

Inria

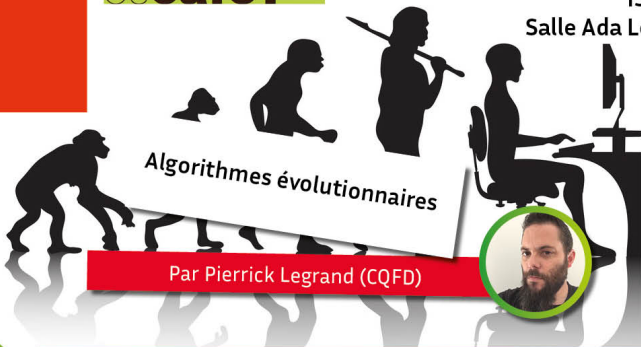
UNI**thé**
OU**café?**

Accessible à tout le monde

Vendredi 12 avril 2019

13h à 14h

Salle Ada Lovelace



Algorithmes évolutionnaires

Par Pierrick Legrand (CQFD)

DÉVELOPPEMENTS ET APPLICATIONS INSPIRÉS DU DARWINISME ARTIFICIEL



Evolutionary Algorithms. Developments and applications inspired by Darwinism

Pierrick Legrand

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Université de Bordeaux

April 2019, 12

PART 1: Artificial Evolution

Inria, CQFD Team
IMB, Institut de Mathématiques de Bordeaux, UMR CNRS 5251
Université de Bordeaux

April 2019, 12

Images courtesy of E. Lutton.

Darwinism

Artificial Darwinism

Evolutionary engine

Genetic Algorithms

Evolution strategies

Genetic Programming

Black Box problem solving

Darwinism

Artificial Darwinism

Evolutionary engine

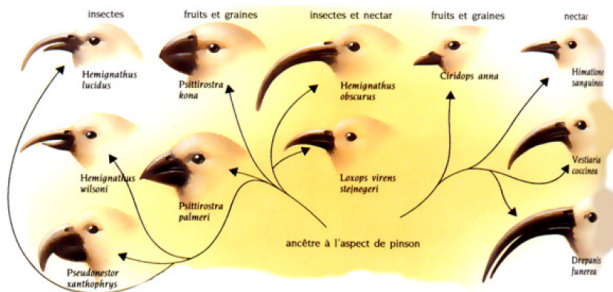
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The Darwin Finch



Simple mechanisms

- 1 Variations, macroscopic and microscopic, within species.
- 2 Fight for survival.
- 3 Natural selection: triumph of the lineage that has a useful variation in its environment.

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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

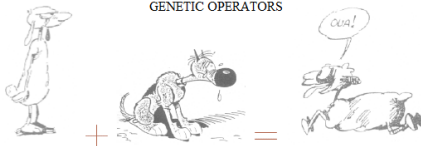
POPULATION



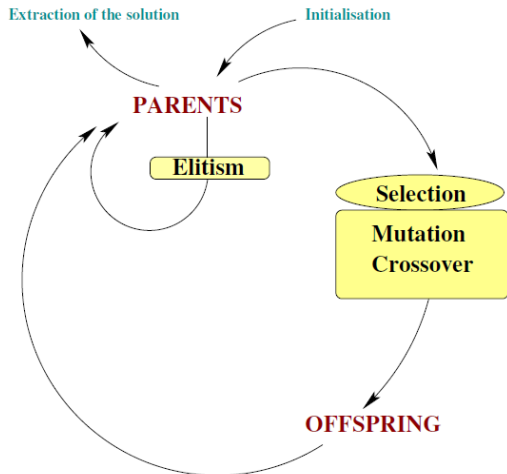
SELECTION



GENETIC OPERATORS

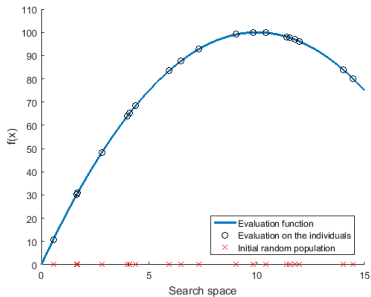


Evolutionary loop

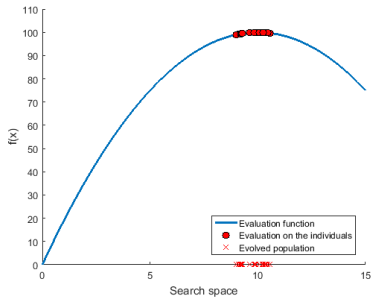


Optimize an "adaptation to the environment"

Potential Solutions = Individuals in a population



Initial random population



Evolved population

Vocabulary

Evolutionary algorithms	Optimization methods
individual	solution
population	set of solutions
chromosome	coding of the solution
crossing or recombination	operation on two codes
mutation	operation on a code
environment	search space
degree of adaptation to the "Fitness" environment	value of the evaluation function
evolution	maximizing the evaluation function

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The evolutionary engine

- 1 Evaluation:** estimate the quality of an individual.
→ "Fitness", "performance", "evaluation function", "adaptation to the environment".
- 2 Selection:** select the best individuals.
→ roulette wheel, selection on the rank, by tournament.
- 3 Reproduction:** apply genetic operators, crossover and mutations, with probabilities P_c and P_m .
- 4 Replacement:** to make the next generation.
→ elitism, percentage of population renewal, strategies $(\mu + \lambda)$ or (μ, λ) .

Initialisation / End of the process

Initialisation

- Sampling of the search space (random, regular)
- introduction of initial solutions
- restrictions on the search space

Stop

After N generations or after convergence...

Extraction of the solutions

The best individual of the last generation !

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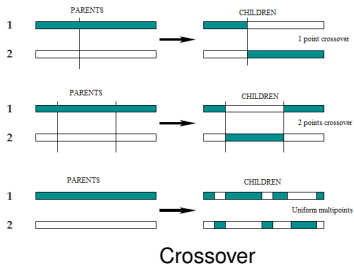
Genetic Programming

Black Box problem solving

Discrete representation: Genetic Algorithms

Each individual is represented by a binary string.

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



Mutation of the genome

0101101010111111001011100101



P_m

0101101010101111001011100101

Mutation

Darwinism

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Black Box problem solving

Continuous representation: Evolution Strategies

Each individual is a vector in R^n .

Hans-Paul Schwefel (1970)

Barycentric crossover

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

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

Gaussian mutation

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

Two parameters P_m and σ .

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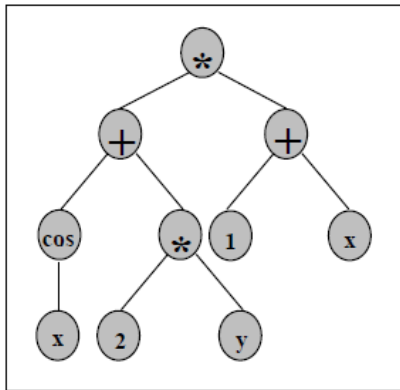
Genetic Programming

Black Box problem solving

Functional representation: Genetic programming

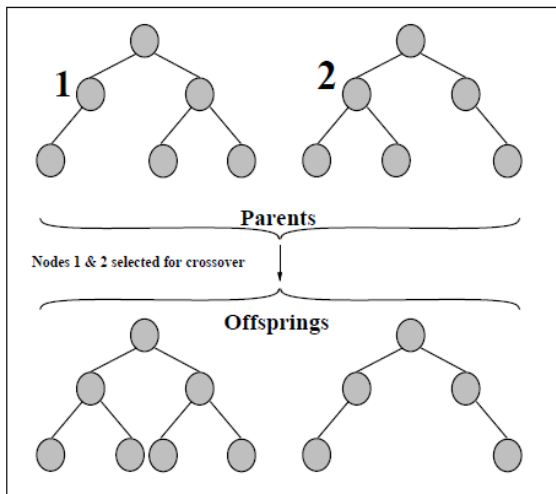
Create programs without programming !
Tree representation

John Koza (1990)

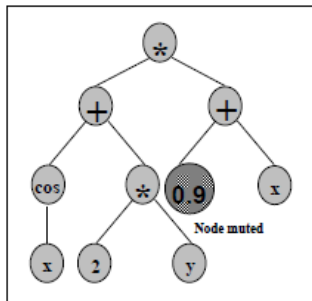
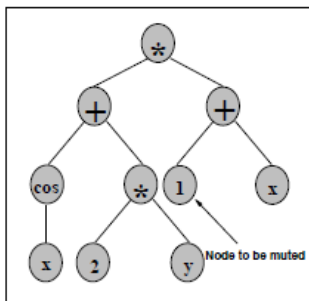


Function $(\cos(x) + 2y)(1 + x)$

GP Crossover



GP Mutation



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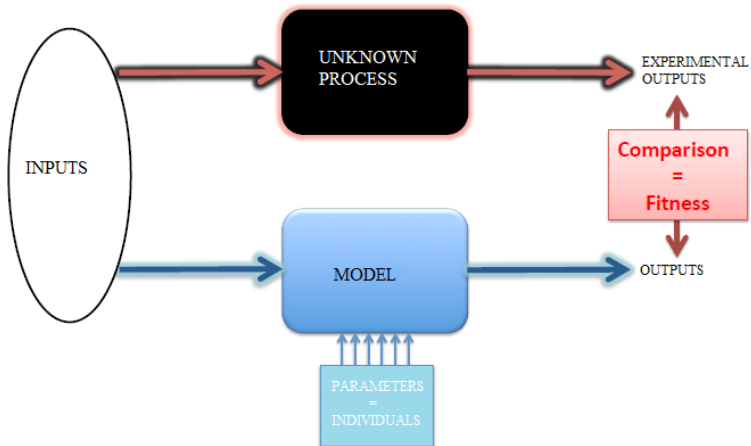
Genetic Algorithms

Evolution strategies

Genetic Programming

Black Box problem solving

Black box inverse problems solving



PART 2: Cochlear implant fitting with evolutionary algorithm

Inria, CQFD Team
IMB, Institut de Mathématiques de Bordeaux, UMR CNRS 5251
Université de Bordeaux

April 2019, 12

Joint work with Vincent Pean, Evelyne Lutton, Claire Bourgeois-Republique, Bruno Frachet, Jacques Levy-Vehel, and Pierre Collet. **RNTS PROJECT 04T550 HEVEA.**

Introduction

Physiological basis of audition

Audition

Deafness

Cochlear Implants

Cochlear implants fitting

Difficulties

Manual fitting

Interactive Evolutionary Algorithms

Experiments

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Interactive Evolutionary Algorithms

Experiments

This project is a collaboration between mathematicians, computer scientists and medical practitioners. The following institutions are involved in this project:

- Hopital Avicenne (B. Frachet)
- Innotech (V. Péan)
- Institut de Mathématiques and University of Bordeaux (P. Legrand)
- INRIA Bordeaux, CQFD TEAM (P. Legrand)
- INRIA Saclay, AVIZ TEAM (E. Lutton)
- INRIA Saclay, REGULARITY TEAM (J. Levy-Vehel)
- MXM-Neurelec
- University of Bourgogne (C. Bourgeois-Republique)
- University of Strasbourg (P. Collet)

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.

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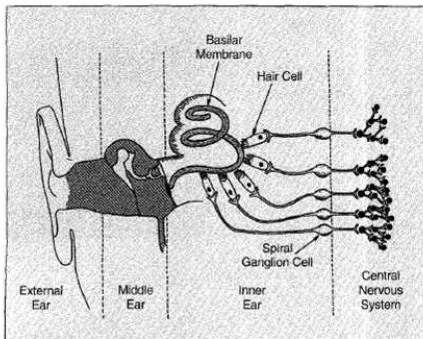
Interactive Evolutionary Algorithms

Experiments

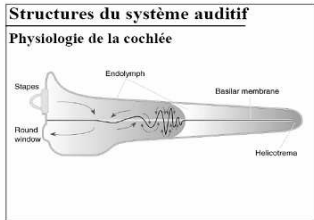
Audition

Transmission of sound to the cochlea

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



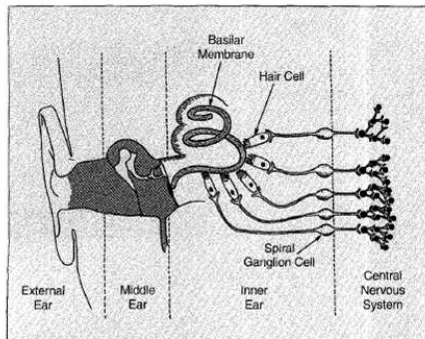
▲ 2. A diagram (not to scale) of the human ear (reprinted with permission from [85]).



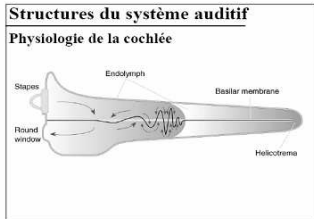
Audition

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.



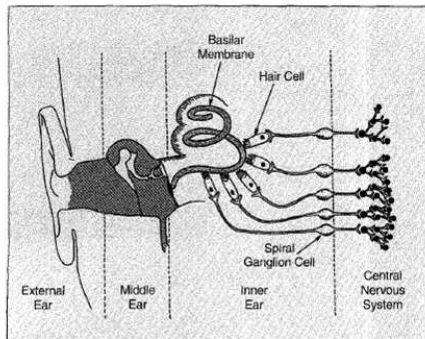
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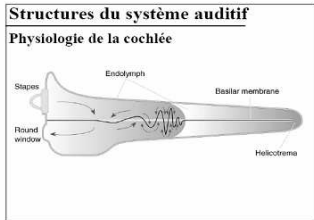
Audition

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.



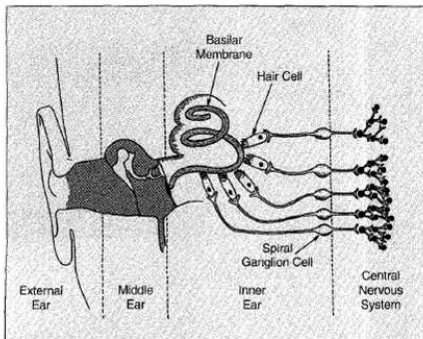
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Audition

Transmission of sound to the cochlea

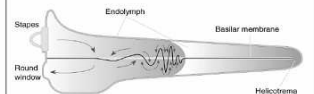
The **external ear** receives the wave of acoustic pressure. The **middle ear** transforms the acoustic wave onto a mechanical vibration. This mechanical vibration moves the oval window (which is connected to the middle ear) and the fluid contained in the **cochlea** is set into motion. The variations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



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Structures du système auditif

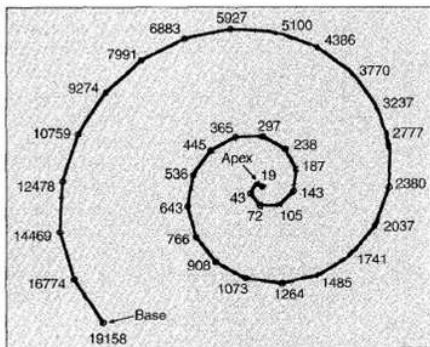
Physiologie de la cochlée



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.

Coding of the auditive nerve

Frequencies coding

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

Frequencies coding

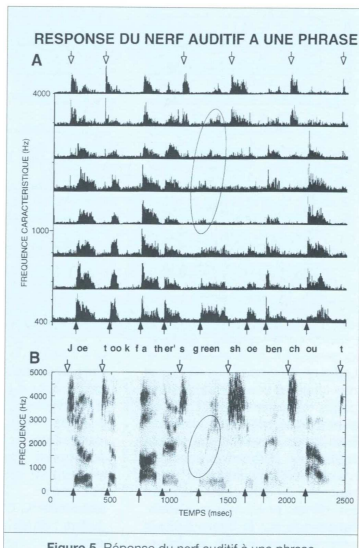
- The movement of the basilar membrane encodes information of the frequency in the acoustic signal.
- The sensory cells which are on the basilar membrane oscillate with the membrane.

Frequencies coding

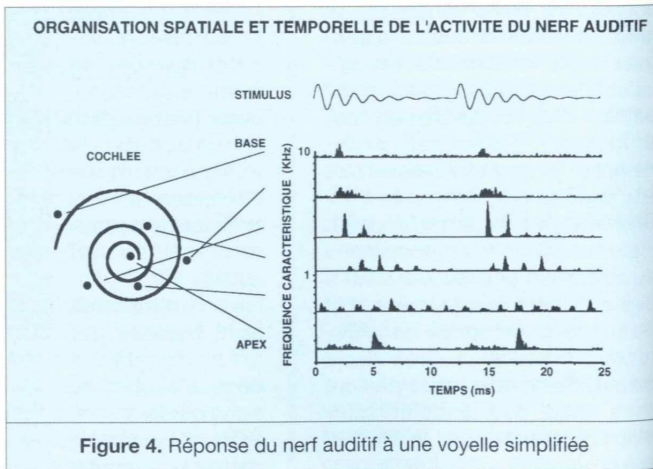
- The movement of the basilar membrane encodes information of the frequency in the acoustic signal.
- The sensory cells which are on the basilar membrane oscillate with the membrane.
- The movement of the sensory cells liberates an electro-chemical substance which leads to discharge the neurons. Then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

Audition

Coding of the auditory nerve

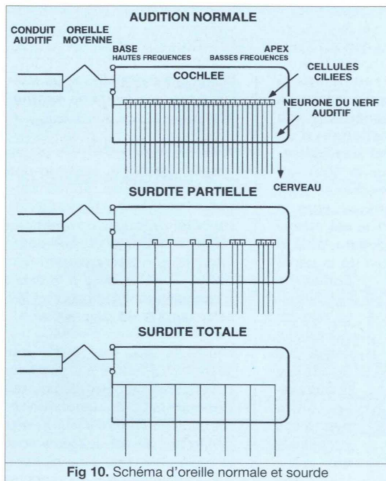


Example : Transmission to the brain.
The acoustic information is conveyed to the brain by electric impulses.



Deafness

Temporal and frequential informations



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

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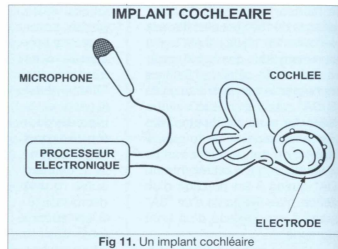
Interactive Evolutionary Algorithms

Experiments

Cochlear implant

Goal :

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



Necessary conditions

Cochlear implants allow to deaf people to hear again if

- The auditive nerve is not damaged.

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- 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.

Necessary conditions

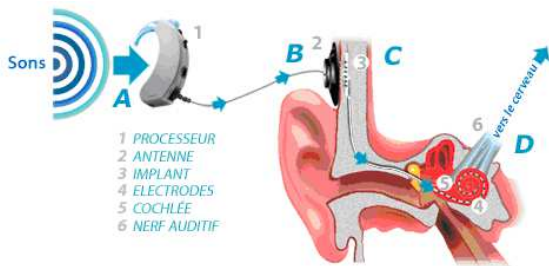
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- Most of the implantations are successful
- Possibility to hear again
- Possibility to hear during a phone call
- Possibility to listen to music.
- **But some people still encounter difficulties** and they prefer to turn off the implant.

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.

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Complexity

Complexity

- Which frequency for each electrode ?

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- Which intensity range for each electrode ?

Complexity

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

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 ?
- ...

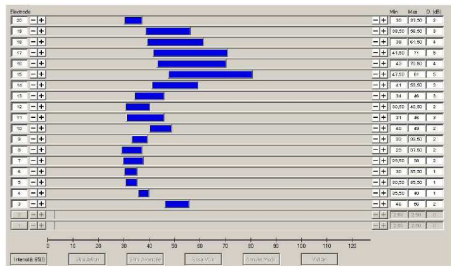
Complexity

- 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...**

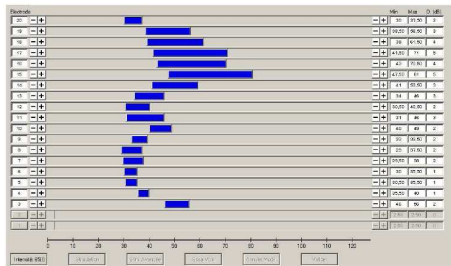
Fitting of the electrodes

- Determinate the functional electrodes.



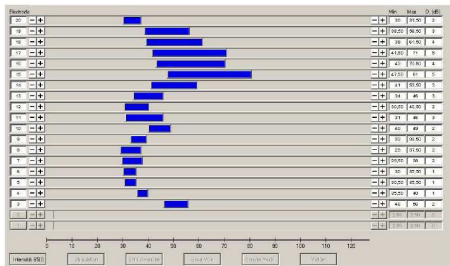
Fitting of the electrodes

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



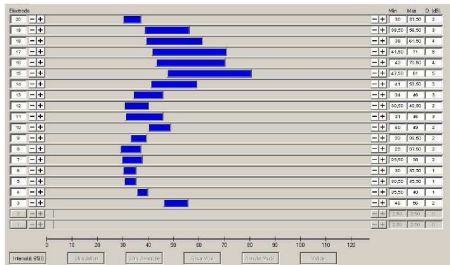
Fitting of the electrodes

- Determinate the functional electrodes.
- Determinate the intensity thresholds T (threshold) and C (comfort).
- The practitioner distributes logarithmically the frequency bands on the electrodes (by his background).



Fitting of the electrodes

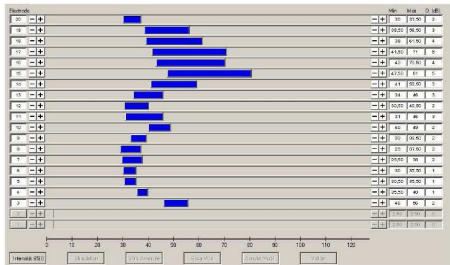
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- The practitioner distributes logarithmically the frequency bands on the electrodes (by his background).
- Then many tests with the patient.



Fitting of the electrodes

- Determinate the functional electrodes.
- Determinate the intensity thresholds T (threshold) and C (comfort).
- The practitioner distributes logarithmically the frequency bands on the electrodes (by his background).
- Then many tests with the patient.

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.

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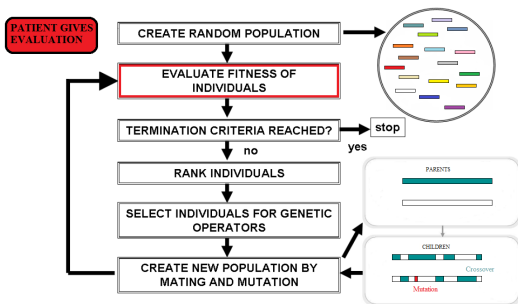
The potential solutions of the problem are individuals in a population.

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.

The potential solutions of the problem are individuals in a population.



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).

Automatic fitting method

Algorithm

- Manual fitting by an expert (for this patient).
- **Initial Population** : 4 parents (=4 fittings P_1, P_2, P_3, P_4) randomly generated (in the range $[T, C]$ of each electrode).

Automatic fitting method

Algorithm

- Manual fitting by an expert (for this patient).
- **Initial Population** : 4 parents (=4 fittings P_1, P_2, P_3, P_4) randomly generated (in the range $[T, C]$ of each electrode).
- **Evaluation** of the population by the patient during auditive tests (VCV and ASSE). Each individual obtains an evaluation : N_1, N_2, N_3, N_4 .

Automatic fitting method

Algorithm

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- **Generation of children** (3 individuals, E_1, E_2, E_3). Two individuals are randomly selected, the best is selected with a high probability. The previous selection is repeated. In this way, two individuals are selected and then crossed in order to obtain a child. This child undergo mutation with a probability pm .

Automatic fitting method

Algorithm

- Manual fitting by an expert (for this patient).
- **Initial Population** : 4 parents (=4 fittings $P1, P2, P3, P4$) randomly generated (in the range $[T, C]$ of each electrode).
- **Evaluation** of the population by the patient during auditive tests (VCV and ASSE). Each individual obtains an evaluation : $N1, N2, N3, N4$.
- **Generation of children** (3 individuals, $E1, E2, E3$). Two individuals are randomly selected, the best is selected with a high probability. The previous selection is repeated. In this way, two individuals are selected and then crossed in order to obtain a child. This child undergo mutation with a probability pm .
- **Evaluation** of the 3 children by the patient: $NE1, NE2, NE3$.

Automatic fitting method

Algorithm

- Manual fitting by an expert (for this patient).
- **Initial Population** : 4 parents (=4 fittings P_1, P_2, P_3, P_4) randomly generated (in the range $[T, C]$ of each electrode).
- **Evaluation** of the population by the patient during auditive tests (VCV and ASSE). Each individual obtains an evaluation : N_1, N_2, N_3, N_4 .
- **Generation of children** (3 individuals, E_1, E_2, E_3). Two individuals are randomly selected, the best is selected with a high probability. The previous selection is repeated. In this way, two individuals are selected and then crossed in order to obtain a child. This child undergo mutation with a probability pm .
- **Evaluation** of the 3 children by the patient: NE_1, NE_2, NE_3 .
- **Generation** of the new population among $P_1, P_2, P_3, P_4, E_1, E_2, E_3$. Random selection of 2 individuals, selection of the best evaluation. A new population is obtained: F_1, F_2, F_3 and F_4 .

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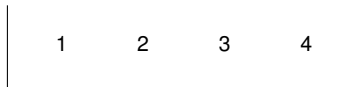
Interactive Evolutionary Algorithms

Experiments

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

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.

PART 3: Evolutionary computation for EEG classification

Inria, CQFD Team
IMB, Institut de Mathématiques de Bordeaux, UMR CNRS 5251
Université de Bordeaux

April 2019, 12

Joint work with Marie Chavent, Frédérique Faïta and Laurent Vezard

EEG data Acquisition

Acquisition Protocole

Feature Extraction

Slope Criterion

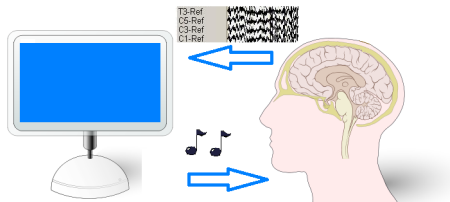
Evolutionary Algorithm

Design

Results

Goals

- **Characterize the state of alertness of a person from his electroencephalogram (EEG).**
- Create a brain-computer interface.
- Influence a person's state of alertness with synthesized music.



EEG data Acquisition

Acquisition Protocole

Feature Extraction

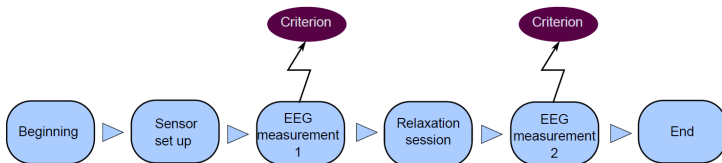
Slope Criterion

Evolutionary Algorithm

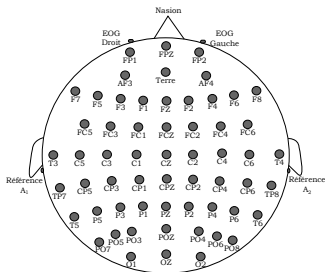
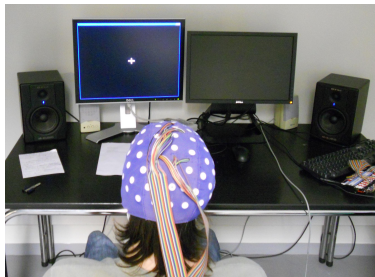
Design

Results

- 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:

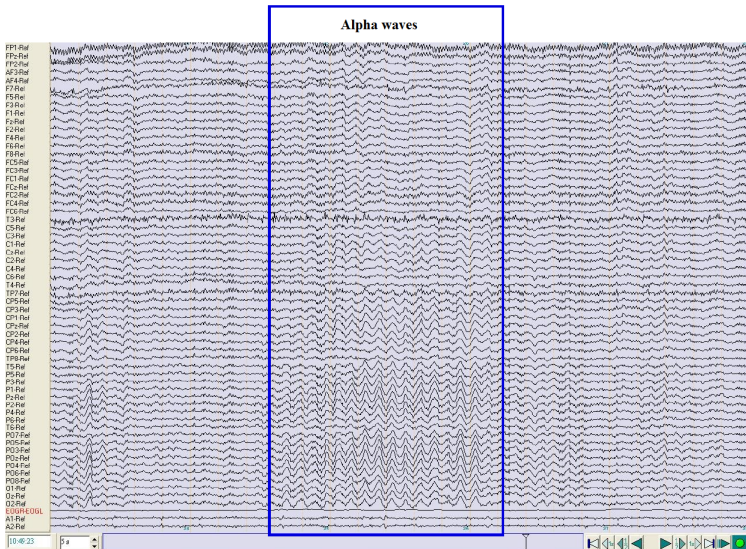
- 58 electrodes renumbered from 1 to 58
- Subjects under 35, right-handed and non-smoker
- 58 subjects ⇒ 16 preserved

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).

3 minutes of EEG recording **after relaxation**.



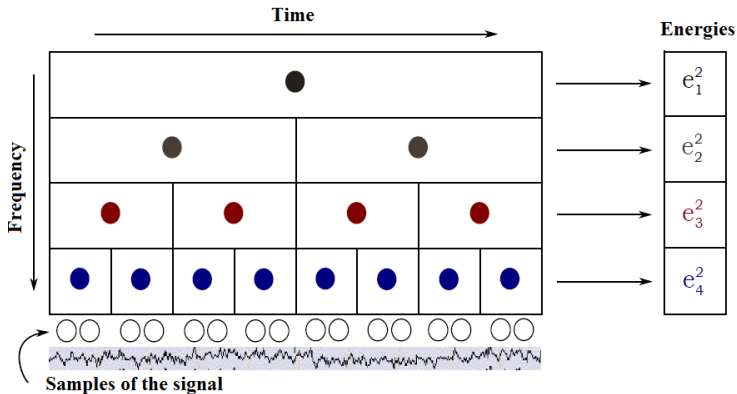
EEG data Acquisition
Acquisition Protocole

Feature Extraction
Slope Criterion

Evolutionary Algorithm
Design
Results

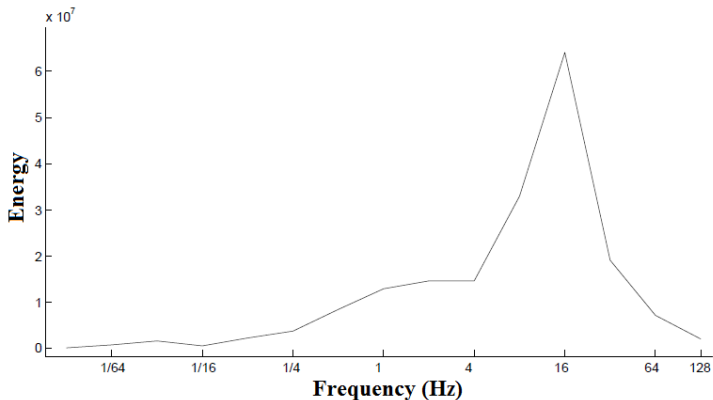
Slope Criterion

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



Slope Criterion

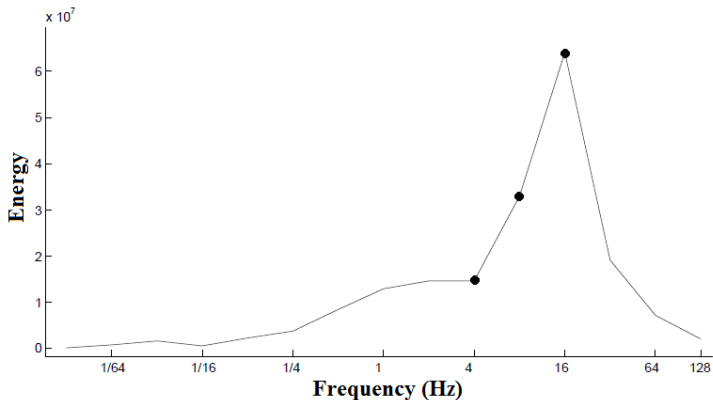
- Alpha: $8 - 12Hz$.
- Waves characteristics of a relaxed state.



Linear regression between 4 and $16Hz$.

Slope Criterion

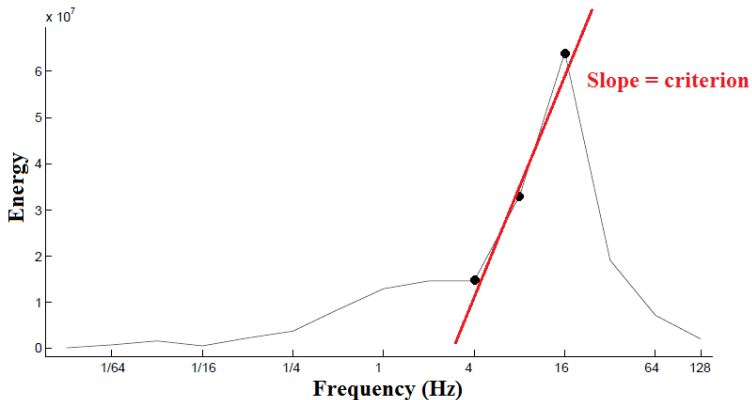
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Linear regression between 4 and 16 Hz.

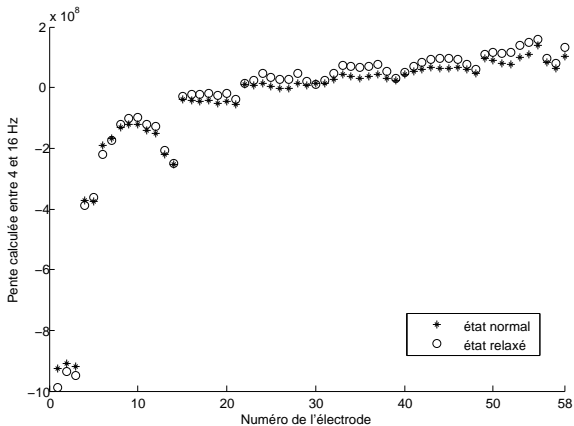
Slope Criterion

- Alpha: 8 – 12Hz.
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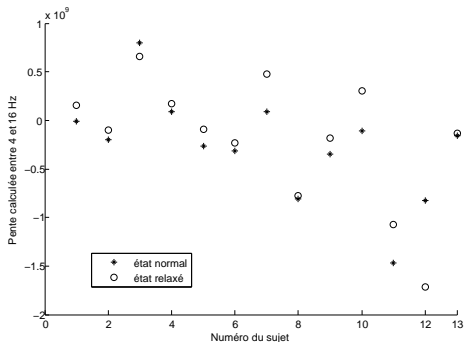
Linear regression between 4 and 16Hz.

Slope Criterion



Slope criterion, sum on subjects for each electrode

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.

Slope Criterion

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.

⇒ **Find the relevant electrodes.**

⇒ **Find the relevant frequencies for the calculation of the slope criterion.**

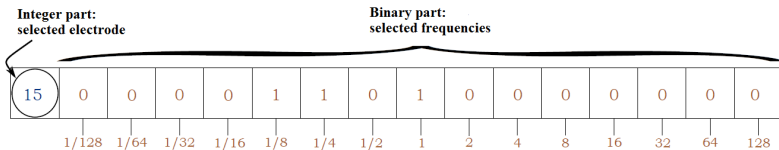
EEG data Acquisition
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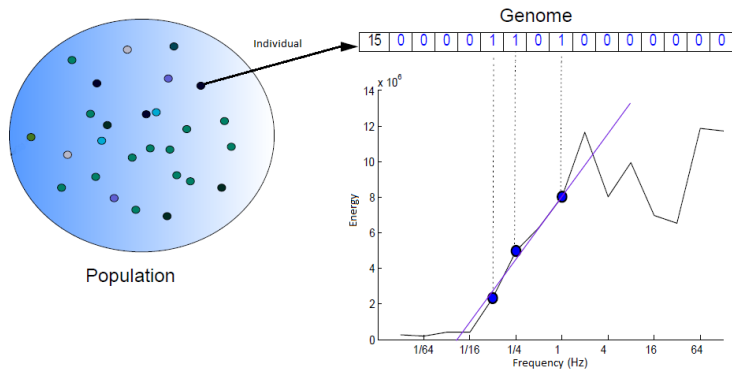
Design

Example of a genome in the evolutionary algorithm



Design

Relationship between the genome and the calculation of the slope criterion



Results

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.

Results

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.

PART 4: Regularity estimation with Genetic Programming

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IMB, Institut de Mathématiques de Bordeaux, UMR CNRS 5251
Université de Bordeaux

April 2019, 12

Joint work with Leonardo Trujillo, Gustavo Olague and Jacques Levy-Vehel

Introduction

Hölderian Regularity

Contribution

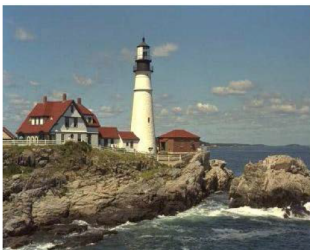
Introduction

Hölderian Regularity

Contribution

Signal Regularity

- In science and engineering there is one fundamental task: Analyzing and processing signals (natural or artificial) to extract useful information.
- Signals can be too big; where is the information located?
- Usually its smart to focus where signal variation is high (for visual data, you can think of borders, corners and textured areas)



O. Le Meur, P. Le Callet, D. Barba, and D. Thoreau.

A Coherent Computational Approach to Model Bottom-Up Visual Attention.

IEEE Trans. Pattern Anal. Mach. Intell. 28, 5 (May 2006), 802-817.

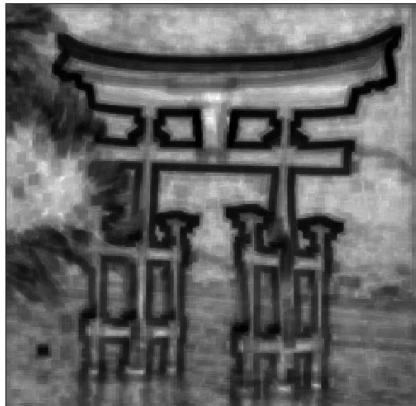
Introduction

Hölderian Regularity

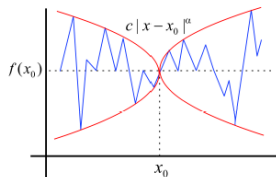
Contribution

Hölder exponent

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



General motivation



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

Hölderian envelope of signal f at point x_0

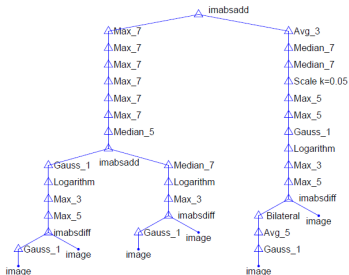
- For real-world signals the Hölder exponent must be estimated for each point.
- Several estimation methods exist, but most methods are SLOW or highly parameterized;
- Therefore their use is not common (particularly in computer vision applications where speed can be of importance)

Introduction

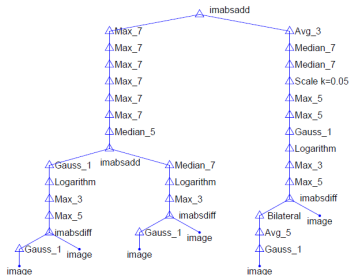
Hölderian Regularity

Contribution

- Evolve estimators of the pointwise Hölder exponent for 2D signals with Genetic Programming!
- GP evolves estimators that are ACCURATE and FAST!
- Evolution is a one-shot process, evolved estimators can be used of-the-shelf!



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- *Leonardo Trujillo, Pierrick Legrand, Gustavo Olague, and Jacques Levy-Vehel. 2012. Evolving estimators of the pointwise Hölder exponent with Genetic Programming. Information Sciences 209 (Nov. 2012), 61-79.*
- *Humies Award Finalist, GECCO 2013.*

Results: Real Images



Original Image



Traditional Method



GP-Estimator



GP-Estimator

Thank you for your attention

