DSP in Biomedicine

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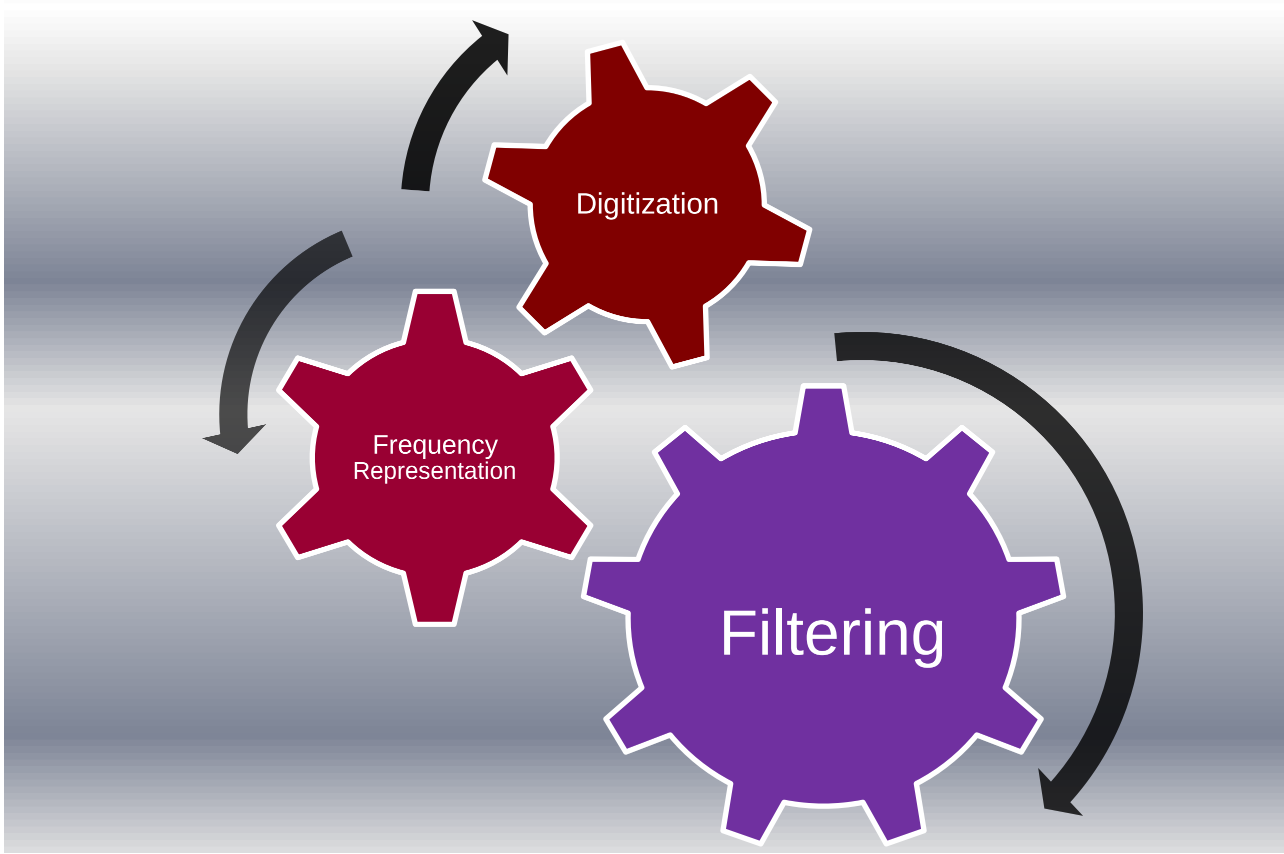
Programming Course

Biosignal Processing



Enhancing-Extracting-Presenting and Handling Information from signals abundant in digital medical reality

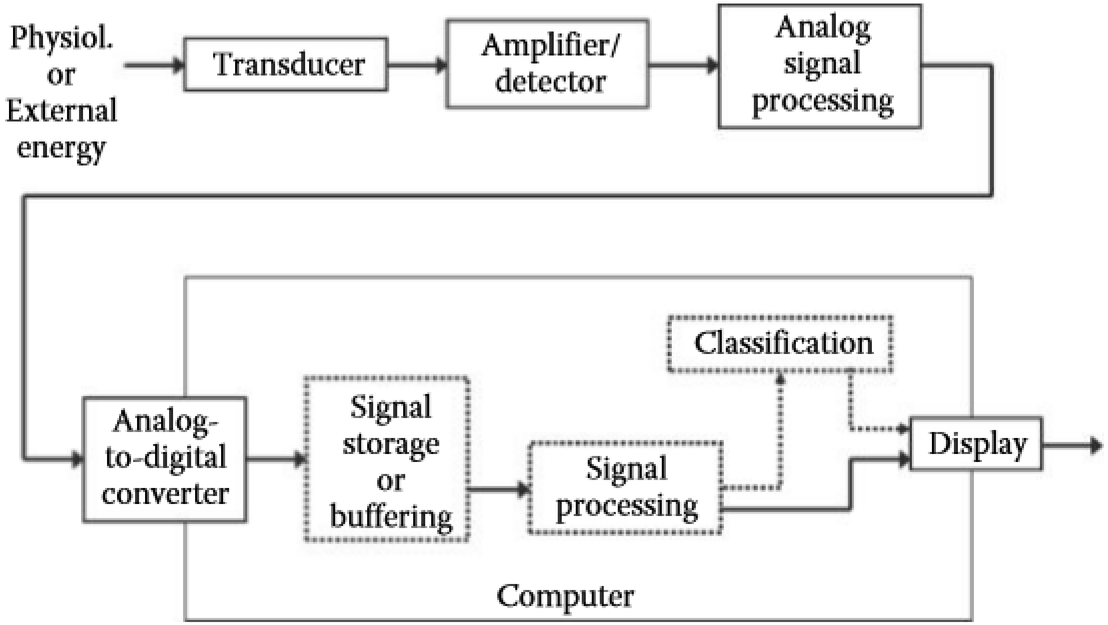
Signal is any variable that carries information about (the behavior or attributes of) a system (some phenomenon).

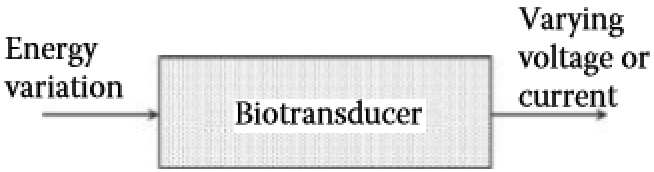
Digital Signal is a sequence of numbers that results from the digitization of an observable quantity.

Biosignals are inherent in life and constitute invaluable tools to gain insights…

Information about internal states of the body can be obtained through the acquisition and interpretation of **biosignals**. Expanding such information is an ongoing endeavor of medicine and medical research.

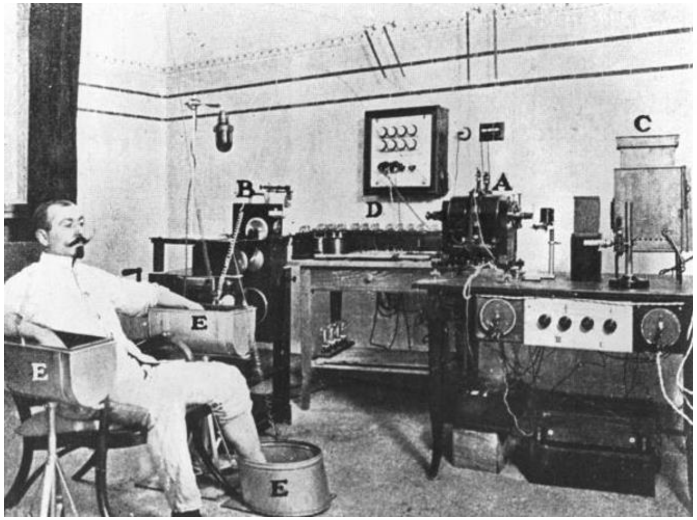
a typical **biomedical measurement** system





Energy	Measurement
Mechanical Length, position, and velocity Force and pressure	Muscle movement, cardiovascular pressures, muscle contractility valve, and other cardiac sounds
Heat	Body temperature and thermography
Electrical	EEG, ECG, EMG, EOG, ERG, EGG, and GSR
Chemical	Ion concentrations

Bio-measurements advances at the same pace with current technology



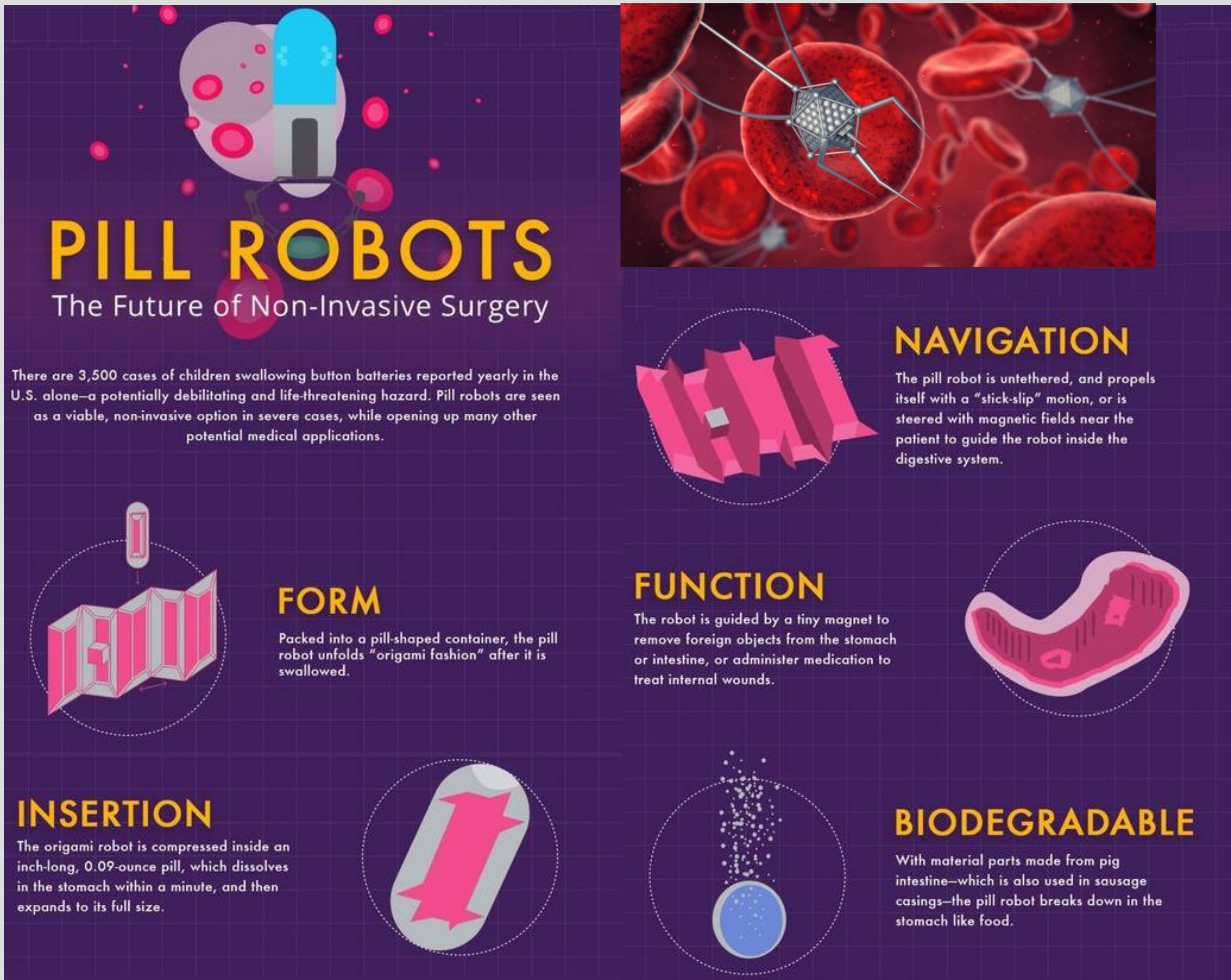
Proteus Digital Health Feedback System
ingestible sensors embedded in tablets,
a skin-worn receiver patch and a mobile

Signal Processing/Analysis techniques constantly evolve to catch up.
Some core-principles however remain unaltered.

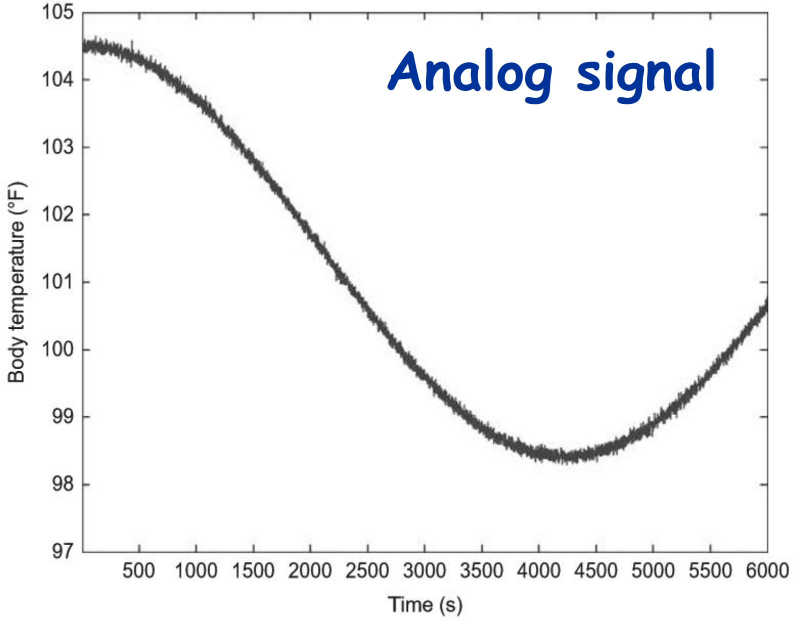
The most common theme :

Biological system → Sensors → Preprocessing and filtering → Feature extraction → Classification and diagnostics

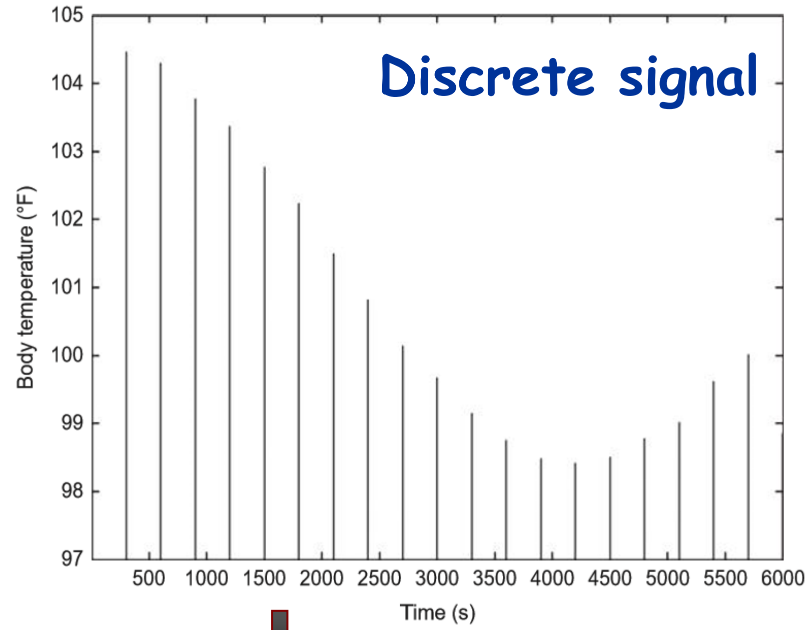
… Nanomedicine

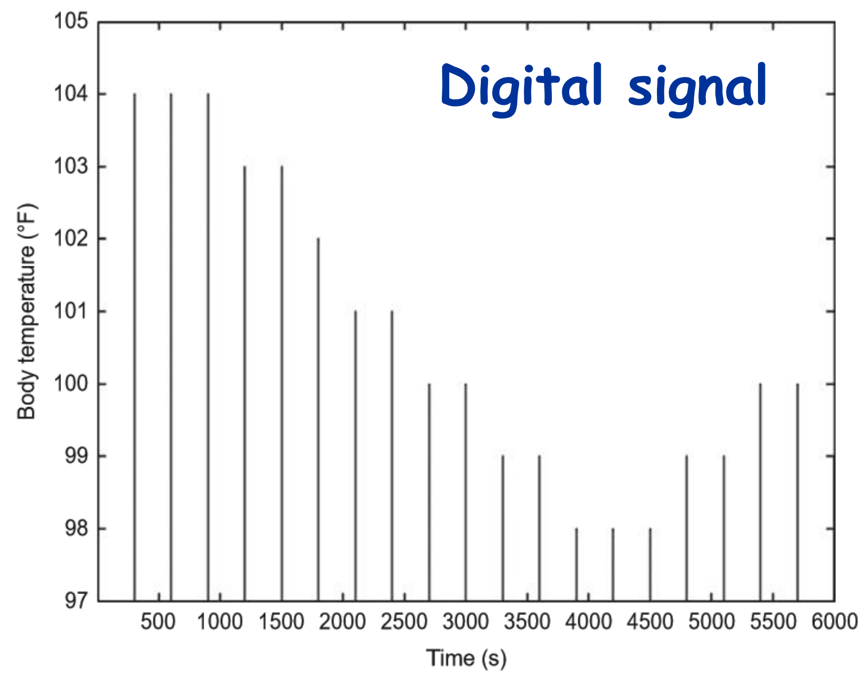


Digitization



Fs

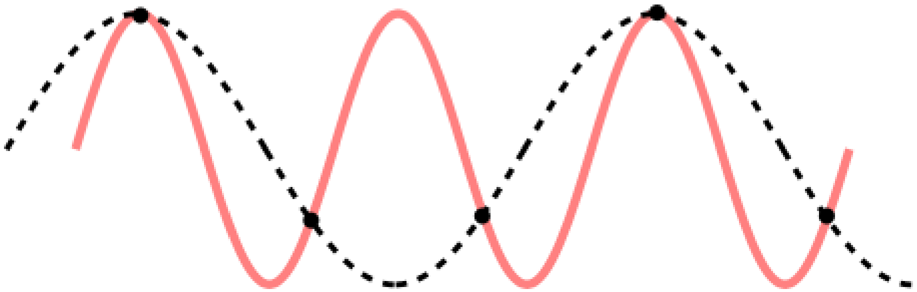




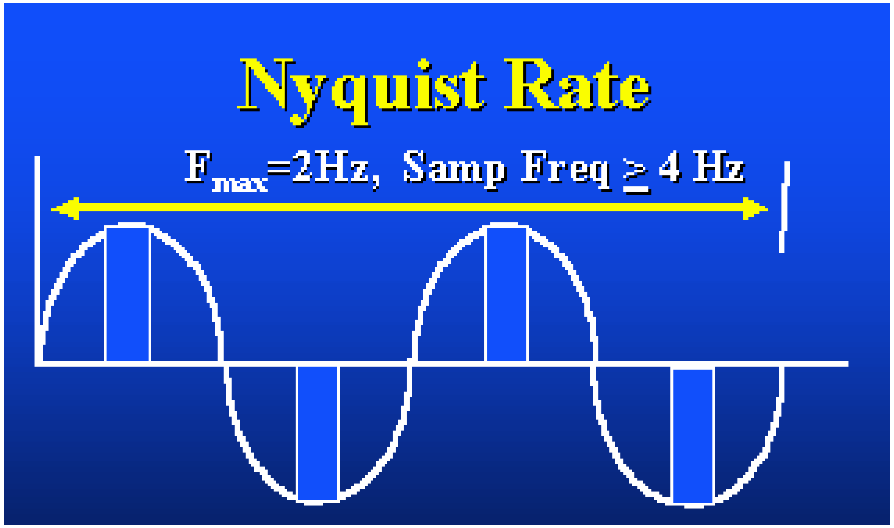
Sampling Frequency: Fs= 1/ Ts

Quantization.

Sampling Theorem - Nyquist Rate



"A signal x(t) with maximum frequency f_{MAX} can be recovered if sampled at frequency $f_S > 2\ f_{MAX}$"

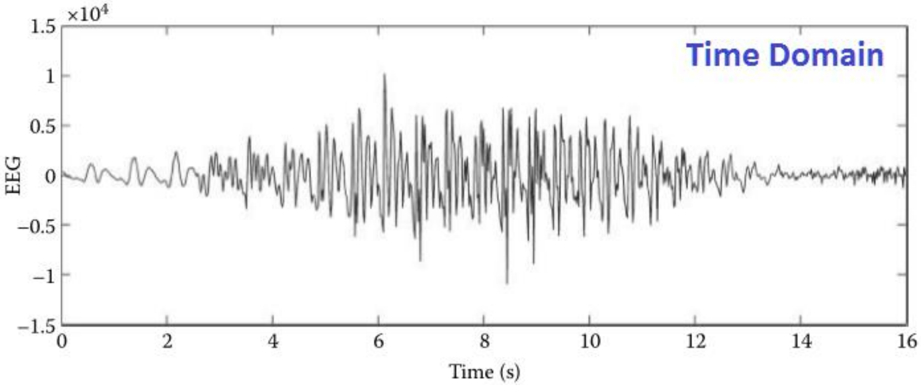


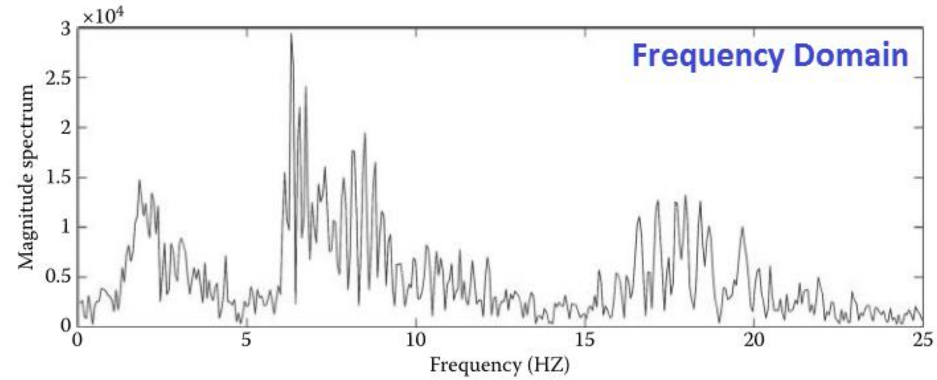
-Aliasing effect

-Anti-aliasing filter

-***Nyquist Frequency***: **$F_N = F_S/2$**

Frequency Representation

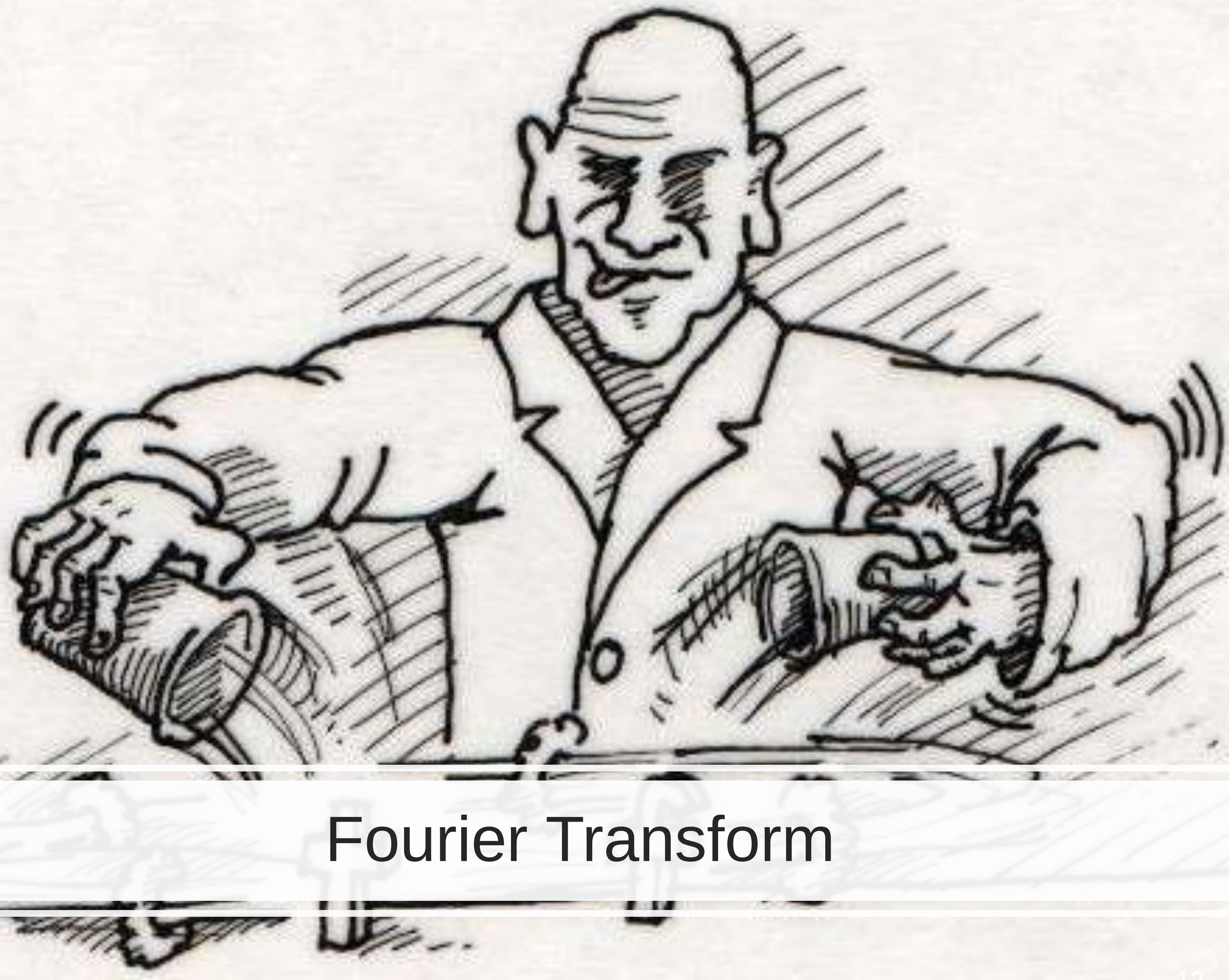




Fourier Transform (FT)

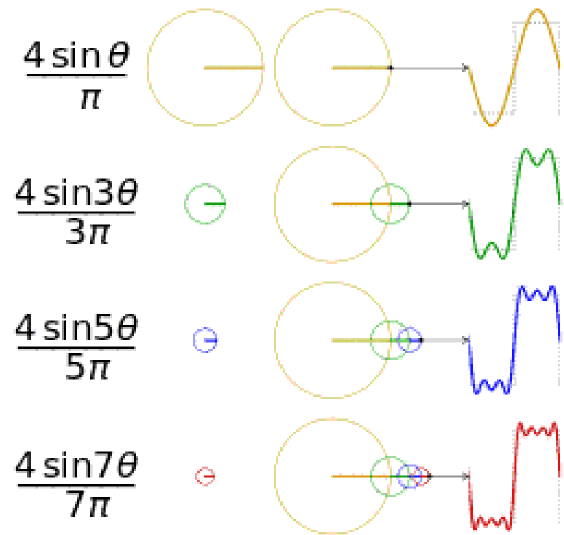
DFT (discrete FT) - FFT (fast-FT)

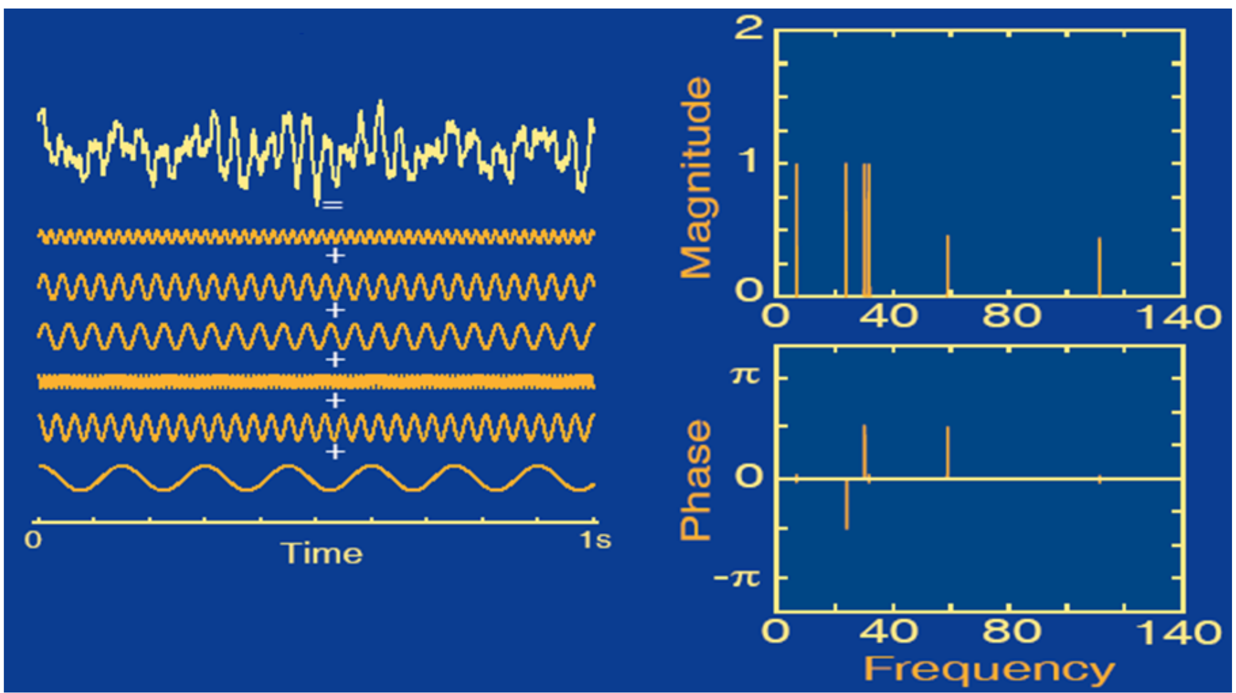
Spectral representation techniques (Welch’s method etc.)



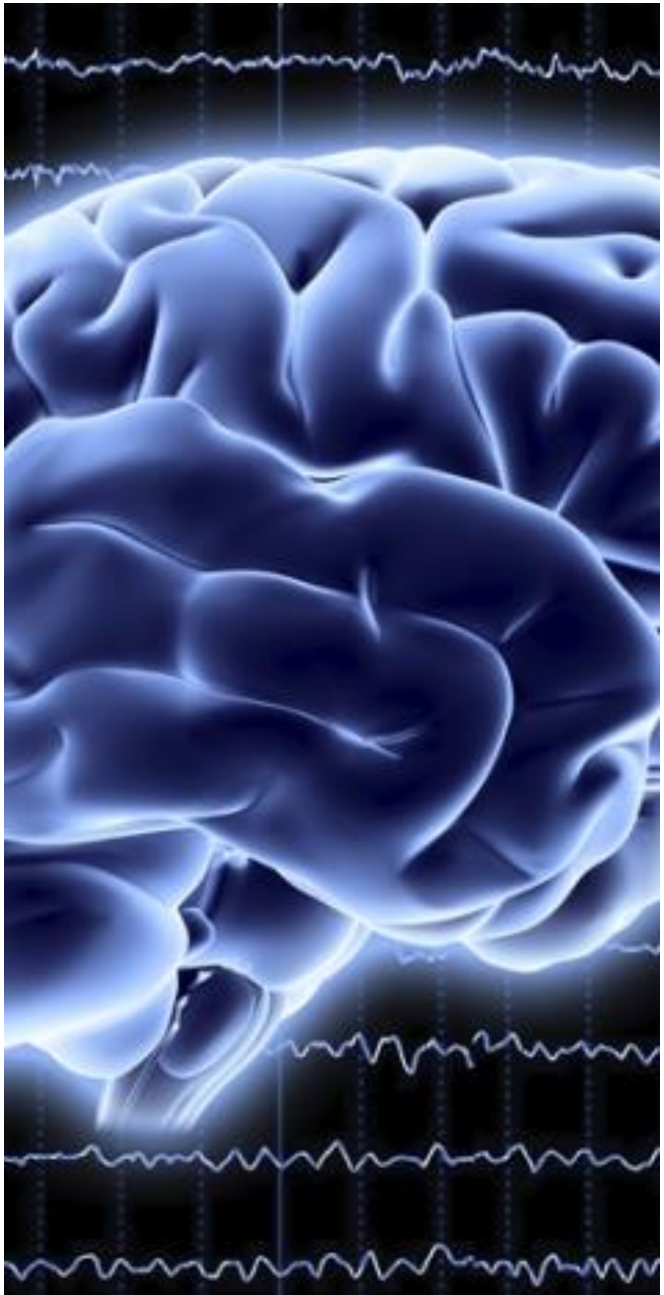
Fourier Transform

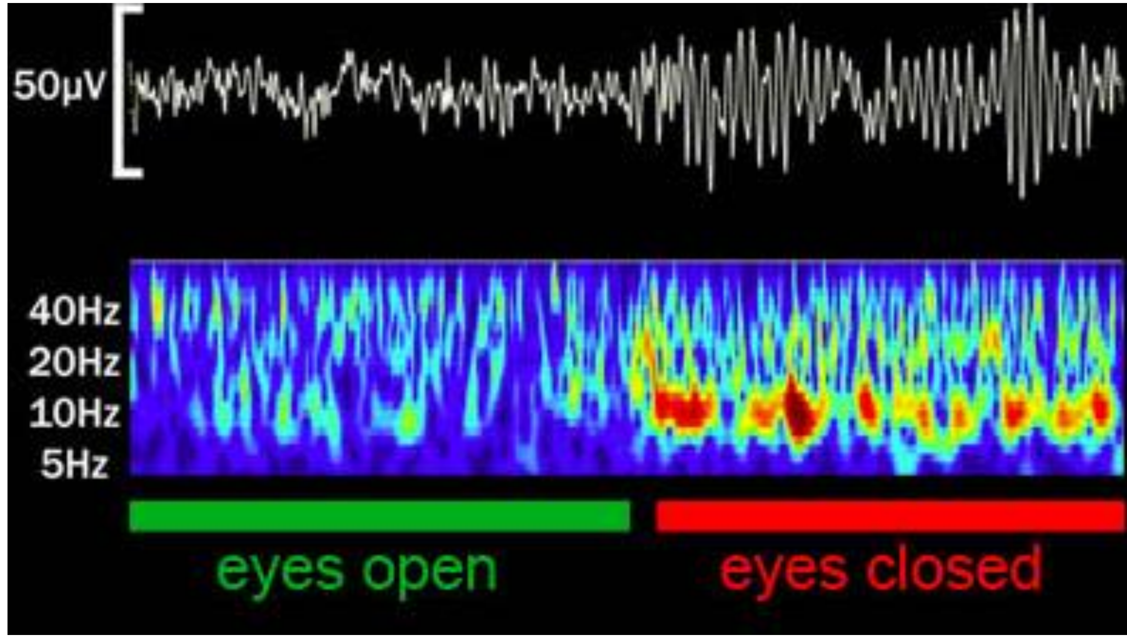
Fourier: "any signal or waveform could be made up just by adding together a series of pure tones (sine waves) with appropriate amplitude and phase "





Frequency spectrum





Brain Signal Spectral Content

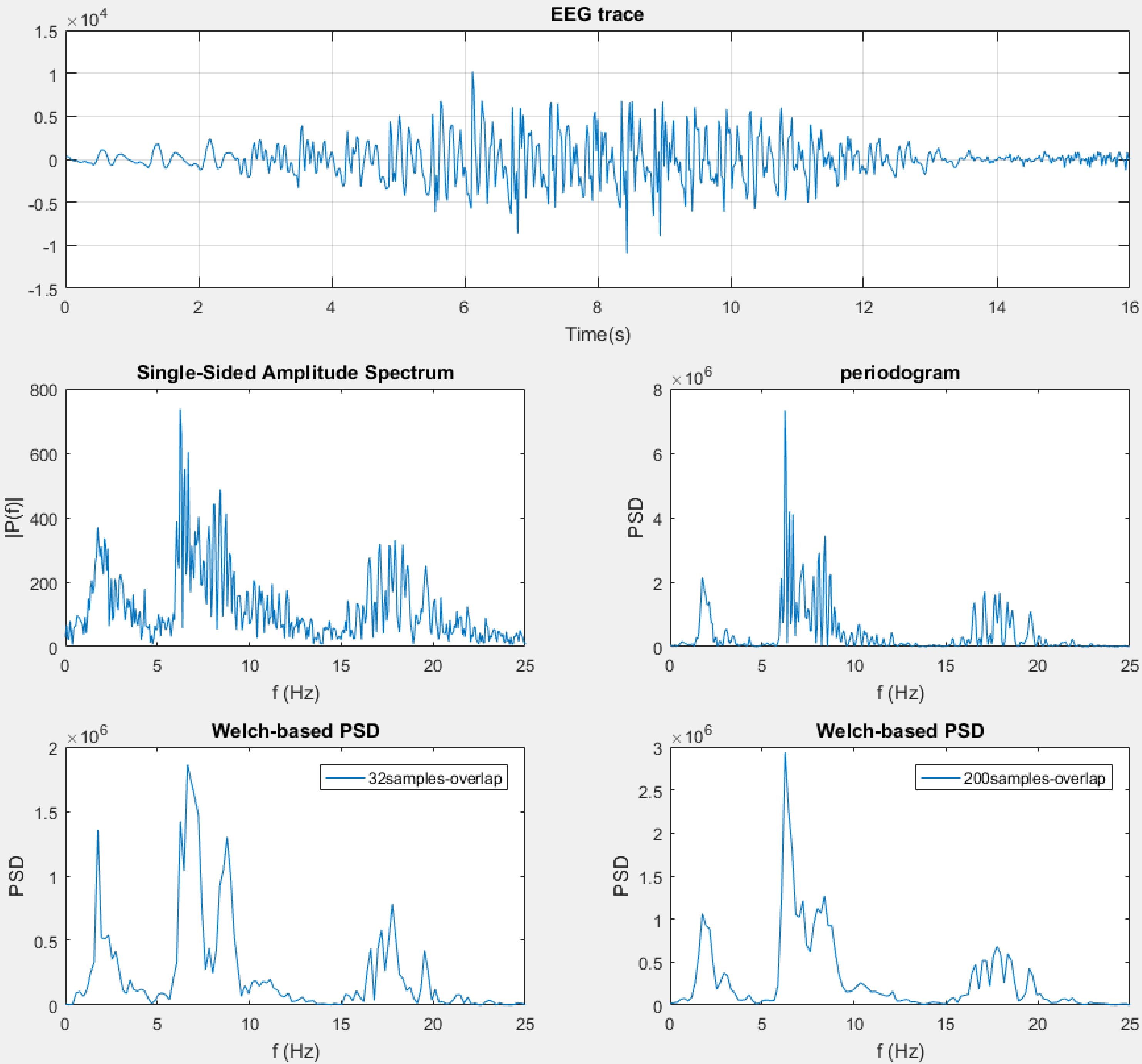
fft periodogram pwelch

+ sptool

1

NL_script_spectral_analysis_EEGtrace.m

```
load eeg_data, Fs=50;, time=[1:numel(eeg)]*(1/Fs);
% frequency-domain representation via FFT
L=numel(eeg);
Y = fft(eeg); %Compute the Discrete Fourier Transform
P2 = abs(Y/L); P1 = P2(1:round(L/2+1));P1(2:end-1) = 2*P1(2:end-1);
%Define the frequency domain f and plot the single-sided amplitude spectrum P1.
f = Fs*(0:round(L/2))/L;
…, plot(f,P1),title('Single-Sided Amplitude Spectrum'),xlabel('f (Hz)'),ylabel('|P(f)|'),xlim([0 25])

% frequency-domain representation via periodogram
[pxx,faxis] = periodogram(eeg,hamming(L),L,Fs,'psd') ;
subplot(3,2,4),plot(faxis,pxx),title('periodogram'),xlabel('f (Hz)'),ylabel('PSD'),xlim([0 25])

% WELCH-technique for estimating PSD
WINDOW=256;NOVERLAP=32;NFFT=256;
[pxx,faxis] = pwelch(eeg,WINDOW,NOVERLAP,NFFT,Fs,'onesided');
subplot(3,2,5),plot(faxis,pxx),xlabel('f (Hz)'),ylabel('PSD'),xlim([0 25]),title('Welch-based
PSD'),legend('32samples-overlap ')
```


EEG trace
× 10^4
Time(s)
Single-Sided Amplitude Spectrum
|P(f)|
f (Hz)
periodogram
× 10^6
PSD
f (Hz)
Welch-based PSD
× 10^6
32samples-overlap
PSD
f (Hz)
Welch-based PSD
× 10^6
200samples-overlap
PSD
f (Hz)

Biosignals are certainly **nonstationary**, with frequency content changing over time.

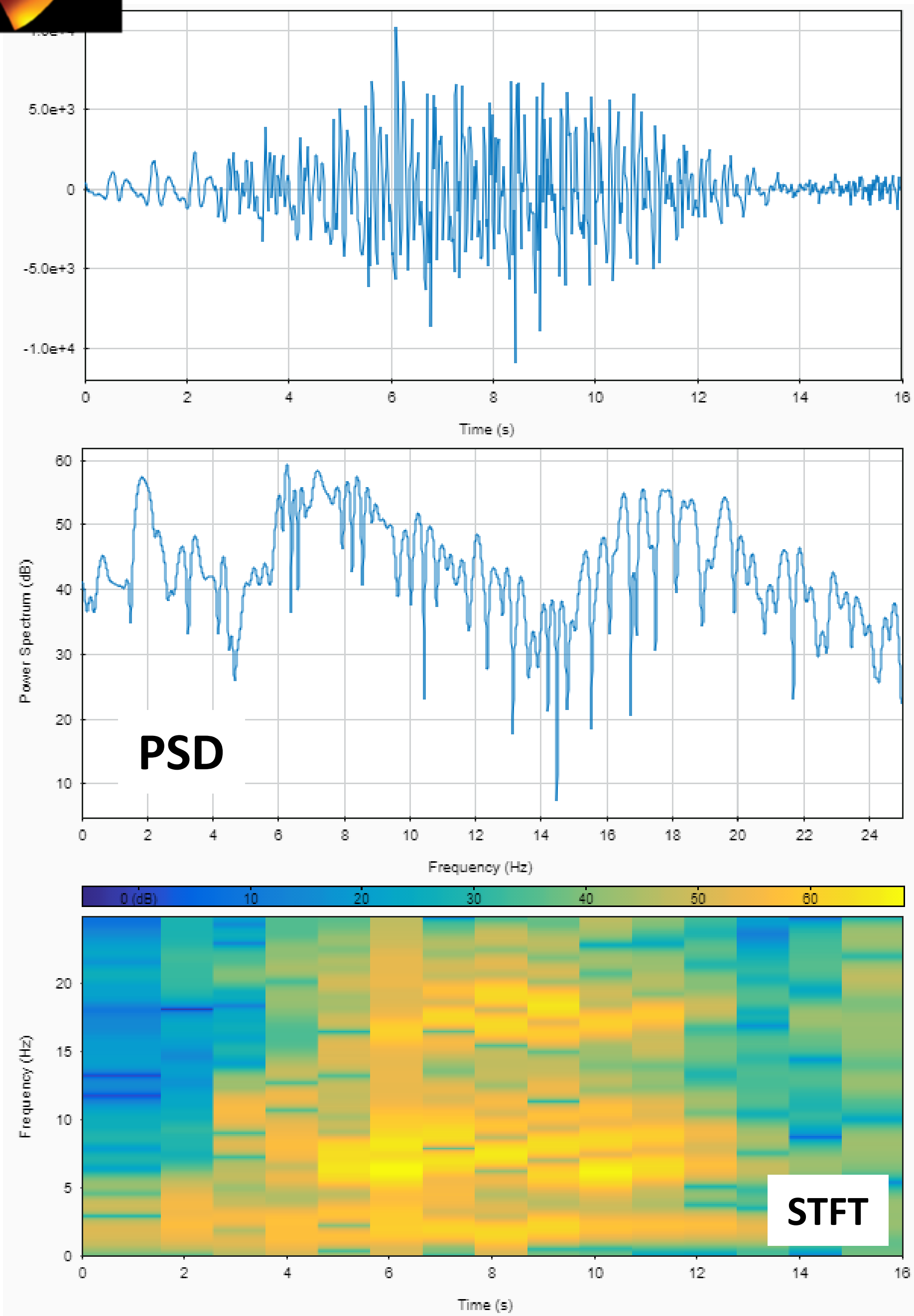
Such reflections of dynamics constitute the most interesting part of the signal.

Spectro-temporal analysis is the way to deal with them.

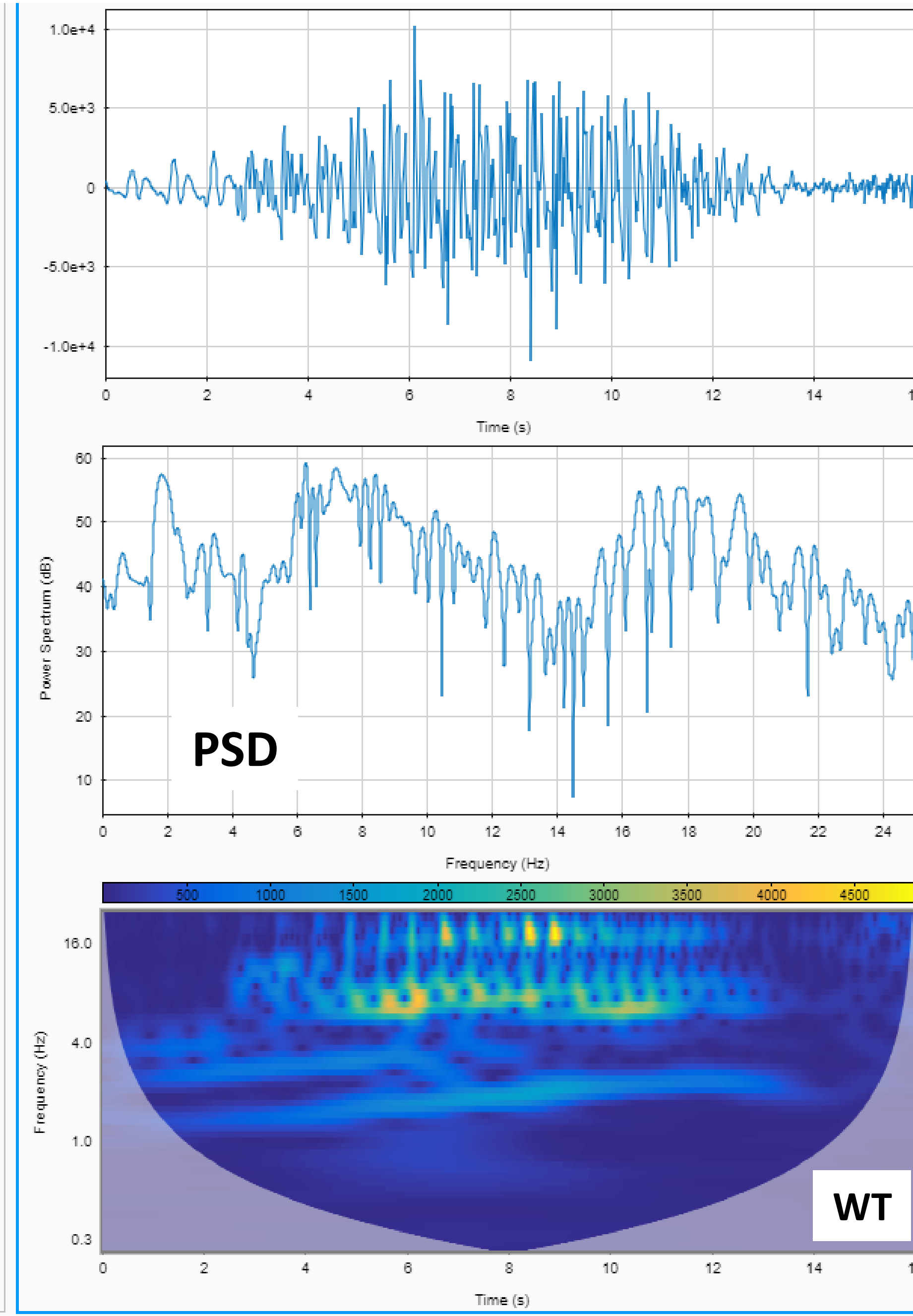
Two main ways to achieve it :
Short-Time-Fourier Transform (STFT) and ***Wavelet-Transform (WT)***

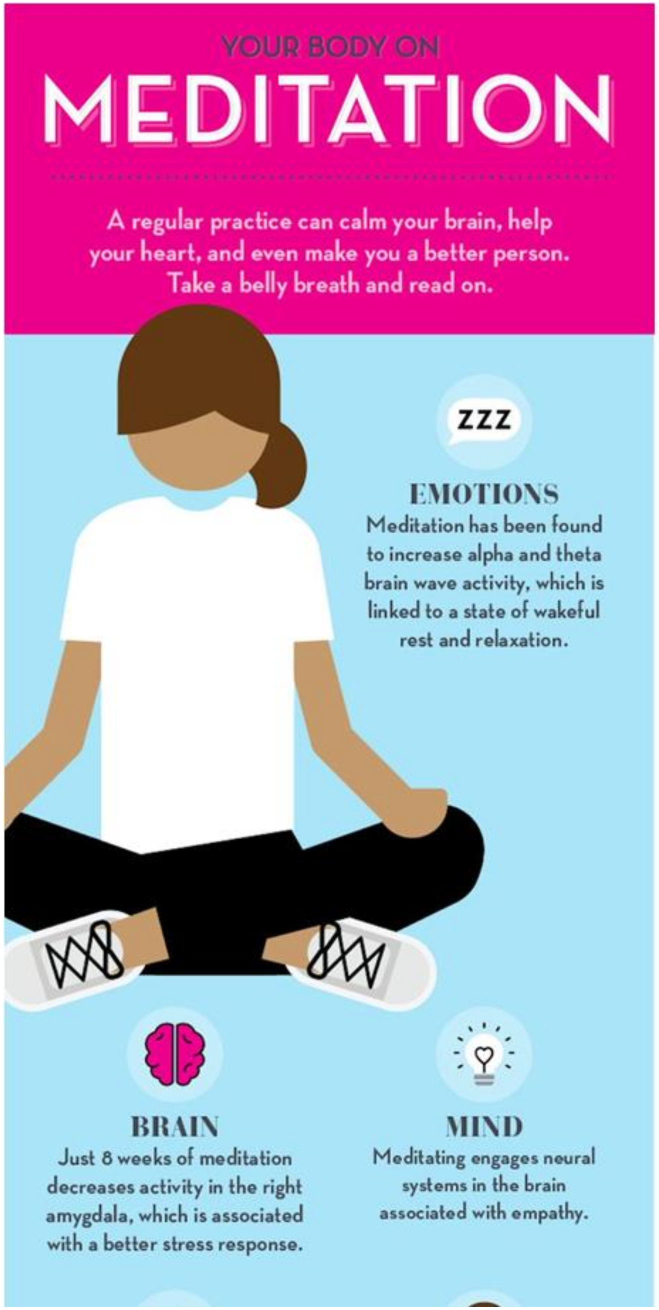
signalAnalyzer App

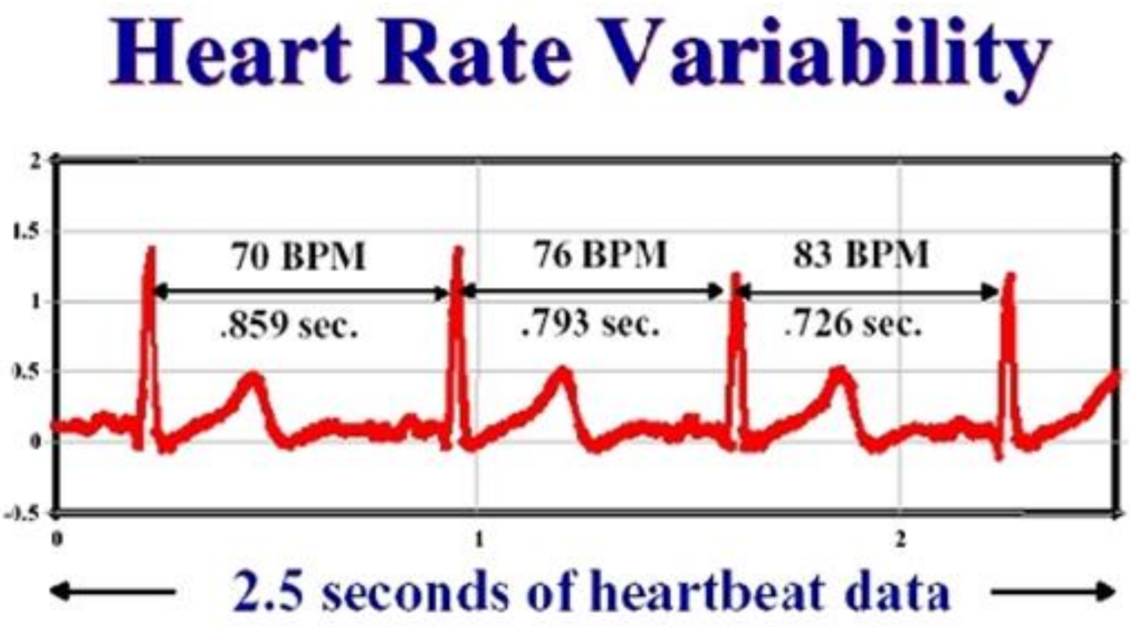
EEG trace



EEG trace







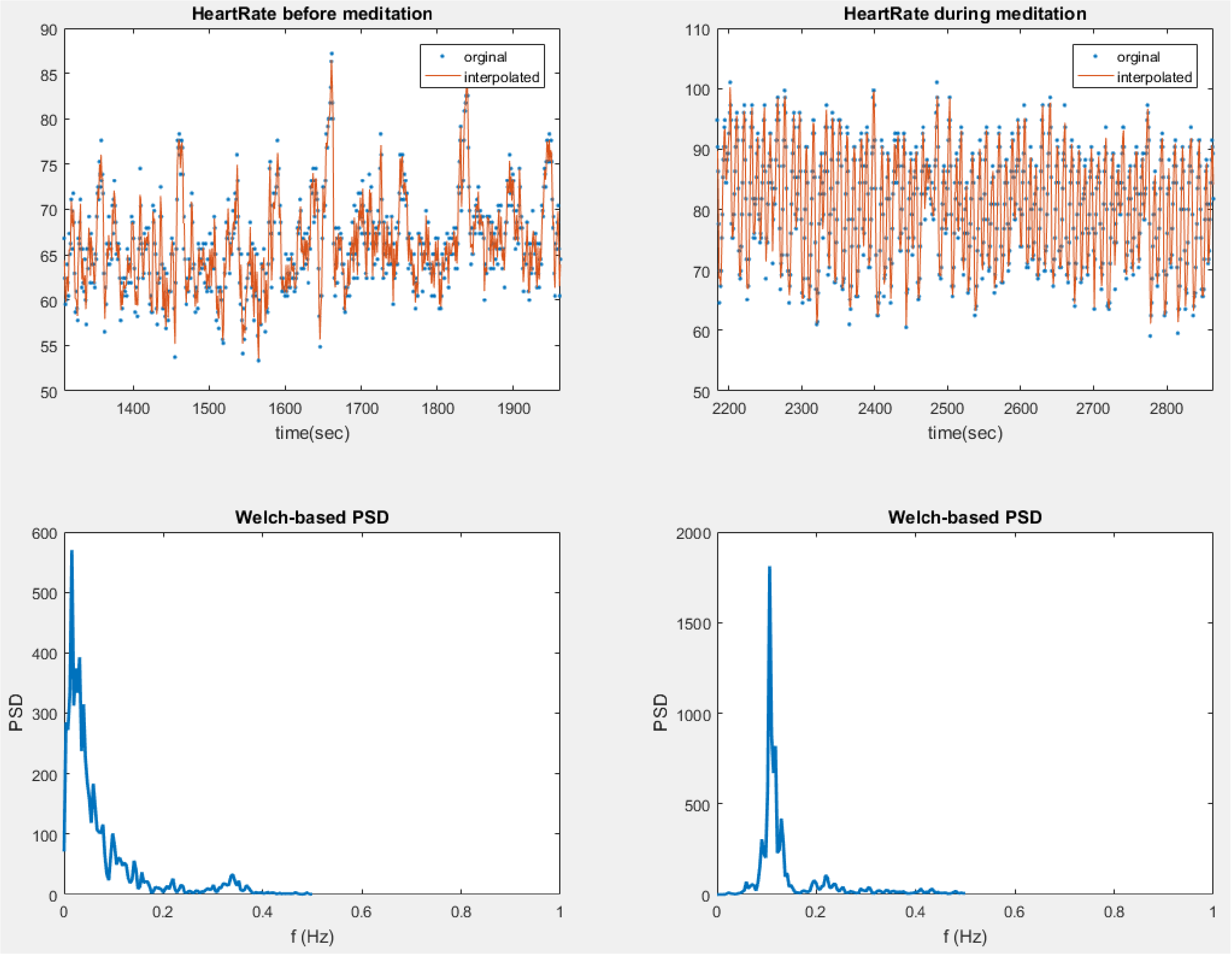
Meditation and HRV

Spectral analysis for *non-uniformly* sampled signals

2

NL_script_spectral_analysis_HeartRate_signals.m

```
load Hr_pre, fs=1; ts=1/fs;

% form a reqular time-axis (equally spaced time intervals)
timeaxis=[ceil(t_pre(1)):ts:floor(t_pre(end))];

% using the given time-signal pairs ''predict'' the signal at timeaxis
hr_pre_interpolated=interp1(t_pre,hr_pre,timeaxis);



WINDOW=256;NOVERLAP=200;NFFT=256;
[pxx,faxis] = pwelch(detrend(hr_pre_interpolated),WINDOW,NOVERLAP,NFFT,fs,'onesided');
% Note: detrend is necessary


load Hr_med,

timeaxis_med=[ceil(t_med(1)):ts:floor(t_med(end))];
hr_med_interpolated=interp1(t_med,hr_med,timeaxis_med);


WINDOW=256;NOVERLAP=200;NFFT=256;
[pxx,faxis] = pwelch(diff(hr_med_interpolated),WINDOW,NOVERLAP,NFFT,fs,'onesided');
subplot(2,2,4),plot(faxis,pxx),xlabel('f (Hz)'),ylabel('PSD'),xlim([0 1]),title('Welch-based PSD')
```



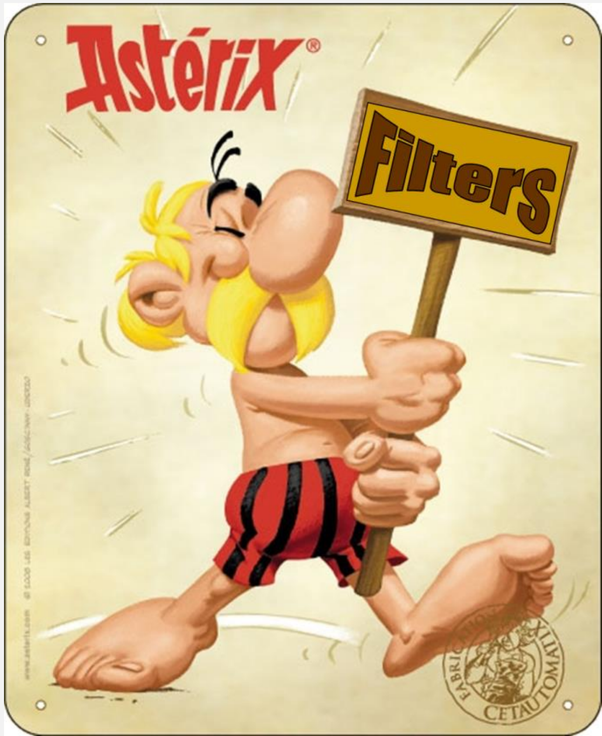
State-specific spectral characteristics can easily be defined

Filtering

Signal Averaging

Time-Domain operations

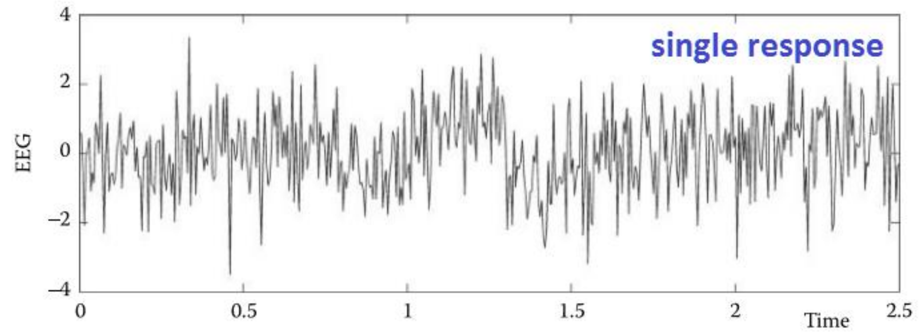
FT-based Filter Design



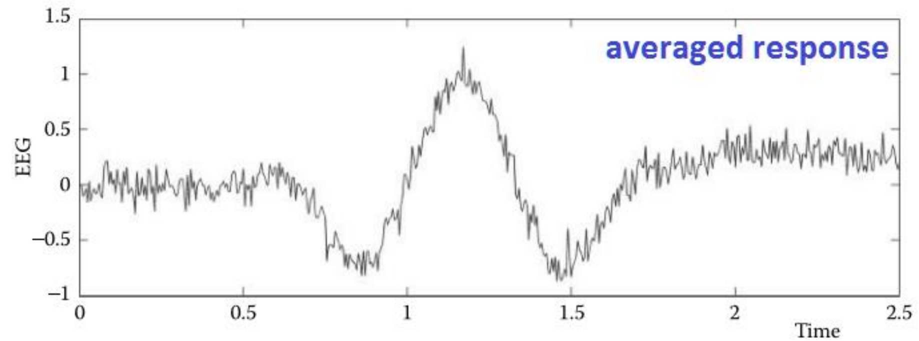
Signal Averaging : denoising repetitive signal waveforms

e.g. heart-beat in high resolution ECG
and single-trial Evoked Responses

Under the
'**constant signal**' + '**noise**' model,
the underlying signals recovers better
with more repetitions



$$x_i(n) = s(n) + noise_i(n), \quad i = 1 : N_{trials}$$

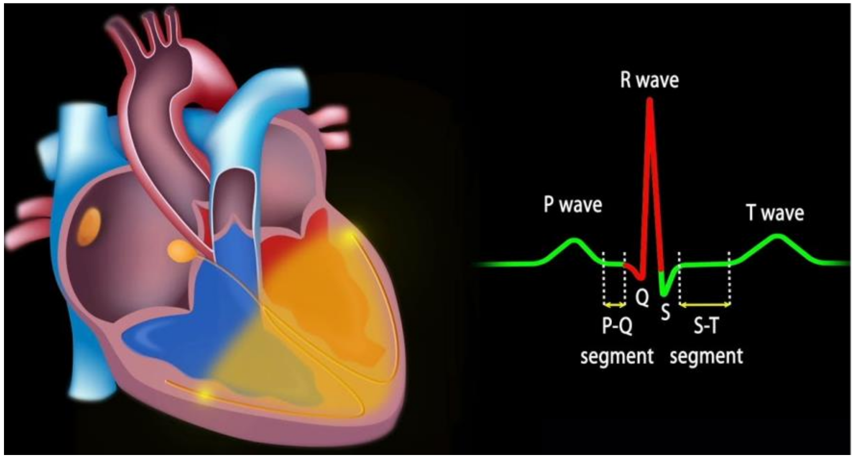


$$\frac{1}{N_{trials}} \sum_{1}^{N_{trials}} x_i(n) = \frac{1}{N_{trials}} \sum_{1}^{N_{trials}} [s(n) + noise_i(n)] \Rightarrow$$

$$x_{ave}(n) = s(n) + res\_noise(n),$$

$$var(res\_noise) = 1/N_{trials} \; var(noise_i)$$

High-resolution ECG-example

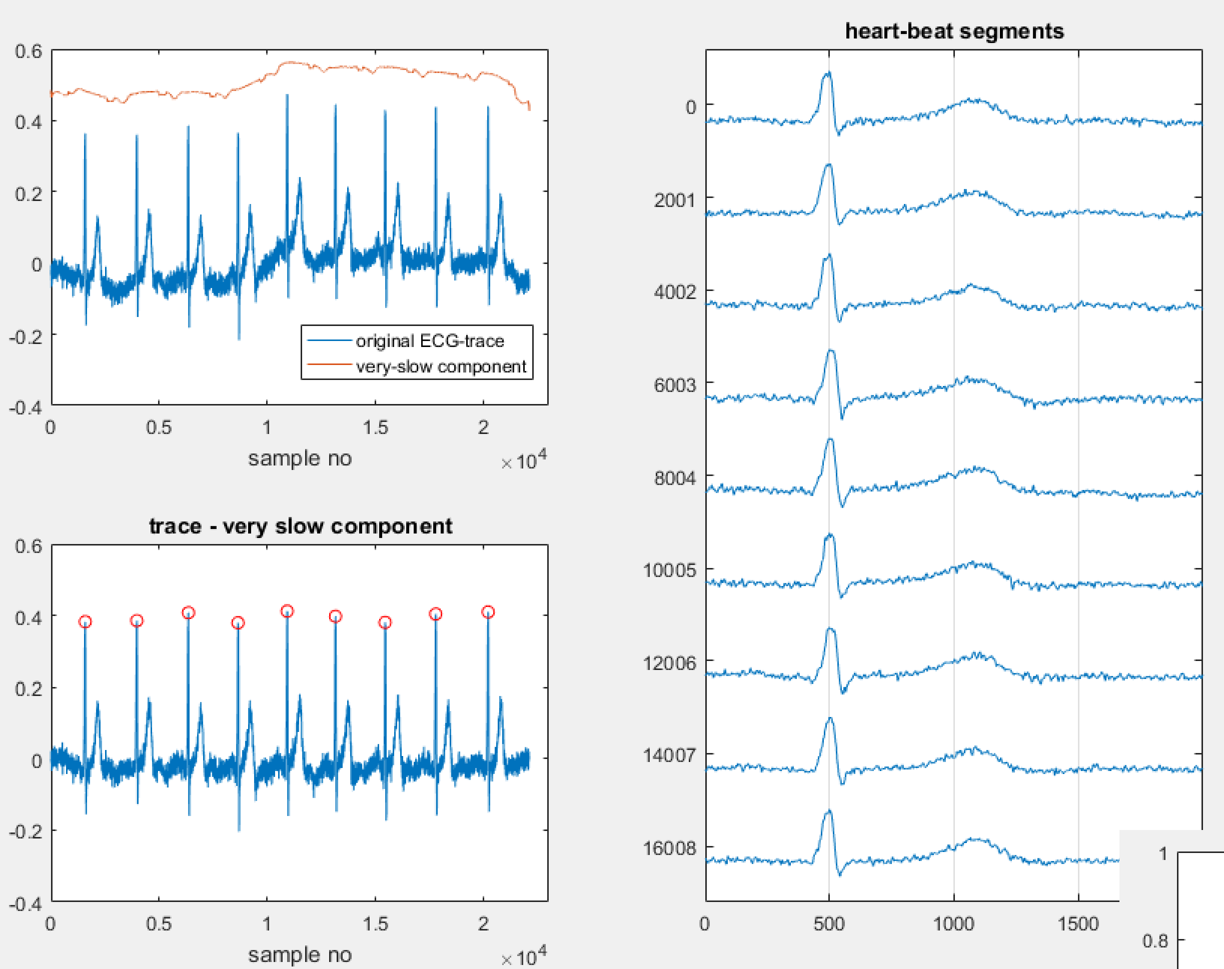


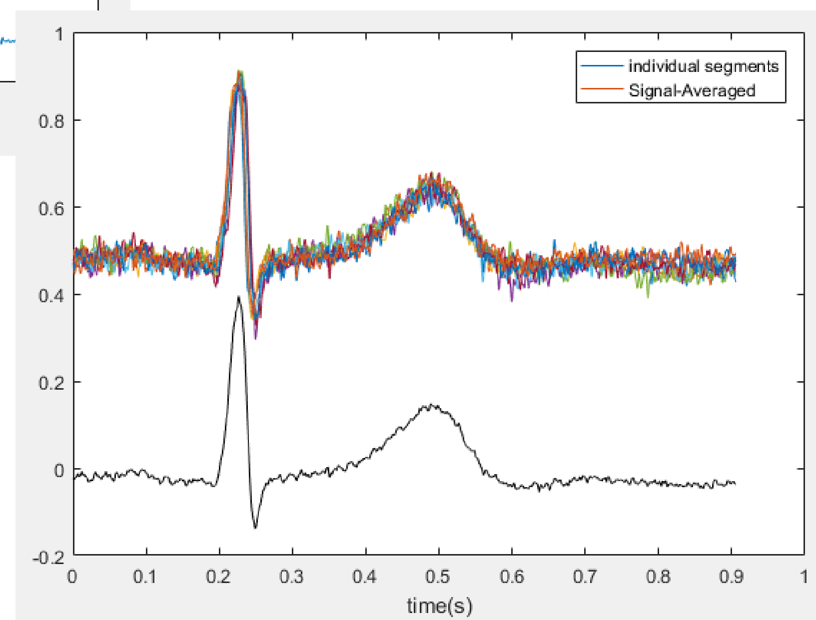
smooth → findpeaks → mean

3

NL_script_denoising_signalAveraging_highresolution_ECG.m

```
x=load('ECGtest.csv');                 % Load the test signal
fs = 2210;                              % Sampling Frequency

t=[1:numel(x)]; %dicrete_time #samples
%time=[1:numel(x)]*(1/fs); % time in sec
figure(1),clf,subplot(2,2,1),plot(t,x,t,smooth(x,2051)+0.5),legend('original ECG-trace','very-slow
component'),xlabel('sample no'),xlim([0,23000])
subplot(2,2,3),plot(t,x-smooth(x,2051)),hold on,title('trace - very slow component'),xlabel('sample
no'),xlim([0,23000])


% detecting the R-peak based on the denoised -trace
x2= x-smooth(x,2051);
[PKS,LOCS]=findpeaks(x2,t,'minpeakheight',0.3,'MinPeakDistance',100);
 plot(LOCS,PKS,'ro'),hold

% segmenting around the QRS complex
ECG_traces=[];for i=1:numel(LOCS)
              segment=x2(LOCS(i)-500:LOCS(i)+1500)';
              ECG_traces(i,:)=segment;end

plot(time,ECG_traces+0.5,time,mean(ECG_traces),'k'),
xlabel('time(s)'),legend('individual segments','Signal-Averaged')
```


original ECG-trace
very-slow component
sample no
$\times 10^4$
trace - very slow component
sample no
$\times 10^4$
heart-beat segments
0
2001
4002
6003
8004
10005
12006
14007
16008


individual segments
Signal-Averaged
time(s)

Frequency selective filters

Filters are systems (of programs) that alter the signal with the scope of enhancing/extracting the useful information.

$$x(n) \longrightarrow \boxed{h(n)} \longrightarrow y(n) \qquad \mathbf{y(n) = h(n) * x(n)}$$

$$a_o\, y(n) + a_1\, y(n\text{-}1) + \ldots + a_N\, y(n\text{-}N) = b_o\, x(n) + b_1\, x(n\text{-}1) + \ldots + \ldots.b_M\, x(n\text{-}M)$$

'Designing a Filter' means defining the coefficients $\{a_i\}$ and $\{b_i\}$ in the above ***Difference equation***

e.g. moving average filter $\vec{b} = \left[\ \frac{1}{3}\ \ \frac{1}{3}\ \ \frac{1}{3}\ \right] =: h(n)$

$\mathbf{x(n)}$ = [x(1) x(2) x(3) x(4) x(5) …..]

(*1/3) → +

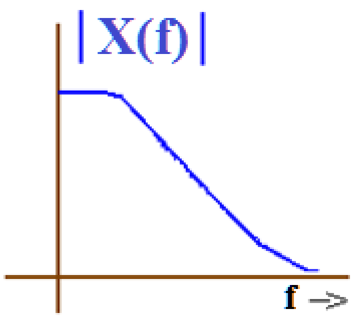
$\mathbf{y(n)}$ = [**y(2) y(3) y(4) …..**]

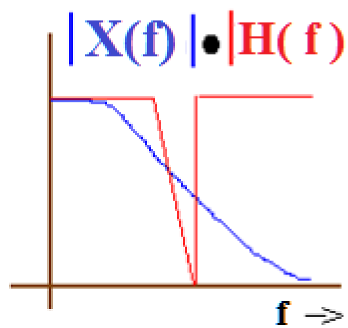
y = smooth(x,3)

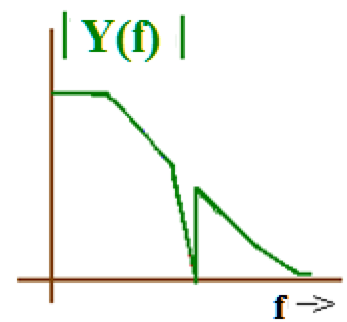
Frequency selective filters are filters that are designed in Frequency Domain thanks to *convolution theorem*

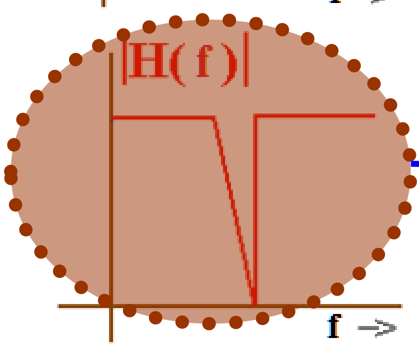
$Y(f) \longrightarrow \boxed{H(f)} \longrightarrow Y(f)$ $\quad$ $\mathbf{Y(f) = H(f) \, . \, X(f)}$

"we define the **frequency response H(f)**
& translate it into **Difference Equation** "



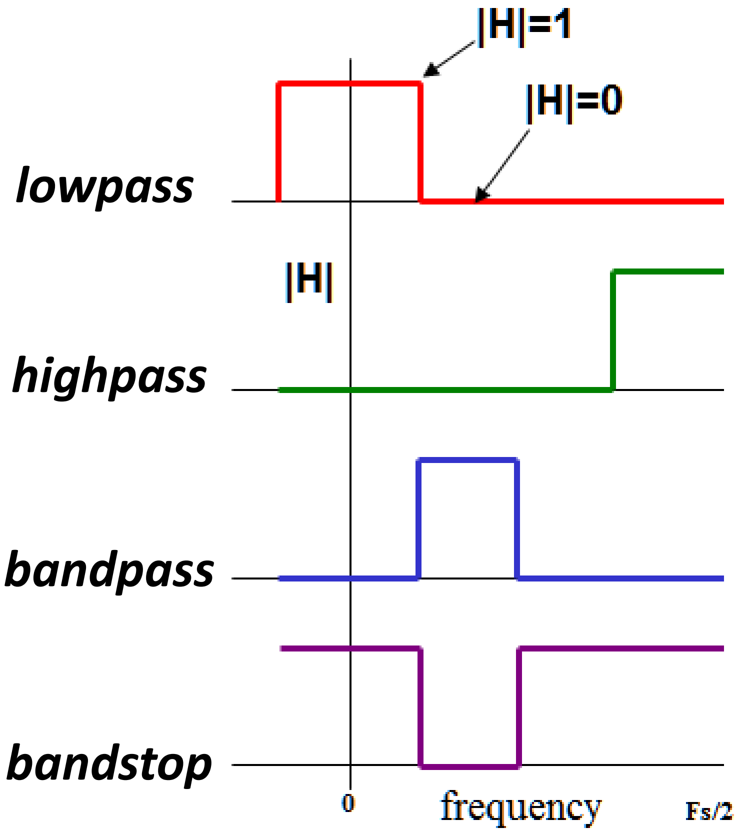






$$\boxed{y(n) = a_1 \, y(n-1) - b_1 \, x(n-1)}$$

Basic types of filters



Based on the form of ***difference equation*** there are two main kinds of linear filters: the ***FIR filters*** (with no recursive terms) and the ***IIR filters*** (using both b_i and a_i coeff's) which –in MATLAB- are designed with distinct commands, e.g.

B = fir1(N, Fc) **[B,A] = butter(N,Fc)**

but applied with the same command ***filter*** or ***filtfilt***

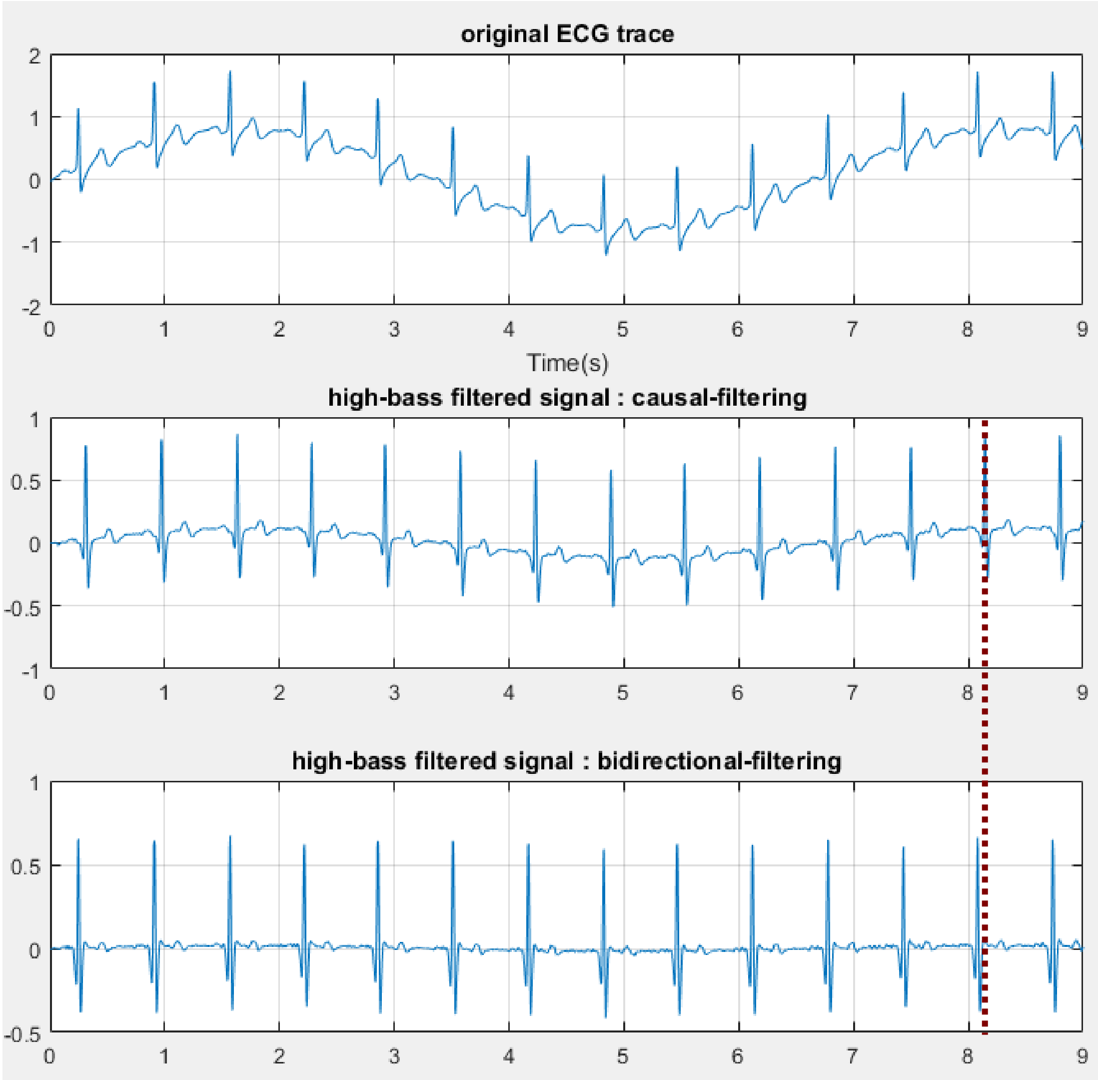
Y = filter(B,A,X)

Denoising ECG

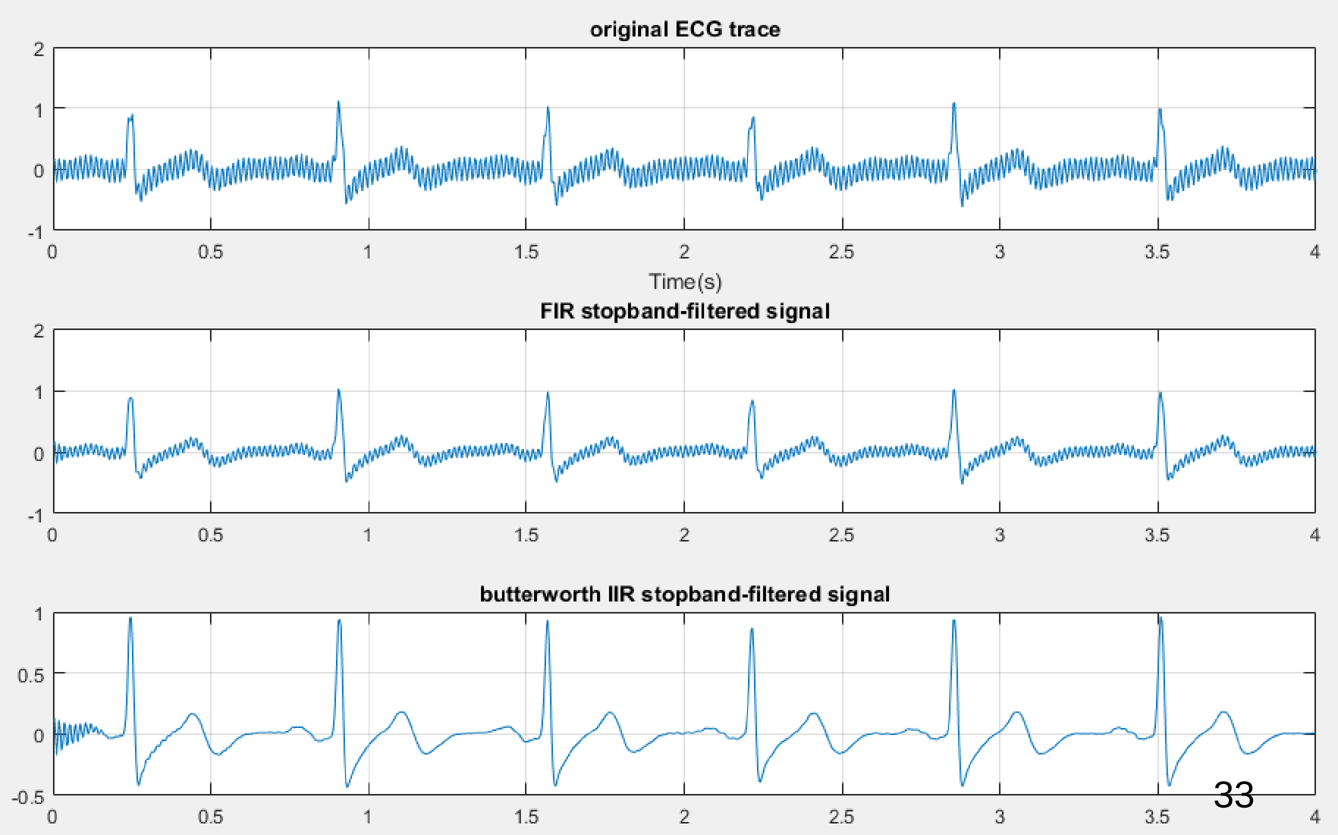
```
load ECG_9, Fs=250
% design an a high-pass FIR 32-order filter with cutoff at 8 Hz
b=fir1(32,8/(Fs/2),'high');
filtered_x1= filter(b,1,x); % apply the filter in causal mode

filtered_x2=filtfilt(b,1,x); % apply the filter in zero-phase mode.
```

4

NL_script_filtering_ECG_signal_to_Cancel_Respiratory_artifact.m



```
load ECG_60Hz_data, Fs=250
% design a stop-band FIR 36-order filter
% for removing powerline noise @ 60 Hz

b=fir1(36,[58 62]/(Fs/2),'stop');
filtered_x=filtfilt(b,1,x); % apply the filter in zero-phase mode

% design a stop-band IIR 3-order filter
[b,a]=butter(3,[58 62]/(Fs/2),'stop');
filtered_x=filtfilt(b,a,x); % apply the filter in zero-phase (bidirectional) mode
```



5

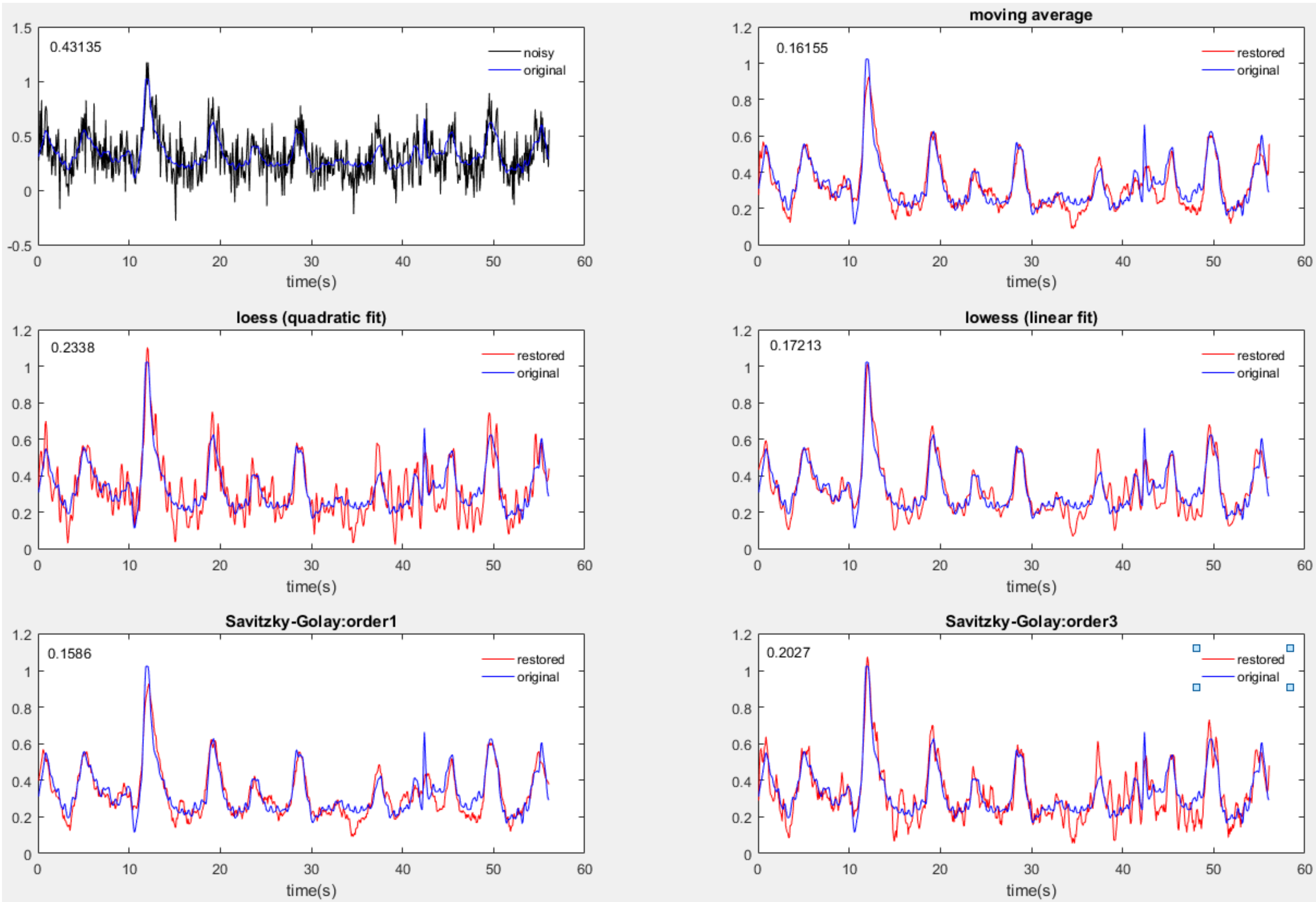
NL_script_filtering_powerlinenoise_from_ECGtrace.m

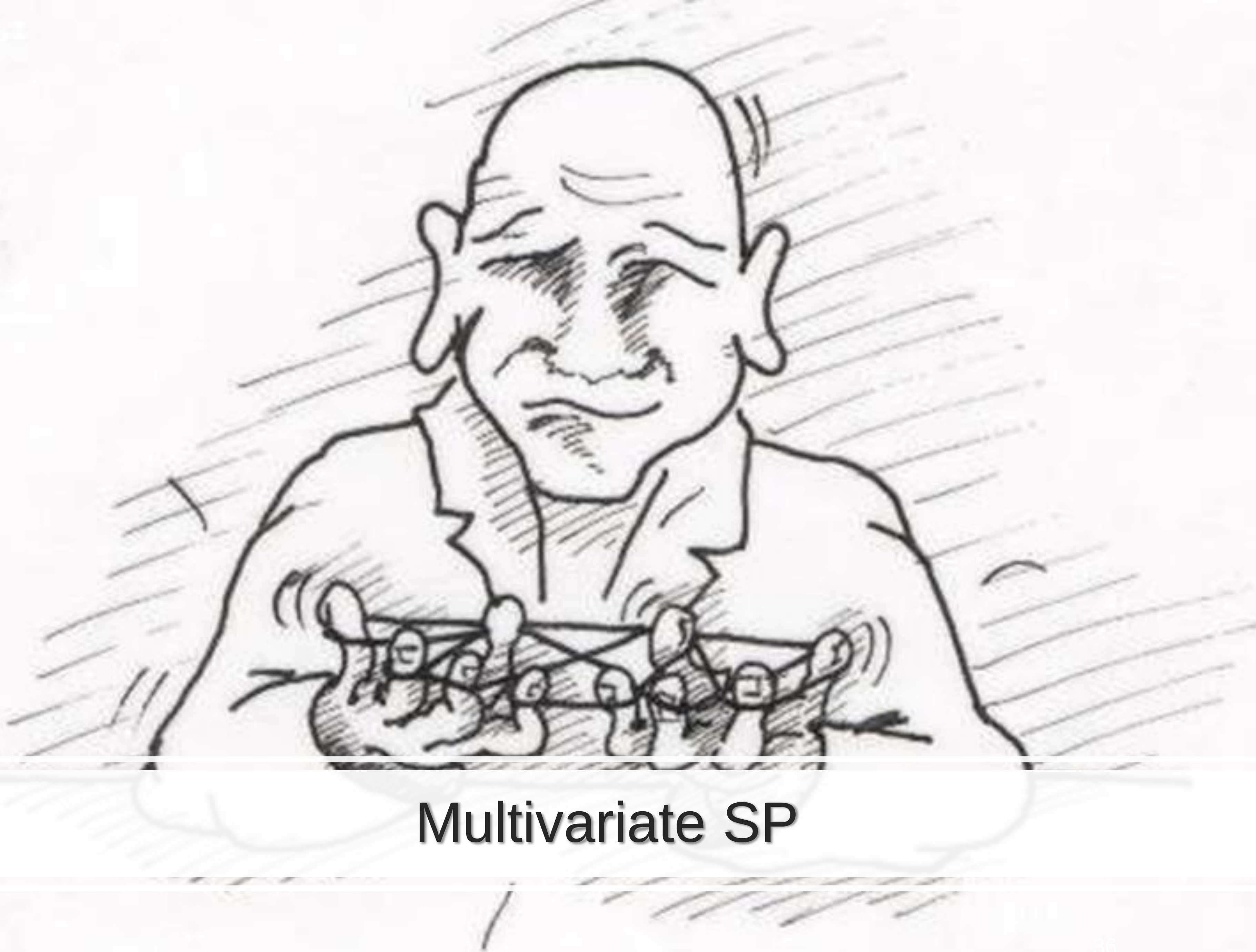
Denoising respiratory signal

smooth | linear fit | quadratic | sgolay

6

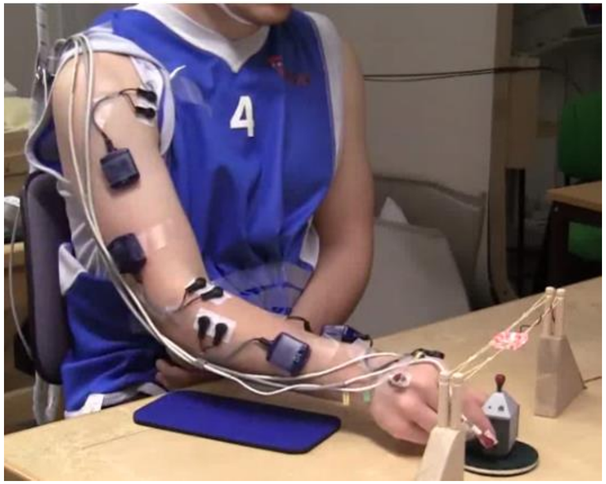
NL_script_filtering_respiratory_noisy_Signal.m





Multivariate SP

Multichannel signals (e.g. high density EEG, ECG) are harder to analyze due to their increased data-volume.



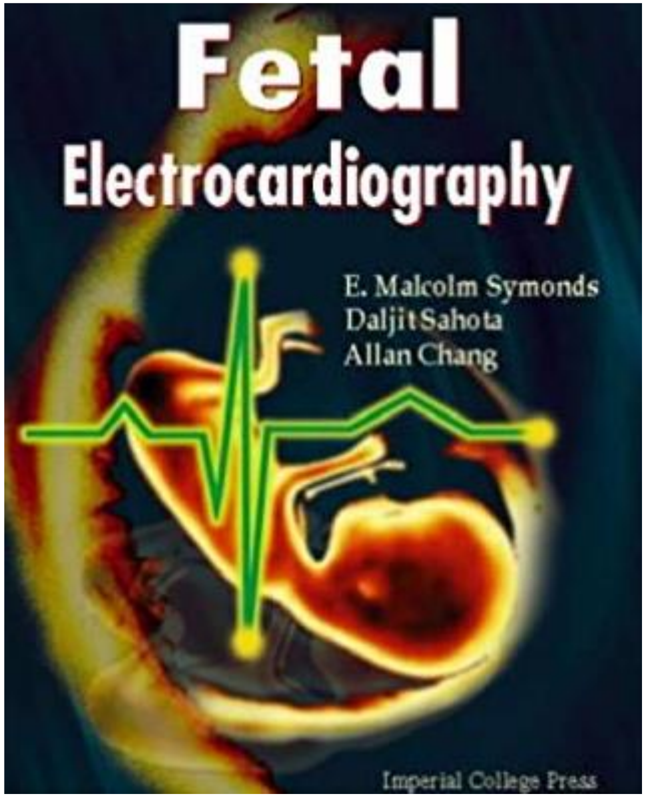
Considering the inherent redundancies, ***multivariate techniques*** are often exploited to provide convenient summaries, suppress background noise, and identify 'unique' signal sources

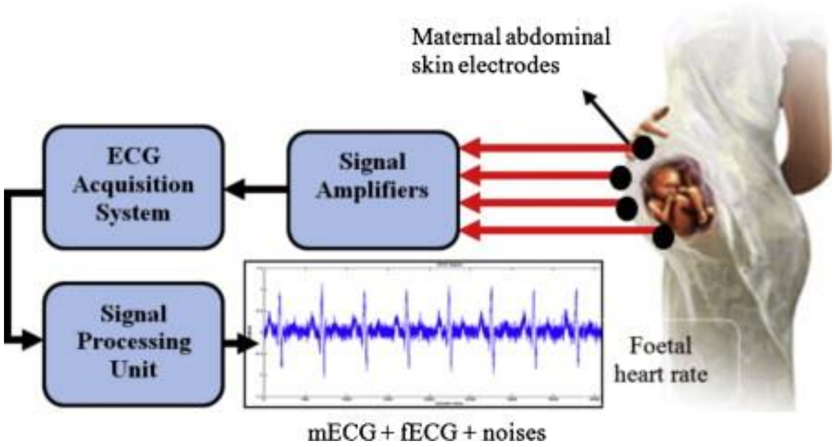
In a simplified set up, the multiple sensor traces are described as a 'linear' combination of ***source-signals***, each of different origin and carrying its own biological meaning.

$$\begin{bmatrix} \mathrm{x}_{sensor1}(\mathrm{t}) \\ \mathrm{x}_{sensor2}(\mathrm{t}) \\ \dots \\ \mathrm{x}_{sensorN}(\mathrm{t}) \end{bmatrix} \cong [\mathbf{A}_{N\times\mathbf{2}}] \begin{bmatrix} \mathrm{x}_{sourse1}(\mathrm{t}) \\ \mathrm{x}_{sourse2}(\mathrm{t}) \end{bmatrix}$$

Principal Component Analysis (PCA)
and ***Independent component analysis*** (ICA)
are common practice tools

Isolating Fetal ECG





ICA

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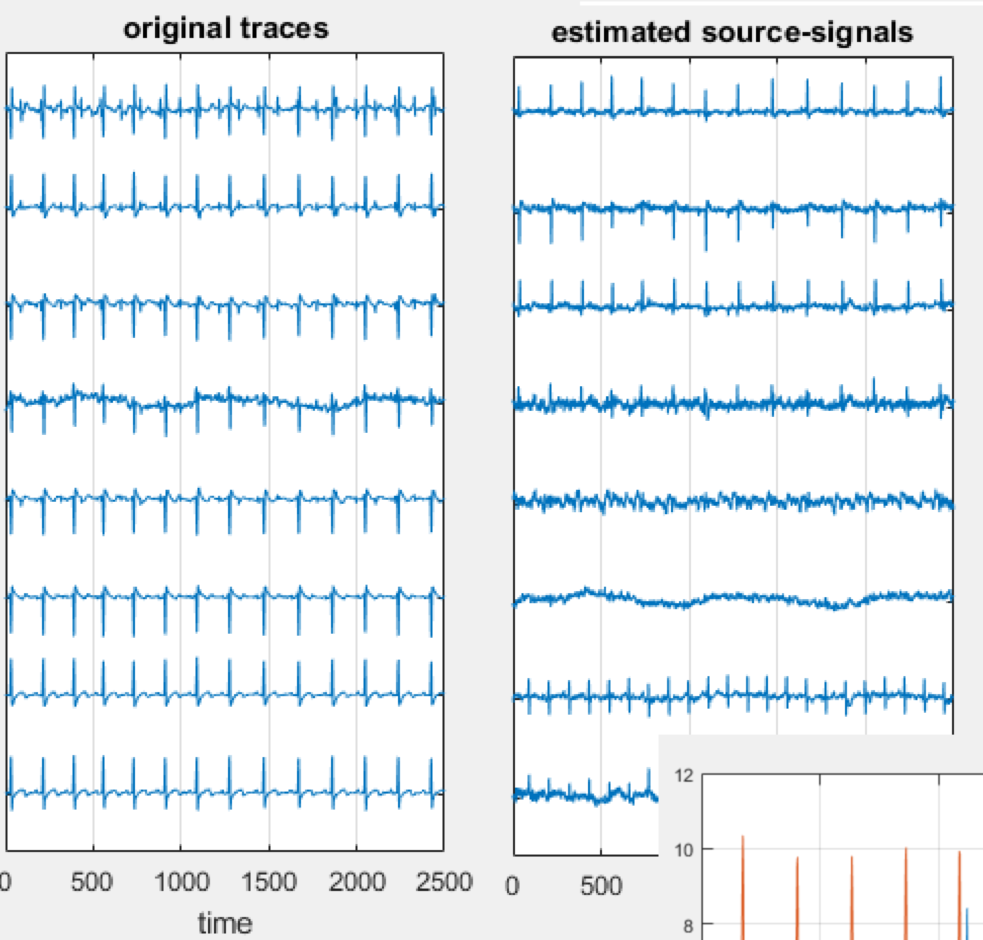
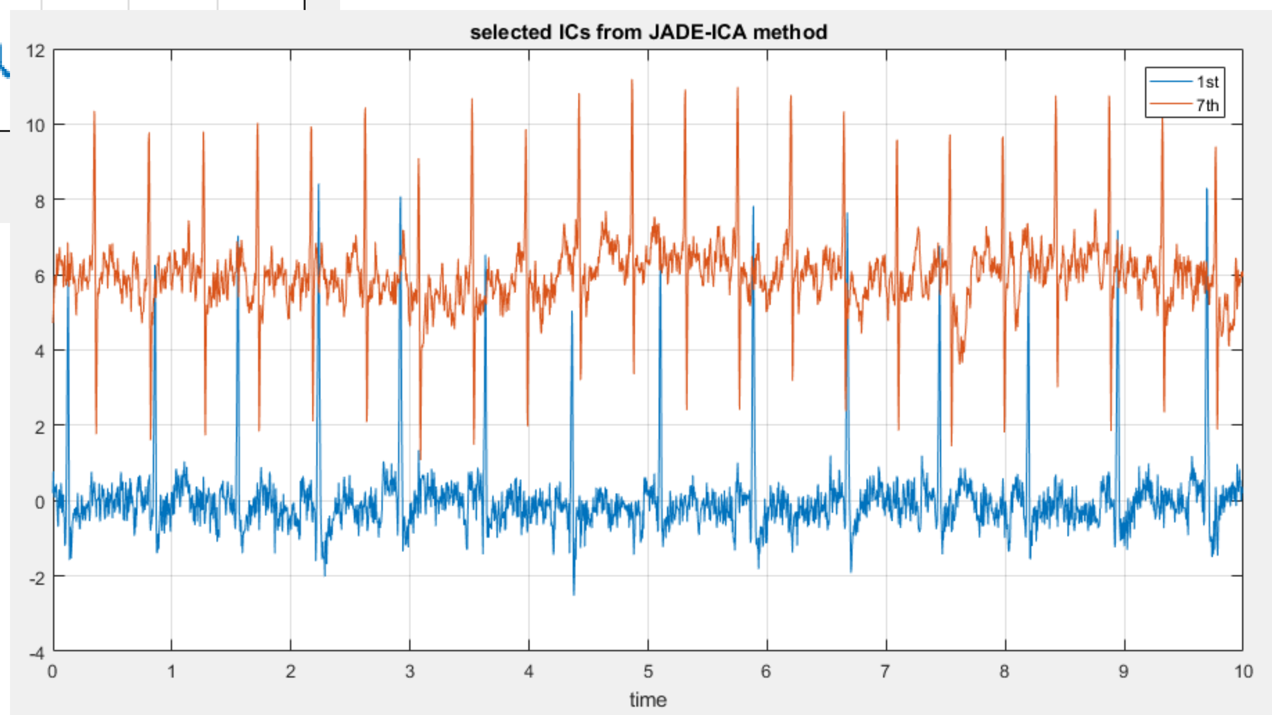
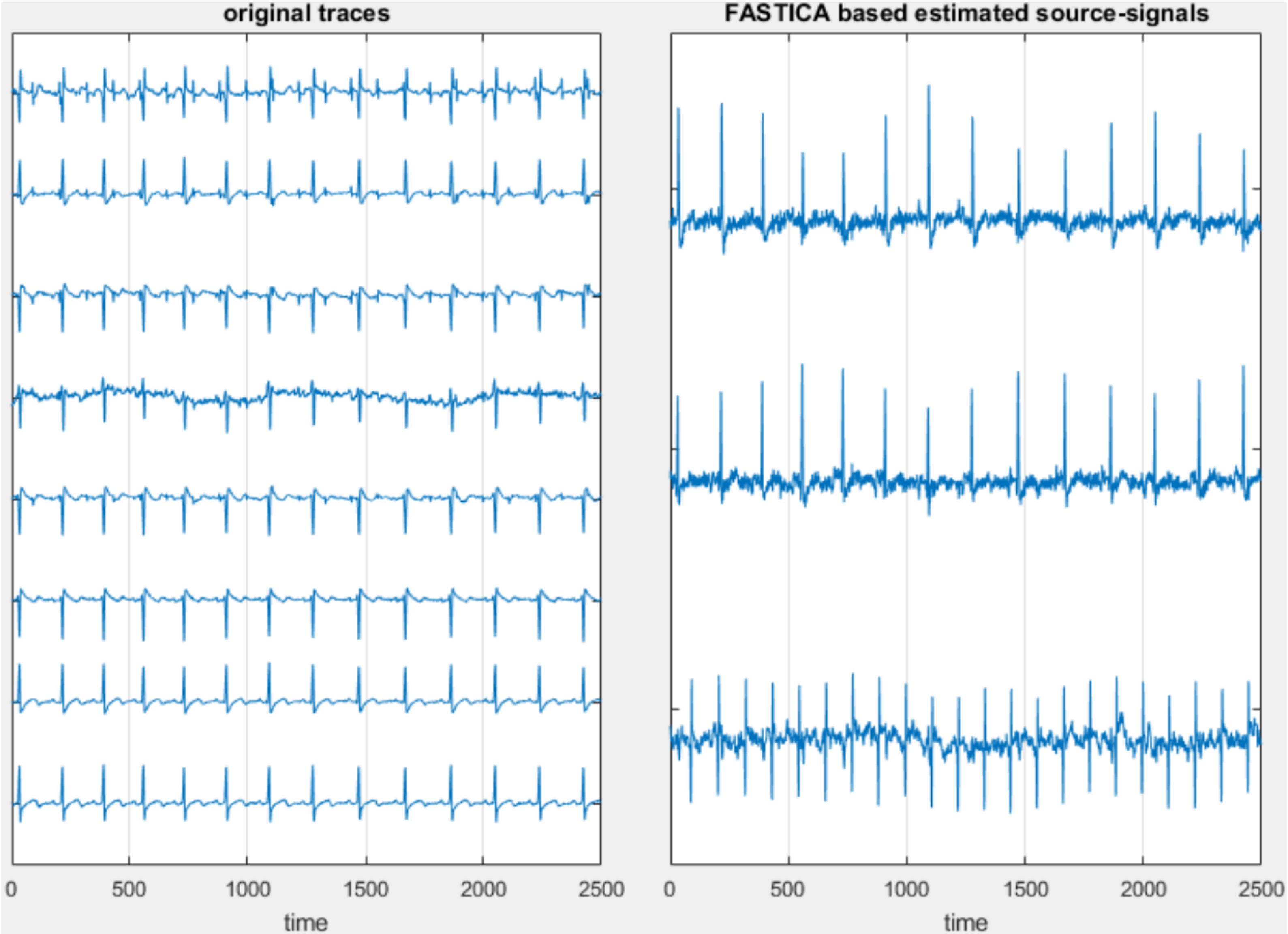
NL_script_unmixing_foetal_from_maternalECG.m

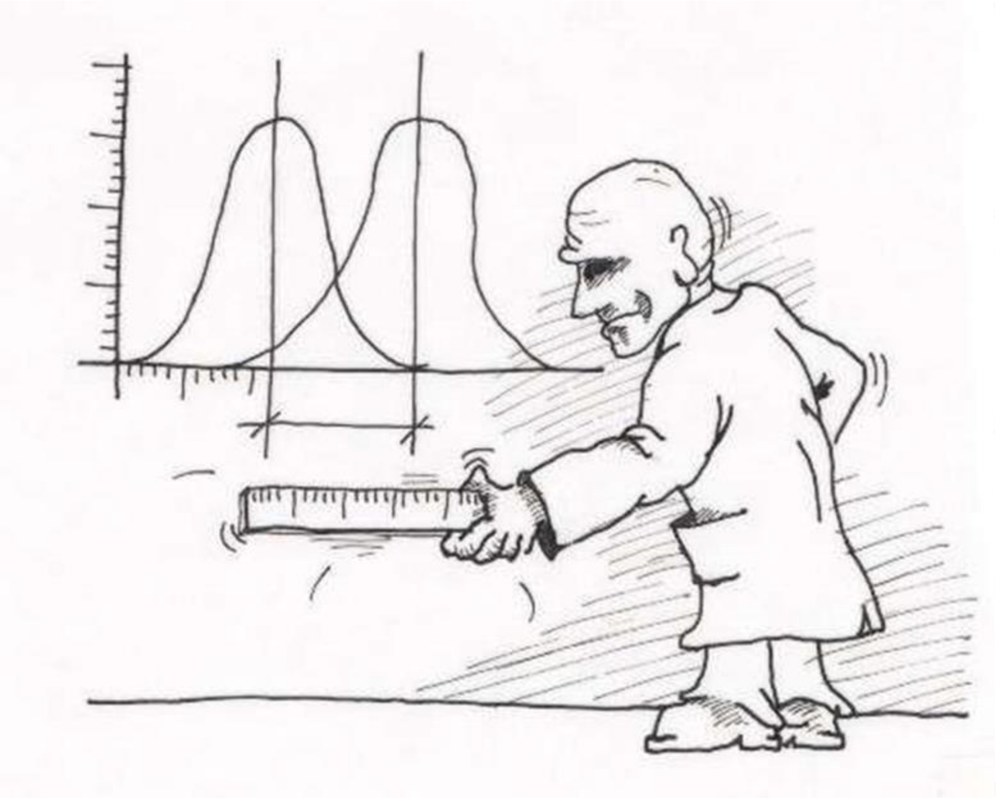
$$\mathbf{B} = A^{-1}$$

```
X=load('FOETAL_ECG.dat');  time=X(:,1)' ; ECGdata=X(:,2:9)';

B=jadeR(ECGdata); % deriving the unmixing-matrix
Sources=B*ECGdata; % estimating the ICs (source-signal)

display('selecting the 1st and 7th ICs from the JADE-ICA method')


% PART-II using FAST-ICA toolbox
% you need to set FASTICA_toolbox in the path
[sources] = fastica (ECGdata,'numOfIC', 3);
                    %  [icasig] = fastica (ECGdata, 'lastEig', 5, 'numOfIC', 3);
```


original traces
estimated source-signals
0
500
1000
1500
2000
2500
time

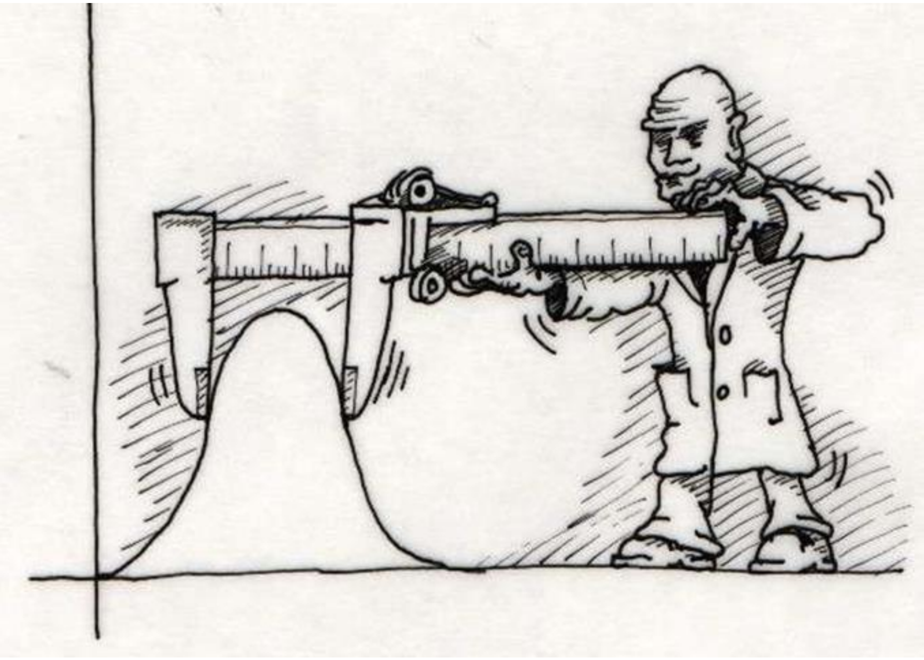

selected ICs from JADE-ICA method
1st
7th
12
10
8
6
4
2
0
-2
-4
0 1 2 3 4 5 6 7 8 9 10
time


original traces
FASTICA based estimated source-signals
0
500
1000
1500
2000
2500
time
0
500
1000
1500
2000
2500
time



Deriving Signal Attributes

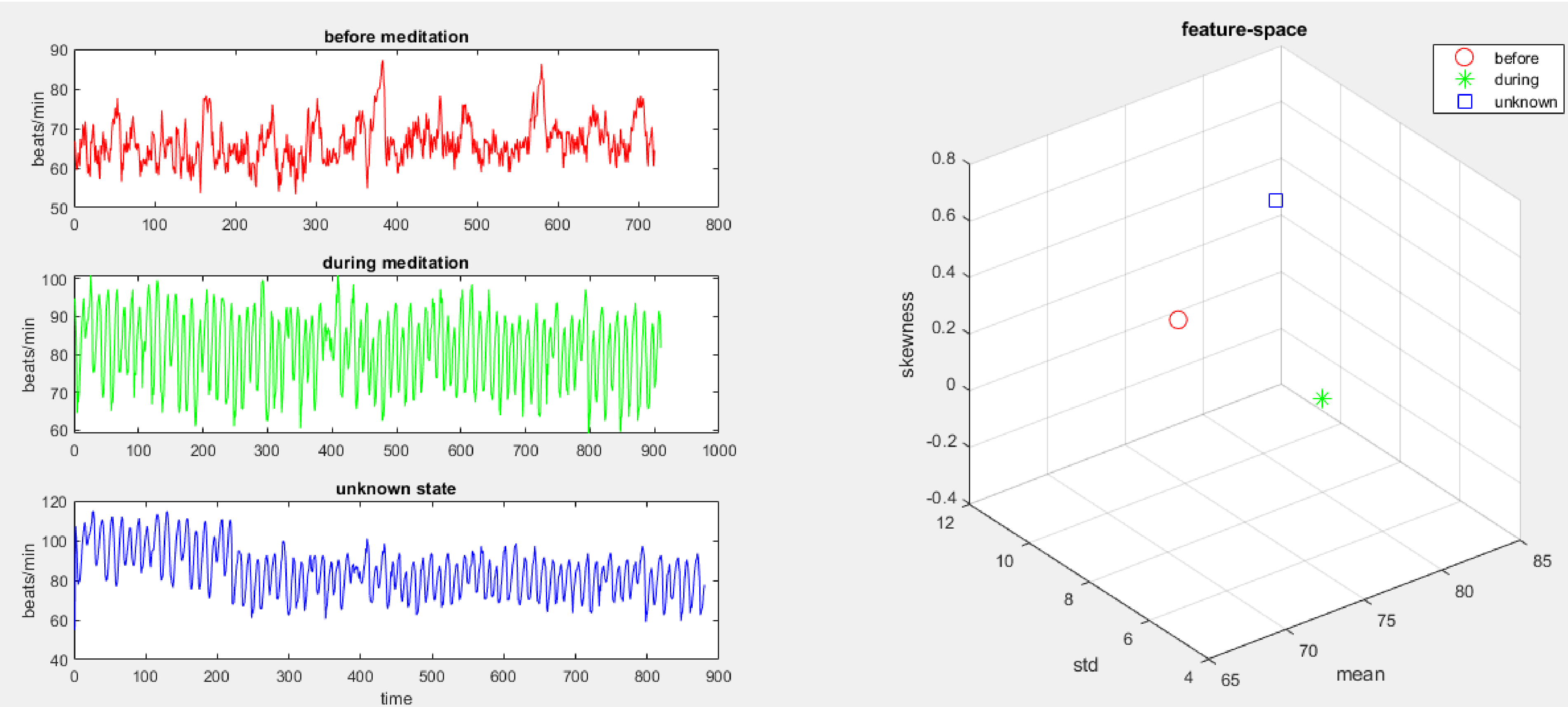
Apart from the **Spectral content**,
time-domain characteristics
and **statistical descriptors**
can be utilized to form
'biological signatures
of a disease
or state'



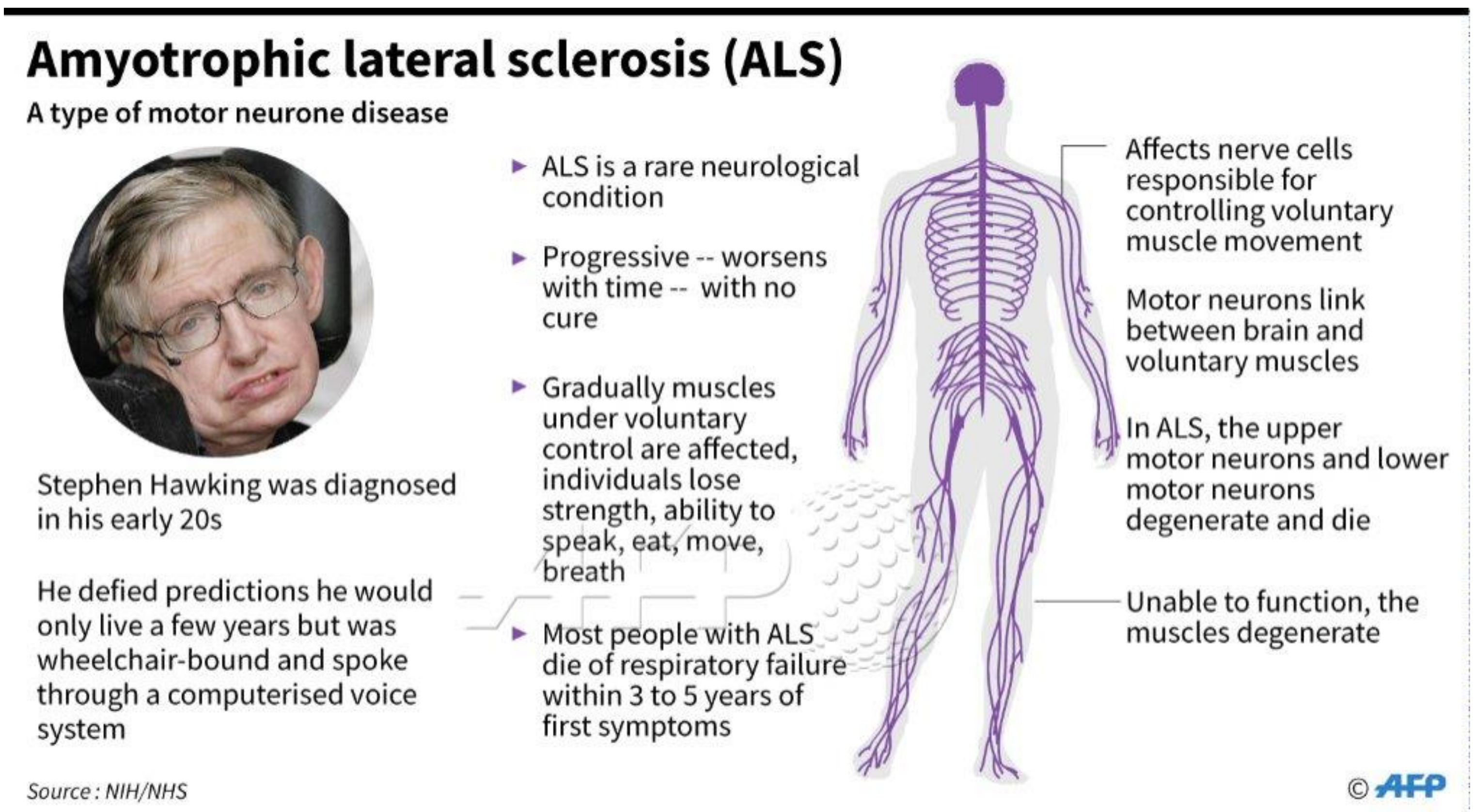
mean std skewness

8

NL_script_stat_features_from_HR_signal.m



Gait Signal Analysis



midcross diff dtw

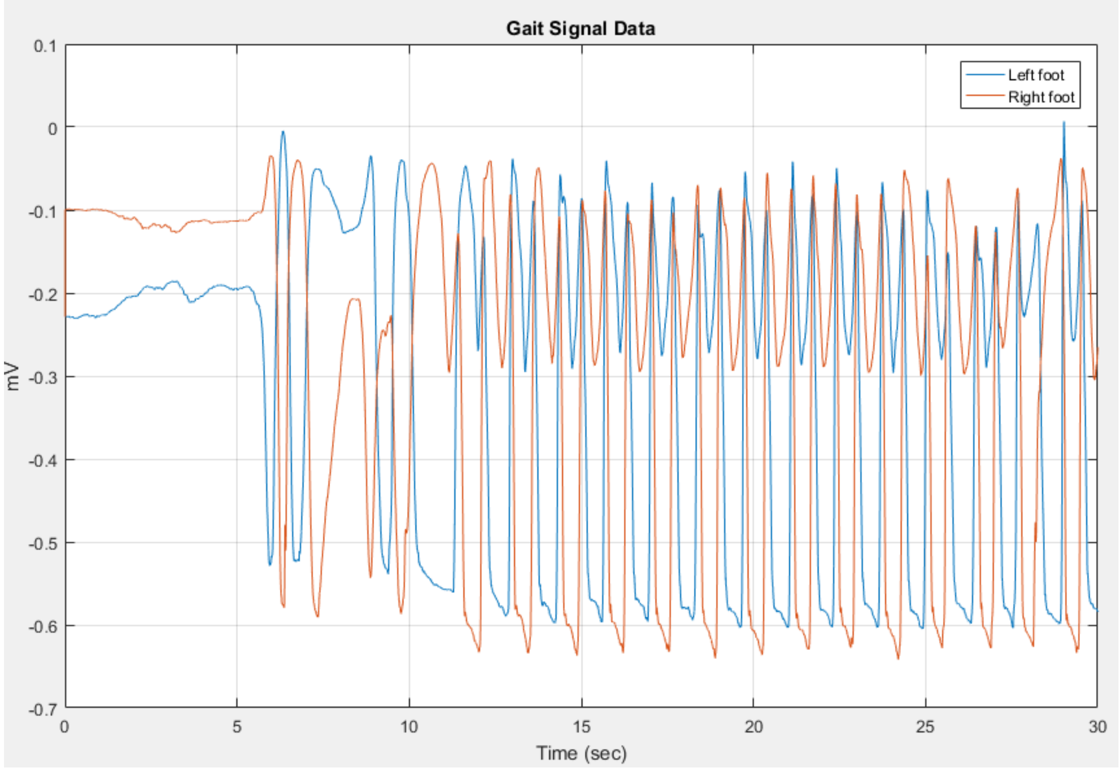
Matlab Live Editor

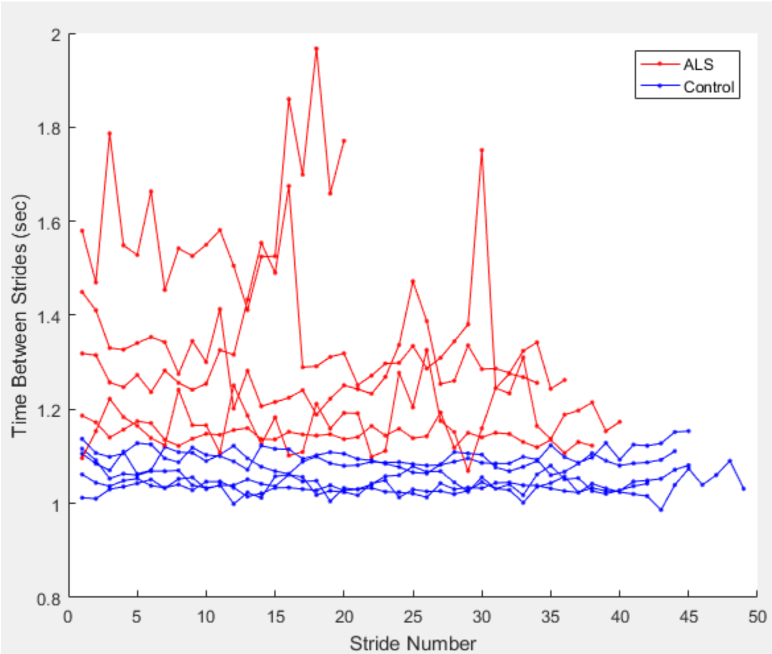
Extracting Classification Features from Gait Signals

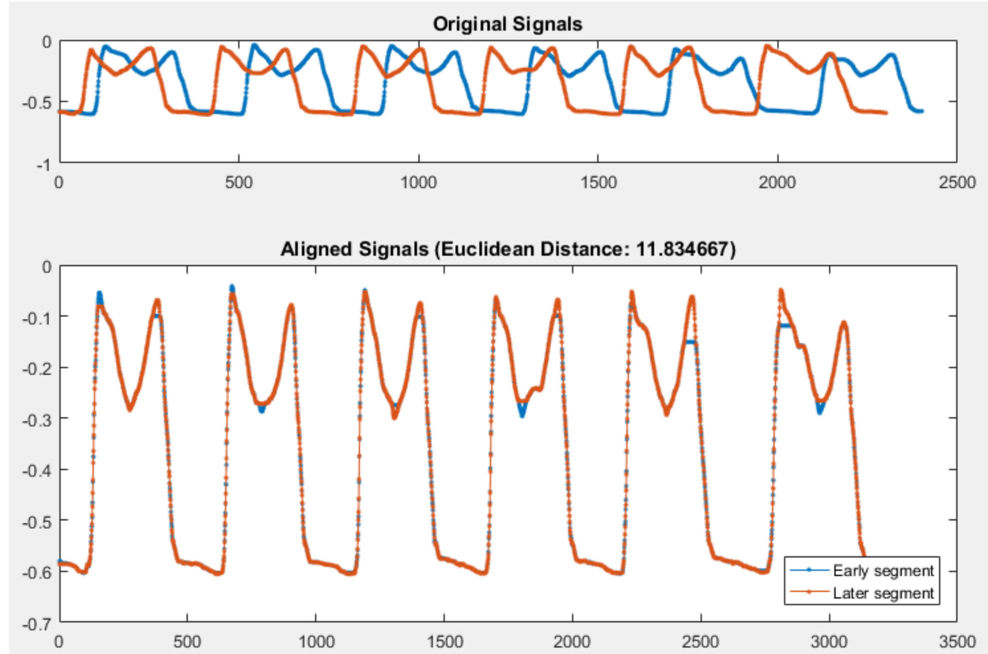
\>> **GaitAnalysisExample**

Data from a study of the walking patterns of patients with neurodegenerative disease

5 patients with *Amyotrophic Lateral Sclerosis* (**ALS**) and 5 controls

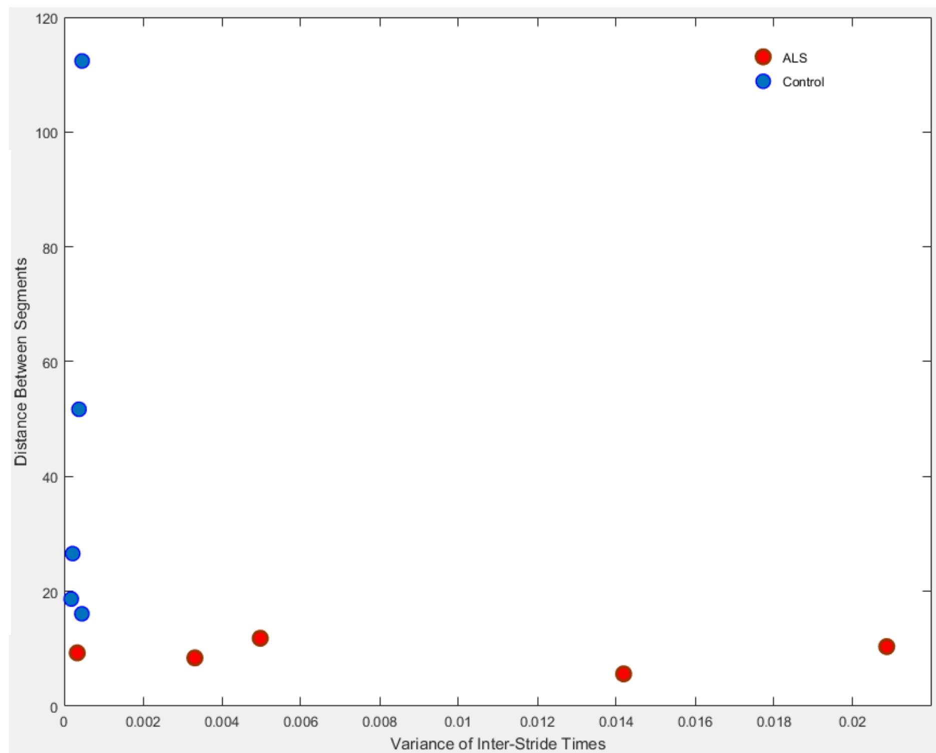






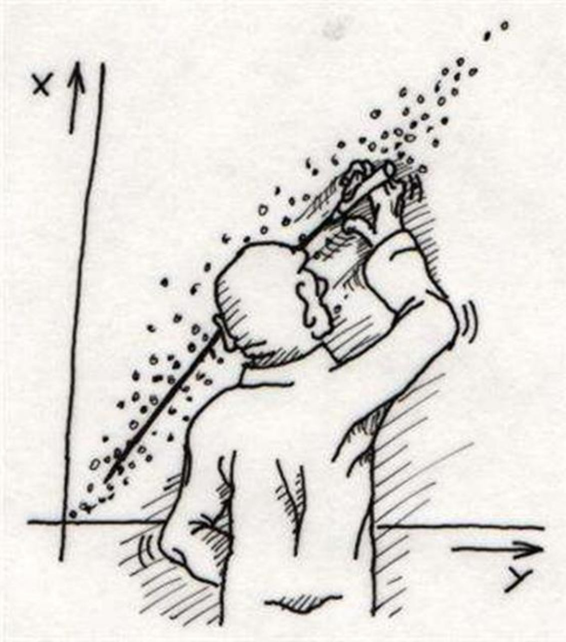
ALS patients seem to have
a **larger variance**
in inter-stride times,

but a **smaller distance**
via ***dtw*** between segments



What can be done with all these Signal Attributes ?

Machine Learning → **Biomarkers**



ML & Rehabilitation

COX-media radio reporter **Jamie Dupree**

AI in Medicine

The polypill concept