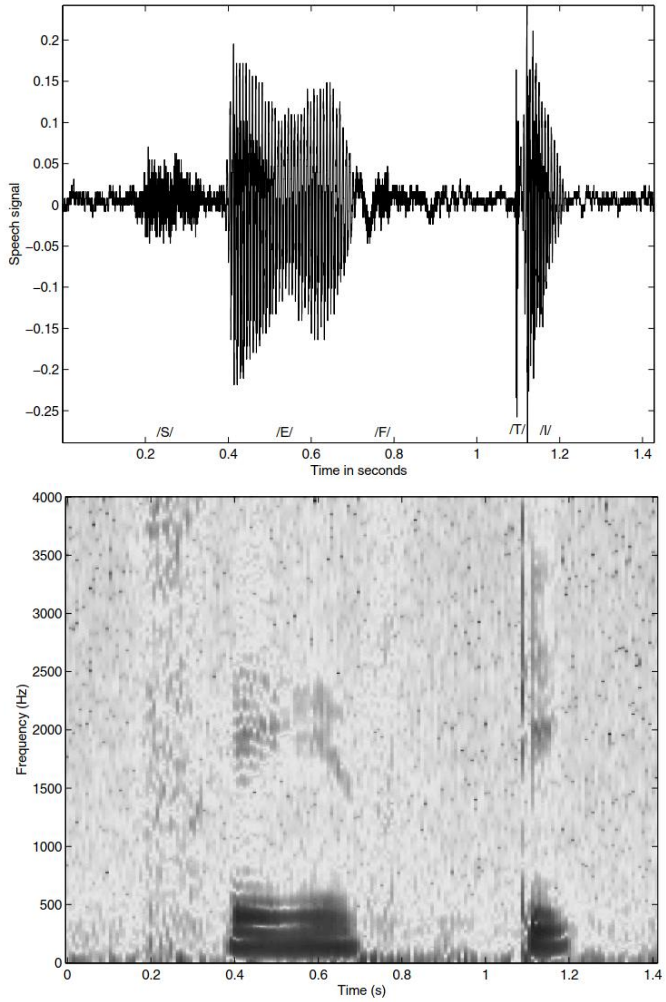
Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

STFT – Analysis window

- We may advance the window (with size *M*):
  - M samples at a time: no overlap
  - One sample at a time: adjacent windows have an overlap of $(M-1)$ samples.
  - $\frac{M}{2}$ samples at a time: an overlap of $\frac{M}{2}$ samples
- Some overlap is desirable in order to maintain continuity
- Duration of the segment (M): the window should be
  - Short enough to ensure that the segment is stationary
  - Long enough to permit meaningful analysis of low-frequency components
- We cannot simultaneously obtain arbitrarily high resolution along both the time and frequency axes

Example – Speech signal (1)

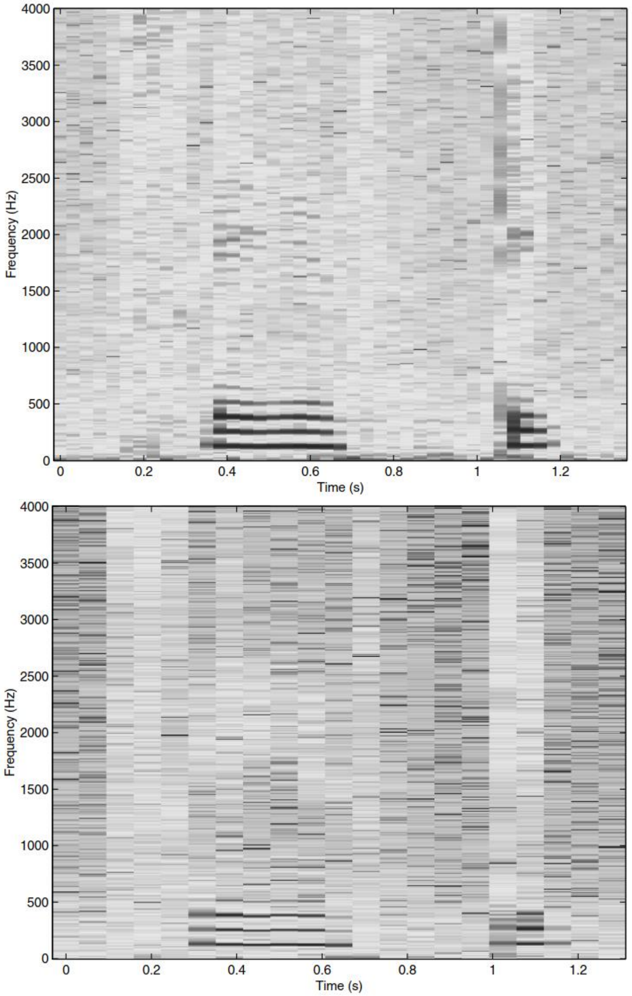
- The speech signal (fs = $8\ kHz$) of the word "Safety"
- In the spectrograms, the darkness at each point being proportional to the log PSD
- The analysis window duration is 16 ms (128 samples)
- The window advance interval is 8 ms
- The high-frequency nature of the fricatives is indicated (and plosive).



Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

Example – Speech signal (2)

- In the upper figure:
  - The window duration is 64 ms (512 samples)
  - The window advance interval is 32 ms
- In the lower figure:
  - The window duration is 128 ms (1024 samples)
  - The window advance interval is 64 ms
- Increasing the length of the analysis window provides better frequency resolution while at the same time reducing the temporal resolution
- Decreasing the window length causes the reverse effects

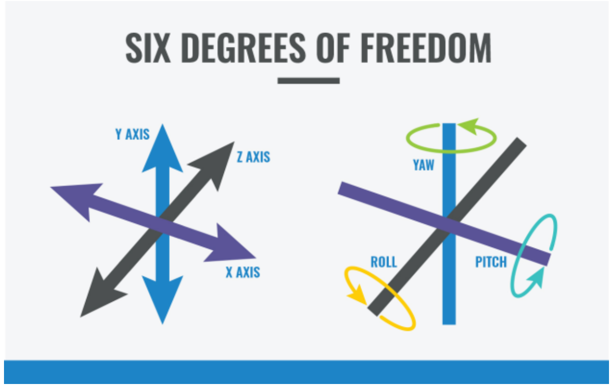


Rangayyan, R. M. *Biomedical signal analysis*. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

Analysis of SCG and GCG

SCG and GCG

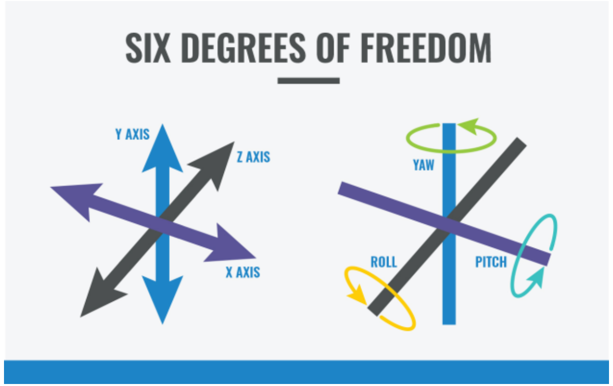
- Seismocardiography (SCG) is recorded by attaching an accelerometer to the chest approximately on top of the heart
- Gyrocardiography (GCG) is a similar technique for capturing rotational movement of the chest caused by the mechanical activity of the heart



https://www.ceva-dsp.com/ourblog/what-is-an-imu-sensor/

SCG and GCG together

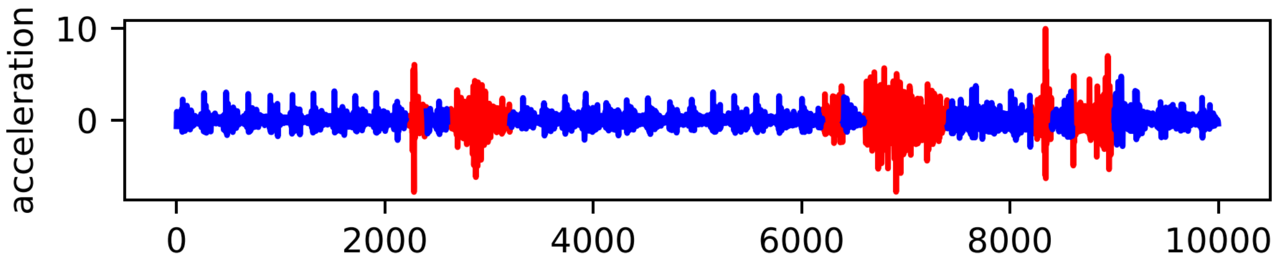
- Nowadays, we usually record both SCG and GCG signals. This results in a 6-dimensional signal value. In other words, 3 values for X,Y, and Z axis of acceleration and 3 values for X, Y, and Z axis of angular motion



https://www.ceva-dsp.com/ourblog/what-is-an-imu-sensor/

SCG and GCG preprocessing

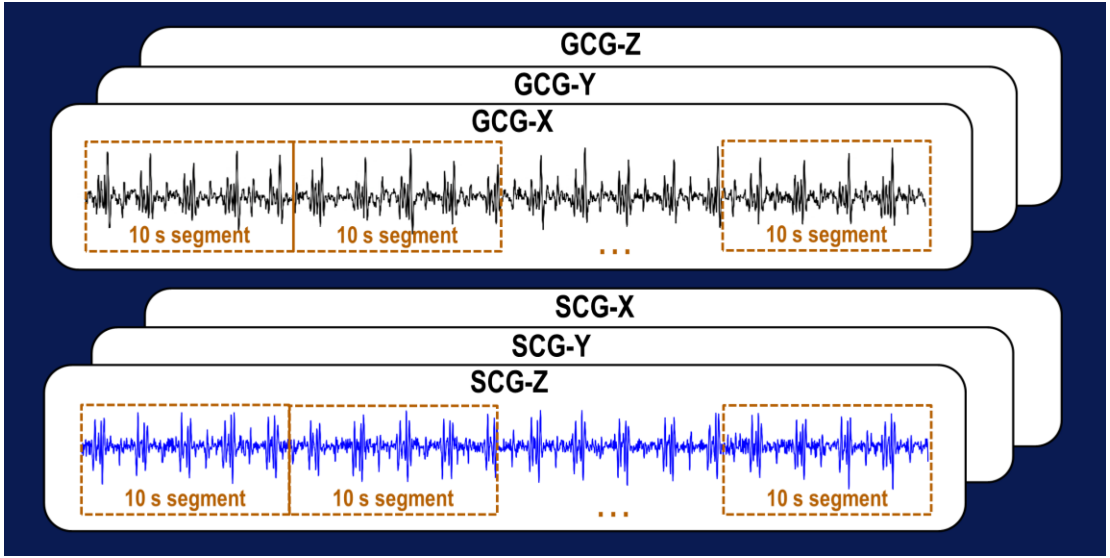
- ❑ Baseline wander and noise removal
  - ▪ filtering with Butterworth filter of order 4 and pass band 3-40 Hz
- ❑ Motion artifact rejection
  - SCG is a motion tracking technique. If human body moves during SCG collection, there will be motion artefacts
    - Body movement and chest movements



Mehrang, Saeed, et al. "Machine Learning Based Classification of Myocardial Infarction Conditions Using Smartphone-Derived Seismo-and Gyrocardiography." *2018 Computing in Cardiology Conference (CinC)*. Vol. 45. IEEE, 2018.

Segmentation prior feature extraction

- Here we have SCG and GCG signals segmented by 10-second segments

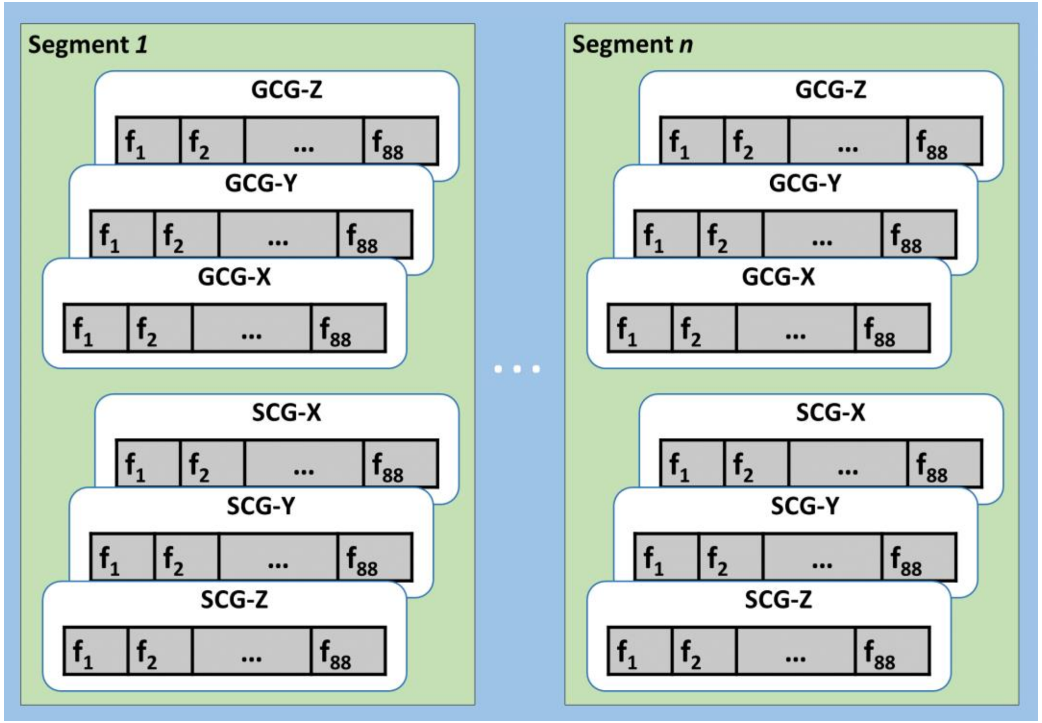


Feature extraction (1)

- ❑ Time domain analysis
  - Mean, standard deviation, median, interquartile range, entropy, zero crossing, cross-correlation, auto-correlation, mutual information, complexity, mobility, etc.
- ❑ Frequency domain analysis
  - Dominant frequency in Fourier domain, Fourier transform entropy, relative Fourier energy entropy, relative energy of each axis, etc.
- ❑ Time-frequency domain analysis
  - Short Time Fourier Transform (STFT)

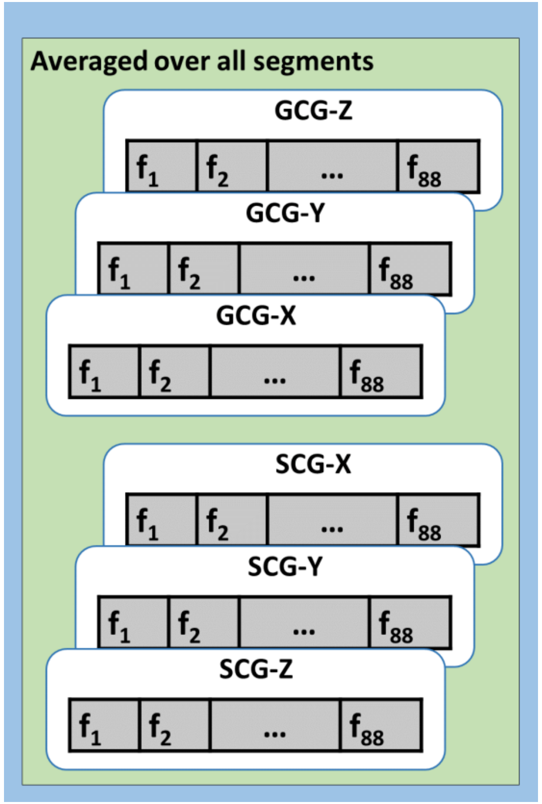
Feature extraction (2)

- For instance, 88 Features are extracted from each segment in each axis.



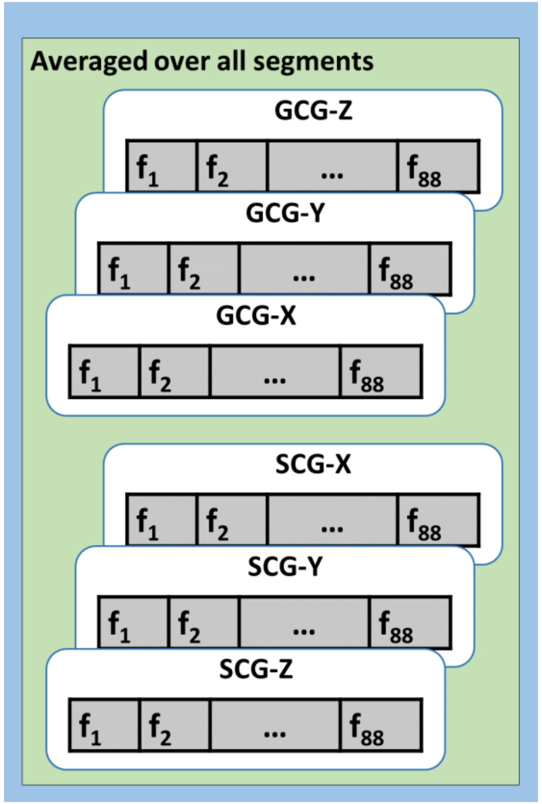
Averaging over all segments

- Averages will be calculated for each feature in each axis over the segments
- f_1 in GCG-Z is the average value of f_1 over all segments. This applies to all the other 5 axes.



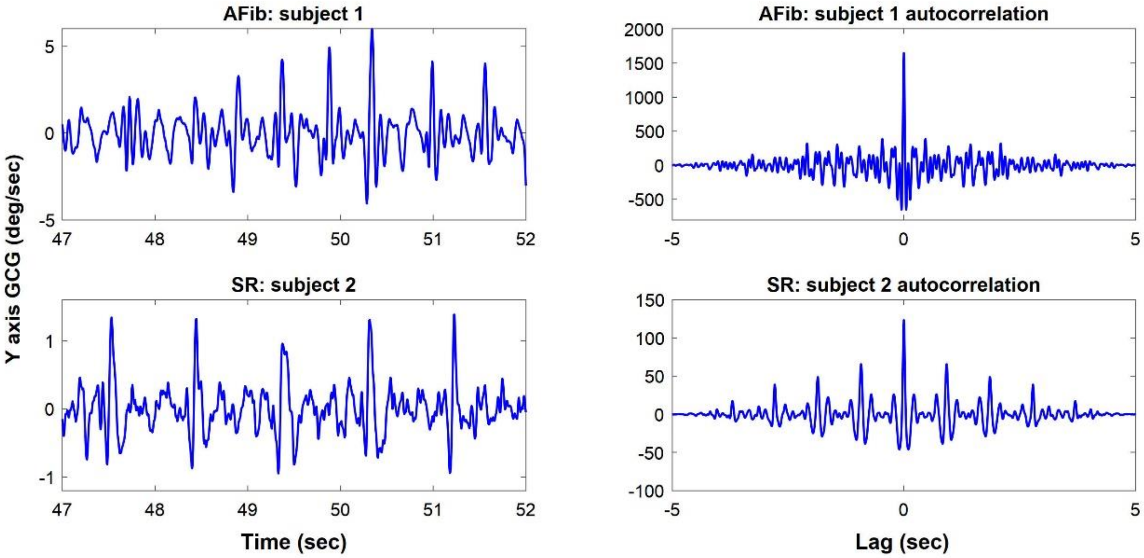
Why averaging?

- We need a robust view of a measurement
  - Random noise is removed
- In every measurement, we segment the signals into shorter episodes, extract features, and then average the features to get a robust view of every feature.



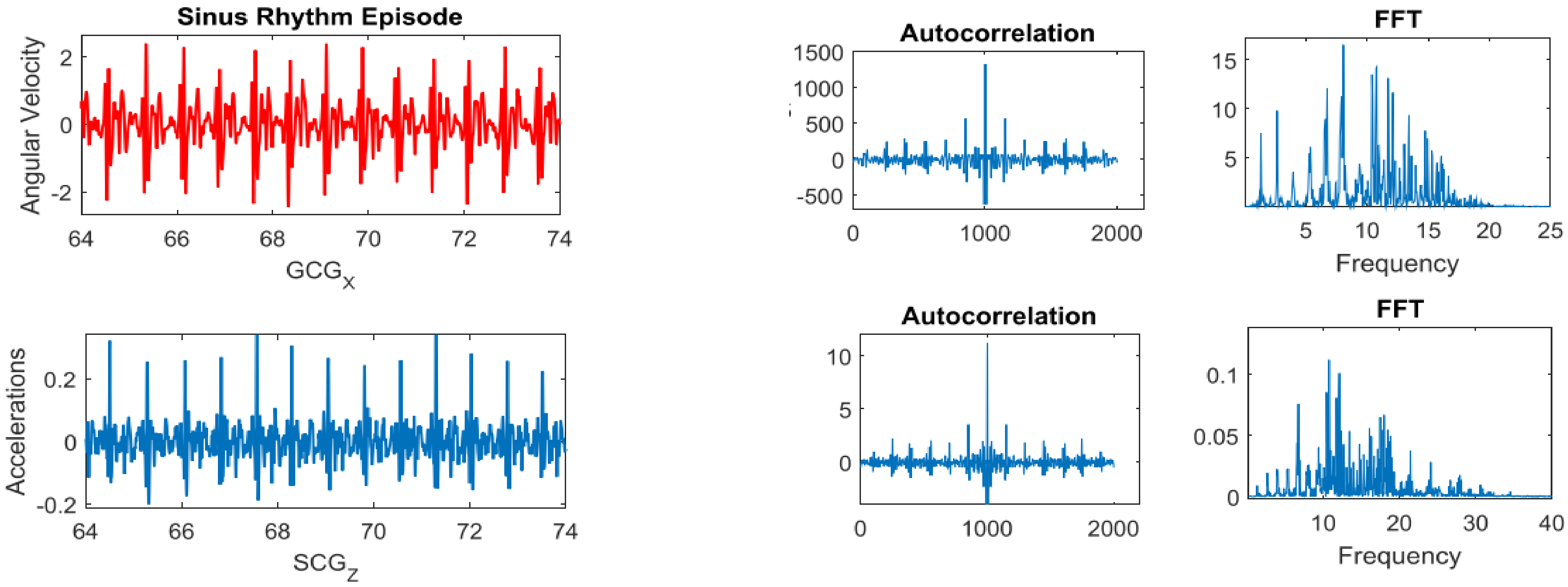
Autocorrelation (time domain)

- Auto-correlation for arrhythmia (atrial fibrillation) detection



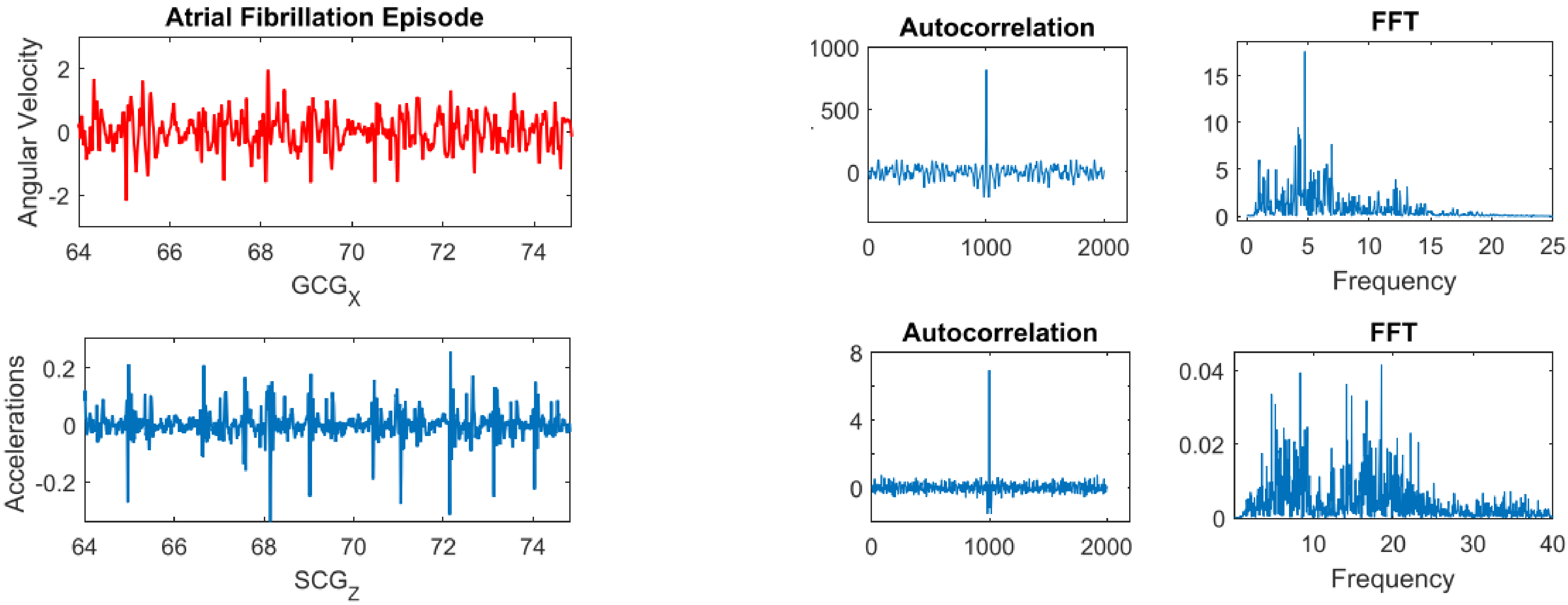
Mehrang, Saeed, et al. "Reliability of Self-Applied Smartphone Mechanocardiography for Atrial Fibrillation Detection." *IEEE Access* 7 (2019): 146801-146812.

Autocorrelation and DFT – Normal



- Tadi, Mojtaba Jafari, et al. "Comprehensive Analysis of Cardiogenic Vibrations for Automated Detection of Atrial Fibrillation Using Smartphone Mechanocardiograms." *IEEE Sensors Journal* 19.6 (2018): 2230-2242.
- https://www.dspguide.com/ch11/5.htm

Autocorrelation and DFT – Atrial fibrillation



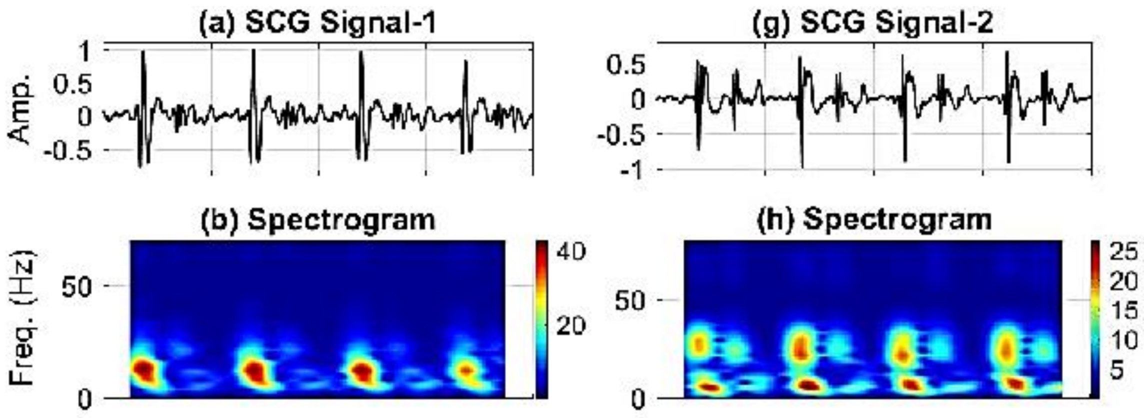
Tadi, Mojtaba Jafari, et al. "Comprehensive Analysis of Cardiogenic Vibrations for Automated Detection of Atrial Fibrillation Using Smartphone Mechanocardiograms." *IEEE Sensors Journal* 19.6 (2018): 2230-2242.

Frequency domain analysis

- **Dominant frequency:** the frequency that has the greatest magnitude in the Fourier domain.
  - Note that the DC frequency cannot be dominant frequency. We need to remove DC frequency before calculating dominant frequency.
  - Dominant frequency in sub-segments of a signal
  - Variations of dominant frequency among sub-segments: this parameter resembles heart rate variability but it is measured in frequency domain instead of time domain.

Time-frequency domain analysis

- **Spectrogram:** it helps us getting a view of time-frequency domain within a segment. Below are two short segments of SCG signals and their spectrograms.



Choudhary, Tilendra, L. N. Sharma, and M. K. Bhuyan. "Spectracentrogram: A Time-Frequency Distribution for Signal Processing Applications." 2018 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS). Vol. 3. IEEE, 2018.

Classification and Decision-making

Feature extraction

- Different features can be extracted from the biosignals:
  - ECG: RR interval, Duration of the ST segment, etc.
  - EMG: RMS value, turns count, etc.
  - SCG: mean, standard deviation, dominant frequency
- The features show the characteristics of the events
- The classification methods are utilized to categorize the events.
  - The inputs are the features
  - The output shows
    - if there is a disease or not
    - or the type of the disease

Rule-based methods

- The rule-based methods are any classification scheme that make use of IF-THEN rules for classification
- Rules can be set by experts or extracted from the data (depending on the application)
- There is a rule for each sample
- The data is classified using the rules

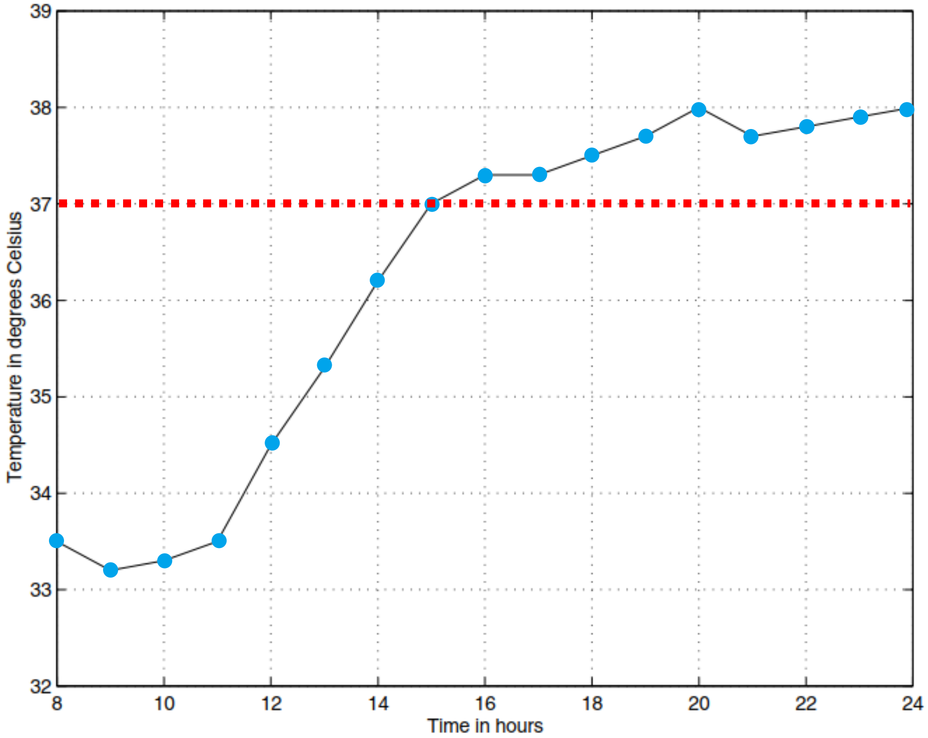
Example – simple threshold

Most infections cause a rise in the body temperature (BT)

Our measurement is discrete => ***x(n)***

$$\boldsymbol{x}(\boldsymbol{n}) = [\boldsymbol{x_1}\ \boldsymbol{x_2}\ \boldsymbol{x_3} \ldots \boldsymbol{x_N}]$$

E.g., to detect a disease: if the value of BT is higher than a threshold (e.g., 37ºC)



Rangayyan, R. M. Biomedical signal analysis. 2nd Edition, Vol. 33. John Wiley & Sons, 2015.

Example – Early Warning Score

- Monitoring of vital signs allows early-detection of health deterioration.
- Early Warning Score (EWS) is a scoring method used in hospitals for assessment of patients' conditions.
- Higher scores are statistically linked to increased likelihood of health deterioration.

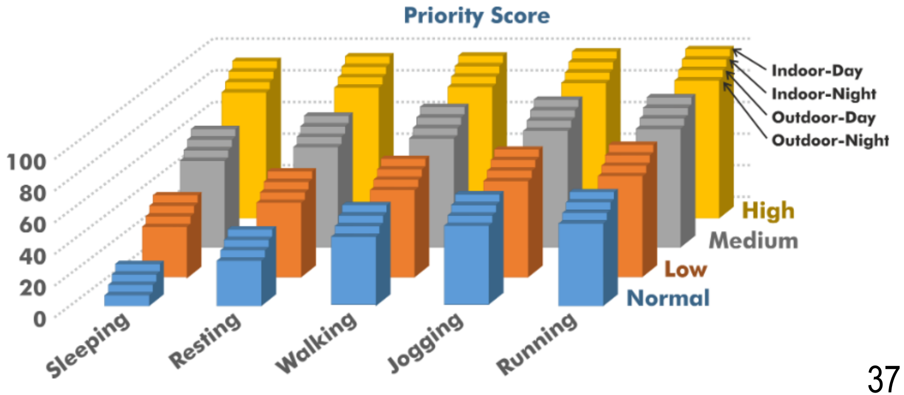
Physiological parameters	3	2	1	0	1	2	3
Respiration rate (breaths/minute)		0-8		9-14	15-20	21-29	30+
Oxygen saturation (%)	0%-84%	85%-89%	90%-94%	95%-100%			
Temperature (oC)		0-35		35.1-38.0		38.1-39.5	39.6+
Systolic BP (mmHg)	0-69	70-80	81-100	101-149	150-169	170-179	180+
Heart rate (beats/minute)	0-39	40-50	51-59	60-100	101-110	111-129	130+
Level of consciousness				A	V	P	U

* A=Alert, V=response to voice, P=response to pain, U=unresponsive

Alam, N., et al. "The impact of the use of the Early Warning Score (EWS) on patient outcomes: a systematic review." Resuscitation 85.5 (2014): 587-594.

Example – Early Warning Score – Cont.

- Remote health monitoring systems includes sensors with limited resources (batteries)
- **From the system perspective:** A trade-off between energy-efficiency and measurement accuracy is needed
- A look-up table can be defined to reconfigure the system in a real-time fashion by observing the **EWS values**, **physical activity**, and **environmental situation**.
- More details can be found:
  - Anzanpour, A. et al., 2017, March. Self-awareness in remote health monitoring systems using wearable electronics. In Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017 (pp. 1056-1061). IEEE.



Machine learning

- ❑ Machine learning techniques learn from examples data and past experience to perform specific tasks
  - E.g., categorize events into different classes
- ❑ Machine learning can extract models from the observation
  - Models can be defined as relationships between the variables (features) that describe the events.
- ❑ Trained models are used for the test data (to classify or predict)

Two references:

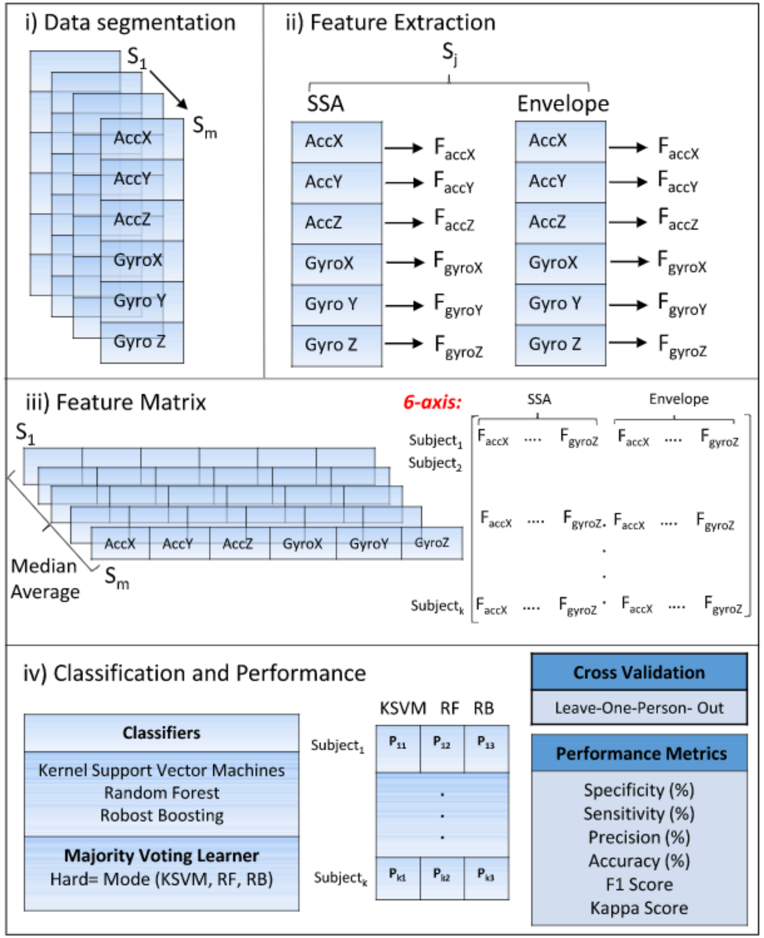
- Yaser S. Abu-Mostafa, Malik Magdon-Ismail, and Hsuan-Tien Lin. 2012. Learning from Data. AMLBook.
- Thomas Mitchell. 2012. Machine Learning. McGraw-Hill Education - Europe

Use in healthcare

- ❑ Abnormity (Disease) detection
  - If the input data is normal vs abnormal
  - Classify the diseases
- ❑ Body functions evaluation
  - E.g., neuromuscular system
- ❑ System optimization
- ❑ Others

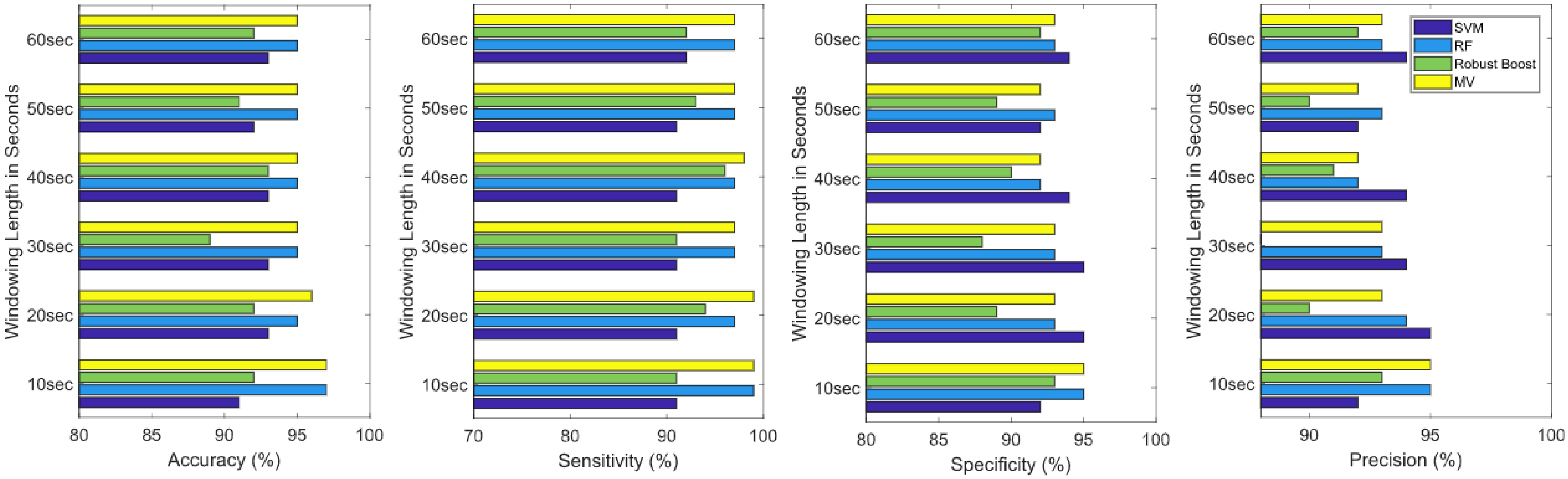
Example - Atrial fibrillation detection using SCG-GCG

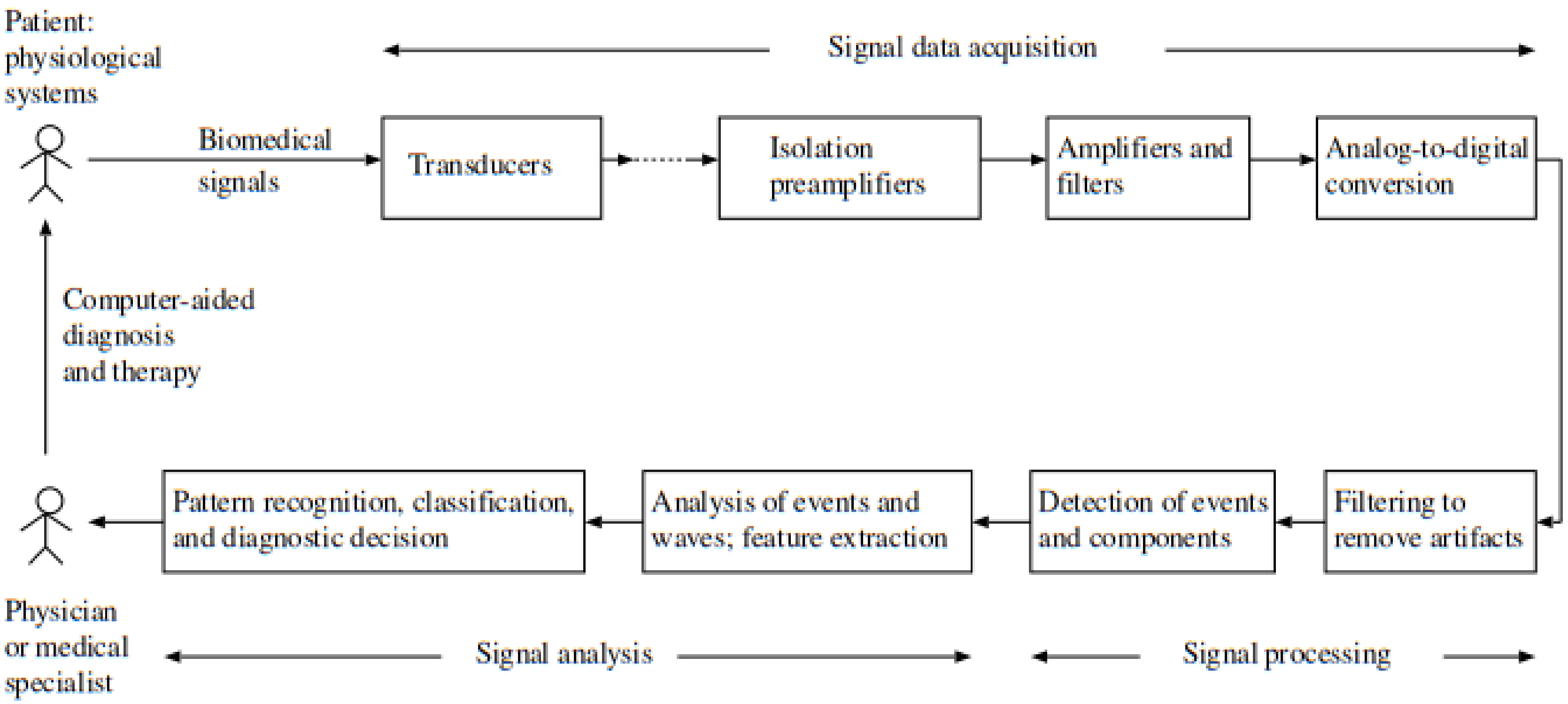
- Jafari Tadi, M. et al. "Comprehensive Analysis of Cardiogenic Vibrations for Automated Detection of Atrial Fibrillation Using Smartphone Mechanocardiograms." IEEE Sensors Journal 19.6 (2018): 2230-2242.
- Early diagnosis of AFib is a key step in the prevention of stroke and heart failure
- The SCG and GCG signals are collected from 435 users, including 190 AFib and 245 sinus rhythm cases, using a smartphone.
- The data analysis pipeline includes:



Example - Atrial fibrillation detection using SCG-GCG – Cont.

- Classification performance in the cross-validation study with three classifiers and majority voting





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Conclusion

In this session, we learned about:

- ❑ Time-frequency analysis
- ❑ Analysis of SCG and GCG
- ❑ Classification and decision-making

In the next lecture, we will have:

- ❑ A visiting lecturer from the Digital Health Technology group (UTU)
- ❑ Principal Component Analysis: a case study on finding respiration signal in high-dimensional sensor data

Thank You

Questions?

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