Artificial evolution, fractal analysis and applications

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November 5, 2021

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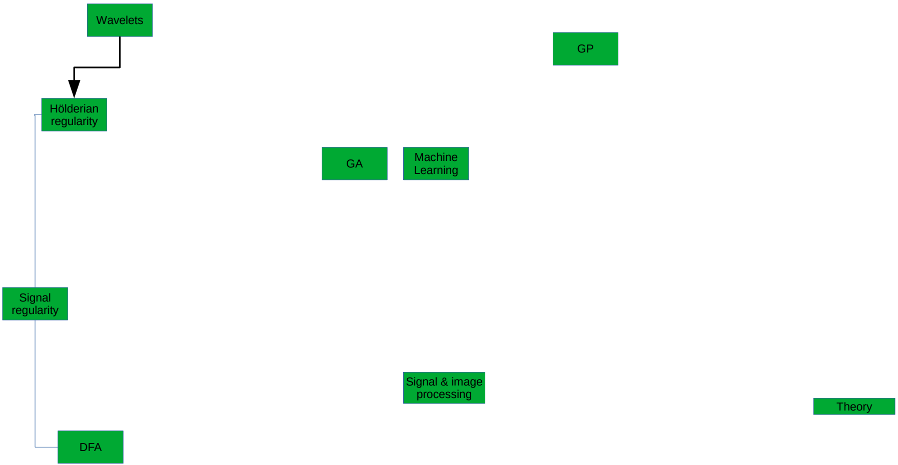
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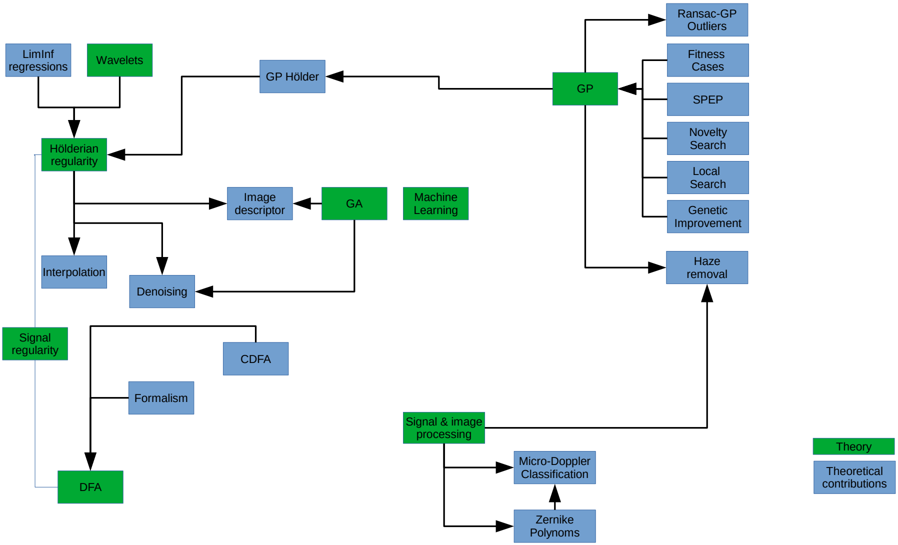
Hölderian regularity
GA
Machine Learning
Signal regularity
Signal & image processing
Theory
DFA



Ransac-GP Outliers
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Wavelets
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Fitness Cases
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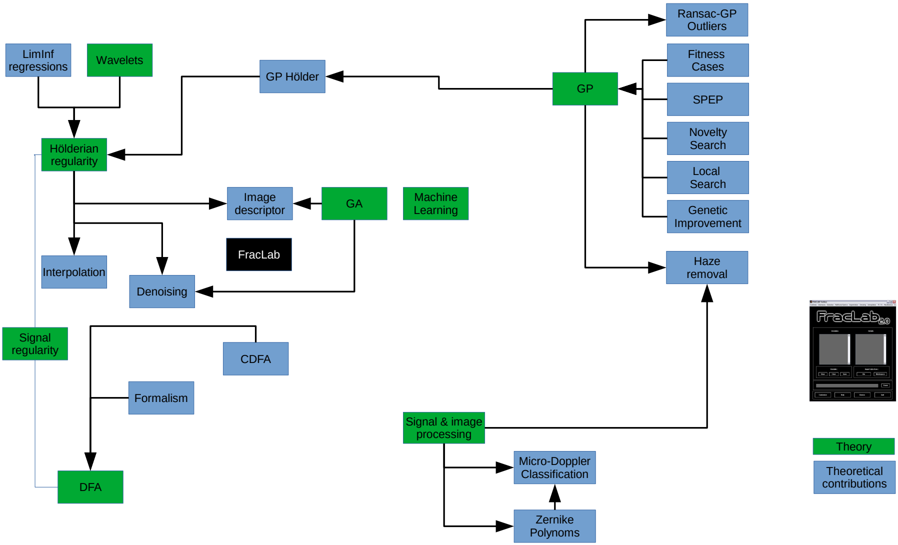
Micro-Doppler Classification
Theoretical contributions
DFA
Zernike Polynoms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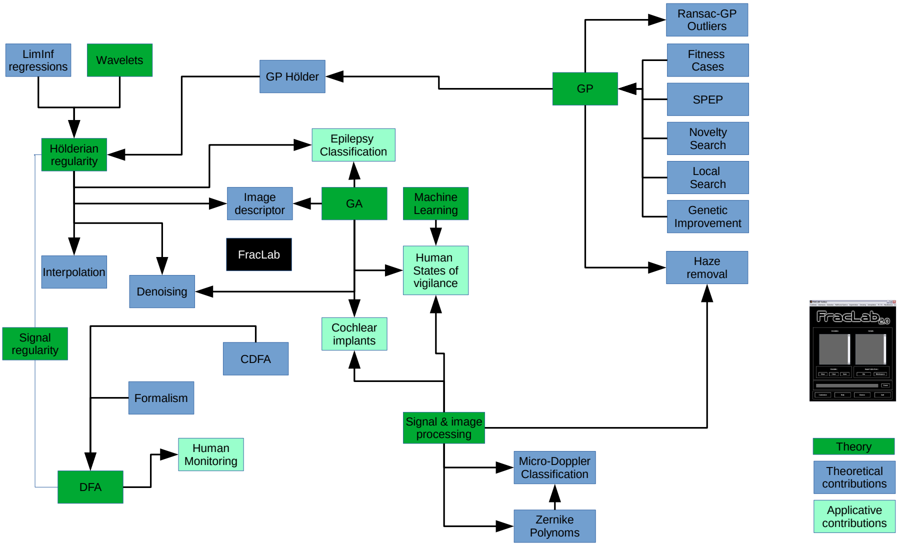

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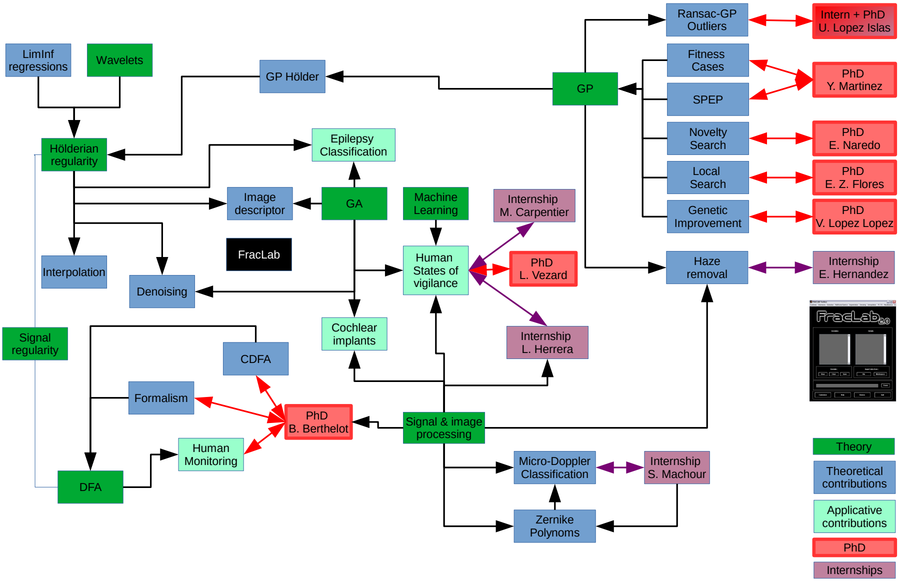

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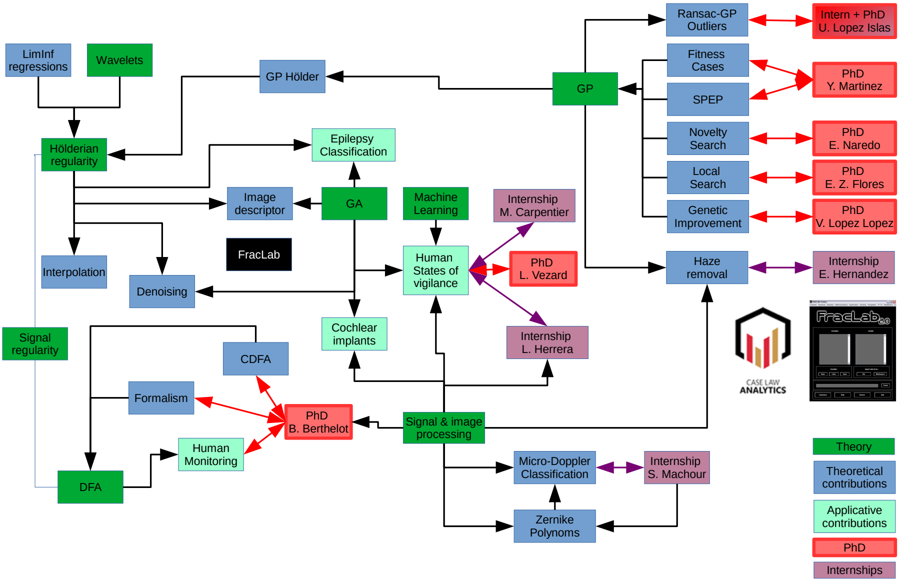

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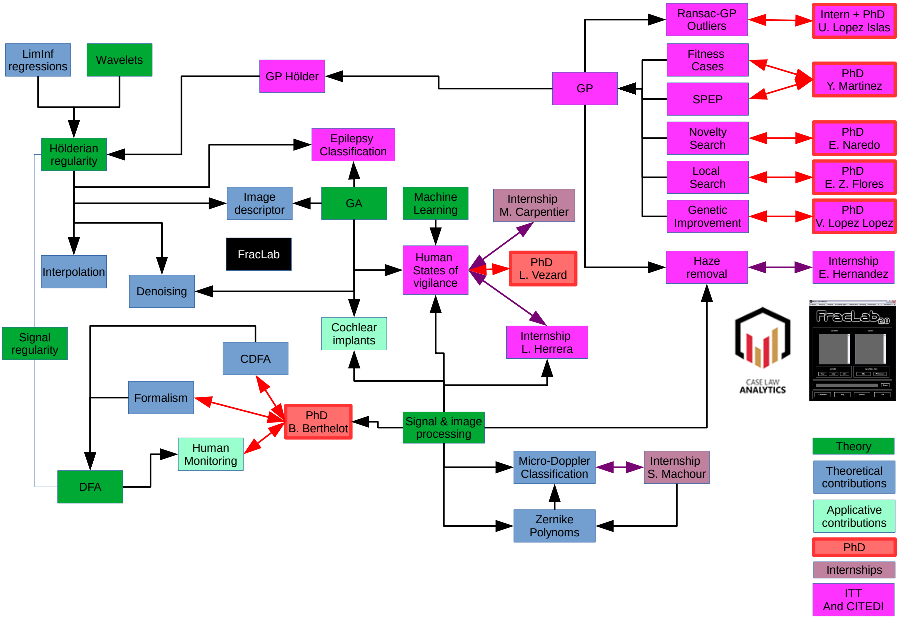

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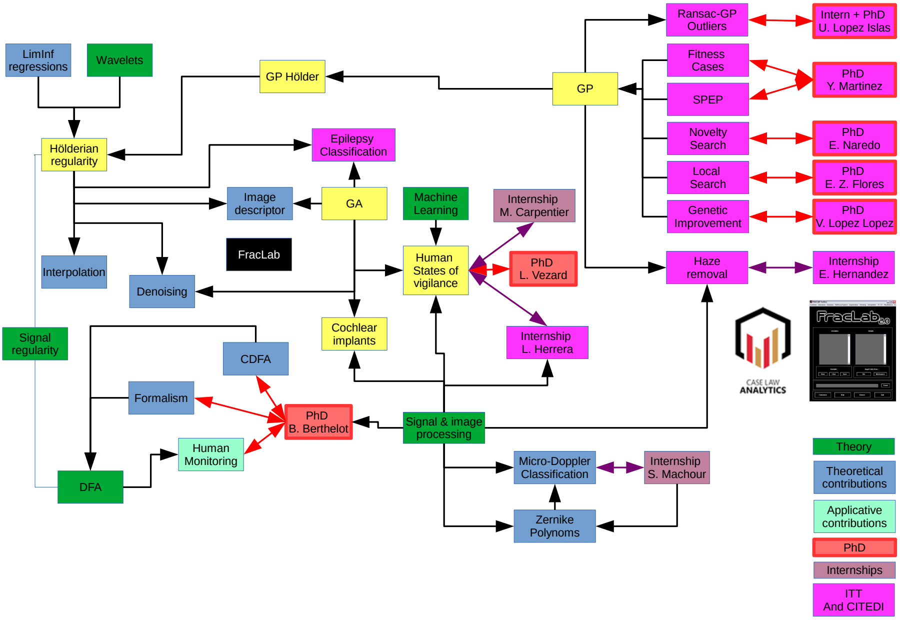
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PART 1: Artificial Evolution

- Definitions

PART 2: Estimation of signal regularity

- Hölderian regularity

PART 3: Applications

- Cochlear implant fitting with evolutionary algorithm
- Evolutionary computation for EEG classification
- Regularity estimation with Genetic Programming

PART 1: Artificial Evolution

Artificial Darwinism

- A set of techniques grouped under a generic term
- Ingredients
- Evolutionary loop
- Example

Genetic Algorithms

- Discrete representation: Genetic Algorithms

Evolution strategies

- Continuous representation: Evolution Strategies

Genetic Programming

- Functional representation: Genetic programming
- Example: Using GP for regression

Artificial Darwinism

Stochastic optimization which uses mechanisms inspired by the biological evolution, such as:

- reproduction,
- mutation,
- selection and
- survival of the strongest individuals

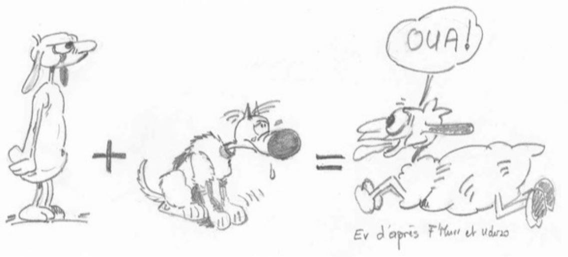
A set of techniques grouped under a generic term

Evolutionary Algorithms	Genetic Algorithms (GA)
	Evolution Strategies (ES)
	Genetic Programming (GP)
	...

Ingredients

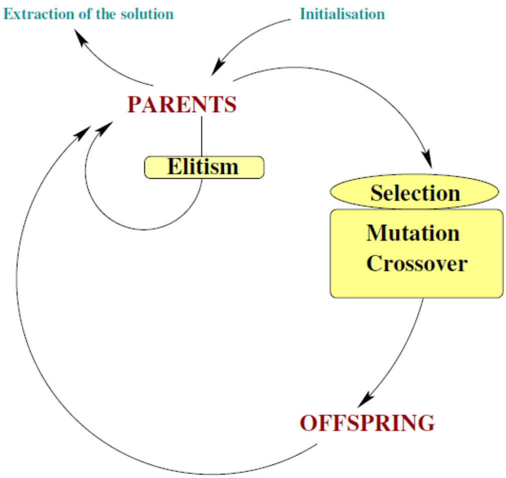
Selection

Population

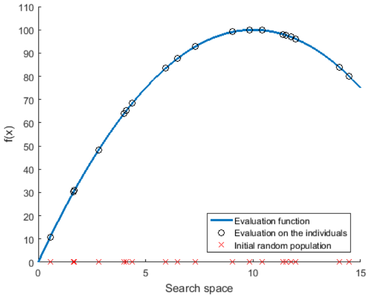


Genetic Operators

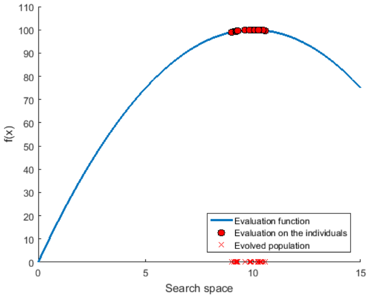
Evolutionary loop



Potential Solutions = Individuals in a population



Initial random population

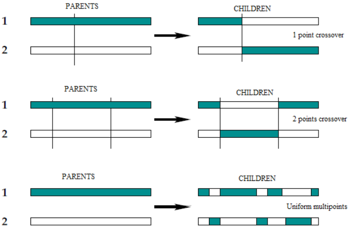


Evolved population

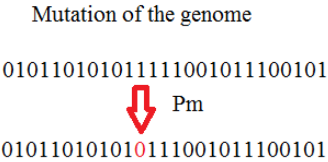
Discrete representation: Genetic Algorithms

Each individual is represented by a binary string.

John H. Holland (1960, 1975), David Goldberg (1989)



Crossover



Mutation

Each individual is a vector in R^n.

Hans-Paul Schwefel (1970)

Barycentric crossover

$\forall i \in \{1, .., n\}, x_i^{children} = \alpha x_i^{father} + (1-\alpha) x_i^{mother}$

α random value in $[-\epsilon, 1+\epsilon]$.

Gaussian mutation

$\forall i \in \{1, .., n\}, x_i^{children} = x_i^{children} + N(0, \sigma)$

Two parameters P_m and σ.

Continuous representation: Evolution Strategies

Each individual is a vector in R^n.

Hans-Paul Schwefel (1970)

Barycentric crossover

$\forall i \in \{1, .., n\}, x_i^{children} = \alpha x_i^{father} + (1-\alpha) x_i^{mother}$

α random value in $[-\epsilon, 1+\epsilon]$.

Gaussian mutation

$\forall i \in \{1, .., n\}, x_i^{children} = x_i^{children} + N(0, \sigma)$

Two parameters P_m and σ.

Demo

Artificial Darwinism

A set of techniques grouped under a generic term

Ingredients

Evolutionary loop

Example

Genetic Algorithms

Discrete representation: Genetic Algorithms

Evolution strategies

Continuous representation: Evolution Strategies

Genetic Programming

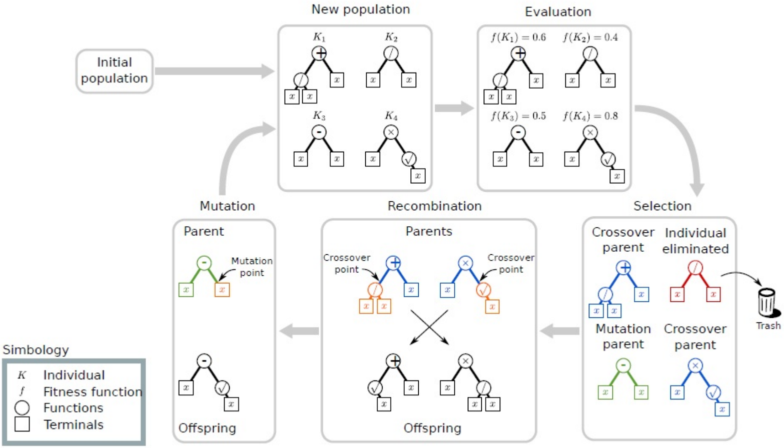
Functional representation: Genetic programming

Example: Using GP for regression

Functional representation: Genetic programming

Definition

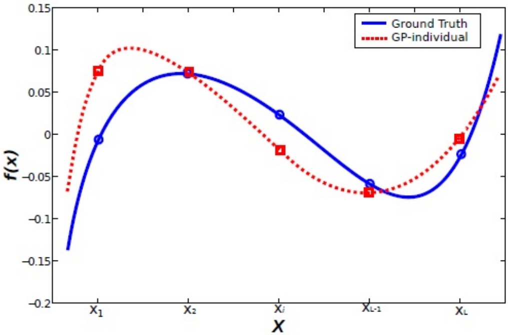
Genetic programming (GP) is an evolutionary computation (EC) technique that automatically solves problems without requiring the user to know or specify the form or structure of the solution in advance [Koza, 1992].



Symbolic Regression

Given a set of input data X and a set of desired outputs Y, find a function f such that:
$f(X_i) = Y_i \quad \forall i \in \{1, N\}$

	X	Y
1	0.2	0.00
2	0.4	0.06
..	...	...
N	0.9	-0.03



PART 2: Estimation of signal regularity

Hölderian regularity

Definitions

Signal Regularity

Estimation

Oscillations

Regression of wavelet coefficients

Application

Estimation on synthetic signal

Signal Regularity

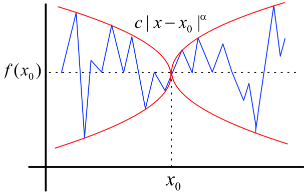
The Hölder pointwise exponent is the most common tool used to measure the regularity of a signal at a given point.

Definition

Let f be a function from $\mathbb{R}$ to $\mathbb{R}$, $s > 0$, $s \in \mathbb{R} \backslash \mathbb{N}$ and $x_0 \in \mathbb{R}$. Then $f \in C^s(x_0)$ if and only if there is a real $\eta > 0$, a polynomial P of degree smaller than s and a constant c such that

$$\forall x \in B(x_0, \eta), \quad |f(x) - P(x - x_0)| \leq c|x - x_0|^s$$

By definition, the pointwise exponent of f at x_0, noted $\alpha_p(x_0)$ is the supremum of s such as $f \in C^s(x_0)$.



Hölderian envelope of a signal at the point x_0.

Definitions
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A function $f(t)$ is Hölderian of exponent $\alpha \in [0.1[$ at t if there is a constant c such that for any t' in a neighbourhood of t,

$$|f(t) - f(t')| \leq c|t - t'|^{\alpha}$$

In terms of oscillations, this condition can be written:
A function $f(t)$ is Hölderian of exponent α at t, with $0 < \alpha < 1$ if there is a constant c such that for any τ,

$$osc_{\tau}(t) \leq c\tau^{\alpha}$$

with

$$osc_{\tau}(t) = \sup_{|t-t'| \leq \tau} f(t') - \inf_{|t-t'| \leq \tau} f(t') = \sup_{t',t'' \in [t-\tau, t+\tau]} |f(t') - f(t'')|$$

Then the regularity estimator will be constructed at each point as **the slope of the regression of the logarithm of the oscillation as a function of the size of the ball in which the oscillation is calculated.**

Theorem

(S. Jaffard)

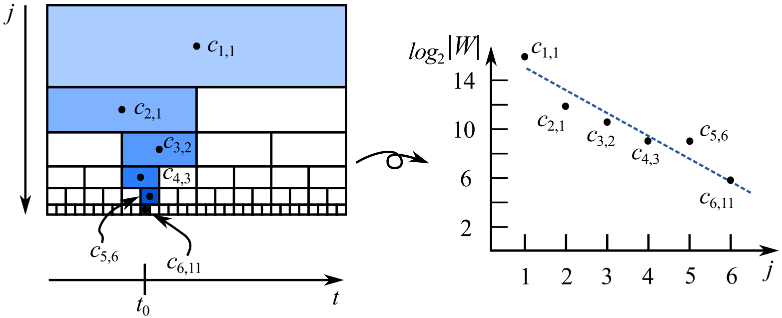
$$|c_{j,k}| \leq \; c2^{-j(\alpha+\frac{1}{2})}(1+|2^j t_0 - k|)^{\alpha} \quad \forall j,k \in \mathbb{Z}^2$$

Conversely ;

$$If \quad \forall j,k \in \mathbb{Z}^2 \;\; one \;\; has \;\; |c_{j,k}| \leq \; c2^{-j(\alpha+\frac{1}{2})}(1+|2^j t_0 - k|)^{\alpha'}$$

for a $\alpha' < \alpha$ then, the Hölder exponent of f in t_0 is α.

Regression of wavelet coefficients



Regression calculated over a point of the signal. Left image shows a dyadic wavelet decomposition, and the right image display the actual regression calculated over the point t_0, where each dot corresponds to each log_2 of the wavelet coefficient magnitude located above t_0.

Definition

At each point t_0 of the signal, the regularity is estimated by:

$$\alpha(n, t_0) = -p - \frac{1}{2}$$

with p the slope of the least square linear regression of the logarithms of the wavelet coefficients "above" this point as a function of the scales.

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with p the slope of the least square linear regression of the logarithms of the wavelet coefficients "above" this point as a function of the scales.

Theorem

At each point t_0 of the signal decomposed on n scales, we estimate the regularity by the following formula:

$$\boxed{\alpha(n, t_0) = -\frac{1}{2} - K_n \sum_{j=1}^{n} s_j \log_2 |c_{j,k}|}$$

with $K_n = \frac{12}{n(n-1)(n+1)}$ et $s_j = j - \frac{n+1}{2}$. The $c_{j,k}$ are the wavelet coefficients above t_0.

We note k but the value is $\lfloor \frac{t_0+1}{2^{n-j+1}} \rfloor$.

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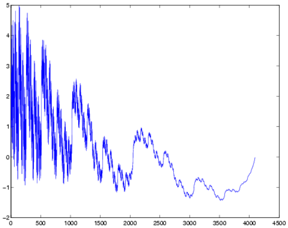
Estimation on synthetic signal



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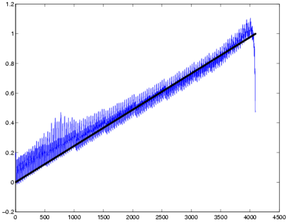

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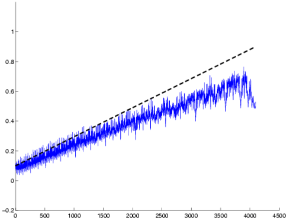

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PART 3: Applications

Cochlear implant fitting with evolutionary algorithm

Introduction

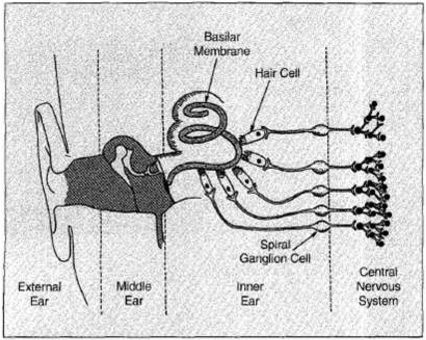
This project is a collaboration between mathematicians, computer scientists and medical practitioners.

The aim is to

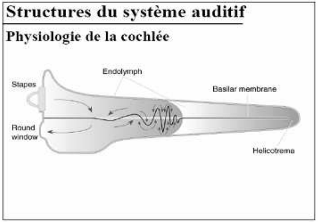
- Simplify the process of cochlear implants fitting (after a deaf patient has been surgically implanted).
- Make the implant more adaptable to the environment.

Transmission of sound to the cochlea

The **external ear** receives the wave of acoustic pressure.

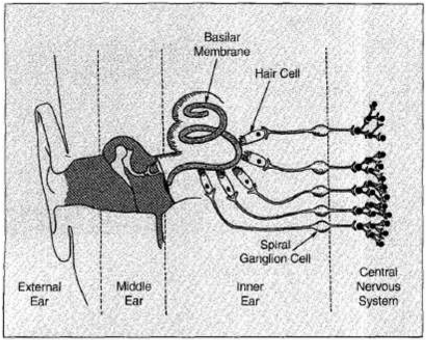


▲ 2. A diagram (not to scale) of the human ear (reprinted with permission from [85]).



Transmission of sound to the cochlea

The **external ear** receives the wave of acoustic pressure. The **middle ear** transforms the acoustic wave onto a mechanical vibration.



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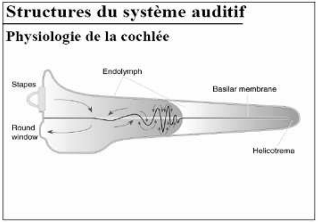
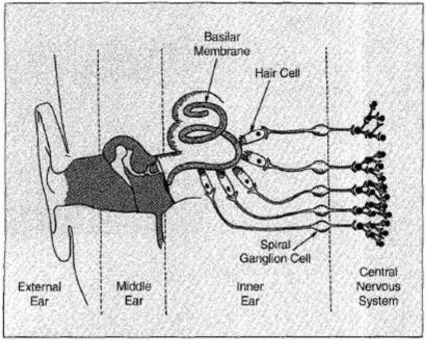


Transmission of sound to the cochlea

The **external ear** receives the wave of acoustic pressure. The **middle ear** transforms the acoustic wave onto a mechanical vibration.This mechanical vibration moves the oval window (which is connected to the middle ear) and the fluid contained in the **cochlea** is set into motion.



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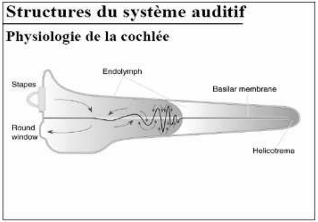
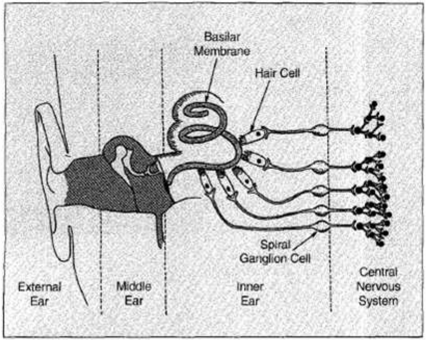


Transmission of sound to the cochlea

The **external ear** receives the wave of acoustic pressure. The **middle ear** transforms the acoustic wave onto a mechanical vibration.This mechanical vibration moves the oval window (which is connected to the middle ear) and the fluid contained in the **cochlea** is set into motion. The variations of pressure in the fluid generates a movement of the basilar membrane.



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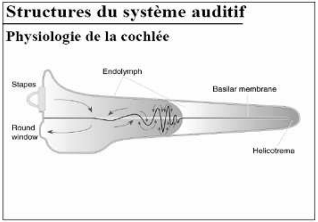
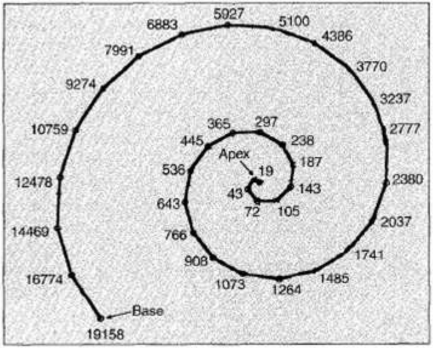


Coding of the cochlea

The basilar membrane is a filter.



▲ 3. *Diagram of the basilar membrane showing the base and the apex. The position of maximum displacement in response to sinusoids of different frequency (in Hz) is indicated.*

Coding of the auditive nerve

Frequencies coding

- The movement of the basilar membrane encodes information of the frequency in the acoustic signal.

Coding of the auditive nerve

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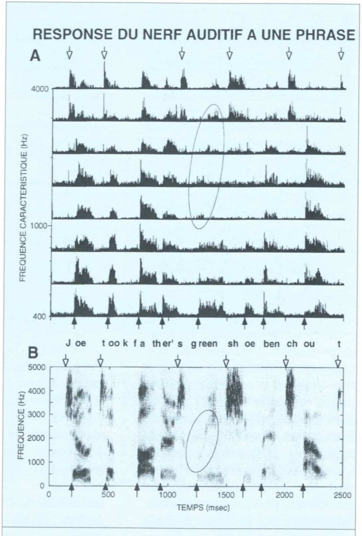
- The sensory cells which are on the basilar membrane oscillate with the membrane.

Coding of the auditive nerve

Frequencies coding

- The movement of the basilar membrane encodes information of the frequency in the acoustic signal.
- The sensory cells which are on the basilar membrane oscillate with the membrane.
- The movement of the sensory cells liberates an electro-chemical substance which leads to discharge the neurons. Then these electrical impulses correspond to an excitation at a given position on the basilar membrane.

Coding of the auditive nerve



Example : Transmission to the brain.
The acoustic information is conveyed to the brain by electric impulses.

Audition

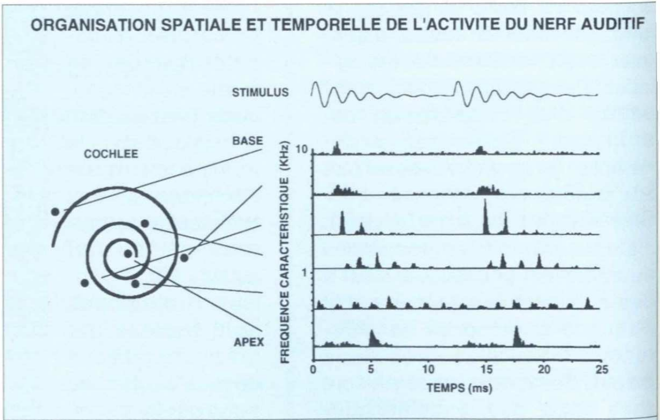


Figure 4. Réponse du nerf auditif à une voyelle simplifiée

Temporal and frequential informations

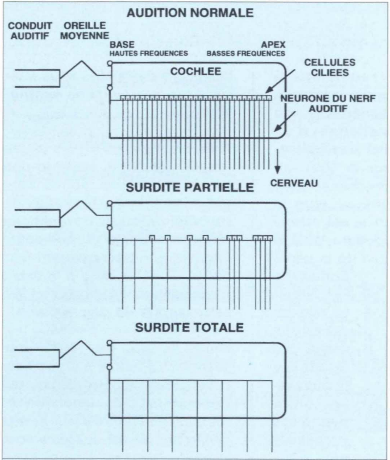


Fig 10. Schéma d'oreille normale et sourde

If the sensory cells are damaged, the auditive system cannot transform the acoustic pressure wave to neuronal impulses.

Cochlear implant

Goal :
To directly stimulate the neurons of the auditive nerve by inserting electrodes in the cochlea.

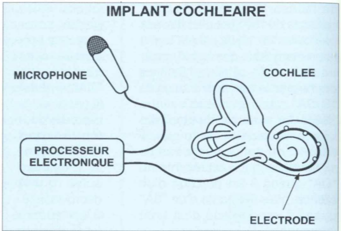


Fig 11. Un implant cochléaire

Necessary conditions

Cochlear implants allow to deaf people to hear again if

- The auditive nerve is not damaged.

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In 2006, 70000 people were implanted. In 2019, 500000.

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In 2006, 70000 people were implanted. In 2019, 500000.

- Most of the implantations are successful

Necessary conditions

Cochlear implants allow to deaf people to hear again if

- The auditive nerve is not damaged.

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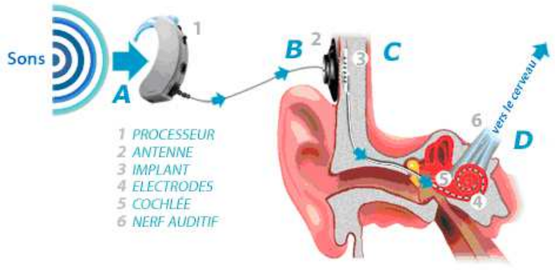
- But some people still encounter difficulties and they prefer to turn off the implant.

This population motivated our work



- A The sound is captured by the microphone, digitalized and processed.
- B The signal is sent to the implant through the skin.
- C The implant gets informations from the outer processor and distributes these informations to the electrodes in the cochlea. Each electrode corresponds to a frequency band of the sound.
- D The nerve endings transmit the electric impulses to the brain and they are interpreted as sounds.

Complexity

Complexity

- Which frequency for each electrode ?

Complexity

- Which frequency for each electrode ?
- Which intensity range for each electrode ?

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Difficulties

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- ...

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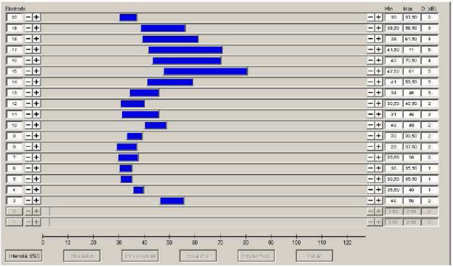
Finding the answer to these questions is a **difficult optimization problem**. This difficulty is not only related to the **dimension of the search space** but also to other causes: **Environment**, **Tiredness**, **brain adaptation**...

Fitting of the electrodes

- Determinate the functional electrodes.



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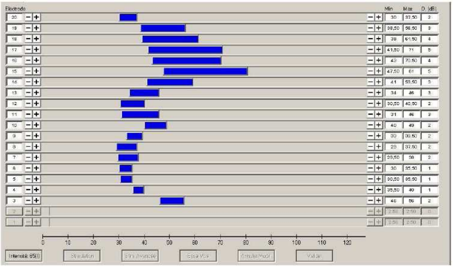

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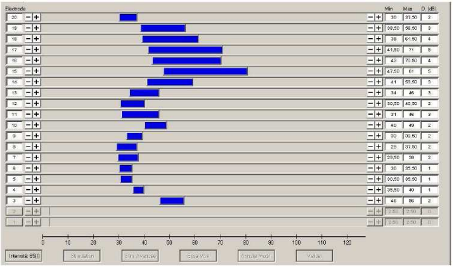

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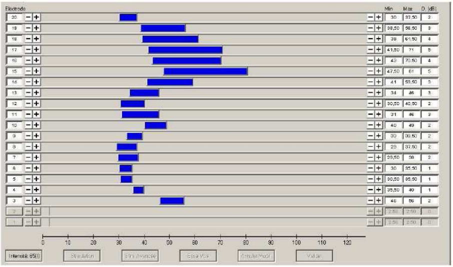

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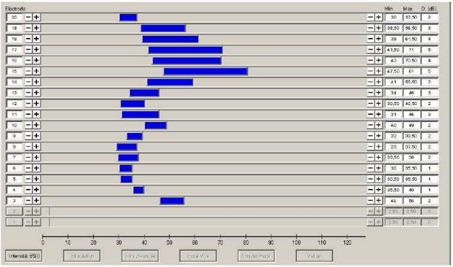
The results are often good but the complete process can take years for some patients.



Contribution: Interactive Evolutionary Algorithm

Stochastic optimization which uses mechanisms inspired by the biological evolution, such as reproduction, mutation, selection and survival of the strongest individuals.

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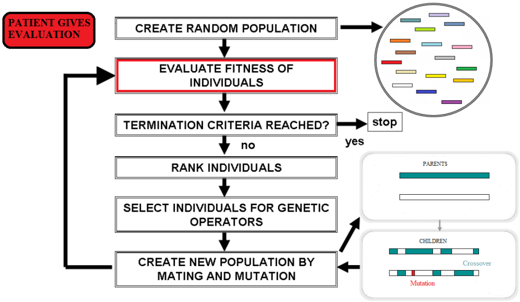

Genotype of an individual

NbOfElectrode	Min Intensity	Max Intensity	Min Frequency	Max Frequency
22	6.45	7.94	506	689
21	9.25	9.43	676	729
...	...	...	...	...
1	7.41	8	6765	7137

Automatic fitting method

Algorithm

- Manual fitting by an expert (for this patient).

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- **Evaluation** of the 3 children by the patient: $NE1$, $NE2$, $NE3$.
- **Generation** of the new population among $P1$, $P2$, $P3$, $P4$, $E1$, $E2$, $E3$. Random selection of 2 individuals, selection of the best evaluation. A new population is obtained: $F1$, $F2$, $F3$ and $F4$.

On mobile device

Audio test

VCV test

The Vowel-Consonant-Vowel (VCV) test is used in clinics to evaluate how well a listener can recognize consonants under different conditions. The stimuli consist of audio recordings of an adult speaking VCV nonsense words. The vowel context is /a/-/a/.

1	2	3	4

ASSE test

- Fifteen speech sounds that can be selected
- Selected speech sound presented 3 times
- Scoring is binary
  - Correct: sound heard
  - False: sound not heard

Results

Patient	ASSE manual	ASSE auto	VCV manual	VCV auto
S1	4/7	7/7	20%	27%
S2	5/7	6/7	35%	37%
S3	5/7	6/7	45%	52%
S4	4/7	7/7	20%	27%

- **This method allows to explore a large number of various possible fitting.**
- **First evolutionary algorithm on mobile device.**
- **Fast and easy to use.**

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- Determinate the sound environment of the patient.
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<u>Result</u> : A "smart" cochlear implant.

Wavelets and energy

A discrete wavelet transform is used in order to estimate the energy of the signal.

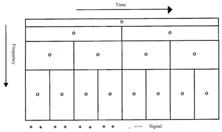
Wavelet coefficient

$C_{j,k}$ denotes the wavelet coefficient at scale j and time k.

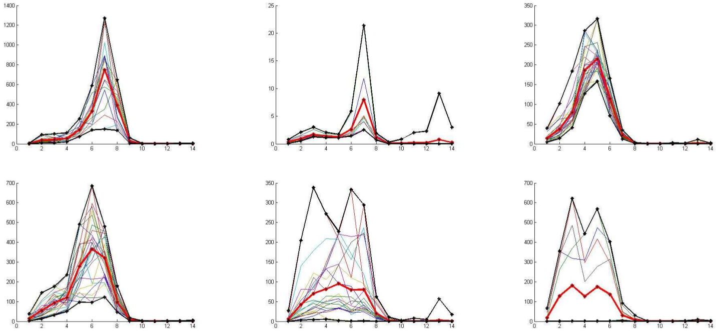
$$C_{j,k} = 2^{-\frac{j}{2}} \int_{-\infty}^{\infty} f(t)\psi(2^{-j}t - k)dt$$

Energy at scale j

$$E_j^2 = \sum_{k=1}^{2^{j-1}} [C_{j,k}]^2$$



Characterization of sound environments



Abscissa: frequency, Ordinate: Energy. Left up: "Car-radio" environment. middle up: "Birds" environment. Right up: "Supermarket" environment. Left down : "road corner" environment. Middle down: "School-yard" environment. Right down: "Lawn mower" environment. Set of values of the energy for each frequency (fine lines), envelope and mean criterion (thick lines).

Classification of sound environment

Family	Learning set	Test set	matching family	Confidence
Car-radio	16	8	Car-radio	100%
Cross-roads	24	13	Crossroads	84 %
Birds	12	7	Birds	100%
School-yard	22	11	School-yard	100%
Supermarket	35	15	Supermarket	100%
Lawn-mower	10	5	Lawn-mower	80%

Conclusions

Exploitation of the results

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- Simplify the process of fitting of cochlear implants.
- Adapt the fitting to the sound environment.
- The programming on pocket PC simplify the use of the developed softwares.
- This work can also be useful for people which do not encounter difficulties with their implant.

Evolutionary computation for EEG classification

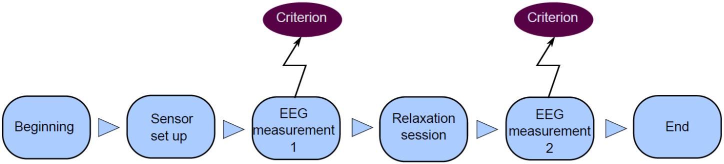
This work is related to the PhD thesis of Laurent Vezard and developed in the context of the PSI Region Project and the ACOBSEC European project. A slightly different version has been published in a book chapter. Eduardo Miranda; Julien Castet; Benjamin Knapp. Guide to Brain-Computer Music Interfacing, Springer, 2014. Work carried out with Laurent Vézard, Marie Chavent, Frédérique Faïta-Aïnseba.

Goal

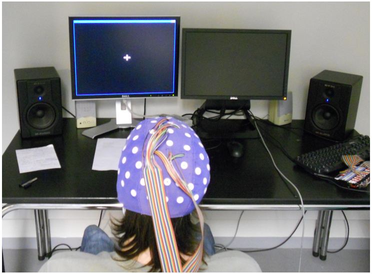
- **Characterize the state of alertness of a person from his electroencephalogram (EEG).**

Acquisition Protocole

- First EEG recording: subject in a normal state of alertness: "normal"
- Second EEG recording: subject in a state of low vigilance: "relax"



Acquisition Protocole



- EEG headset installation time: 45 minuts.
- Subject with open eyes.
- Sampling frequency: 256Hz.
- Recording time: 3 minuts (46000 sample points).

Campaigns:

- 58 electrodes renumbered from 1 to 58
- Subjects under 35, right-handed and non-smoker
- 58 subjects $\Rightarrow$ 16 preserved

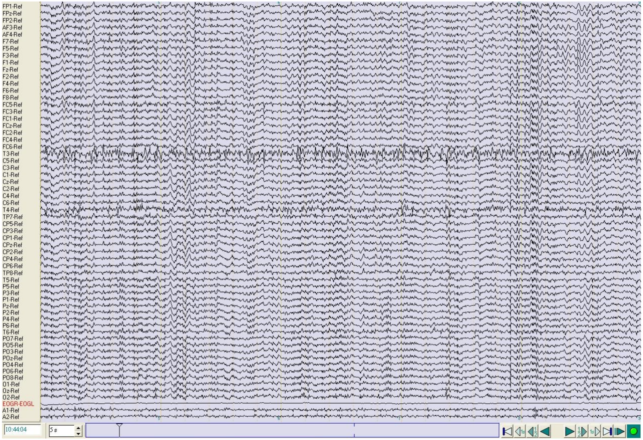
Relaxation session

20 minutes with a recorded voice offering 3 exercises:

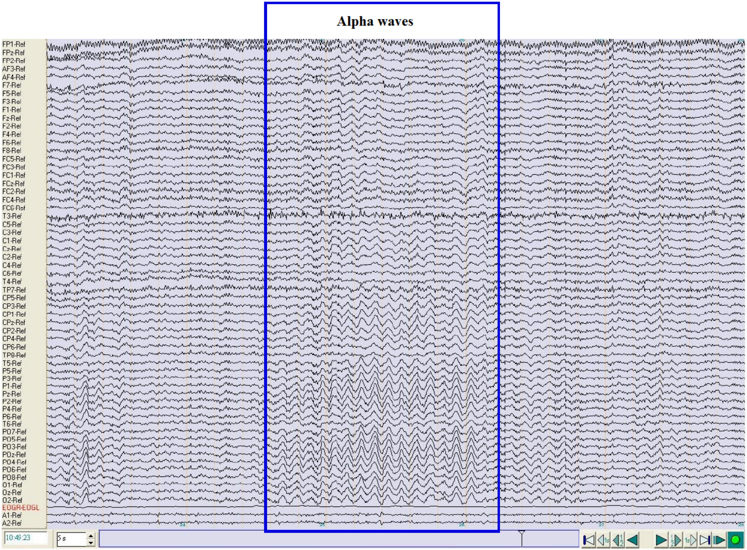
- Autogenic training [Schultz1958]: repetition of sentences, self-hypnosis.
- Progressive muscle relaxation [Jacobson1974].
- Mental visualization (familiar places, smells, noises).

Acquisition Protocole

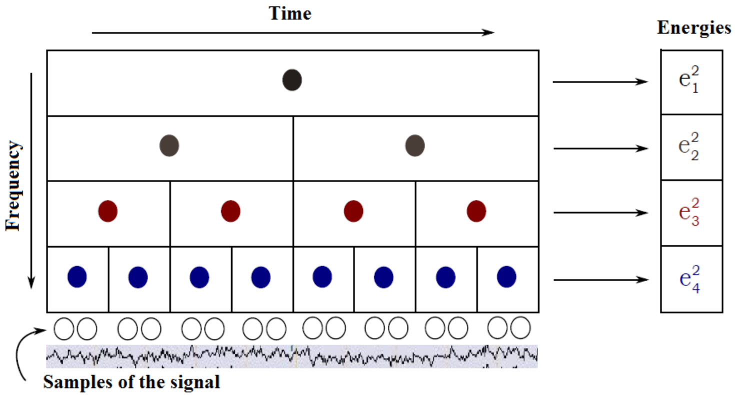
3 minutes of EEG recording before relaxation.



3 minutes of EEG recording after relaxation.

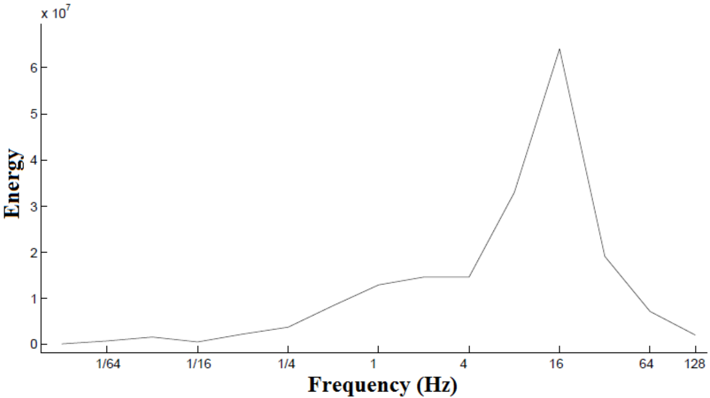


The dyadic grid gives a spatio-frequential representation of the discrete dyadic wavelet decomposition



Slope Criterion

- Alpha: $8 - 12Hz$.
- Waves characteristics of a relaxed state.



Linear regression between 4 and $16Hz$.

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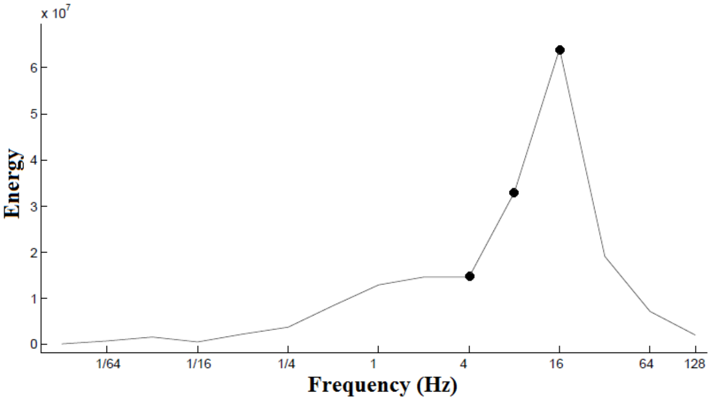

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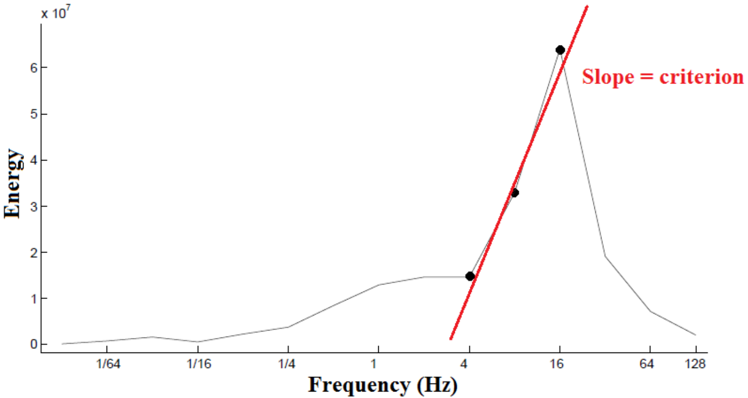

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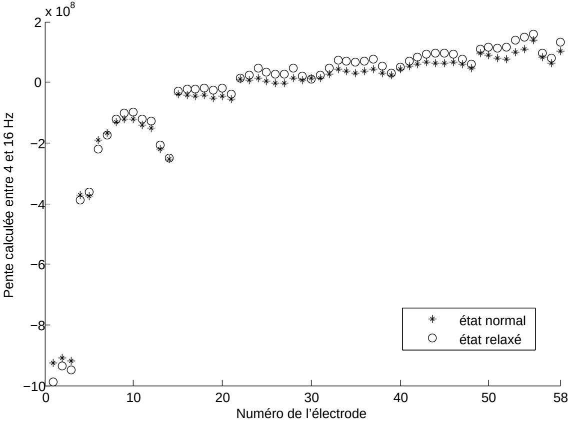

Slope criterion, sum on subjects for each electrode

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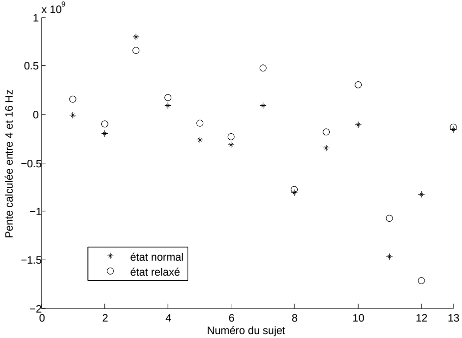


Slope criterion, sum on electrodes for each subjects

⇒ Very strong inter-subject variability

⇒ This criterion that does not allow to build a powerful classifier for different subjects.

Classification: Usual methods

	K nearest neighbors	Binary decision trees	Random forests	Discriminant PLS	Sparse Discriminant PLS
Mean	37.28	33.98	32.03	40.63	36.25
Standard Deviation	10.47	5.15	6.46	8.55	7.96

Mean and standard deviations of Correct Classification Rates for different classification methods applied on slope criterion.

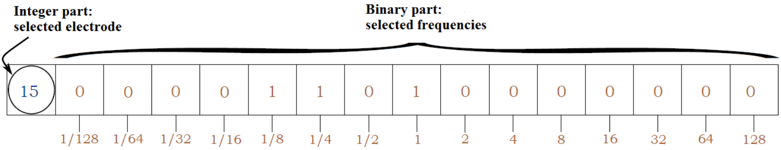
This approach is not efficient

Our contribution: Design a relevant **evolutionary algorithm** to solve this task of classification.

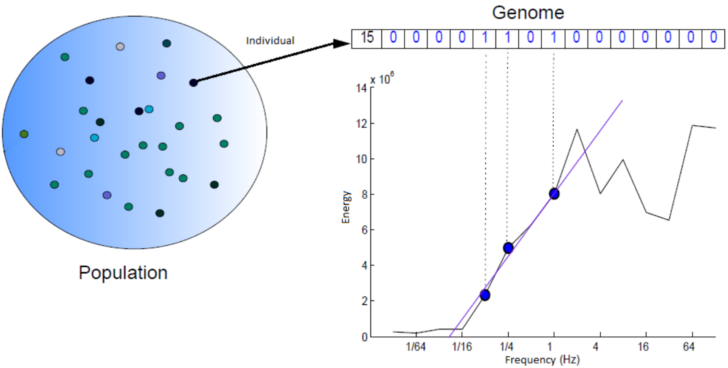
$\Rightarrow$ **Find the relevant electrodes.**

$\Rightarrow$ **Find the relevant frequencies for the calculation of the slope criterion.**

Example of a genome in the evolutionary algorithm



Relationship between the genome and the calculation of the slope criterion



Average correct classification rate

Evaluation Method	CCR	
	Mean	Standard deviation
CART	86.68	1.87
SVC	83.49	2.37

Average and standard deviations of the correct classification rates obtained for the 100 runs of the evolutionary algorithm and for two methods of evaluation.

Best genome

Evaluation method	BEST genome		
	Selected electrode	Selected frequency (Hz)	Correct classification rates
CART	F4	$1/8$, $1/4$, 2, 4 et 64	$89,33\%$
SVC	F2	$1/32$, $1/16$, 2, 4, 8, 64 et 128	$89,33\%$

Table summarizing the two best genomes found during the 100 runs of the genetic algorithm with two methods of evaluation.

Regularity estimation with Genetic Programming

Joint work with Leonardo Trujillo, Gustavo Olague and Jacques Levy-Vehel. *Evolving estimators of the pointwise Hölder exponent with Genetic Programming. Information Sciences 209 (Nov. 2012), 61-79*.

Hölderian Regularity

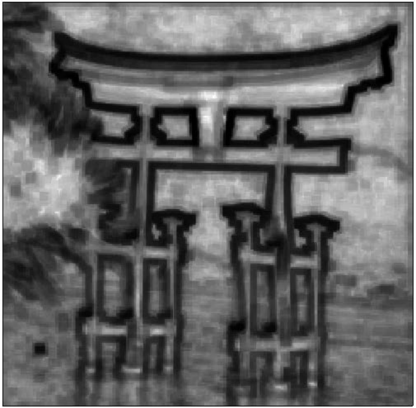
Contribution

Training set

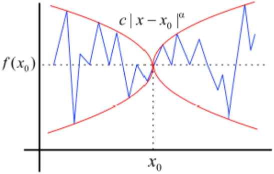
Results

Hölder exponent

Mathematical tool that measures the regularity of a signal around each point.



General motivation



$$\alpha_p(x_0) = \liminf_{h \to 0} \frac{\log |f(x_0+h) - f(x_0)|}{\log |h|}$$

Hölderian envelope of signal f at point x_0

- For real-world signals the Hölder exponent must be **estimated** for each point.

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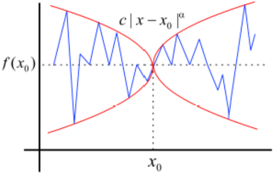

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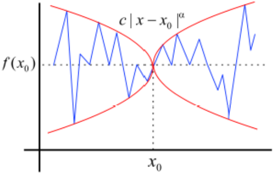
Hölderian envelope of signal f at point x_0

- For real-world signals the Hölder exponent must be **estimated** for each point.
- Several estimation methods exist, but most methods are **slow** or **highly parameterized**;

General motivation



Hölderian envelope of signal f at point x_0

$$\alpha_p(x_0) = \liminf_{h \to 0} \frac{\log |f(x_0 + h) - f(x_0)|}{\log |h|}$$

- For real-world signals the Hölder exponent must be **estimated** for each point.
- Several estimation methods exist, but most methods are **slow** or **highly parameterized**;
- **Therefore there use is not common** (particularly in applications where speed can be of importance)

Hölderian Regularity

Contribution

Training set

Results

Contribution

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Awards

- Best Paper Award in the track Genetic Programming, GECCO 2010, Portland, Oregon.
- Humies Award Finalist, GECCO 2013, Amsterdam, The Netherland.

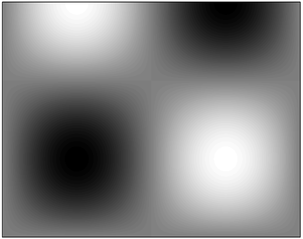
We generate three groups of images with **FracLab**, using three different functions that take as input the point coordinates (x, y) of an image and provide as output the desired regularity; these functions are:

1. a *Polynomial* $p_1(x, y) = 0.1 + 0.8xy$;
2. a *Sine* $p_2(x, y) = 0.5 + 0.2(sin(2\pi x))(cos(\frac{3}{2}\pi y))$;
3. an *Exponential* $p_3(x, y) = 0.3 + \frac{0.3}{1+e^{-100(x-0.7)}}$.

These functions provide the prescribed regularity needed to build the synthetic images used for training and testing of our evolved operators.

Training set

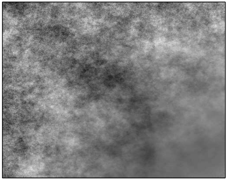
(a) Polynomial p_1



(b) Sine p_2

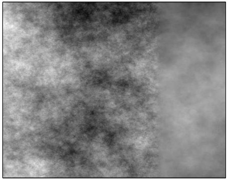
(c) Exponential p_3

Training set

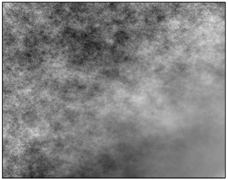


(a) Polynomial

(b) Sine

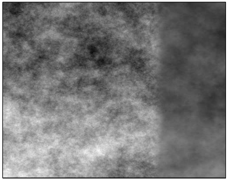


(c) Exponential



(d) Polynomial

(e) Sine



(f) Exponential

These images have a prescribed regularity given by functions p_1 (Polynomial), p_2 (Sine) and p_3 (Exponential).

Hölderian Regularity

Contribution

Training set

Results

Results: Real Images

Original Image

Traditional Method

GP-Estimator

GP-Estimator