Biomedical Signals: Detection and classification using modelling and graph theory. Applications in Neurology and Uterine Electromyography

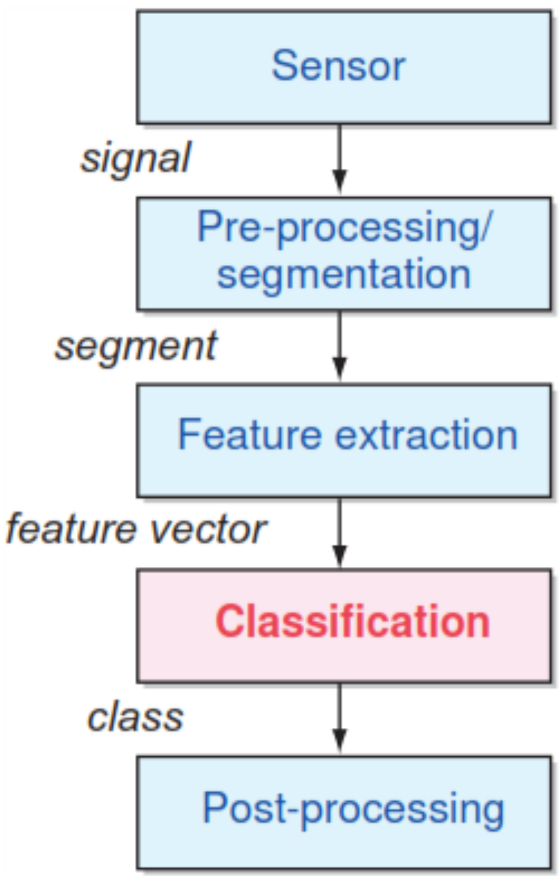
Prof. Mohamad KHALIL

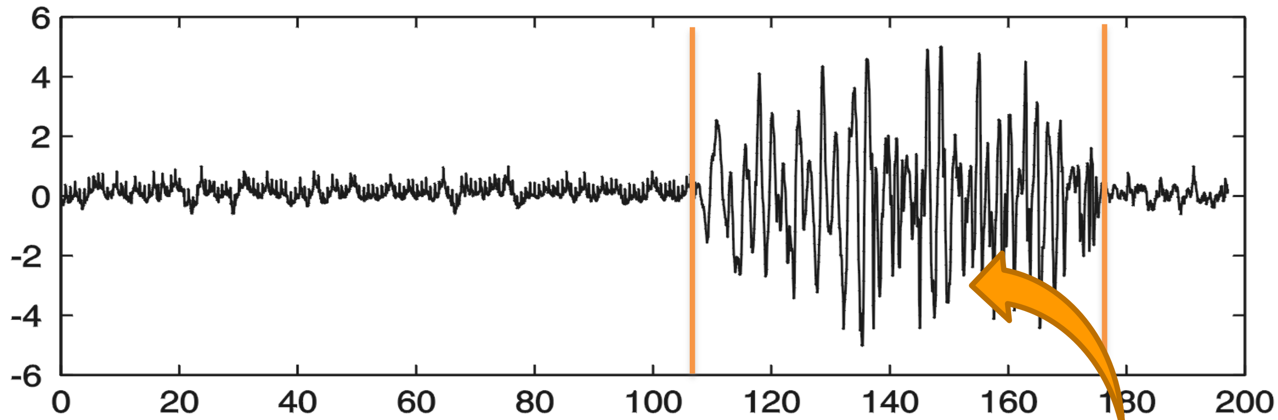
Lebanese university, faculty of engineering, Section 1
Director of the AZM research center in biotechnology and applications, Doctoral School, Lebanese university

Université Paris Saclay, Laboratoire IBISC, Every, November 17, 2022

Pattern recognition: Signal Processing

Classification system parts



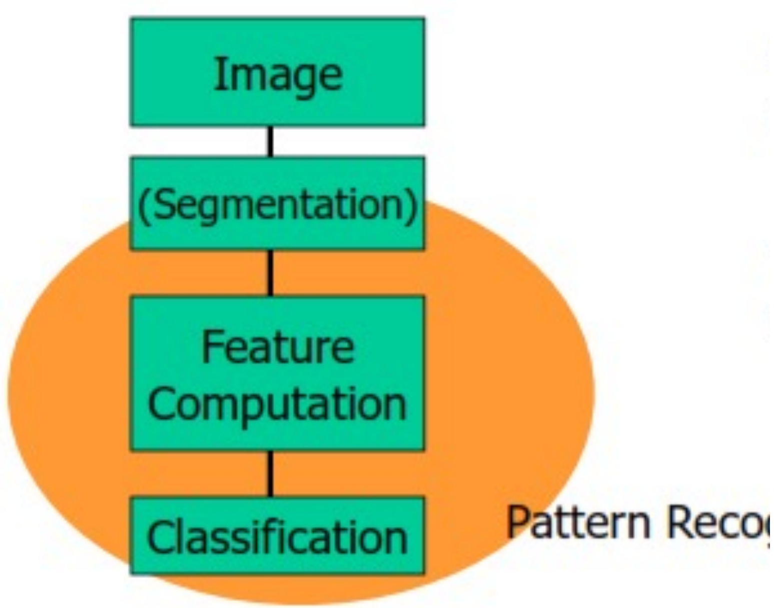


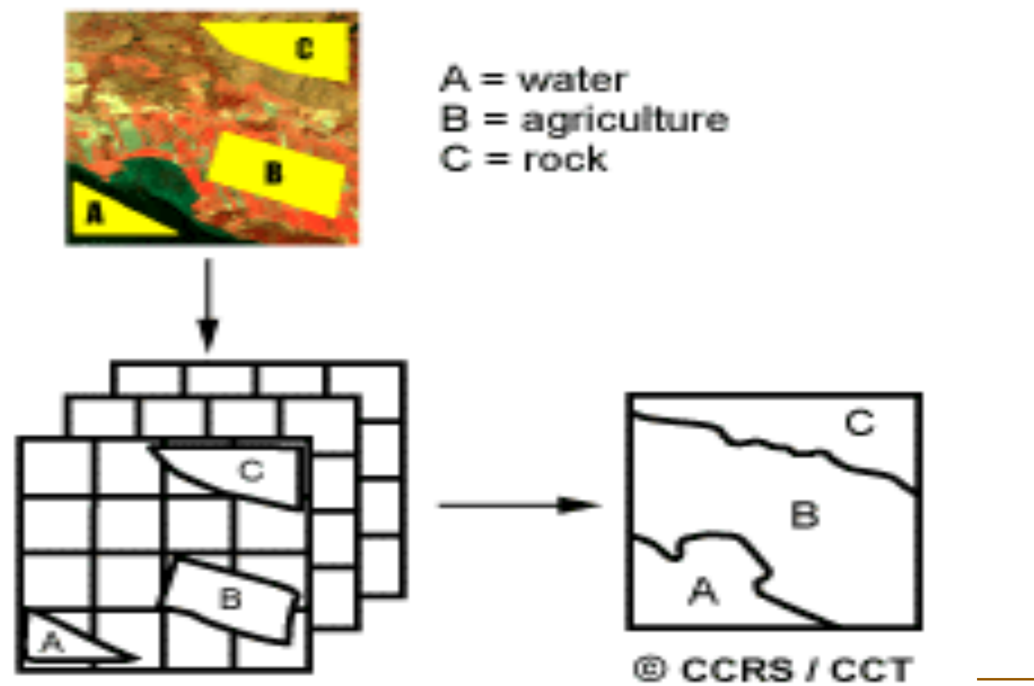
- Formant extraction

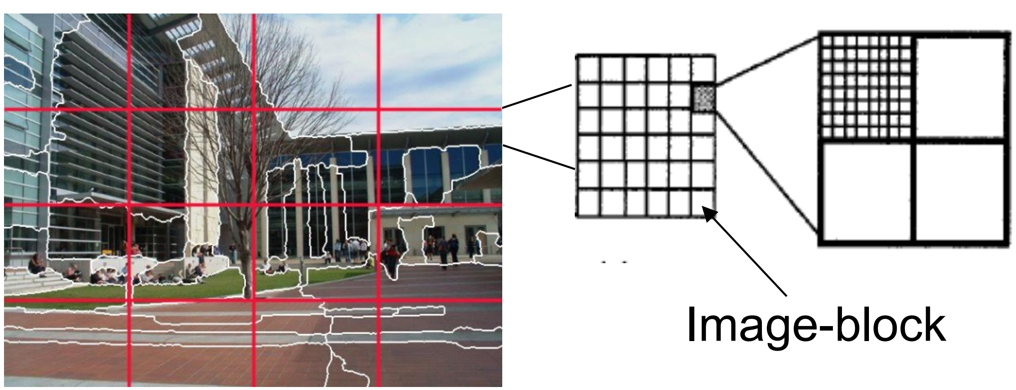
Class?

- Context constraints
- Costs/risk

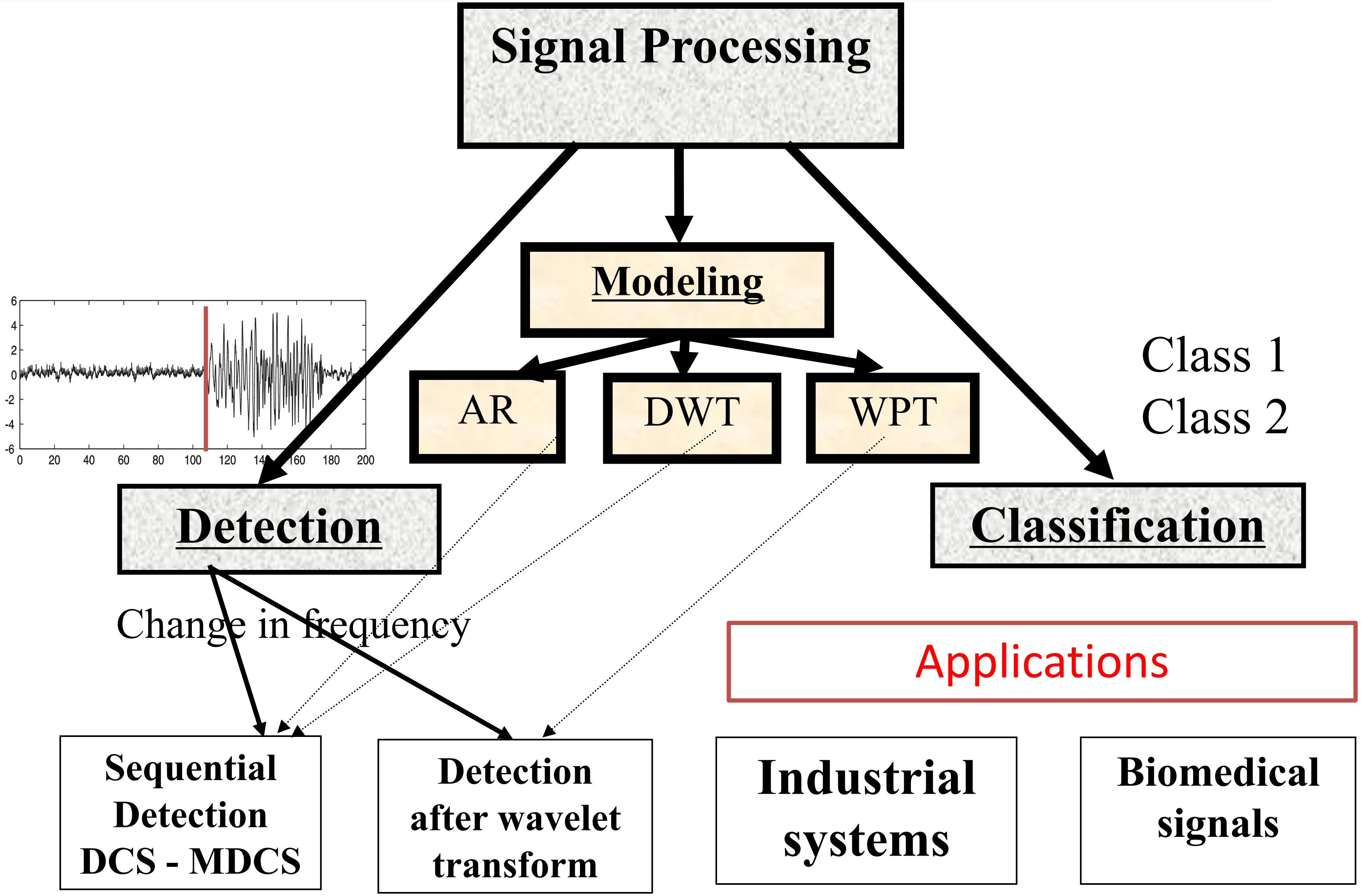
Pattern recognition: Image Processing







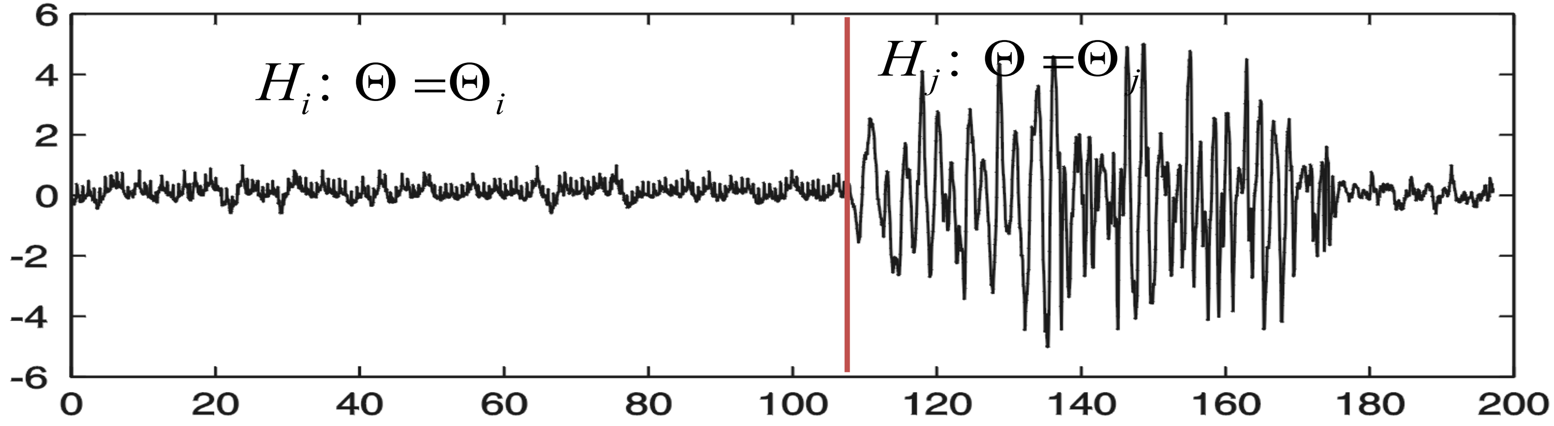
Non Stationary Signal Processing



Plan

- Event detection in non stationary signals
  - Sequential, Dynamic
- Modeling and Parameters extraction
  - Wavelet, Linear and Non linear parameters
- Classification
  - Supervised and unsupervised
- Parameters elimination
  - Wraper and sequential
- Applications

Detection: definition



Hypotheses :

$H_i: \quad \Theta = \Theta_i$	estimated
$H_j: \quad \Theta = \Theta_j$	Known or unknown

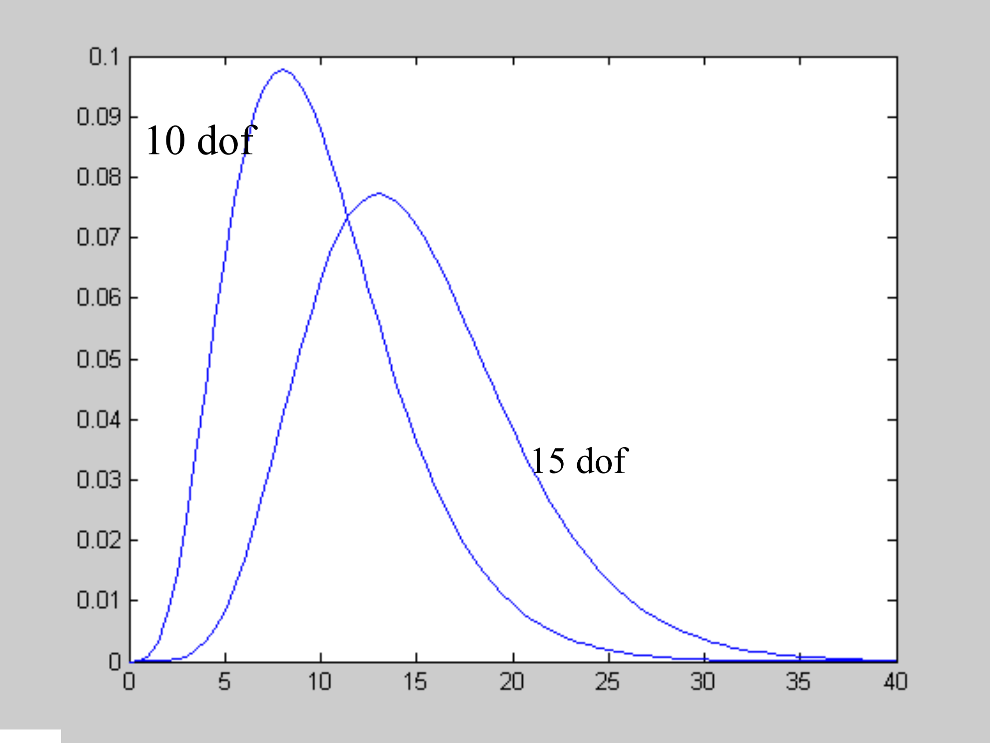
Détection par fenêtrage

- Test de Chi2

$$Si \quad Z_1, Z_2, \ldots, Z_k \quad \approx N(0;1)$$

$$\sum_{i=1}^{k} Z_i^2 \approx \chi^2_{(k)}$$

chi2 with k degree of freedom



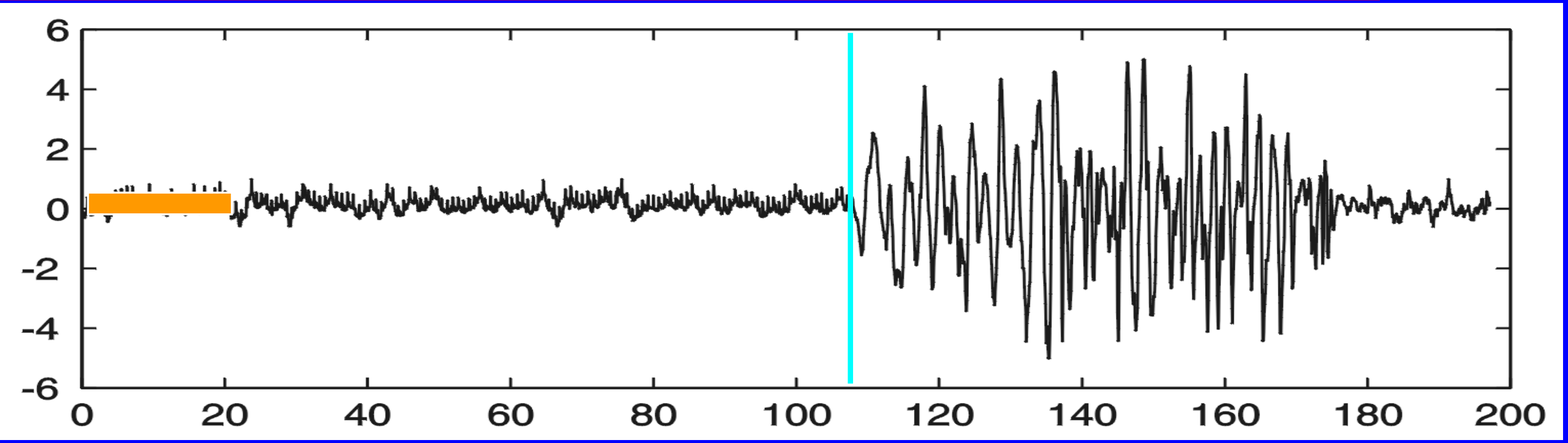
$$\chi^2_{(k)} = \frac{1}{2^{k/2}\Gamma(k/2)} x^{k/2-1} e^{-x/2}$$

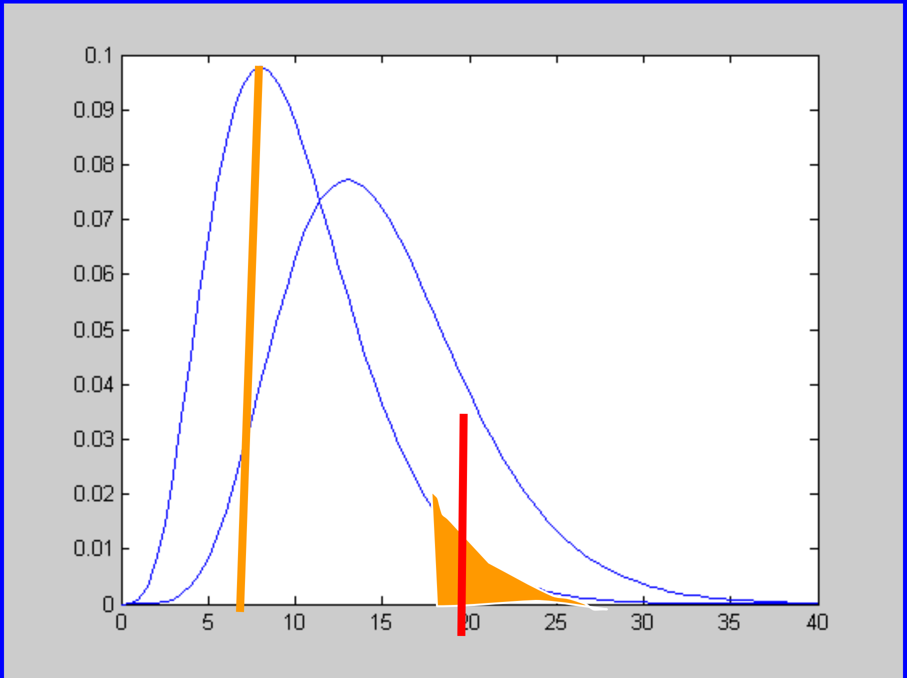
$$\Gamma(k) = \int_0^\infty x^{k-1} e^{-x} dx$$

E[chi2]=k

Variance of Chi2=2k

Détection par fenêtrage



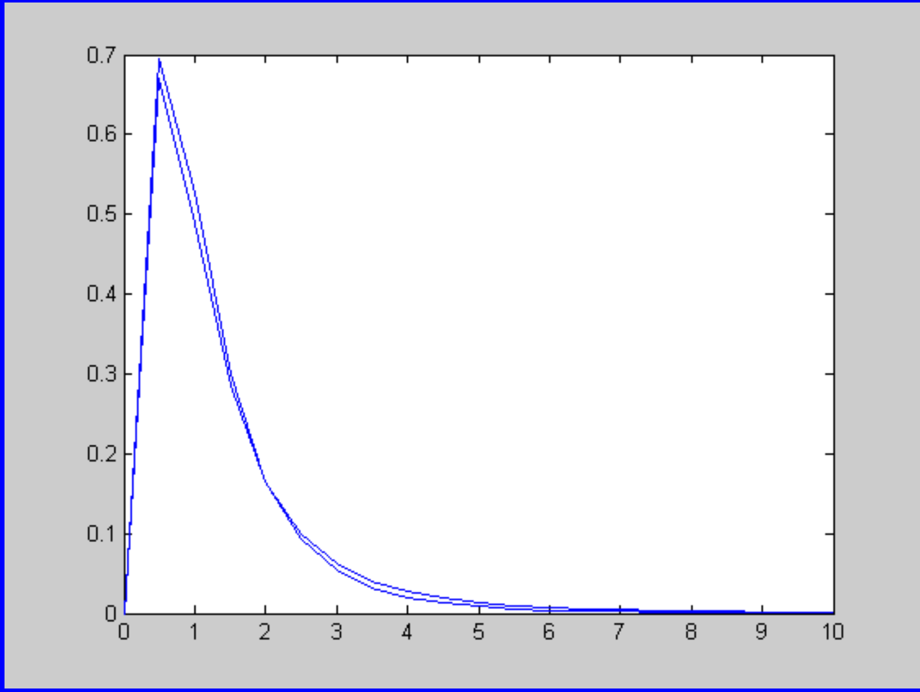


Détection par fenêtrage

Student distribution

$$Si \quad Z \approx N(0;1) \quad \frac{Z}{\sqrt{\frac{\chi_k^2}{k}}} \approx t(k)$$

Student with k degree of freedom

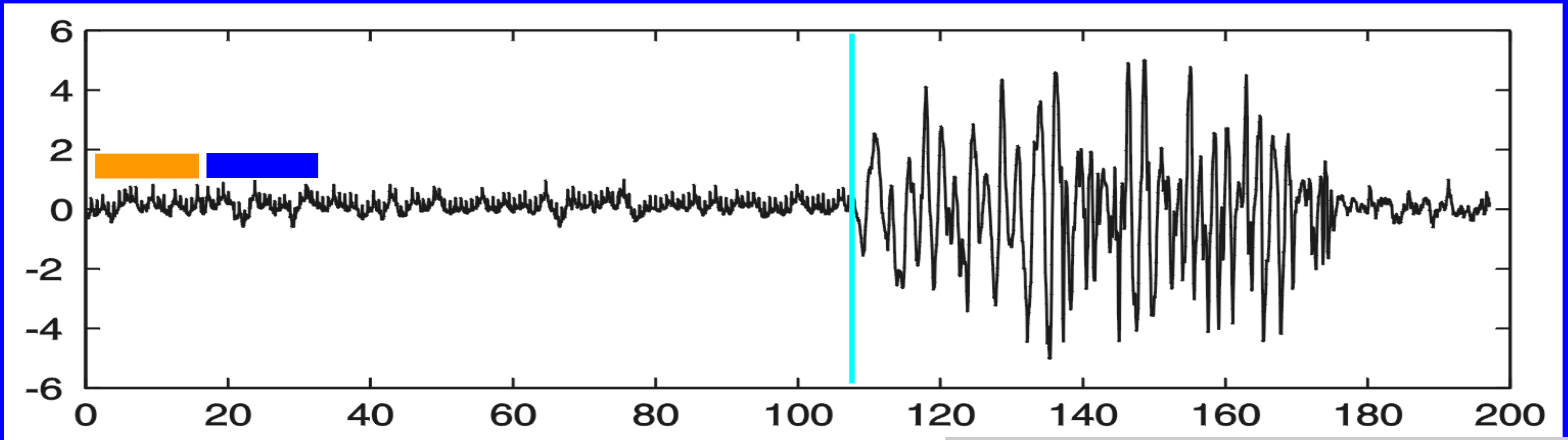


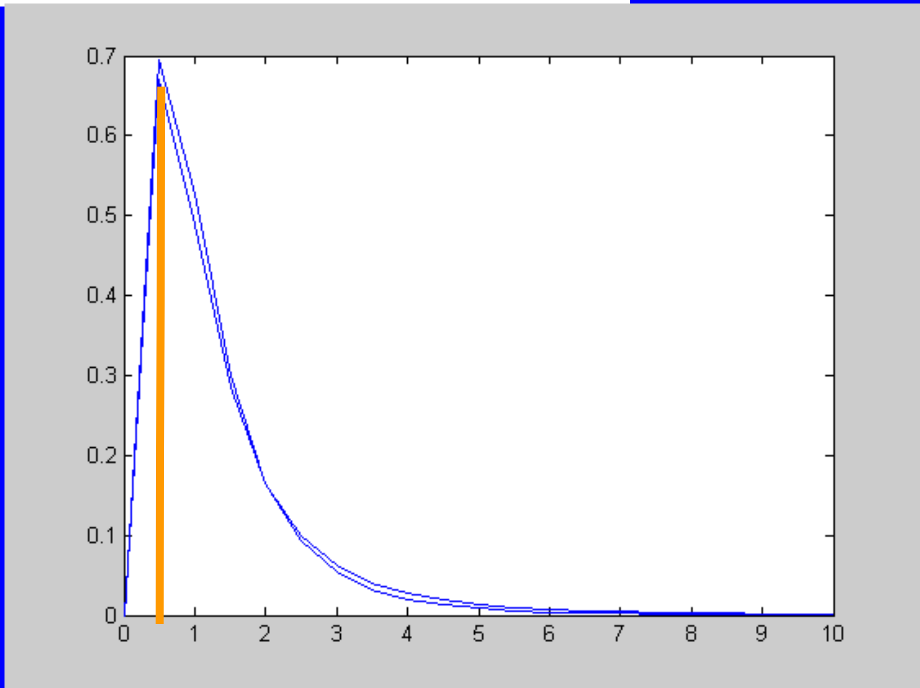
Fisher-Snédécor Distribution

$$\frac{\frac{\chi_k^2}{k}}{\frac{\chi_l^2}{l}} \approx F(k;l)$$

Fisher with k and l degree of freedom

Détection par fenêtrage





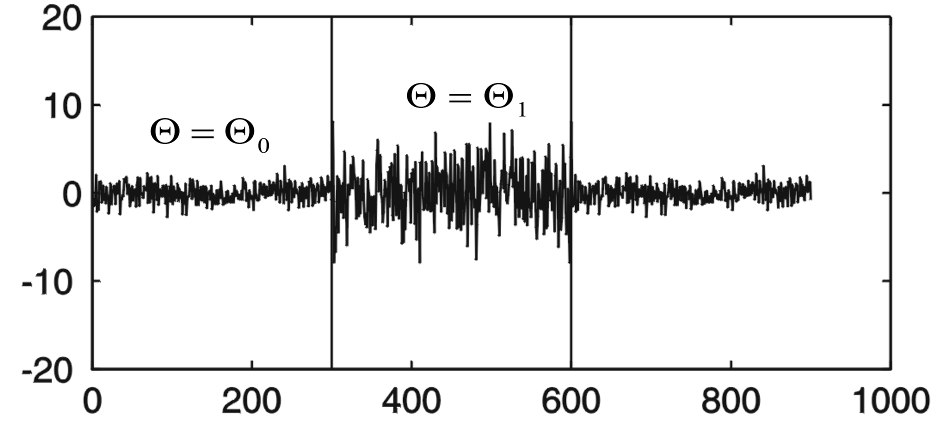
Sequential detection

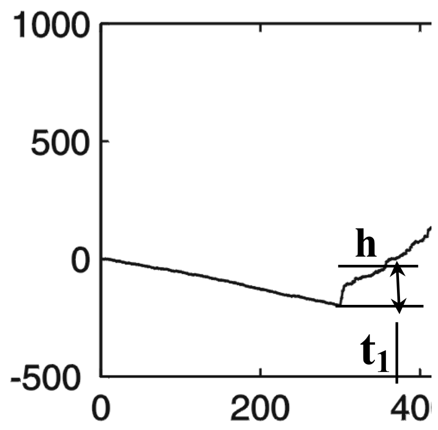
- Cumulative sum: sum of logarithm of likelihood ratio

$$S_t = \sum_{i=1}^{t} \log \frac{f_{\Theta_1}(x_i)}{f_{\Theta_0}(x_i)}$$

Stop time

$$t_1 = \inf\left\{ n \geq 1 : S_n - \min_{0 \leq t \leq n} S_t \geq h \right\}$$

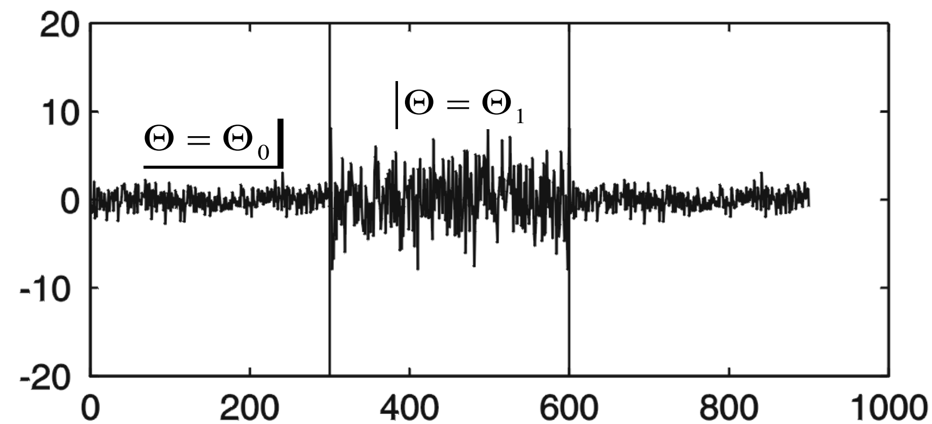




Sequential detection: Known parameters

- Cumulative sum: sum of logarithm of likelihood ration

$$S_t = \sum_{i=1}^{t} \log \frac{f_{\Theta_1}(x_i)}{f_{\Theta_0}(x_i)}$$



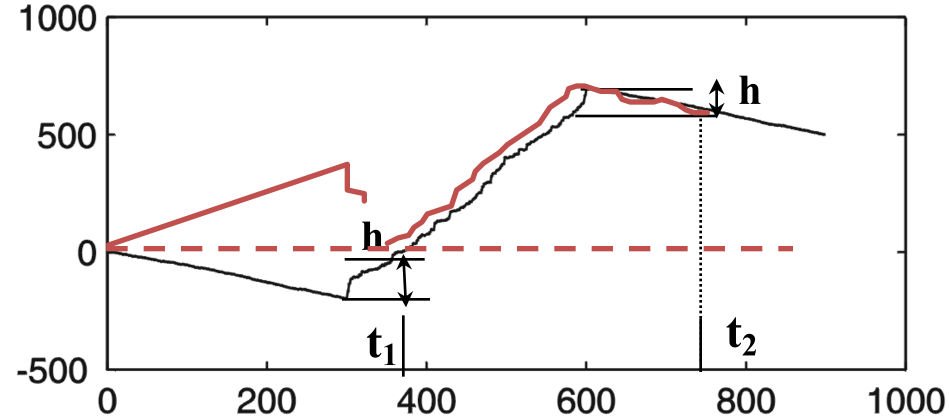
Stop time

$$t_1 = \inf\left\{ n \geq 1 : S_n - \min_{0 \leq t \leq n} S_t \geq h \right\}$$

$$t_2 = \inf\left\{ n \geq t_1 : \max_{t_1 \leq t \leq n} S_t - S_n \geq h \right\}$$

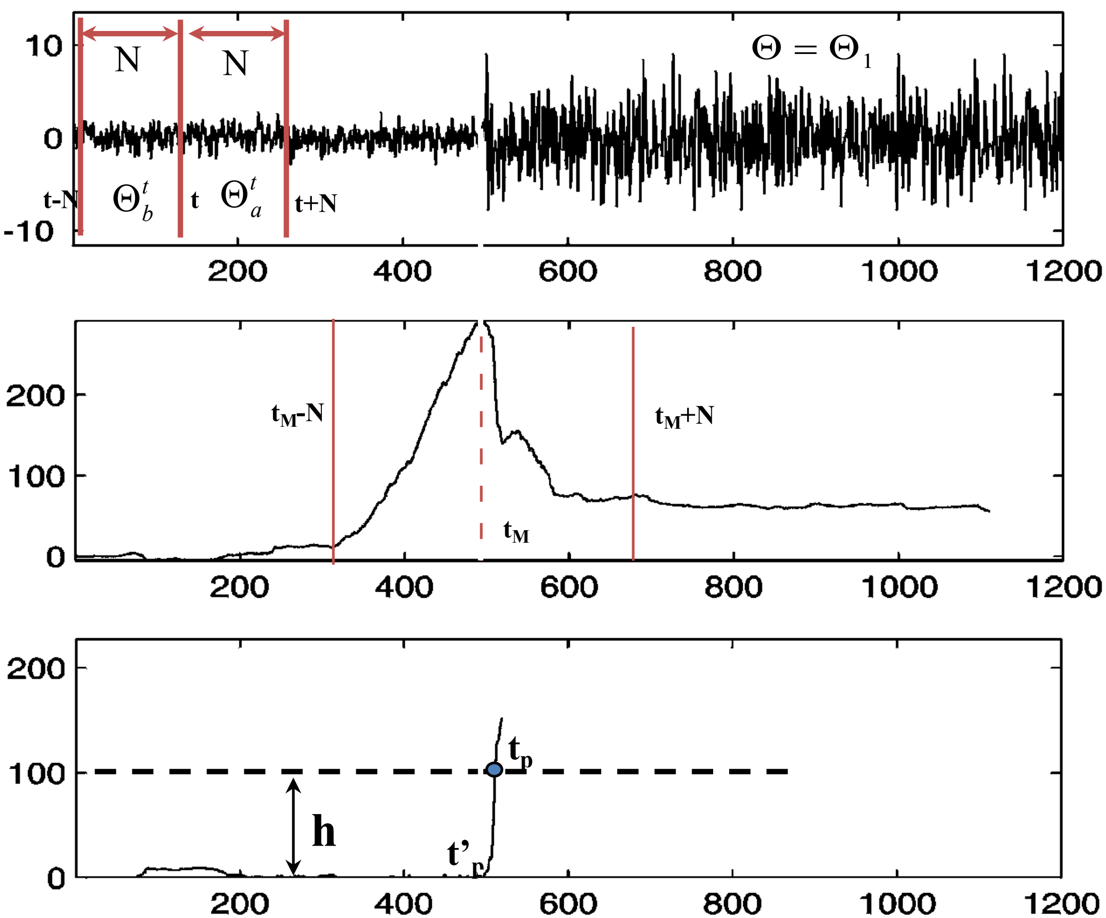
Generalized equation:

$$t_p = \inf\left\{ n \geq t_{p-1} : \max_{t_{p-1} \leq t \leq n} \left|S_t\right| - \left|S_n\right| \geq h \right\}$$



Dynamic Cumulative Sum (DCS): unknown parameters

- Principle



Instantaneous segments

$$H_b^t:\quad X_i; i = \{t-N, \ldots, t-1\} \rightarrow f_{\Theta_b^t}$$

$$H_a^t:\quad X_i; i = \{t, \ldots, t+N-1\} \rightarrow f_{\Theta_a^t}$$

Dynamic cumulative Sum

$$DCS(H_a^t, H_b^t) = \sum_{i=t_{p-1}}^{t} \log \frac{f_{\Theta_a^i}(X_i)}{f_{\Theta_b^i}(X_i)}$$

Detection Function

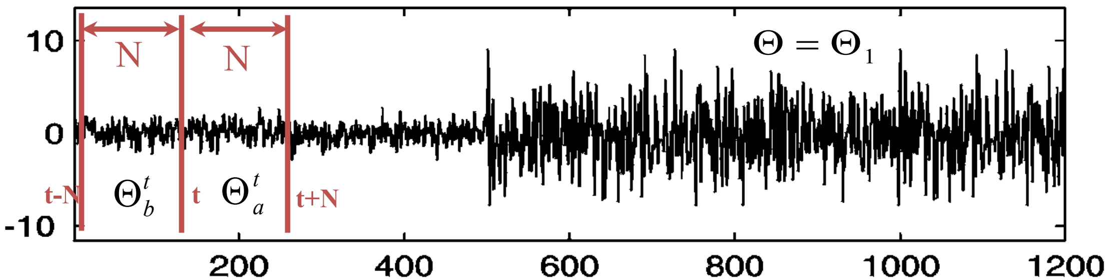
$$g(t) = \max_{t_{p-1}<j<t}\left[DCS(H_a^j, H_b^j)\right] - DCS(H_a^t, H_b^t)$$

Stop time

$$t_p = \inf\left\{n > t_{p-1} : g(n) > h\right\}$$

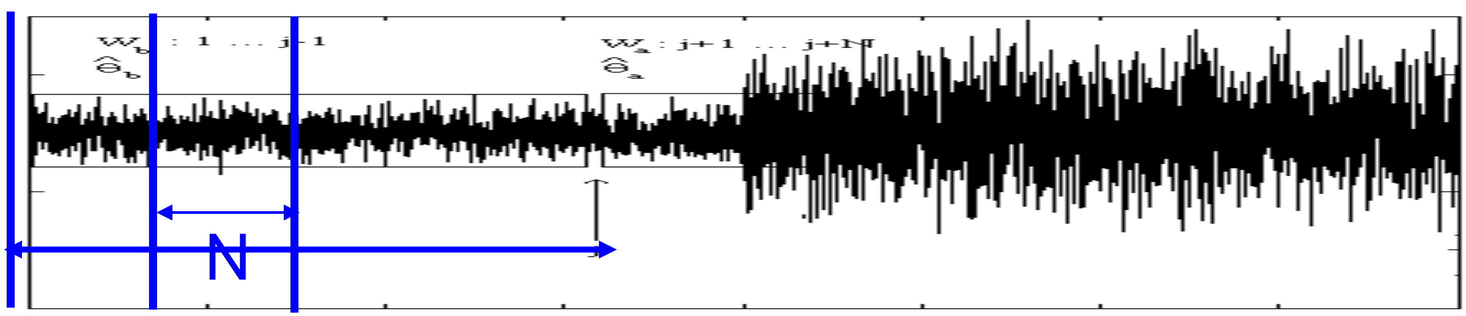
Modified Dynamic Cumulative Sum (MDCS)

- Non symmetric Windows



Dynamic Cumulative Sum

$$DCS(H_a^t, H_b^t) = \sum_{i=t_{p-1}}^{t} \log \frac{f_{\Theta_a^i}(X_i)}{f_{\Theta_b^i}(X_i)}$$



$$\begin{cases} W_b^j : 1.....j-1 \rightarrow \hat{\theta}_b^j \\ W_a^j : j+1.....j+N \rightarrow \hat{\theta}_a^j \end{cases}$$

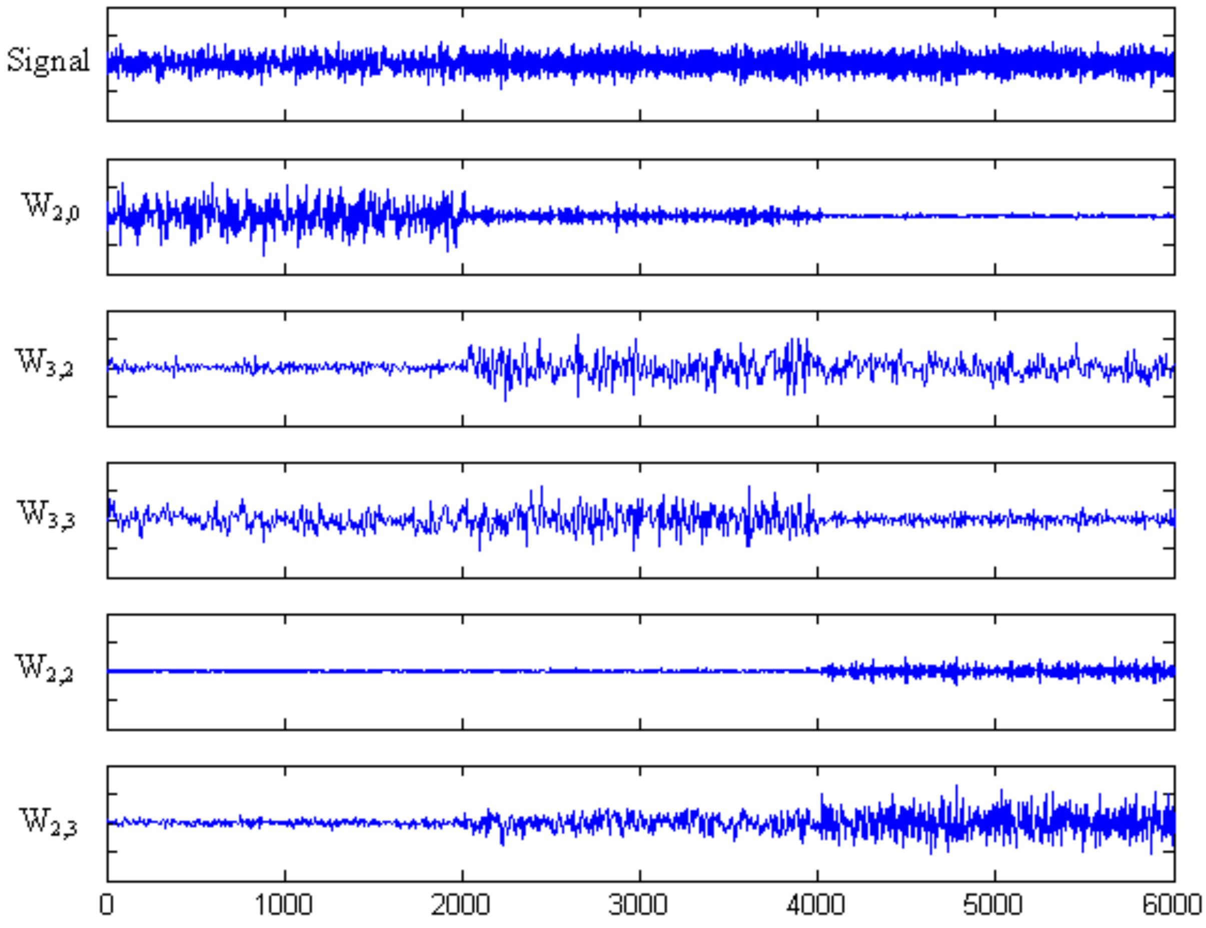
Plan

- Event detection in non stationary signals
  - Sequential, Dynamic
- Modeling and Parameters extraction
  - Wavelet transform, Linear and Non linear parameters extraction
- Classification
  - Supervised and unsupervised
- Parameters elimination
  - Wraper and sequential
- Applications

Signal modeling

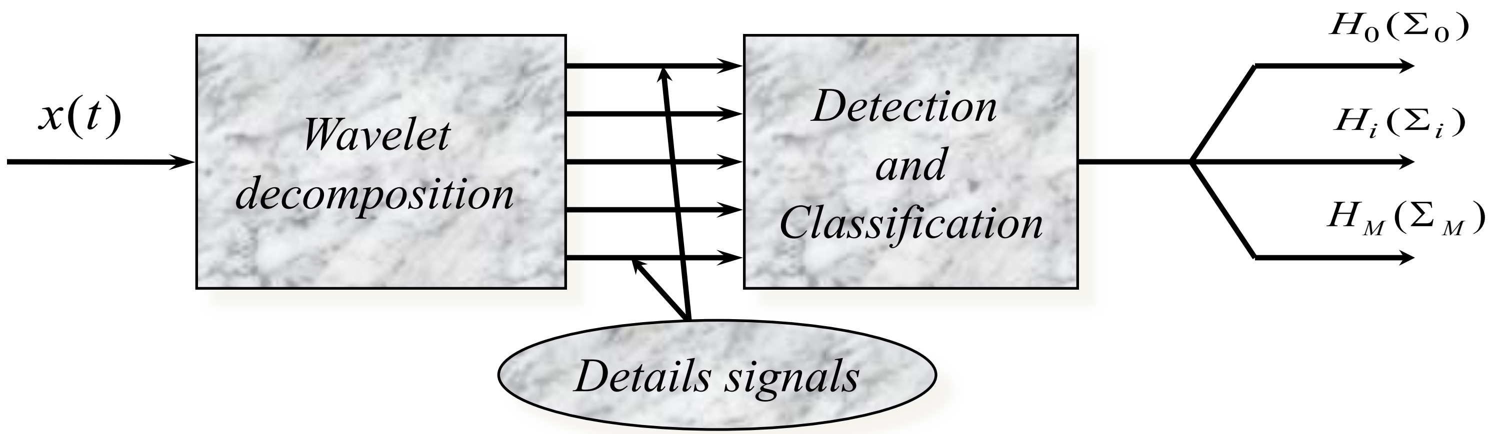
Wavelet transform

Problem statement



Modeling by wavelet transform

- Wavelet : explore the frequency content



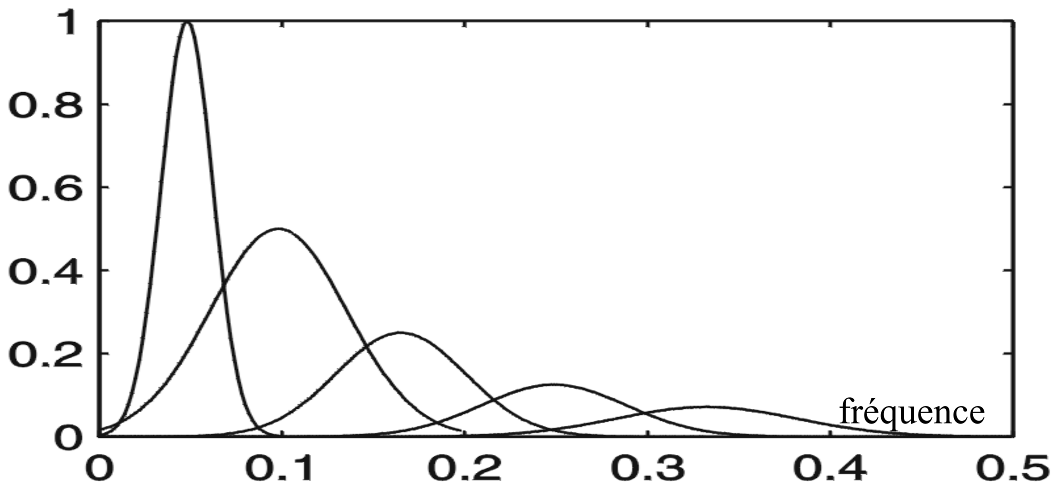
» Each detail contains specific frequency band

Wavelet Theory

- Wavelet: principle

$$T_x^{\psi}(a,b)=\int_{-\infty}^{+\infty}x(t)\psi_{ab}(t)dt$$

$$\psi_{ab}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$ → Wavelet

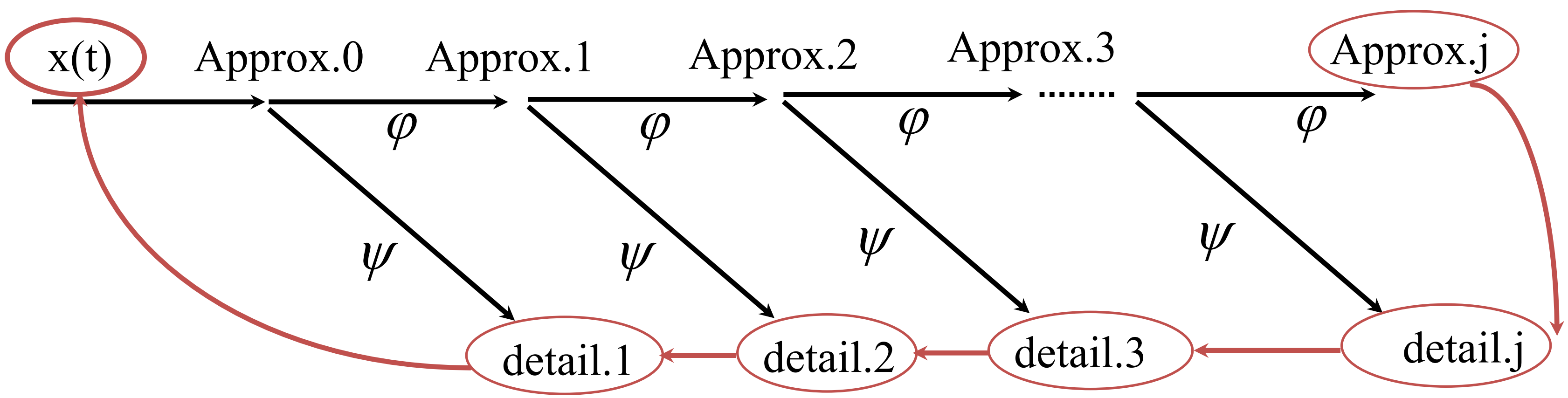


=

Wavelet theory

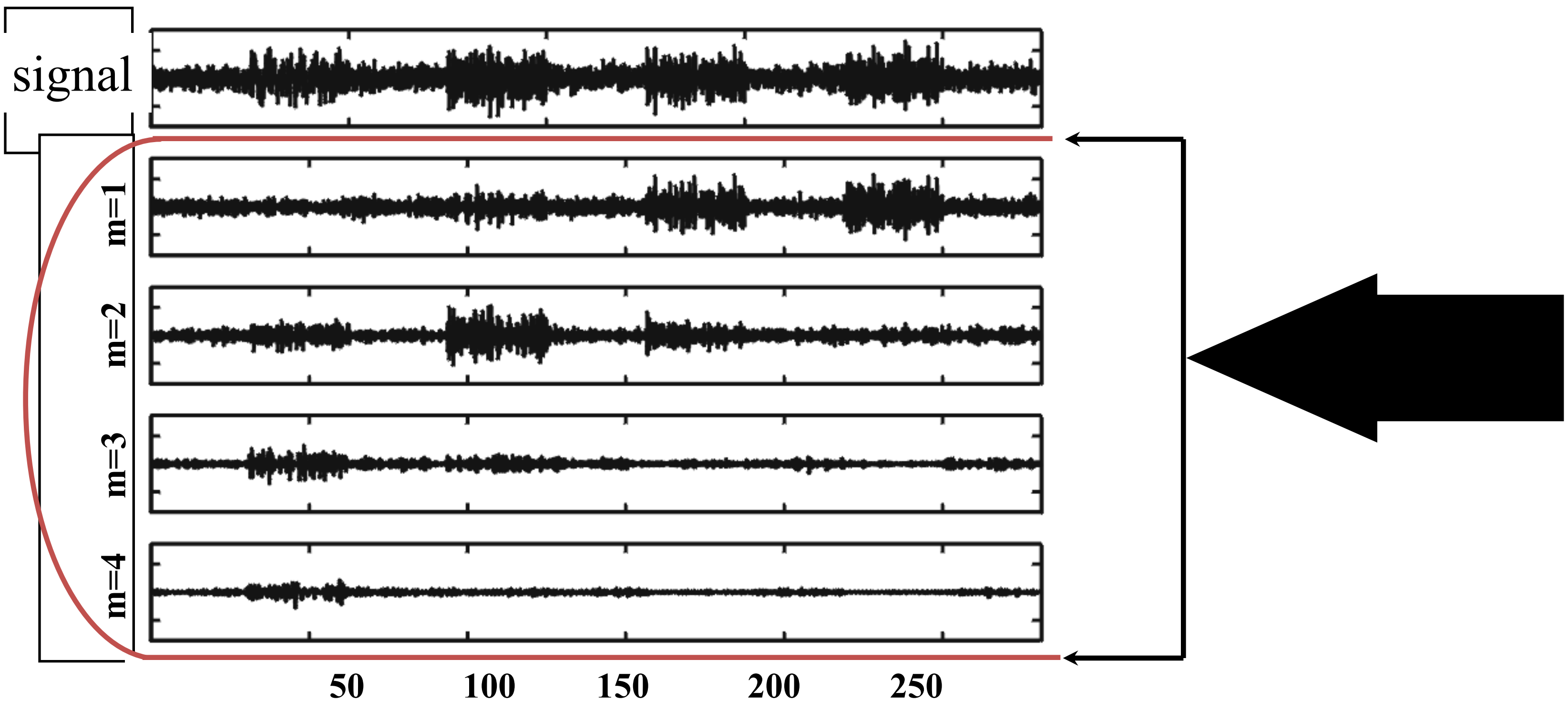
- Wavelet
  - Multiresolution analysis : $a=2^{-m}$, $b=n.2^{-m}$
  - Signal= details + approximations

$$\psi_{nm}(t) = 2^{m/2}\psi(2^m t - n) \qquad \varphi_{nm}(t) = 2^{m/2}\varphi(2^m t - n)$$

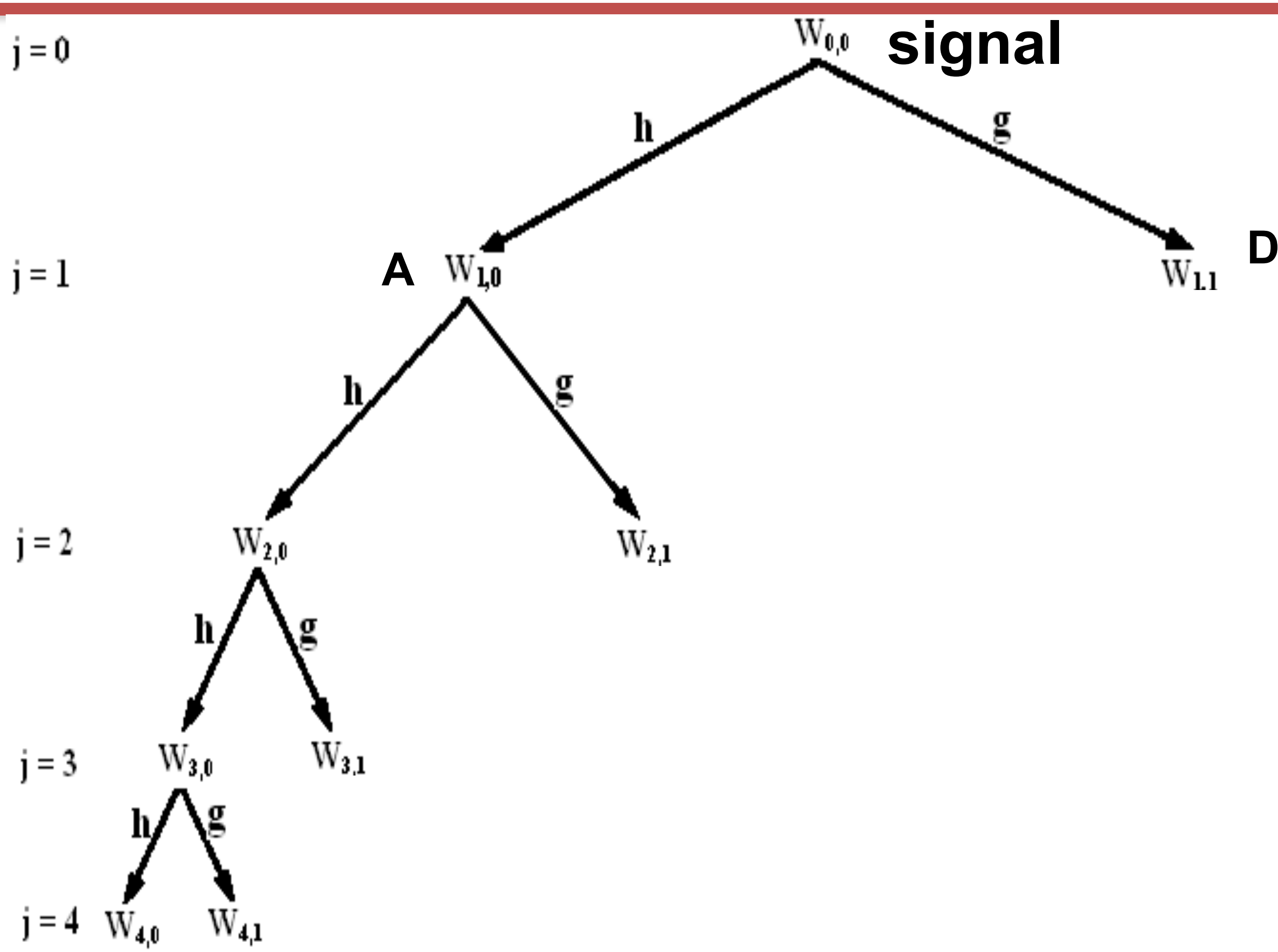


$$d_x(n,m) = \int_{-\infty}^{+\infty} x(t)\psi_{nm}(t) \qquad \text{detail}_k(t) = \sum_n d_x(n,k)\psi_{nm}(t)$$

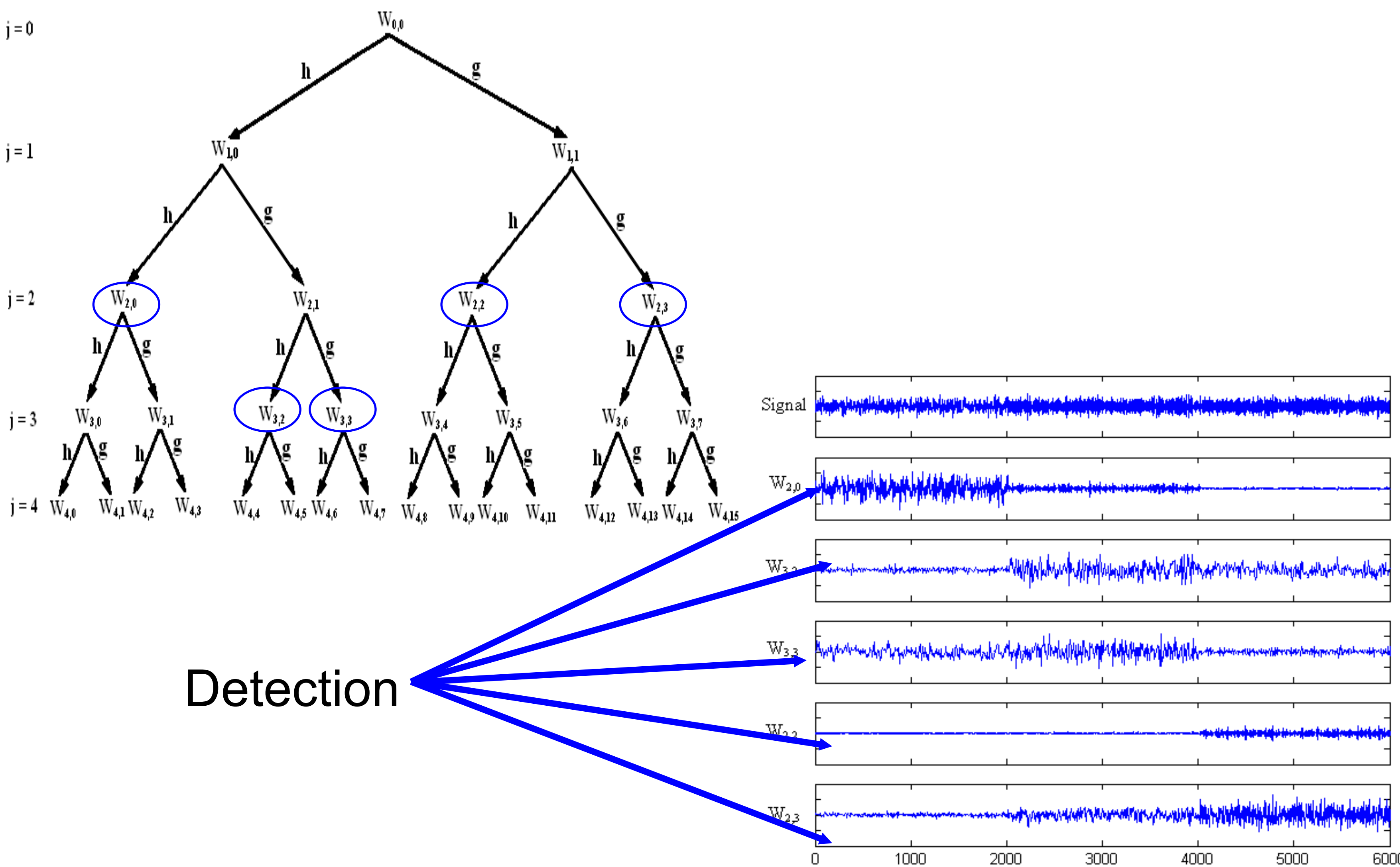
Wavelet: Example of decomposition



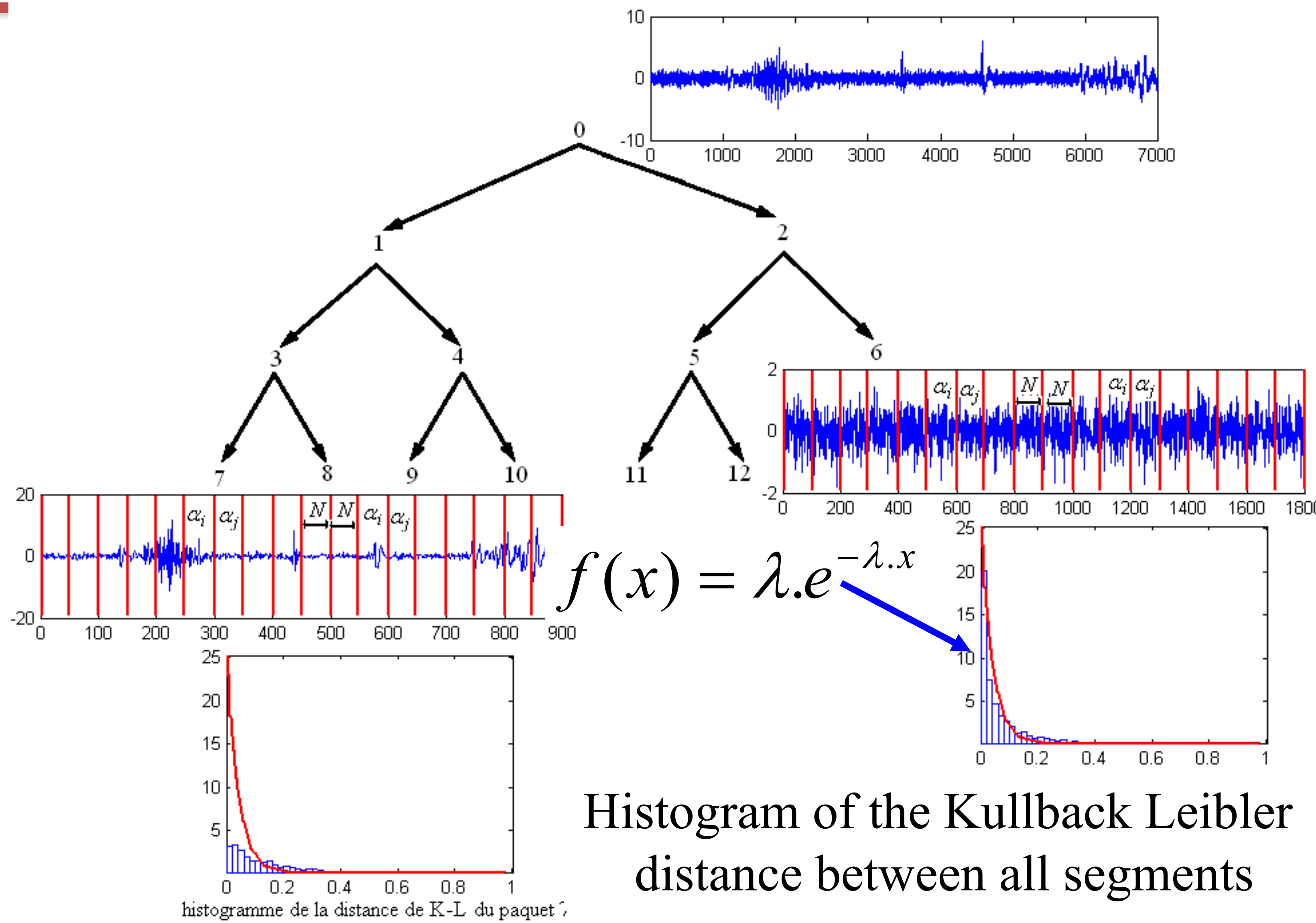
Decomposition into wavelet Packet



Wavelet Packet decomposition



Choose Best Wavelet Decomposition



$$f(x) = \lambda . e^{-\lambda . x}$$

Histogram of the Kullback Leibler distance between all segments

Features Extraction

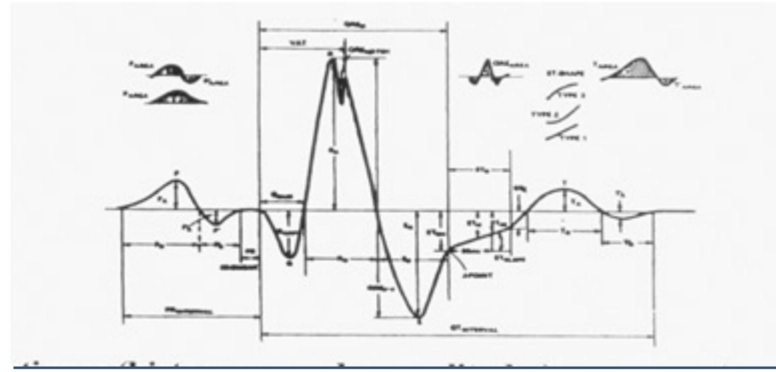
Linear features

Frequency parameters

Features after wavelet transform

Non linear features

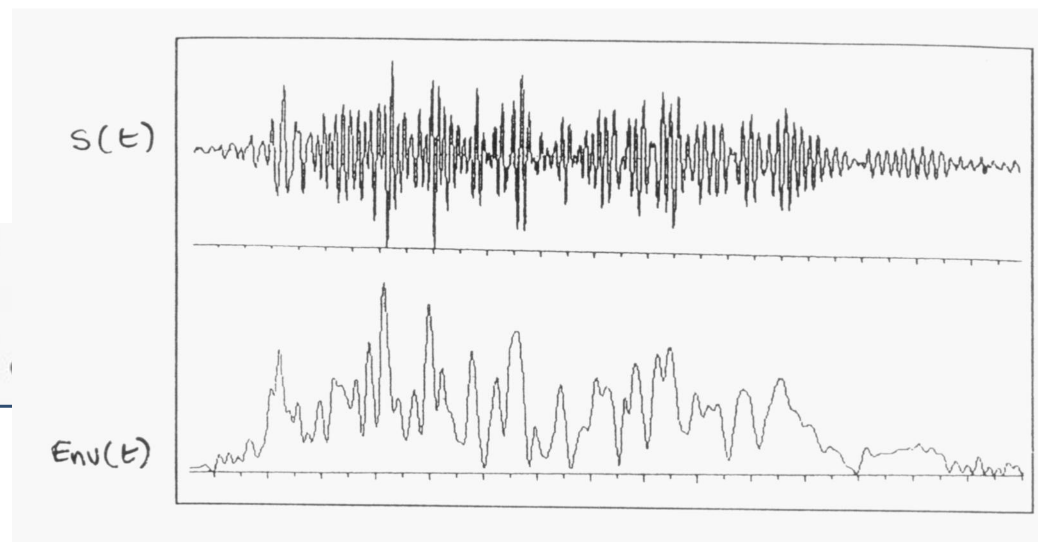
Statistical Parameters



- Direct parameters
  - Min, max, Slope, duration
- Statistical parameters
  - Mean, Variance, Moment (M3 Skewness, M4 Kurtosis)
- Power and RMS
- Envelop

$$\mathrm{Env}(t) = \sqrt{|s(t)|^2 + |\tilde{s}(t)|^2}$$

avec $\tilde{s}(t) = \frac{1}{\pi t} * s(t)$



Frequency parameters

Spectral moment formula

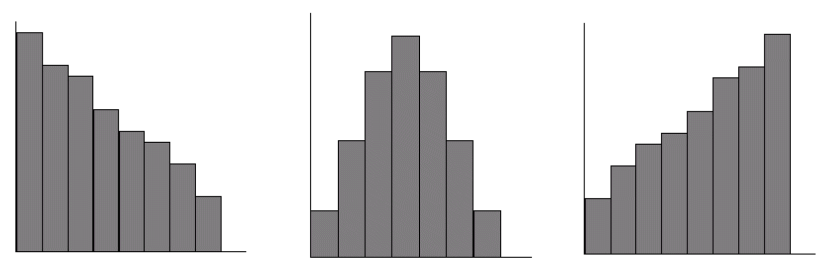
$$M_r = 2\int_0^\infty f^r S_x(f)\,df$$

$S_x(f)$: Periodogram

1- Power of the signal : M0
2- Mean frequency: MPF=M1/M0
3- Dissymmetry coefficient: CD (Skewness)

$$CD = \frac{M_3^{\,*}}{\sqrt{M_2^{\,3*}}}$$

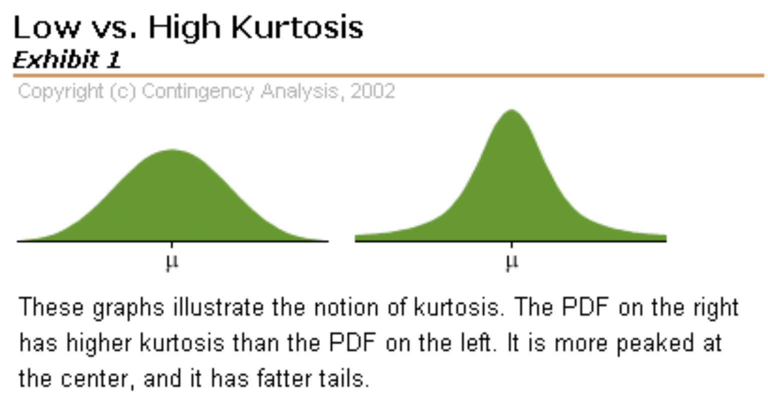
$$Mr^* = 2\int_0^\infty (f - MPF)^r S_x(f)\,df$$



Frequency parameters

4- Kurtosis (pate coefficients)

$$CA = \frac{M_4^{\ *}}{M_2^{\ 2*}}$$



5- Median frequency Fmed:

compose the surface under S(f) into 2 equals area

$$\int_0^{Fmed} S_x(f)df = \int_{Fmed}^{F\max} S_x(f)df$$

6- Peak of frequency

7-relative energy by frequency band

$$W_n = \frac{\int_{f_{n-1}}^{f_n} S_x(f)df}{M_0}$$

$$fn = \frac{n}{N} f_{\max} \qquad \text{et} \quad 1 < \mathrm{n} < \mathrm{N}$$

Frequency parameters

8- Ratio H/L (High/Low):

$$\frac{H}{L}=\frac{\int_{f_H1}^{f_{H2}} S_x(f)df}{\int_{f_L1}^{f_{L2}} S_x(f)df}$$

$$H=[H1,H2] \quad L=[L1,L2]$$

9- Percentiles or fractiles fk:

$$\int_{f_{p-1}}^{f_p} S_x(f)df = k\int_0^{F\max} S_x(f)df$$

$$0<k\leq 1$$

10 – Spectral Entropy

$$H=-\int_0^{f_{\max}} S_x(f)\ln[S_x(f)]df$$

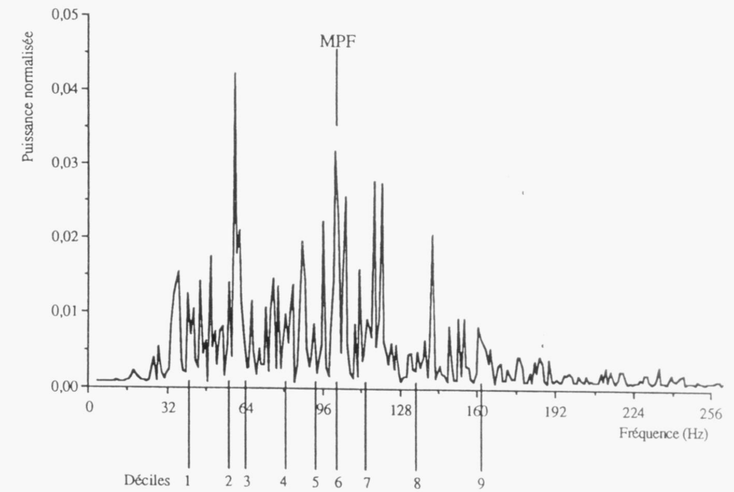
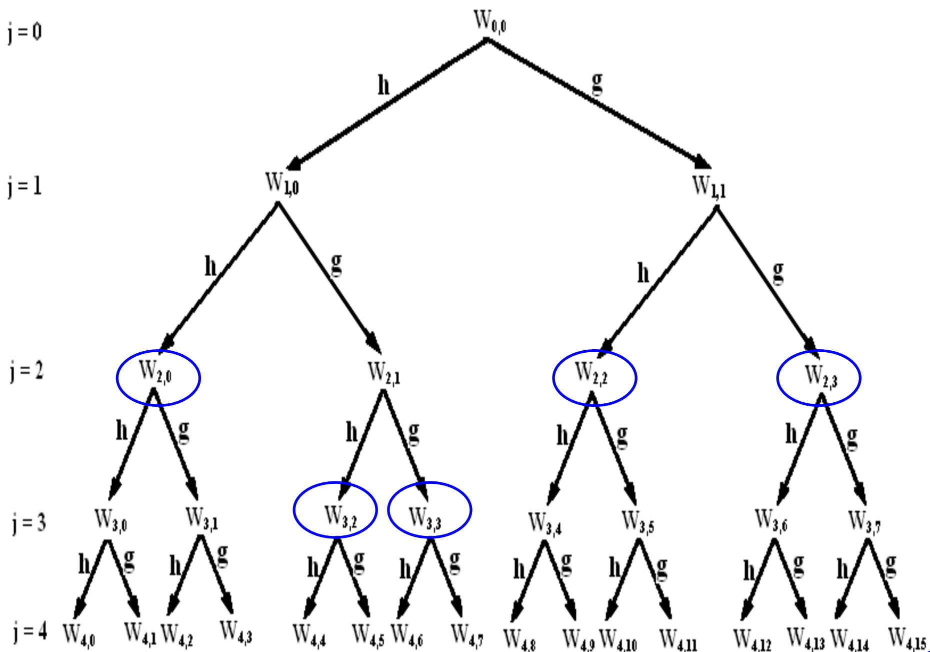


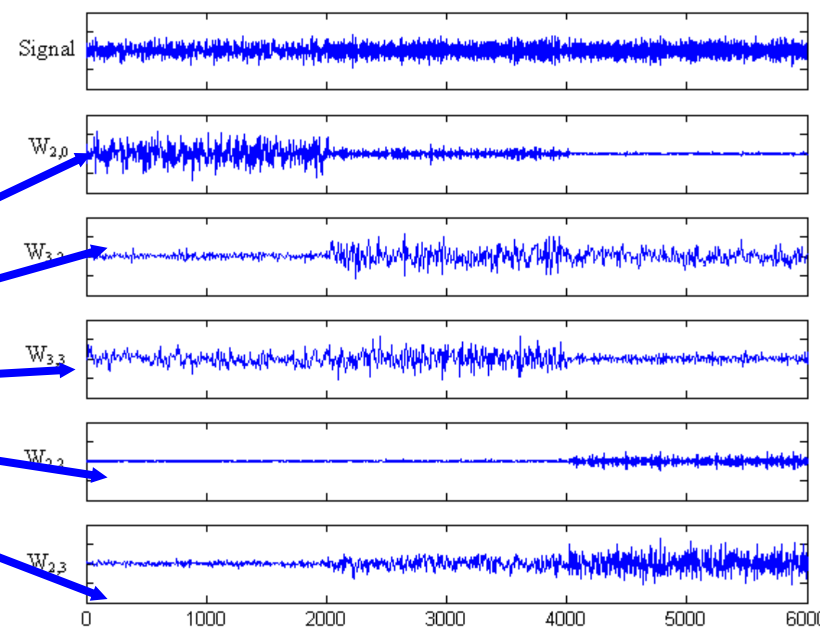
Figure 3.4: Paramétrage du spectre EMG.

Les déciles permettent de témoigner de la forme fine du spectre. La MPF représente sa moyenne statistique. L'entropie est significative de la variance spectrale et ne peut être représentée sur cette figure.

Parameters related to wavelet



Variances
of segments



Non linear features

- Time reversibility
- Sample Entropy
- Lyapunov Exponent
- Delay vector variance
- Detrended Fluctuation Analysis

Summary

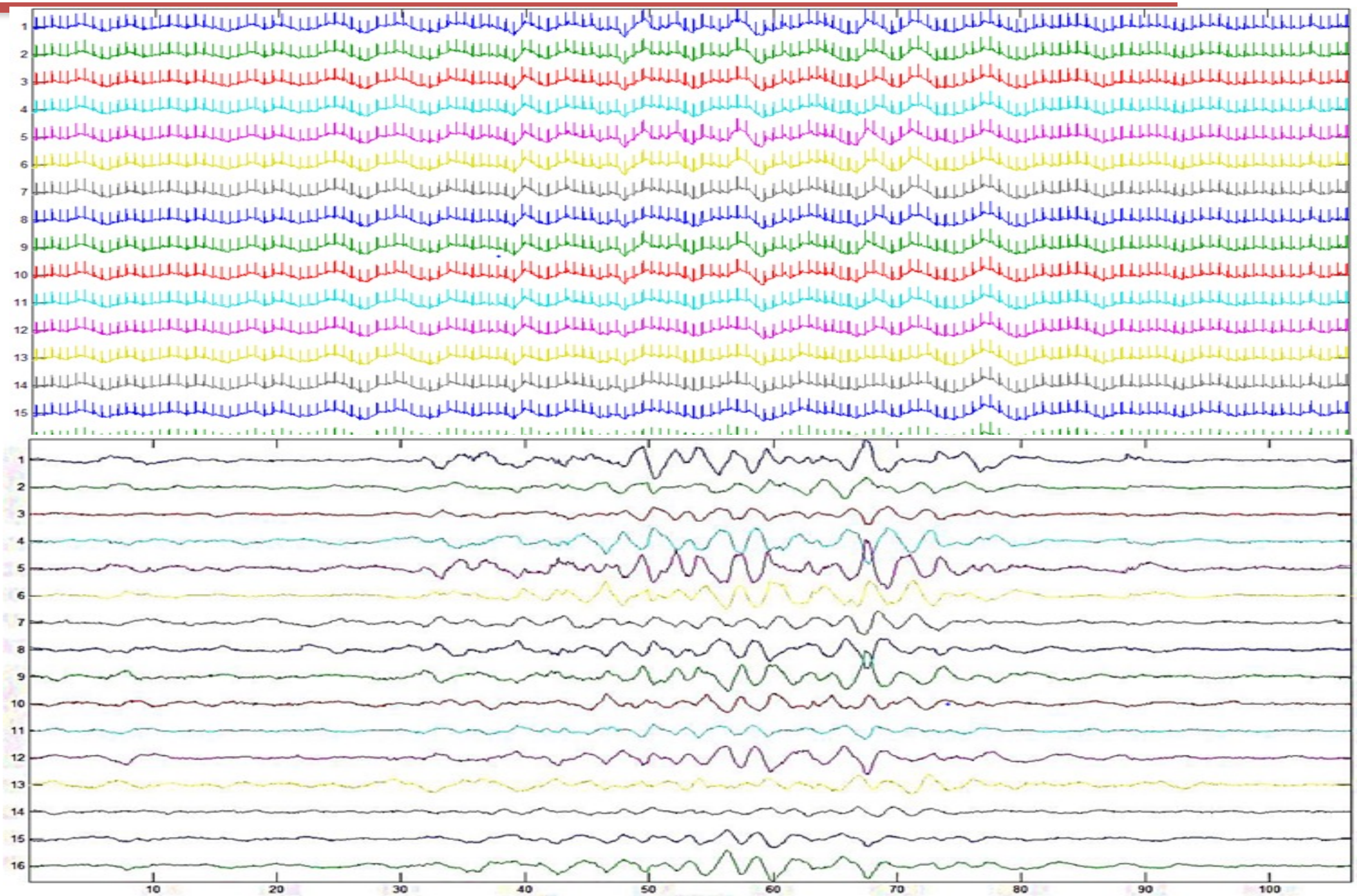
- For any mono dimensional signal x(t)
  - Statistical related parameters (6)
  - Frequency related parameters (30)
  - Wavelet related (7-10)
  - Non linear parameters (10)

Any segment x(t) has at least 55 parameters

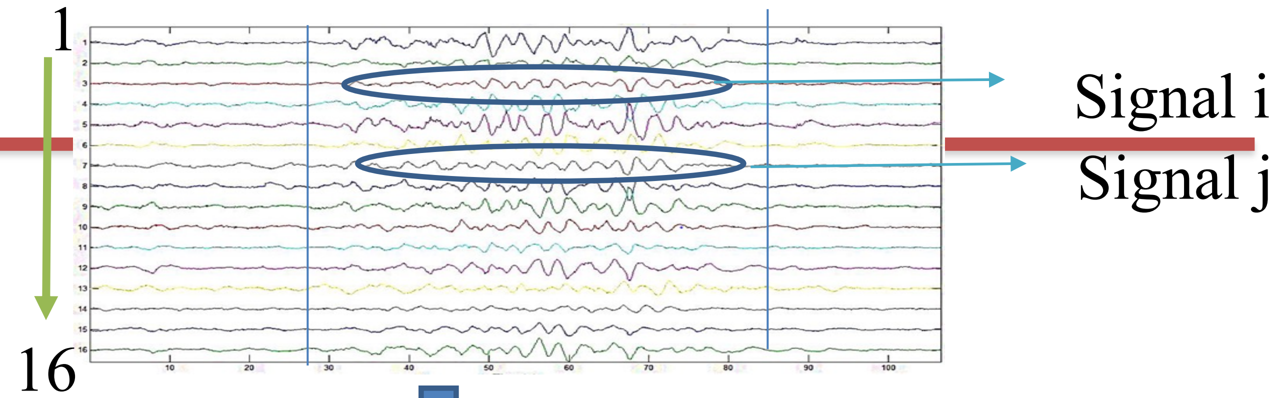
More?

Graph from multichannel signals

Features from multichannel signals

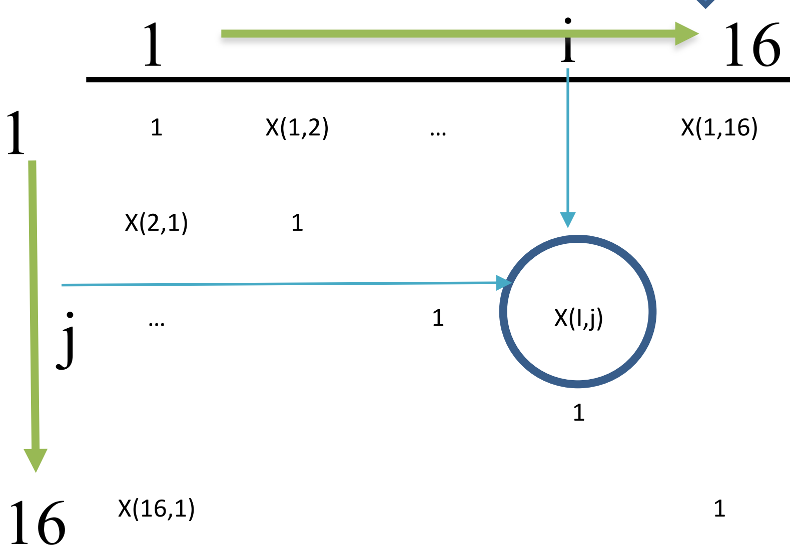


Graph estimation from multichannels

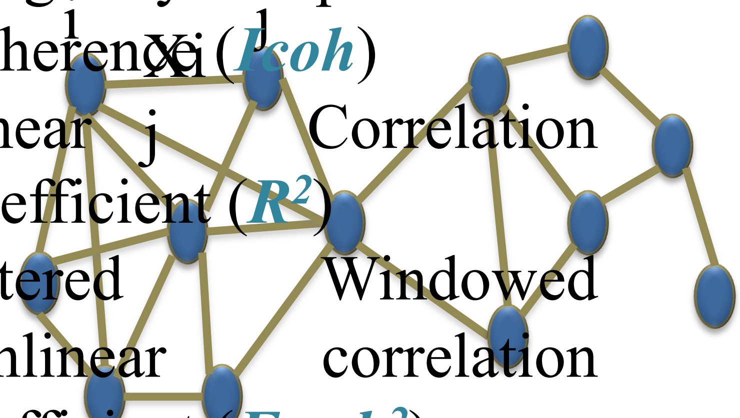


Connectivity Methods:

- Imaginary part of Coherence (*Icoh*)
- Linear Correlation Coefficient (*R^2*)
- Filtered Windowed nonlinear correlation coefficient (*Fw_h²*)

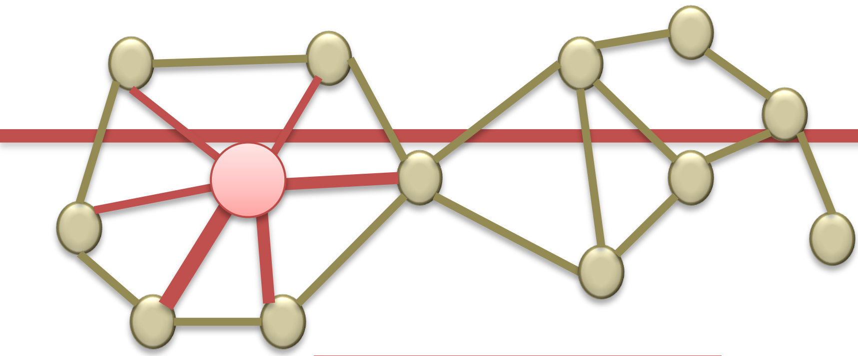


Connectivity Matrix

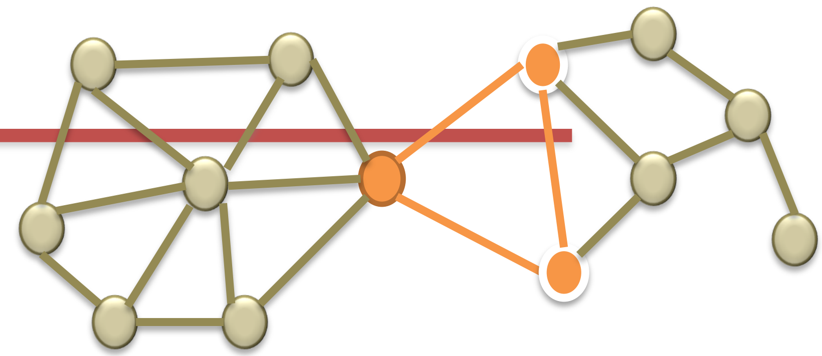


Graph

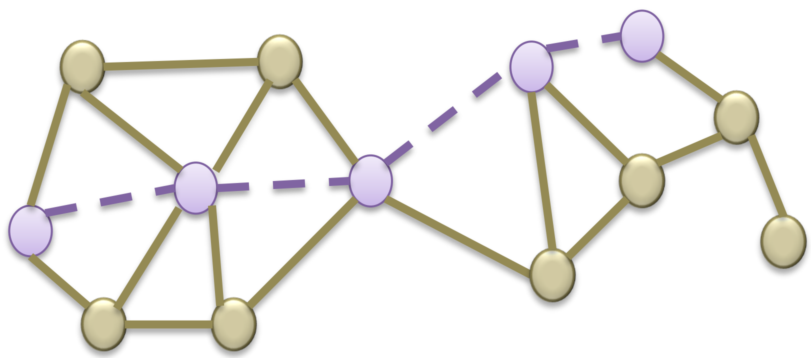
Graph Theory – Features extraction fron multichannels



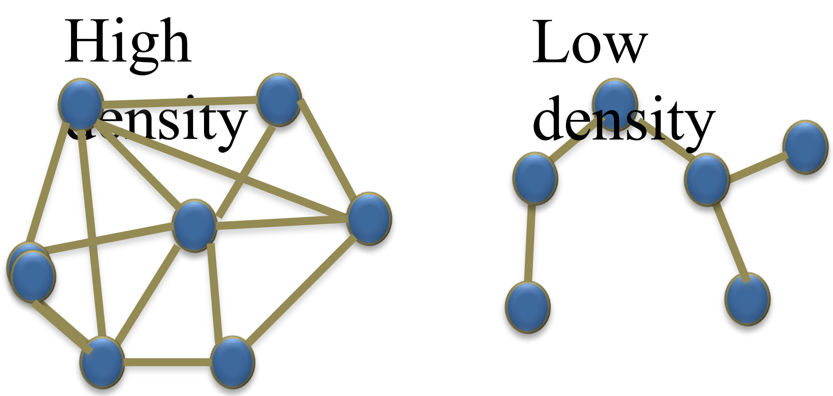
(a) Strength



(b) Clustering Coefficient



(c) Shortest Path Length -> Efficiency



(d) Density

Summary

- For any mono dimensional signal x(t)
  - Statistical related parameters (6)
  - Frequency related parameters (30)
  - Wavelet related (7-10)
  - Non linear parameters (10)
- For mulltichannel signal
  - Graph parameters

After detection and feature extraction→classification

Classification

Supervised

Unsupervised

SIGNAL

$X_1, X_2.....X_d$

Features

Classe C_i

Pattern Recognition: Design Cycle

How to design a PR system?

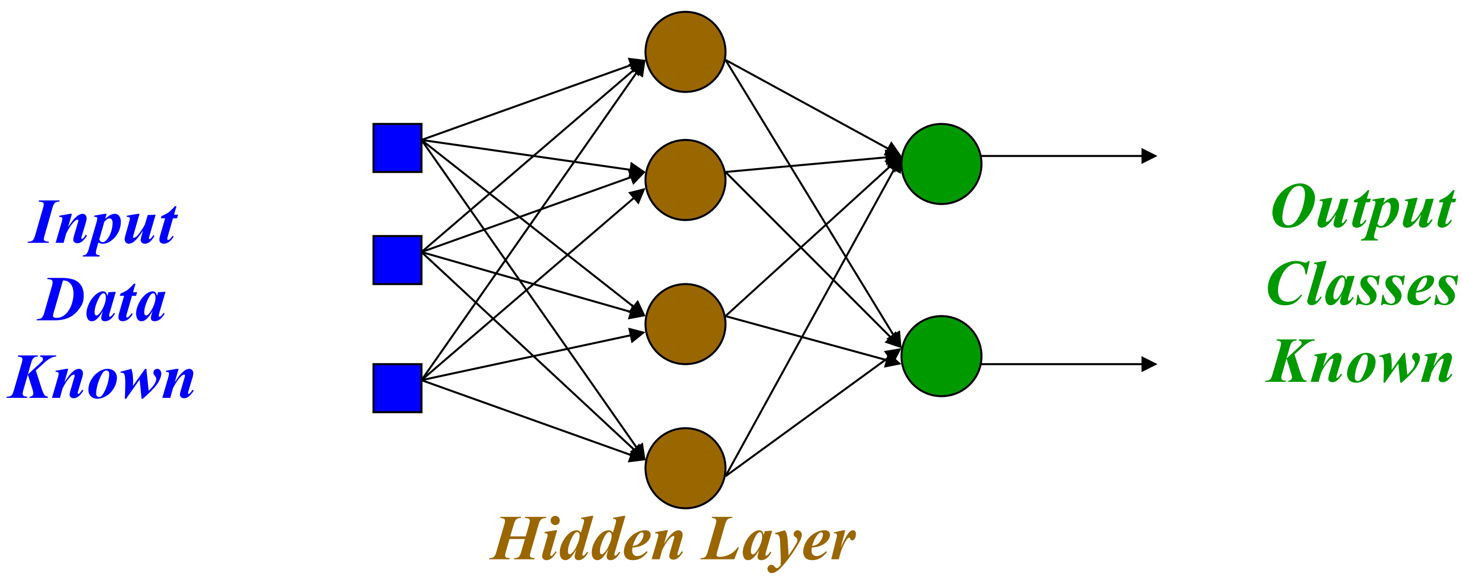
- Collect data and classify by hand

- Preprocess by segmenting fish from background

- Extract possibly discriminating features
  - length, lightness,width,number of fins,etc.
- Classifier design
  - Choose model
  - Train classifier on part of collected data (training data)
- Test classifier on the rest of collected data (test data) i.e. the data not used for training
  - Should classify new data (new fish images) well

Classification: Supervised

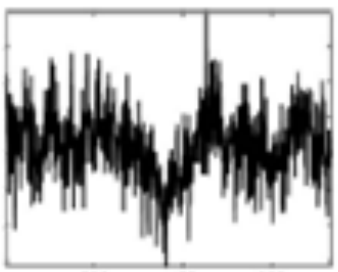
- Supervised learning
  - A teacher provides a category label or cost for each pattern in the training set:
    - <u>Input and output are known</u>



Classification: an example

“Classify the detected events from the signal

Event===random signal or image



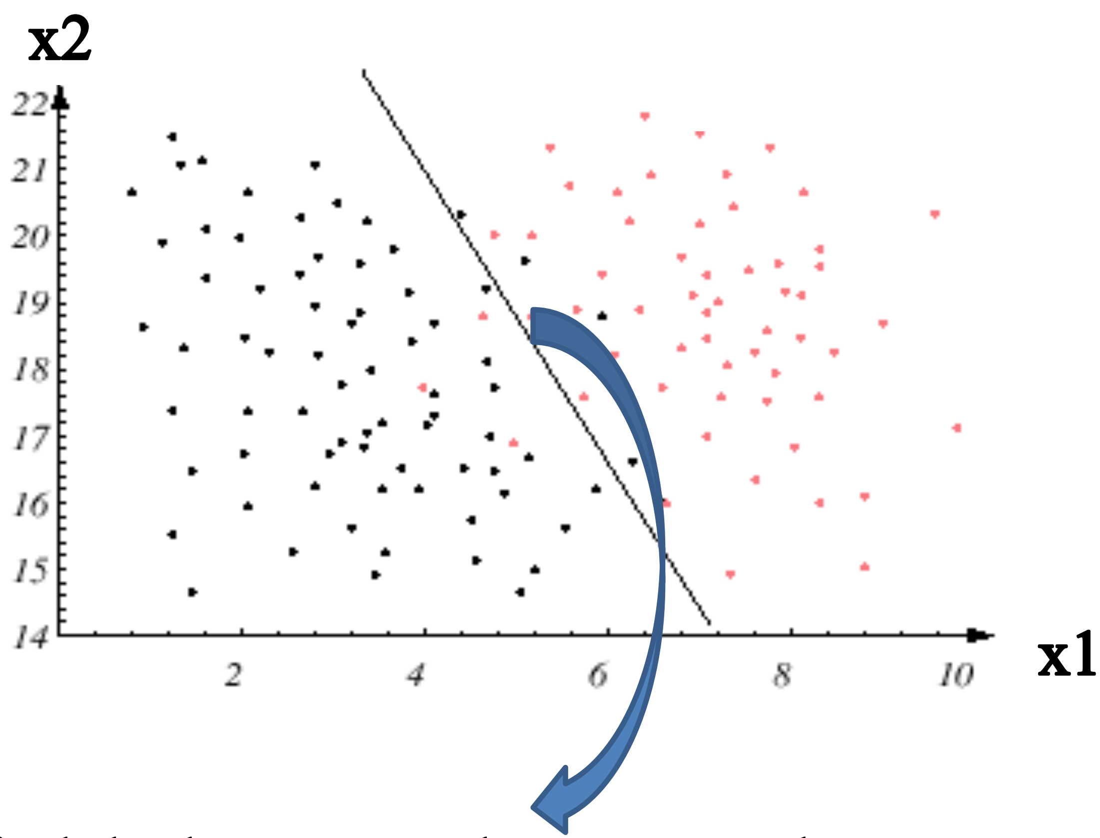
Parameter 1: x1

Event

Parameter 2: x2

Classification: an example

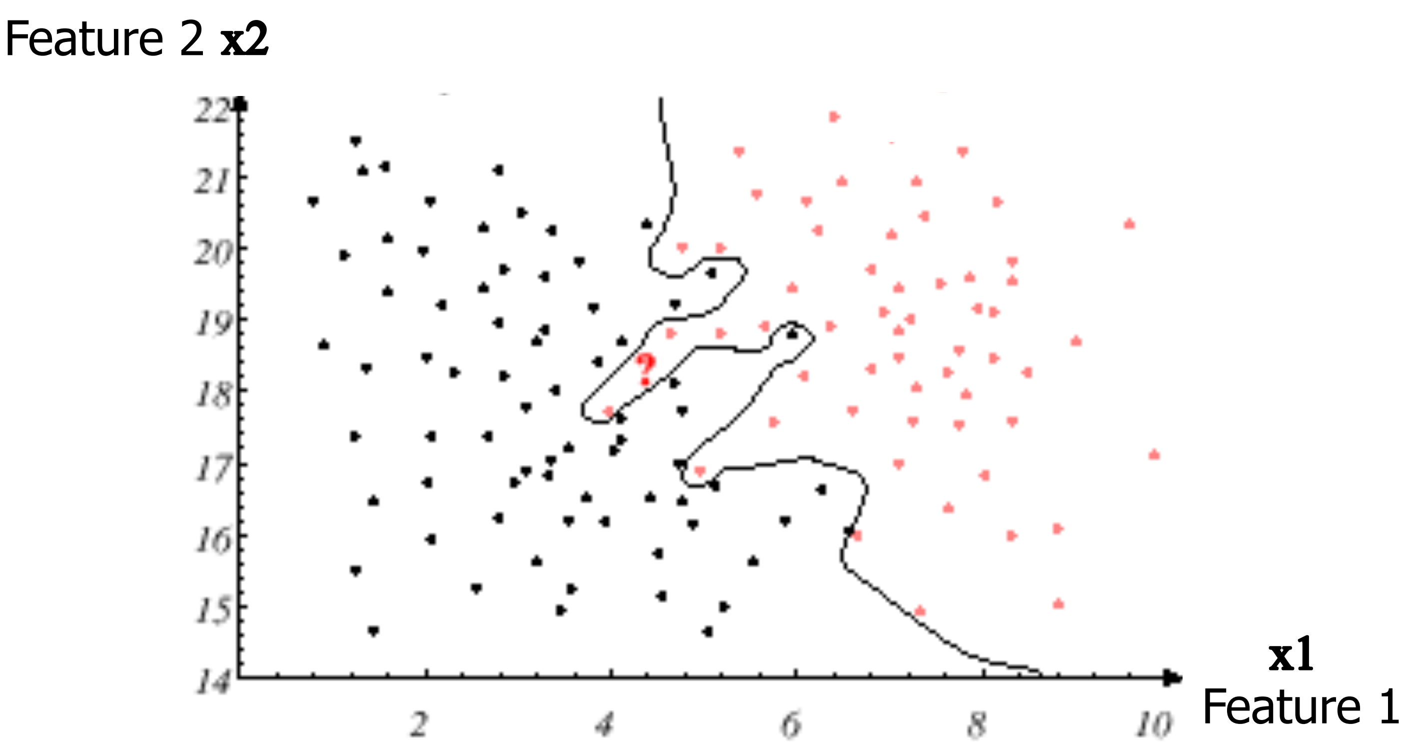
event → $x = [x_1, x_2]$



Learning: find the best curve that separate between two classes

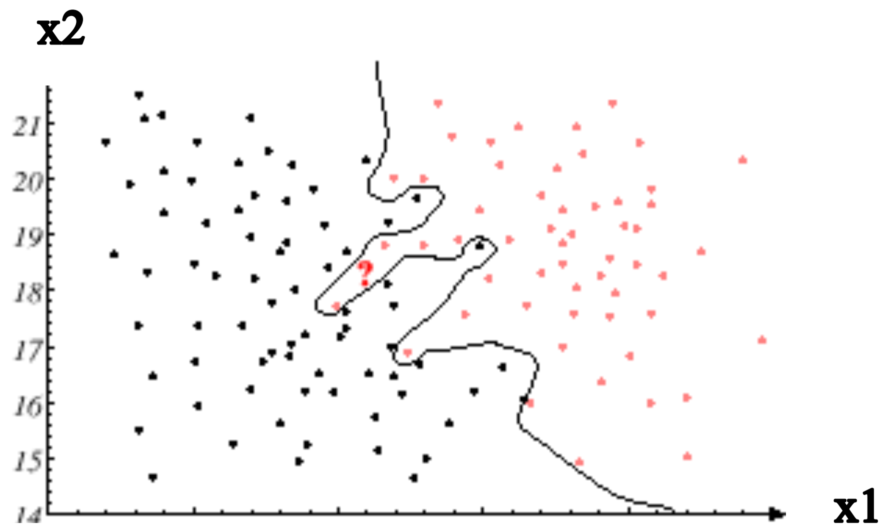
Classification

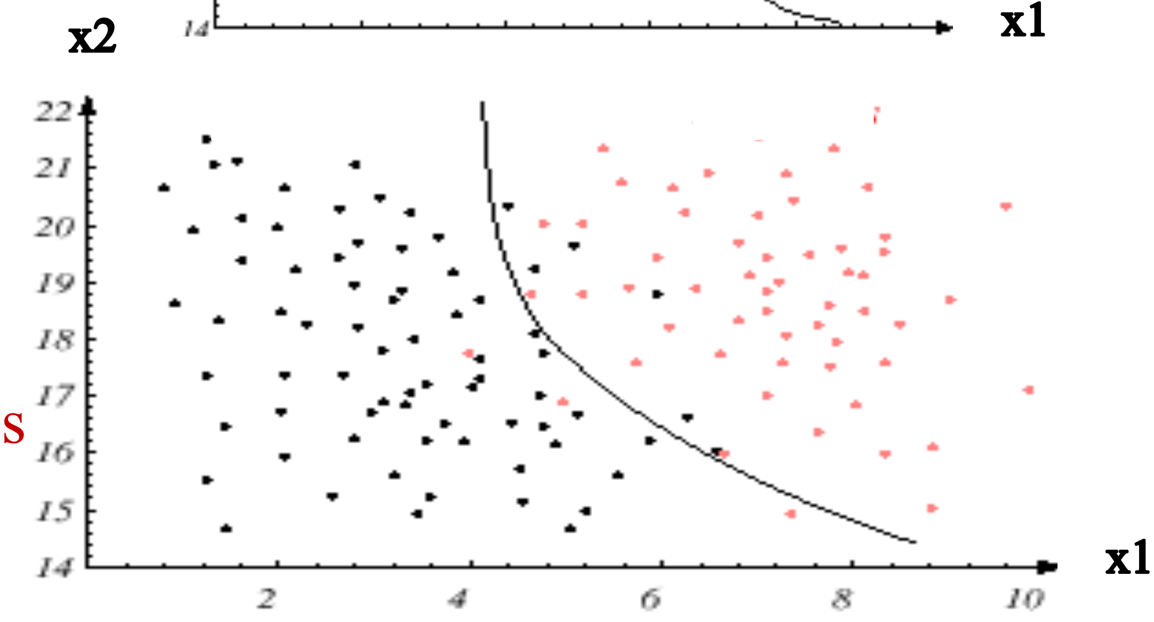
- Best decision boundary: provides an optimal performance



Boundaries

- Aim of designing a classifier is to correctly classify novel input





Complexity depends
on the number of samples

Methods for classification: Supervised classification

- Statistical methods: likelihood ratio
- Bayesian networks methods

Need Statistical equations

- Neural networks bases methods : FF, SVM, RBF, SOM….
- Parzen methods (Non parametric)
- K nearest neighbors

Classification: Parzen Window

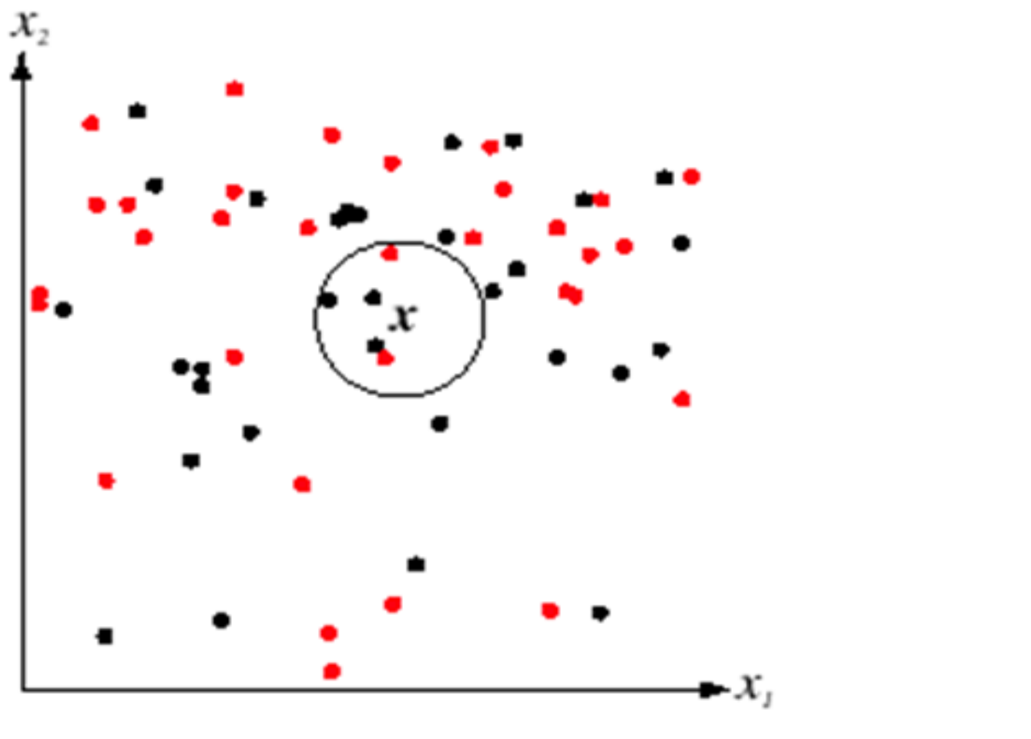
- Estimation of the probability density function

Soit:

$$\boxed{p_n(x) = \frac{k_n/n}{V_n}}$$

NUMBER OF SAMPLE IN THE VOLUME

VOLUME



Classification: Parzen windows

- Probability density function must be estimated using

$$p_n(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{V_n}\phi\left(\frac{x - x_i}{h_n}\right)$$

$$k_n = \sum_{i=1}^{i=n}\varphi\left(\frac{x - x_i}{h_n}\right)$$

φ is a Gaussian function to take the effect of all points

- Likelihood ration may be used

$$\Lambda(x) = \frac{p(x/w2)}{p(x/w1)} \underset{w2}{\overset{w1}{\lessgtr}} \frac{p(w1)}{p(w2)}$$

Plan

- Event detection in non stationary signals
  - Windowing, Sequential, Dynamic
- Modeling and Parameters extraction
  - Wavelet, Linear and Non linear parameters
- Classification
  - Supervised and unsupervised
- Parameters elimination
  - Filter methods, Wrapper methods, LASSO, BPSO
- Applications

Feature selection principle

- From 16 channels:

16*30 = 480 features can be extracted

4 features from graph

Aim of feature selection:

Choose the relevant features

Parameters selection

The two popular methods of Parameters selection are:

Filter methods

assess the relevance of features by looking only at the intrinsic properties of the data.

Wrapper methods

explores the space of features subsets to optimize the induction algorithm that uses the subset for classification.

Parameters selection: Filter method

F-SCORE:

- ✓ Is a novel filter model which calculates the discriminative ability of each feature

$$F(i) \equiv \frac{(\overline{x}_i^{(+)} - \overline{x}_i)^2 + (\overline{x}_i^{(-)} - \overline{x}_i)^2}{\frac{1}{n_+-1}\sum_{k=1}^{n+}(x_{k,i}^{(+)} - \overline{x}_i^{(+)})^2 + \frac{1}{n_1-1}\sum_{k=1}^{n-}(x_{k,i}^{(-)} - \overline{x}_i^{(-)})^2}$$

where $\overline{x}_i^{(+)}, \overline{x}_i^{(-)}$ and $\overline{x}_i$ are the averages of the ith feature of the positive, negative and whole datasets; n_+ and n_- are the number of positive and negative instances, respectively; and $x_{k,i}^{(+)}$ and $x_{k,i}^{(-)}$ are the ith feature of the kth positive instance and the ith feature of the kth negative instance.

- ✓ F-score is a simple and effective algorithm including variable ranking as a principal selection mechanism. The larger the F-score is, the more likely the feature is more significant

Features selection: F-score

- F-score example

	Class1						class2				
Feature 1	3	3.1	2.9	2.8	3.3	3.5	6	6.3	5.6	5.2	5
Feature 2	5	5.1	5.3	4.9	4.8	4.8	5	5.5	5.2	4.8	5
Feature 3	10.1	10	9.5	9	9.7	9.1	3	3.4	5	4	2

- Sort the F-scoring:
  - Feature 3 Best
  - Feature 1
  - Feature 2

Features selection: Filter method, Relief

- Feature Weight based algorithm
- "Near hit" instance of X = instance of the same class closest to X.
- "Near miss" instance of X = instance of different class closest to X.

1. Start with an empty set of parameters $Y=\Phi$
2. Initialize all weights W_j to 0
3. For i=1:m (m=NoSample)
   a. Pick at random an instance R_i from the set of observations.
   b. Find its Near Hit (H) and its Near Miss(M)
   c. For j=1:N (N= number of parameters)
      $W_j = W_j - diff(R_j,H_j)^2/m + diff(R_j,M_j)^2/m$
4. For j=1:N
   a. If $W_j >$ Threshold
      Add the parameter x_j to Y
5. Return Y

✓threshold = mean value of the different weights

Relief-F takes k neighbors instead of one single neighbor.

Disadvantage: Relief and Relief-F don't allow to remove redundant parameters.

Parameters selection: Wrapper method

A-Deterministic:

✓Sequential Forward Selection (SFS)

✓Sequential backward Selection (SBS)

✓Plus-l minus-r selection(LRS)

✓Bidirectional search (BDS)

✓Sequential Forward Floating sequential (SFFS)

✓Sequential Floating Backward Sequential (SFBS)

B-Randomized:

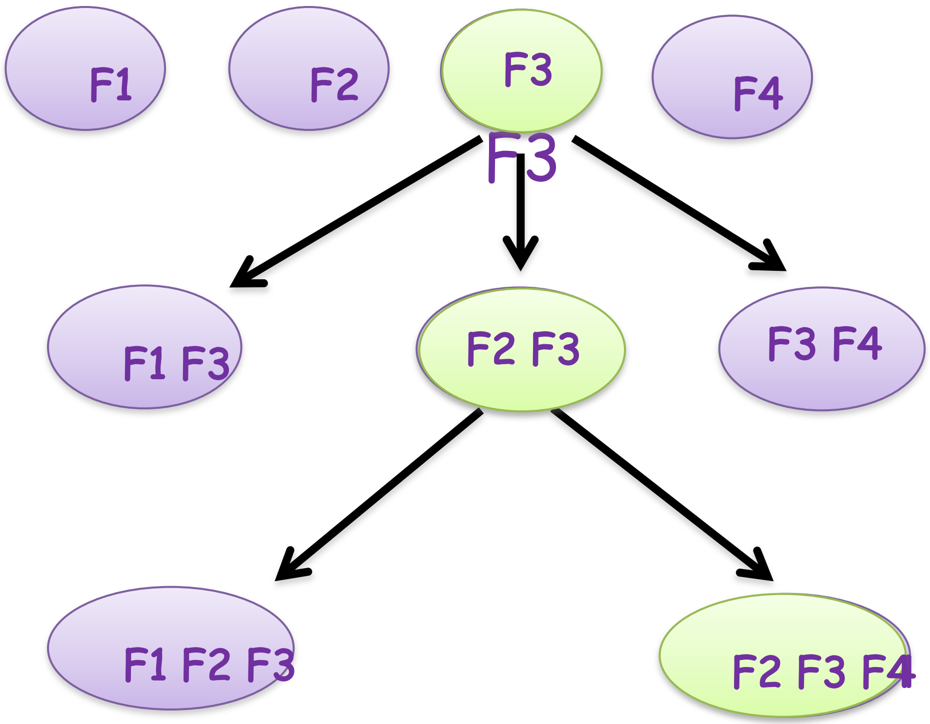
✓Particle swarm optimization (PSO)

✓Genetic Algorithm (GA)

✓LASSO

Parameters selection: Wrapper method

Sequential Forward Selection (SFS):

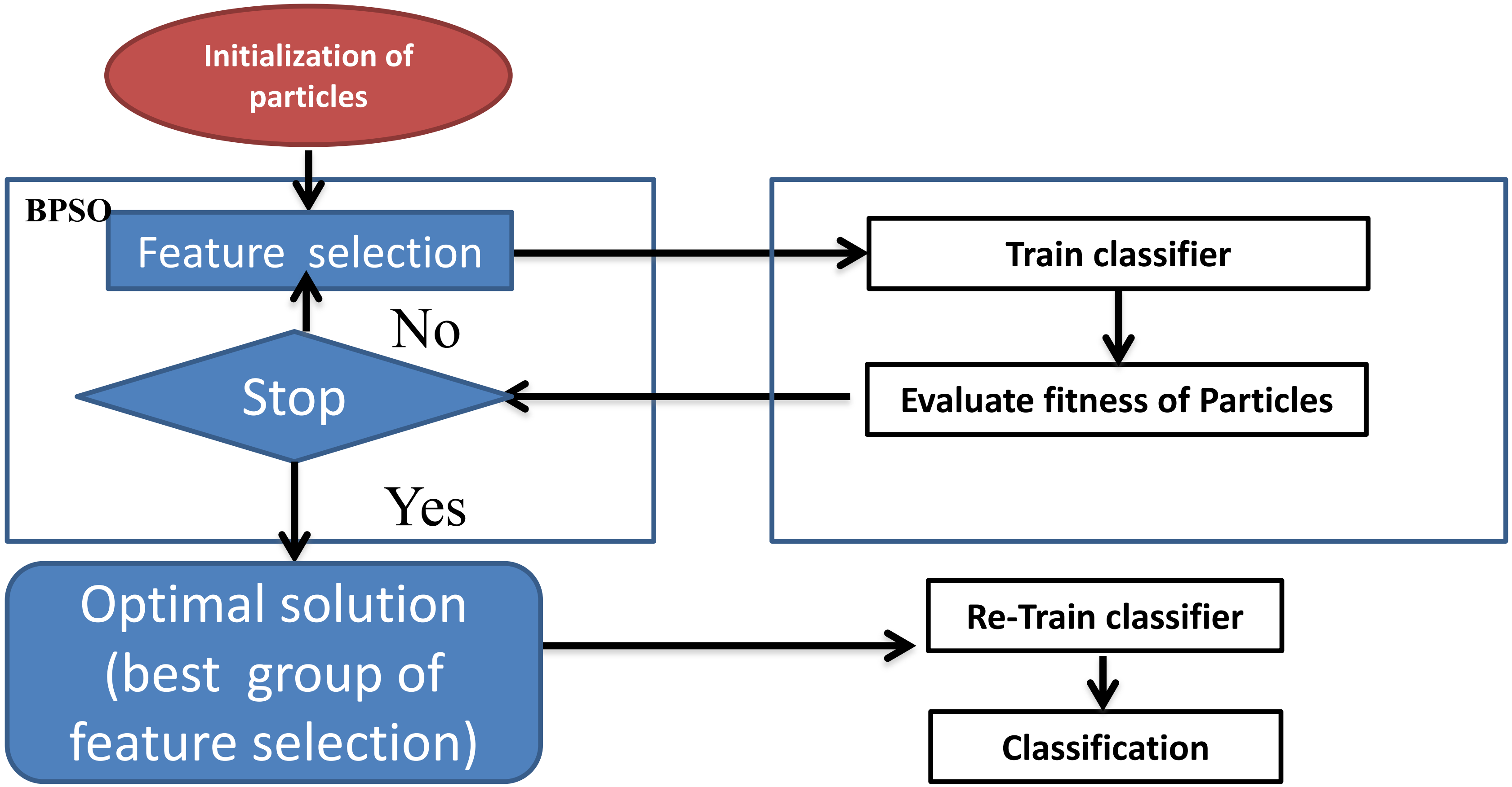


Sequential Forward Selection (SFS):
The value of the criterion, the objective function (J), is calculated for each feature by use of a classifier.

Finally we chose the combination of features that gives the best J

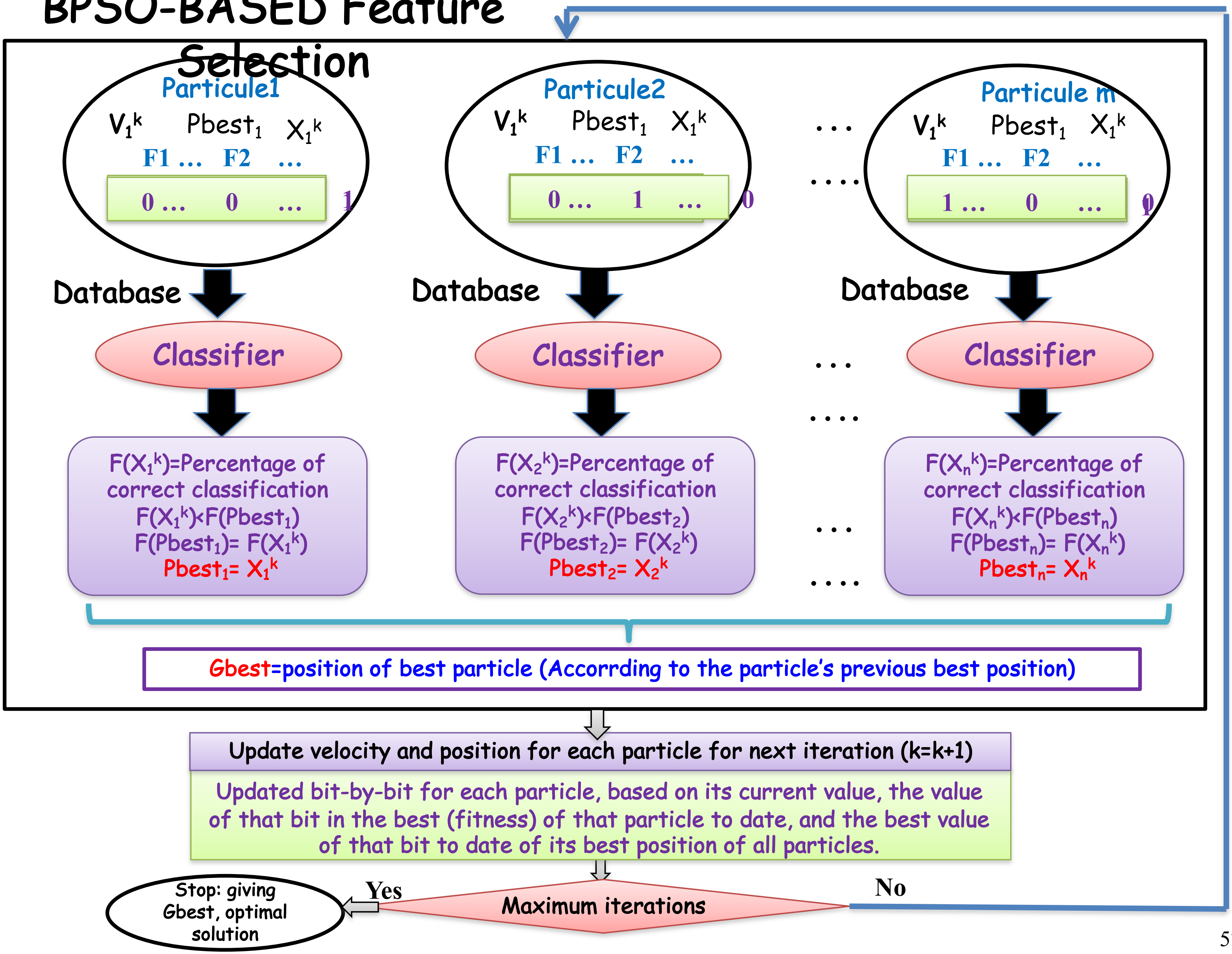
Parameters selection: Wrapper method
Binary Particle swarm Optimisation

BPSO-Based Feature Selection :

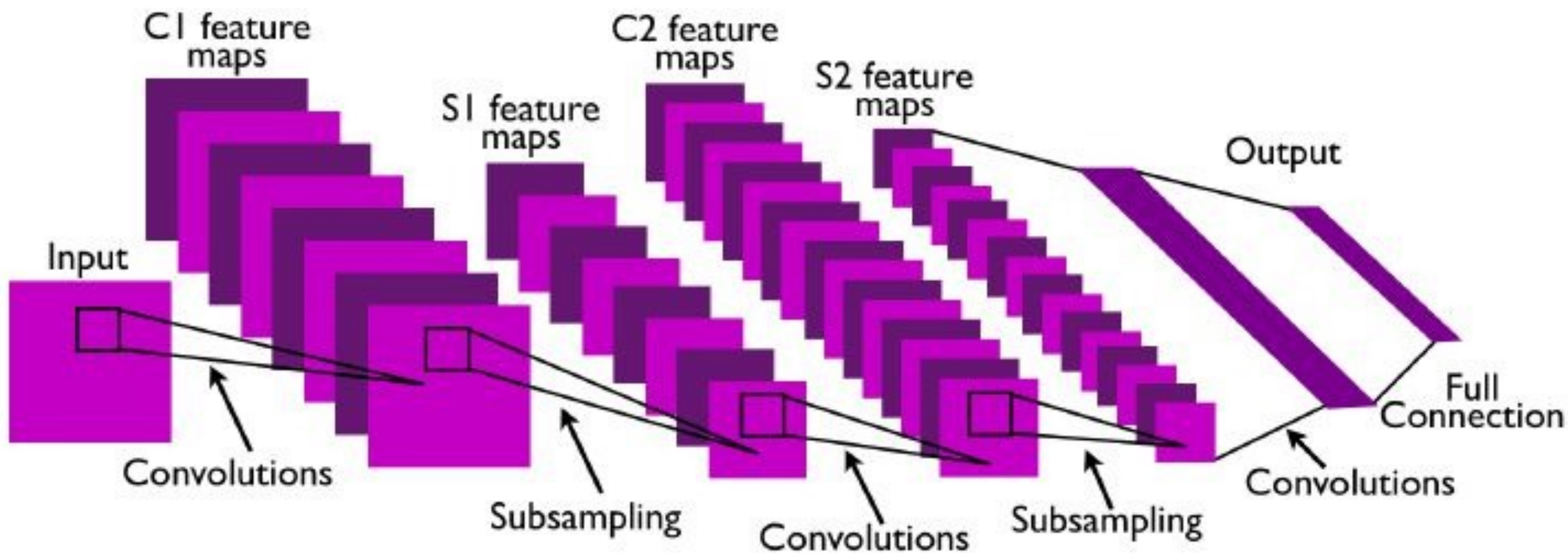


Ranaee et al.2010

BPSO-BASED Feature Selection



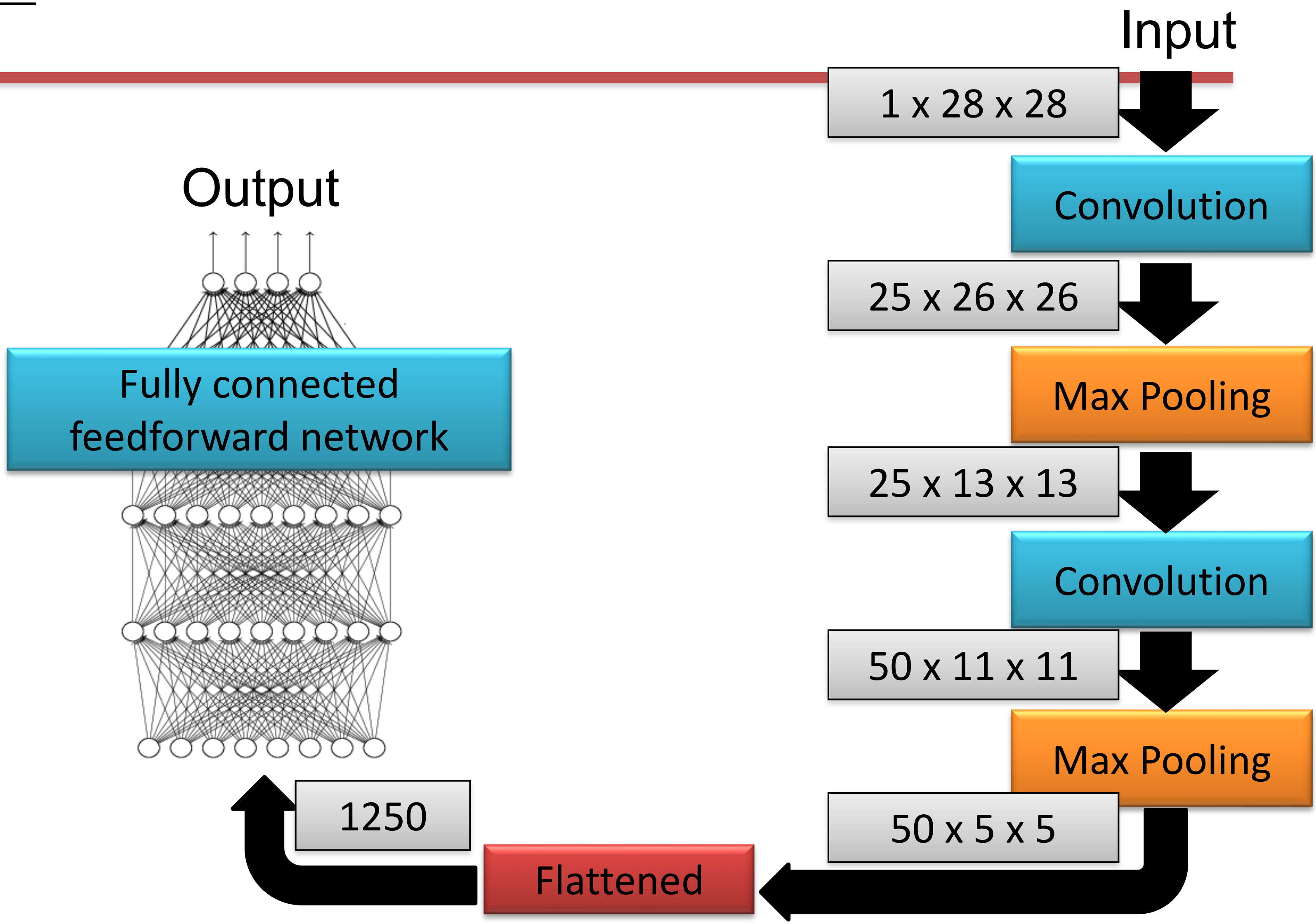
Convolutional Neural Networks



- Convolutional layers, followed by nonlinear activation and subsampling
- Output of hidden layers (feature maps) = features learnt by the CNN
- Before classification, fully connected layers (as in "standard" NN)

Convolutional NN

Transform the signal to an image using Scalogram or Spectrogram



Plan

- Event detection in non stationary signals
  - Windowing, Sequential, Dynamic
- Modeling and Parameters extraction
  - Wavelet, Linear and Non linear parameters
- Classification
  - Supervised and unsupervised
- Parameters elimination
  - Filter methods, Wrapper methods, LASSO, BPSO
- Applications

APPLICATIONS

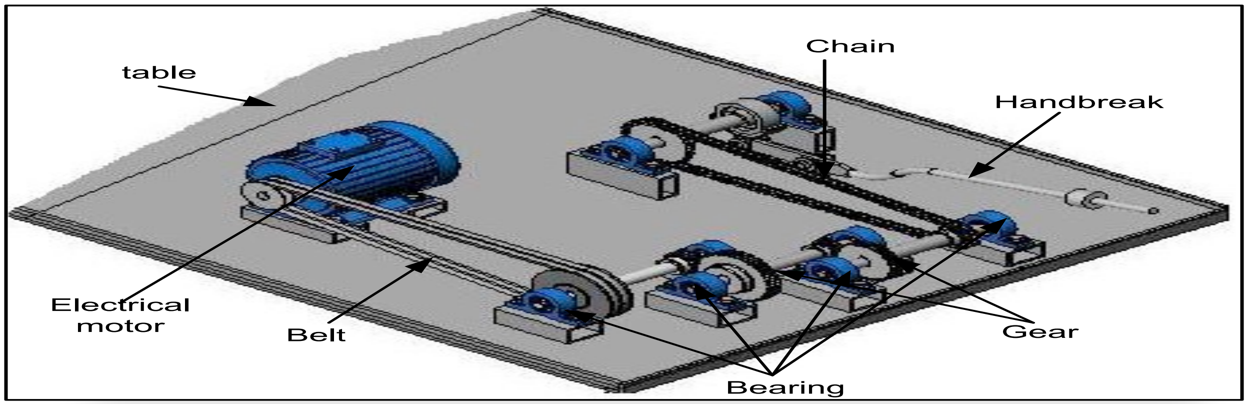
Application1: Fault detection in industrial machine

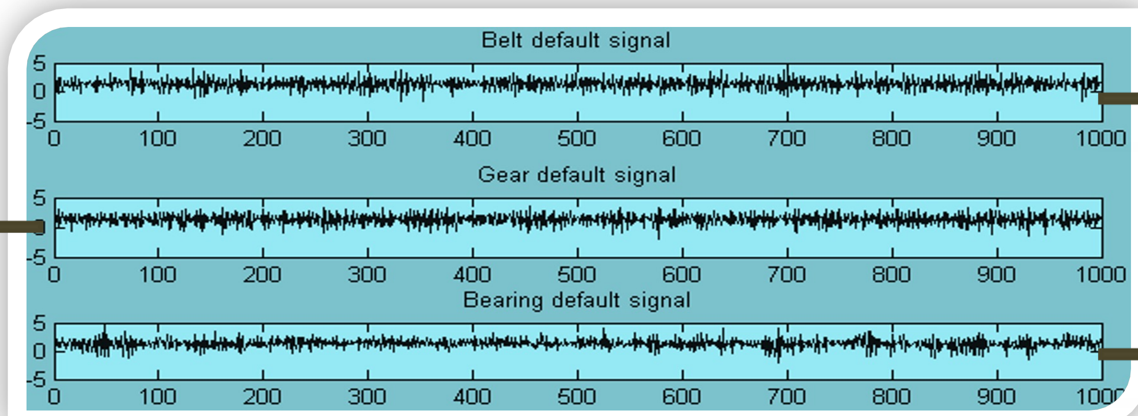
Acceleration signal

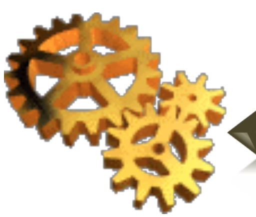
Collaboration: Le Havre- Troyes-France

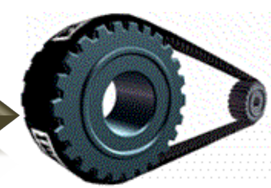
Application 1: Fault Detection

- Mechanical system is exposed to three types of faults: Gear, Belt, bear

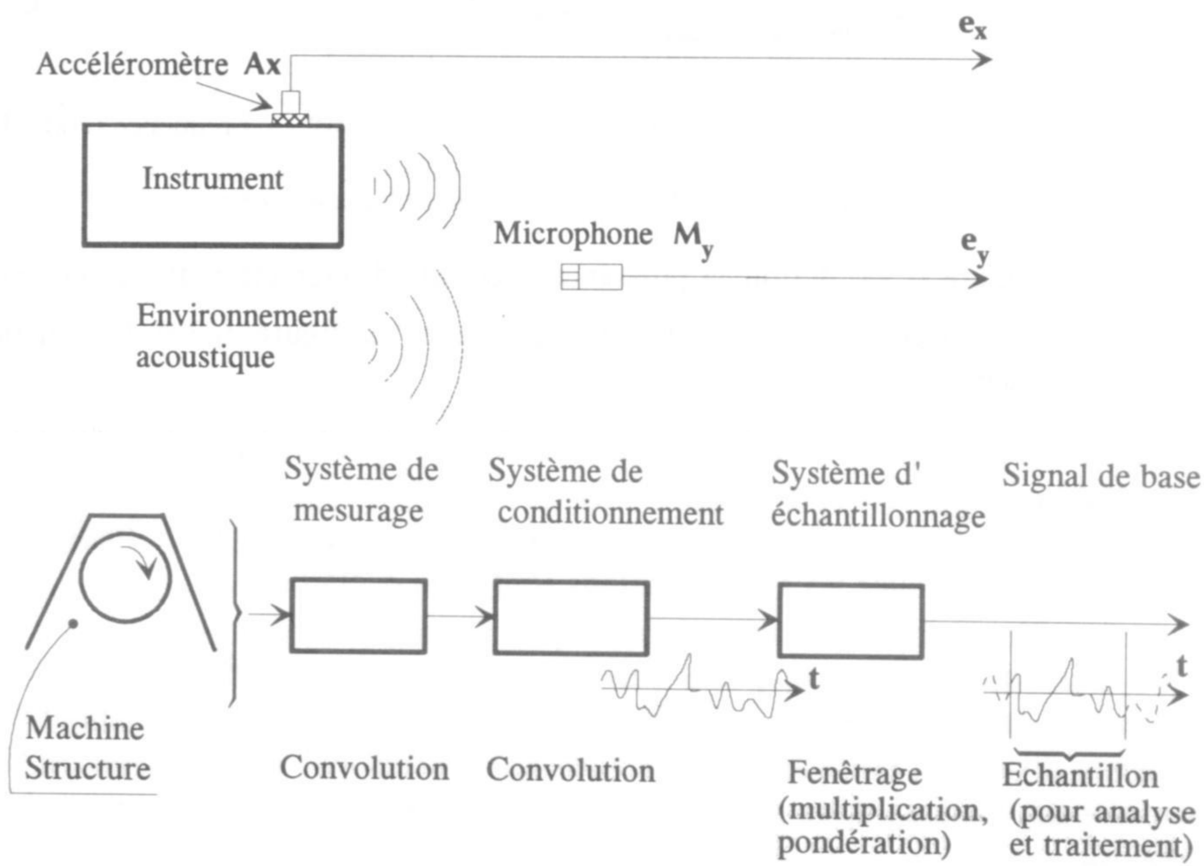






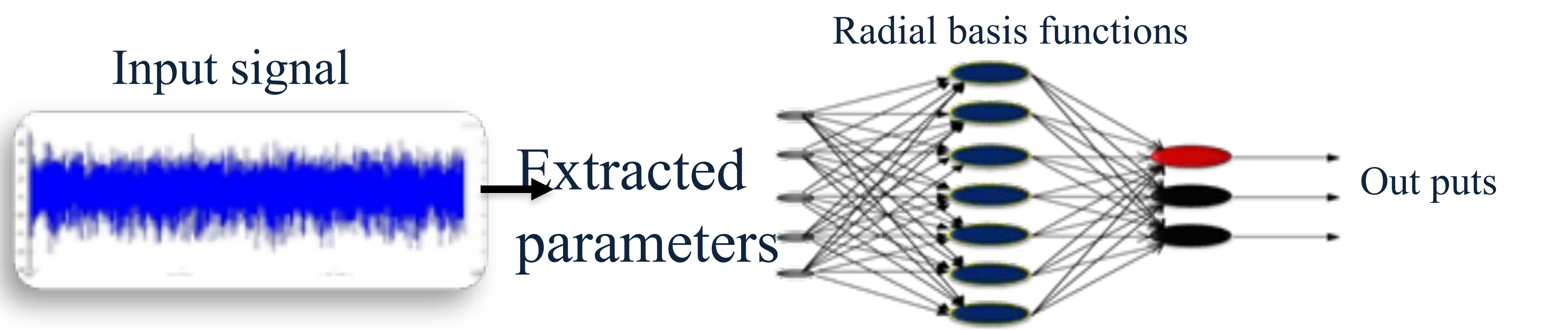


Fault Detection: Origin of signals

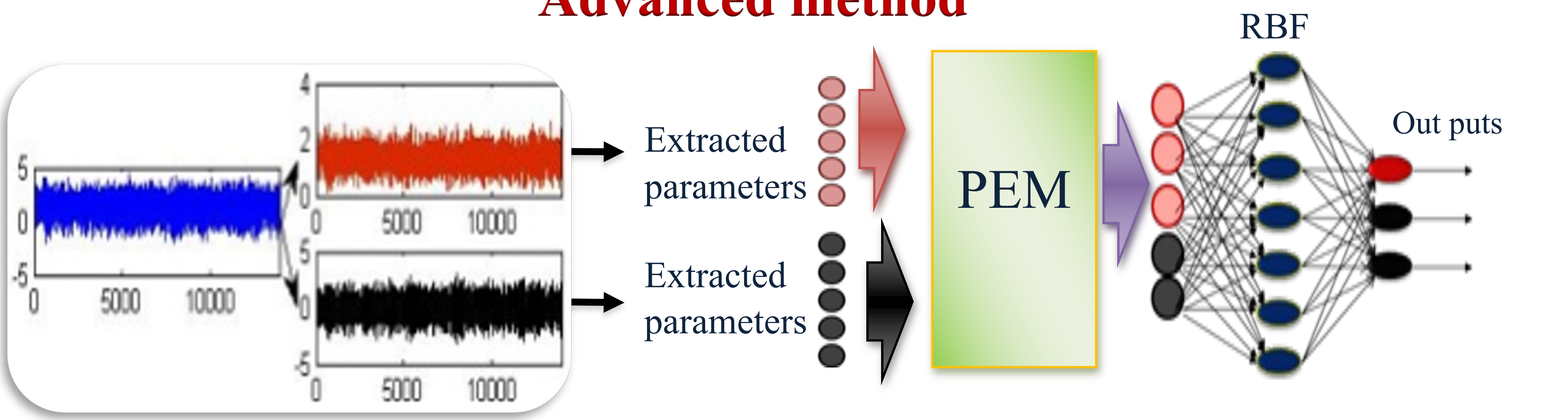


Application 1: Methods for fault detection and diagnosis

Usual method



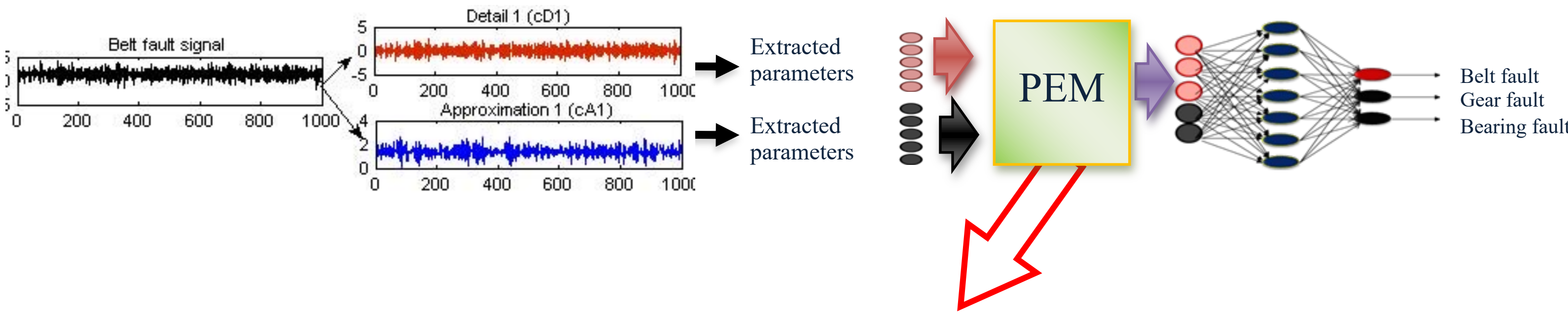
Advanced method



Application 1: Methods for fault detection and diagnosis

- Advanced method applied on mechanical system
  - 10 signals of each type for training the network
    - 40 signals of each type for classification

Signals are decomposed using Daubechies 4 wavelet



	Level 1		Level 2		
Parameters	**App cA_1**	**Detail cD_1**	**App cA_2**	**Detail cD_1**	**Detail cD_2**
Variance	✓	✓	✓	✓	χ
Kurtosis	✓	✓	✓	✓	χ
Skewness	χ	χ	χ	χ	χ
Moment of 3^{rd} order	χ	χ	χ	χ	χ

Application 1: Results

Different types of fault signals	Level 1			Level 2		
	Well classified	Non-classified	Percentage of errors	Well classified	Non-classified	Percentage of errors
40 fault belt signals	40	0	0 %	40	0	0 %
40 fault gear signals	40	0	0 %	40	0	0 %
40 fault bearing signals	39	1	2.5 %	38	2	5 %

- Comparison between usual and advanced method

	Average total errors of mechanical system	
Usual method	16 %	
Advanced method	Level 1	Level 2
	0.8 %	1.6 %

Application 2: Detection of preterm Deliveries

Processing of Uterine EMG signals

Collaboration: UTC- Compiegne-France

Application 2: Preterm Deliveries Detection

Term birth
(Between 37 weeks and 40 weeks of pregnancy)

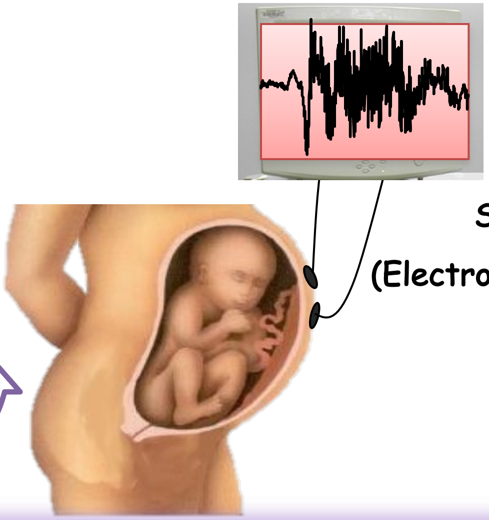
Preterm birth
(<37 week of pregnancy)

Application 2: Preterm Deliveries Detection

Uterine contractility

Ineffective contractions (Pregnancy)	Effective contractions (Labor)
Low cell excitability	*High cell excitability*
Localized	*Uterine synchronisation*

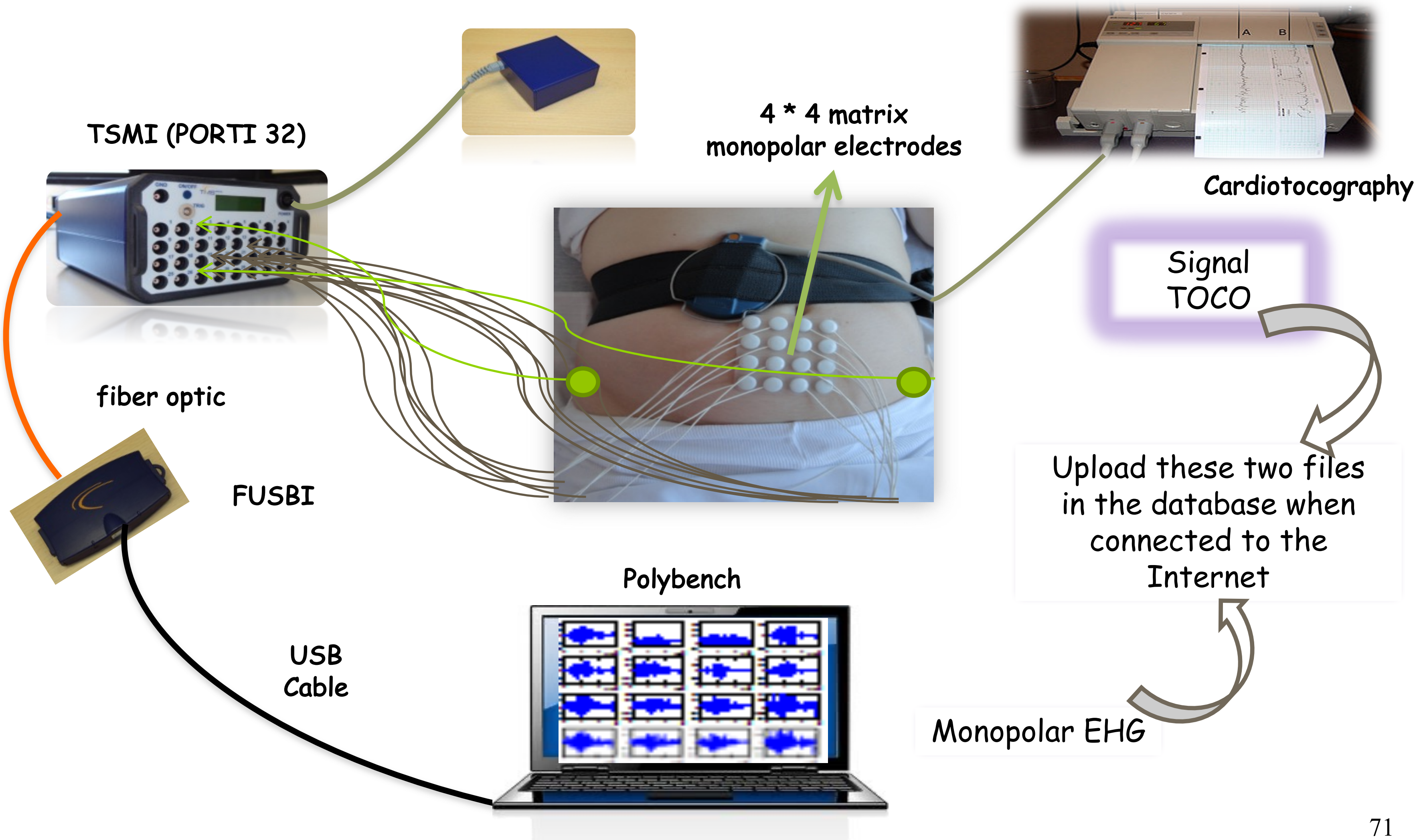
Method to monitor the effectiveness of uterine contraction



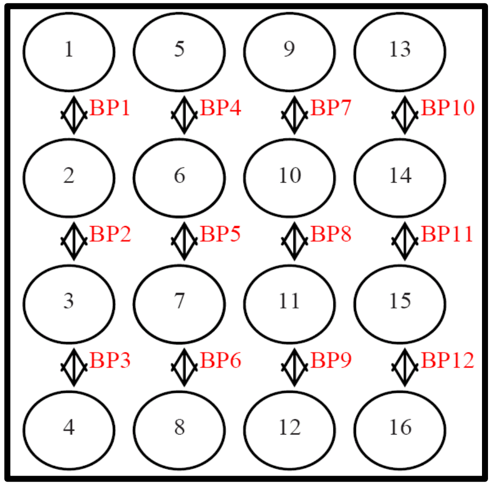
Surface EMG

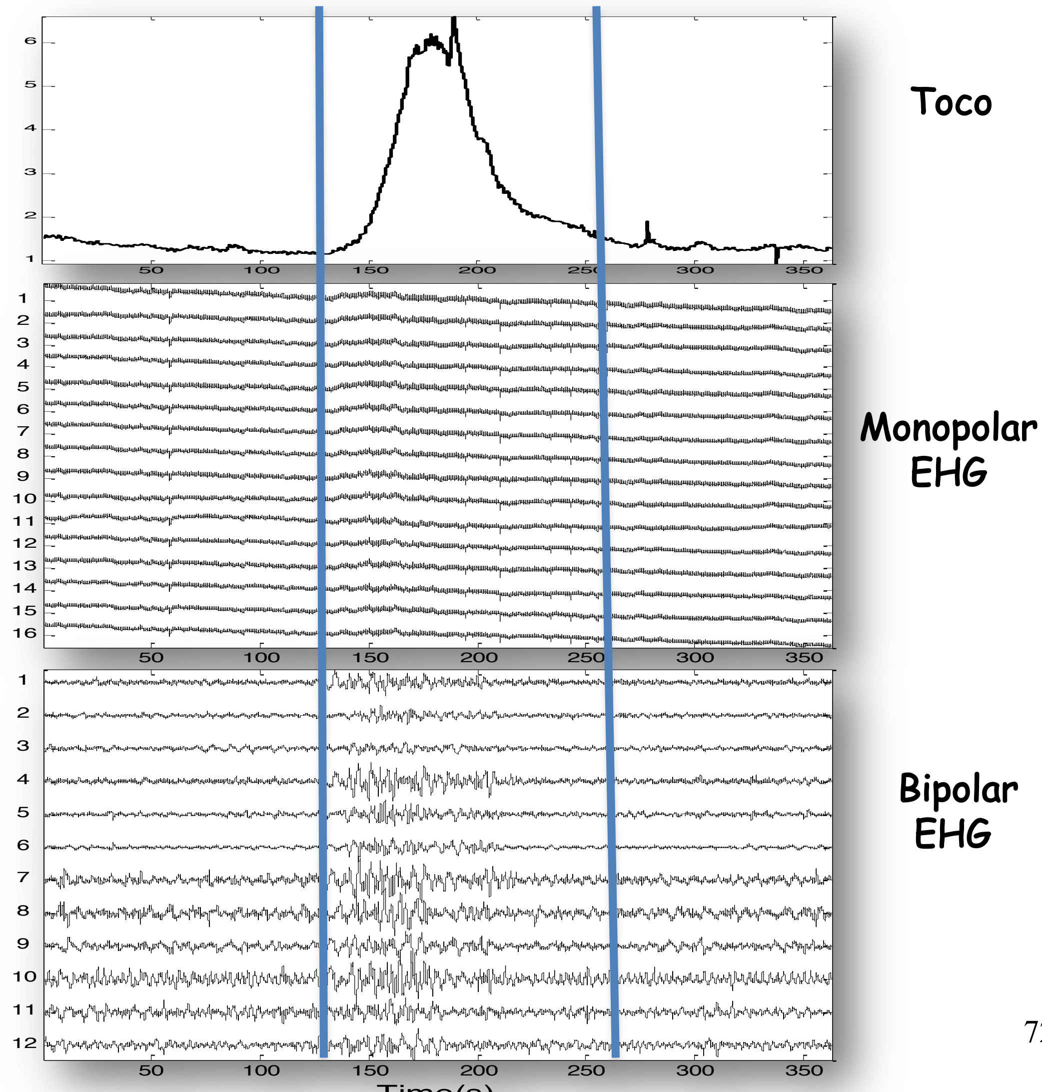
(Electrohysterogram, EHG)

Application 2: Preterm Deliveries Detection



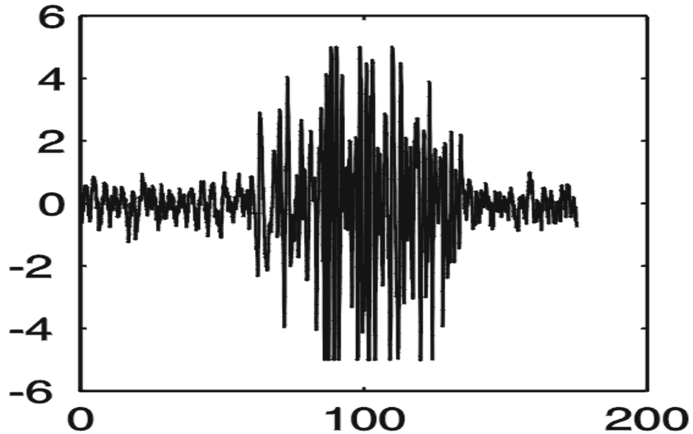
Application 2: Preterm Deliveries Detection-EMG signals



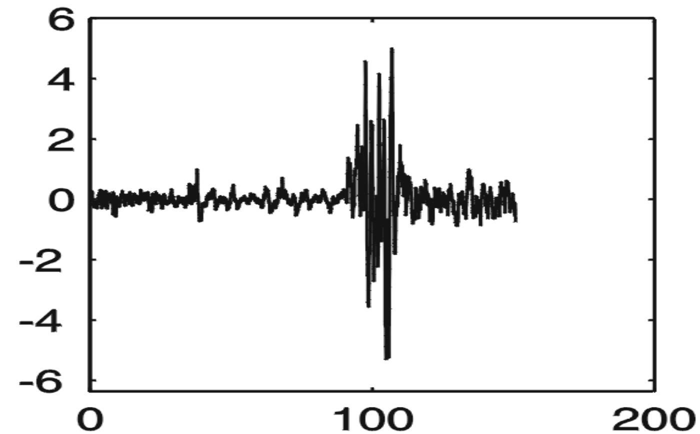


Application 2: Preterm Deliveries Detection, Content of the Uterine Signal

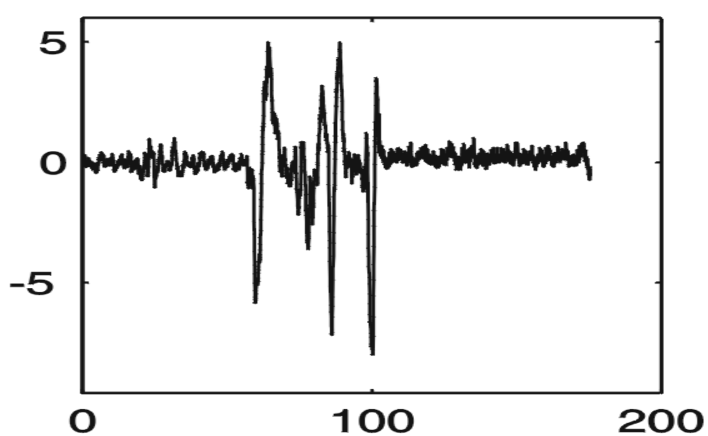
Uterine Contraction



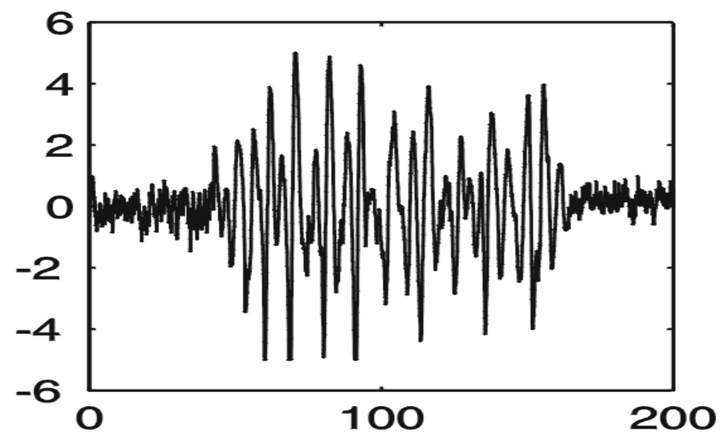
Alvarez Waves



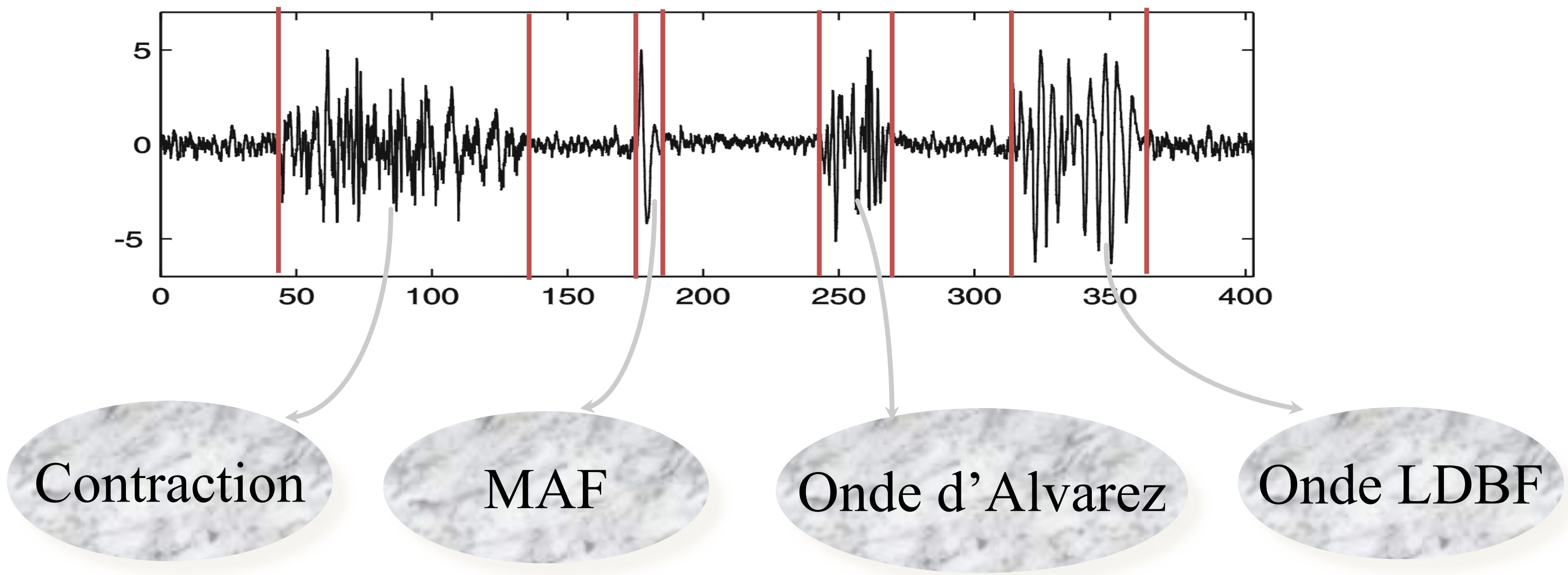
Fetal Motion



LDBF Waves

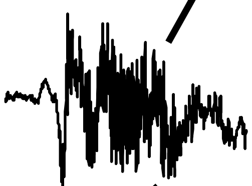


Application 2: Preterm Deliveries Detection



- Detect the events
- Extract the parameters
- Classify

Application 2:Uterine EMG: Parameters extraction



Uterine contraction

Linear Parameters

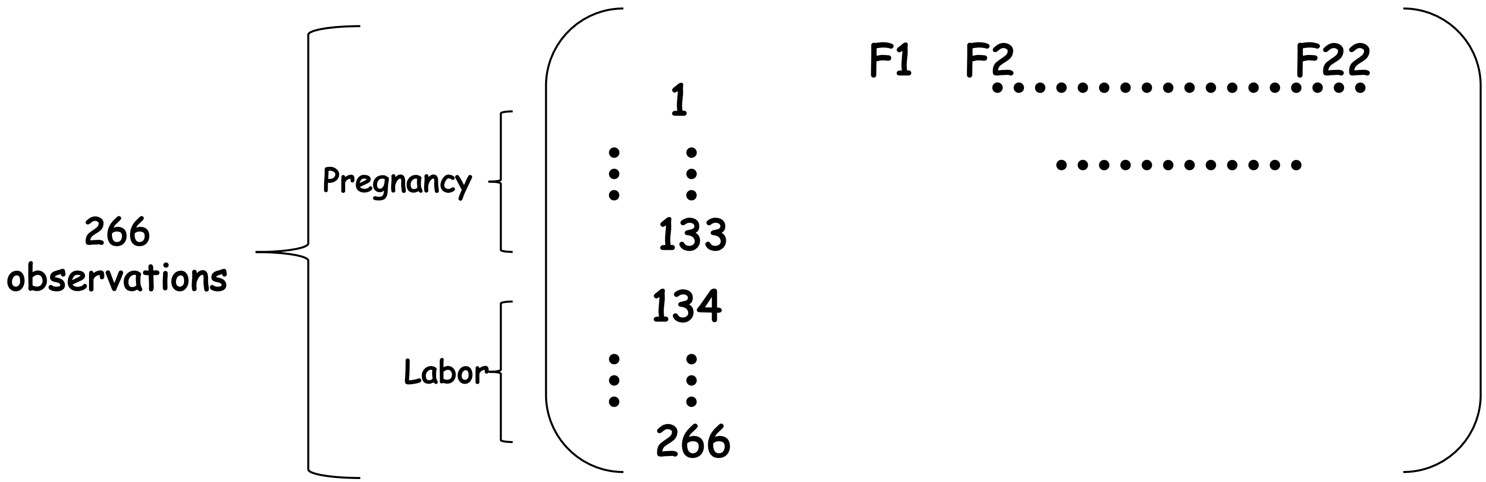
- **Frequency parameters:**
  - Deciles (D1…D9)
  - Mean frequency (MPF)
  - Peak Frequency (PF)
  - Three Kurtogram components (K1,K2 and K4)
- **Wavelet decomposition**
  - Variance on the following detail levels 3, 4, 5, 6 and 7 (W1…W5)

Nonlinear parameters

- Lyapunov exponent (LE)
- Sample Entropy (SE)
- Variance entropy (VarEn)

22 Parameters

Application 2: Parameters extraction for classification between Pregnancy and Labor



classifiers	Binary particle swarm optimization (gbest)	Fitness (%)
QDA	SE,VarEn,W1,W3,W4, D1, D3,D4, D5, D7, D9, MPF, K1, K2, K3	92.48
LDA	LE, SE, VarEn, W2, W3, W5, D1,D2, D3, D4, D6, D8, D9, MPF, K1	92.48
KNN	VarEn, W1, W2, D2, D3, D5, D7, D8	91.22

Results of BPSO On Real Data

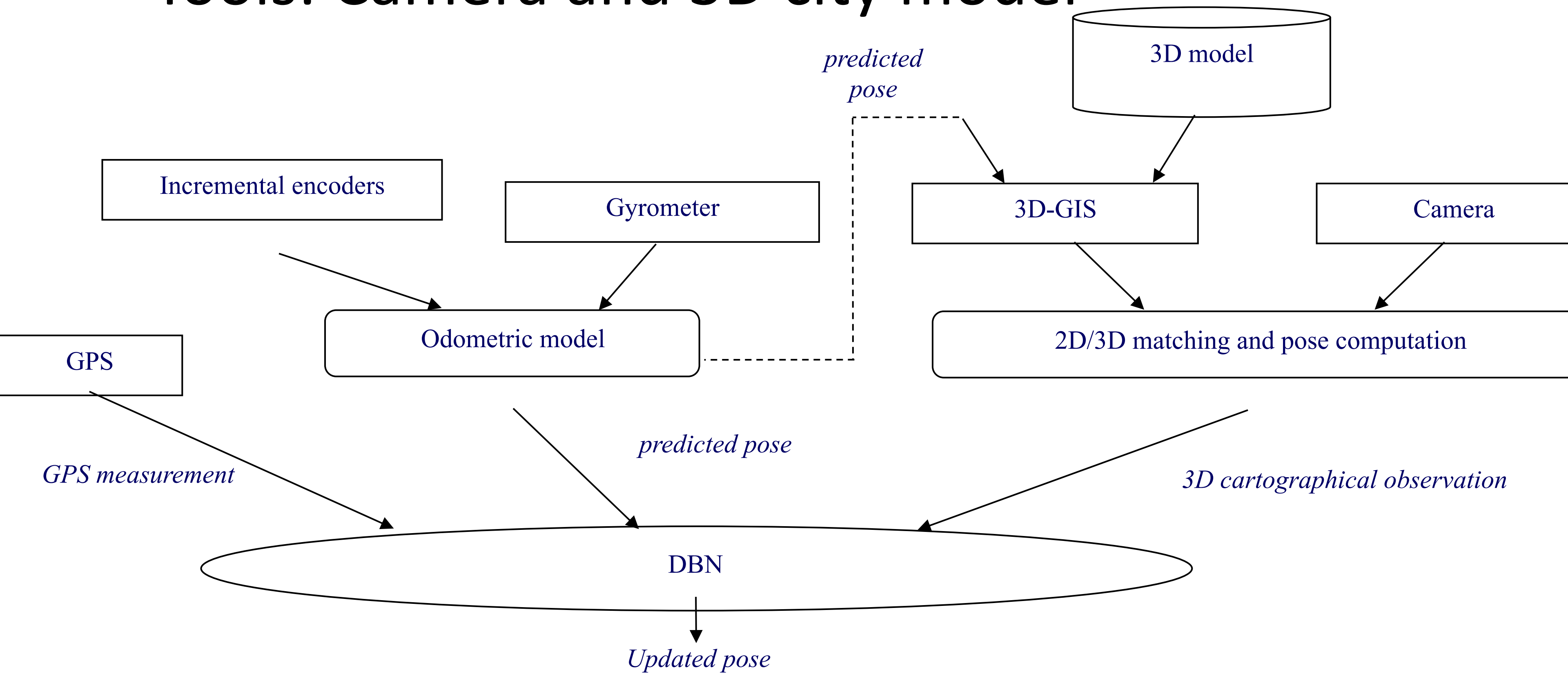
Application 3:
Geo-localisation using 3D database

Image Processing

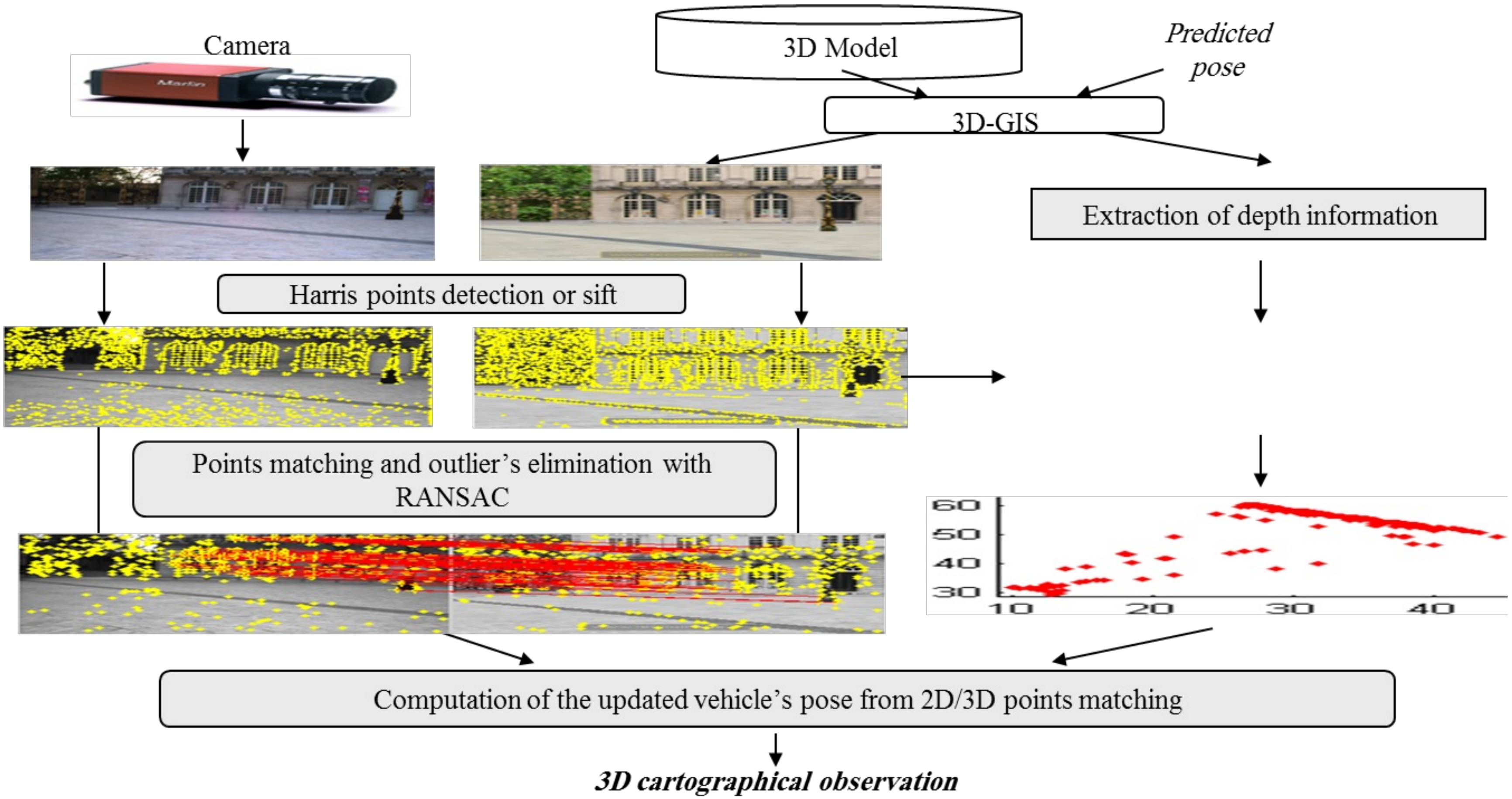
Collaboration : LAGIS-Lille- France

Application 3: Geolocalisation

- Aim: Detect the car position when GPS stops
- Tools: Camera and 3D city model



Application 3: Image Comparision



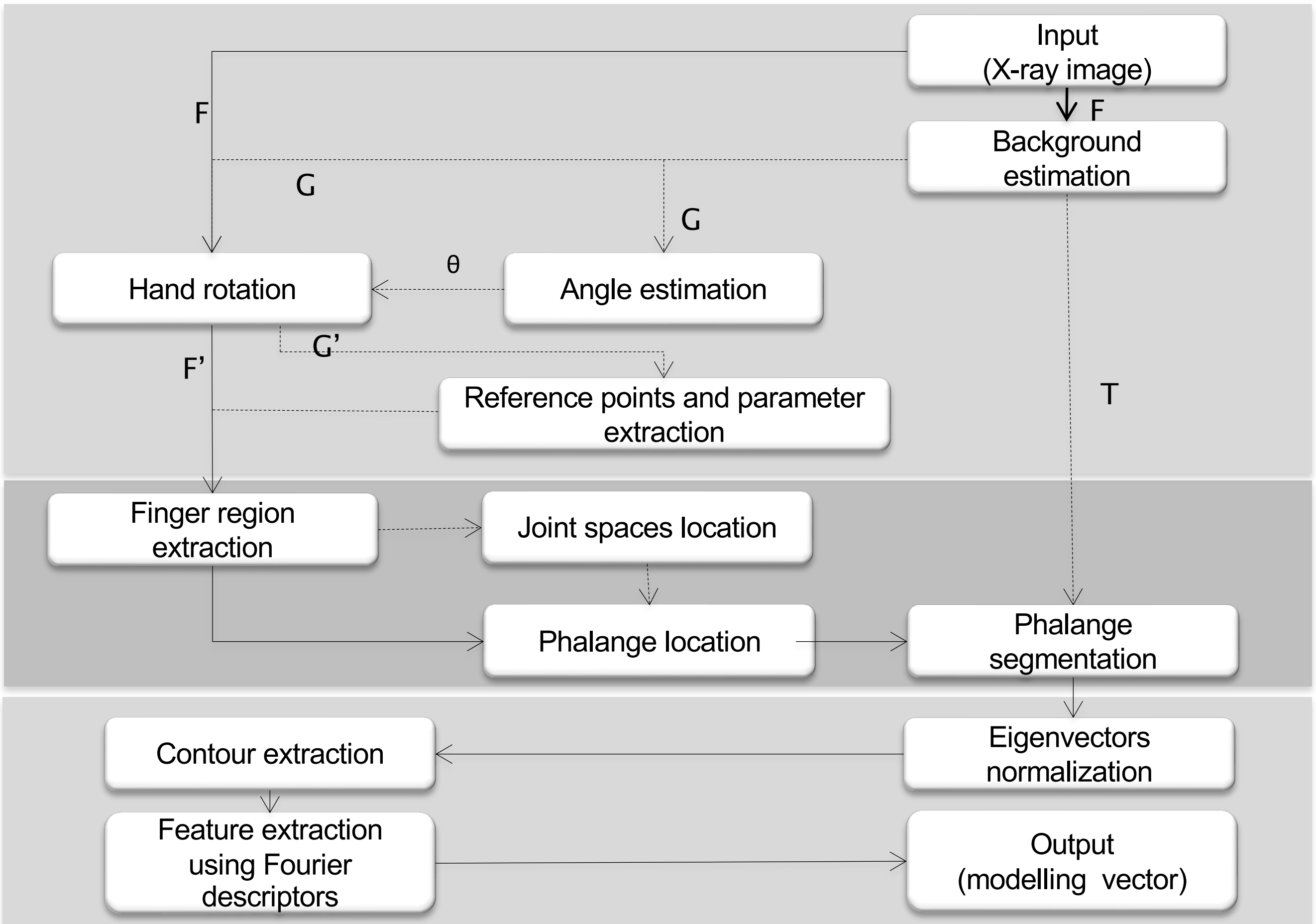
Application 4:

An Automatic Algorithm For Human Identification Using Hand X-Ray Images

Image Processing for Biometry

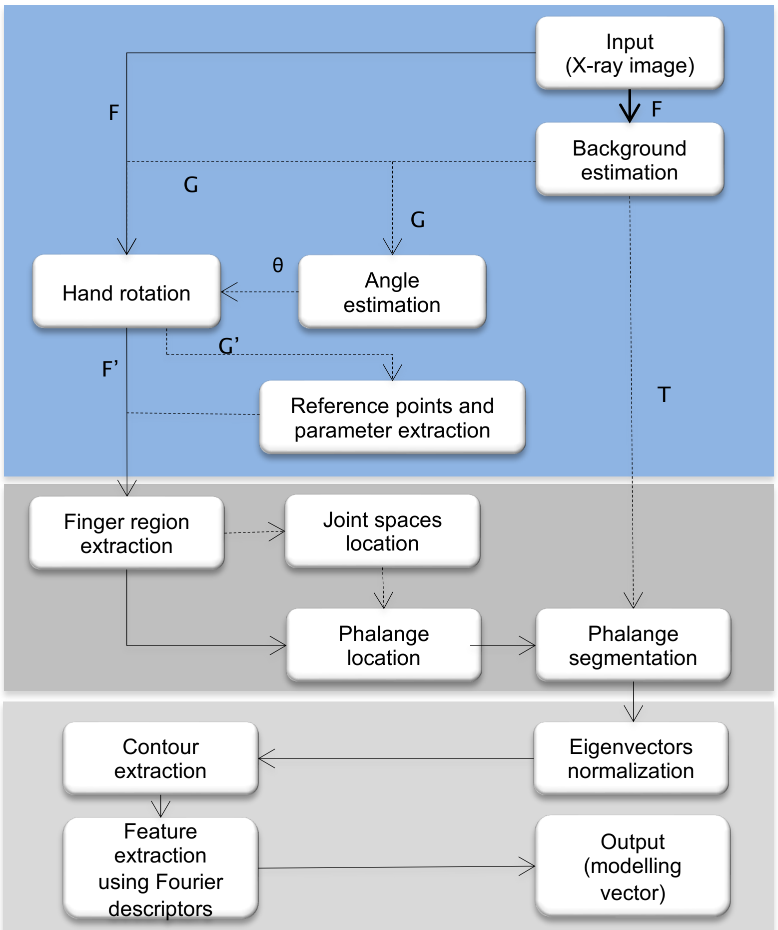
Collaboration Paris 12- France

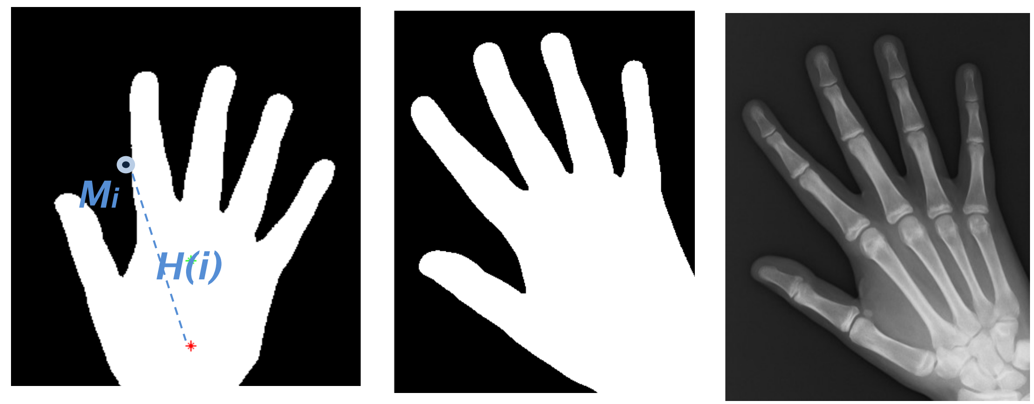
Application 4: Biometry

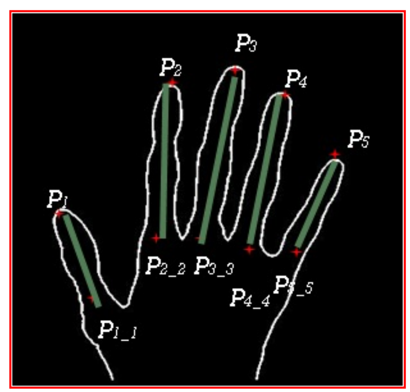


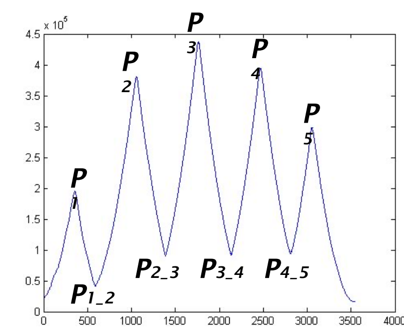
$$Hand \approx \{v_1, v_2, v_3, \dots, v_{14}\}$$

Application 4: Biometry

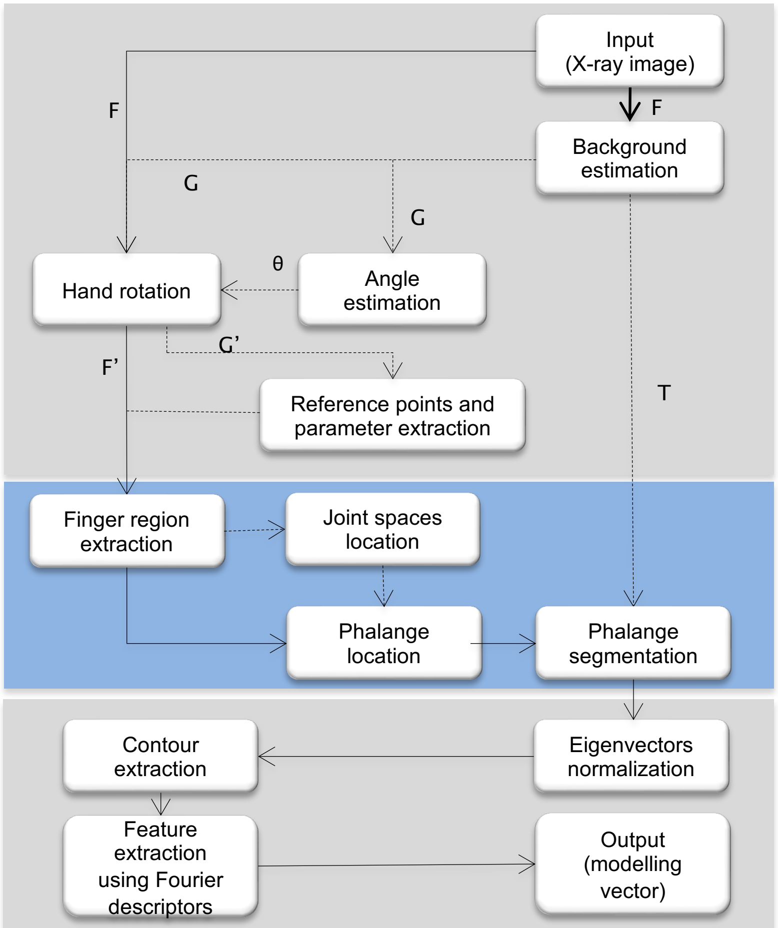


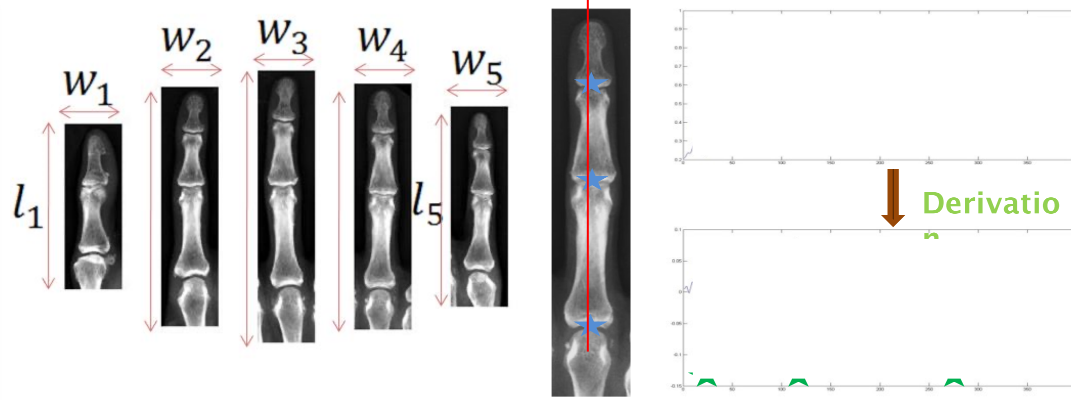


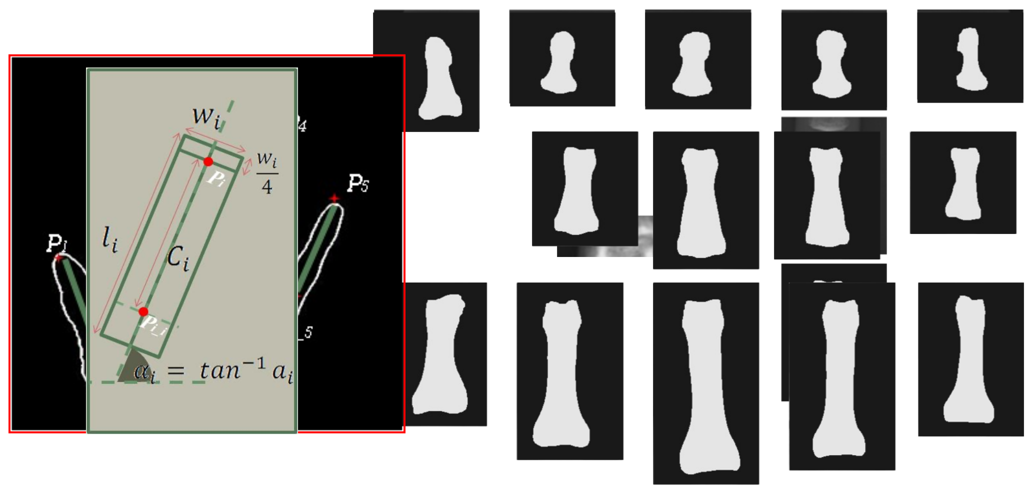




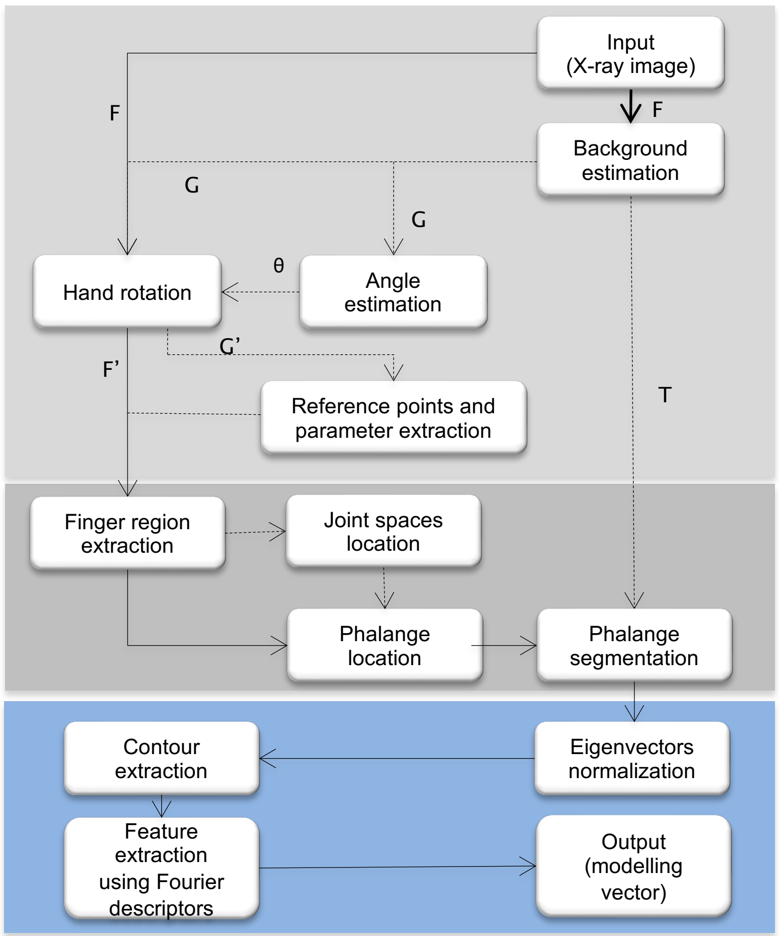
Application 4: Biometry

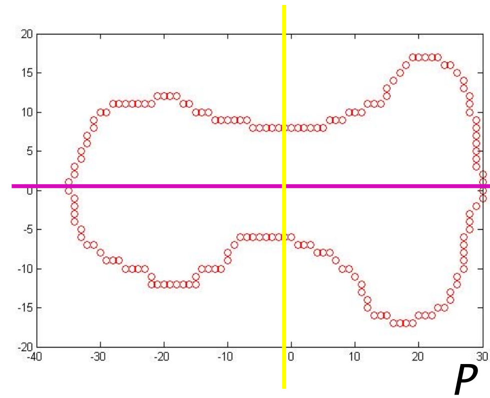


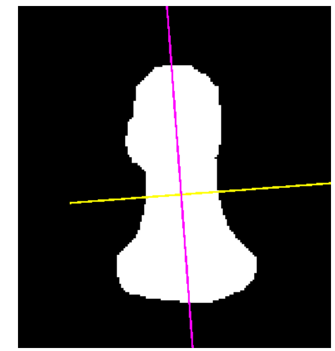




Application 4: Biometry



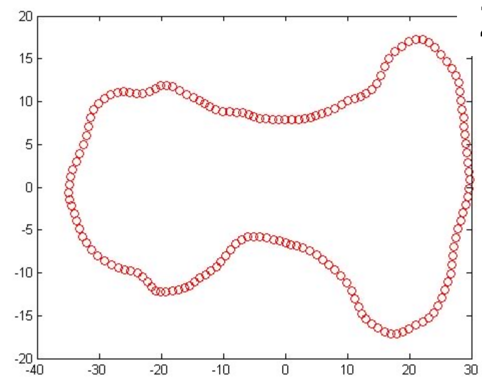


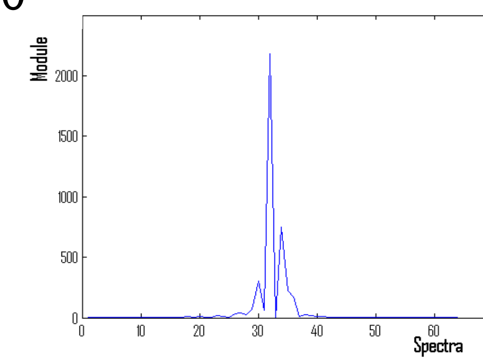


$n = ?$

$P = ?$

20





$$Hand \approx \{v_1, v_2, v_3, \ldots, v_{14}\}$$

Classification

150 hands

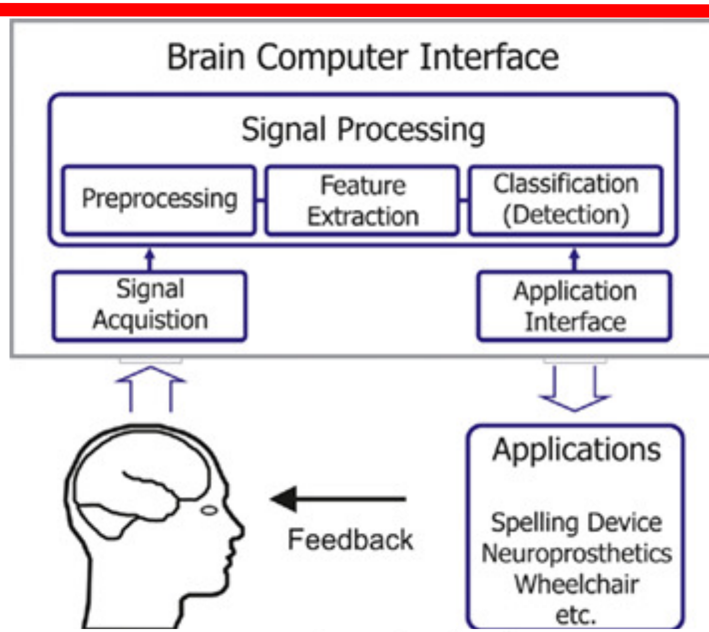
97% recognition

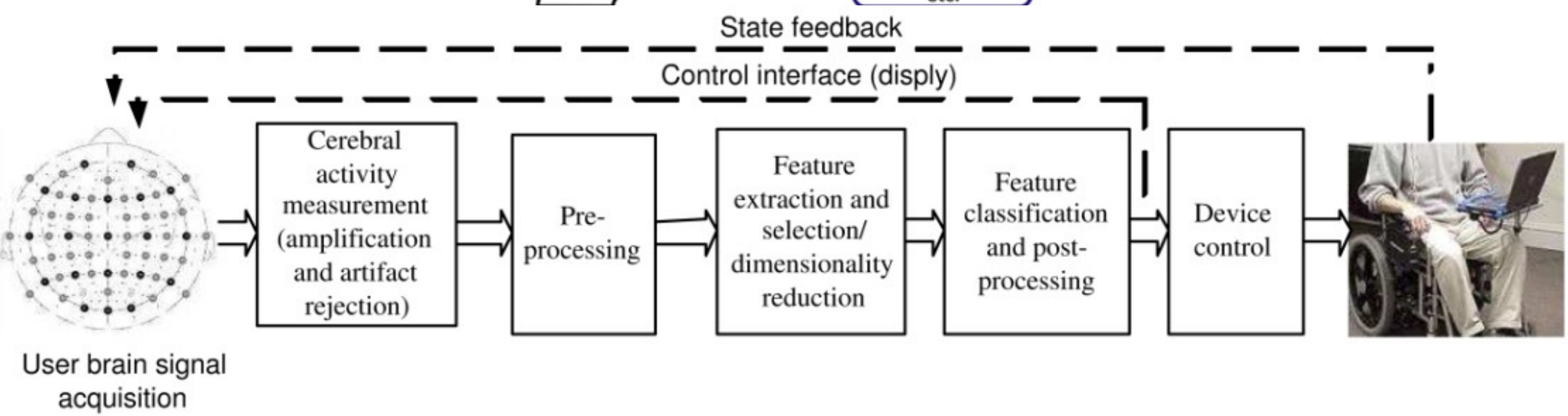
Application 5

EEG- Electroencephalography

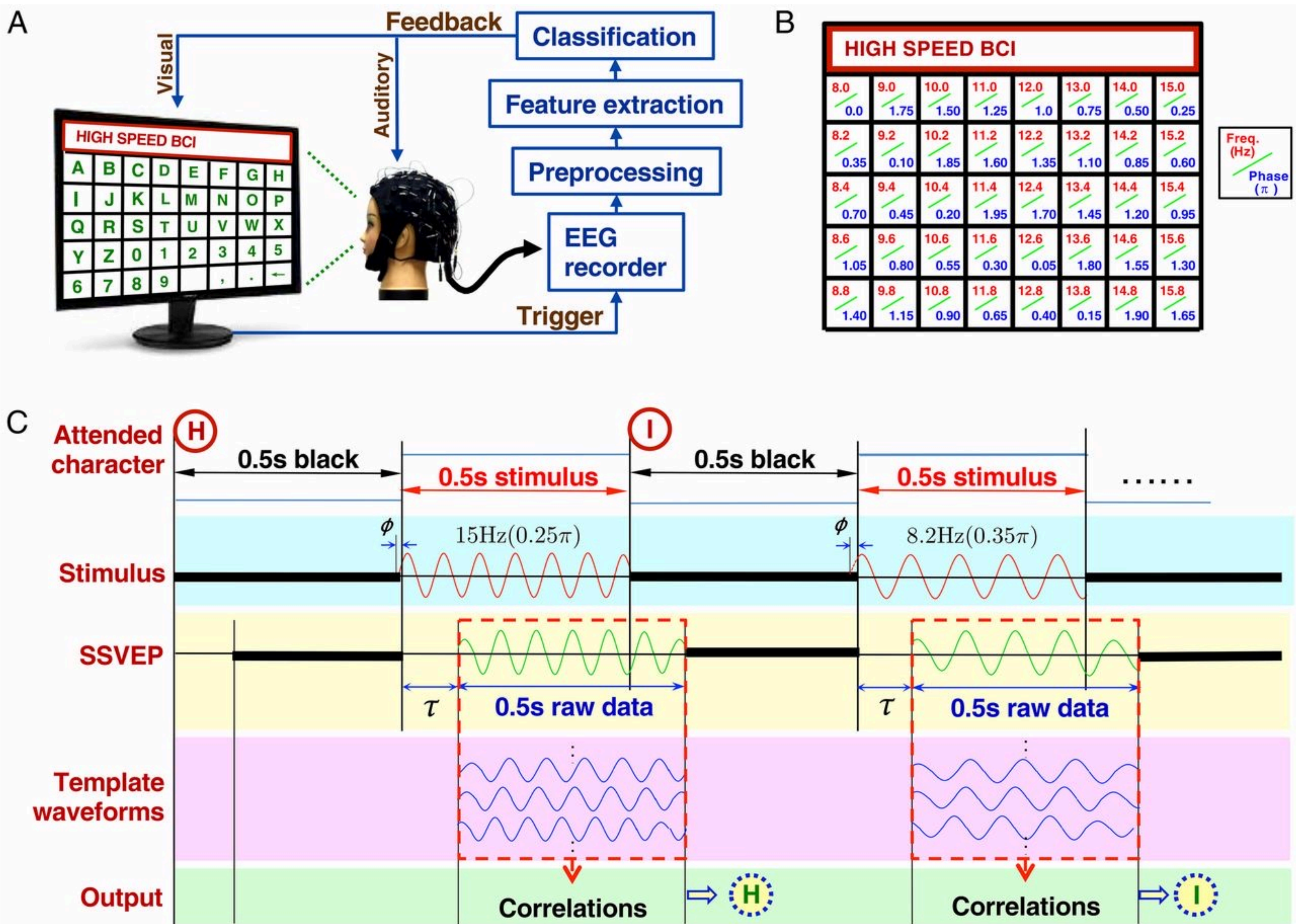
Brain Computer Interface

EEG: Electroencephalography





EEG: Typing and spelling
EEG



BCI: Color's based

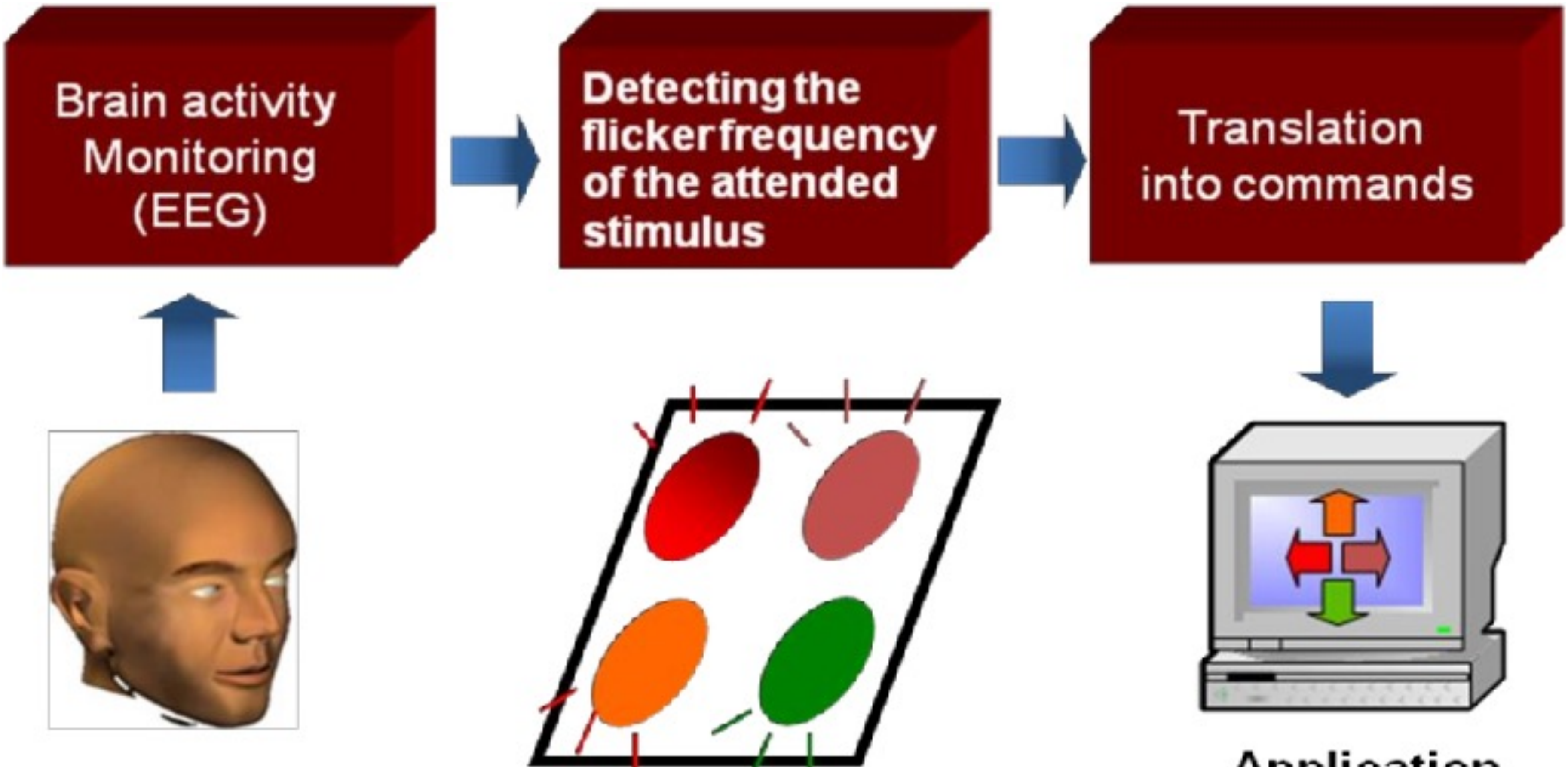
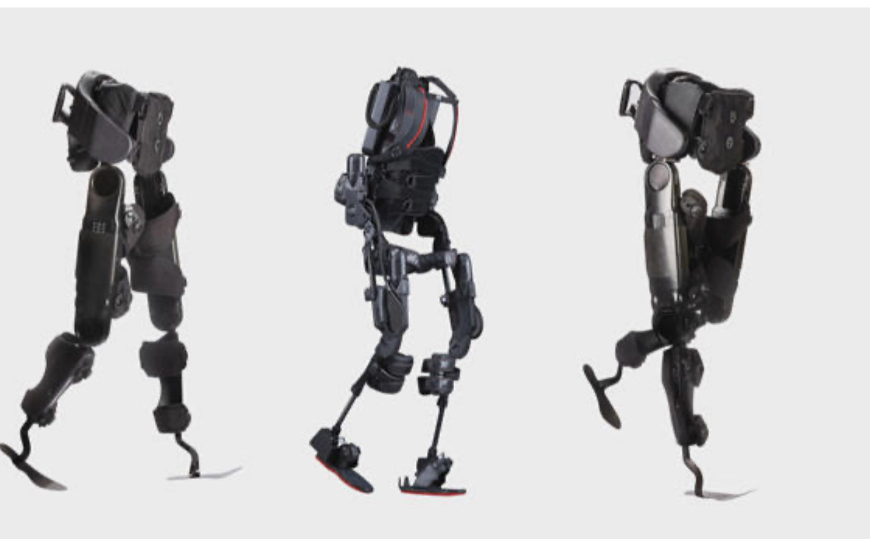
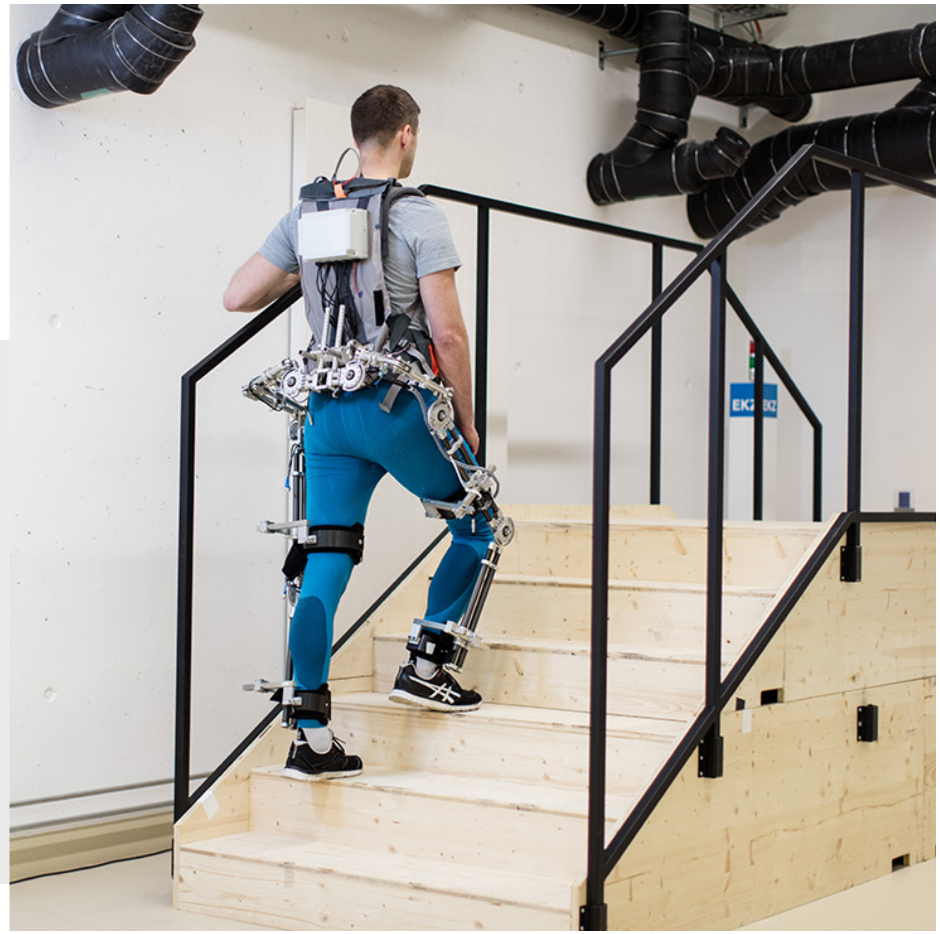


Figure 2. SSVEP based BCI

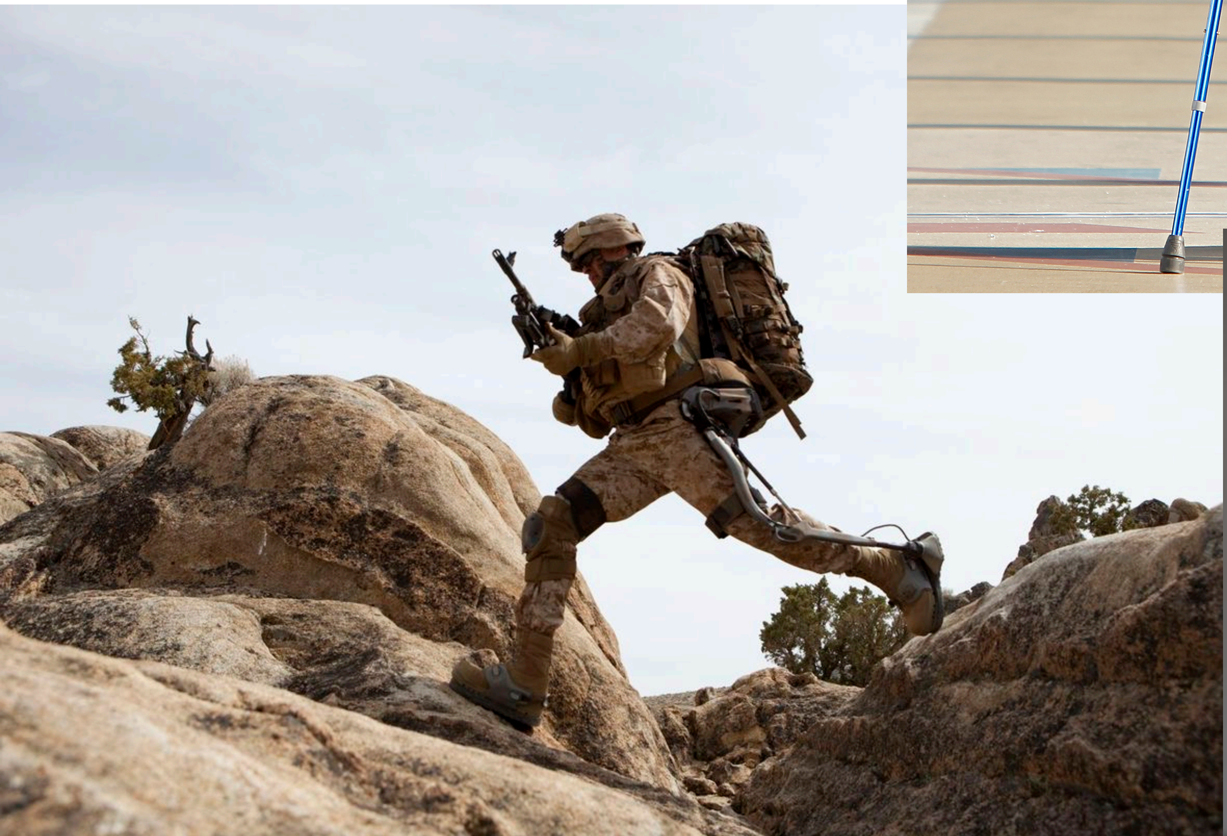
Figure 1 Setup of the BCI System

Exoskeleton

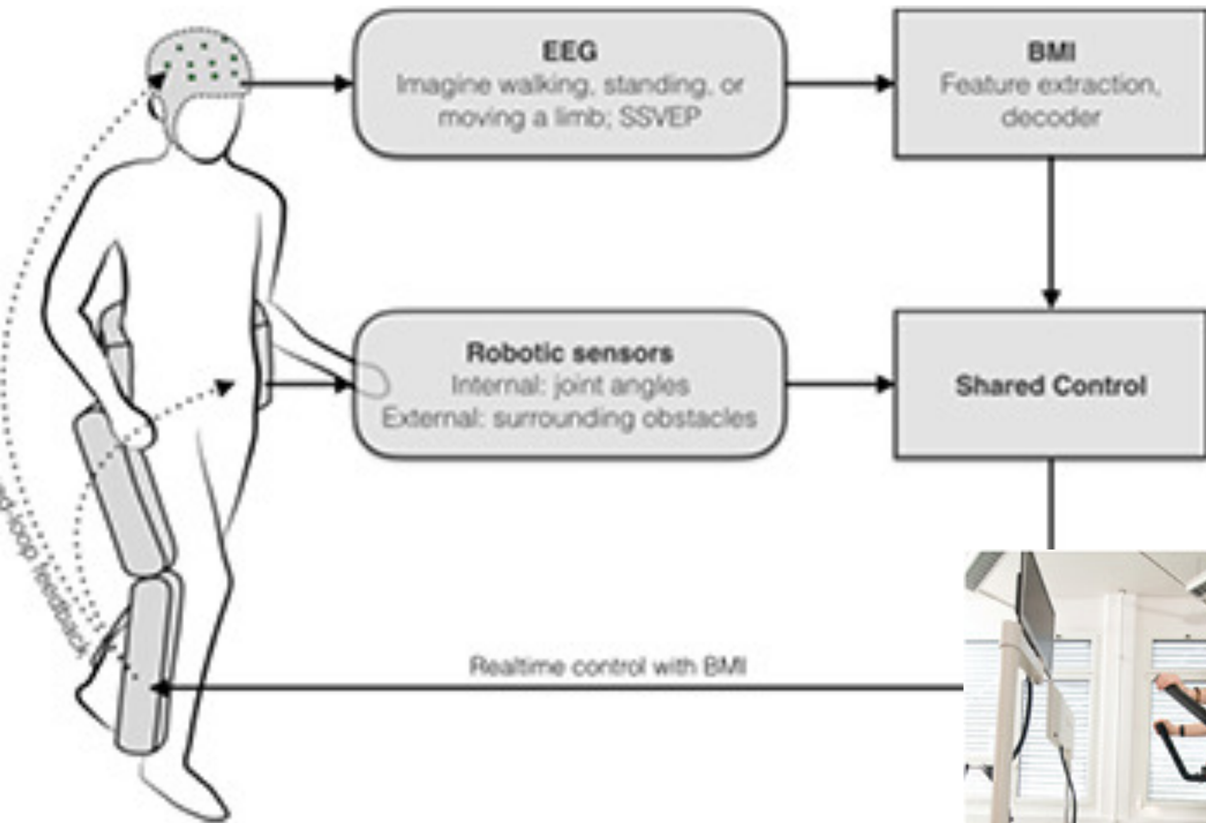




Exoskeleton


Future: EEG +Exoskeleton



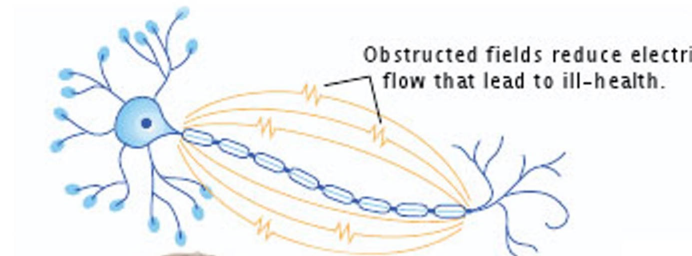
Application 6

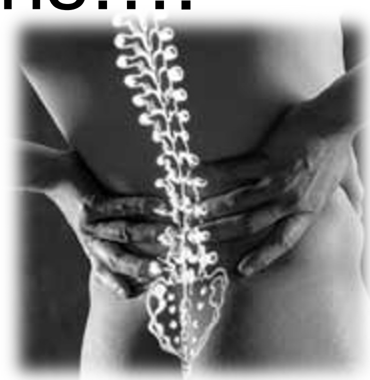
Stabilometer: Loss Of Balance Causes

Stabilometer: Loss Of Balance Causes

The main causes of imbalance are:

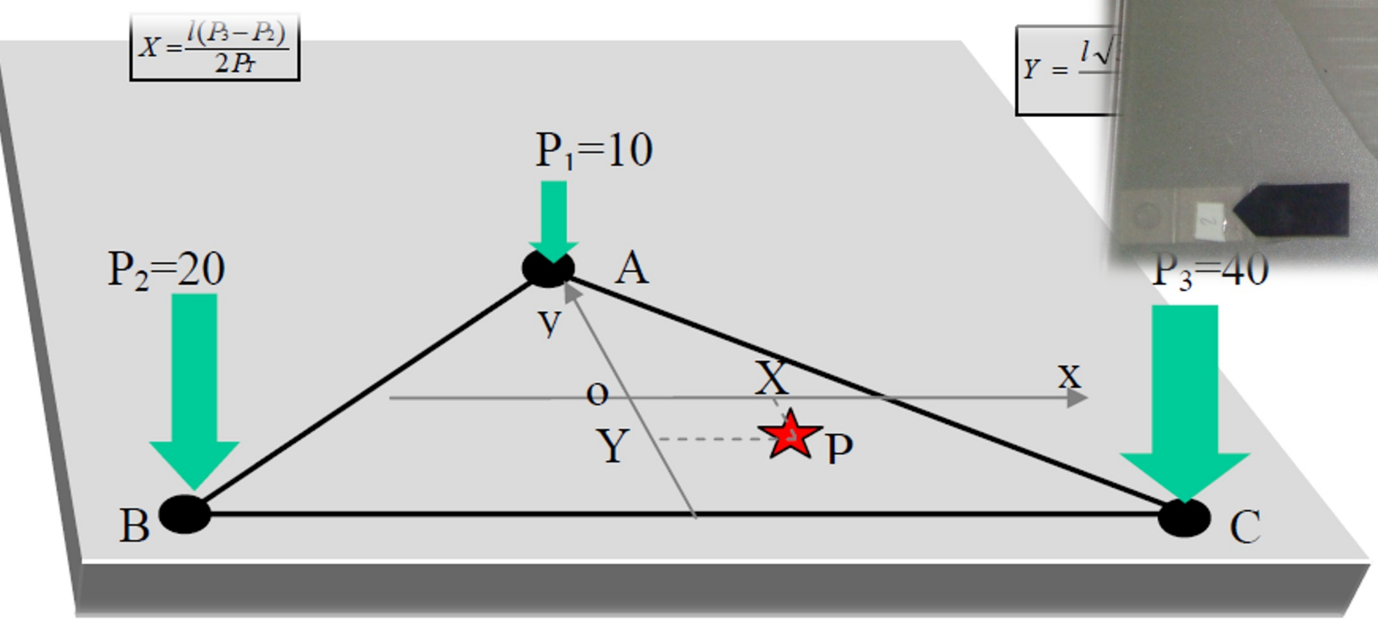
- Nerves disease.
- Muscles disease.
- Spinal cord disease.
- Brain disease.
- Medications….



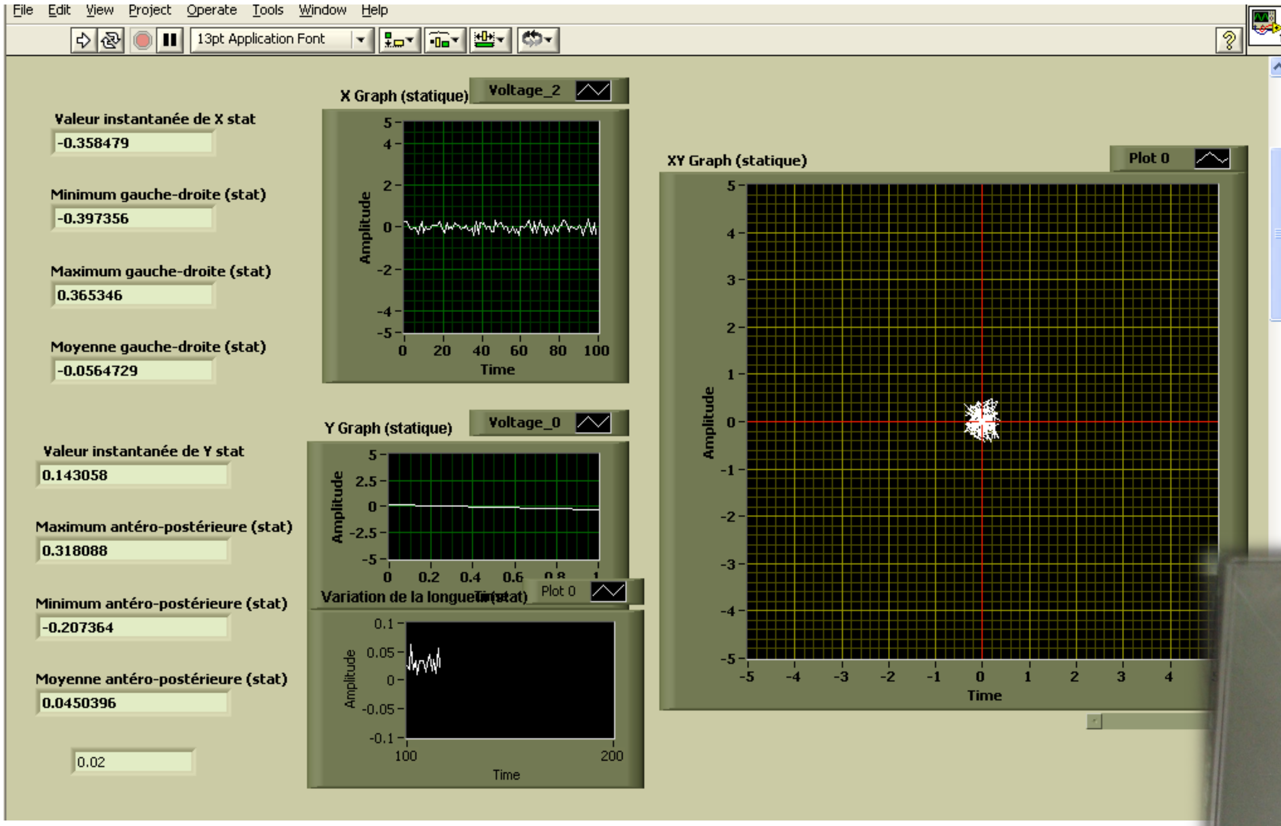


Stabilometer

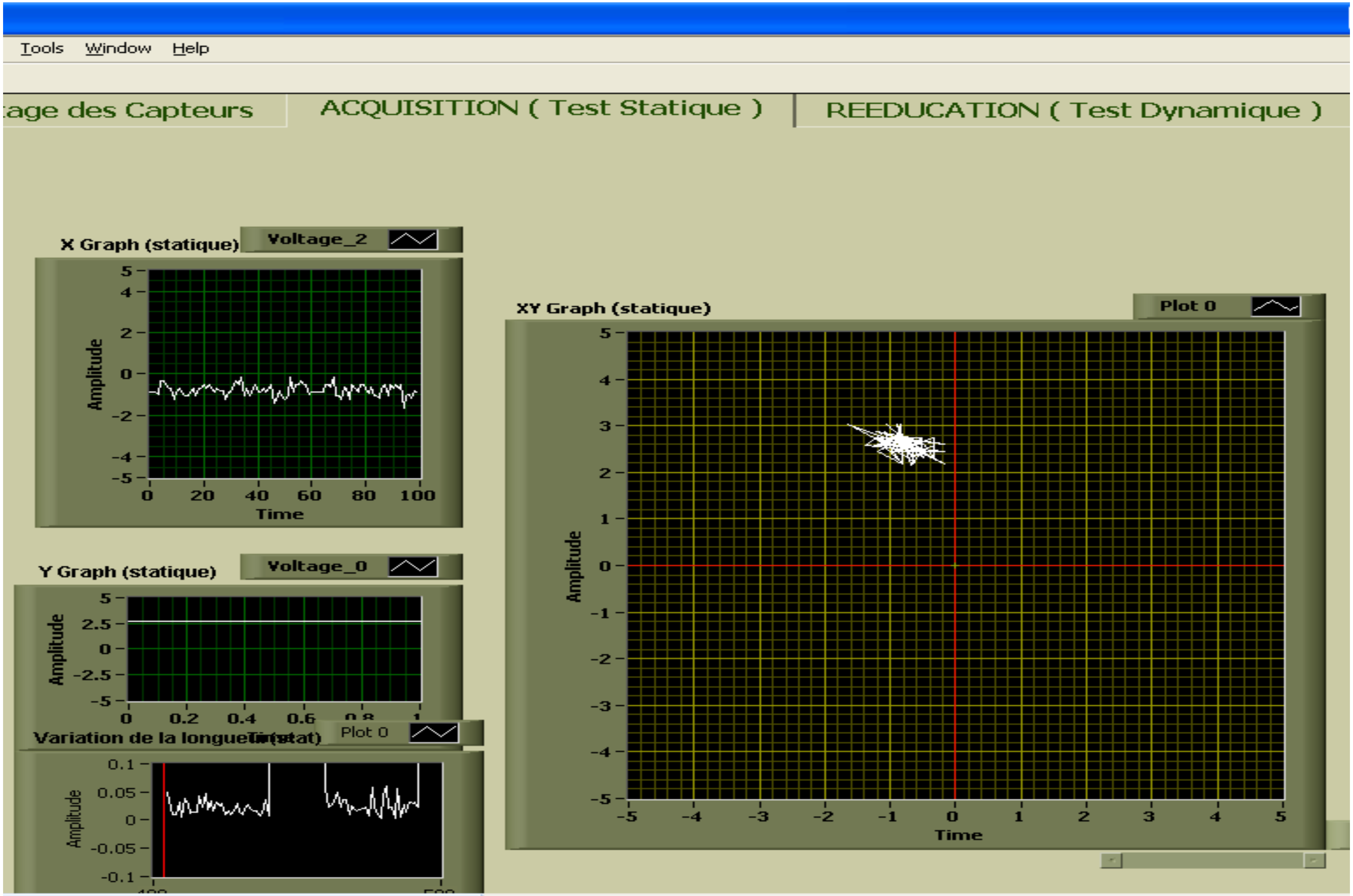
Measure the center of gravity



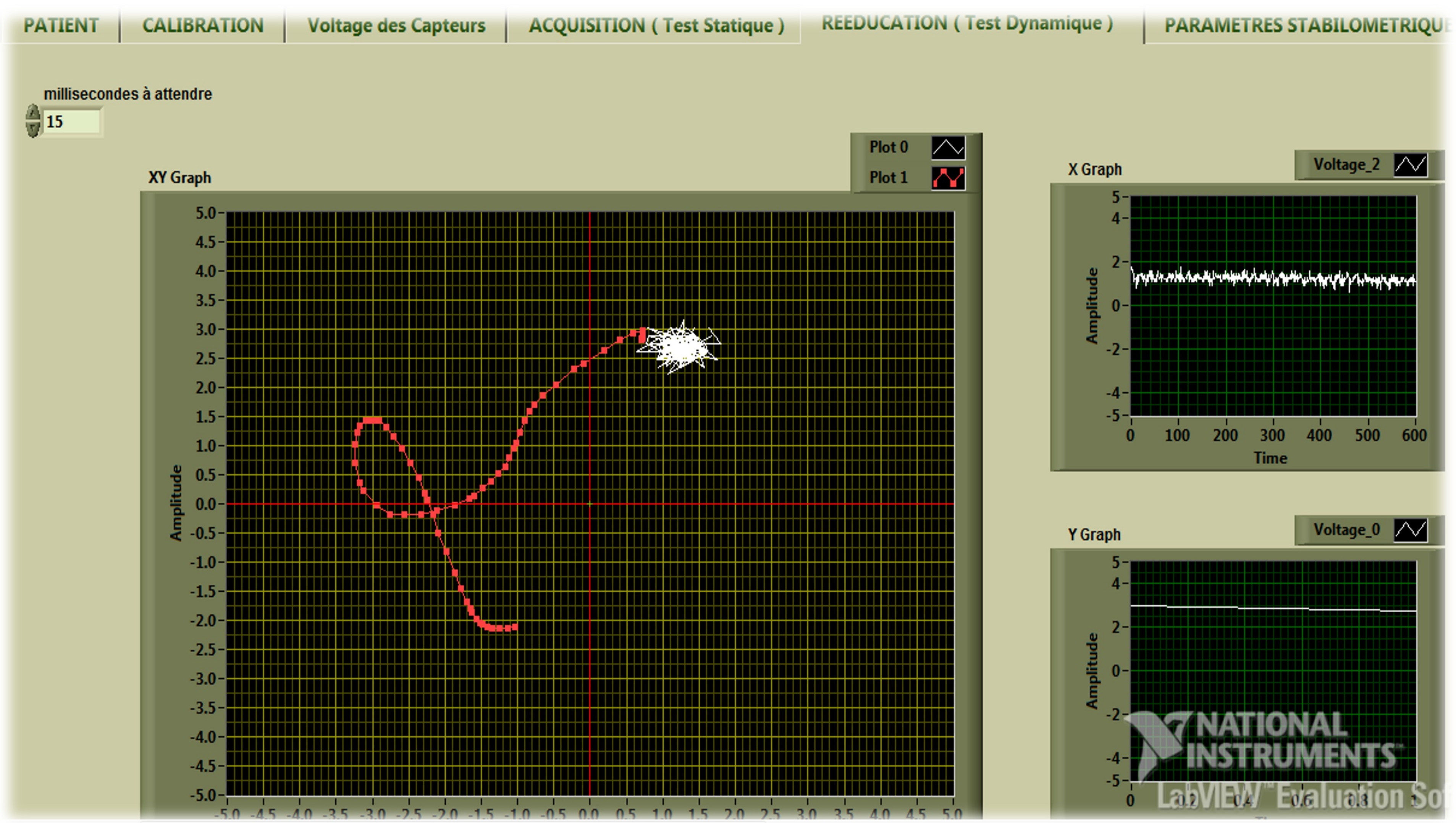
Stabilometer: Normal



Problem in stability



Reeducation using Stabilometer

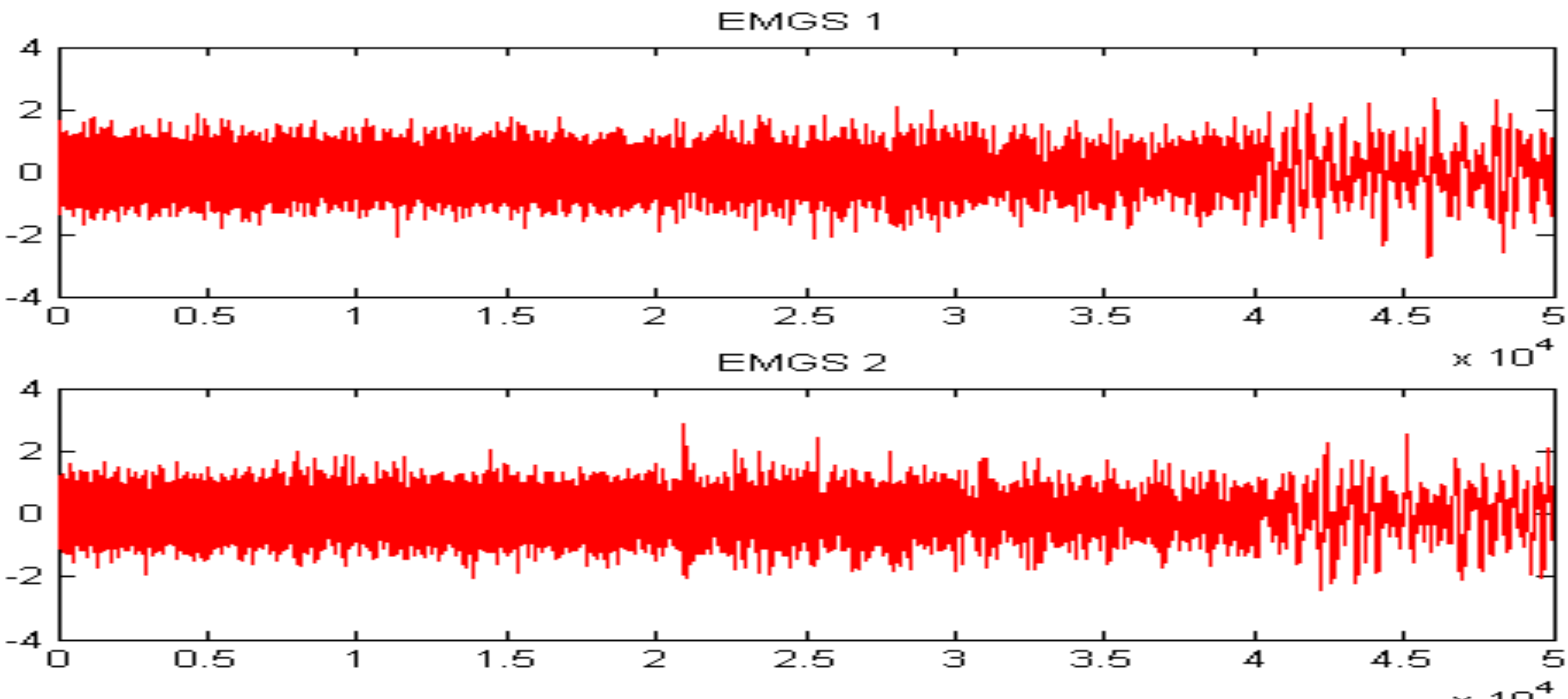


Application 7

Muscle Fatigue

Muscle Fatigue

- *Etude des signaux musculaires pour la détection du siège de la voiture le plus confortable. Collaborations: Renault*



Les signaux EMG longue durée

- Evaluation de l'inconfort d'un opérateur assis en situation de pilotage de longue durée

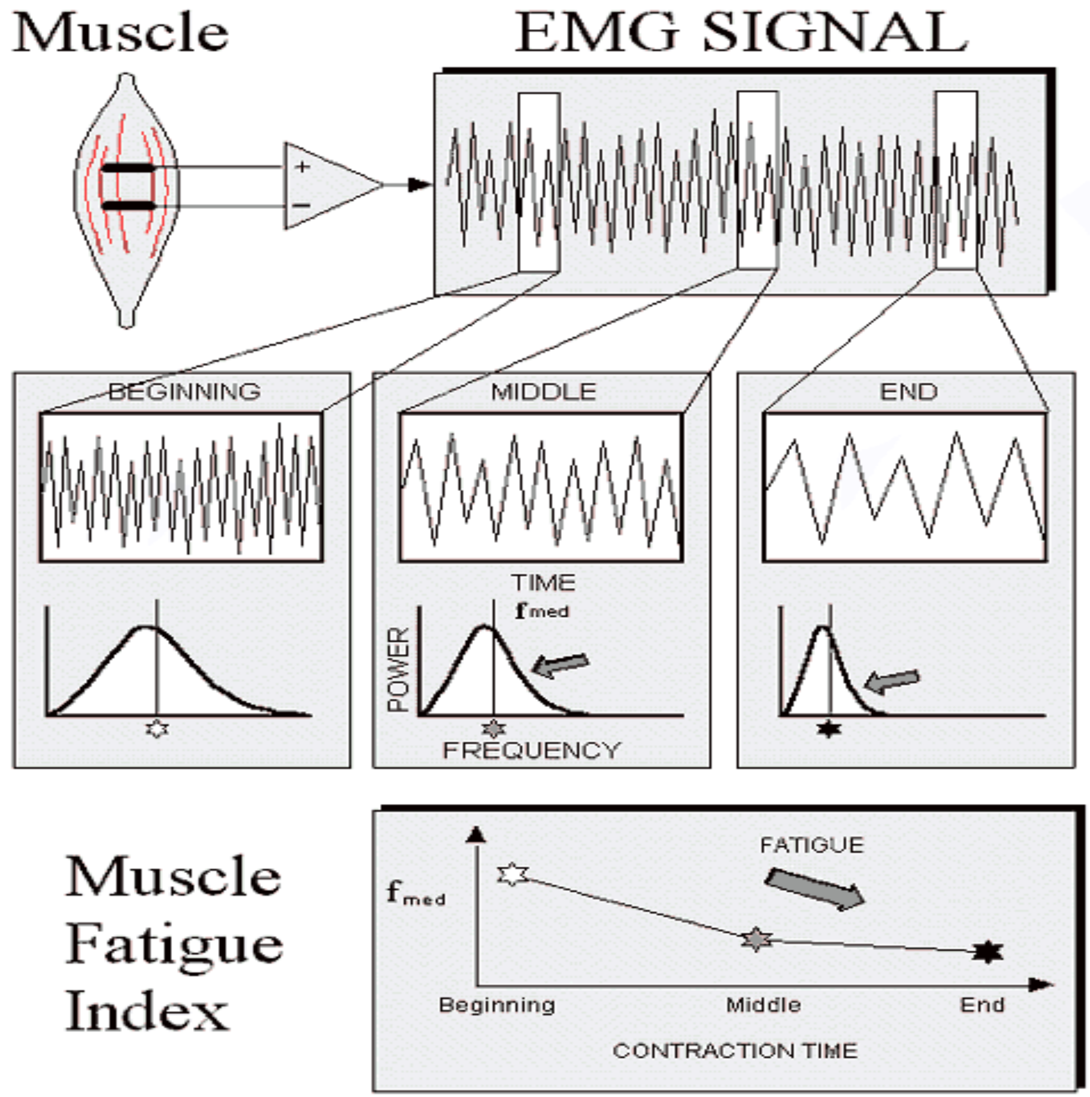
le spectre de l'EMG se compresse avec la fatigue

- <u>Fréquence médiane : identifier l'apparition et la progression de la fatigue musculaire.</u>

Fatigue using EMG

- Traitement:

Analyse de la fatigue : Le signal change sa fréquence en fonction de la fatigue

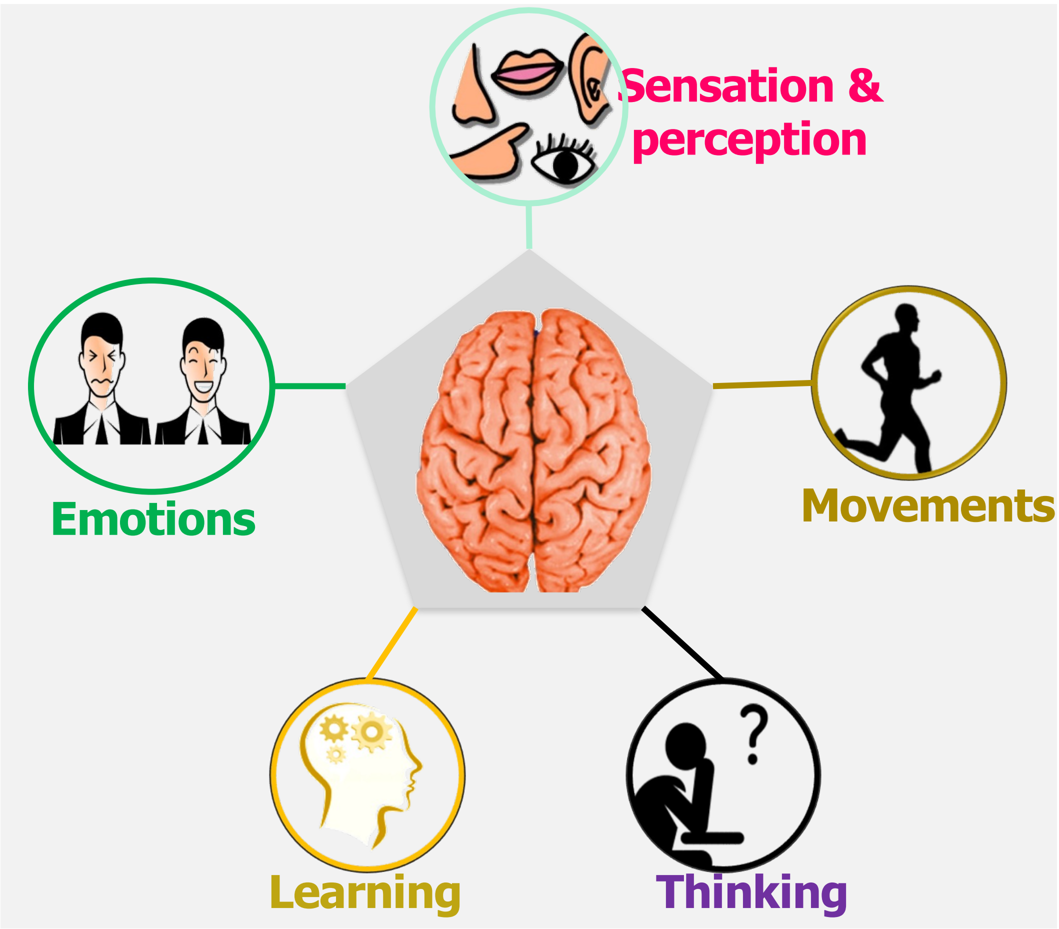


Application 8

Dense EEG
Brain Diseases :

Tracking dynamic – Parkinson
Epilepsy, Alzheimer, Depression

The brain: a complex system

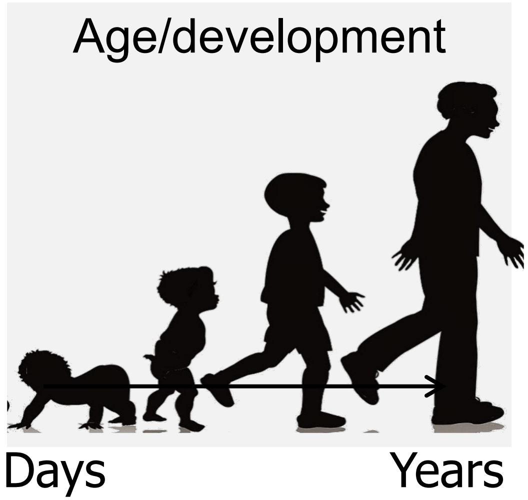


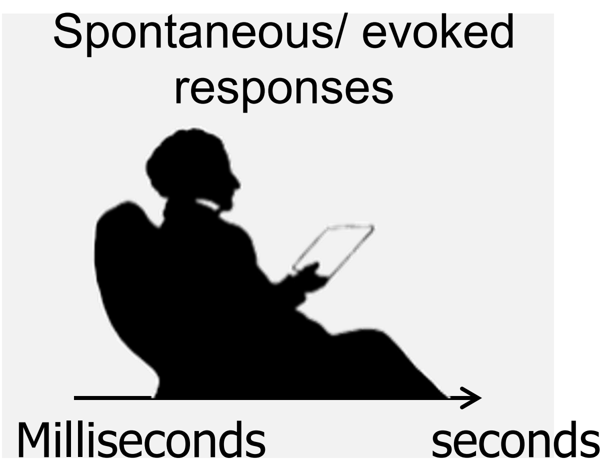
- Most complex organ in the nervous system
- Oversees many aspects of physiology

➔ It is continuously processing and integrating information

First objective

•**The brain is a dynamic network** *[Allen, Cerebral Cortex, 2012] [Hutchison, Neuroimage, 2013].*





- **A big challenge is to track the dynamics of brain connectivity at sub-second time scale**

[Allen, Cerebral Cortex, 2012] [Hutchison, Neuroimage, 2013].

contribution 1:

Develop new methods to track the dynamics of brain networks at sub-second time scale

Second objective

- The brain disorders are **network diseases**

Clinical needs ➔
- **Easy to use**
- **Direct**
- **Non invasive**

➔ **Identify the pathological networks**

- **Advantages:**

Understand the brain disorder

Develop diagnostic tools

Help in therapeutic tools

contribution 2:

Develop EEG network-based neuromarkers of brain disorders

Second objective

• The brain disorders are network diseases

Clinical needs ➔ - Easy to use
- Direct
- Non invasive

➔ Identify the pathological networks

• **Advantages:**

Understand the brain disorder

Develop diagnostic tools

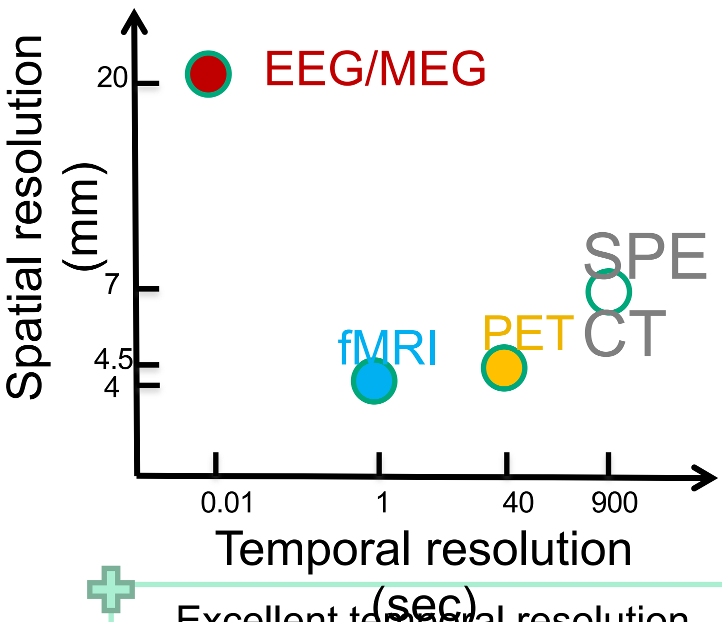
Help in therapeutic tools

contribution 2:

Develop EEG network-based neuromarkers of brain disorders

Neuroimaging techniques

Neuroimaging techniques used to construct the functional brain networks:



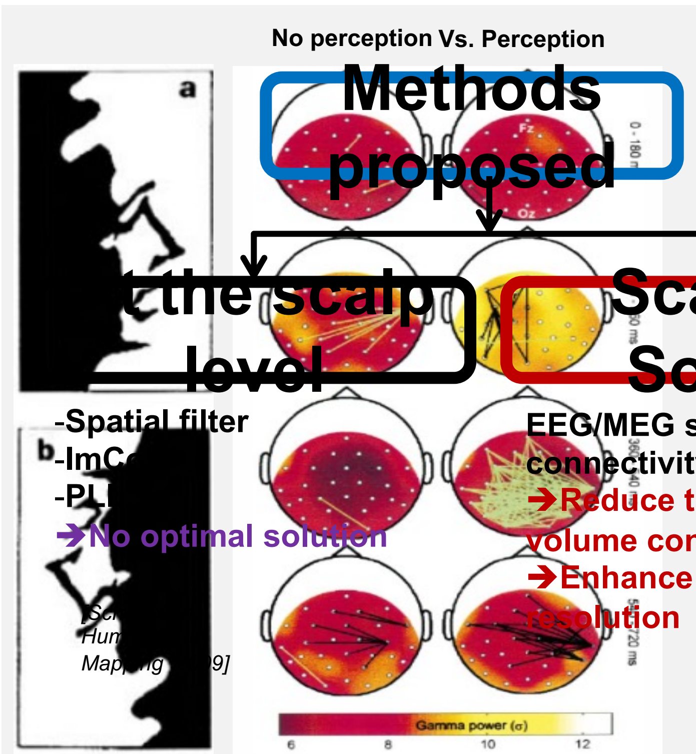
- Excellent temporal resolution
- Good spatial resolution
- Non-invasive
- Easy to use

Main features of dense-EEG:

- Excellent time resolution (Fs= 1000 Hz)
  - Good spatial resolution (256 electrodes).
  - Full coverage of the subject's head (basal & face electrodes)

EEG scalp connectivity

•**Scalp EEG based networks were widely used** *[Uhlaas et al. 2006]*



[Rodriguez et al., Nature, 1999]

Methods proposed

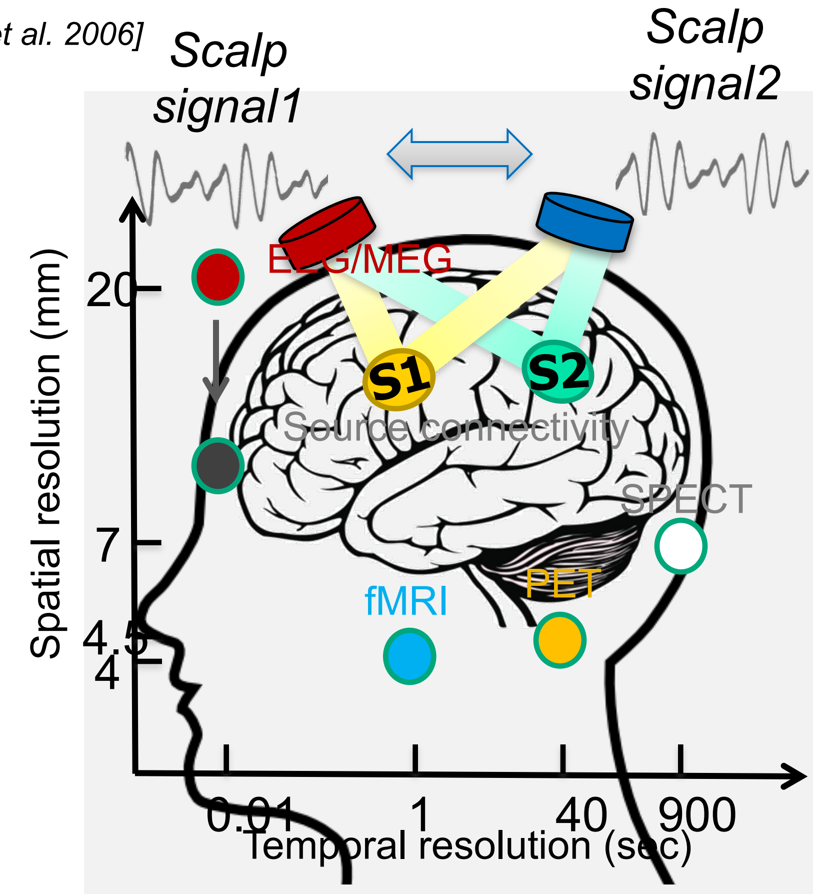
t the scalp level

-Spatial filter
-ImC
-PL
➔No optimal solution

[Sc Hum Mapping 9]

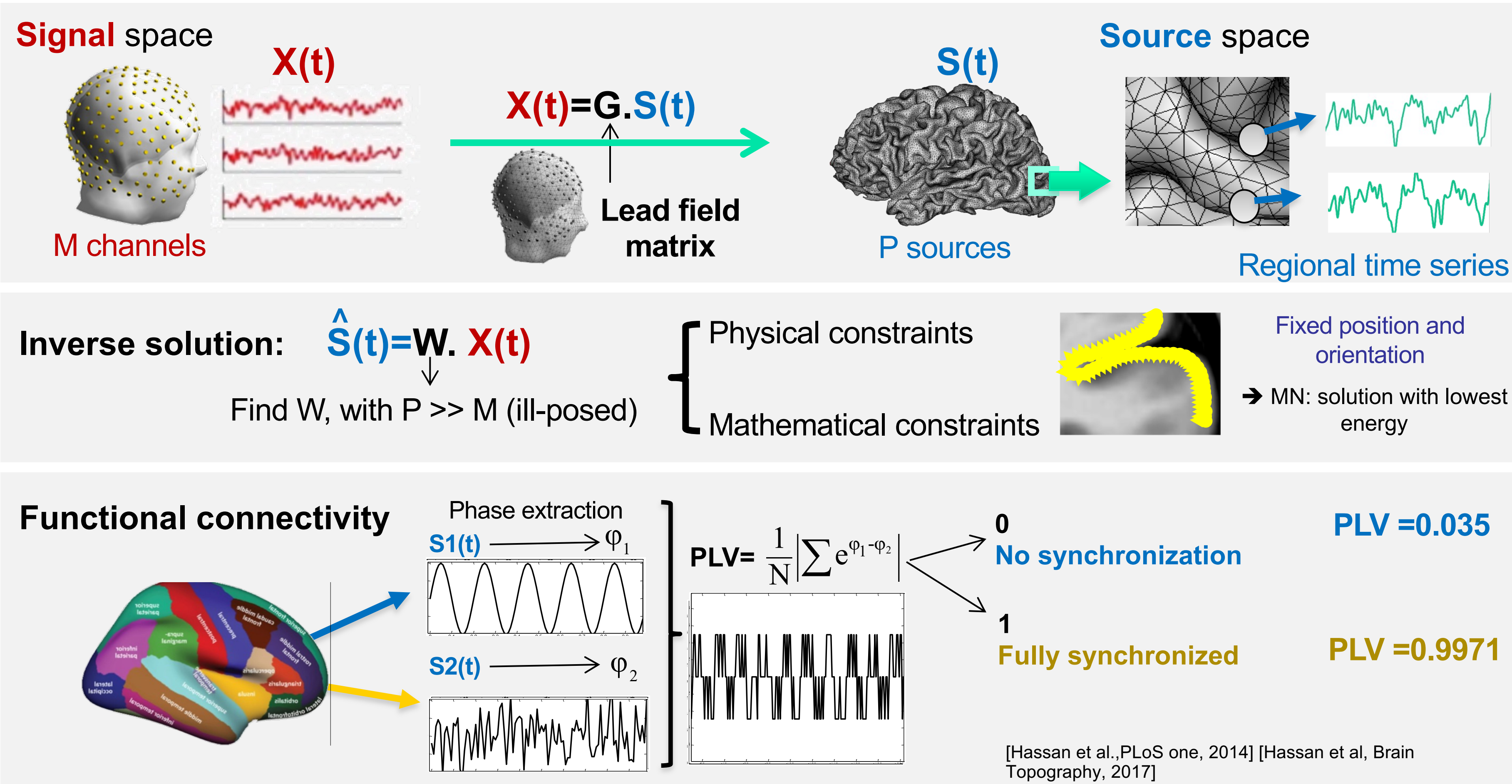
Scalp ➔ Source

EEG/MEG source connectivity
➔Reduce the effect of volume conduction
➔Enhance the spatial resolution



⚠ **Volume conduction problem**

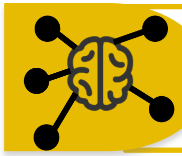
EEG source connectivity



Tracking dynamics of functional brain networks

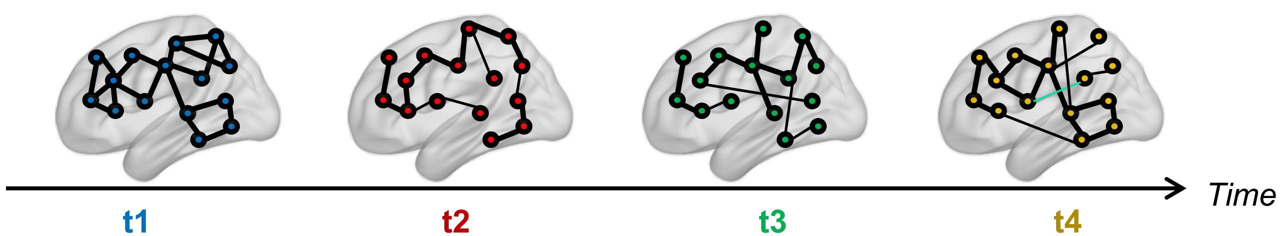
- **We addressed two main challenges:**

Tracking the dynamic characteristics **of the resting brain** at very fast time-scale (sub-second)



Developing a new **automatic** tool to explore the **dynamic changes of the modular structures** of the brain

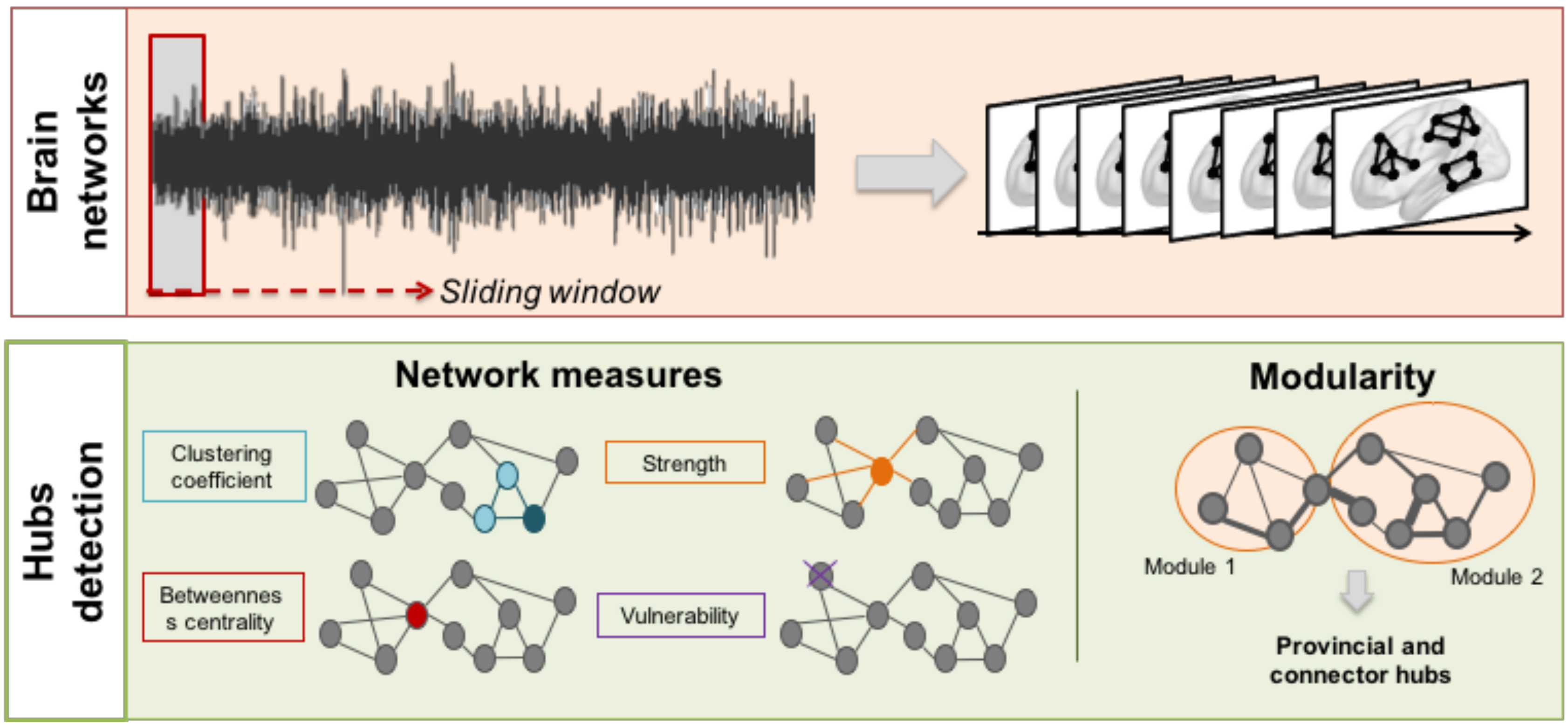
- **Approach:**



What are the characteristics of each pattern?
How they transition over time?
Are there repeating structures?

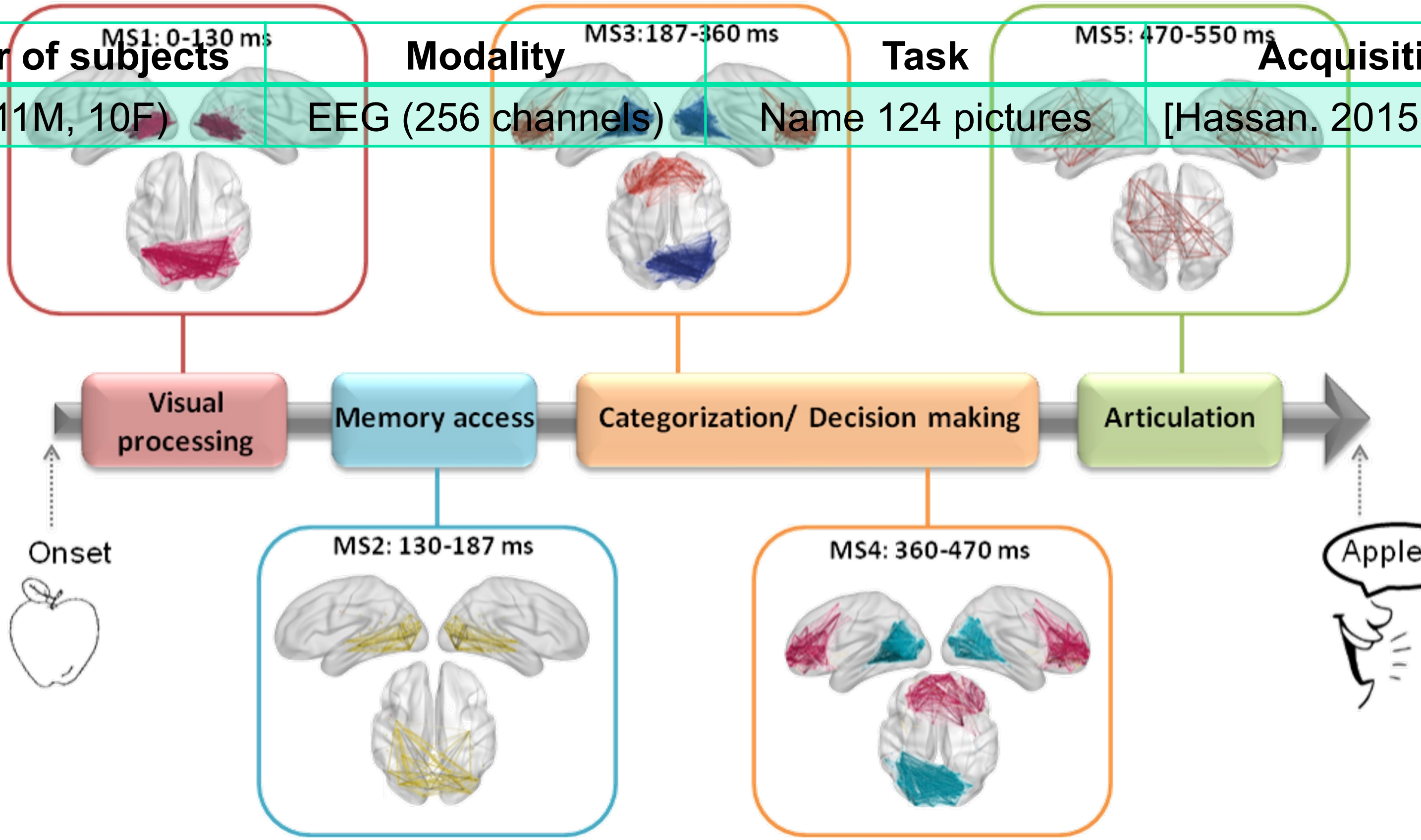
Tracking dynamics of functional brain networks

Track the **dynamic characteristics** of the resting brain and detect hubs **at very fast time-scale (sub-second)**



A1: Results on EEG data (Picture naming task)

Number of subjects	Modality	Task	Acquisition
21 (11M, 10F)	EEG (256 channels)	Name 124 pictures	[Hassan. 2015, Cortex]

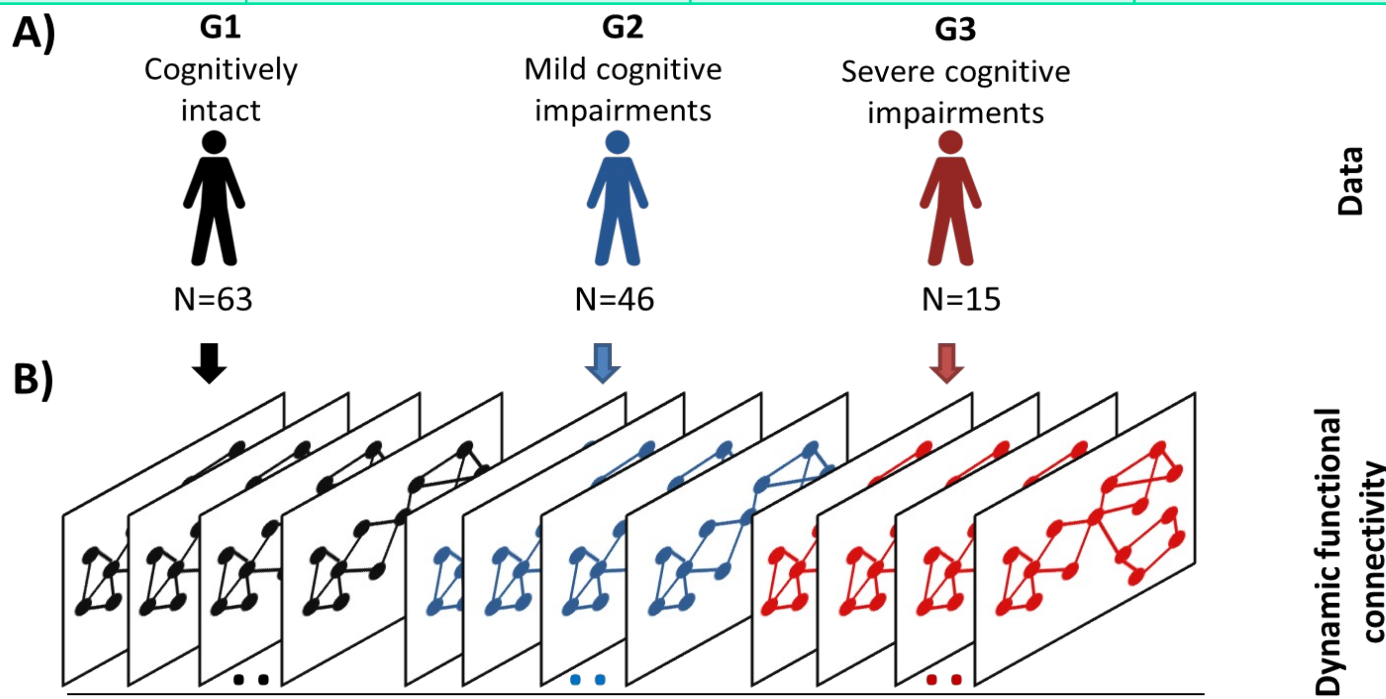


[Kabbara et al. 2018,Submitted]

•Ability to **track the different modular brain states** (from onset to reaction)

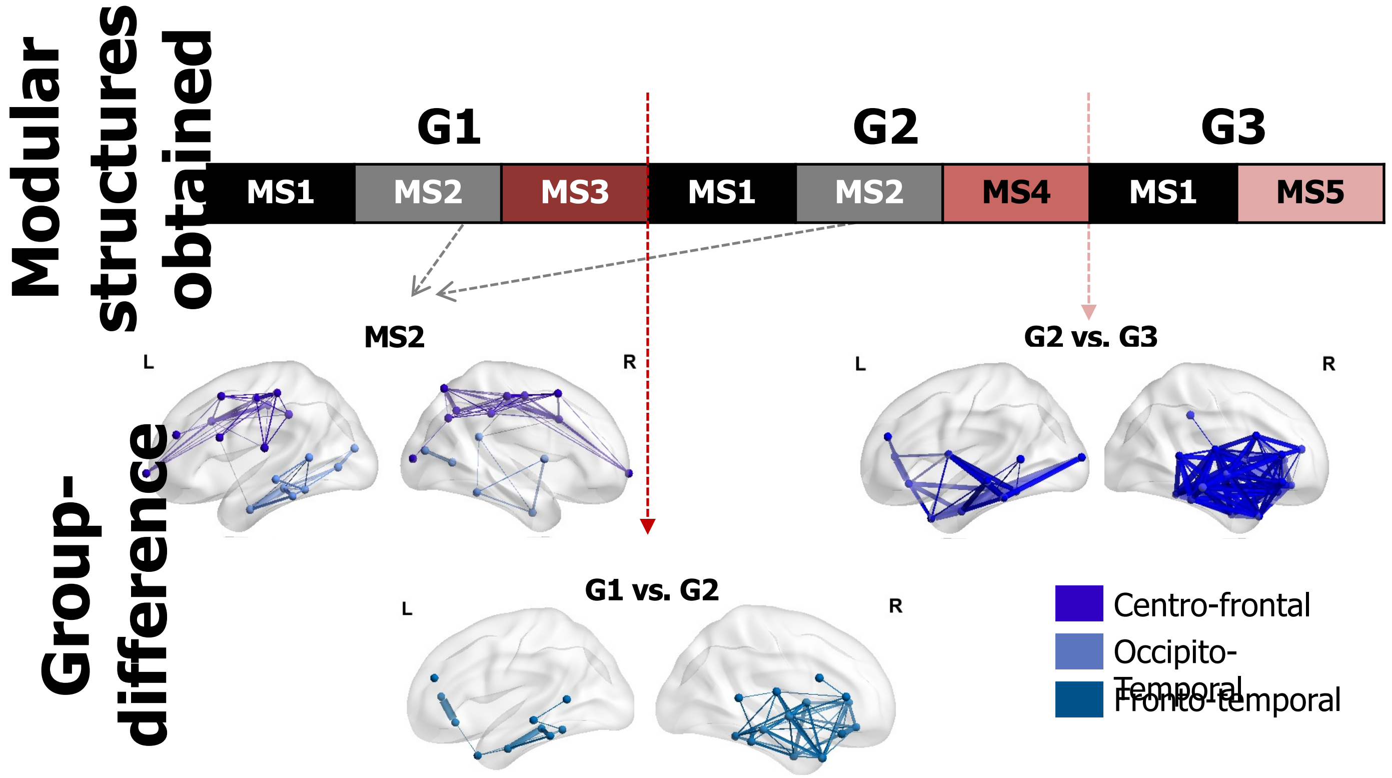
A2: Results on EEG data (Parkinson)

Number of subjects	Modality	Task	Acquisition
124 (11M, 10F)	EEG (128 channels)	Resting state	[Dujardin, Parkinsonism and Related Disorders,2015]



[Kabbara et al. 2018, Submitted]

Results on EEG data (Parkinson)



[Kabbara et al. 2018, Submitted]

•The number of MS **decreased** from 3 to 2 MSs in G3

• **G1 vs. G3:** distributed modular alterations (compared to G1 vs. G2)

A3: Clinical application: Epilepsy

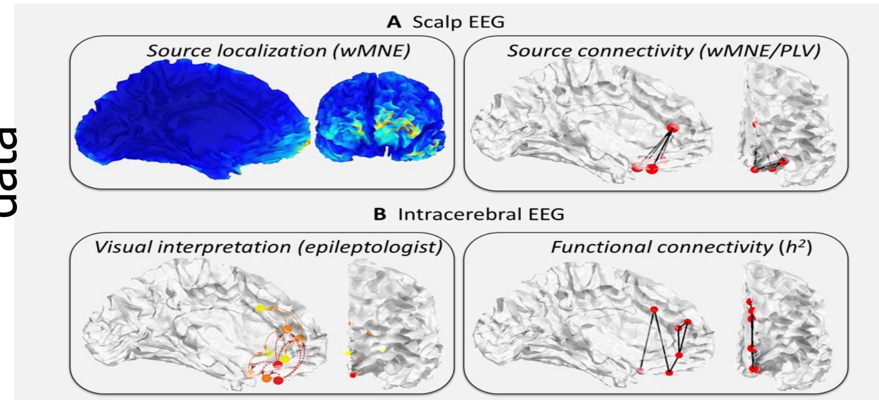
- ~ **50 million** people worldwide

- **30%** are drug resistant

- Solution: Surgery ➔ **accurately identify the epileptogenic network**
- SEEG is the most used technique ➔ **Invasive and expensive**

EEG Connectivity based analysis

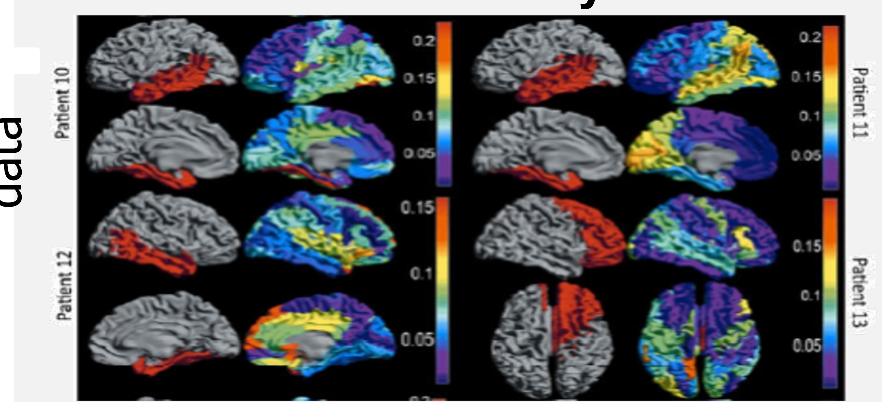
Spike data



[Hassan. Brain Topography, 2017]

Network analysis

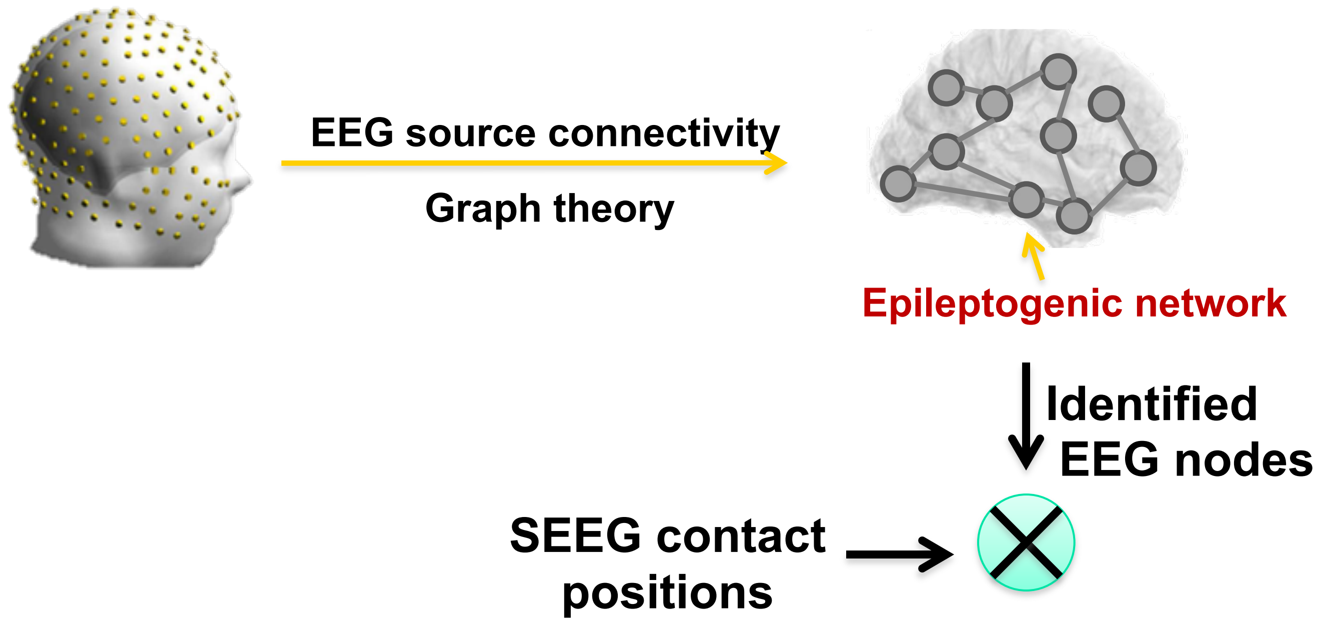
Interictal data



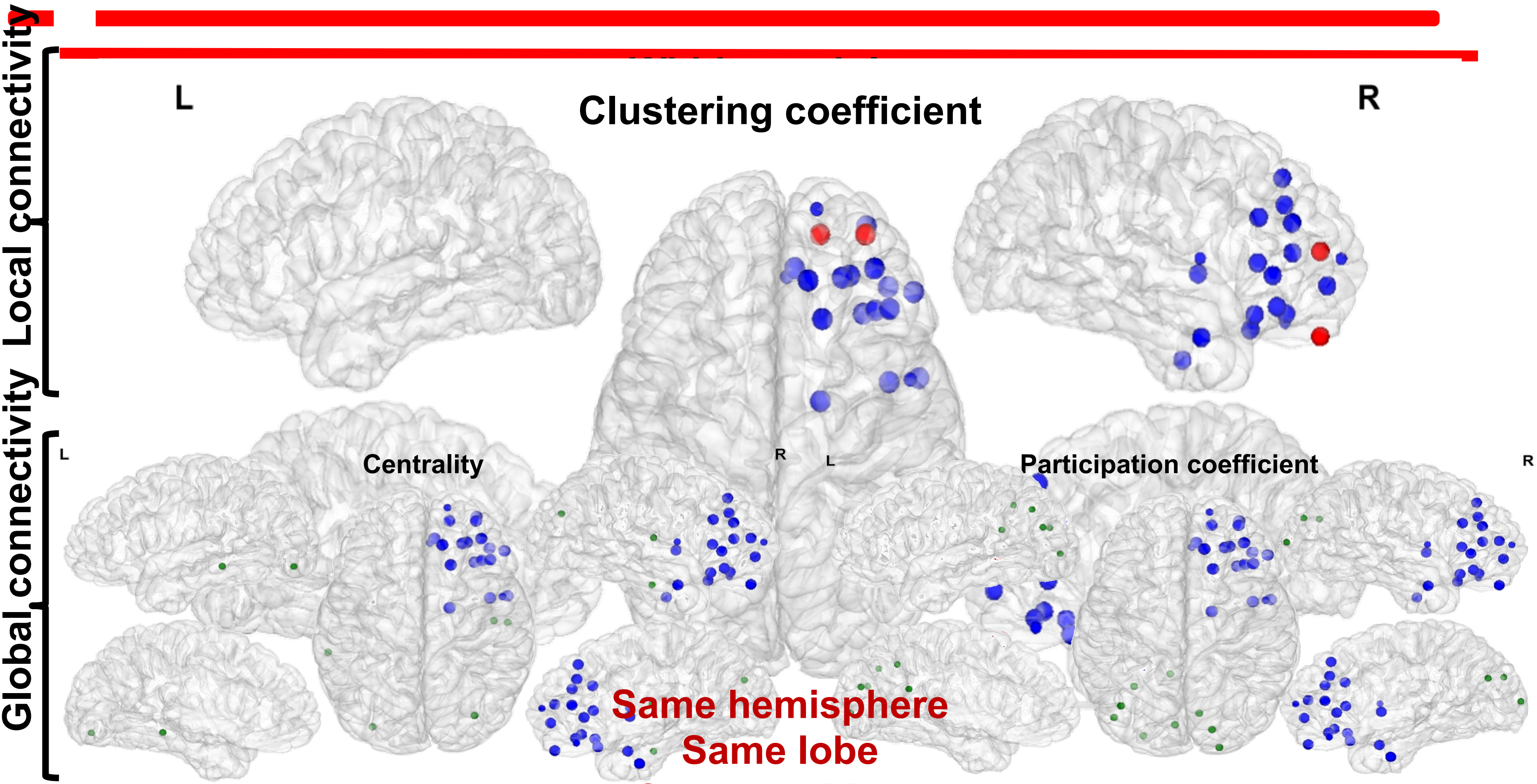
[Nissen , Epilepsia,2016]

Pipeline

Number of subjects	Modality	Task	Acquisition
18 (13M, 5F)	Dense-EEG, SEEG	Resting state	Rennes hospital



Results

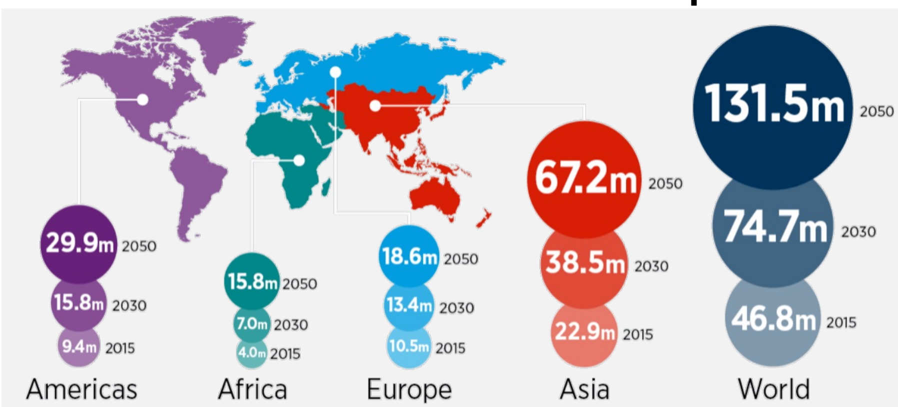


Same hemisphere
Same lobe
Close positions

SEEG
EEG
EEG & SEEG

A4: clinical application: Alzheimer's disease

Alzheimer's disease numbers and prevalence



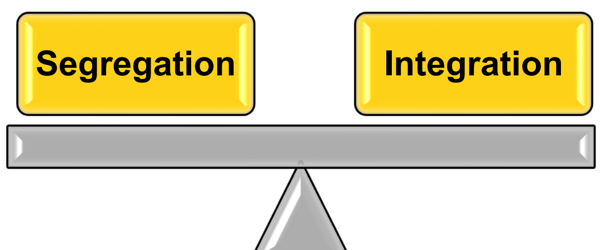
Background - EEG connectivity-based methods:

- Alterations **in the functional connectivity** at theta and alpha2 bands *[Canuet, Plos One, 2011]*

- **Relationship** between the dysfunctional connections and cognitive decline *[Hata, Cl inical Neurophysiology, 2016]*

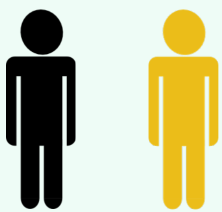
- **Changes in topological** characteristics *[Vecchio, Clinical Neurophysiology, 2016]*

Objective: To what extent the AD modifies the brain network **segregation** (local information processing) and **integration** (global information processing)?



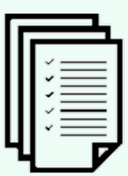
Pipeline

Data acquisition



10 healthy controls

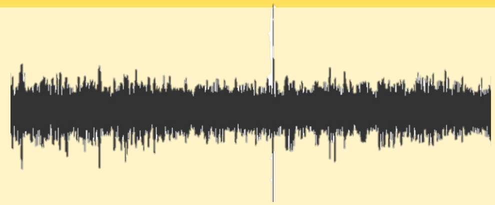
10 AD patients



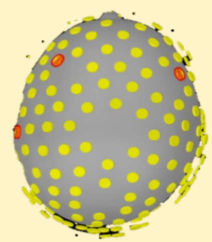
EEG
(32 channels)
Recorded for 10 mins

MMSE test

Pre-processing



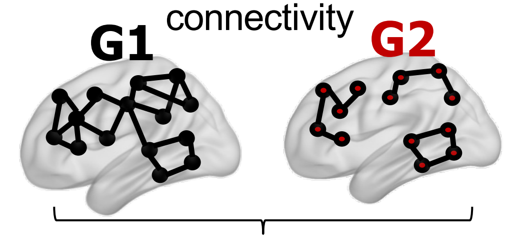
Signal filtering [3 - 45 Hz]



Bad channels interpolation

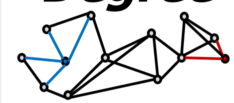
Brain networks

Construct the brain connectivity



Between group analysis

Degree

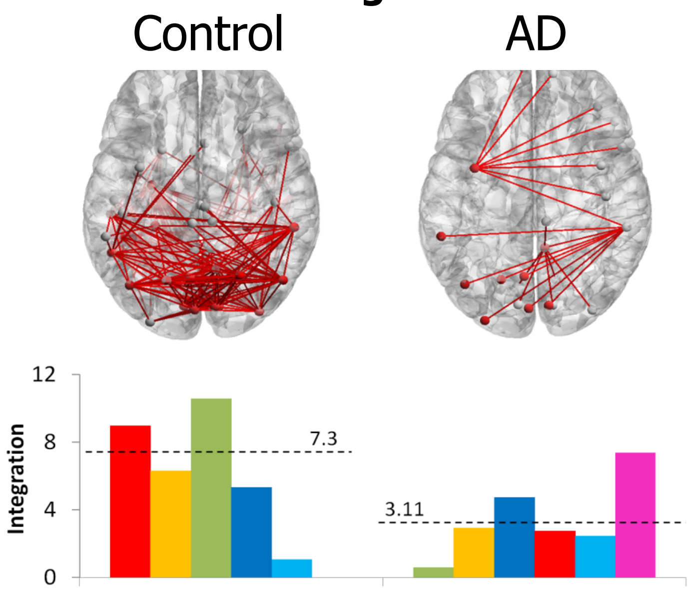


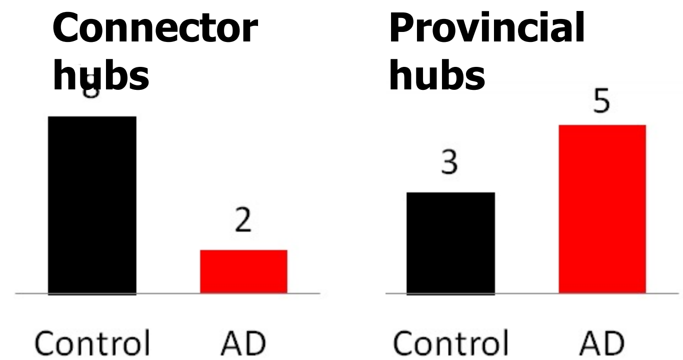
Clustering coefficient

Modularity and hubs

Results

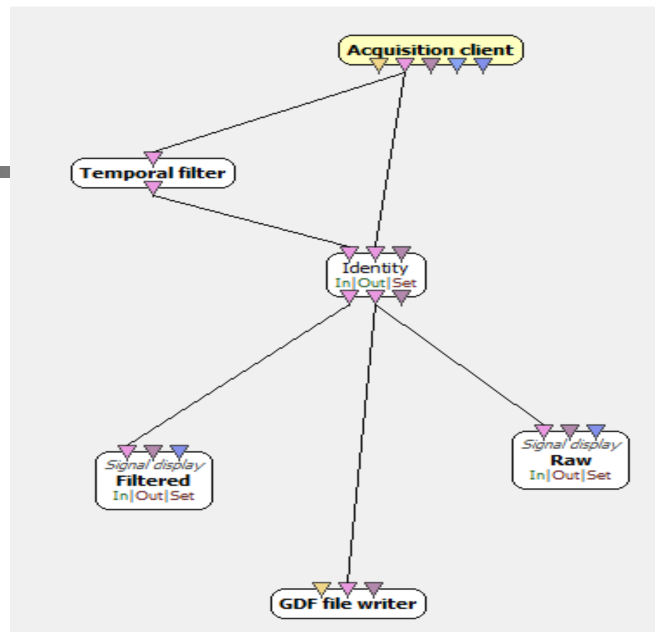
Inter-modular connections (Integration)

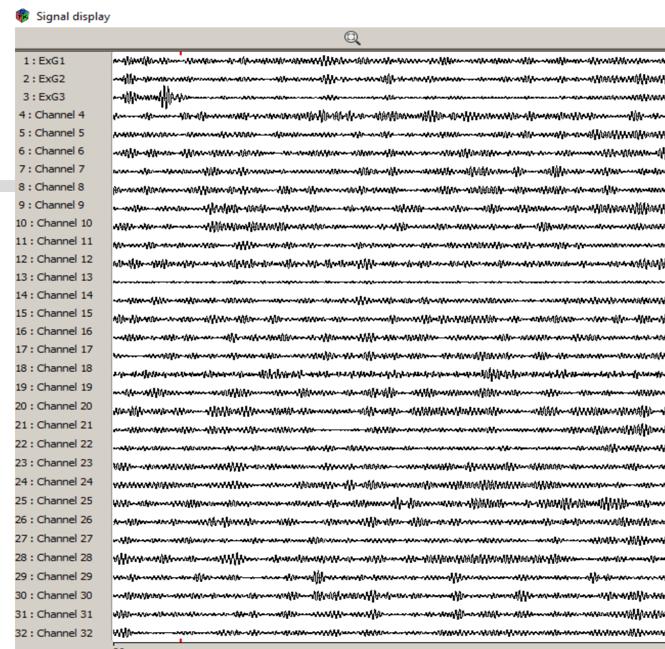




AD networks are characterized by **lower** global information processing and **higher** local information processing.

A5: Major Depression Disease MDD

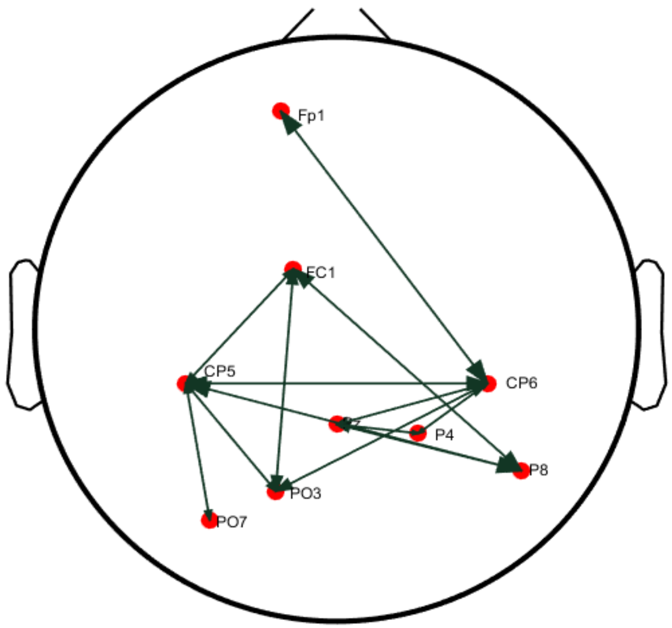




Third clinical application: Major Depression Disease MDD

Control and MDD : Difference

Edge Wise Analysis



Third clinical application: Major Depression Disease MDD

Node Wise Analysis

	Control		MDD	
	mean	standard deviation	mean	standard deviation
global Efficiency	0.4	0.12	0.15	0.06
Betweenness Centrality	32.5	2.34	18.76	1.3

Summary of presentation

Any random signal

- Detection
- Parameters extraction
- Parameters elimination
- Classification model
- Future work with CNN

Any multichannel signal

- Graph related analysis
- For EEG it is a Brain network→CNN?

Merci

Mohamad.khalil@ul.edu.lb