

# Acquisition and Analysis of Biosignals

## DTEK0042

### Biosignal analysis II

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# Introduction

So far, we learned:

- ☐ Objectives of biomedical signal analysis
- ☐ Correlation techniques (e.g., EEG)
- ☐ Waveform analysis and feature extraction in biosignals (e.g., ECG)

In this session, we will learn:

- ☐ Frequency domain analysis
- ☐ Analysis of PPG
- ☐ Waveform analysis of EMG and PCG

# Biosignal analysis

- ❑ Biomedical signals carry signatures of physiological events
- ❑ The objective is to use **different time-domain and frequency domain techniques** to analyze these events
  - Differentiate normal events from abnormal events
- ❑ The features are selected with respect to the biosignals and applications

# Frequency domain analysis

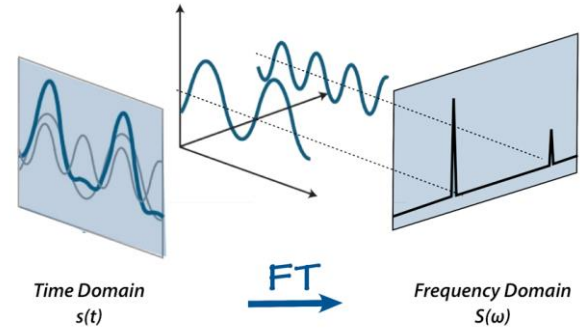
# Frequency domain features

- ❑ Many biomedical systems exhibit rhythms that are more readily expressed in terms of frequency than temporal measures
  - E.g., Heart cycle
  - E.g., EEG rhythms
- ❑ Features are extracted from the amplitude or energy of the signal as a function of frequency

# Fourier Transform

- ❑ **Fourier Transform:** decomposes a function of time (a *signal*) into its frequencies

$$X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t} dt$$



<http://mriquestions.com/fourier-transform-ft.html>

- ❑ **Discrete-time Fourier Transform:**

$$X(\omega) = \sum_{n=-\infty}^{\infty} x(n)e^{-i\omega n}$$

- ❑ **Inverse FT/ Inverse DTFT:** transform a continuous or discrete spectrum into a function for the amplitude with the given spectrum
- ❑ **Fast Fourier Transform** is an efficient algorithm for computing the Discrete Fourier Transform.

# Energy / power of the signal

- ❑ Let's consider the signal as  $x(t)$
- ❑ The **energy distribution** or **density function** is defined as  $x^2(t)$  where  $0 \leq t \leq T$
- ❑ The total energy of the signal is:

$$E_x = \int_0^T x^2(t) dt$$

$$E_x = \sum_{n=0}^K x^2(n)$$

- ❑ Power is the energy of a signal divided by the signal length

# Power Spectral Density (PSD)

## ❑ Power Spectral Density (PSD)

- shows the signal's power content as a function of frequency
- Fourier transform of the auto-correlation

## ❑ PSD can be calculated using Welch's method<sup>1</sup>:

1. The time signal is divided into successive blocks,
2. Computing the discrete Fourier transform of each block and then computing the squared magnitude of the result
3. Averaging

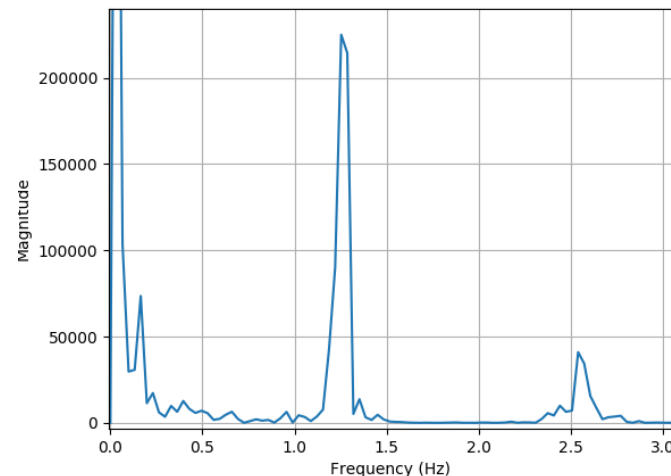
$$S_{xx} = \frac{1}{M} \sum_{m=0}^{M-1} |DFT(x_m)|^2 \triangleq \{|X_m(\omega_k)|^2\}_m$$

<sup>1</sup> Welch, P., 1967. The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. IEEE Transactions on audio and electroacoustics, 15(2), pp.70-73.



# PSD analysis

- ❑ We may study the shape of the spectrum graphically and observe its general characteristics
- ❑ Since the PSD is a nonnegative function, we may readily treat it as a PDF, and compute statistics using moments.
  - Moments of PSDs may be useful in characterizing the general trends in the distribution of the power of a signal over its bandwidth
  - The higher-order moments are sensitive to noise in the PSD estimate and may not be reliable measures if the PSD pattern is not simple
- ❑ We may also detect peaks corresponding to resonance, measure their bandwidth, and derive measures of concentration of power in specific frequency bands of interest.



# Moments of PSD – Mean (1)

- Mean frequency is a useful measure of the concentration of signal power

The diagram illustrates the formula for the mean frequency  $\overline{f_{Hz}}$  in terms of the sampling frequency  $f_s$ , the number of samples  $N$ , the discrete-time Fourier transform (DTFT) coefficients  $X(k)$ , and the total power  $E_x$ . Red arrows point from descriptive text labels to the corresponding parts of the equation.

$$\overline{f_{Hz}} = \frac{f_s}{N} \frac{2 \sum_{k=0}^{N/2} k S_{xx}(k)}{E_x}$$

Annotations:

- Sampling frequency** points to  $f_s$ .
- PSD of  $x(n)$**  points to  $S_{xx}(k)$ .
- Number of samples in the DFT-based representation of the PSD** points to  $N$ .
- Total power of the signal** points to  $E_x$ .

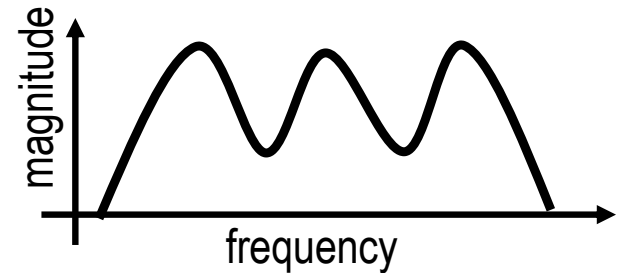
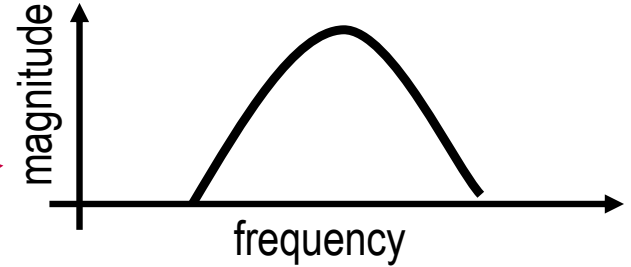
The total power  $E_x$  is defined as:

$$E_x = \frac{1}{N} \sum_{k=0}^{N-1} |X(k)|^2$$

# Moments of PSD – Mean (2)

## □ Mean frequency:

- Indicates the resonance frequency in the case of unimodal distributions.
- Not useful when PSD is uniform
- Not useful when there are multiple resonance frequencies (Multimodal PSD)



# Moments of PSD - Median

- ❑ Median frequency is the frequency which splits the PSD in half:
- ❑ Median frequency:

$$f_{med} = \frac{m}{N} f_s$$

With the largest  $m$  that:

$$\frac{2}{E_x} \sum_{k=0}^m S_{xx}(k) < \frac{1}{2}; \quad 0 \leq m \leq \frac{N}{2}$$

# Moments of PSD - Variance

□ Variance:

$$f_{m2} = \left(\frac{f_s}{N}\right)^2 \frac{2 \sum_{k=0}^{N/2} (k - \bar{k})^2 S_{xx}(k)}{E_x}$$

Frequency sampling index corresponding to the mean frequency

$$\bar{k} = N \frac{\bar{f}_{Hz}}{f_s}$$

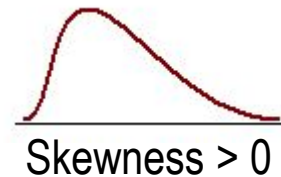
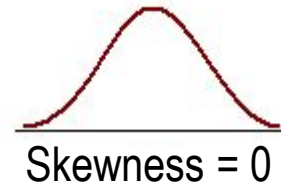
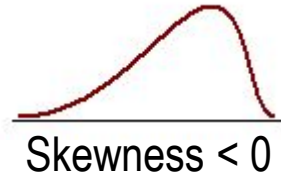
□ Standard deviation (root of variance) provides a measure of spectral spread

# Moments of PSD - Skewness

- ❑ Skewness is a measure of the asymmetry
- ❑ Skewness is zero if the density function is symmetric about the mean frequency

$$Skewness = \frac{f_{m3}}{(f_{m2})^{3/2}}$$

$$f_{m3} = \left(\frac{f_s}{N}\right)^3 \frac{2 \sum_{k=0}^{N/2} (k - \bar{k})^3 S_{xx}(k)}{E_x}$$

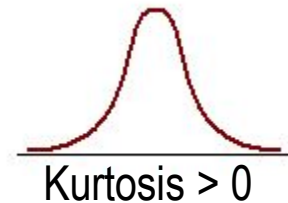
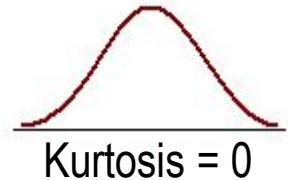
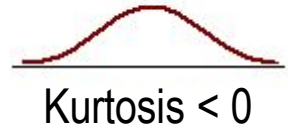


# Moments of PSD - Kurtosis

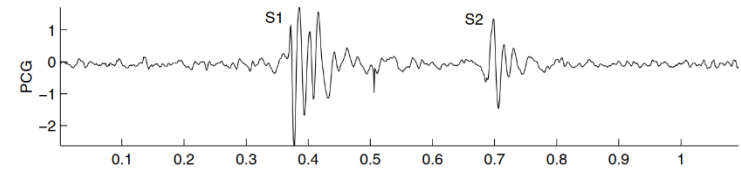
□ Kurtosis indicates if the PSD is a long-tailed function

$$Kurtosis = \frac{f_{m4}}{(f_{m2})^2}$$

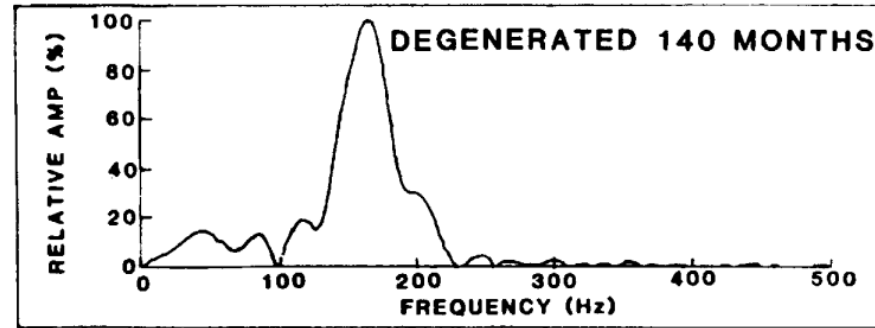
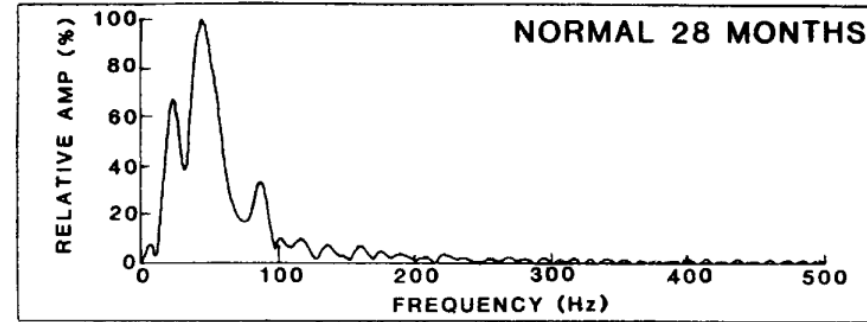
$$f_{m4} = \left(\frac{f_s}{N}\right)^4 \frac{2 \sum_{k=0}^{N/2} (k - \bar{k})^4 S_{xx}(k)}{E_x}$$



# Example – PSD of PCG



- ❑ Power spectra of S1 in the case of normal and degenerated porcine (pig) bioprosthetic valves implanted in the mitral position
- ❑ The increased stiffness is expected to lead to higher-frequency components in the opening or closing sounds of the valve



Durand, L.G., et al., 1990. Comparison of pattern recognition methods for computer-assisted classification of spectra of heart sounds in patients with a porcine bioprosthetic valve implanted in the mitral position. IEEE Transactions on Biomedical Engineering, 37(12), pp.1121-1129.



# Note

❑ Such statistical analysis can be used for time-domain analysis

- Waveform analysis

❑ Examples:

- PPG
- EEG
- Acceleration data

# Power band

- ❑ The power of the signal in a given frequency band  $[f_1, f_2]$  can be computed as

$$\frac{2}{E_x} \int_{f=f_1}^{f_2} |X(f)|^2 df$$

Or

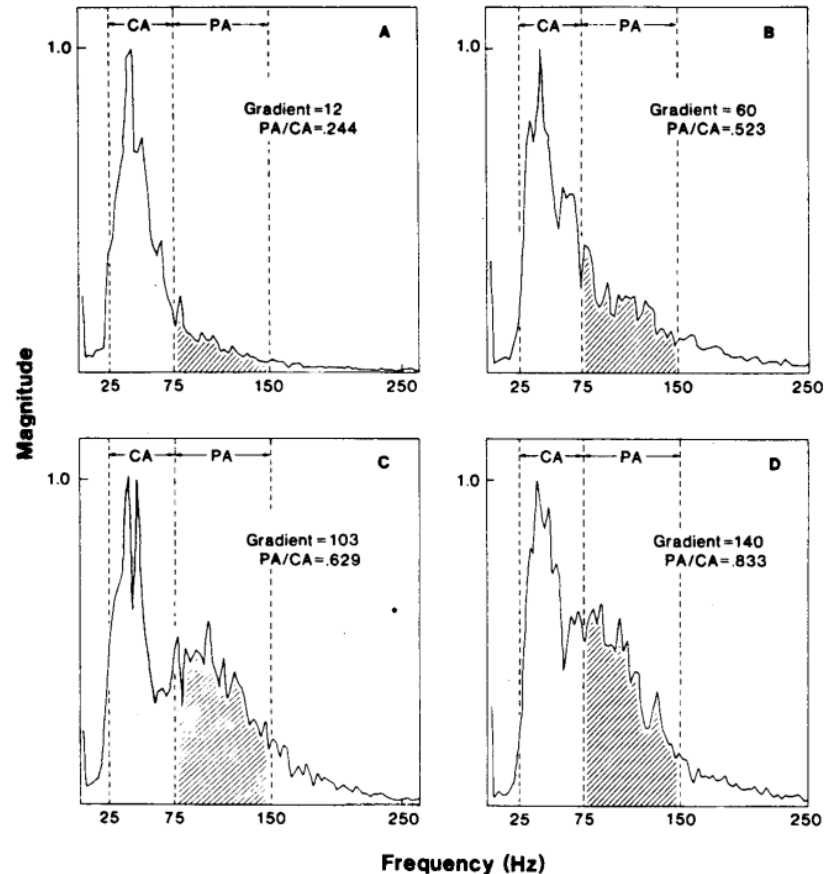
$$\frac{2}{NE_x} \sum_{k=k_1}^{k_2} |X(k)|^2$$

**$k_1$  and  $k_2$  are the DFT indices corresponding to  $f_1$  and  $f_2$**

- ❑ Spectral power ratios also provide information
  - E.g., diagnostic purposes

# Example – PSD of PCG

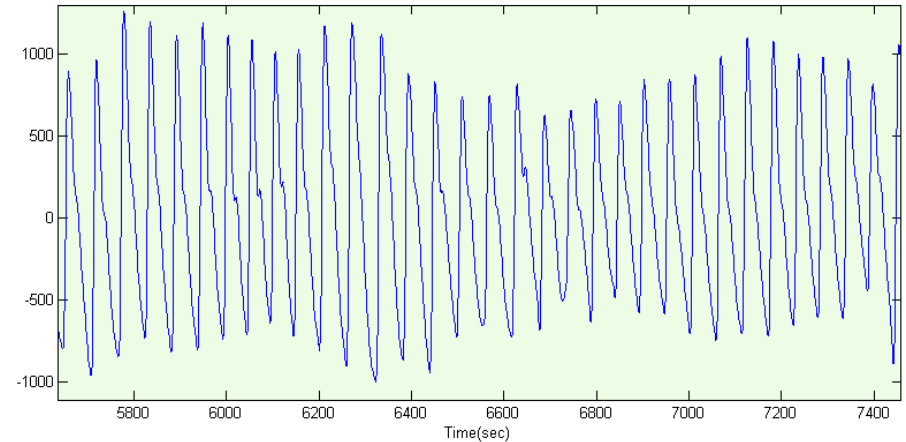
- ❑ Synchronized averaging of the PSDs of PCG signals over several cardiac cycles
- ❑ PSDs of four patients with aortic stenosis of different levels of severity
- ❑ Constant Area (CA) is related to normal sounds and Predictive Area (PA) is related to murmurs
- ❑ The ratio correlates well with the severity of aortic stenosis



# Analysis of PPG

# PPG signal

- ❑ PPG is the signal which indicates blood volumetric changes in the tissue
- ❑ PPG includes various health information:
  - Extract vital signs

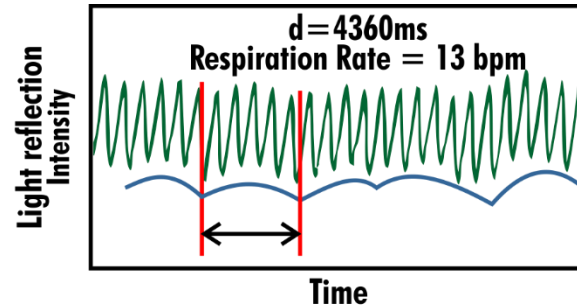
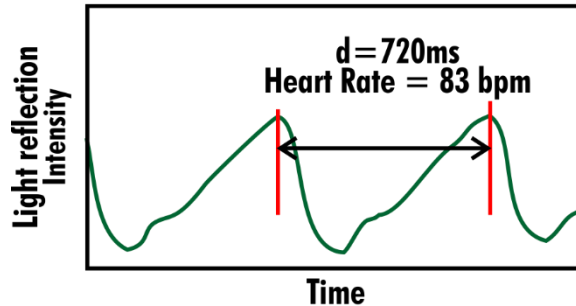


<https://en.wikipedia.org/wiki/File:PPG.PNG>

# PPG – heart rate and respiration rate

❑ The PPG variations<sup>1,2</sup> are related to:

- Heart cycles
- Respiration cycles => slowly varying baseline or low frequency components



❑ The oscillations can be investigated by spectral analysis of the signal

- Calculating the DFT or PSD of the signal

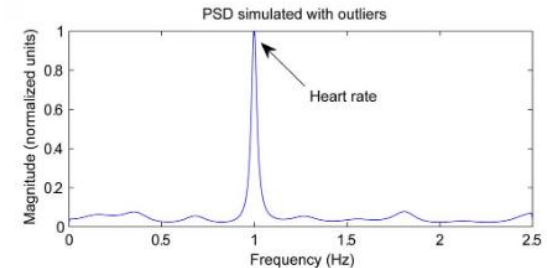
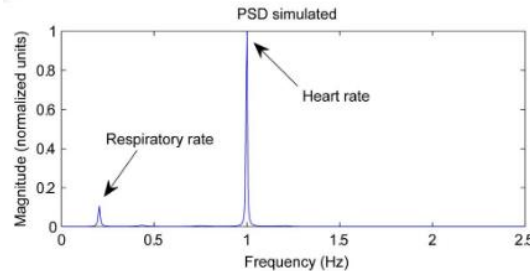
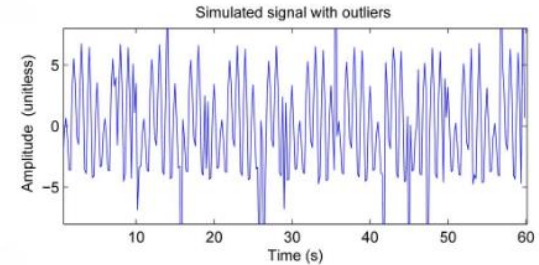
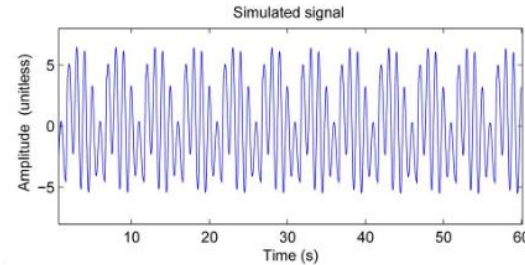
<sup>1</sup> Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological measurement*, 28(3), R1.

<sup>2</sup> Anzanpour A. et al., Edge-Assisted Control for Healthcare Internet-of-Things: A Case Study on PPG-based Early Warning Score, *ACM Transactions on Internet of Things*, 2020.

# Spectral analysis of PPG

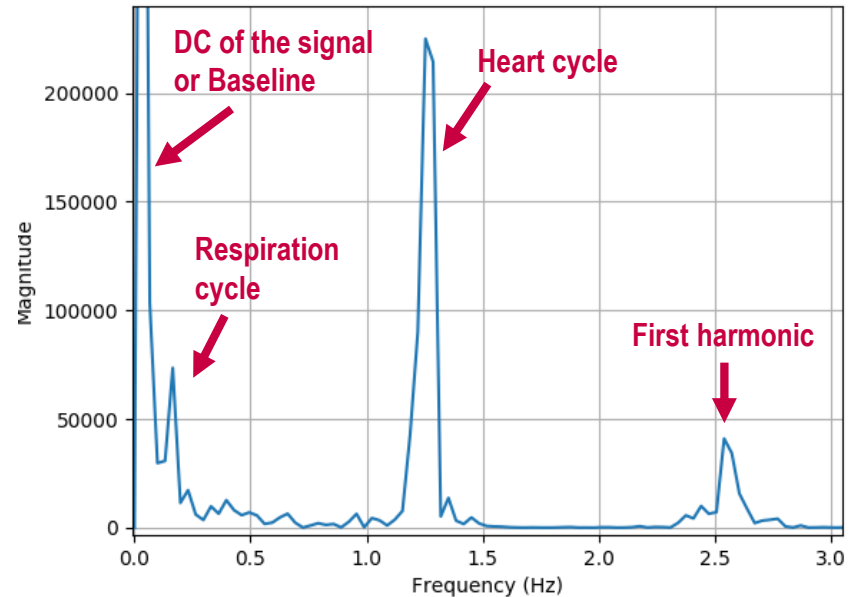
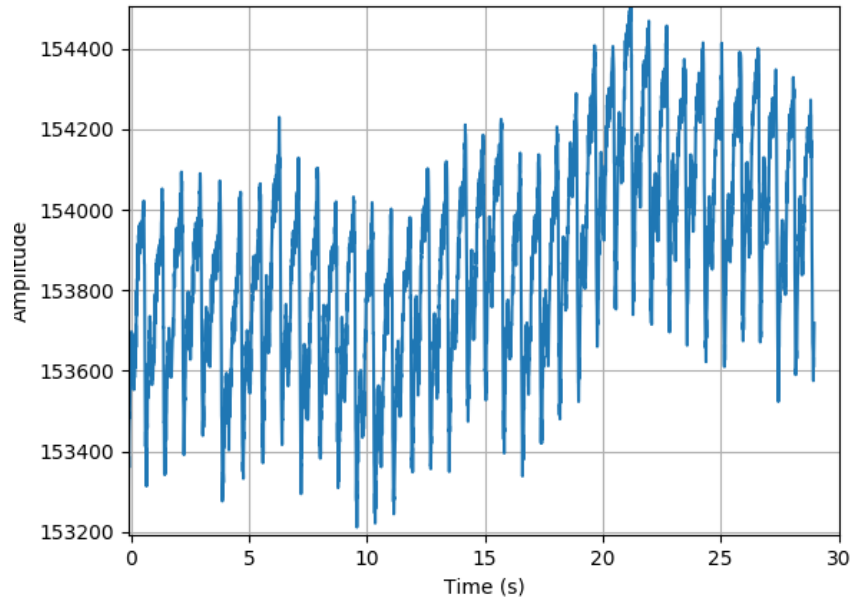
- ❑ The respiration and heart cycles can be tracked in the frequency domain
- ❑ Features can be extracted:
  - Dominant frequencies of heart and respiration cycles => Real-time heart/respiration rate detection
- ❑ However, noise might cover the respiration

**Simulated signal with 0.2 Hz modulation respiratory frequency (12 breaths/min), 1 Hz cardiac frequency (60 beats/min)**



# Heart rate and respiration rate

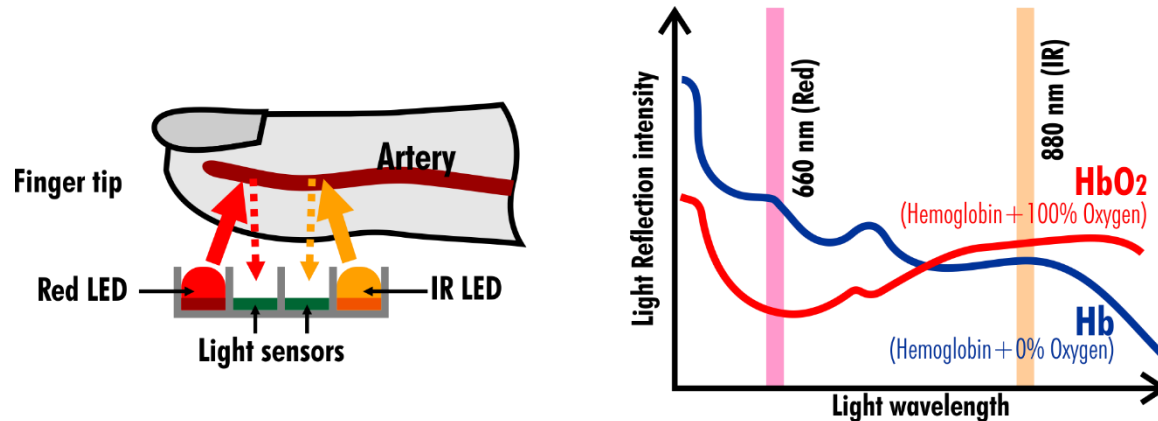
□ PPG signal (IR) and PSD of the signal





# PPG - SpO<sub>2</sub> (1)

- ❑ SpO<sub>2</sub>, also known as oxygen saturation, is the amount of oxygen-carrying hemoglobin in the blood relative to the total hemoglobin
- ❑ Red and infrared light are used



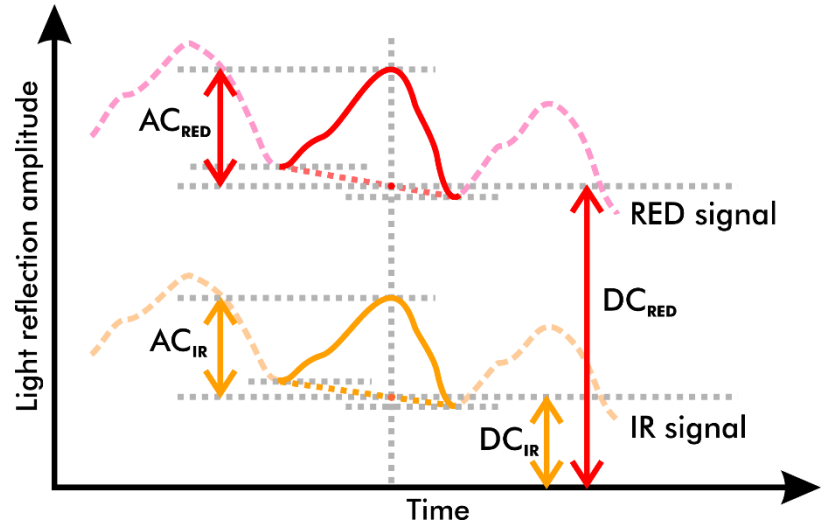
# PPG - SpO<sub>2</sub> (2)

- SpO<sub>2</sub> is calculated from the alternative currents and direct currents of the IR and red signals

$$R = \frac{AC_{red} \cdot DC_{IR}}{AC_{IR} \cdot DC_{red}}$$

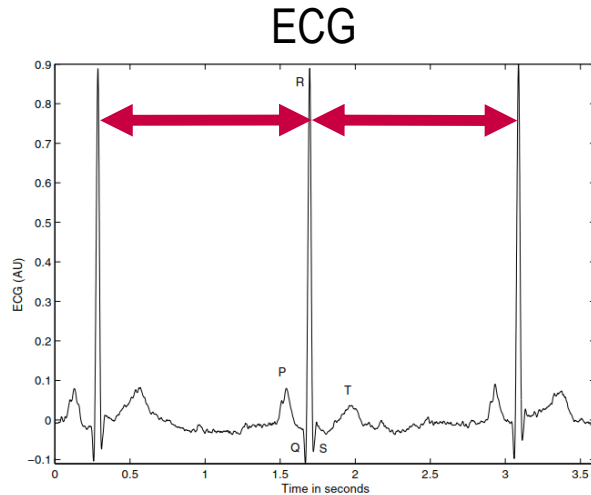
$$SpO_2 = \alpha R^2 + \beta R + \gamma$$

$\alpha$ ,  $\beta$ ,  $\gamma$  and are constants retrieved from the sensor's specification

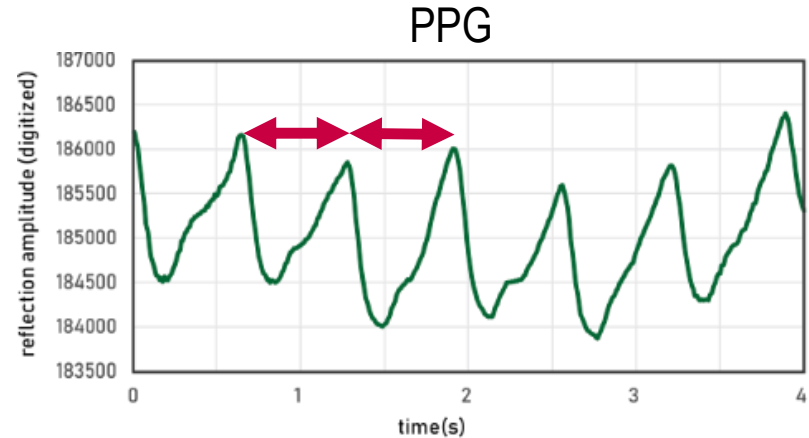


# Interbeat interval (IBI)

- ❑ Interbeat interval (IBI) is the time interval between two successive peaks in the signal



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



Anzanpour A., Amiri D., Azimi I., Levorato M., Dutt N., Liljeberg P., Rahmani A., Edge-Assisted Control for Healthcare Internet-of-Things: A Case Study on PPG-based Early Warning Score, ACM Transactions on Internet of Things, 2020.

# Heart rate variability – time domain

□ From the **HRV** signal, different time-domain parameters <sup>1</sup> can be extracted:

1. Root Mean Square of Successive RR-interval Differences (RMSSD)
  - Values can be affected by age, stress, diseases, etc.
2. Standard deviation of NN intervals (SDNN)
3. Percentage of successive RR intervals that differ by more than 50 ms
  - Diagnostic information in a wide range of conditions (e.g., lower in hypertensive patients)

# Heart rate variability – frequency domain

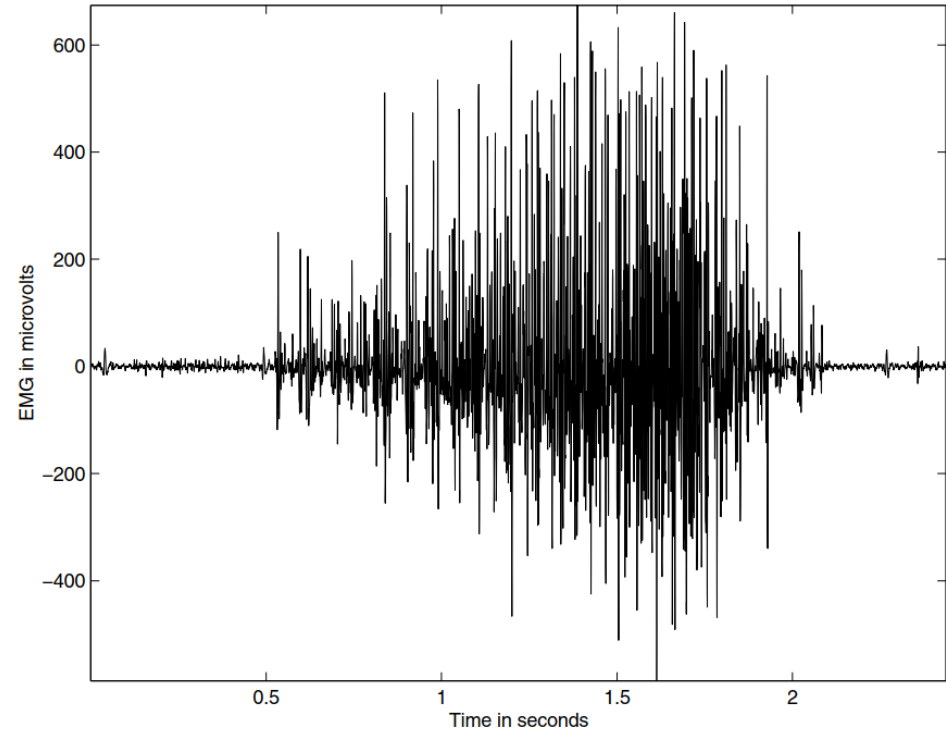
□ From the **HRV** signal, different frequency-domain parameters <sup>1</sup> can be extracted:

1. Absolute power of the very-low-frequency band (0.0033–0.04 Hz)
2. Absolute power of the low-frequency band (0.04–0.15 Hz)
3. Absolute power of the high-frequency band (0.15–0.4 Hz)
4. Ratio of LF-to-HF power

# Waveform analysis of PCG and EMG

# EMG and PCG waveform analysis

- ❑ Signals with complex patterns such as the EMG and PCG may not permit direct analysis of their wave shape
- ❑ In these signals, the general trends in the level of the overall activity might be important

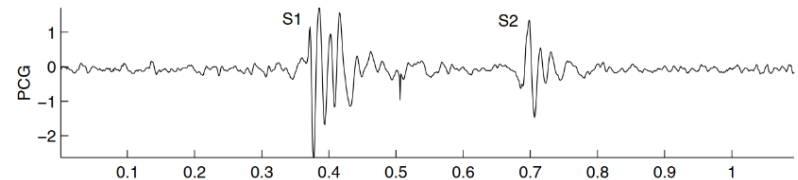


# The RMS value

- ❑ The root-mean-square (RMS) value shows average power of the signal

$$RMS(n) = \left[ \frac{1}{M} \sum_{k=0}^{M-1} x^2(n-k) \right]^{\frac{1}{2}}$$

- ❑ M is size of the window which is much less than duration of the signal.
- ❑ The RMS is for short-time analysis of nonstationary signals
- ❑ It can be used to identify systolic and diastolic segments of the signals



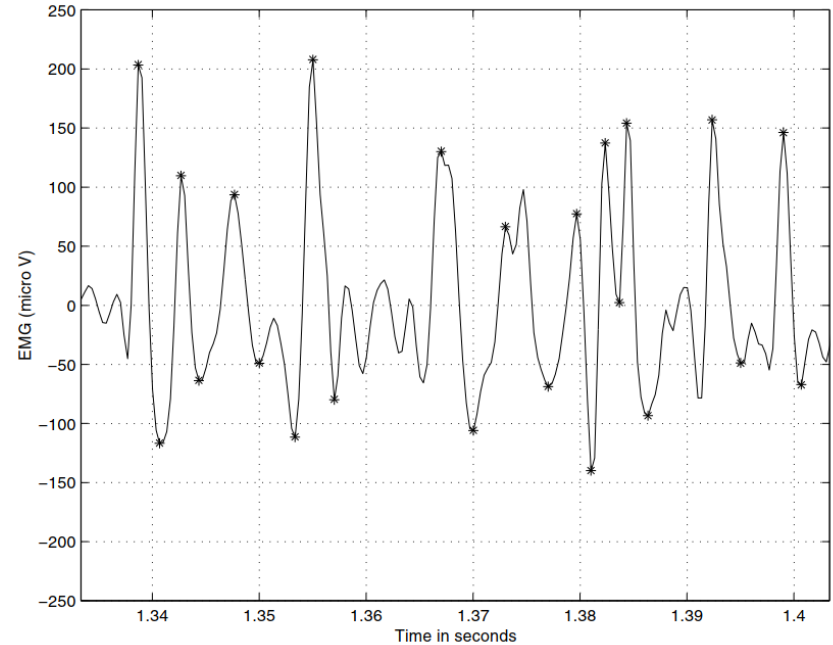


# Zero crossing rate

- ❑ It is the number of times the signal crosses the reference (e.g., zero-activity line) within a specified interval
- ❑ It could be easily affected by DC bias or baseline wander.
- ❑ ZCR has been used in practical applications such as
  - Speech signal analysis to perform speech-versus-silence decision and to discriminate between voiced and unvoiced sounds
  - PCG analysis for the detection of murmurs

# Turns count

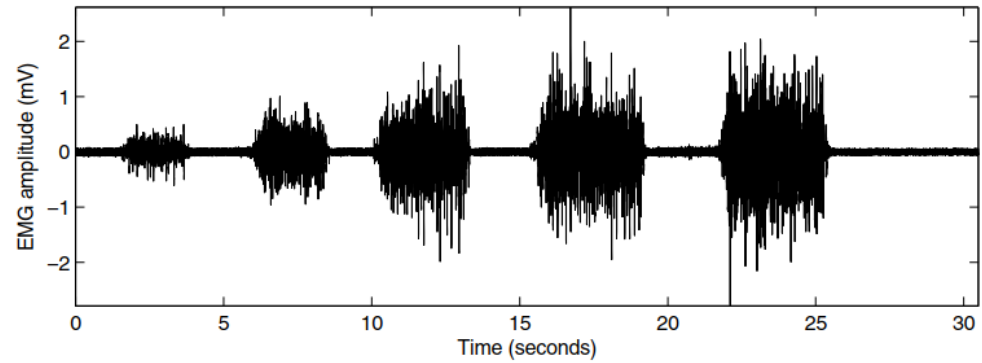
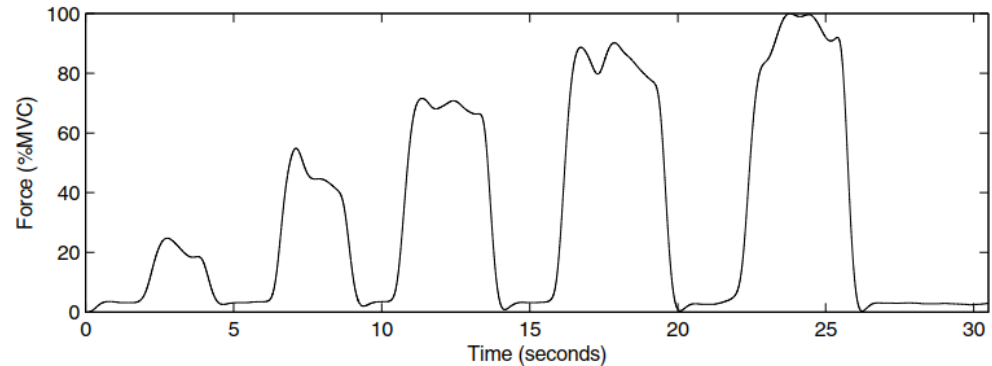
- ❑ It is the number of turning point in the signal
- ❑ Turns that are greater than a threshold is considered to avoid fluctuations due to noise
- ❑ It can be used to analyze the level of activity in EMG signals



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

# Example – EMG (1)

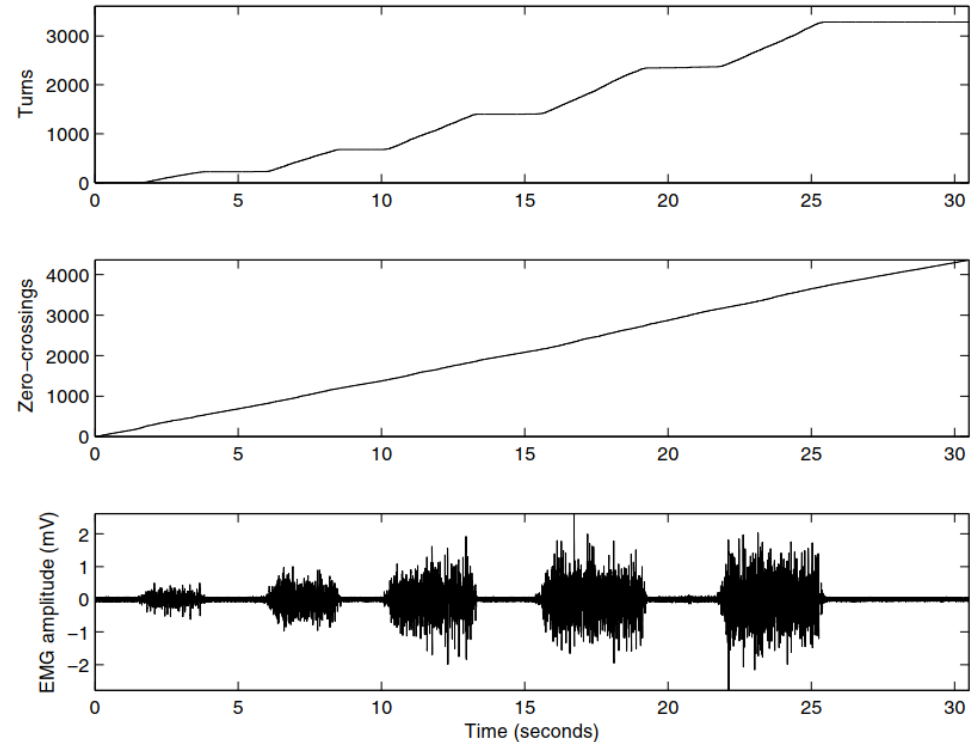
- ❑ Force and EMG signals recorded from the forearm muscle of a subject
- ❑ Contractions using a gripping device



# Example – EMG (2)

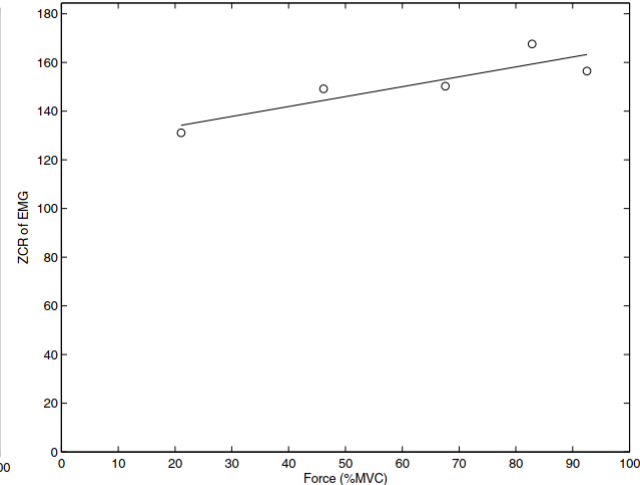
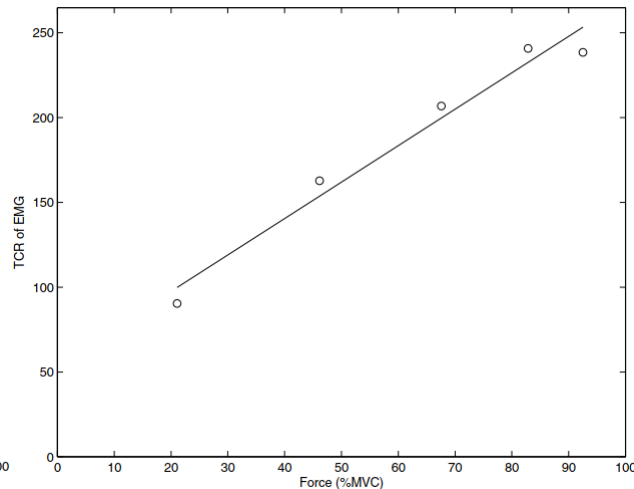
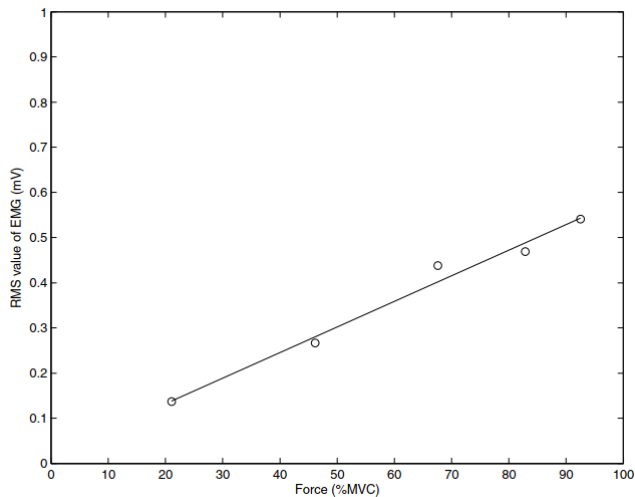
- ❑ The cumulative number of significant turns detected increases **only** during the periods of contraction and not during the periods of rest.
- ❑ Therefore, in this example, turns count is a better indicator of muscular force in comparison to zero-crossing rate

Cumulative count of zero-crossings, and cumulative number of significant turns



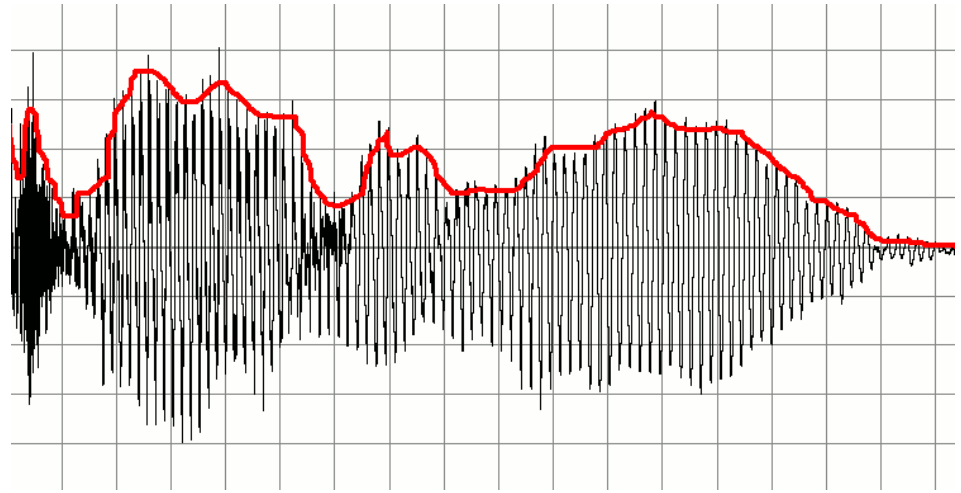
# Example – EMG (3)

□ Variation of the RMS value, Turns count and Zero-crossing rate in EMG in each contraction



# Envelope of the signal (1)

- ❑ The **envelope** of the overall signal carries important information
- ❑ It represents the total averaged activity
- ❑ In this feature, high-frequency variations may not be of interest



[https://en.wikipedia.org/wiki/File:C\\_Envelope\\_follower.png](https://en.wikipedia.org/wiki/File:C_Envelope_follower.png)

# Envelope of the signal (2)

- ❑ The envelope of a signal is to obtain the absolute value of the signal at each time instant
- ❑ This procedure will create abrupt discontinuities at time instants when the original signal values change sign
- ❑ The discontinuities create high-frequency components of significant magnitude. This calls for the application of a lowpass filter with a relatively low bandwidth in the range of 0–10 or 0–50 Hz

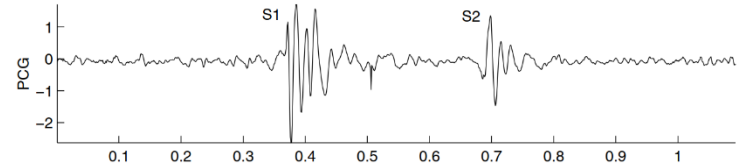
# Envelope extraction

□ There are different methods to extract the envelope of the signal:

1. Synchronized averaging
2. Amplitude demodulation
3. The envelopogram
  - Using Hilbert transform
  - The magnitude of the analytic signal



# Synchronized averaging of PCG envelopes



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

## ❑ In this method:

1. The PCG signal is smoothed using a low-pass filter
2. The heart cycles are extracted
  - ECG signal can be used to detect the position of S1
3. Synchronized averaging is performed

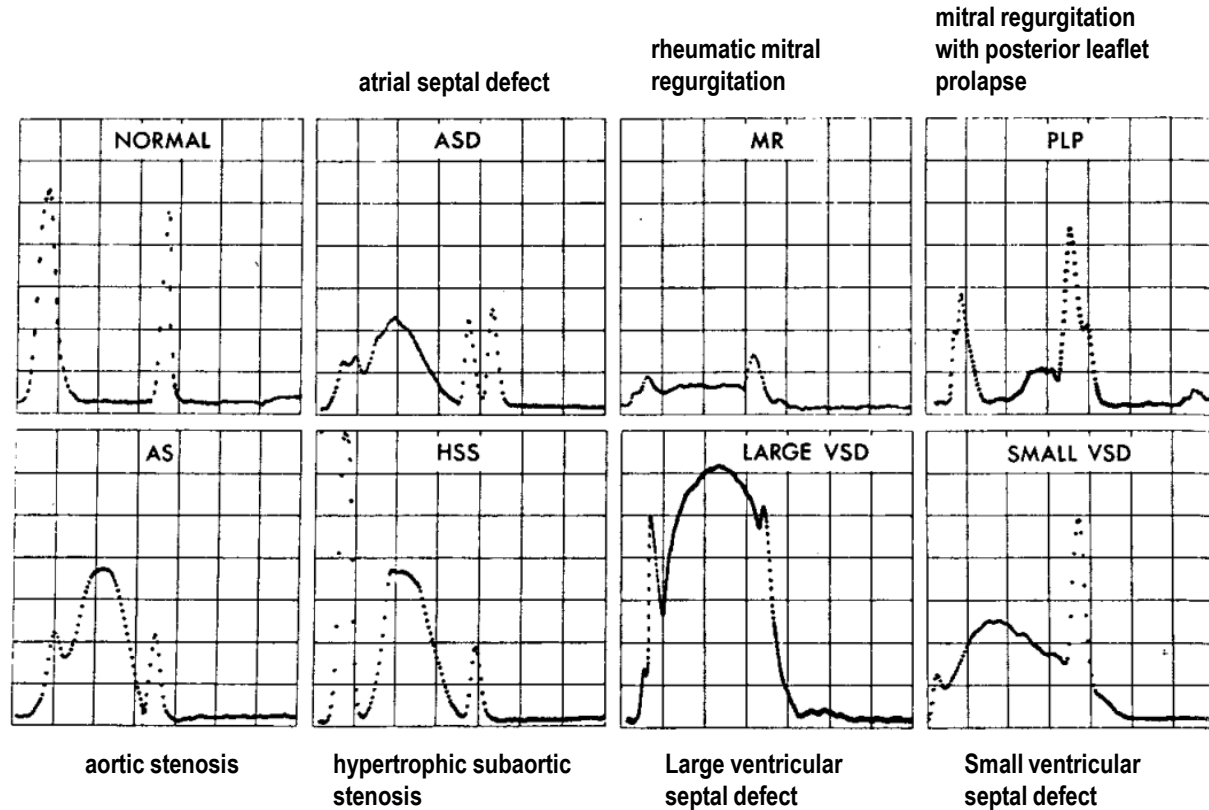
The output is the envelop

## ❑ The PCG envelopes were averaged over up to 128 heart cycles to get repeatable averaged envelopes

- Reduce the effects of noise but the time boundaries of heart events are blurred if the heart rate is not constant during the averaging procedure

# Example 1

- ❑ Averaged envelopes of the PCG signals of a normal subject and patients with diseases
- ❑ Different features can be extracted from the envelopes:
  - Number of peaks
  - Duration
  - Height



# Example 2

- ❑ EMG signal over two breath cycles from the parasternal intercostal and diaphragm muscles of a dog recorded via implanted electrodes
- ❑ The envelop is correlated with the inspiratory airflow
- ❑ Respiration rate can be obtained using a peak detection method



**The envelop of EMG signal**



**Inspiratory airflow**

# Conclusion

In this session, we learned about:

- ❑ Frequency domain analysis
- ❑ The analysis of different signals, including PCG, PPG, and EMG

In the next lecture, we will learn about:

- ❑ Time-Frequency Analysis
- ❑ Analysis of SCG and GCG
- ❑ Classification techniques

**Thank You**  
Questions?



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