



Lecture 4

Biosignal Processing

Digital Signal Processing and Analysis
in Biomedical Systems



Contents

- Preprocessing as first step of signal analysis
- Biosignal acquisition
- ADC
- Filtration (linear, Wiener, Kalman, Savitzky–Golay, adaptive)

Useful parameters of biosignals

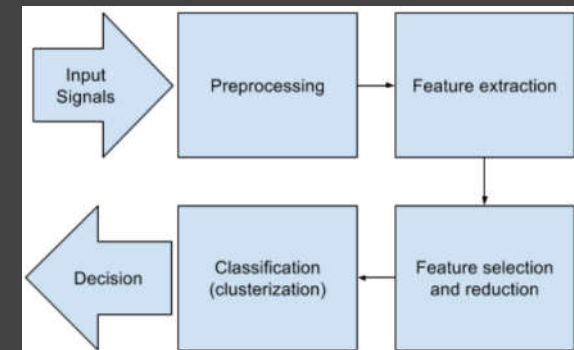
1. Waveform shape
2. Rate of change (spectral content)
3. Magnitude/duration
4. Onset/offset of events
5. Similarity/synchronicity with other signals

Biomedical signal analysis steps

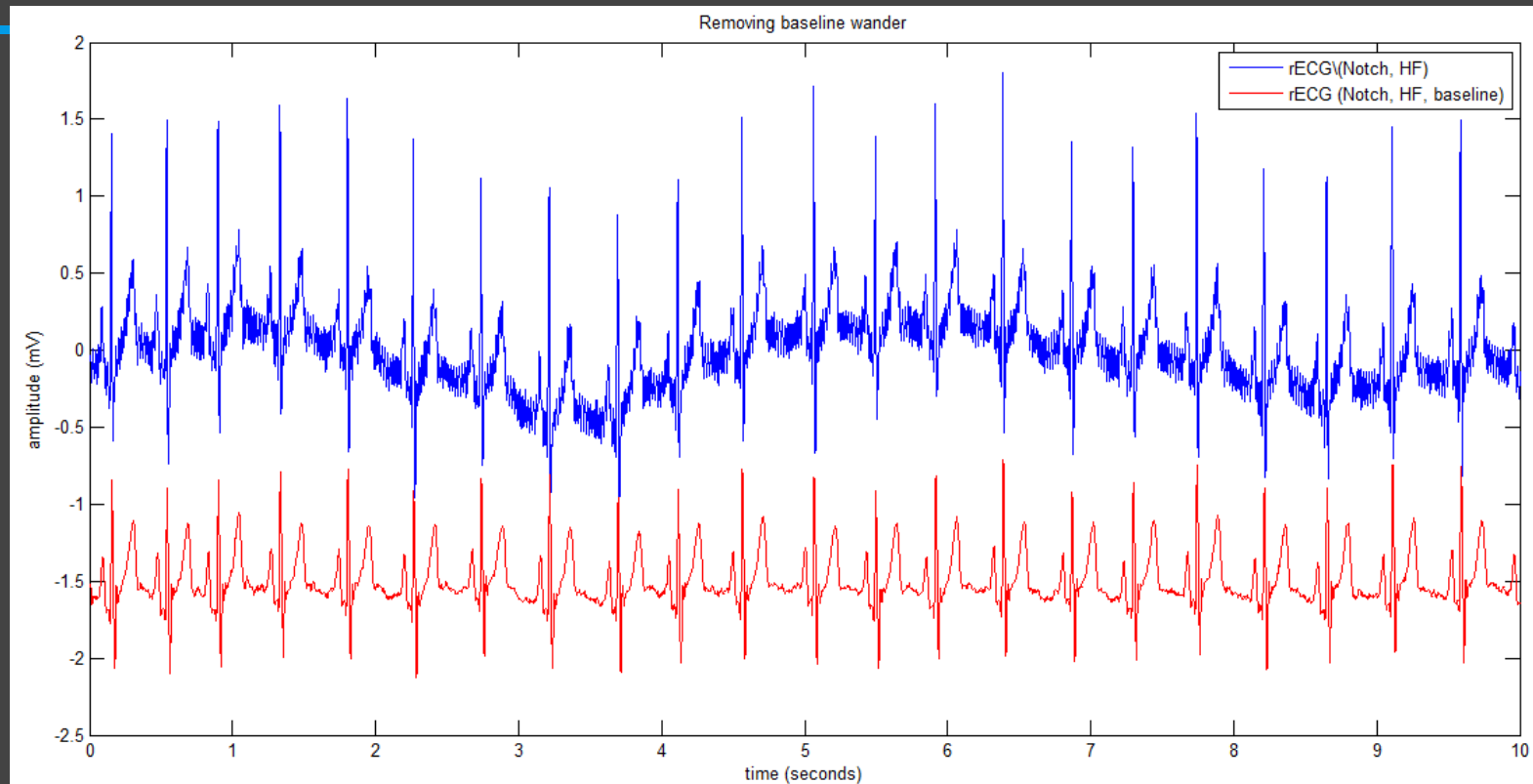
Physiological information often cannot be available directly from the **raw recorded** signals:

- it can be masked by **other biologic signals** (artefacts),
- or hidden in **noise**.

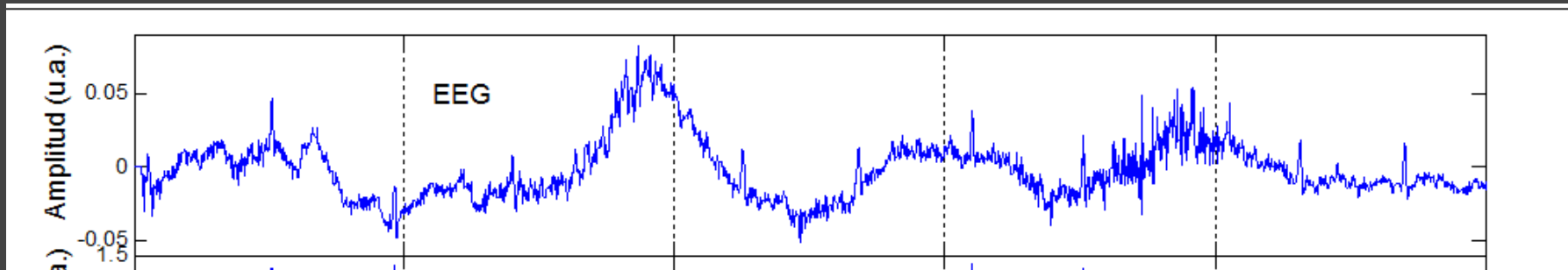
Additional (preliminary) processing is usually required to enhance the relevant information and to extract from it the parameters that quantify the behavior of the system under study.



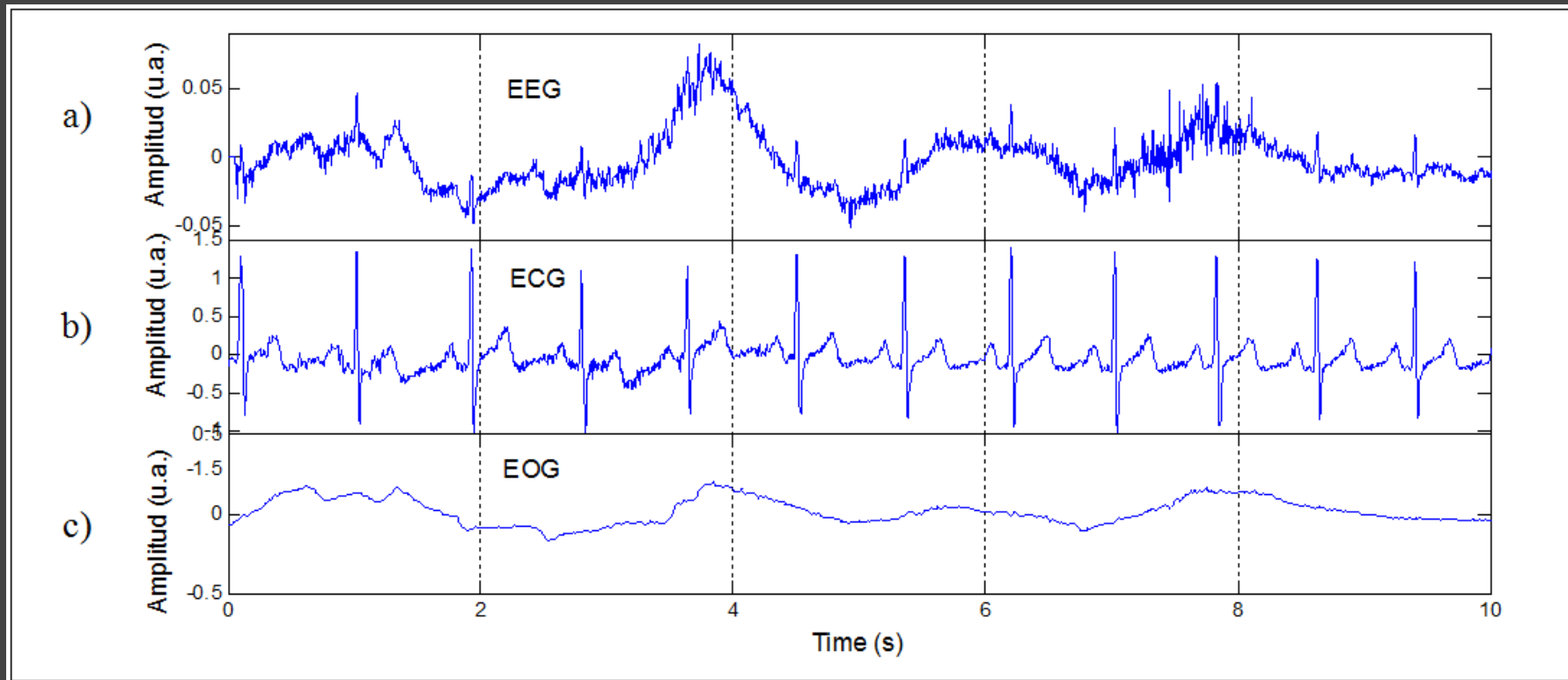
Noisy ECG



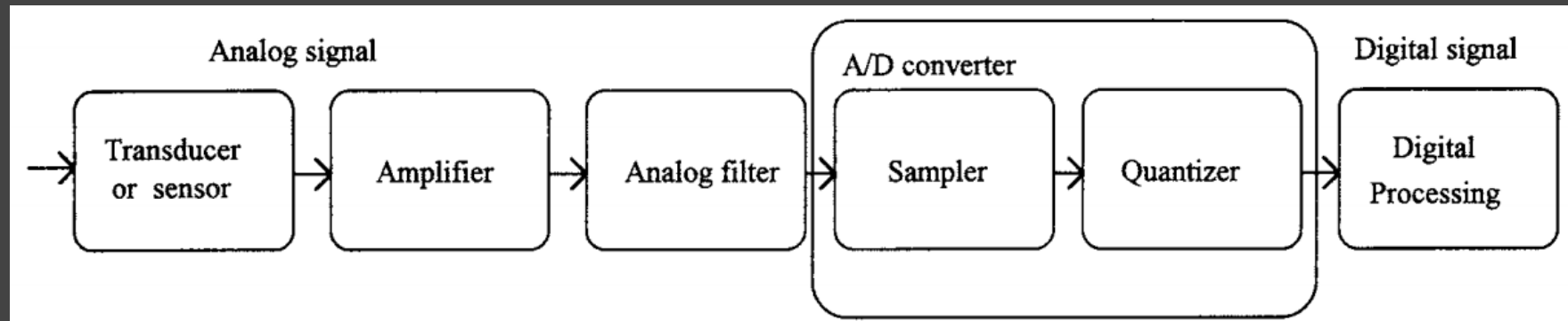
EEG with low-frequency component and spikes



EEG corrupted with ECG and EOG



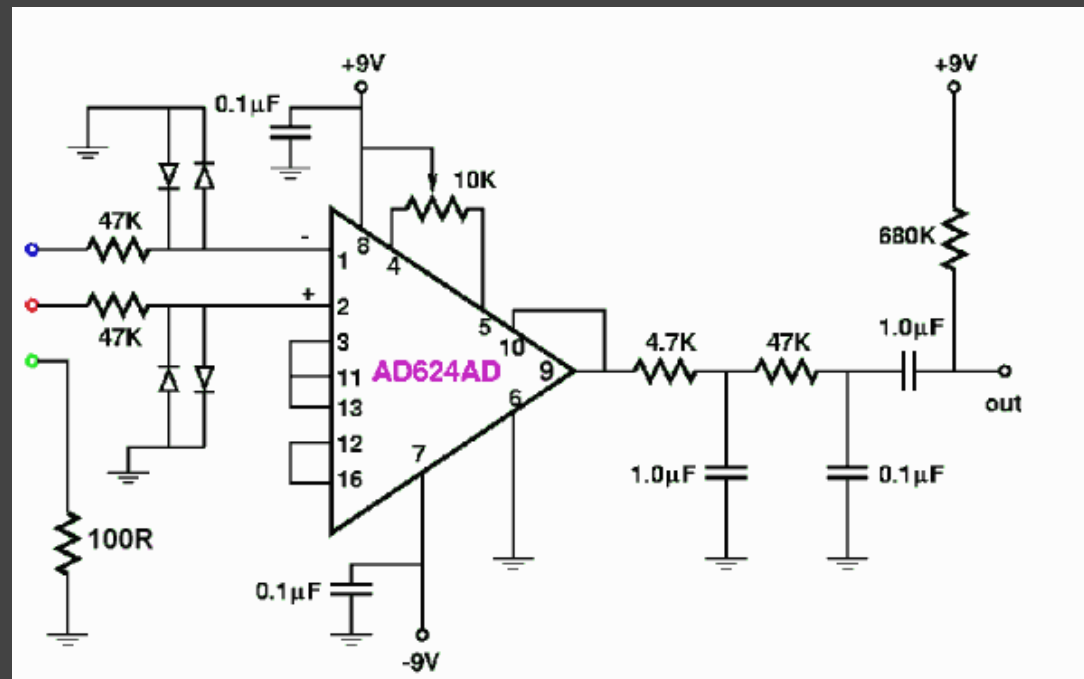
Biosignal processing block diagram



Processing – changing the characteristics of a signal.

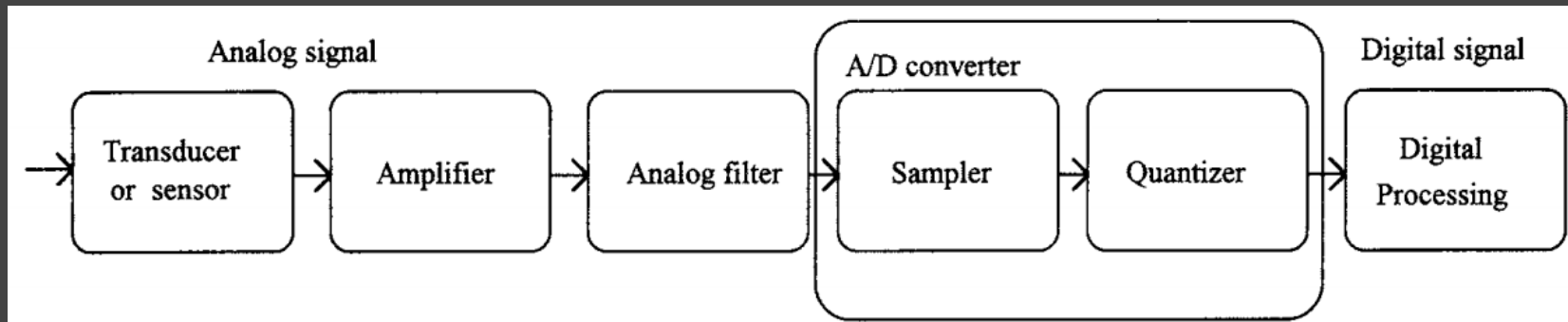
Analog signal processing

- Detection (protection)
- Amplification
- Filtration (noise suppression, baseline wandering removal)
- Change of the baseline
- Change of dynamic range



Digital signal processing

- Sampling
- Segmentation
- Accumulation (*ECG late potential detection*)
- Averaging (*Evoked response*)
- Digital Filtration

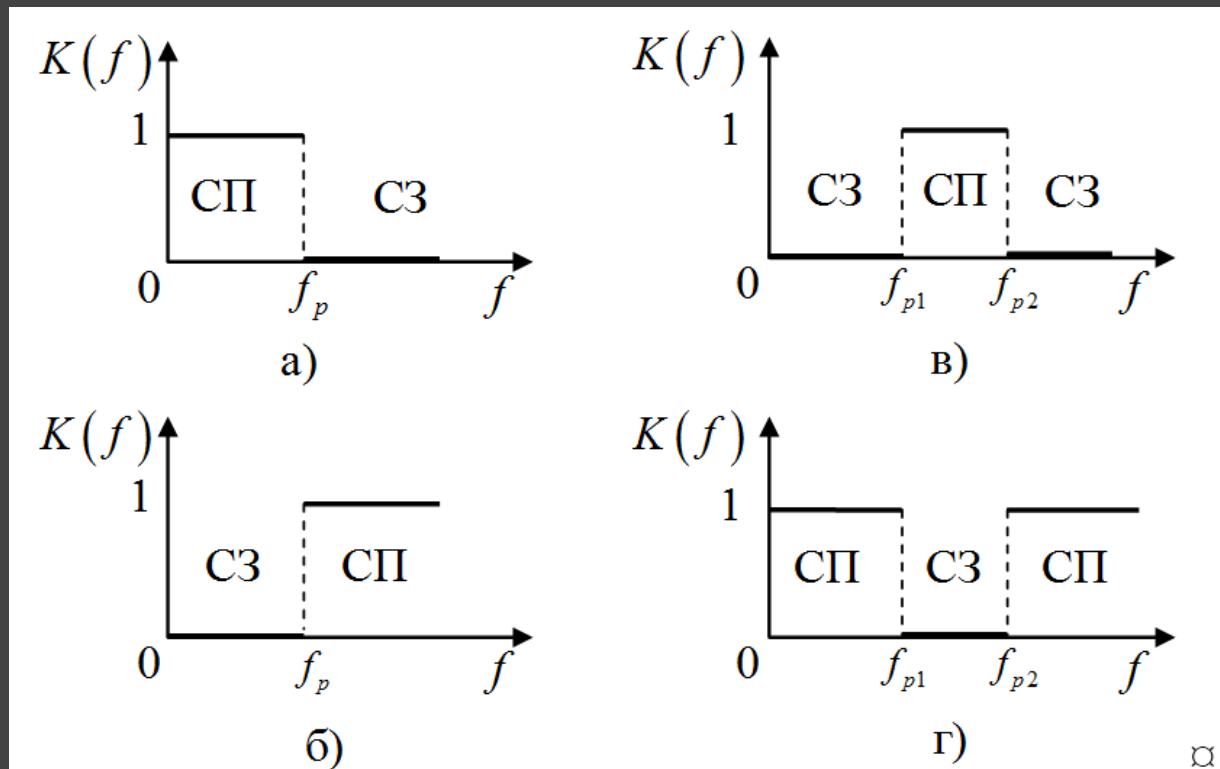


Filtration

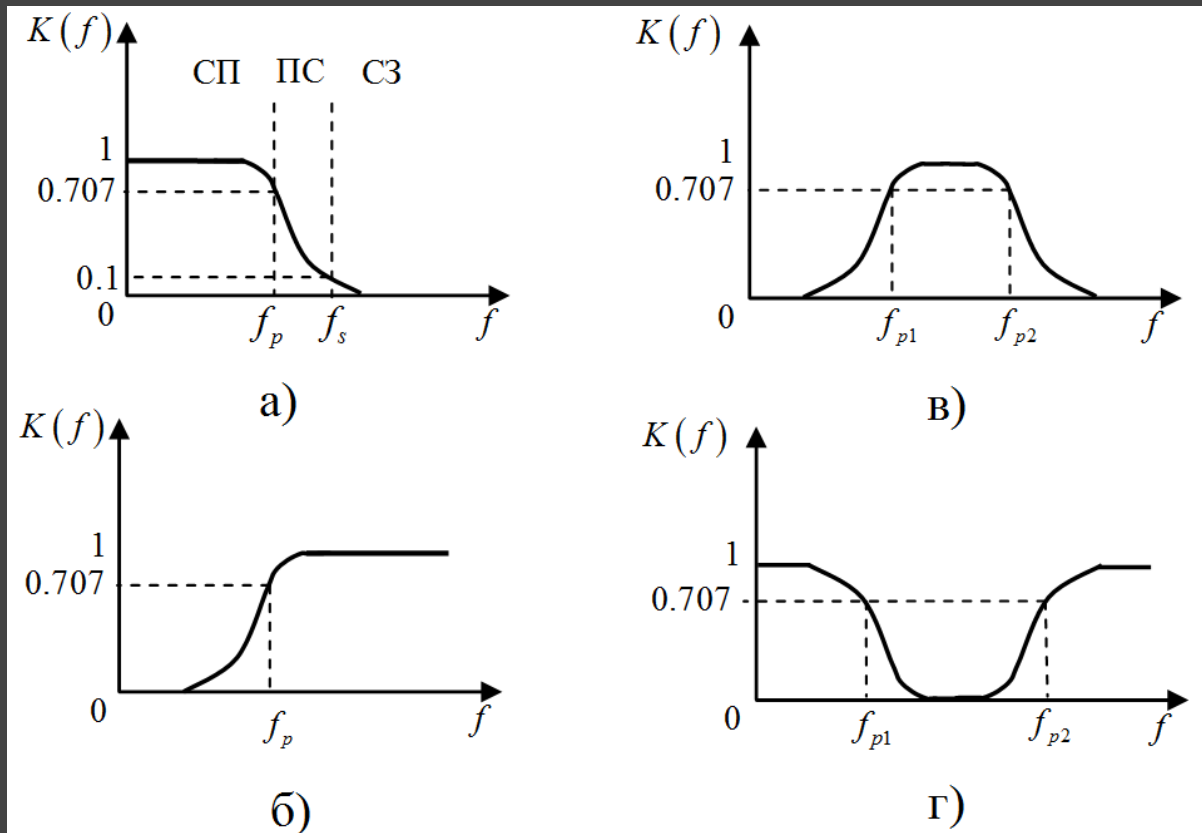
Filter is a system that **suppresses or removes** some unwanted component or feature from a signal. Most often, filtration – the change of spectral content of a signal. Filters:

- **linear** or non-linear,
- **time-invariant** or time-variant,
- **causal** or not-causal,
- analog or **digital**,
- **discrete-time** (sampled) or continuous-time,
- passive or **active** type of continuous-time filter
- infinite impulse response (IIR) or **finite impulse response** (FIR) type of discrete-time or digital filter.

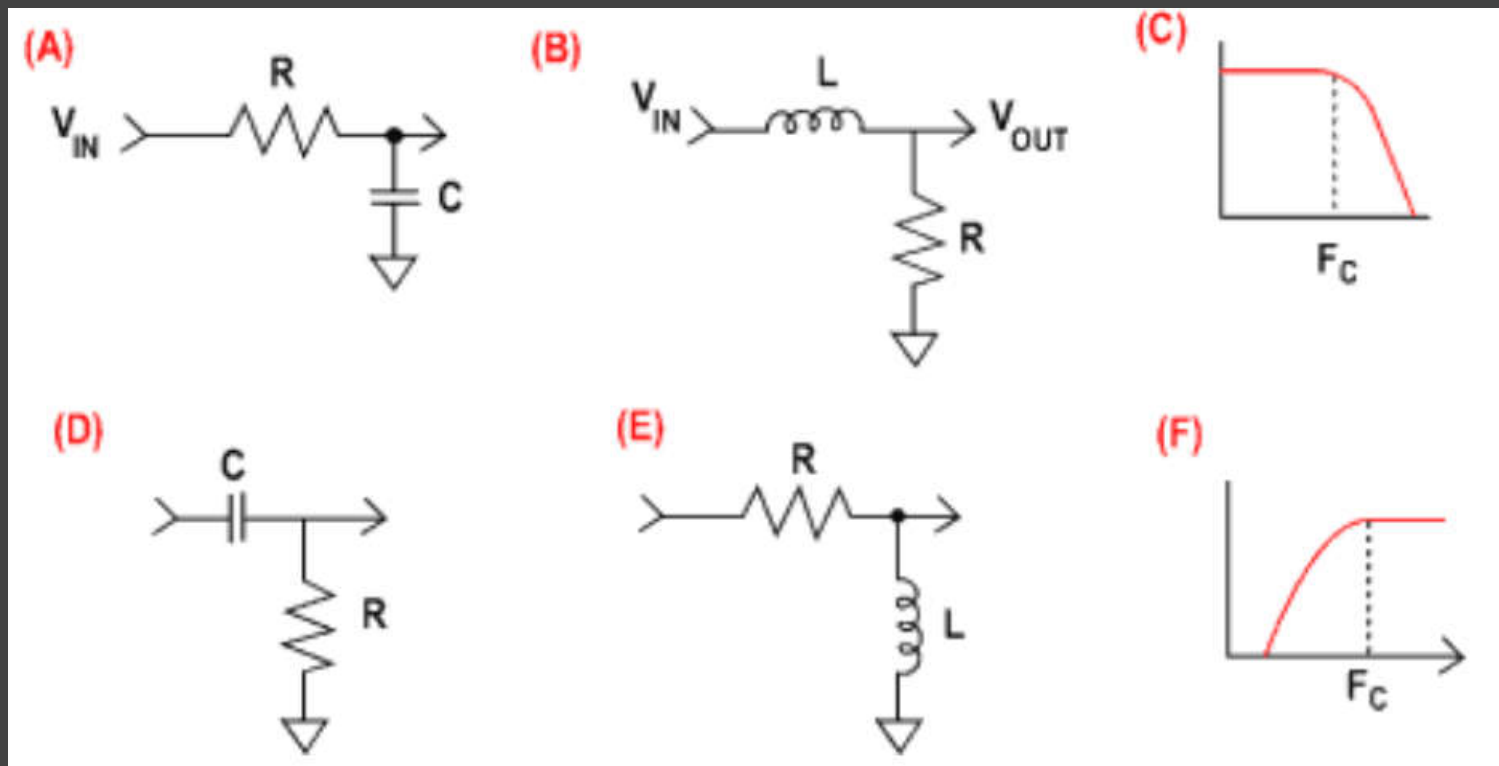
Analog (continuous) filters (ideal)



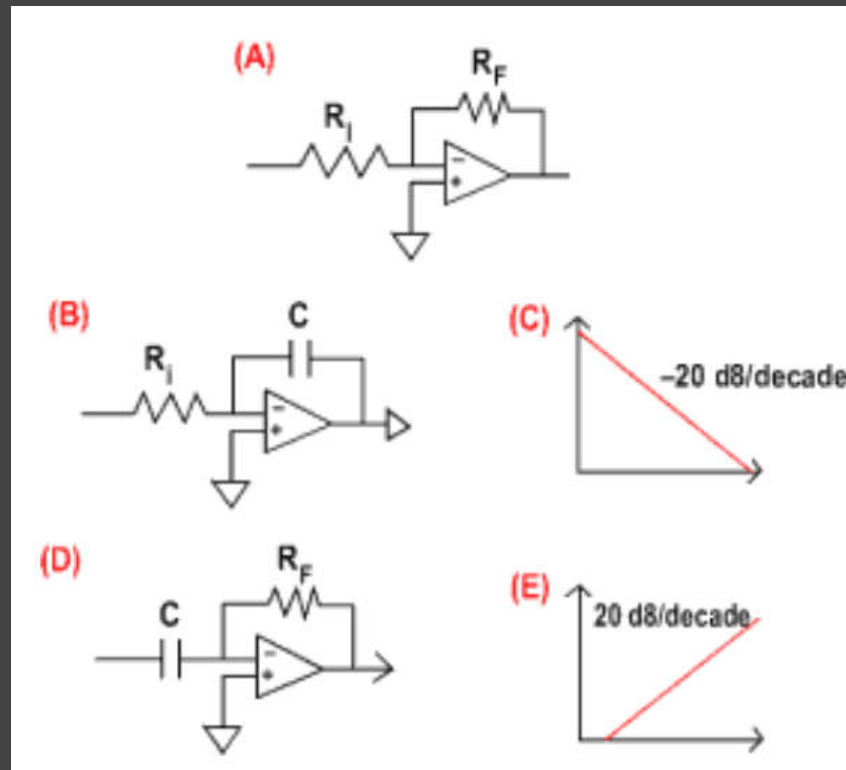
Analog (continuous) filters (real)



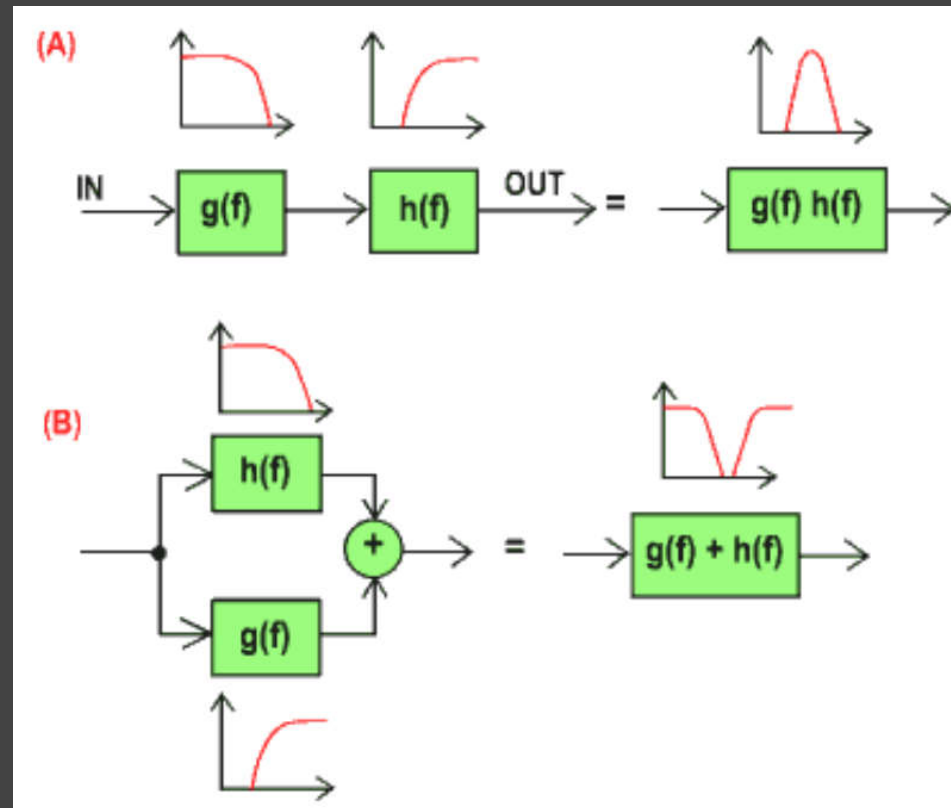
Basic schemes of passive analog filters



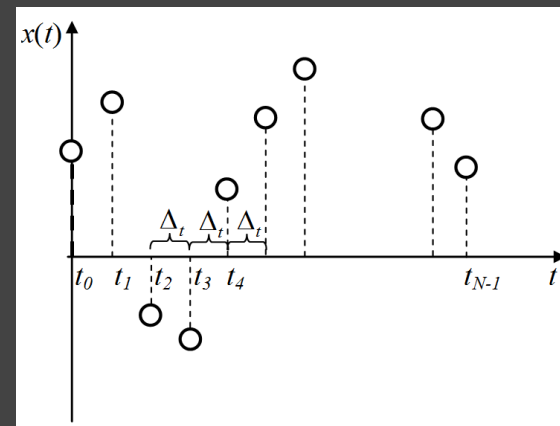
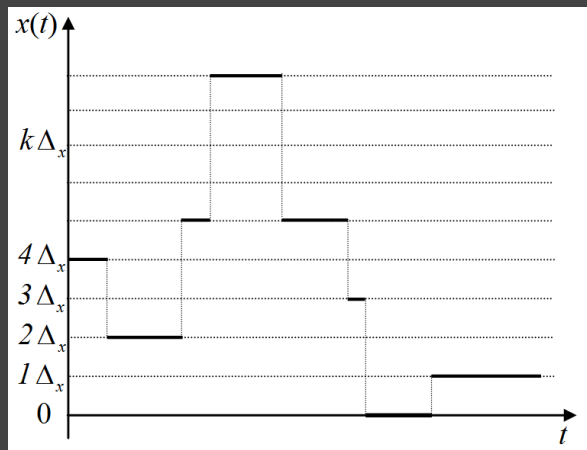
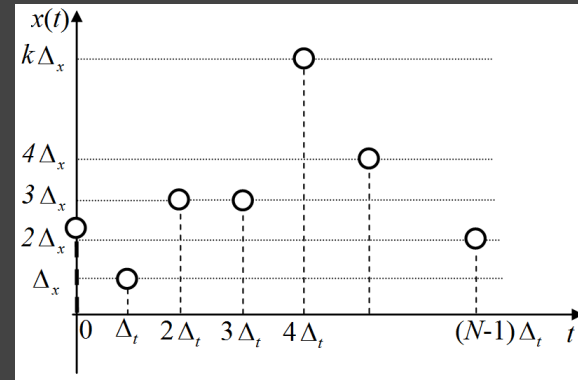
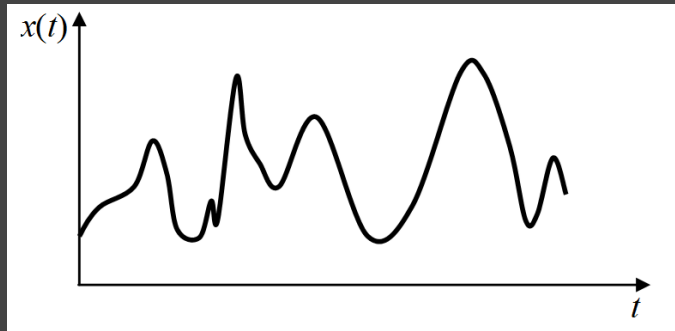
Basic schemes of active analog filters



Combining simple filters

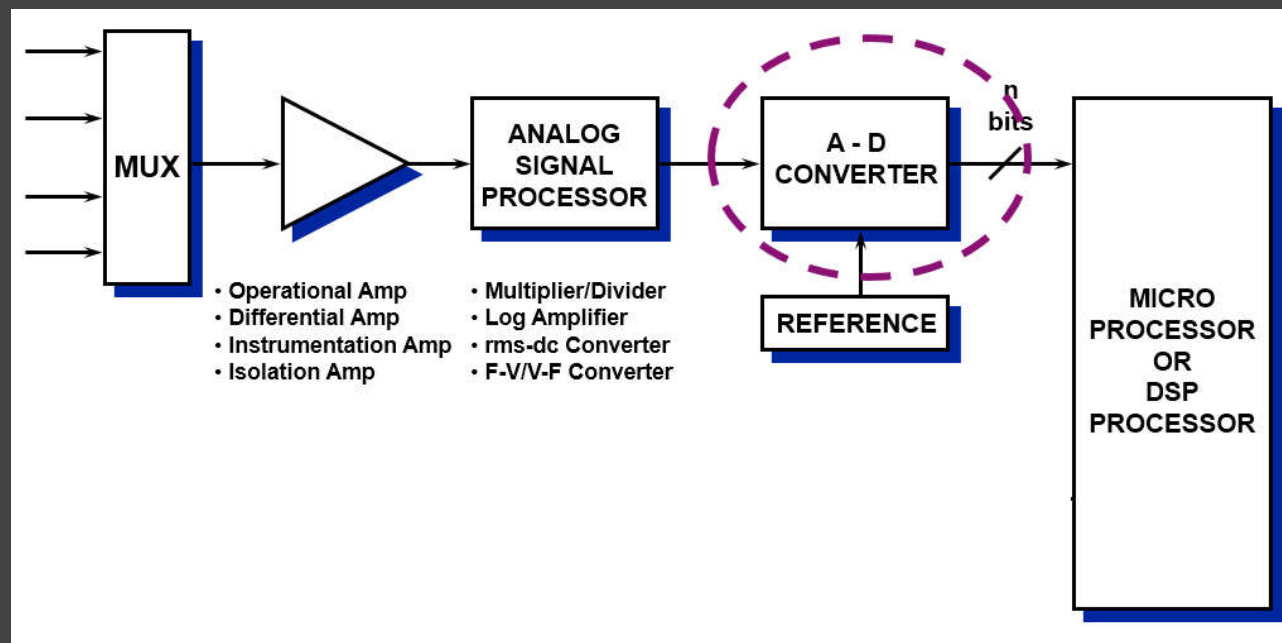


Four types of signals

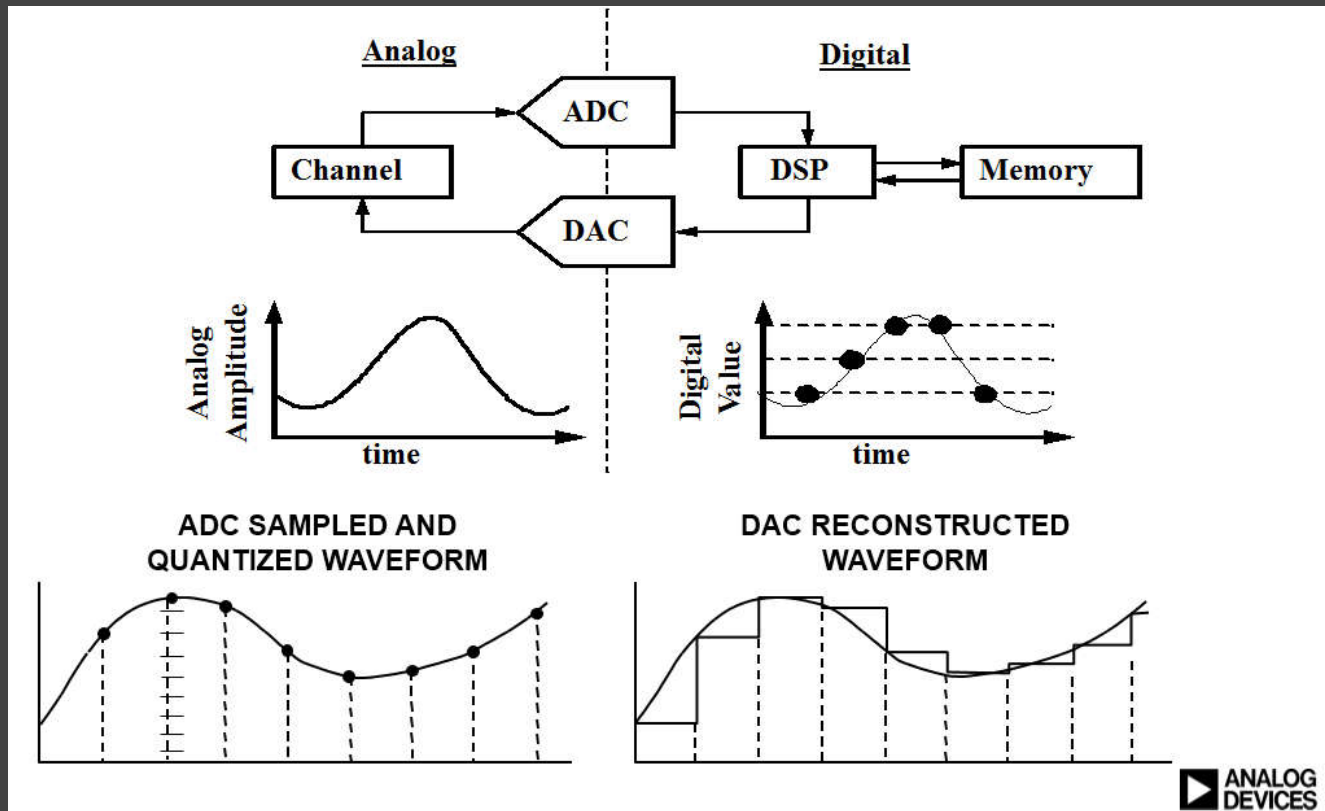


Analog-to-digital conversion

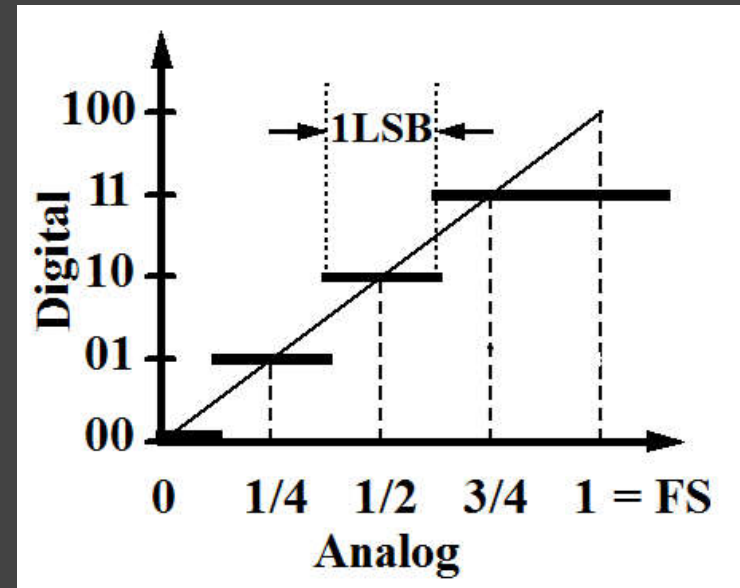
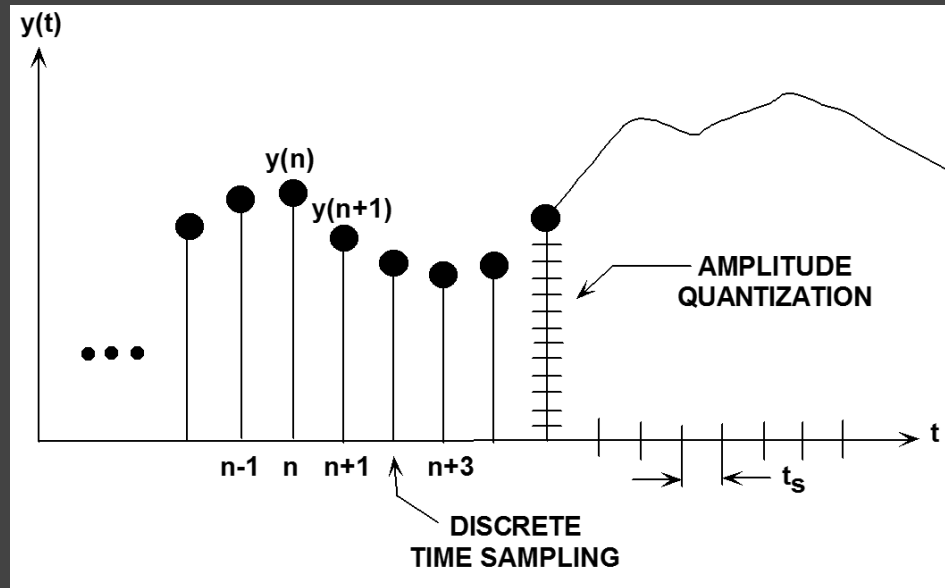
ADC converts **analog** signals into **binary** code.



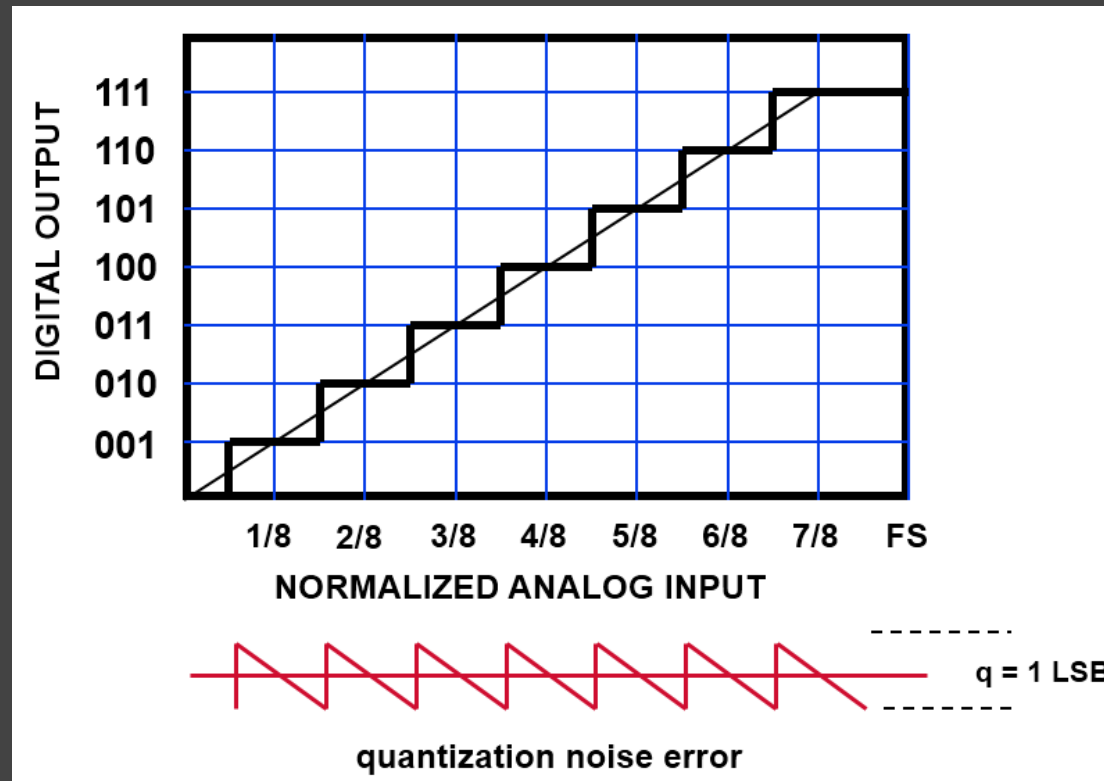
Real digital system



Sampling and Quantization



Quantization noise

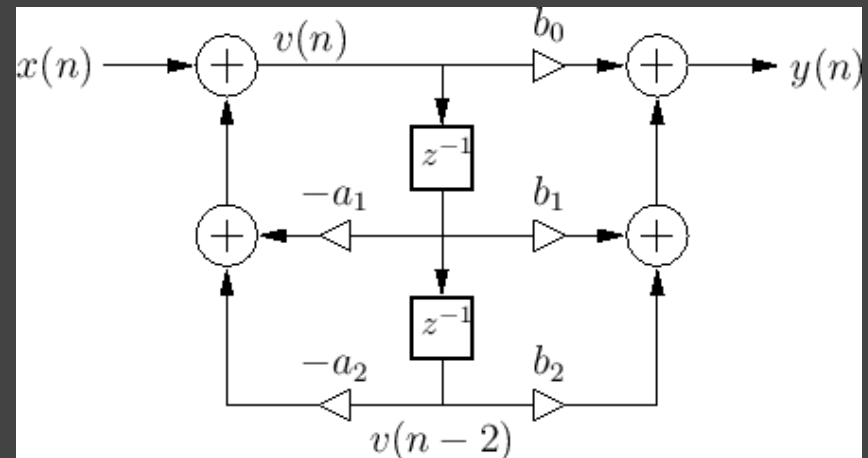
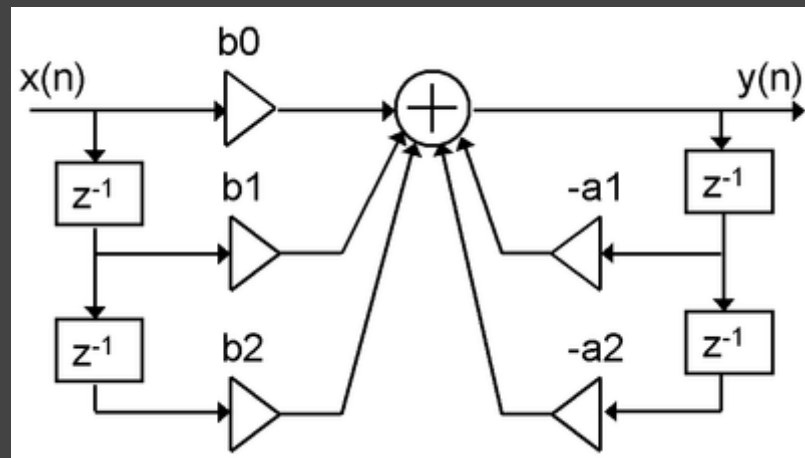


Digital filters

Digital filter is a system that performs **mathematical operations on a sampled**, discrete-time signal to reduce or enhance certain aspects of that signal.

$$\sum_{k=0}^{N-1} a_k y[n-k] = \sum_{m=0}^{M-1} b_m x[n-m],$$
$$y[n] = \sum_{m=0}^{M-1} b_m x[n-m] - \sum_{k=1}^{N-1} a_k y[n-k].$$

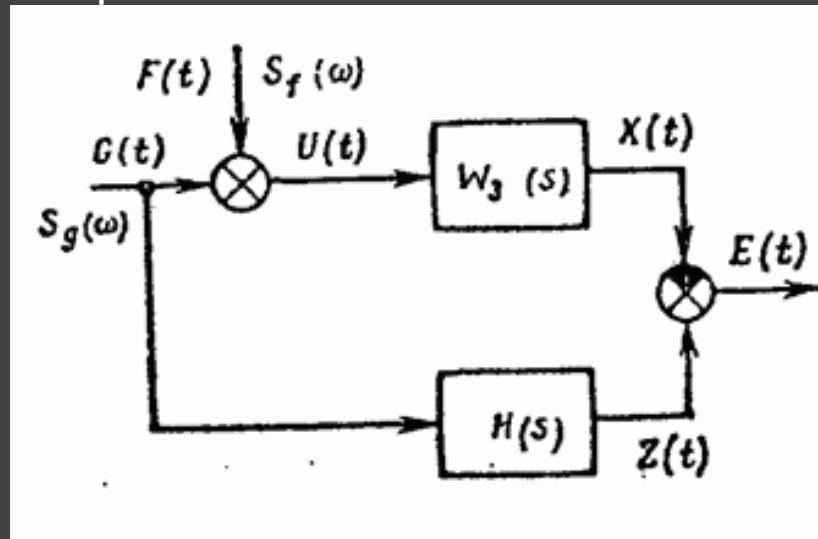
Filter structures



Optimal filtration – Wiener filter

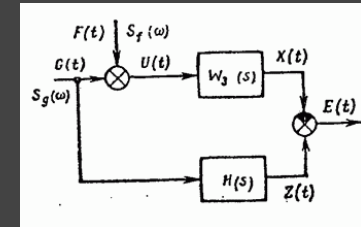
Wiener filter is a filter used to produce an **estimate of a random signal** by linear time-invariant (LTI) filtering of an observed noisy **process**, assuming known stationary signal and additive noise spectra.

The Wiener filter designing procedure minimizes the mean square error between the estimated random process and the desired process.



Wiener–Hopf equation

Applicable when signal and noise are **correlated** zero-mean stationary processes.



Impulse response:

$$\int_{-\infty}^{+\infty} h_{opt}(t) R_u(\tau - t) dt - R_{zu}(\tau) = 0, \quad \tau \geq 0.$$

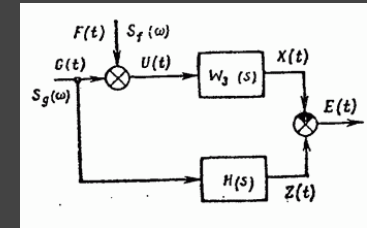
$$R_u(\tau) = R_g(\tau) + R_f(\tau) + R_{gf}(\tau) + R_{fg}(\tau)$$

Correlation of the input signal

$$R_{zu}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T z(t) u(t + \tau) dt$$

Correlation of the input and output signals

Wiener optimal filter



$$W_{opt}(j\omega) = \frac{1}{2\pi\Psi(j\omega)} \int_0^{\infty} e^{-j\omega t} dt \int_{-\infty}^{\infty} \frac{S_{zu}(j\omega)}{\Psi(-j\omega)} e^{j\omega t} d\omega$$

Transfer function in frequency domain

$$S_{zu}(j\omega) = S_{zg}(j\omega) + S_{zf}(j\omega)$$

Spectral density of input and output signals

$$\Psi(j\omega)\Psi(-j\omega) = |\Psi(j\omega)|^2 = S_u(\omega) = S_g(\omega) + S_f(\omega) + S_{gf}(\omega) + S_{fg}(\omega)$$

$$S_{gf}(j\omega) = S_{fg}(j\omega) = S_{zf}(j\omega) = 0$$

Applicable when signal and noise are *non-correlated!*

Kalman filter

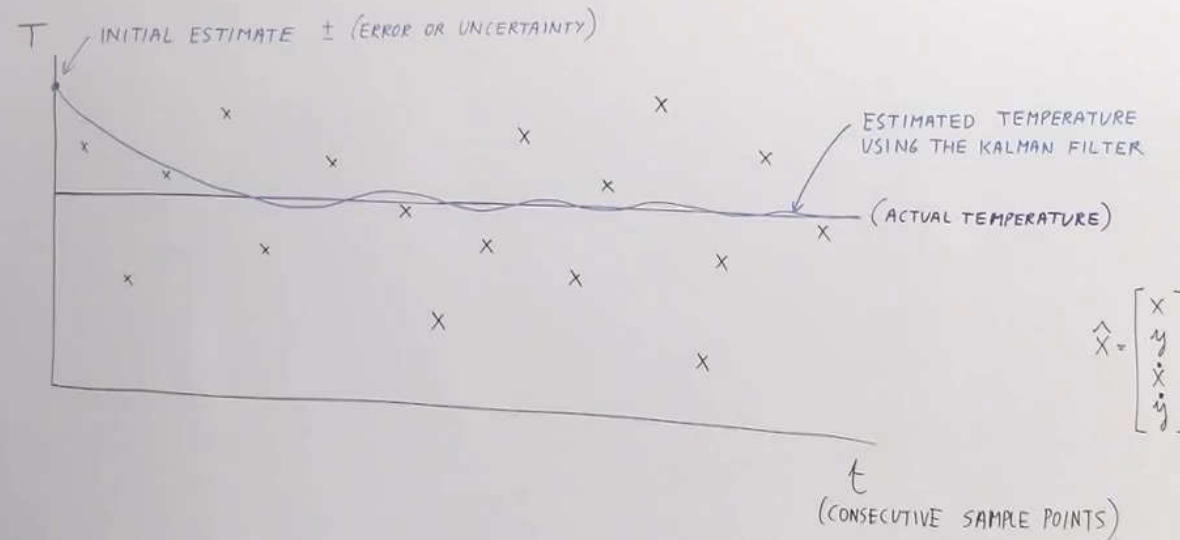
Kalman filtering is an **algorithm** that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables.

Used for computer vision, tracking, navigation, models of movement control.

Kalman filter – 1

SPECIAL TOPIC 1 · THE KALMAN FILTER (1) WHAT IS A KALMAN FILTER?

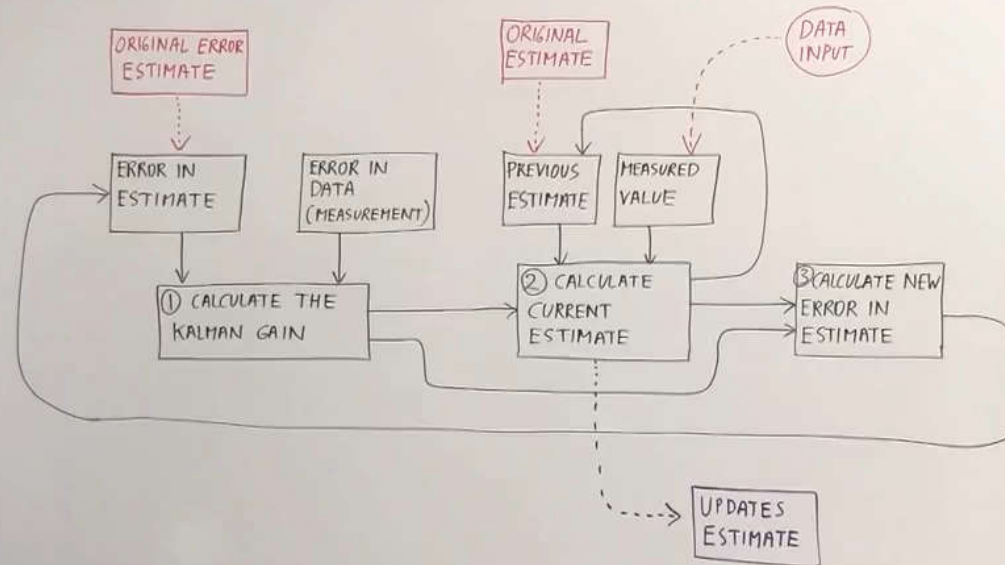
IT IS AN ITERATIVE MATHEMATICAL PROCESS THAT USES A SET OF EQUATIONS AND CONSECUTIVE DATA INPUTS TO QUICKLY ESTIMATE THE TRUE VALUE, POSITION, VELOCITY, ETC OF THE OBJECT BEING MEASURED, WHEN THE MEASURED VALUES CONTAIN UNPREDICTED OR RANDOM ERROR, UNCERTAINTY, OR VARIATION



Check out <http://ilectureonline.com> for more videos.

Kalman filter – 2

SPECIAL TOPIC 1 : THE KALMAN FILTER (2) FLOWCHART OF A SIMPLE EXAMPLE (SINGLE MEASURED VALUE)



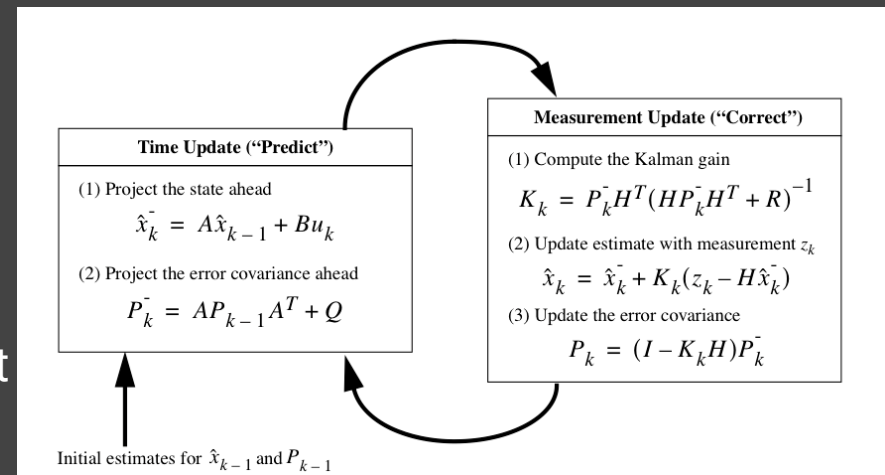
Check out <http://ilectureonline.com> for more videos.

Operation of Kalman filter

The algorithm works in a **two-step process**.

In the prediction step, the Kalman filter produces **estimates of the current state variables**, along with their uncertainties.

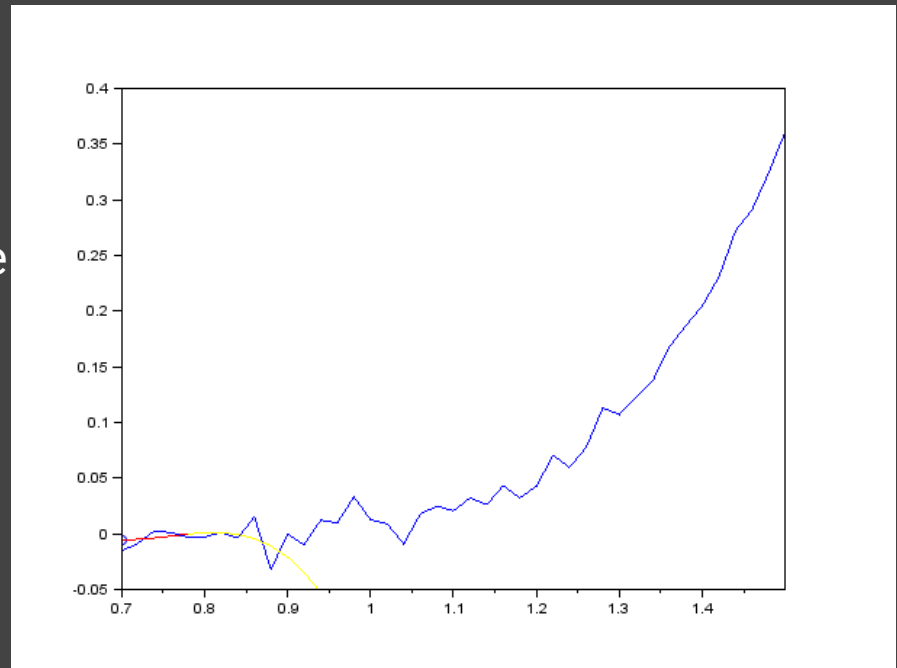
Once the outcome of the next measurement is observed, these **estimates are updated using a weighted average**, with more weight being given to estimates with higher certainty. The algorithm is recursive. It can run in real time.



Savitzky–Golay filter

Savitzky–Golay filter is a digital filter that can be applied to a set of **digital data points** for the purpose of smoothing the data, that is, to increase the signal-to-noise ratio without greatly distorting the signal.

This is achieved by **fitting** successive subsets of adjacent data points **with a low-degree polynomial** by the method of linear least squares.



Adaptive filter

Adaptive filtering involves the **changing of linear filter parameters** (coefficients) over time, to **adapt to changing signal characteristics**.

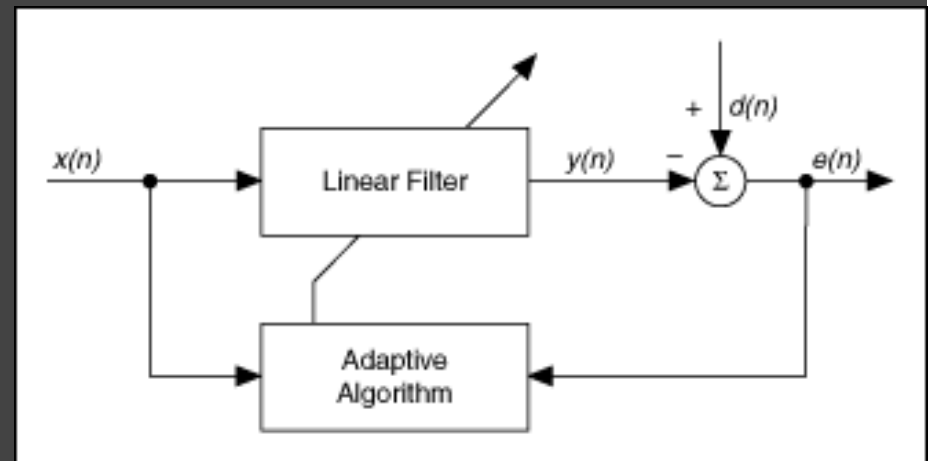
Adaptive filters can complete some signal processing tasks that traditional digital filters cannot:

- Remove noise whose power spectrum **changes over time**,
- Signal prediction,
- Adaptive feedback cancellation,
- Echo cancellation,
- Online system identification.

Adaptive Filtration

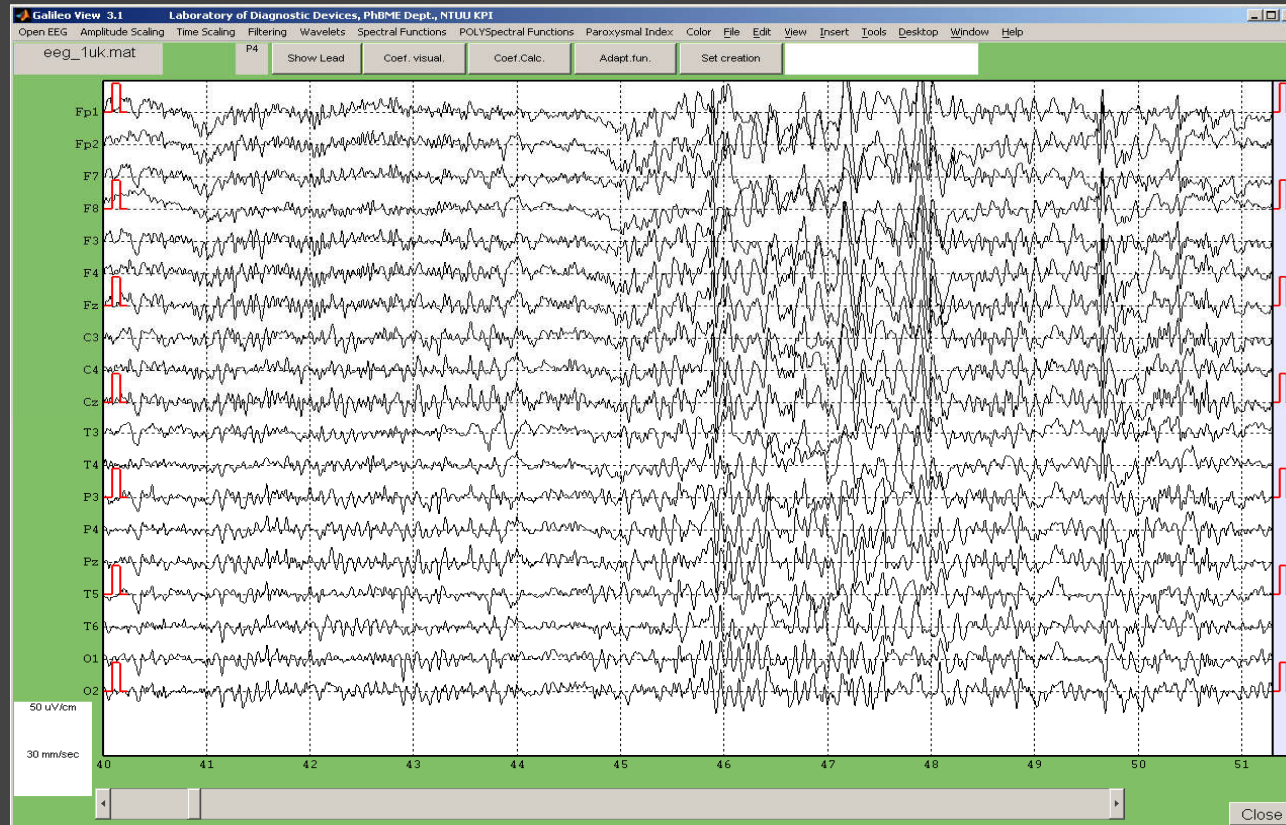
- $x(n)$ is the input signal to a linear filter at time n
- $y(n)$ is the corresponding output signal
- $d(n)$ is an additional input signal to the adaptive filter
- $e(n)$ is the error signal that denotes the difference between $d(n)$ and $y(n)$

An adaptive algorithm adjusts the coefficients of the linear filter iteratively to minimize the power of $e(n)$. For different applications, you choose the input and output signals $x(n)$, $d(n)$, $y(n)$, and $e(n)$ in different ways.



Waveform shape detection

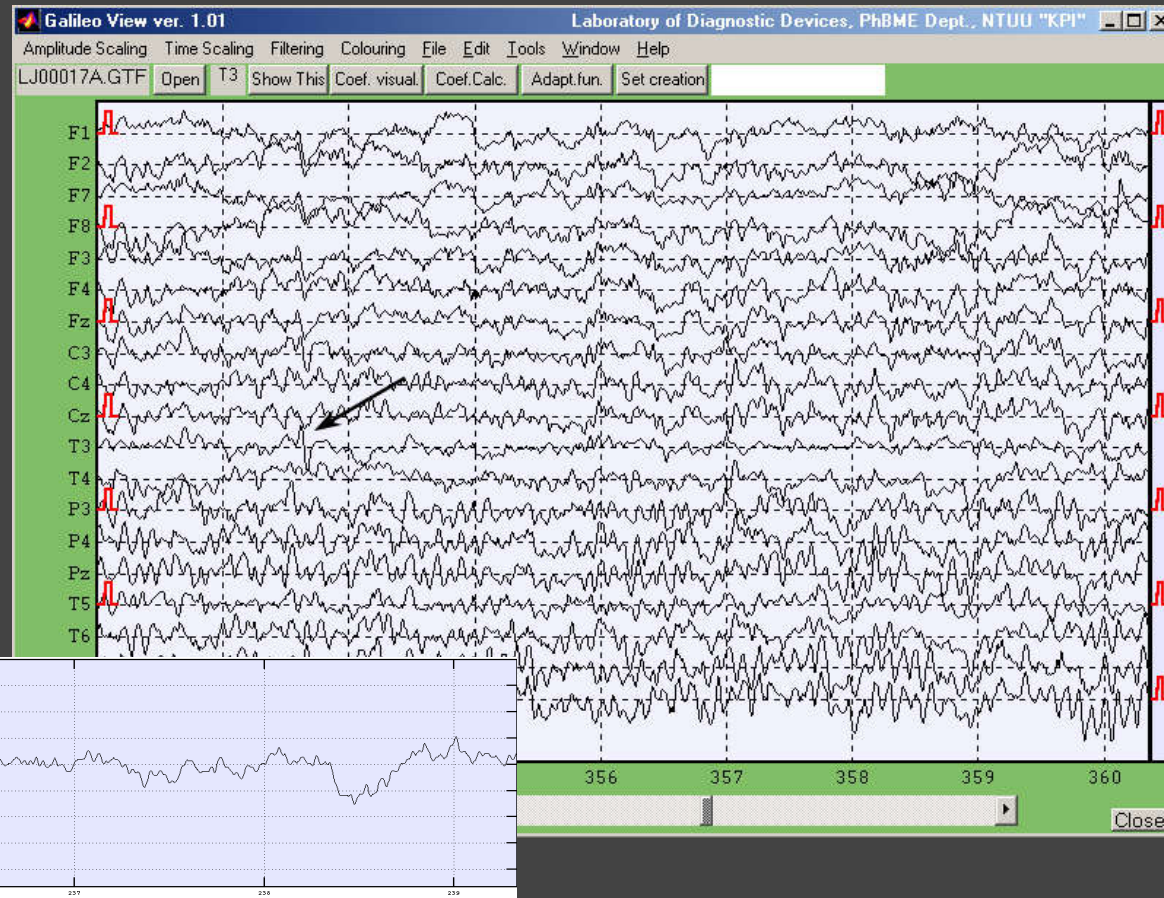
EEG during epileptic seizure





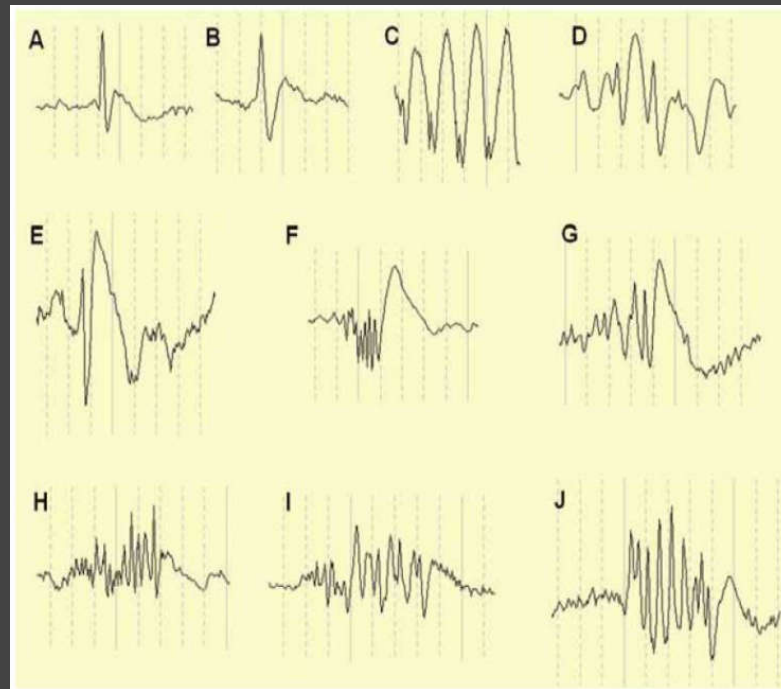
EEG of epileptic subject – rare complexes

At the **early stages of disease**, epileptiform complexes are rare, non-prominent and low-magnitude.

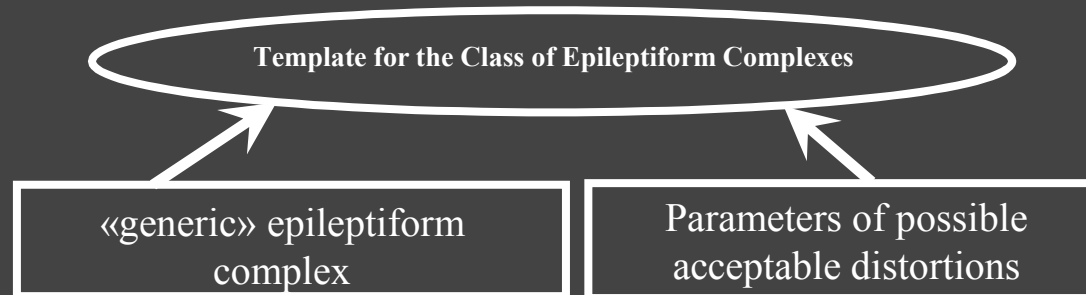


Epileptic Patterns

Epileptic oscillation complexes in human electroencephalogram - complexes of a sharp wave and a slow wave, indicating the presence of **neuronal epileptic discharges** in the brain.



Pattern Recognition by Template Matching

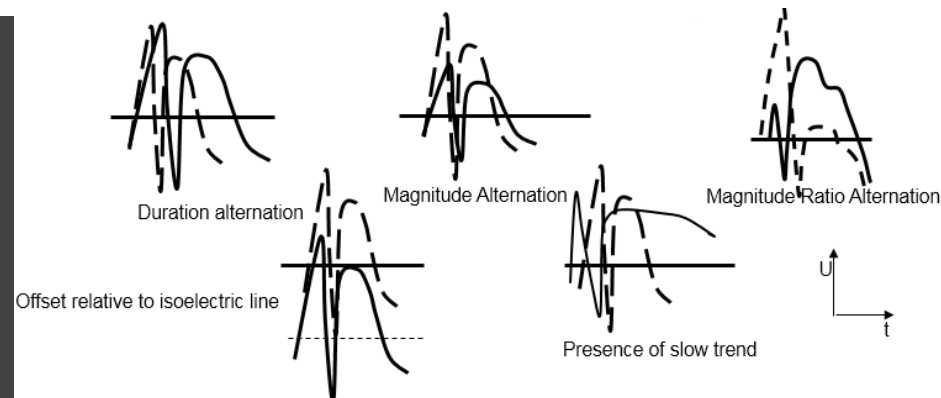


Template for the class:

$$\{\eta(n)\}_{K_1} = \langle C_{K_1} + S_{K_1} + A_{K_1} \cdot \eta(L_{K_1}), V_{K_1} \rangle$$

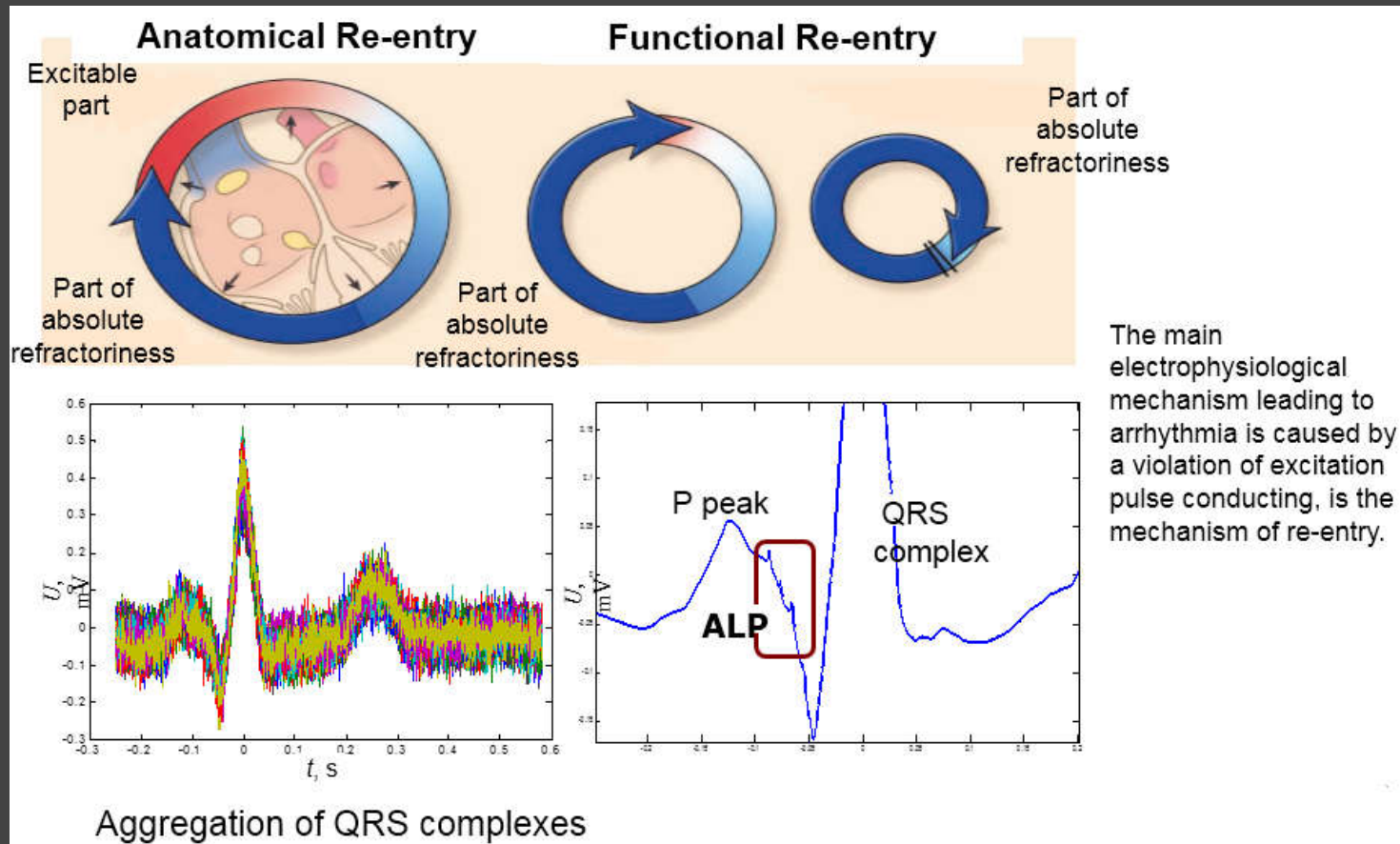
Pseudometric:

$$d_A(\eta_{K_1}, f) = \min_{i=1, Q} \left(\max_{n=1, Z} |\eta(n) - f(n)| \right)$$



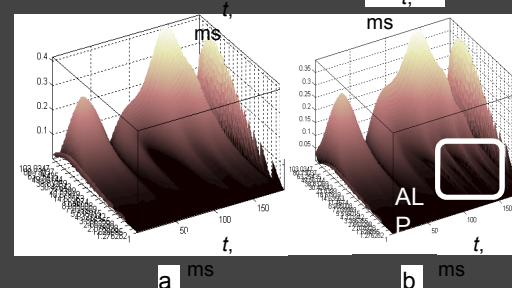
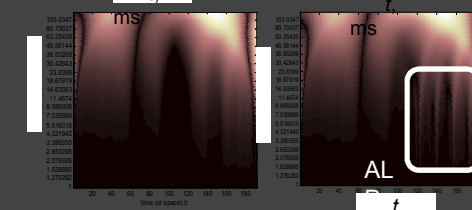
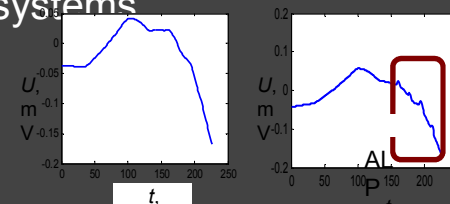
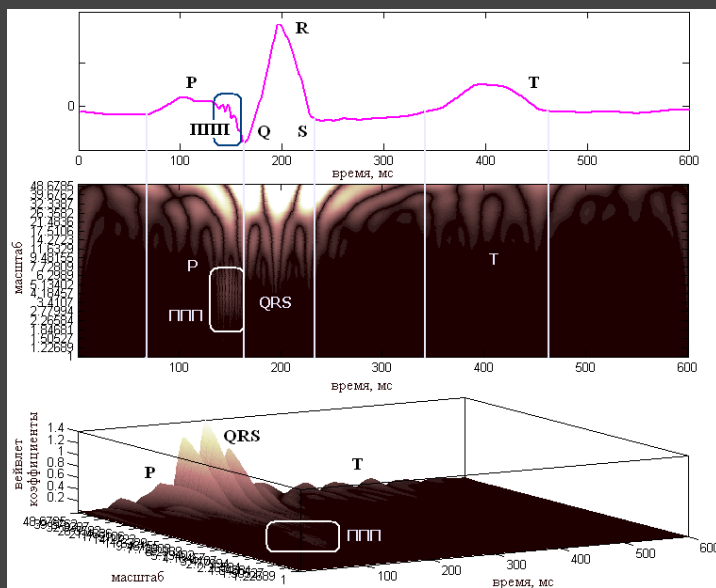
High-resolution ECG accumulation

Athrial late potentials in ECG as early signs of arrhythmias

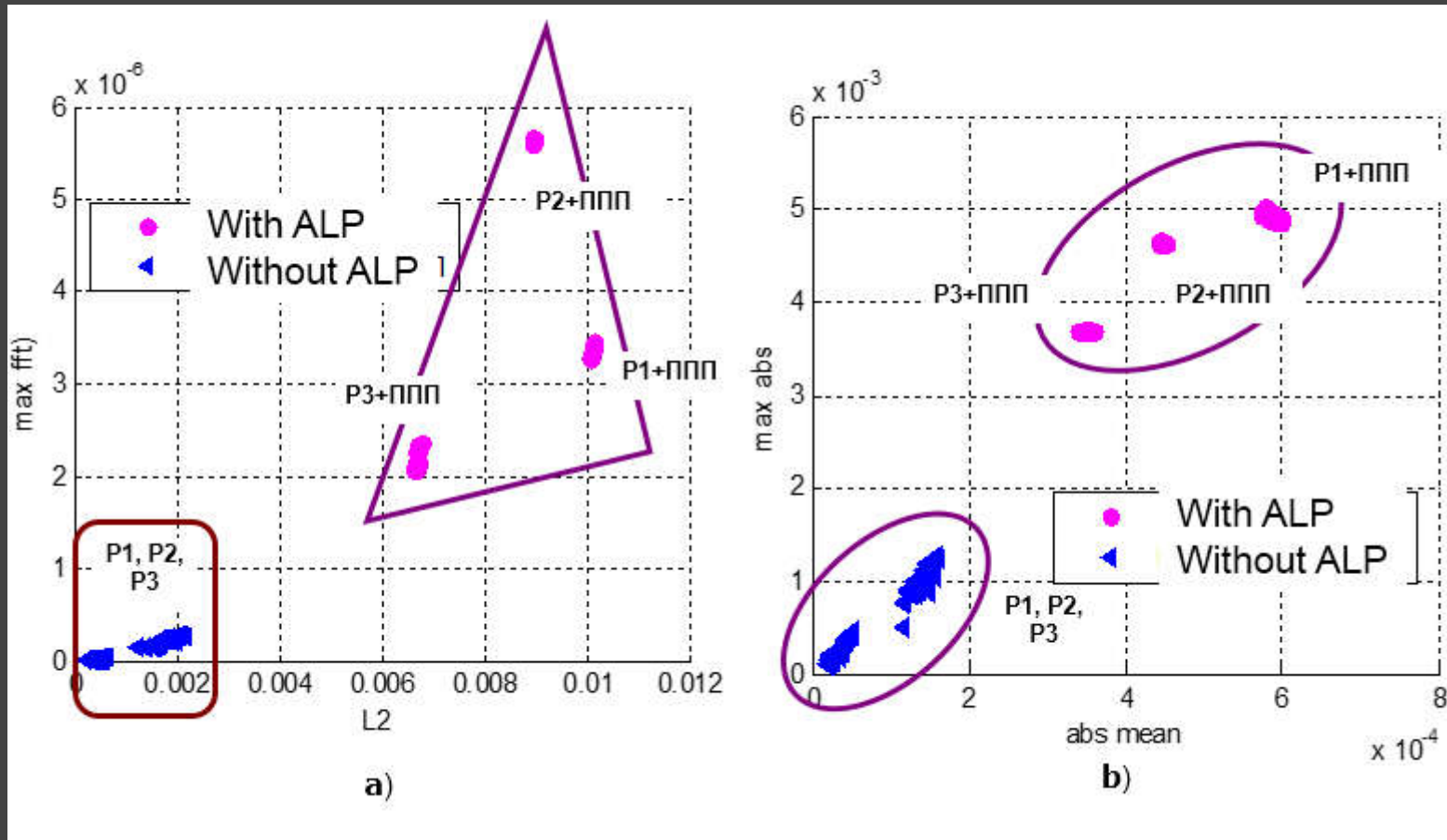


Noninvasive detection of ALP by wavelet transform

Investigation of possibilities of joint use of wavelet transforms and expansions in the basis of eigenvectors, as well as the development of algorithms for pattern recognition in ALP detection will improve diagnostic accuracy in modern ECG systems



Athrial Late Potentials in ECG classification

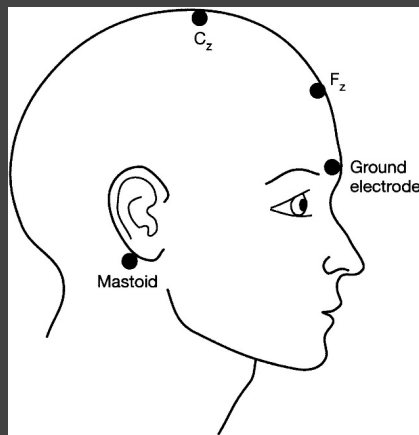


Auditory evoked response averaging

EEG auditory evoked potentials

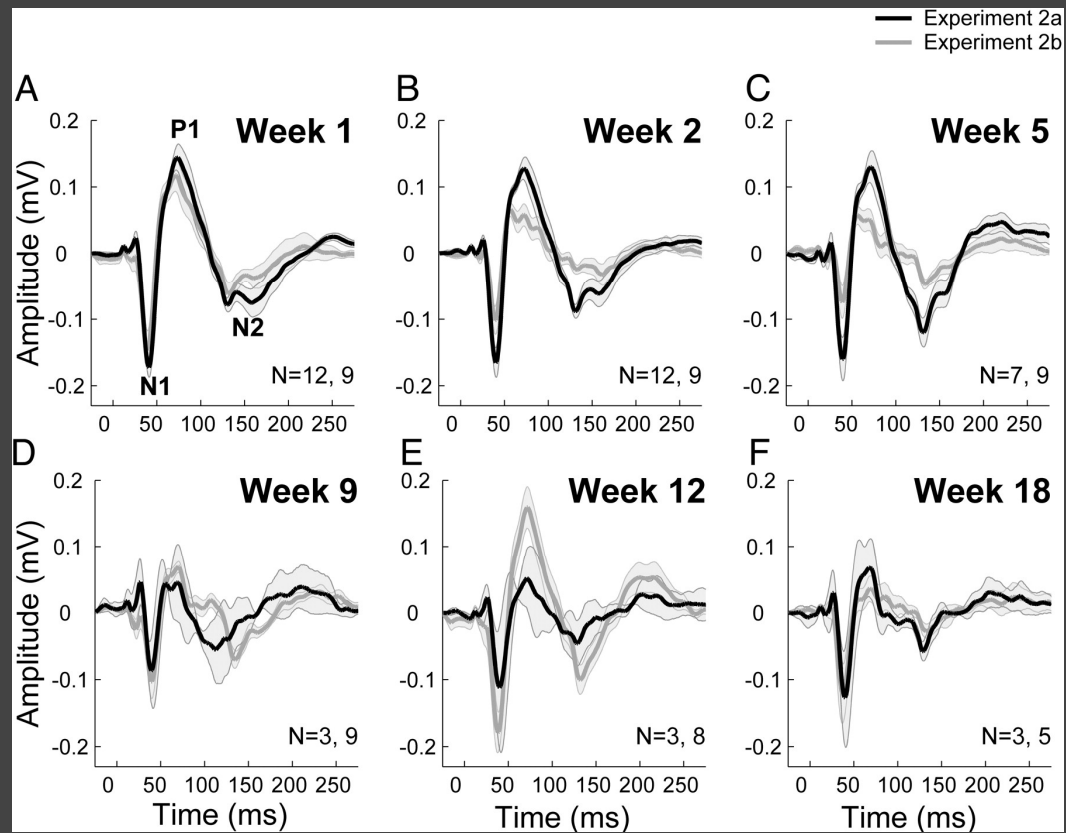
Auditory brainstem response (ABR) is a neurologic test of auditory brainstem function in response to auditory (click) stimuli.

It's a set of seven positive waves recorded during the first 10 seconds after a click stimuli. They are labeled as I - VII



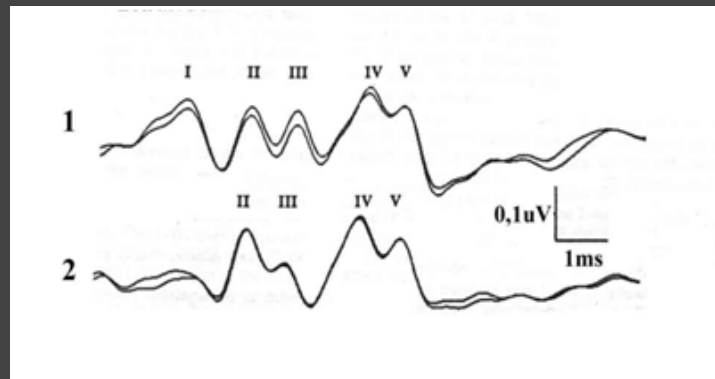
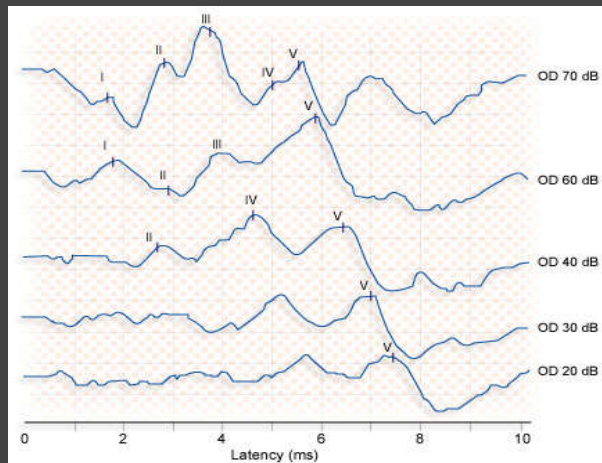
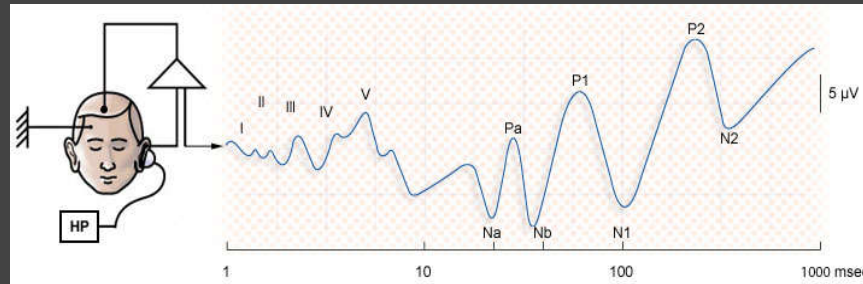
- Cz (at vertex) (recording electrode)
- Ipsilateral ear lobule or mastoid process (reference electrode)
- Contra lateral ear lobule (act as a ground)

AEP averaging



AEP signal parameters

There are short-, medium- and long-latency AEP but most often hearing diagnosed with the **medium-latency AEP**.



I

II

III

IV

V

Latency (ms) 1,6-1,8

2,7-3,0

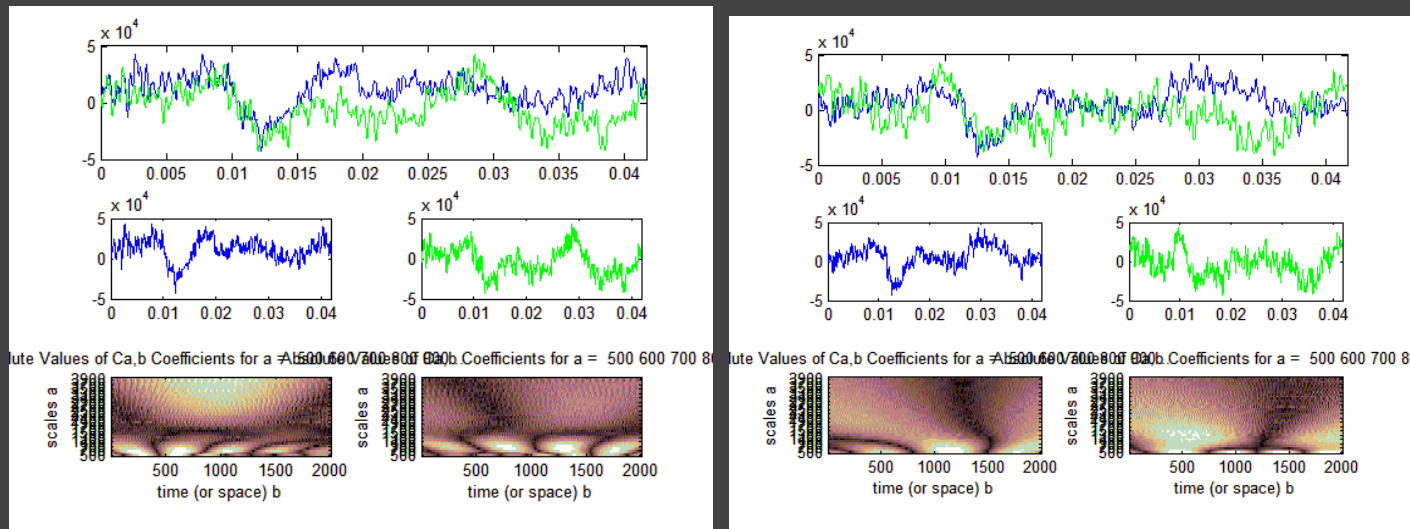
3,7-4,1

4,9-5,3

5,7-6,0

Techniques of AEP signal analysis

Wavelet transform



Methods based on continuous wavelet transform (CWT) are used, which can be applied to detection of V-wave in noise signal.

Sensitivity – 83 %

Selectivity – 87 %

Specificity – 75 %