Biosignals and Systems

Some Problems and Applications

Problems in biomedical signal processing

- Accessibility of the variables to measurement
- Patient safety, preference for noninvasiveness
- Indirect measurements (variables of interest are not accessible)
- Variability of the signal source
- Interactions among physiological system
- Acquisition interference

[10] B H Brown, R H Smallwood, D C Barber, P V Lawford and D R Hose, ‘‘ **MEDICAL PHYSICS AND BIOMEDICAL ENGINEERING**’’

[3] Alan V.Oppenheim, Ronald W.Schafer, John R.Buck, ‘‘ **Discrete-Time Signal Processing**’’, Prentice-Hall, Inc.1999,1989

Problems in biomedical signal processing-Artefacts and interference

- Interference from other physiological systems (e.g. muscle artifacts in EEG recordings)
- Low-level signals (e.g. microvolts in EEG) require very sensitive amplifiers; they are easily sensitive to interference.
- Limited possibilities for shielding or other protection - Nonlinearity and obscurity of the system under study
- basically all biological systems exhibit nonlinearities while most of the methods are based on the assumption of linearity
- exact structures and true function of many physiological systems are often not known

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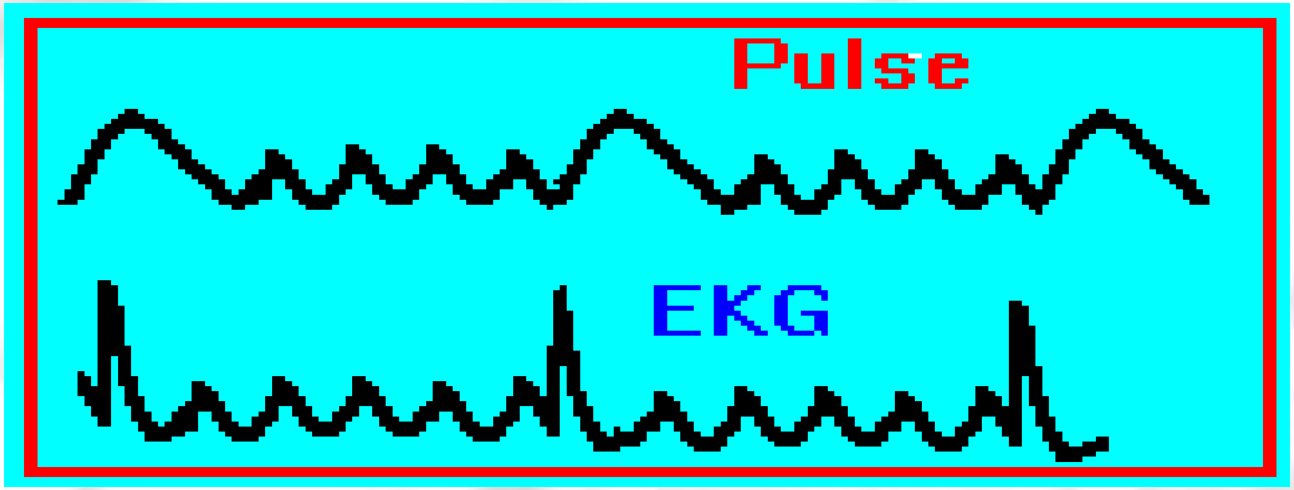
Problems in biomedical signal processing-Artefacts and interference

- Some EEG artefacts



Pulse wave artefact: movement of electrode arising from patient pulse under the electrode.

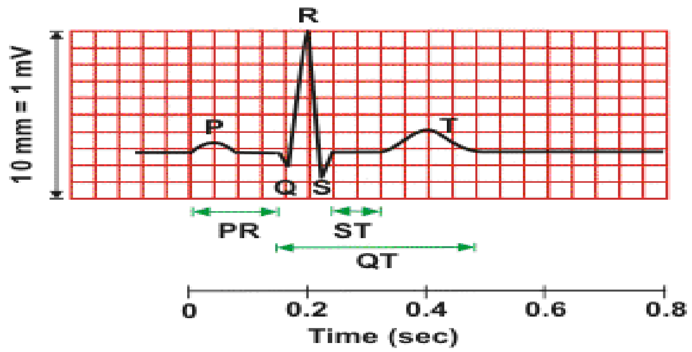
ECG signal artefact: ECG signal also picked up by the EEG electrodes.

Both easily recognized because they are periodic.

[19] http://www.brown.edu/Departments/Clinical_Neurosciences/louis/artefct.html

APPLICATION-ECG

- The electrocardiogram (ECG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. The surface ECG is obtained by recording the potential difference between two electrodes placed on the surface of the skin. A single normal cycle of the ECG represents the successive atrial depolarisation/repolarisation and ventricular depolarisation/repolarisation which occurs with every heart beat.
- Simply put, the ECG (EKG) is a device that measures and records the electrical activity of the heart from electrodes placed on the skin in specific locations
- A typical ECG period consists of P,Q,R,S,T and U waves



P wave (0.08 - 0.10 s)
QRS (0.06 - 0.10 s)
P-R interval (0.12 - 0.20 s)
Q-T_c interval ($\leq$ 0.44 s)*

$*QT_c = QT/\sqrt{RR}$

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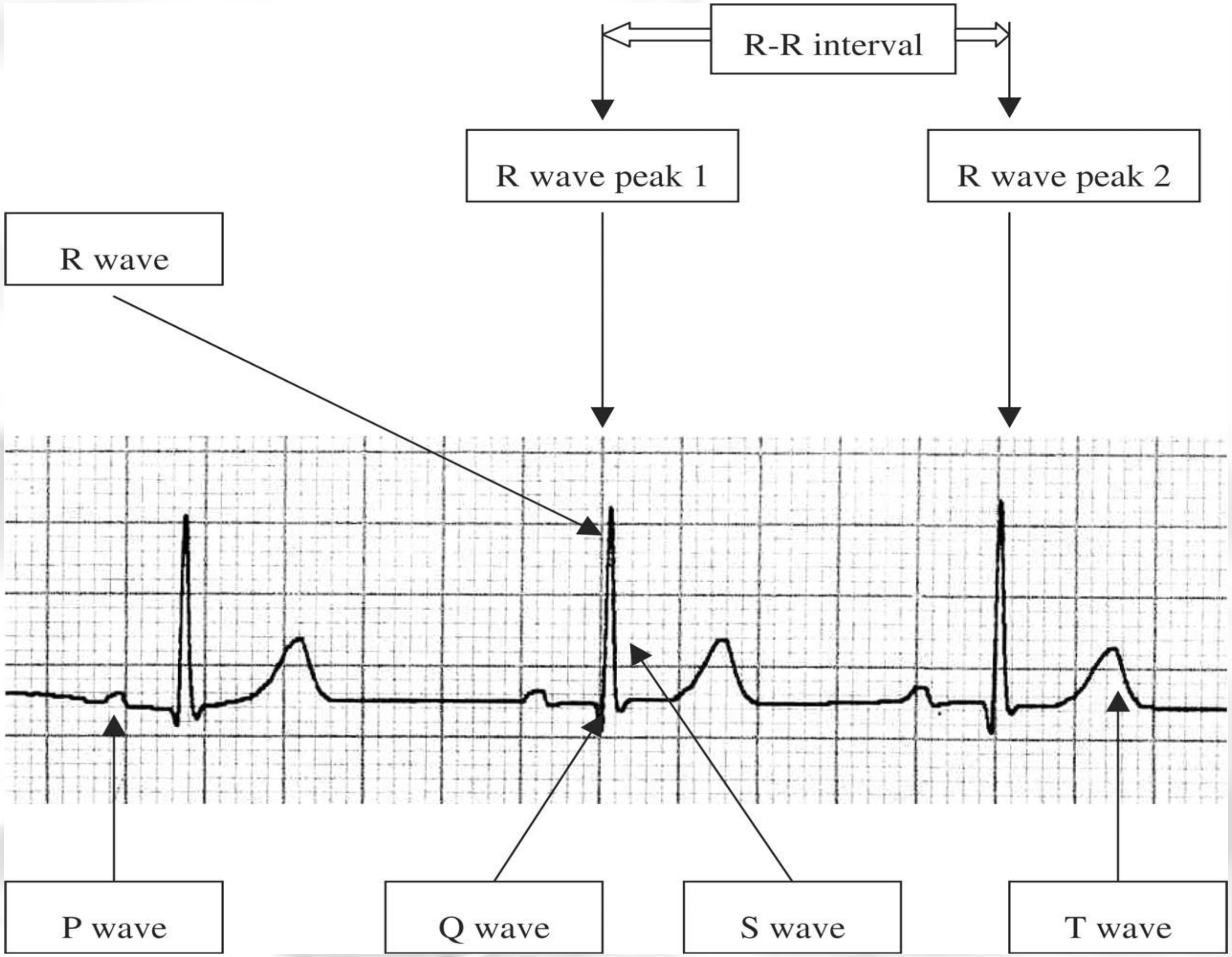
APPLICATION-ECG

The normal electrocardiogram with component waves labelled.



<u>P wave</u>: the sequential activation (depolarization) of the right and left atria
<u>QRS complexes</u>: right and left ventricular depolarization
<u>T wave</u>: ventricular repolarization
<u>U wave</u>: origin not clear, probably ”afterdepolarizations” in the ventrices

Reed M et al. QJM 2005;98:87-95

[10] B H Brown, R H Smallwood,‘‘ **MEDICAL PHYSICS AND BIOMEDICAL ENGINEERING**’’, University of Sheffield,1999
[13] Chaudhuri S.,Pawar T.D.,Duttagupta S., ‘‘ **Ambulation Analysis in Wearable ECG** ’’, Springer,2009
[14] Gari D.Clifford,Francisco Azuaje,Patrick E.McSharry, ‘‘ **Advanced Methods and Tools for ECG Data Analysis** ’’,Artech House Publishers

APPLICATION-ECG Filtering

- Three common noise sources
  - Baseline wander
  - Power line interference
  - Muscle noise
- When filtering any biomedical signal care should be taken not to alter the desired information in any way
- A major concern is how the QRS complex influences the output of the filter; to the filter they often pose a large unwanted impulse
- Possible distortion caused by the filter should be carefully quantified

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APPLICATION-ECG Filtering

- Both baseline wander and powerline interference removal are mainly a question of filtering out a narrow band of lower-than-ECG frequency interference.
  - The main problems are the resulting artifacts and how to optimally remove the noise
- Muscle noise, on the other hand, is more difficult as it overlaps with actual ECG data
- For the varying noise types (baseline wander and muscle noise) an adaptive approach seems quite appropriate, if the detection can be done well. For power line interference, the nonlinear approach seems valid as ringing artifacts are almost unavoidable otherwise

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APPLICATION-QRS detection

- QRS detection is important in all kinds of ECG signal processing
- QRS detector must be able to detect a large number of different QRS morphologies
- QRS detector must not lock onto certain types of rhythms but treat next possible detection as if it could occur almost anywhere
- Typical structure of QRS detector algorithm: preprocessing (linear filter, nonlinear transformation) and decision rule
- For different purposes (e.g. stress testing or intensive care monitoring), different kinds of filtering, transformations and thresholding are needed
- Multi-lead QRS detectors

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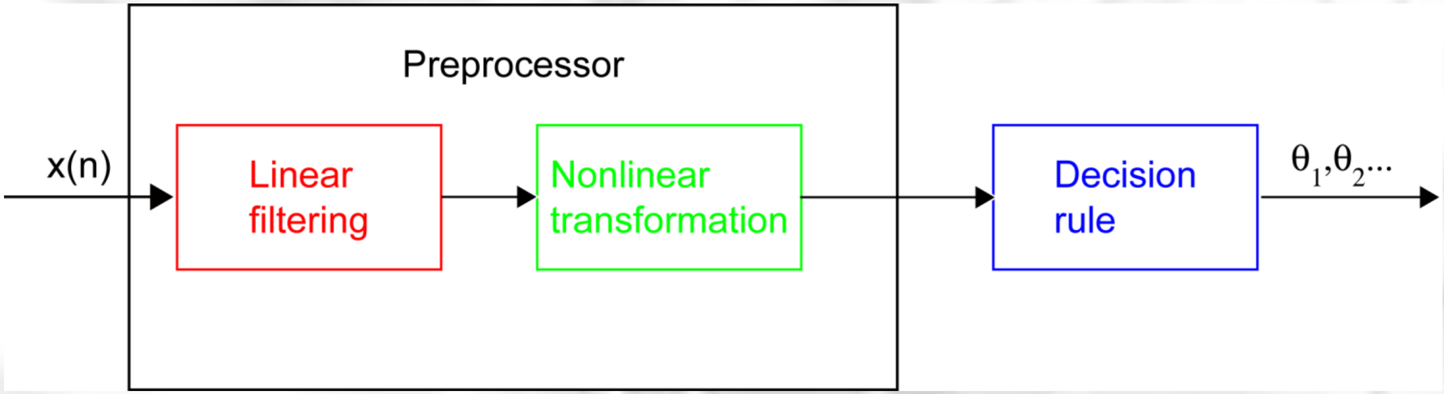
APPLICATION-QRS detection

- Bandpass characteristics to preserve essential spectral content (e.g. enhance QRS, suppress P and T wave), typical center frequency 10 - 25 Hz and bandwidth 5 - 10 Hz
- Enhance QRS complex from background noise, transform each QRS complex into single positive peak
- Test whether a QRS complex is present or not (e.g. a simple amplitude threshold)



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APPLICATION-Estimation Problem

- Maximum likelihood (ML) estimation technique to derive detector structure
- Starting point: same signal model as for derivation of Woody method for alignment of evoked responses with varying latencies

$$x(n)=\begin{cases}\upsilon(n) & 0 \le n \le \theta-1\\ s(n-\theta)+\upsilon(n) & \theta \le n \le \theta+D-1\\ \upsilon(n) & \theta+D \le n \le N-1\end{cases}$$

x (n) observed signal
s (n) QRS, known morphology
υ(n) noise

θ QRS occurrence time
D duration of s (n)
N observation interval

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APPLICATION-QRS detection

Unknown time of occurrence θ

ML estimate of occurrence time θ

(value that maximizes log likelihood function:)

$$\hat{\theta} = \arg\max_{\theta} \ln p(x;\theta)$$

PDF of observed signal

equivalent to finding peak amplitude in signal y(θ)

$$\hat{\theta} = \arg\max_{\theta} y(\theta)$$

filtering operation

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APPLICATION-QRS detection

y (θ) is output of matched filter h(n)

$$y(\theta) = \sum_{n=\theta}^{\theta+D-1} x(n)h(\theta - n)$$

False detection, because assumed one QRS complex present in N

$\longrightarrow$ thresholding

$$\bar{y}(\hat{\theta}) \rangle n$$

$\Longrightarrow$ detected QRS complexes at $\theta_1, \theta_2, \ldots$

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APPLICATION-QRS detection

Unknown time of occurrence and amplitude a

observed signal $$x(n) = as(n-\theta) + \upsilon(n)$$

maximize log-likelihood function

$$[\hat{\theta}, \hat{\alpha}] = \arg\max_{\theta} \ln p_{\upsilon}(x;\theta,a)$$

ML estimator of θ

$$\hat{\theta} = \arg\max_{\theta} \left[\frac{E_s}{2\sigma_{\upsilon}^2} \left[\bar{y}^2(\theta) \right] \right]$$

thresholding $$\bar{y}^2(\hat{\theta}) \rangle n$$

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APPLICATION-QRS detection

Unknown time of occurrence, amplitude and width

width parameter ℓ in model of QRS waveform $s(n,l)$

ML estimator of θ

$$\hat{\theta} = \arg\max_{\theta}\left(\frac{1}{2\sigma_{\upsilon}^{2}} \max_{l}\left[E_s(l)\,\overline{y}^{2}(\theta,l)\right]\right)$$

Energy of s(n) a function of ℓ, can not be omitted from estimation of θ

$$E_s(\theta,l) = \sum_{n=\theta}^{\theta+D-1} s^2(n-\theta,l)$$

[20] Veena Hegde, "**Review of Data Analysis Methods for Denoising and Characterising ECG**'', November 2009
[21] Timo Bragge, Mika P.Tarvainen and Pasi A.Karjalainen, "**High-Resolution QRS Detection Algorithm for Sparsely Sampled ECG Recordings**'', IEEE Trans Biomed Eng, August 2004
[22] J.Pan and W.Tompkins, "**A real-time QRS detection algorithm**'', IEEE Trans Biomed ENG,vol.32,no.3,pp.230-236, March 1985

APPLICATION-QRS detection

Easier approach to model width: s(n) composed of two identical waveforms, q(n), of which one is shifted ℓ samples in time and with opposite sign

$$s(n,l) = q(n) - q(n-l)$$

$$\hat{\theta} = \arg\max_{\theta}\left(\frac{E_q}{\sigma_\upsilon^2}\max_{l}\left[(1-\rho_q(l))(\bar{y}_q(\theta) - \bar{y}_q(\theta - l)^2)\right]\right)$$

maximized when $\overline{y}_o(\theta)$ and $\overline{y}_o(\theta - l)^2$ positive maximum and negative minimum

$\rightarrow$ Approximate, but computationally efficient ML estimator determines local extreme values of filtered signal for estimation of θ

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APPLICATION-QRS detection

Peak-and-valley picking strategy:

- Use of local extreme values as basis for QRS detection
- Base of several QRS detectors
- Distance between two extreme values must be within certain limits to qualify as a cardiac waveform
- Also used in data compression of ECG signals

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APPLICATION-Linear Filtering

- To enhance QRS from background noise
- Examples of linear, time-invariant filters for QRS detection:
  - Filter that emphasizes segments of signal containing rapid transients (i.e. QRS complexes)
    - Only suitable for resting ECG and good SNR
  - Filter that emphasizes rapid transients + low pass filter
  - Family of filters, which allow large variability in signal and noise properties

$$H(z) = (1 - z^{-L_1})(1 + z^{-1})^{L_2}$$

difference between input and delayed input

lowpass filter

- Suitable for long-term ECG recordings (because no multipliers)
- Filter matched to a certain waveform not possible in practice
  - ⇨ Optimize linear filter parameters (e.g. L_1 and L_2)

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APPLICATION-Decision Rule

- To determine whether or not a QRS complex has occurred
- Fixed threshold η
- Adaptive threshold
  - QRS amplitude and morphology may change drastically during a course of just a few seconds
- Here only amplitude-related decision rules
- Noise measurements
- Interval-dependent QRS detection threshold
  - Threshold updated once for every new detection and is then held fixed during following interval until threshold is exceeded and a new detection is found
- Time-dependent QRS detection threshold

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APPLICATION-Performance Evaluation

- Before a QRS detector can be implemented in a clinical setup
  - Determine suitable parameter values
  - Evaluate the performance for the set of chosen parameters
- Performance evaluation
  - Calculated theoretically or
  - Estimated from database of ECG recordings containing large variety of QRS morphologies and noise types

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APPLICATION-Performance Evaluation

- Estimate performance from ECG recordings database

P_D: probability of true detection
P_F: probability of false detection
P_M: probability of missed detection
N_D: number of correctly detected complexes
N_F: number of false alarms
N_M: number of missed beats
θ_j:estimated occurrence time
θ_i:annotation time
$\Delta\theta$:matching window

$$\hat{P}_D = \frac{N_D}{N_D + N_M}$$

$$\hat{P}_F = \frac{N_F}{N_D + N_F}$$

A beat detected when

$$\left|\hat{\theta}_j - \theta_i\right| \leq \Delta\theta$$

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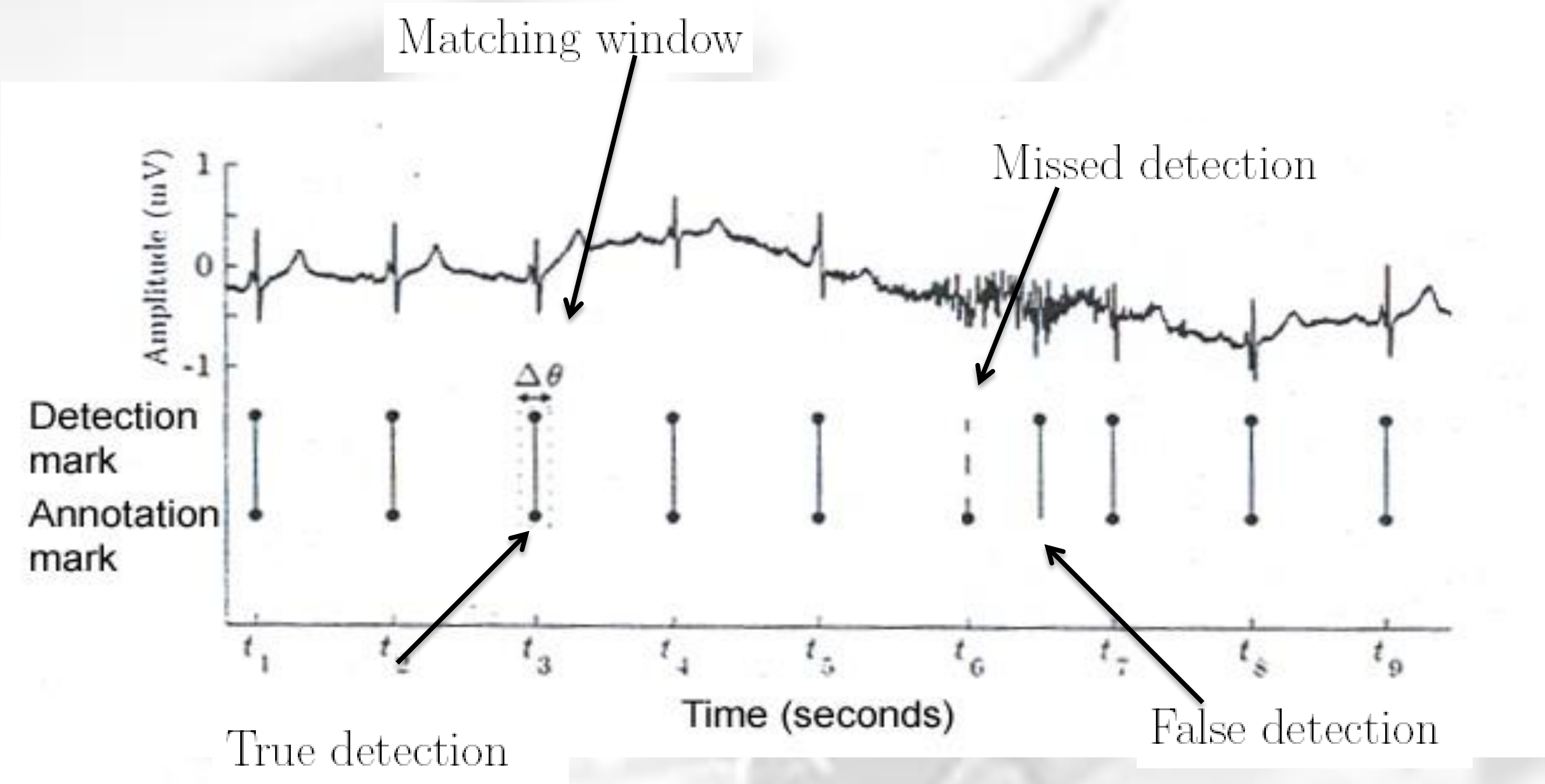
APPLICATION-Performance Evaluation



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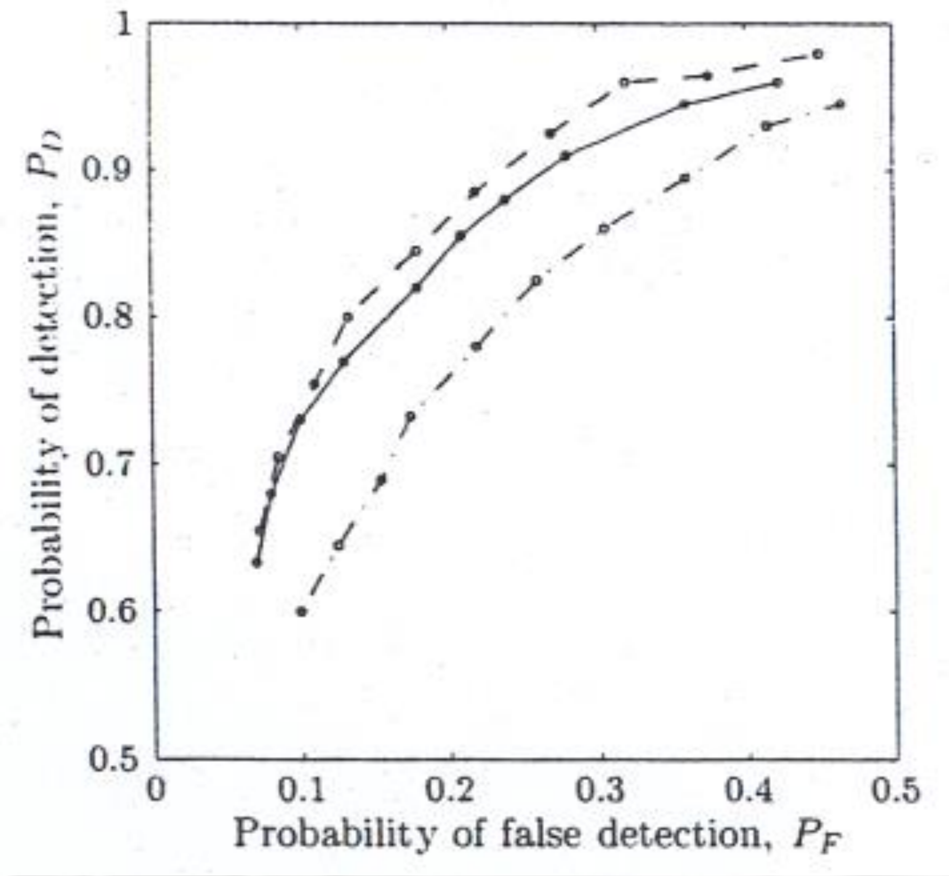
APPLICATIONS-ECG-Performance Evaluation

Receiver operating characteristics (ROC)

- Study behaviour of detector for different parameter values
- Choose parameter with acceptable trade-off between P_D and P_F



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PROBLEMS-Short questions

1. Would you consider a nerve action potential as a continuous or discontinuous signal?
2. Is the ECG a periodic signal?
3. What is the result of carrying out a Fourier transform on a rectangular impulse in time?
4. Is the variance of a data set equal to the square root of the standard deviation?
5. Is an EMG signal periodic?
6. What is the convolution integral?
7. What do you get if you multiply the Fourier transform of a signal by the frequency response of a system?
8. Measurements are made on a group of subjects during a period of sleep. It is found that the probability of measuring a heart rate of less than 50 bpm is 0.03.In the same subjects a pulse oximeter is used to measure oxygen saturation PO_2 and it is found that the probability of measuring a value of PO_2 below 83% is 0.04. If the two measurements are statistically independent then what should be the probability of finding both a low heart rate and low oxygen saturation at the same time?
   If you actually find the probability of both the low heart rate and low oxygen saturation occurring at the same time to be 0.025 then what conclusion would you draw?

[10] B H Brown, R H Smallwood, D C Barber, P V Lawford and D R Hose, ‘‘ **MEDICAL PHYSICS AND BIOMEDICAL ENGINEERING**’’

PROBLEMS-Answers

1. A nerve action potential should probably be considered as discontinuous as it moves very rapidly between the two states of polarization and depolarization.
2. The ECG is periodic, although the R-R interval is not strictly constant.
3. You obtain a frequency spectrum of the form $\sin(t)/t$ if you carry out a Fourier transform on a rectangular impulse.
4. No, the variance is equal to the square of the standard deviation.
5. An EMG signal is not periodic. It is the summation of many muscle action potentials which are asynchronous.
6. The convolution integral gives the output of a system in terms of the input and the characteristic response of the system to a unit impulse.
7. If you multiply the FT of a signal by the frequency response of a system then you get the FT of the output from the system.
8. The combined probability if the two measurements are independent would be 0.0012. If the probability found was 0.025 then the conclusion would be that heart rate and oxygen saturation measurements are not statistically independent. This would not be a surprising finding as the two measurements have a physiological link.