Pázmány Péter Catholic University
Faculty of Information Technology and Bionics

Biomedical Signal Processing
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Event detection

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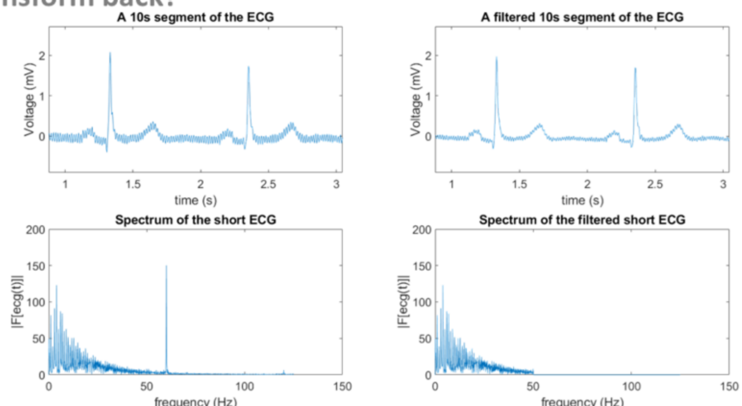
An interesting question from lab

- **Why don't we simply multiply by zero the unwanted frequencies, and transform back?**



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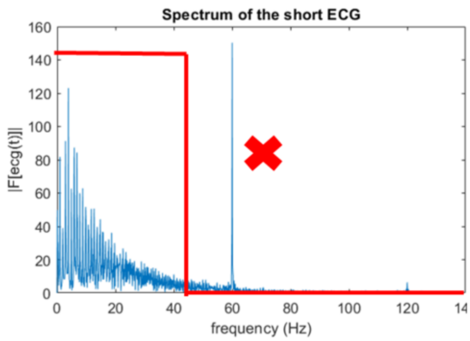
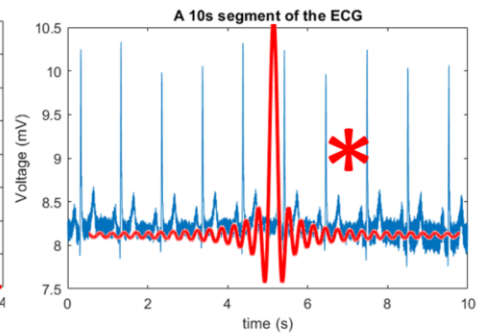
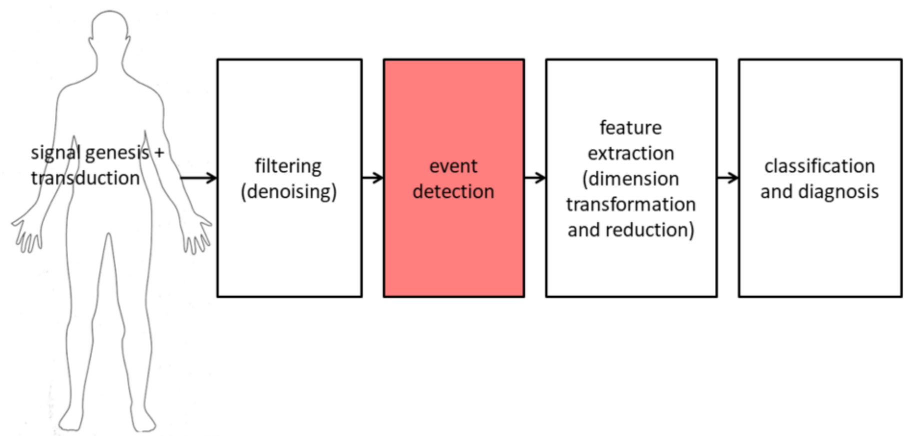




The BSP Flow Chart



Today’s goal

- **What events can interest us?**
- **Getting to know the classical detection pipeline:**
  - Linear filtering
  - Envelope detection (non-linear transformation
  - Decision rules:
    - Adaptive thresholding
    - Pan Tompkins algorithm
    - Hidden Markov

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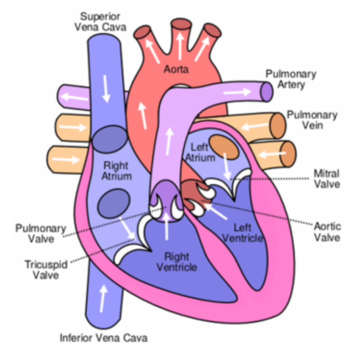
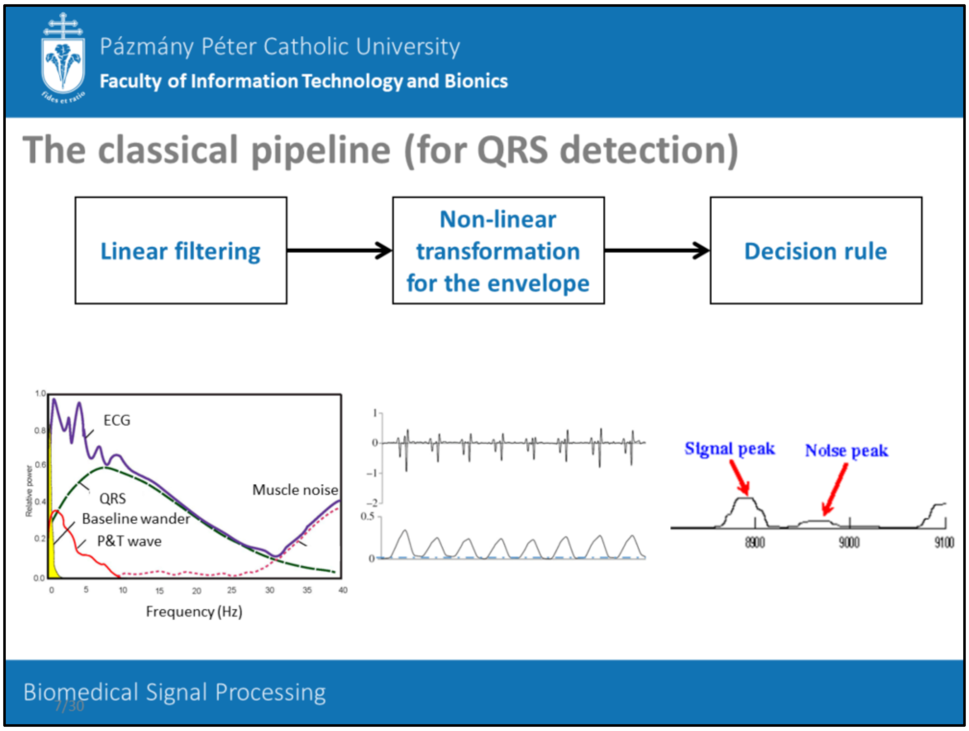
Motivation

- **Detect events – e.g. QRS complex**
- **Separate superimposed events**
  - S_1: bicuspid and tricuspid AV
  - S_2: aortic and pulmonary
  - intramuscular/cortical EMG/EEG



Detection:
Finding ‚events’, like the QRS complex, muscle contraction, dichroitic notch…

Separation:
In the S1 sound both the closure of the bi- and tricuspid valves can be heard. Similarly in S2 the aortic and pulmonary valves close simultaneously. In an EEG signal facial muscles can compromise the signal, like EOG last time.
In event detection one task can be to separate these events.



The classical pipeline

Linear filtering:

- remove noise, EMG signal and other ECG signal components (P-wave, T-wave)
- center frequency of QRS: 10-25 Hz
- bandwidth: 5-10 Hz

Non-linear transformation to detect the envelope of the signal:

- Finding the local energy
- Hilbert transformation

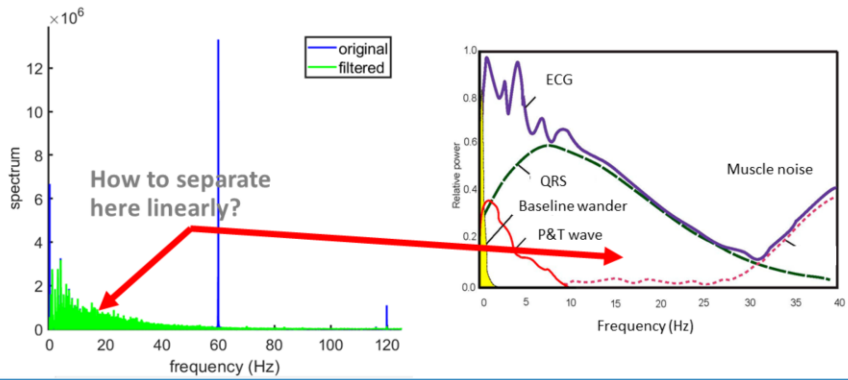
Decision rule:

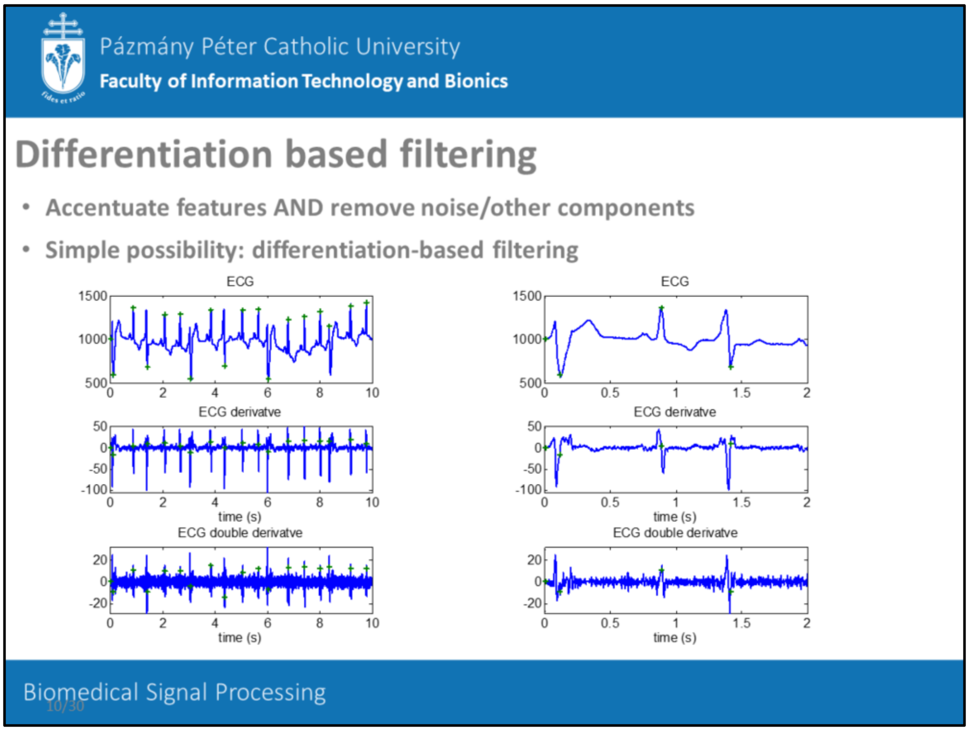
- Is the peak of the envelope above a set threshold?
- Or adaptive thresholding

LINEAR FILTERING

Linear filtering

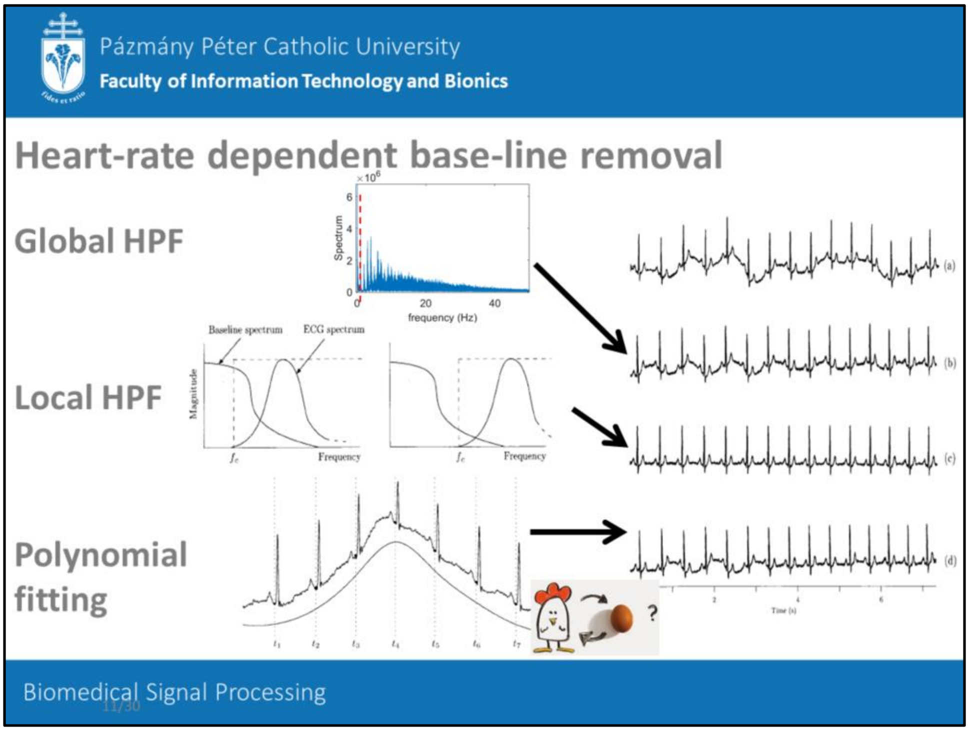
- Filters from previous class,
  eg. Butterworth bandpass/bandstop filters





Noise and ,other components can be viewed equally, it deends only on your point of view.

Why is it good, why not?
For accentuating the sharp changes in the QRS complex (10-25 Hz), and smoothing the lower frequency components (P&T ~0Hz, baseline wander ~<1 Hz) a differentiation can be useful. However, higher frequency noise will be also amplified, as visible above.



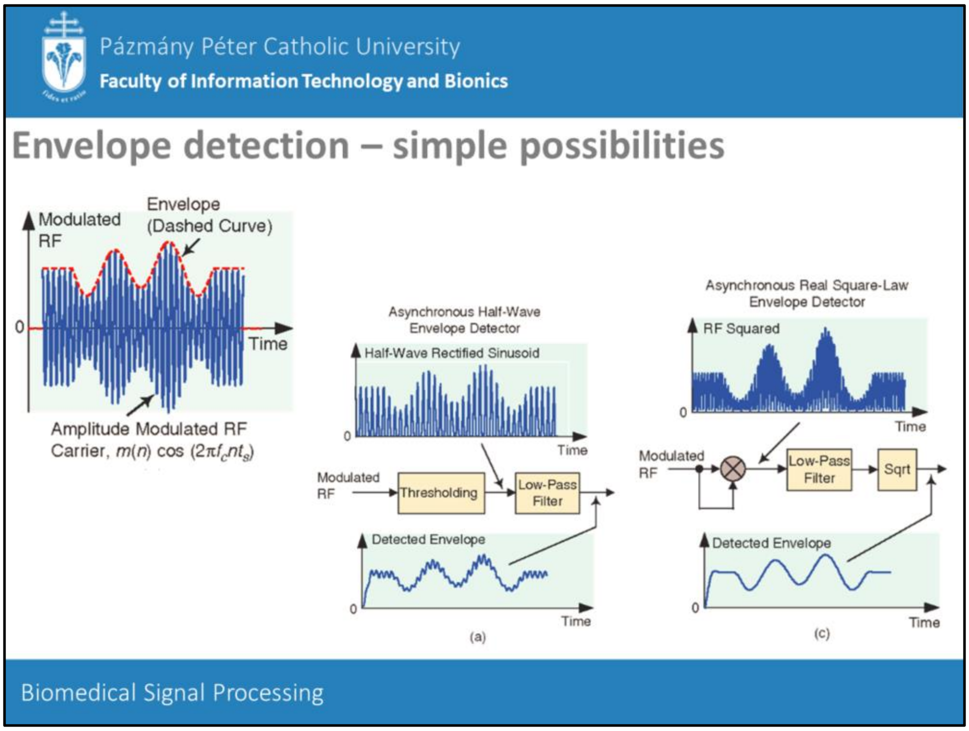
How to remove the baseline wander (caused by breathing and/or cable movement)
The baseline wander is well visible in the top line of the figure on the left. The frequency of the wander varies, just like the heart rate, making the two frequency bands sometimes to overlap

1.) in the second row a simple time-invariant HPF is used, filtering out frequencies above the threshold. However, the overlapping baseline and QRS bands can not be separated.

2.) For solving the overlap, adaptive filtering can be used. When the heartrate is higher, the QRS band will be shifted. With different heartrates a different threshold for the separation is efficient,, as depicted on the middle left image. If we detect the heartrate thorough the ECG recording, the threshold can be set adaptively.

3.) Another method uses the found events. The Q peaks are fitted onto a polynomial, and this polynomial is substracted from the signal.
This is kind of the chicken-egg causality, as if we want to detect events, where the first step is filtering, how can ve detect the events? However, this can be useful with manually annoted recordings.

ENVELOPE DETECTION



https://www.semanticscholar.org/paper/Digital-Envelope-Detection%3A-The-Good%2C-the-Bad%2C-and-Lyons/0a2a92f9967444ac0579bc5f1b81655a0174c75a

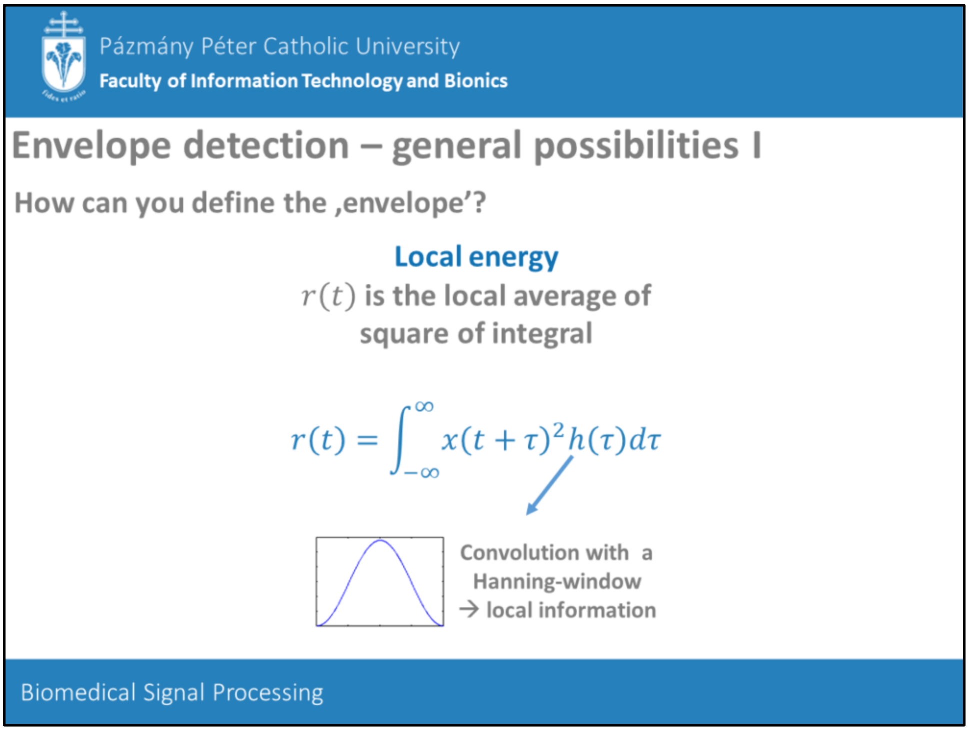
Examples for envelope detection

The problem solved by envelope detection is to acquire a fluctuating-amplitude sinusoidal discrete signal where the positive-amplitude fluctuations, i.e., the sinusoid's envelope, contain some sort of desired information and to extract that information.
An example of such a sinusoid is the amplitude modulated radio-frequency (RF) signal shown in Figure on the left. The dashed curve in that figure represents the RF signal's m(n) envelope, and it is the goal of envelope detection to extract and make available that envelope signal as shown in Figure

a) „The negative values of the RF signal are set to zero (thresholding, half-wave rectification). The high-frequency oscillation is filtered out by a low-pass filter. Due to the *harmonics*, i.e., multiples of the incoming fc carrier frequency, generated by the nonlinear half-wave rectification in (a), and possible spectral *aliasing* depending on the system's fs sample rate, careful spectrum analysis of the half-wave rectified sinusoid is necessary to help you determine the appropriate cutoff frequency of the digital low-pass filter."
b) This filter uses the square-law detector.

$$\left(A[1 + m(t)]\cos(2\pi f_c t)\right)^2 = A^2[1 + 2m(t) + m^2(t)]\cos^2(2\pi f_c t) =$$
$$A^2[1 + 2m(t) + m^2(t)]\frac{1}{2}[1 + \cos(4\pi f_c t)]$$

now we will have terms of $m(t)$, which contain no high-frequency carrier, we can obtain it with aLPF



Local energy:
We calculate the energy as the square of the signal. To have local information about the changes of this energy, it is convolved with a Hanning function → Moving average. The width of this function will give the ‚locality

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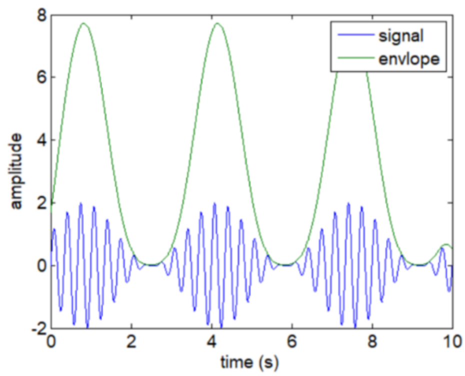
Envelope detection – local energy

Let's see, how method I performs on a simple signal. What can be the drawback of the method?



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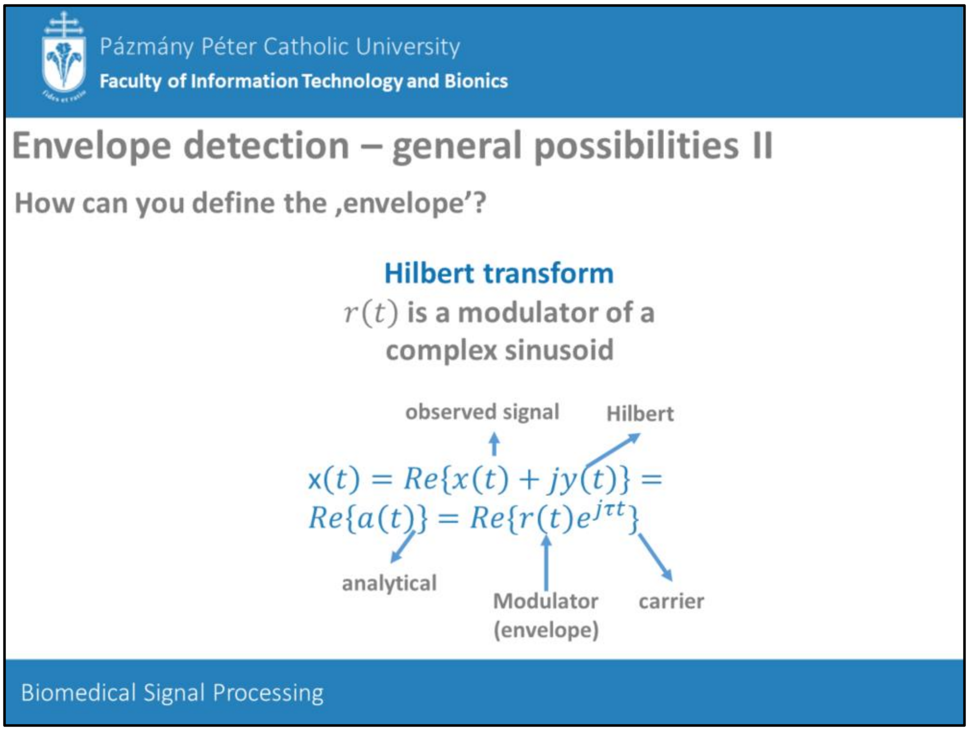
As before with moving average: how big should the window be? We should now the frequency of the events..



Hilbert transform:
We can define the observed signal as the real part of a supposed complex signal (we can measure only real things'). The imaginary part of this signal is the Hilbert transform. And most importantly, this made-up complex signal is such, that its magnitude is the envelope of the observed signal.

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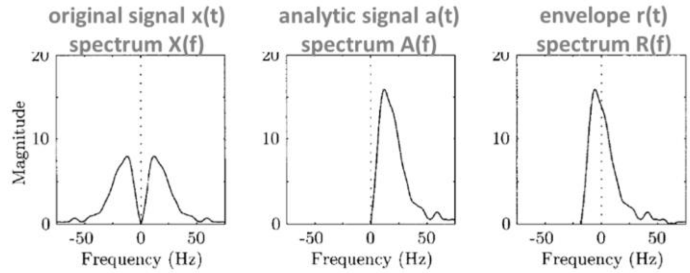
Envelope detection – Hilbert transform



$A(f) = \mathcal{F}\{a(t)\} = X(f) + jY(f)$
$H(f) = -jsign(f)$
$Y(f) = H(f) \cdot X(f)$

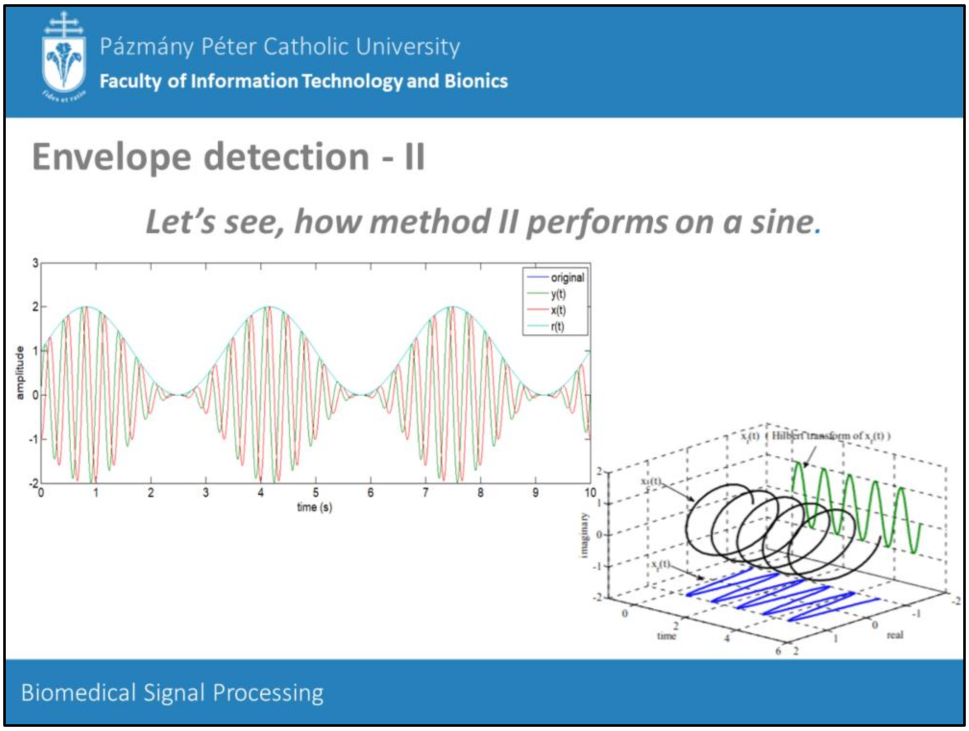
$$A(f) = X(f) + sign(f)X(f) = \begin{cases} 2X(f) \; for \; f > 0 \\ 0 \qquad otherwise \end{cases}$$

$r(t) = |\mathcal{F}^{-1}\{A(f)\}|$

The concept of the Hilbert transform is that the observed signal is the real part of a complex signal, which has an absolute value equaling the envelope.
But how can this complex signal be determed?

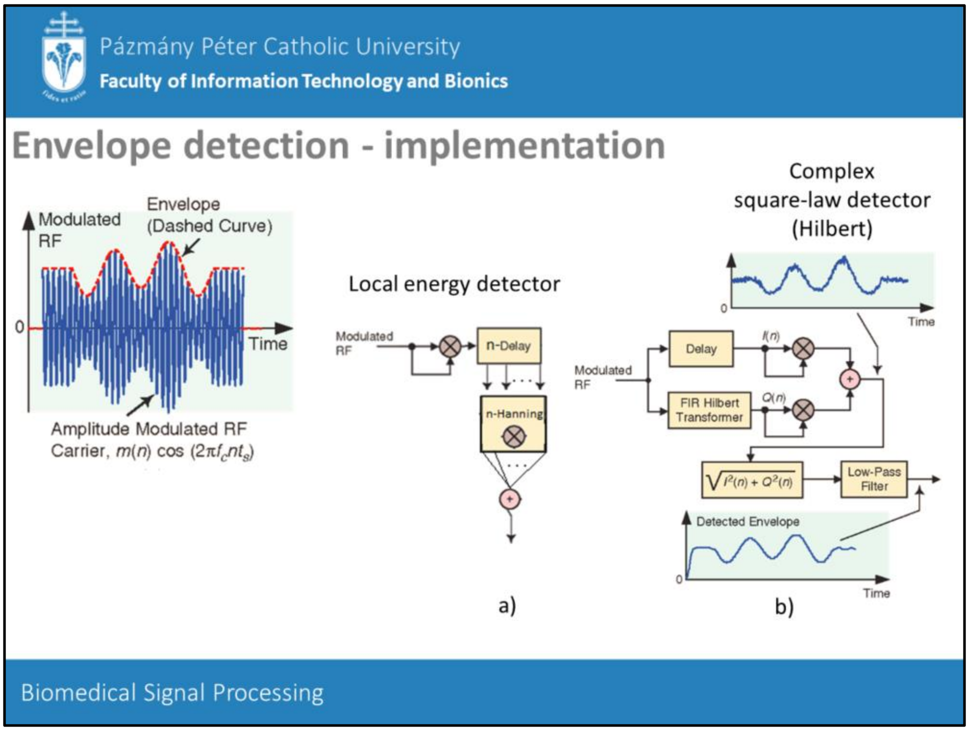
The Hilbert transform can be calculated from the observed signal.
Hilbert transform: calculated in the frequency domain. Its FFT is the FFT of the observed signal multiplied by $jsign(f)$. It means a phase shift of 90 degrees.

This way the analytical signal will be 0 for the negative frequencies, and 2*X(f) for the positive frequencies.
From this we can see, that a(t) is complex, as the real part of the spectrum is symmetric,



The hilbert transform, 90°phase shift of a sine is a cosine
Remember, for a nice result the signal should be around 0 (substract the mean of the signal)

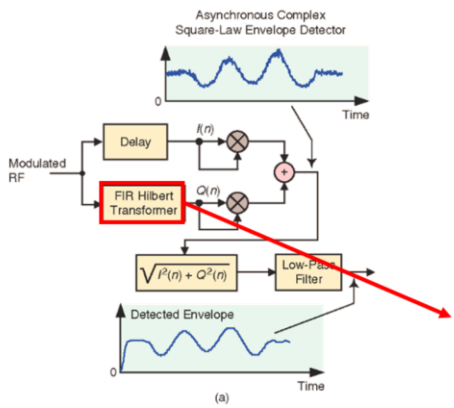
https://pdfs.semanticscholar.org/b460/c670670f1eafd291eb5868ac86304983fc21.pdf



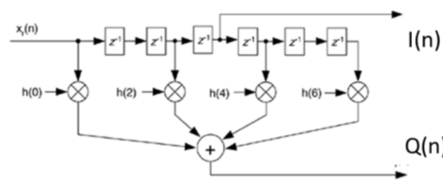
a) Local energy detector: a discrete FIR- filter. N samples are delayed, each of them is multiplied by the corresponding nth value of the n-point Hanning function. The integral in discrete time is a finite sum.

b) Hilbert envelope detector: The Hilbert transform of the signal is calculated by a FIR filter (see next slide). The original signal is also stored, it is delayed by the group delay of the Hilbert FIR to have a synchronous output. The envelope is calculated as the square root of the sum of the squares of the input (I) and Hilbert (Q) signals

FIR Hilbert transformer

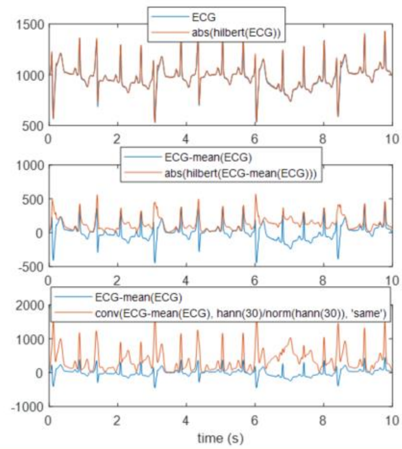


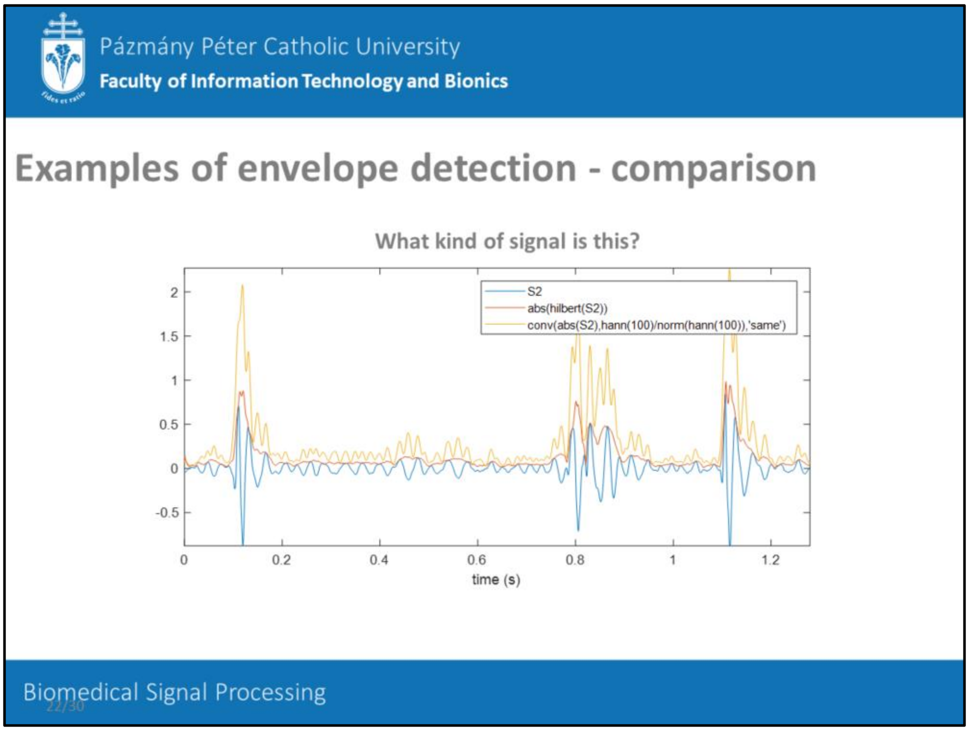
- $h(n) = \mathcal{F}^{-1}[H(f)] = \mathcal{F}^{-1}[jsign(f)]$
- $h(n) = \begin{cases} \frac{\frac{2}{\pi}\left(sim^2\left(\frac{\pi n}{2}\right)\right)}{n} & n \neq 0 \\ 0 & n = 0 \end{cases}$
- Truncate to make a FIR



$h(n)$ is the inverse Fourier of $H(f) = j \cdot\ sign(f)$, the impulse response function turning the observed signal to its Hilbert transform.
This impulse response is not absolutely summable, so an approximation of it has to be defined for realization, either as an IIR or FIR.

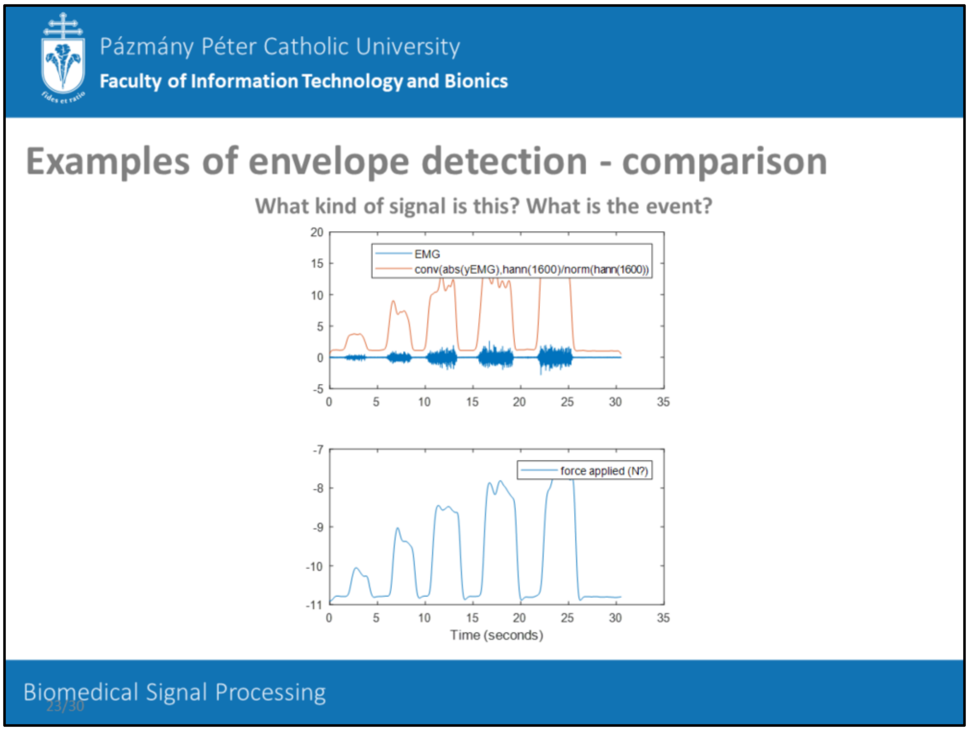
Examples of envelope detection - comparison





PCG

Hilbert transform does not need parameters ☺



why not use abs(hilbert(.)) here? would follow signal too closely, here it’s nice to be able to set integration time ourselves

DECISION RULES

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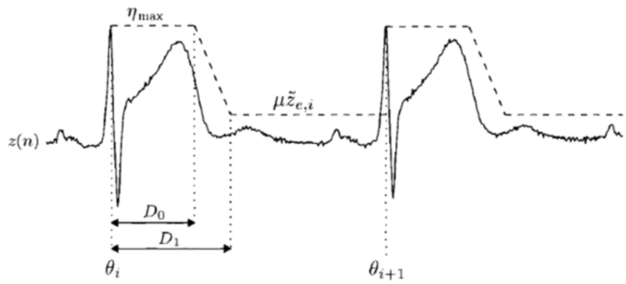
Detection rule – example for QRS

What should the threshold be?

- Use previous events' threshold
- Forgetting function for ‚older' events



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25/30

A constant threshold as detection rule is rarely working.

A solution is to pick the previously found event(s), and use its threshold for calculating the detection threshold of the next event.
If you use n number of previous events as reference for the threshold, older events should have less of an influence. This can be realized by taking them into account with linearly/exponentially decaying weight.
In the latter, useful to keep threshold constant during „eye-closing period" 160-200 ms (Sörnmo: „absolute refractory period during which the heart is unresponsive to electrical stimuli")

EXAMPLES - QRS

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Pan-Tompkins algorithm for QRS detection

The parameters are for f_s= 200Hz

- Lowpass FIR filter with integer coefficients

$$y(n) = 2y(n-1) - y(n-2) + 1/32[x(n) - 2x(n-6) + x(n-12)]$$

- Highpass FIR filter with integer coefficients

$$y(n) = y(n-1) + [-1/32x(n) + x(n-16) - x(n-17) + x(n-32)/32]$$

- Derivative operation

$$y(n) = 1/8\,[2x(n) + x(n-1) - x(n-3) - 2x(n-4)]$$

- Squaring
- Integration

$$y(n) = 1/N[x(n-(N-1)) + \cdots + x(n)], N = 30$$

- Adaptive thresholding

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Note the steps, discussed earlier!

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Pan-Tompkins adaptive thresholding

For peak to be signal peak, it must either

- exceed Threshold I1 in first step of analysis
- or if such cannot be found, Threshold I2 if searchback is applied (whereupon a more complicated set of rules applies, see article for details)

SPKI = 0.125 PEAKI + 0.875 SPKI

(if PEAKI is the signal peak)

NPKI = 0.125 PEAKI + 0.875 NPKI

(if PEAKI is the noise peak)

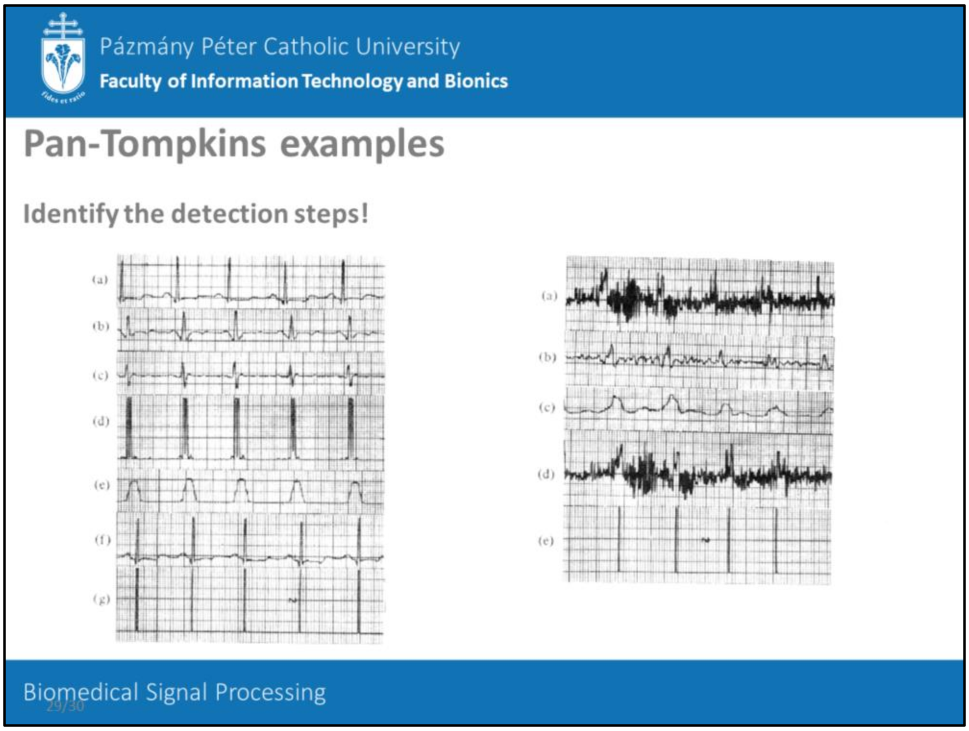
THRESHOLD I1 = NPKI + 0.25 (SPKI − NPKI)

THRESHOLD I2 = 0.5 THRESHOLD I1

where all the variables refer to the integration waveform:

PEAKI is the overall peak,
SPKI is the running estimate of the signal peak,
NPKI is the running estimate of the noise peak,
THRESHOLD I1 is the first threshold applied, and
THRESHOLD I2 is the second threshold applied.

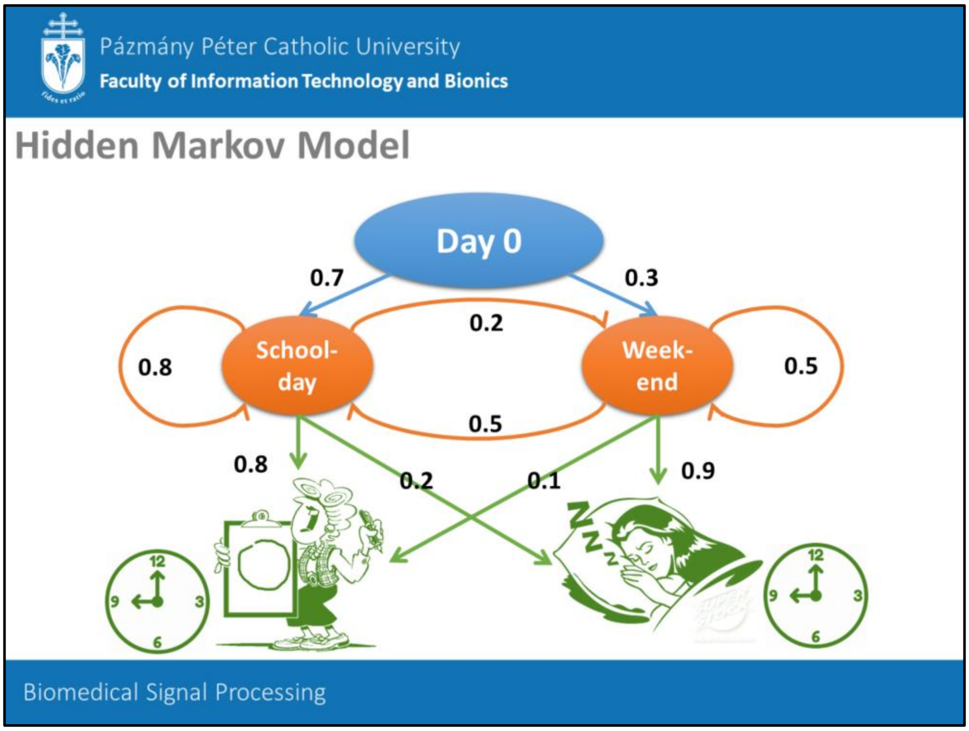
Threshold I1 is the first, „dumb"' threshold to be exceeded; running estimate which basically asks for noise peak to be exceeded by 25% of difference between signal peak and noise peak
I2 is half of this, where we search back for first instance of I2 after we failed to find I1 within some time frame where we expect it



Left:
a) Original signal
b) Bandpass filtered
c) Differntiated
d) Squared
e) Moving-window Integration
f) Original signal delayed by filter delays (to be comparable with f)
g) Location of R-peaks

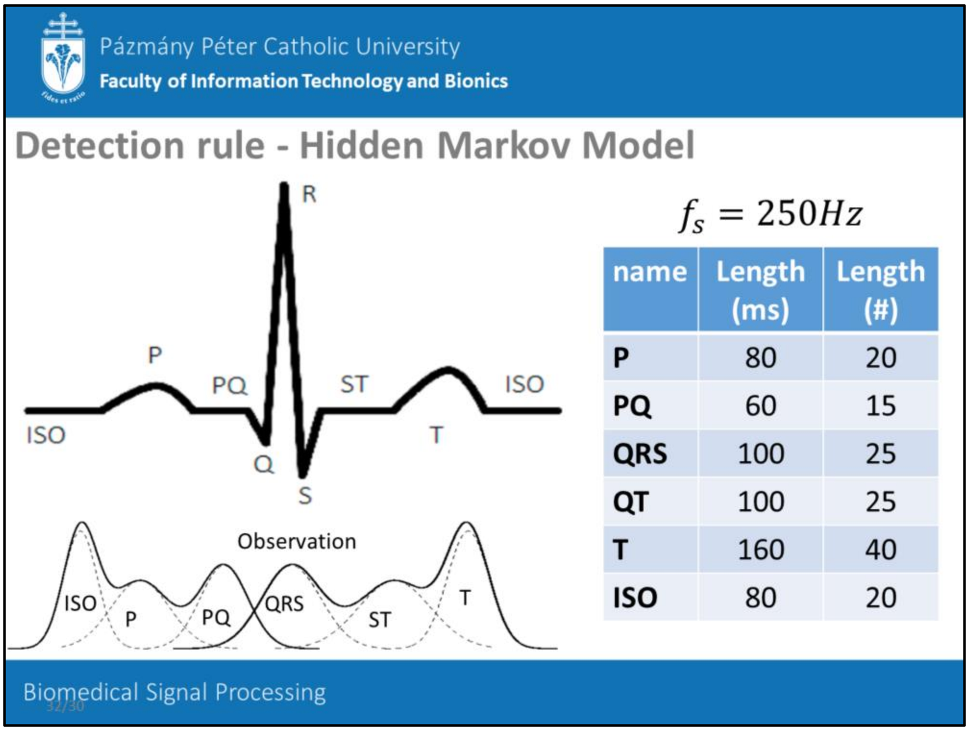
Noise contained signal on the right:
a) Original
b) Bandpass filtered
c) Moving-window integration
d) Delayed original ECG
e) R eak locations

OTHER METHODS



Task: observing whether I am sleeping at 9 o'clock, or I am at the university, guess whether it is a schoolday or a weekend day

- The hidden states of the HMM: School day or Holiday
- The observed states: I am sleeping at 9 o'clock, I am at the University at 9 o'clock
- The initial probabilities: 0.7 for having a schoolday (~5/7), 0.3 for having s holiday.
- State transitions: If it is a holiday, with 0.5 probability the next day will be holiday too, with 0.5 it is a schoolday (if it is Saturday, Sunday is holiday, if it is Sunday, Monday is school day). If it is schoolday, with 4/5 probability the next day will be too
- Observation probabilities: if it is a schoolday, I am at the university at 9o'clock usually (0.8), sometimes still in bad (0.2). If it is a holyday, most likely I will be in bad (0.9), or rarely I go to the university (0.1)



name	Length (ms)	Length (#)
P	80	20
PQ	60	15
QRS	100	25
QT	100	25
T	160	40
ISO	80	20

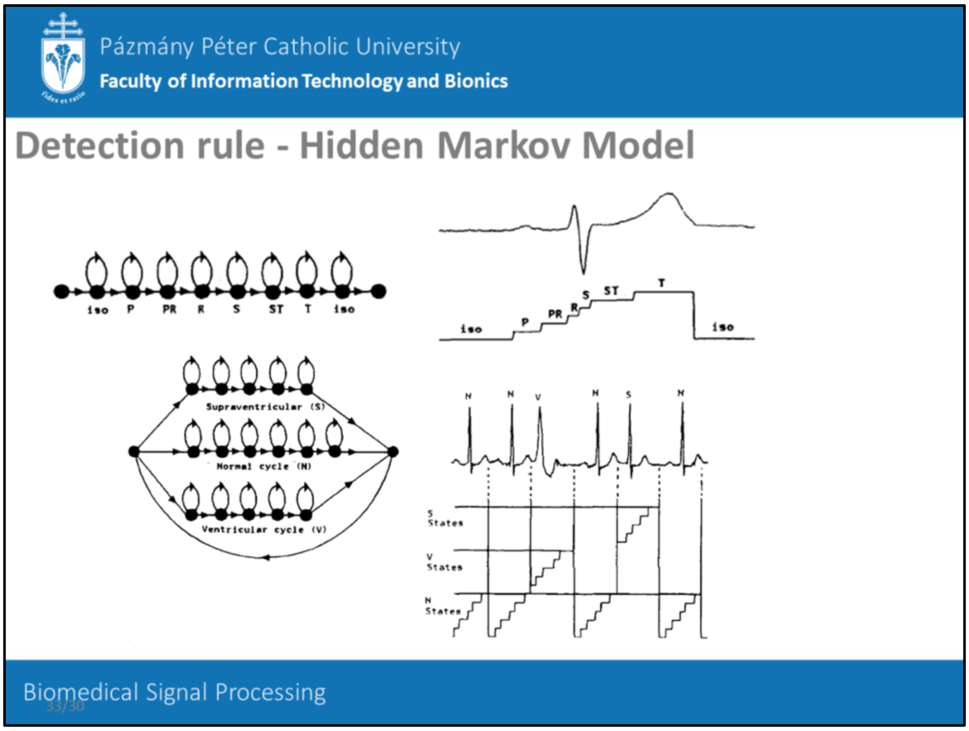
It is natural to view the ECG signal as the result of a generative process, in which each waveform feature is generated by the corresponding cardiological state of the heart. In addition, the ECG state sequence obeys the Markov property, since each state is solely dependent on the previous state. Thus, hidden Markov models (HMMs) would seem ideally suited to the task of segmenting an ECG signal into its constituent waveform features.

In HMM modeling, there are two classical methods, i.e., the Baum-Welch algorithm and the supervised learning algorithm for obtaining the parameters of the system.

A symple example: for a simple forward model (all states happens, no skipping of waves)

- State transition: depending on the length of the wave: for P wave 19/20 samples is followed by a P sample, 1 by a PQ, etc…
- Pbservation: a gaussian mixture model. Each state is observed correctly more likely in the middle of the segment, in the edges it overlaps with other waves. Observation probability: probability of wave during its own duration divided by sum of all probabilities during the particular wave's duration

https://papers.nips.cc/paper/2347-markov-models-for-automated-ecg-interval-analysis.pdf



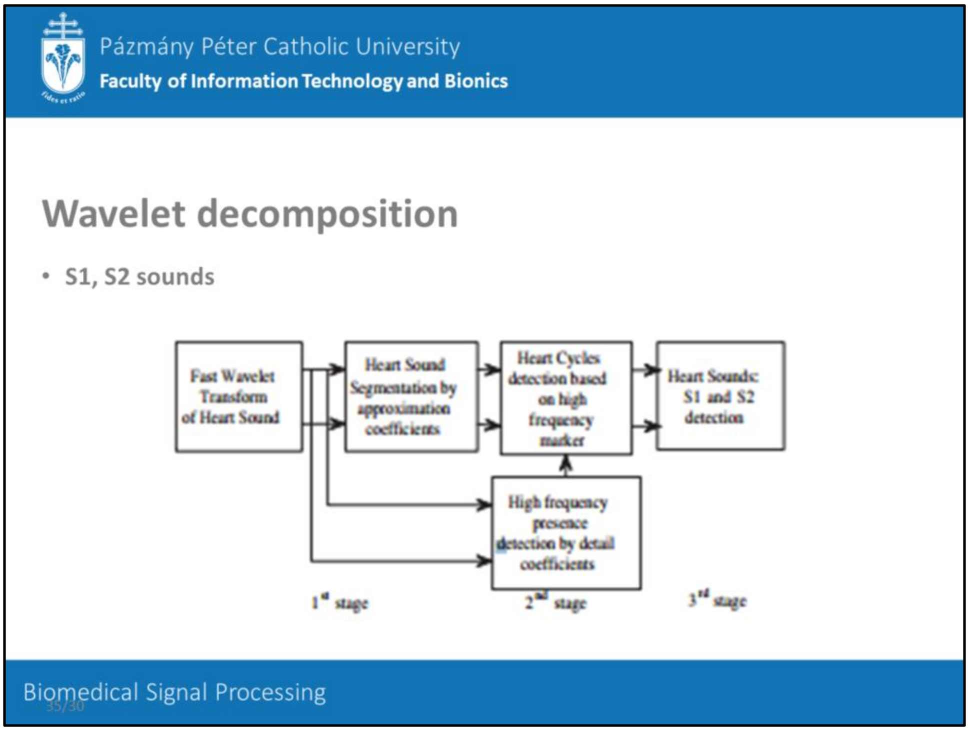
An HMM is a stochastic state machine, characterized by the following parameter set:
$\lambda = (A, B, \pi)$
where A is the matrix of state-transition probabilities (probability of staying in S state, or going to R state) , B is the observation probability (eg. probability of measuring the P wave), and π is the initial state probability.

The HMMs can model a waveform sequence namely, the duration of each waveform and interval within a beat. Moreover, the intra-individual variability of the beat length, particularly due to the heart rate variations, can be incorporated into the model state transitions. Another advantage of the HMMs is their ability to carry out at the same time three different tasks: beat detection, segmentation and classification. Furthermore, the HMMs replace the heuristic rules commonly used for waveform detection, which generally requires thresholds

(PDF) ECG Signal Analysis through Hidden Markov Models. Available from: https://www.researchgate.net/publication/6872005_ECG_Signal_Analysis_through_Hidden_Markov_Models [accessed Aug 31 2018].

Detection of P wave

- Find QRS complex
- Extract QRS complex (set it to isoelectric line)
- Then search P wave (second largest in amplitude out of P, QRS, T)



We will discuss wavelet decomposition in later lectures.

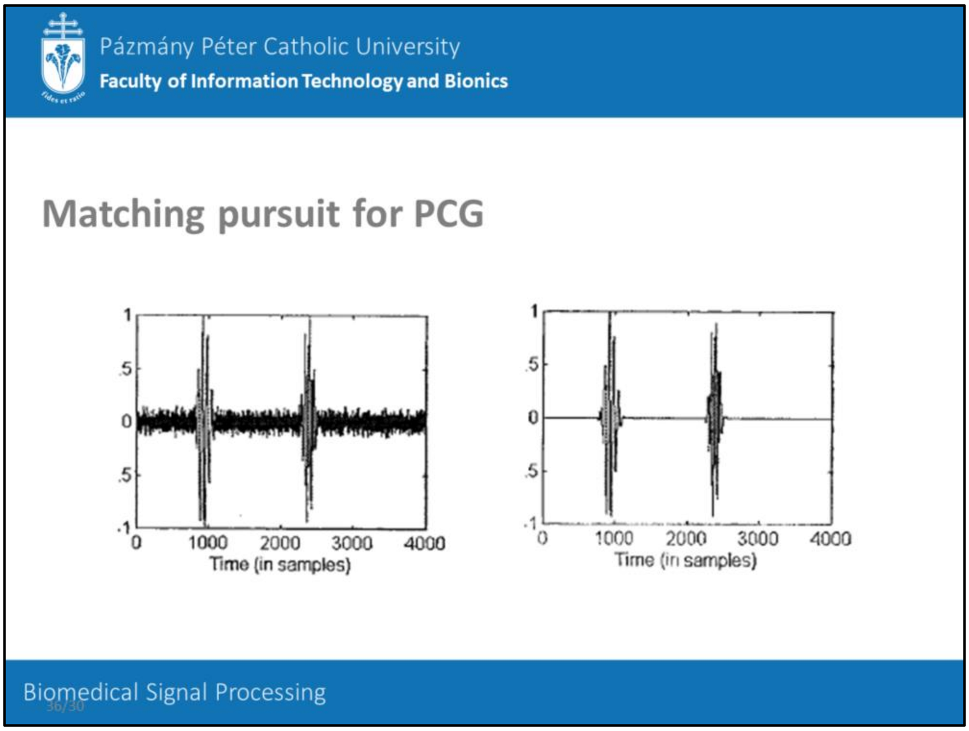
f is the frequecy of the wavelets found to build up the signal:

Low f coefficients detect heart sounds (LF energy detection, like envelope)

High f coefficients differentiate between S1, S2

(A wavelet decomposition can be realized by matching ursuit, see next slide)

A biomedical signal segmentation algorithm for event detection based on slope tracing
[, 10.1109/IEMBS.2009.5333874]



Also to be discussed on later lectures

Assume you have model S1, S2 waves. Than you use these signal with different amplitudes and shifts, and try to build up the original signal step-by-step: you find the shift-amplitude pair which correlates best with the signal, substract it, and repeat, until the norm goes under a threshold.
The shifts used for the building will tell you the location of the events.

Left: Original signal
Right: Model built from sample waves

Other events? How to detect?

- **BP, PPG**
  - heart cycle, dicrotic notch
- **EMG**
  - movement
- **EEG**
  - sleep spindle
  - epileptic seizure

Feature? (dicrotic notch, inversion)
Energy in some freq band? (EMG, EEG)
Maybe more than one feature – cf later classification lecture

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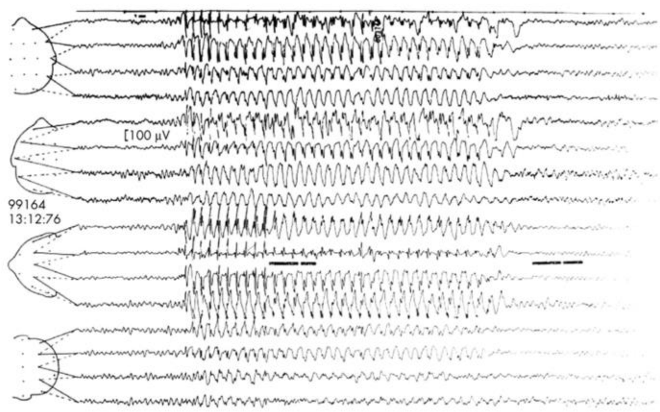
How would you detect an epileptic seizure?



Summary on Classmarker

References (apologies for any errors)

Motivation (4): http://commons.wikimedia.org/wiki/File:Heart_labelled_large.png

QRS detection (6): SL pp. 381, 428, 487

Heart-rate-dependent base-line removal (8): SL pp. 467-470

Envelope detection (10): Ádám Balogh (2012): Analysis of the Heart Sounds and Murmurs of Fetuses and Preterm Infants, p. 36-37

Hilbert-transform-based envelope detection (11): SL pp. 501-503

Envelope detection on biomedical device (12): SL p. 503

Detection rule (15): SL pp. 504-507

Pan-Tompkins algorithm for QRS detection (16): Pan and Tompkins (1985): A real-time QRS detection algorithm; R p. 187-190

Pan-Tompkins adaptive thresholding (17): Pan and Tompkins (1985): A real-time QRS detection algorithm

Pan-Tompkins examples (18): Pan and Tompkins (1985): A real-time QRS detection algorithm

Detection rule using Hidden Markov Model: Coast et al. (1990): An Approach to Cardiac Arrhythmia Analysis Using Hidden Markov Models

Sparse decomposition (24): Malioutov (2001): a sparse signal reconstruction perspective for source localization with sensor arrays, p. 33

Matching pursuit (25), Basis pursuit as Linear Programming problem (26): Matching pursuit vs Basis Pursuit (27): Gyöngy and Coviello (2011): Passive Cavitation Mapping with Temporal Sparsity Constraint

Matching pursuit for PCG (28): Zhang et al. (1998): Analysis-synthesis of the phonocardiogram based on the matching pursuit method

R: Rangayyan (2002): Biomedical Signal Analysis: A Case Study Approach

SL: Sörnmo and Laguna (2005): Bioelectric Signal Processing