

# PROCESSING, FEATURE EXTRACTION AND SHAPE REPRESENTATION OF THE ECG, I

- Basic stages of ECG signal processing
- ECG filtering
- Basic stages of ECG signal processing
- QRS complex detection
- The principles of QRS complex detection
- QRS complex detection
- QRS complex detection, performance evaluation
- Heart beat detection in multimodal data
- (Challenges in ECG signal processing today)
- (ECG filtering)
- (ECG filtering, power line interference)
- (Wave delineation)
- (Sophisticated QRS complex detection)
- (QRS complex detection, performance evaluation)

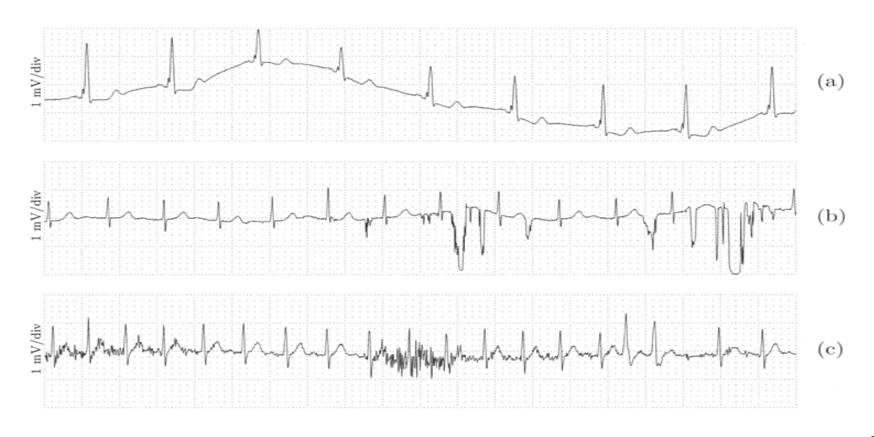


### Basic stages of ECG signal processing

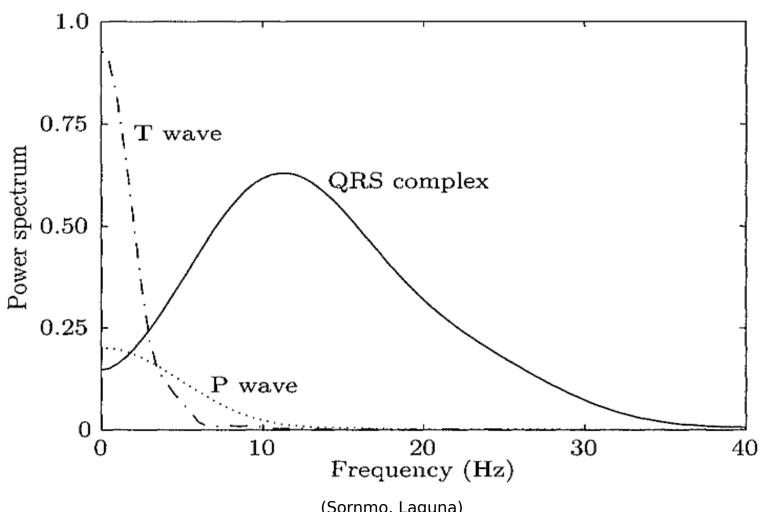
- ECG filtering
- QRS complex detection
  - → (Wave delineation)
- QRS complex classification
  - → (Rhythm classification)
  - → Ischaemia detection (classifying ischaemic events, detecting transient ischaemic episodes, and their precise beginnings, extrema and ends)



• (a) Baseline wander, (b) electrode motion artifacts, (c) electromyogram noise





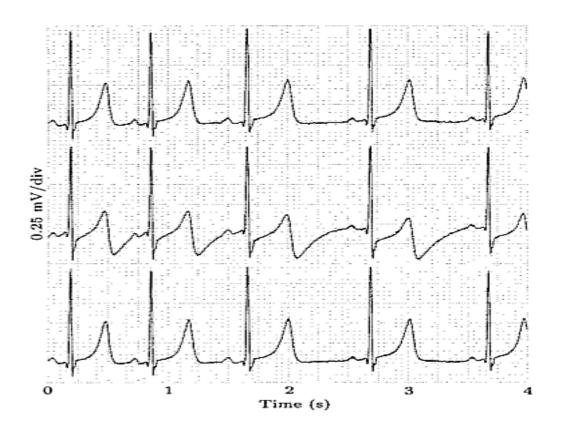


(Sornmo, Laguna)

Biomedical signal and image processing

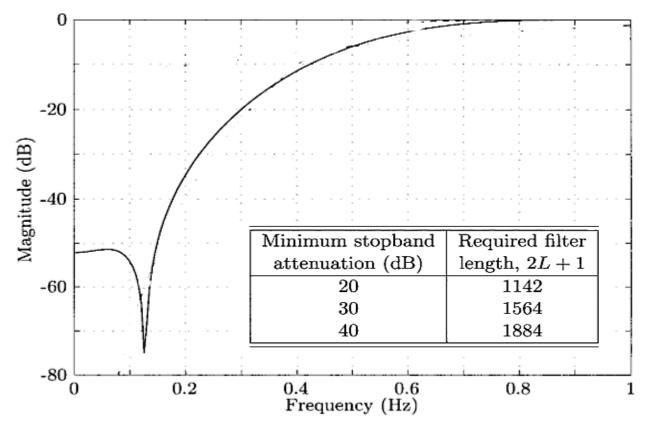


• Linear time-invariant filtering (middle → IIR filter, bottom → FIR filter)





• FIR filter (1142 coefficients), linear time-invariant filtering (cutoff at  $Fc = 0.6 \, Hz$ ,  $Fs = 250 \, smp/sec$ )



(Sornmo, Laguna)
Biomedical signal and image processing



• The original ECG signal, linear FIR filtering



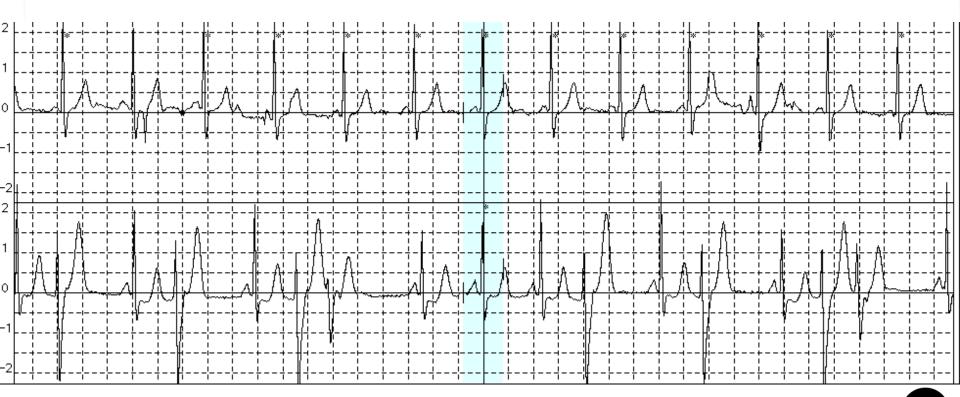


### Basic stages of ECG signal processing

- ECG filtering
- QRS complex detection
  - → (Wave delineation)
- QRS complex classification
  - → (Rhythm classification)
  - → Ischaemia detection (classifying ischaemic events, detecting transient ischaemic episodes, and their precise beginnings, extrema and ends)



- Exercises 1.a 1.e: QRS complex detection (detecting heart beats)
- Each heartbeat has QRS complex (a region within heartbeat with highest dynamic)

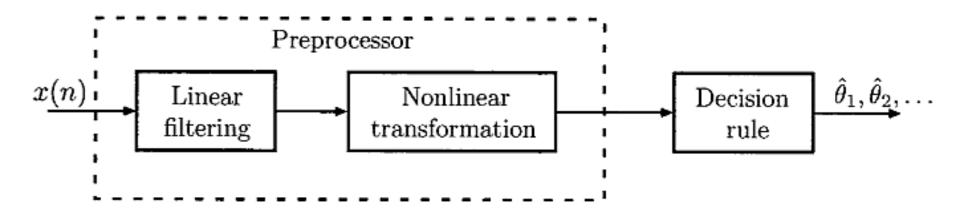




### The principles of QRS complex detection

- Approaches based on signal derivatives or digital filters
- Wavelet-based QRS detection approaches
- Approaches based on matched filters
- Other approaches (adaptive filters, hidden Markov models, mathematical morphology, length transform, neural networks, ...)

 Block diagram of a QRS complex detector based on signal derivatives or digital filters





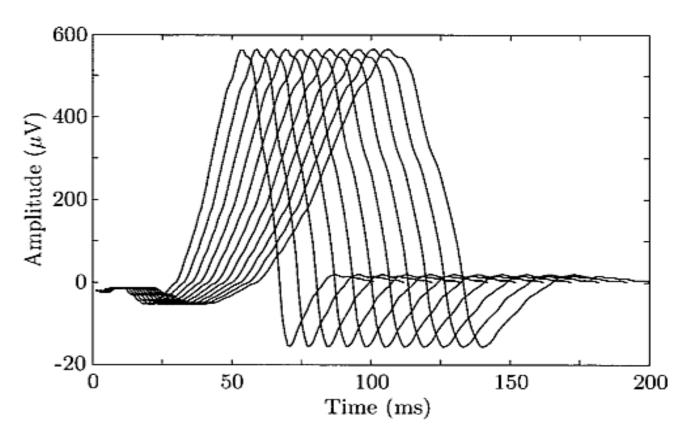
2 Ġ

Why QRS complex detection is problematic?

Time (s)

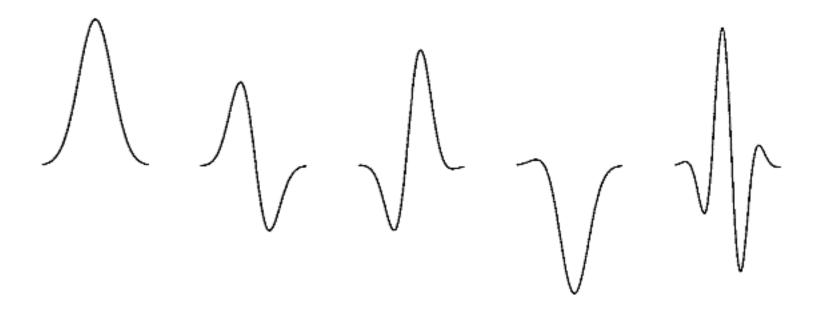


 Why QRS complex detection is problematic? (identical morphology but different durations)

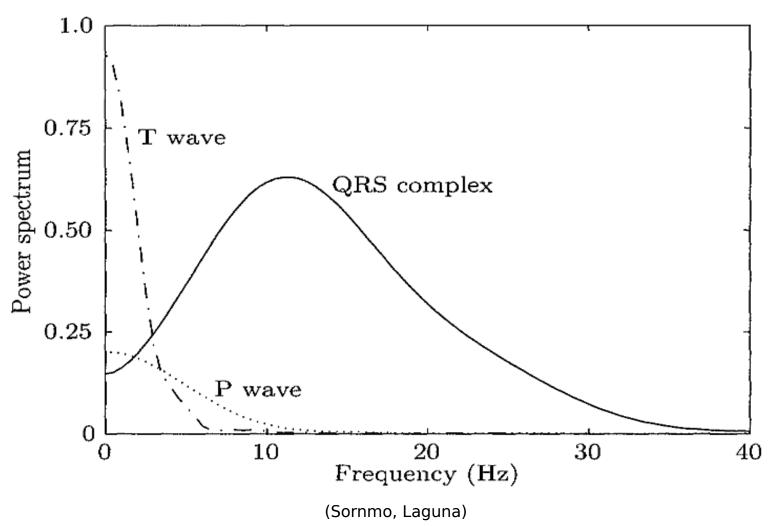




 Why QRS complex detection is problematic? (monophasic and biphasic waveshapes)

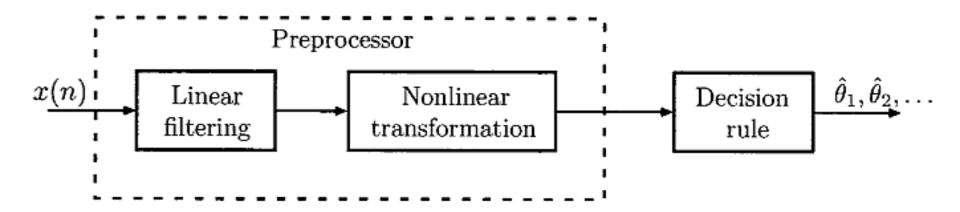








- Phases of QRS complex detection
  - Linear filtering (extracting/emphasizing slopes and peaks of QRS complex)
  - Nonlinear transformation (energy collector) to get the detection function
  - Decision rule
  - Determining stable fiducial point (FP)



Linear filtering and nonlinear transformation

d[n] - detection function

N - number of simultaneous ECG leads

H1 - filter sensitive on slopes (Q-R and R-S) of QRS complex

H2 - filter sensitive on peaks (Q, R, and S) of QRS complex

*G* - low-pass moving average filter

$$d[n] = G(\left(\sum_{i=1}^{N} \left(|H_{1}(x_{i}[n])| + |H_{2}(x_{i}[n])|\right)^{2}\right)$$



#### Linear filtering

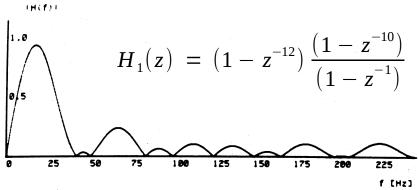
 $(H_1(z) - \text{extracts slopes}, H_2(z) - \text{extracts peaks}, F_S = 500 \text{ smp/sec})$ 

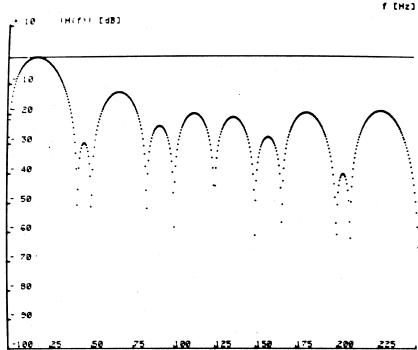
$$d[n] = G\left(\left(\sum_{i=1}^{N} \left(\left|H_{1}(x_{i}[n])\right| + \left|H_{2}(x_{i}[n])\right|\right)\right)^{2}\right)$$

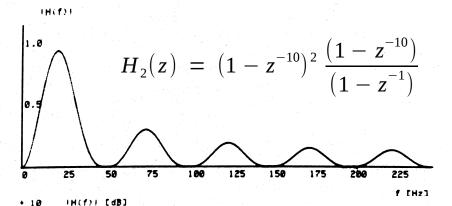
$$H_{1,2}(z) = (1 - z^{-m})^{M} \frac{(1 - z^{-n})}{(1 - z^{-1})}$$

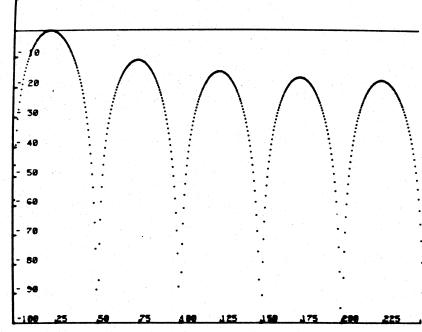
$$H_1(z) = (1-z^{-12}) \frac{(1-z^{-10})}{(1-z^{-1})} \quad H_2(z) = (1-z^{-10})^2 \frac{(1-z^{-10})}{(1-z^{-1})}$$













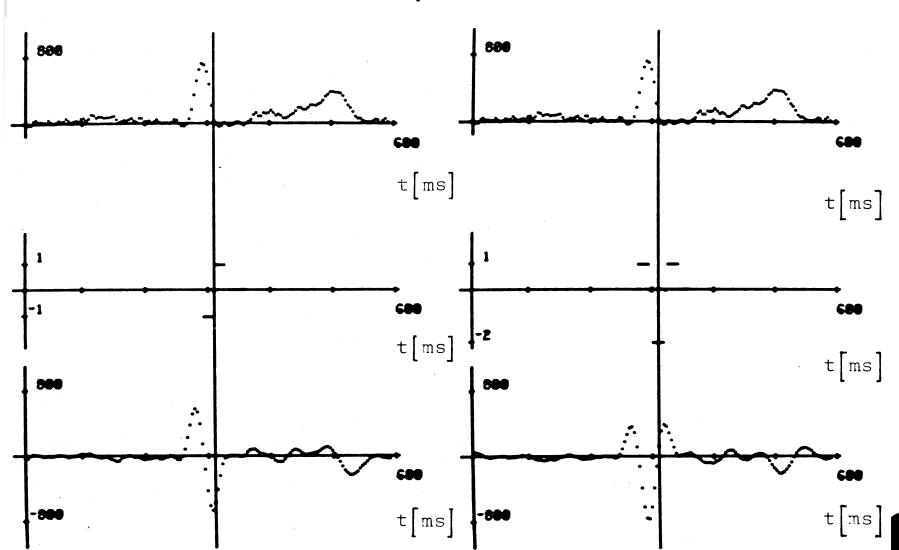
### Linear filtering

- Transfer functions
- Difference equations
- Impulse responses

$$H_1(z) = (1 - z^{-12}) \frac{(1 - z^{-10})}{(1 - z^{-1})}$$

$$H_2(z) = (1 - z^{-10})^2 \frac{(1 - z^{-10})}{(1 - z^{-1})}$$







Nonlinear transformation

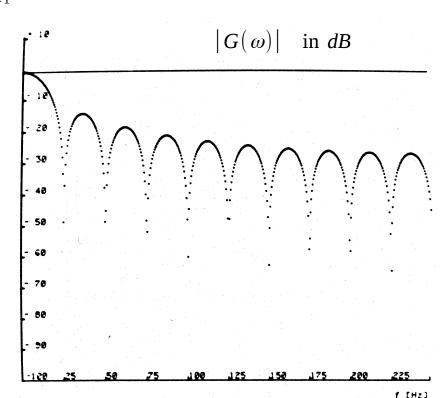
$$d[n] = G\left(\left(\sum_{i=1}^{N} \left(\left|H_{1}(x_{i}[n])\right| + \left|H_{2}(x_{i}[n])\right|\right)\right)^{2}\right)$$

$$u[n] = \sum_{i=1}^{N} \left(\left|y_{1,i}[n - (T_{2} - T_{1})]\right| + \left|y_{2,i}[n]\right|\right)$$

$$v[n] = (u[n])^2$$

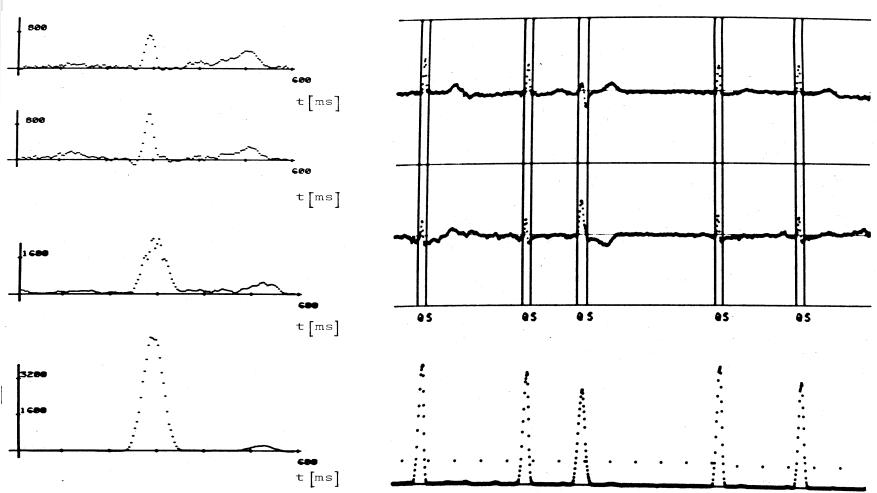
$$G(z) = \frac{(1-z^{-20})}{(1-z^{-1})}$$

$$d[n] = d[n-1] + v[n] - v[n-20]$$





• Original signals, after filtering and summing, and the detection function, d[n]

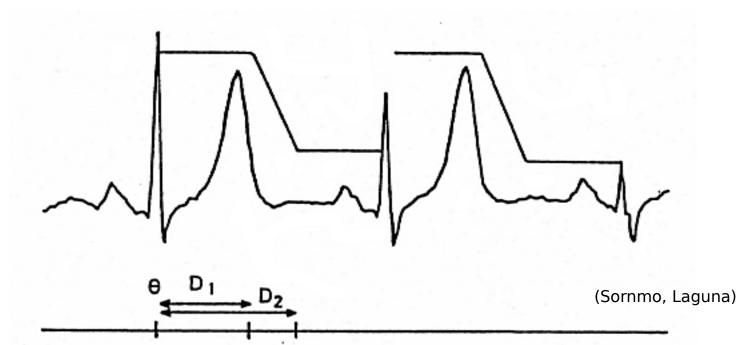




Decision rule

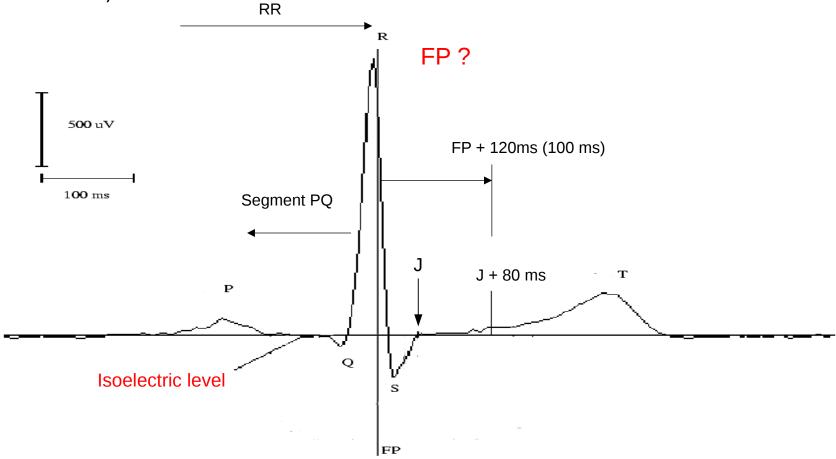
$$\eta[n] = \begin{cases} \alpha_1, & n = \theta + 1, \dots, \theta + D_1 \\ d[n], & n = \theta + D_1 + 1, \dots, \theta + D_2 \\ \alpha_2, & n = \theta + D_2, \dots \end{cases}$$

$$\alpha_1 \ge d[\theta + D_1 + 1] > \dots > d[\theta + D_2] = \alpha_2$$



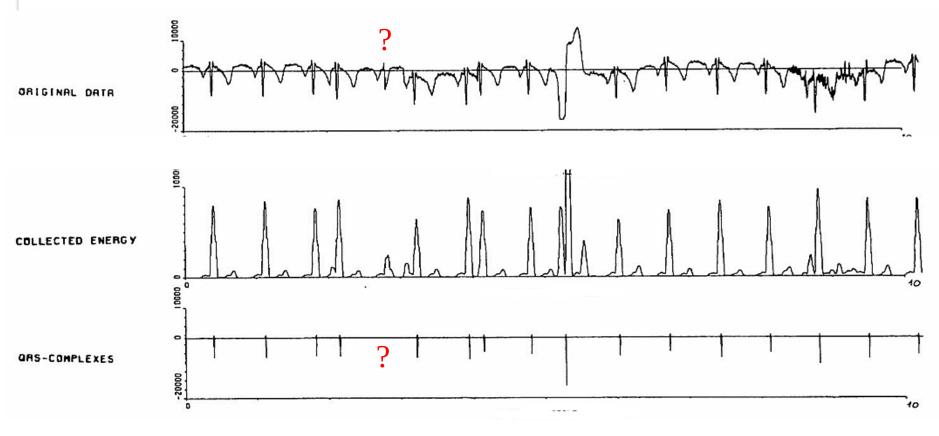


• What is Fiducial Point (FP), or reference point? (usually peak of the detection function)





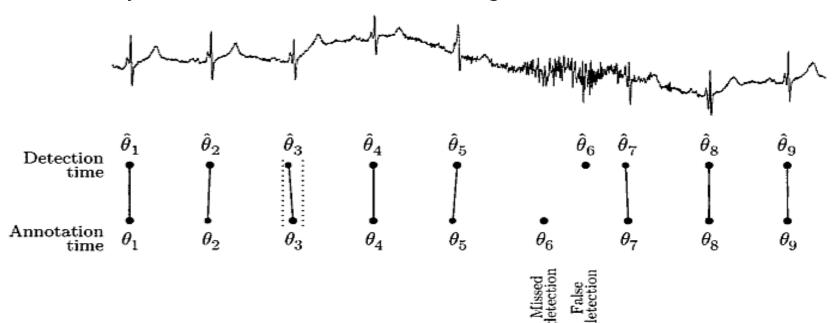
• Original ECG signal, detection function and detected QRS complexes





#### Example

- True detection of an event
- Missed detection of an event
- False detection of an event
- ? True rejection of a *non-event* ? true negative (*tn*)
- true positive (tp)
- false negative (fn)
- false positive (fp)





Performance evaluation

Classic event oriented performance matrix

		Analyzer	Analyzer
		EVENT	NON-EVENT
Reference	event	TP	FN
Reference	non-event	FP	(TN)

*TP* – number of correctly detected events

*FN* – number of missed events

*FP* – number of falsely detected events

TN – number of correctly rejected non-events (undefined for detection task!)



#### Performance evaluation

		Analyzer	Analyzer
		EVENT	NON-EVENT
Reference	event	TP	FN
Reference	non-event	FP	(TN)

### Sensitivity:

$$Se = \frac{TP}{TP + FN}$$

The proportion of events which were detected

### Positive predictivity:

$$+P = \frac{TP}{TP + FP}$$

The proportion of detections which actually were events



Performance evaluation

		Analyzer	Analyzer
		EVENT	NON-EVENT
Reference	event	TP	FN
Reference	non-event	FP	(TN)

### Sensitivity:

$$Se = \frac{TP}{TP + FN} \approx p \text{ (EVENT | event)}$$

An estimate of the likelihood of detecting an event

### Positive predictivity:

$$+P = \frac{TP}{TP + FP} \approx p \text{ (event | EVENT)}$$

An estimate of the likelihood that a detection is an event

Approaches based on signal derivatives and digital filters (Pangerc Urška)
 (MIT BIH arrhythmia DB)

$$Se \approx 99.90\% + P \approx 99.92\%$$

 QRS detection based on matched filters (Haar-like filters) (Ding J J) (MIT BIH arrhythmia DB)

$$Se \approx 99.93\% + P \approx 99.88\%$$

<u>Silva I, Moody B, Behar J, Johnson A, Oster J, Clifford G D, and Moody G B, Editorial: Robust detection of heart be ats in multimodal data, Physiological Measurement, Vol 36, pp. 1629-44, 2015</u>

Pangerc U, and Jager F, Robust detection of heart beats in multimodal records using slope- and peak-sensitive band-pass filters, Physiological Measurement, Vol 36, pp. 1645-64, 2015

Ding J J, Huang C W, Ho Y L, Hung C S, Lin Y H, and Chen Y H, An efficient selection, scoring, and variation ratio test algorithm for ECG R-wave peak detection, Experimental & Clinical Cardiology Journal, Vol 20, pp. 4256-63, 2014

Elgendi, M, Eskofier B, Dokos S, and Abbot D, Revisiting QRS Detection Methodologies for Portable Wearable, Battery-Operated, and Wireless ECG Systems, PLoS One, Vol 9, e84018, 2014



### Heart beat detection in multimodal data

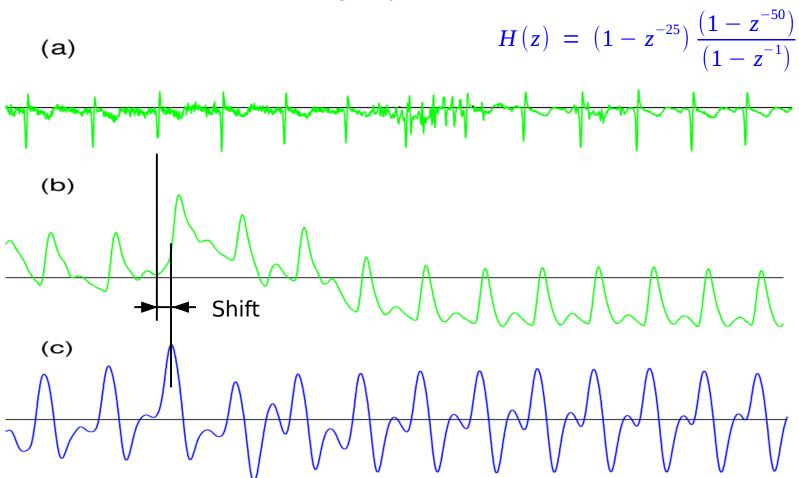
- Exercises 1.f 1.g: Heart beat detection using ECG and pulsatile signals
- Use ECG signal and one of the pulsatile signals like: BP, ABP, PAP, PLETH





### Heart beat detection in multimodal data

• a) ECG, b) BP, c) BP filtered by slope sensitive filter:





### (Challenges in ECG signal processing today)

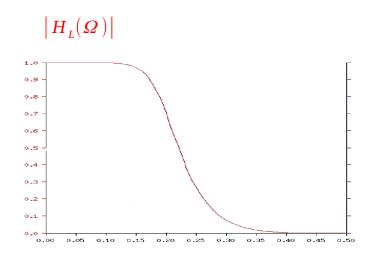
- Robust heart heat detection
- Signal quality estimation
- Reliable P wave identification
- Reliable QT interval estimation
- Distinguishing ischaemic from non-ischaemic ST changes
- Reliable heart beat classification
- Reliable rhythm analysis
- (Robust, reliable in-band signal filtering or source separation)
- (Identification of lead position misplacements or sensor shifts)
- (ECG modeling and parameter fitting)
- (The mapping of diagnostic ECG parameters to disease classifications or predictive metrics)
- (Global context pattern analysis)



 Digital Butterworth filters have a smooth frequency response and are computationally non-intensive (linear time-invariant filtering)

• Low-pass 
$$|H_L(\Omega)|^2 = \frac{1}{1 + (\frac{\Omega}{\Omega_C})^{2N}}$$

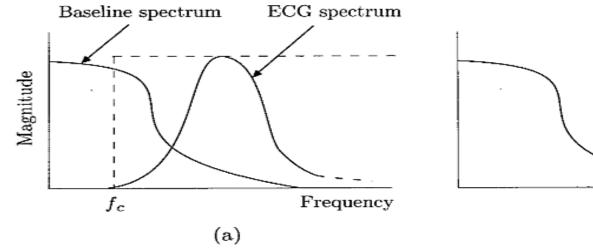
• (High-pass) 
$$|H_H(\Omega)|^2 = \frac{1}{1+(\frac{\Omega_C}{\Omega})^{2N}}$$

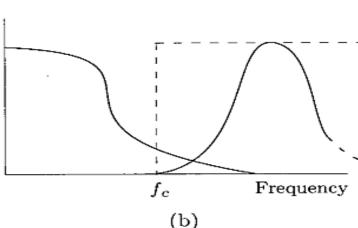


• Their major drawback, the phase-shifting, is especially troublesome when using high-pass filtering (will discuss Butterworth high-pass filter for EMG analysis)



- Linear time-variant filtering (heart rate dependent filtering)
- Cut-off frequency  $f_c(n)$  is inversely proportional to the instantaneous RR interval estimate RR(n),  $f_c(n) \sim 1 / RR(n)$
- The time-varying cut-off frequency  $f_c(n)$  is used to design a high-pass filter h(k,n) at every time instant n, where k denotes discrete time within the impulse response.
  - (a) low heart rate, (b) high heart rate

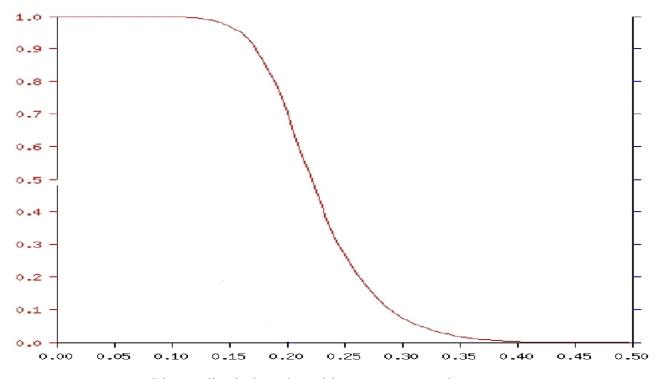






• Butterworth low-pass filtering N = 2,  $Fs = 200 \, smp/sec$  Cut-off (-3dB) at 40 Hz

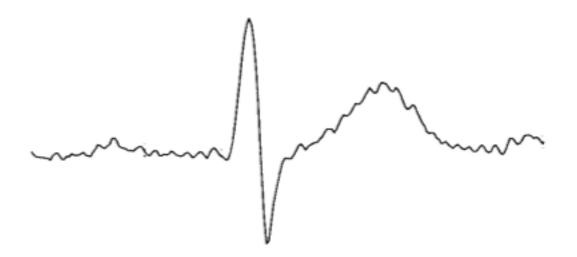
$$|H_L(\Omega)|^2 = \frac{1}{1 + (\frac{\Omega}{\Omega_C})^{2N}}$$





# (ECG filtering, power line interference)

• Power line interference (50/60 Hz)





### (ECG filtering, power line interference)

 Power line interference (50/60 Hz) (two zeros, two poles to make stop-band narrower)

$$z_{1,2} = e^{\pm j\omega_0}$$

$$H(z) = (1 - z_1 z^{-1})(1 - z_2 z^{-1})$$

$$= 1 - 2\cos(\omega_0)z^{-1} + z^{-2}$$

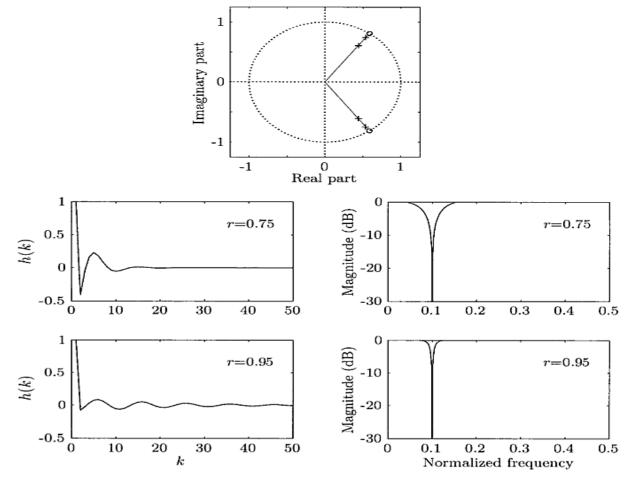
$$p_{1,2} = re^{\pm j\omega_0}$$

$$H(z) = \frac{(1 - z_1 z^{-1})(1 - z_2 z^{-1})}{(1 - p_1 z^{-1})(1 - p_2 z^{-1})}$$
$$= \frac{1 - 2\cos(\omega_0)z^{-1} + z^{-2}}{1 - 2r\cos(\omega_0)z^{-1} + r^2 z^{-2}}$$



# (ECG filtering, power line interference)

 Power line interference (50/60 Hz)

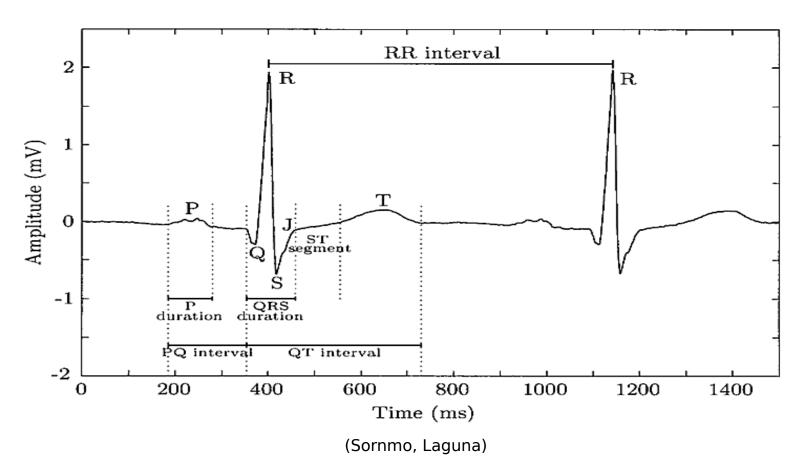


(Sornmo, Laguna)
Biomedical signal and image processing



### (Wave delineation)

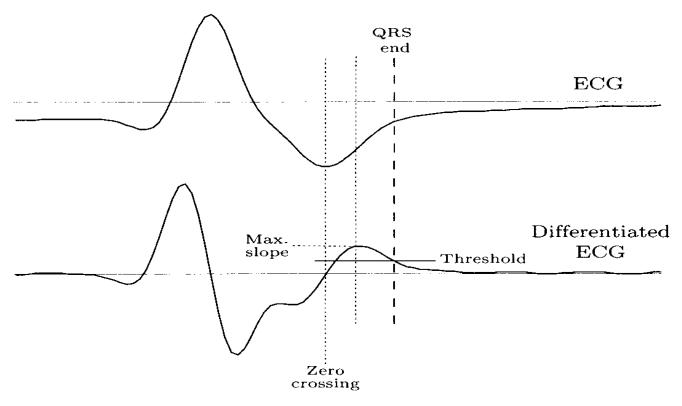
 P wave onset and offset, QRS complex onset and offset (J point), T wave onset and offset, PQ interval, QT interval





### (Wave delineation)

• Determining the position of QRS offset (end) (J point), the Threshold is expressed as a percentage of Maximum slope found

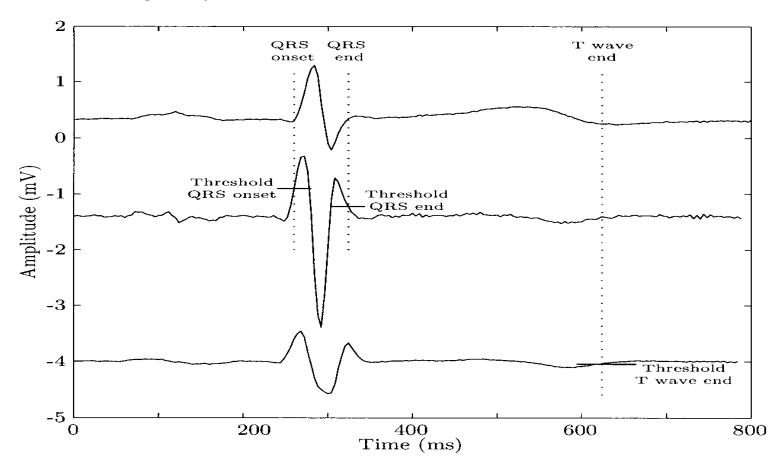


(Sornmo, Laguna)



### (Wave delineation)

• Determining the position of QRS onset, QRS offset and T wave end

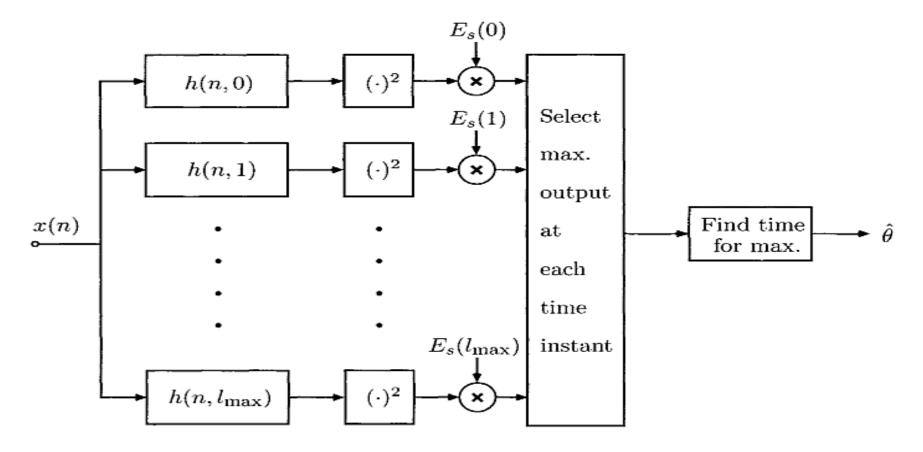


(Sornmo, Laguna)



### (Sophisticated QRS complex detection)

Block diagram of a sophisticated QRS complex detector





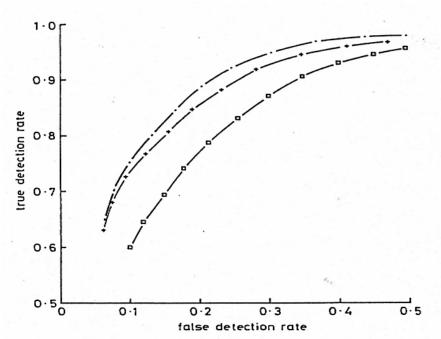
- Evaluation of three different QRS complex detectors
   (each symbol corresponds to a certain value of the detection threshold)
- Missed detections False Negatives (FN), False detections False Positives (FP)

  True detection rate (Se)

  Sensitivity (Se),

  False detection rate (Se)

  Positive predictivity (Se), Se = TP / (TP + FN)False detection rate (Se)
- Correct detections:
   True positives (TP)
- Correct rejections?
   True Negatives (TN)
   are undefined for the detection task!



(Sornmo, Laguna)