# Artificial evolution, fractal analysis and applications

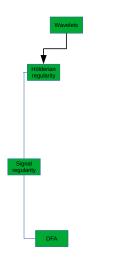
Pierrick Legrand November 5, 2021

Inria, ASTRAL team Institute of Mathematics of Bordeaux University of Bordeaux, France



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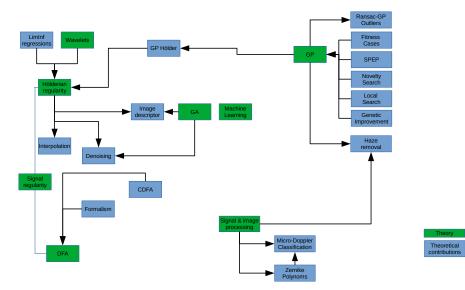


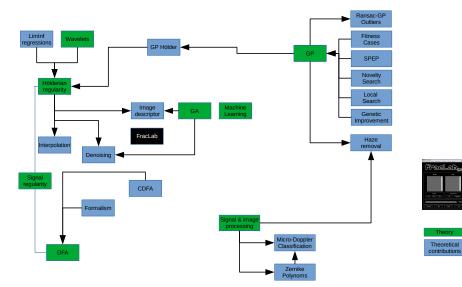


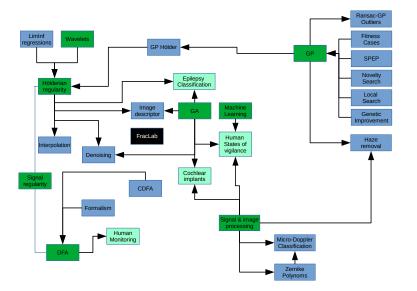




Theory

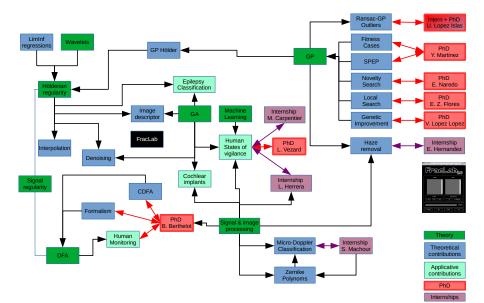


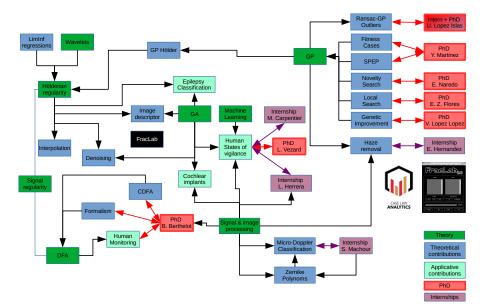


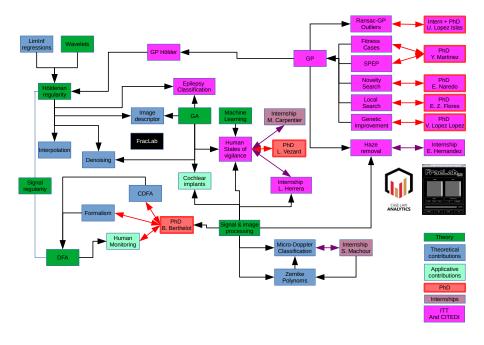


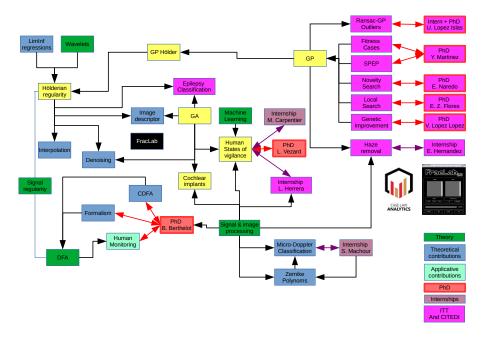












# PART 1: Artificial Evolution

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

Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming

# PART 1: Artificial Evolution

Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming

Artificial Darwinism ●○○○○○	Genetic Algorithms	Evolution Strategies	Genetic Programming

# 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	Genetic Algorithms	Evolution Strategies	Genetic Programming

#### Artificial Darwinism

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

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

Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming
A set of techniques grouped up	nder a generic term		

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

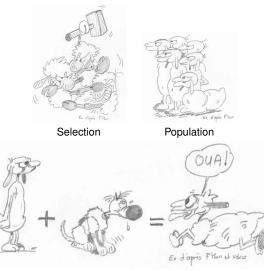
Artificial	Darwinism

Ingredients

#### Genetic Algorithms

Evolution Strategies

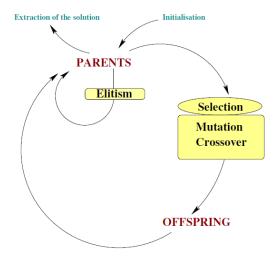
Genetic Programming



**Genetic Operators** 

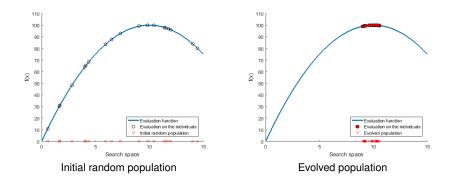
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Artificial Darwinism ○○○○●○	Genetic Algorithms	Evolution Strategies	Genetic Programming
Evolutionary loop			



Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming
Example			

Potential Solutions = Individuals in a population



Artificial Darwinism	Genetic Algorithms ●○	Evolution Strategies	Genetic Programming

# Artificial Darwinism

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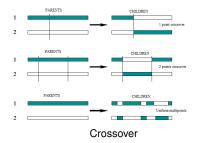
# **Genetic Programming**

Functional representation: Genetic programming Example: Using GP for regression

Artificial Darwinism	Genetic Algorithms ○●	Evolution Strategies	Genetic Programming
Discrete representation: Gener	ic Algorithms		

Each individual is represented by a binary string.

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



Mutation of the genome 010110101011111001011100101 Pm 010110101010111001011100101

Mutation

Artificial Darwinism	Genetic Algorithms	Evolution Strategies ●○	Genetic Programming

## Artificial Darwinism

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Continuous representation: Evolution Strategies

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Artificial Darwinism	Genetic Algorithms	Evolution Strategies ○●	Genetic Programming
Continuous representation: Ex	volution Strategies		

Each individual is a vector in  $\mathbb{R}^n$ .

Hans-Paul Schwefel (1970)

#### Barycentric crossover

 $\begin{aligned} \forall i \in \{1,..,n\}, x_i^{children} &= \alpha x_i^{father} + (1-\alpha) x_i^{mother} \\ \alpha \text{ random value in } [-\epsilon,1+\epsilon]. \end{aligned}$ 

#### Gaussian mutation

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

Artificial Darwinism	Genetic Algorithms	Evolution Strategies ○●	Genetic Programming
Continuous representation: Ex	volution Strategies		

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#### Demo

Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming ●○○

# 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

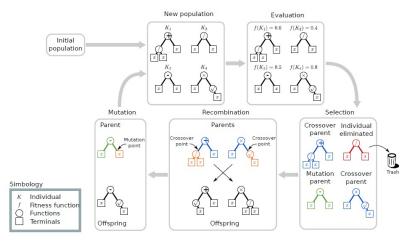
# **Genetic Programming**

Functional representation: Genetic programming Example: Using GP for regression

Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming ○●○
Functional representation: Ger	netic programming		

#### Definition

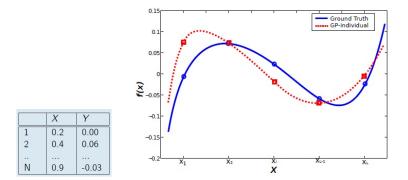
Genetic programming (GP) is an evolutionary computation (EC) technique that automatically solves problems without requiring the user to know or specify the form or structure of the solution in advance [Koza, 1992].



Artificial Darwinism	Genetic Algorithms	Evolution Strategies	Genetic Programming ○○●
Example: Using GP for regress	ion		

#### Symbolic Regression

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



# PART 2: Estimation of signal regularity

# Hölderian regularity

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# Definitions

Signal Regularity

# Estimation

Oscillations Regression of wavelet coefficients

# Application

Estimation on synthetic signal

## Definitions Signal Regularity

# Estimation

Oscillations Regression of wavelet coefficients

Application Estimation on synthetic sign

Definitions ○●	Estimation 00000	Application
Signal Regularity		

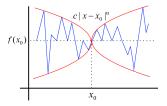
The Hölder pointwise exponent is the most common tool used to measure the regularity of a signal at a given point.

#### Definition

Let f be a function from  $\mathbb{I}$  to  $\mathbb{I}$ , s > 0,  $s \in \mathbb{I} \setminus \mathbb{N}$  and  $x_0 \in \mathbb{I}$ . 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

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

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 Signal Regularity

# Estimation

Oscillations Regression of wavelet coefficients

Application Estimation on synthetic signa

Definitions	Estimation ○●○○○	Application
Oscillations		

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,

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

In terms of oscillations, this condition can be written:

A function f(t) is Hölderian of exponent  $\alpha$  at t, with  $0 < \alpha < 1$  if there is a constant c such that for any  $\tau$ ,

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

with

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

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)

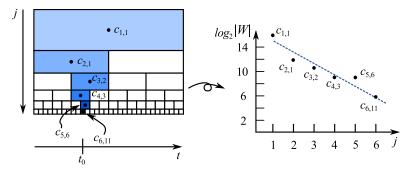
$$|c_{j,k}| \le c2^{-j(\alpha + \frac{1}{2})} (1 + |2^j t_0 - k|)^{\alpha} \quad \forall j, k \in \mathbb{Z}^2$$

Conversely ;

If 
$$\forall j,k \in \mathbb{Z}^2$$
 one has  $|c_{j,k}| \leq c2^{-j(\alpha + \frac{1}{2})}(1 + |2^jt_0 - k|)^{\alpha'}$ 

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

Definitions	Estimation ○○○●○	Application
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  $t_0$ .

Definitions	Estimation ○○○○●	Application
Regression of wavelet coefficients		

#### 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.

Definitions	Estimation ○○○○●	Application
Regression of wavelet coefficients		

#### Definition

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

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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:

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

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  $\lfloor \frac{t_0+1}{2^{n-j+1}} \rfloor.$ 

# Definitions

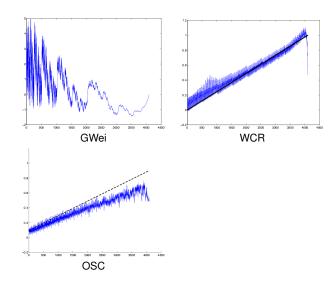
Signal Regularity

## Estimation

Oscillations Regression of wavelet coefficients

Application Estimation on synthetic signal Estimation





# PART 3: Applications

Introduction	Audition	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif	Conclusions

# Cochlear implant fitting with evolutionary algorithm

## Introduction

#### Physiological basis of audition Audition Deafness

## **Cochlear Implants**

## Cochlear implants fitting

Difficulties Manual fitting

## Interactive Evolutionary Algorithms

## Experiments

#### Classification of sound environment Wavelets and energy

Results

## Conclusions

## Introduction

Physiological basis of audition Audition Deafness

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Wavelets and energy Results

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Introduction	Audition	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif	Conclusions
•							

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.

## Introduction

#### Physiological basis of audition Audition Deafness

## **Cochlear Implants**

#### Cochlear implants fitting Difficulties

Manual fitting

## Interactive Evolutionary Algorithms

## Experiments

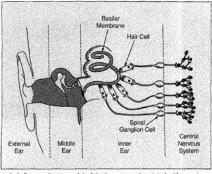
## Classification of sound environment

Wavelets and energy Results

## Conclusions

Introduction	Audition ○●○○○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions
Audition							

The external ear receives the wave of acoustic pressure.



▲ 2. A diagram (not to scale) of the human ear (reprinted with permission from [851)

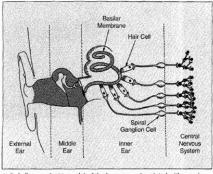
Structures du système auditif Physiologie de la cochlée Basilar membrane Basilar membrane Basilar membrane Headorma

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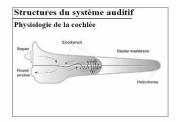
IMB/INRIA/UBX

Introduction	Audition ○●○○○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Audition							

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



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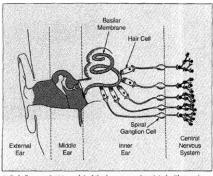


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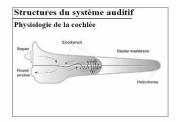
#### IMB/INRIA/UBX

Introduction	Audition ○●○○○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions
Audition							

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.



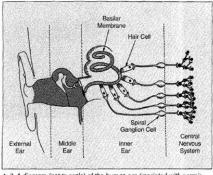
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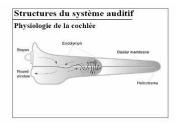
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Introduction	Audition ○●○○○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Audition							

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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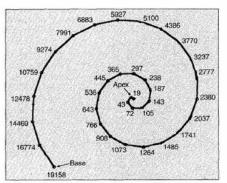
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Introduction	Audition ○○●○○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Audition							

#### 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.

Introduction	Audition ○○○●○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions	
Audition								

#### Frequencies coding

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

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#### Frequencies coding

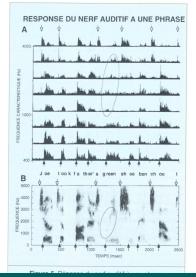
- The movement of the basilar membrane encodes information of the frequency in the acoustic signal.
- The sensory cells which are on the basilar membrane oscillate with the membrane.

Introduction	Audition ○○○●○○○	Implants	Fitting	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions
Audition							

#### 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-chimical substance which leads to discharge the neurons. Then these electrical impulses correspond to an excitation at a given position on the basilar membrane.

Introduction	Audition ○○○○●○○	Implants	Fitting	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Audition							

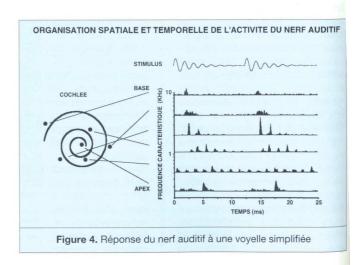


**Example : Transmission to the brain.** The acoustic information is conveyed to

the brain by electric impulses.

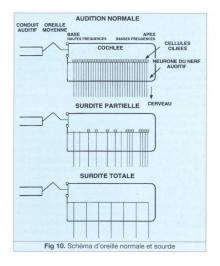
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Deafness						

#### Temporal and frequential informations



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

## Introduction

Physiological basis of audition Audition Deafness

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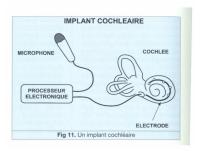
## Conclusions

Introduction	Audition	Fitting	Evolutionary Algorithm	Experiments	Classif	Conclusions

#### Cochlear implant

#### Goal :

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



Introduction	Audition	Fitting	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions

Cochlear implants allow to deaf people to hear again if

• The auditive nerve is not damaged.

Introduction	Audition	 Fitting	Evolutionary Algorithm	Experiments	Classif	Conclusions

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Introduction	Audition	Implants ○○●○	Fitting	Evolutionary Algorithm	Experiments	Classif	Conclusions

Cochlear implants allow to deaf people to hear again if

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

Most of the implantations are successful

Introduction	Audition	 Fitting	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions

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• The auditive nerve is not damaged.

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- · Possibility to hear again

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- Most of the implantations are successful
- Possibility to hear again
- Possibility to hear during a phone call

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- Most of the implantations are successful
- · Possibility to hear again
- Possibility to hear during a phone call
- Possibility to listen to music.
- But some people still encounter difficulties and they prefer to turn off the implant.

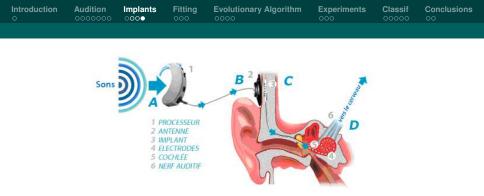
Cochlear implants allow to deaf people to hear again if

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

- Most of the implantations are successful
- Possibility to hear again
- Possibility to hear during a phone call
- Possibility to listen to music.
- 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.

## Introduction

Physiological basis of audition Audition Deafness

## **Cochlear Implants**

#### Cochlear implants fitting Difficulties Manual fitting

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Difficulties							

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Introduction	Audition	Implants	Fitting ○●○	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Difficulties							

• Which frequency for each electrode ?

Introduction	Audition	Implants	Fitting ○●○	Evolutionary Algorithm	Experiments	Classif 00000	Conclusions
Difficulties							

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

Introduction	Audition	Implants	Fitting ○●○	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions
Difficulties	ļ	ļ	ļ	l .	i .	ļ ,	i .

- Which frequency for each electrode ?
- Which intensity range for each electrode ?
- How many electrodes simultaneously activated ?

Introduction	Audition	Implants	Fitting ○●○	Evolutionary Algorithm	Experiments	<b>Classif</b> 00000	Conclusions
Difficulties	ļ	ļ	ļ	l .	i .	ļ ,	i .

### Complexity

- Which frequency for each electrode ?
- Which intensity range for each electrode ?
- How many electrodes simultaneously activated ?
- Should we avoid the activation of two consecutive electrodes ?

• ...

Introduction	Audition	Implants	Fitting ○●○	Evolutionary Algorithm	Experiments	Classif	Conclusions
Difficulties							

### Complexity

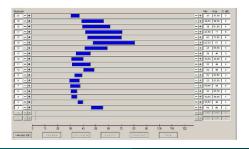
- Which frequency for each electrode ?
- Which intensity range for each electrode ?
- How many electrodes simultaneously activated ?
- Should we avoid the activation of two consecutive electrodes ?

• ...

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**...

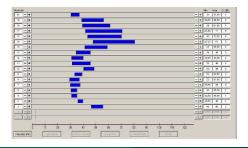
Introduction	Audition	Implants	Fitting ○○●	Evolutionary Algorithm	Experiments	Classif	Conclusions
Manual fitting		ļ					

• Determinate the functional electrodes.



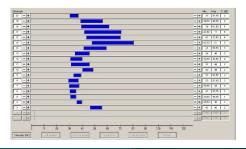
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Manual fitting							

- Determinate the functional electrodes.
- Determinate the intensity thresholds T (threshold) and C (comfort).



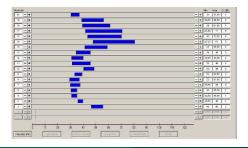
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- Determinate the functional electrodes.
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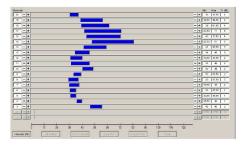
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# The results are often good but the complete process can take years for some patients.



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#### 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. An interactive evolutionary algorithm is a classical evolutionary algorithm with a fitness function given by a human.

### Contribution: Interactive Evolutionary Algorithm

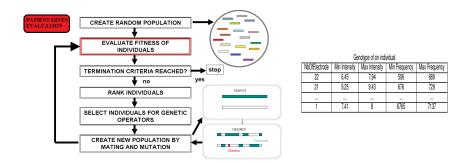
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### Algorithm

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### On mobile device

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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/.

### 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

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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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### Steps

• Determinate the sound environment of the patient.

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- Simplify the process of fitting of cochlear implants.
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- Develop a tool to recognize a previously recorded environment.
- **Record** the corresponding fitting of the prothesis.
- Fit the prothesis automatically to the environment.

### Result : A "smart" cochlear implant.

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#### Wavelets and energy

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

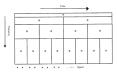
#### Wavelet coefficient

 $C_{j,k}$  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

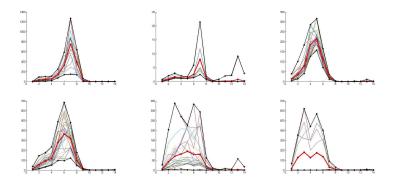




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#### Characterization of sound environments



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).

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### 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%

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### Exploitation of the results

• If an environment is "recognized" with a probability of being in a class higher than 50% then the fitting corresponding to this class is sent into the prothesis.

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- The programming on pocket PC simplify the use of the developed softwares.

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# Conclusion

- 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. EEG data Acquisition Acquisition Protocole

Feature Extraction Slope Criterion

Evolutionary Algorithm Design Results

# Goal

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

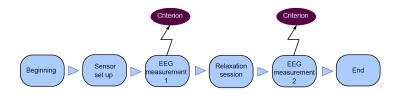
EEG data Acquisition Acquisition Protocole

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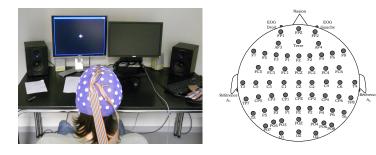
- First EEG recording: subject in a normal state of alertness: "normal"
- Second EEG recording: subject in a state of low vigilance: "relax"



Feature Extraction

Evolutionary Algorithm

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

Feature Extraction

Evolutionary Algorithm

# 3 minutes of EEG recording before relaxation.

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Feature Extraction

#### Acquisition Protocole

# 3 minutes of EEG recording after relaxation.

#### Alpha waves

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Pierrick Legrand

IMB/INRIA/UBX

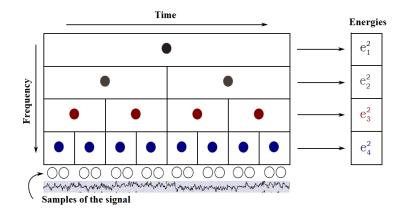
EEG data Acquisition Acquisition Protocole

# Feature Extraction Slope Criterion

Evolutionary Algorithm Design Results

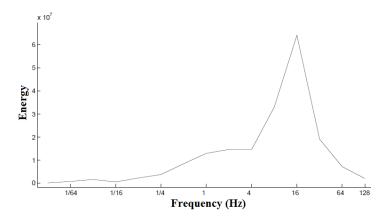
EEG data Acquisition	Feature Extraction ○●○○○○	Evolutionary Algorithm
Slope Criterion		

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



# - Alpha: 8 - 12Hz.

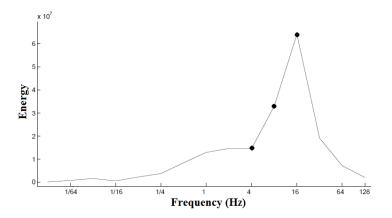
- Waves characteristics of a relaxed state.



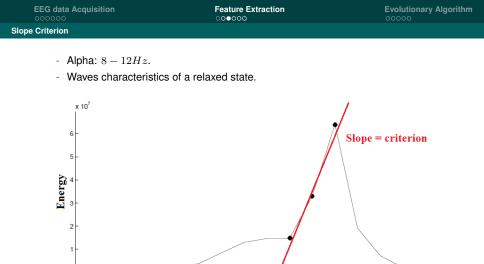
Linear regression between 4 and 16Hz.

# - Alpha: 8 - 12Hz.

- Waves characteristics of a relaxed state.



Linear regression between 4 and 16Hz.



Linear regression between 4 and 16Hz.

1/16

1/4

1/64

0

Frequency (Hz)

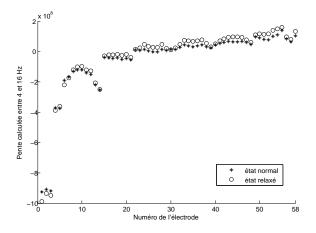
16

4

64 128

# Feature Extraction

#### Slope Criterion

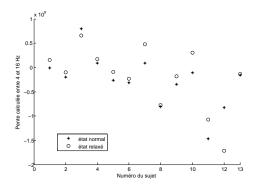


Slope criterion, sum on subjects for each electrode

Pierrick Legrand IMB/INRIA/UBX

Feature Extraction ○○○○●○ Evolutionary Algorithm

#### Slope Criterion



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.

EEG data Acquisition

Feature Extraction ○○○○○● Evolutionary Algorithm

**Slope Criterion** 

## Classification: Usual methods

	K nearest	Binary	Random	Discriminant	Sparse Discriminant
	neighbors	decision trees	forests	PLS	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.

EEG data Acquisition Acquisition Protocole

Feature Extraction Slope Criterion

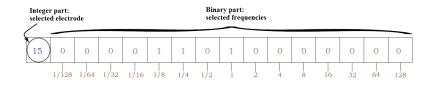
Evolutionary Algorithm Design Results EEG data Acquisition

Feature Extraction

Evolutionary Algorithm

Design

# Example of a genome in the evolutionary algorithm



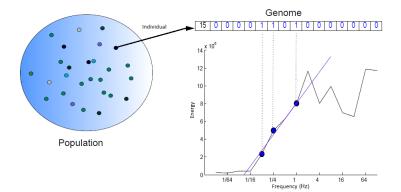
EEG	data	Acquisition

Feature Extraction

Evolutionary Algorithm

Design

# Relationship between the genome and the calculation of the slope criterion



EEG	data	Acq	uisition

Feature Extraction

Results

## Average correct classification rate

Evaluation	CCR		
Method	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.

#### Results

## Best genome

Evaluation	BEST genome		
method	Selected	Selected	Correct classification
	electrode	frequency (Hz)	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

Hölderian Regularity

Contribution Training set

Results

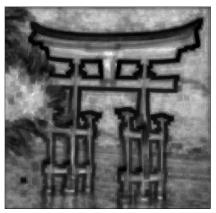
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Contribution	

# Hölder exponent

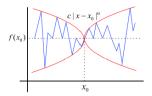
Mathematical tool that measures the regularity of a signal around each point.





Hölderian Regularity	Contribution	Results
000	00000	00

# General motivation



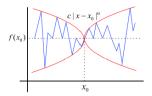
$$\alpha_p(x_0) = \liminf_{h \to 0} \frac{\log |f(x_0 + h) - f(x_0)|}{\log |h|}$$

Hölderian envelope of signal f at point  $x_0$ 

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

Hölderian Regularity	Contribution	Results
000	00000	00

## General motivation



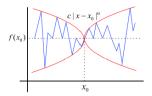


Hölderian envelope of signal f at point  $x_0$ 

- 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;

Hölderian Regularity ○○●	Contribution	Results
	00000	00

# 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.
- 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

• Evolve estimators of the pointwise Hölder exponent for 2D signals with Genetic Programming.

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- GP evolves estimators that are **accurate** and **fast**.

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- · Evolution is a one-shot process, evolved estimators can be used easily.

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- GP evolves estimators that are **accurate** and **fast**.
- · Evolution is a one-shot process, evolved estimators can be used easily.

# 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:

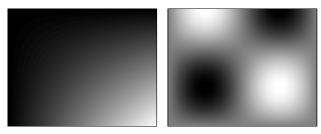
1 a Polynomial 
$$p_1(x, y) = 0.1 + 0.8xy;$$

**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  $p_1$ 

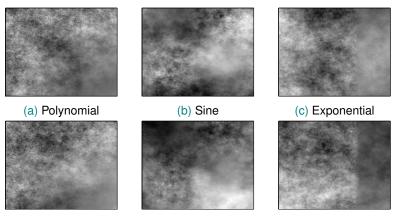




(c) Exponential  $p_3$ 

Training set

#### Contribution ○○○○●



(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 ○●

# **Results: Real Images**



**Original Image** 



**GP-Estimator** 



**Traditional Method** 



**GP-Estimator**